Integrated Productive and Ergonomic Workplace Design in Construction

by

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Abstract

As the construction industry is prone to various hazards, its rate of injuries and fatalities are among the highest. As a result, health and safety has emerged as a crucial aspect of any construction project. Among occupational injuries, Work-related Musculoskeletal Disorders (WMSDs) are reported as the leading cause of disabilities and days away from work. WMSDs are not only associated with worker injuries and discomfort but also impose high costs, diminish productivity, increase absenteeism, lower quality, and decrease job satisfaction. WMSDs can be prevented through ergonomics, which aims to eliminate injuries and disorders associated with overuse of muscles, awkward posture, and repeated motions, by fitting workplace conditions and job demands to worker capacity. However, current practice in workplace design often focuses on productivity improvements rather than on enhancing ergonomic safety. This occurs in spite of the fact that, when ergonomic principles are not fully implemented, the benefits of increased productivity are likely offset by increased medical and workers' compensation costs as well as lost productivity (e.g., absenteeism). Notably, safety and productivity are highly associated, and actions carried out to improve performance can adversely or positively impact safety (and vice versa). However, current approaches used in construction lack the concurrent integration of both production and safety into workplace and operation design and do not fully consider the high association between the two. Thus, this study explores an integrated approach to workplace and labor operation evaluation and design by incorporating both productivity and ergonomic safety into a comprehensive analysis. Such integration enables examination of the trade-off between ergonomic risk and productivity of labor operations, which can potentially provide a framework for designing work environments where not only WMSDs

are prevented but optimum efficiency is also achieved. It also enhances the understanding of safety in conjunction with work environments and production plans in the interest of human well-being in the workplace.

To integrate productivity and safety into workplace evaluation and design, the following stages must be completed: (1) analysis of ergonomic risks associated with worker activities; (2) evaluation of the efficiency of labor operations through motion-level modeling; (3) examination of the causal relationship between production tasks and ergonomic behavior in construction operations; (4) development of a comprehensive framework that integrates data collection, analysis, and results representation while enabling the comparison of different operations scenarios in terms of performance and safety.

To achieve a reliable ergonomic assessment of labor operations, this study uses motion capture data in conjunction with 3D modeling of workplaces to enable an automated ergonomic and biomechanical analysis of existing and non-existing operations. Furthermore, to provide the means to model manual operations at a motion level, the integration of Predetermined Motion Time Systems (PMTSs), which enables cycle time estimation and efficiency evaluation of manual processes, into simulation modeling is examined. Finally, a framework that uses sensing and action recognition for data acquisition, biomechanical simulation, and PMTS-based modeling for efficiency and safety analysis and worker motion generation, path planning, and as-is modeling for visualization and representation of the analysis results is developed. Such a framework enables an automated and reliable evaluation of both efficiency and ergonomic safety of labor operations simultaneously.

Preface

This thesis is an original work by Alireza Golabchi and follows a paper-based format. Various chapters, or portions thereof, have been published or are in revision in peer-reviewed journals.

A version of **Chapter 3** is published as Golabchi, A., Han, S., Seo, J., Han, S., Lee, S., and Al-Hussein, M. (2015). "An Automated Biomechanical Simulation Approach to Ergonomic Job Analysis for Workplace Design." *Journal of Construction Engineering and Management*, 141(8), 04015020, and has been reprinted with the permission of the American Society of Civil Engineers (ASCE). Alireza Golabchi was responsible for concept formation, data collection and analysis, as well as manuscript composition. SangHyeok Han created the workplace 3D model and motion extraction. JoonOh Seo assisted with the linkage of motion capture data to biomechanical analysis. SangUk Han, SangHyun Lee, and Mohamed Al-Hussein had a supervisory role, contributed to concept formation, and performed manuscript edits.

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Chapter 1 Introduction

1.1 BACKGROUND AND PROBLEM STATEMENT

Work-related Musculoskeletal Disorders (WMSDs) have been reported as the leading cause of nonfatal occupational injuries resulting in disabilities and days away from work (Bureau of Labor Statistics 2016). WMSDs are injuries or disorders of the muscles, nerves, tendons, joints, cartilage, and spinal discs (e.g., sprains and strains) in which the working environment has contributed significantly to the unhealthy condition of the worker (NIOSH 1997). WMSDs account for approximately 40% of all lost time claims in Canada (WSIB 2014), and nearly one million people take time away from work annually for treatment of and recovery from WMSD pain in the US (NRCIM 2001). Furthermore, WMSDs impose substantial costs to employers due to lost productivity resulting from absenteeism as well as increased health care, disability, and workers' compensation costs. The annual cost of WMSDs to the Canadian economy, including direct and indirect costs, is estimated to be $20 billion (McGee et al. 2011). Overexertion injuries (e.g., lifting, pushing, pulling, holding, carrying) cost employers $13.4 billion every year, in the form of lost productivity resulting from WMSDs, in the US (NRCIM 2001). Due to the labor-intensiveness of the construction industry, workers are repeatedly exposed to physically challenging manual tasks involving forceful exertion and awkward postures. Consequently, workers in the construction industry are at an approximately 50% higher risk of suffering from WMSDs than workers in other industries (Schneider 2001). WMSDs account for approximately 47% of all disabling injury claims in the construction industry in Canada (OHS 2012).

Despite the high rate of WMSDs in construction, current practice in workplace design often focuses on productivity improvements rather than on enhancing health and safety (e.g., ergonomics) (Freivalds 2014). When ergonomic precautions are not fully considered, however, the benefits of increased productivity are likely offset by the increased medical and workers' compensation costs resulting from WMSDs. Furthermore, safety and productivity are highly associated (Hallowell 2011), as actions carried out to improve performance can adversely or positively impact safety and vice versa. Ergonomic behaviour, in particular, results primarily from physical conditions (e.g., human postures, repetitive movements, duration, and forceful exertion) determined by production tasks (e.g., production rate, job procedures, and workplace layout) (Mitropoulos et al. 2005; Freivalds 2014). However, current approaches used in construction lack the concurrent integration of both production and safety into workplace and operation design and do not fully consider the high association between the two. Thus, this study explores an integrated approach to workplace and operation evaluation and design by incorporating both productivity and safety into a comprehensive ergonomic analysis. The goal of this integration is to enable examination of the association between ergonomic risk factors and efficiency of labor operations, to provide a framework for designing safe and productive work environments.

1.2 RESEARCH OBJECTIVES

This study aims to explore an integrated approach to workplace and operation design that ensures both increased productivity and safety by examining the impact of modifications in operations design on efficiency and ergonomic safety. This is achieved by accomplishing the following objectives:

- Analyze the ergonomic risks associated with human movements using motion capture data obtained through the automation of ergonomic assessment and biomechanical analysis. This objective enables the development of an automated ergonomic approach, which is essential for linking ergonomic evaluation to production tasks, to observe the impact of operations scenario changes on ergonomic behavior. By automating the process of ergonomic risk level identification from human motions, the ergonomic evaluation process becomes quicker, simpler to use, and more reliable, allowing various working methods to be effectively compared in terms of ergonomic safety.

- Improve the accuracy of the ergonomic evaluation process to provide a reliable assessment of ergonomic risk by investigating the impact of motion capture errors on ergonomic analysis results. Since the accurate assessment of ergonomic risks is critical for effective analysis of operations, this objective enables the assurance of a reliable safety evaluation by (1) examining the inaccuracy associated with the inputs of ergonomic assessment tools and (2) developing methods to decrease the impact of this imprecision on analysis results.

- Evaluate the predetermined motion time system approach for modeling manual operations to better understand production factors affecting human movements and ergonomic behavior. This objective (1) verifies the suitability of Predetermined Motion Time Systems (PMTSs) for modeling and analyzing manual construction operations at a motion level and (2) explores the effectiveness of a PMTS-based integrated platform that connects simulation models of processes with ergonomic analysis.

- Understand the causal relationship between production tasks and ergonomic behavior in construction operations by coupling ergonomic and biomechanical simulation with PMTS-based micro motion level simulation. This objective enables the articulation of causal relationships between production and ergonomics, which is critical for (1) integrating productivity and safety assessment into task planning and workplace design and (2) experimenting with various operations scenarios to achieve optimum settings. The micro motion level modeling approach enables modification of operations production factors as well as the observation of the impact of these modifications on the level of ergonomic risks.

- Develop a framework that integrates the tools and systems used for data collection, analysis, and representation. This objective ensures that the different methods of the productivity and safety analysis are integrated for the unified, automated, simple-to-use, and reliable evaluation and design of labor operations. Furthermore, it enables the examination of the interconnections between the various systems to identify how available approaches can be leveraged to improve the evaluation and design process.

1.3 RESEARCH METHODOLOGY

To integrate productivity and safety, labor operations must be studied and analyzed at a motion level to enable evaluation of the impact of production task changes and worker motions on ergonomic risks. This study uses PMTSs, integrated into discrete-event simulation, to enable the evaluation of various scenarios of an operation at a motion level and the assessment of simulation model efficiency. Motion capture data are also used for biomechanical analysis to reliably evaluate the risk level of various human motions potentially taking place in operations. Additionally, visualization of workplace and worker motions is used for extracting required inputs of the analysis, facilitating managerial decision-making, and communicating and implementing design.

The objectives of this research are achieved through the following stages:

1.3.1 Automated ergonomic analysis

This stage involves the examination of potential of motion capture technologies as an emerging data collection method for ergonomic analysis. The objective of this stage is to enable the (1) extraction of information required for automated ergonomic analysis from motion capture datasets and (2) identification of the impact of motion capture errors on ergonomic analysis results. The extraction of ergonomic analysis inputs (e.g., postures, frequencies, durations, and speeds of actions) from motion capture data (e.g., BVH format) is investigated by converting a motion dataset to the defined body configuration of ergonomic tools and deriving the inputs (e.g., joint angles) for the ergonomic analysis tools. This approach allows for the monitoring and recording of human movements in a digitized form (i.e., 3D skeletal models), which serves as a basis for improved understanding of ergonomic behavior through accurate and quick assessments.

Next, a sensitivity analysis of motion capture errors for ergonomic analysis is performed. To determine the impact of measurement errors on ergonomic assessment and to reflect the errors in the analysis, experiments are conducted to propose a stochastic approach for ergonomic analysis. The results can potentially provide more realistic information by which to evaluate ergonomic risks with motion sensors and human observation that, inevitably, involve varying degrees of measurement and judgment errors. Furthermore, methods and techniques that increase the reliability of the ergonomic evaluation process and eliminate the subjectiveness of the results are developed. Experiments are subsequently carried out to confirm the improvement in the precision of the ergonomic assessment.

This stage facilitates ergonomic analysis in a field setting by automating the risk evaluation processes using motion capture data. The results will also be used at the following stages to understand the effect of production processes on human physical capacity.

1.3.2 Motion data-driven biomechanical analysis

In this stage, biomechanical analysis will be used to assess risk factors that can produce excessive physical loads on a worker's body through a biomechanical analysis using motion data collected from job sites. Biomechanical models provide a quantitative assessment of the musculoskeletal loads during occupational tasks, which help to identify hazardous loading conditions on certain body parts. The objective of this phase is to investigate an automated motion capture approach for biomechanical analysis to provide a more detailed evaluation of the ergonomic risks by comparing forces exerted on different body joints with human capacity. Furthermore, this approach enables modification of motion data to achieve completely safe motions. This research task is carried out by estimating biomechanical analysis inputs from motion capture data by mapping the location of body joints from motion data to the body configuration used by biomechanical analysis models. The results of this stage will be used as the basis of the biomechanical analysis for the integrated workplace design stage.

1.3.3 Manual operation simulation modeling

This stage focuses on discrete-event simulation modeling in motion-level processes to determine required cycle time, repetitions, and physical loads according to various operational scenarios (e.g., working environments, production rates), which enables the examination of the impact of operational changes as ergonomic risk mitigation on productivity, and vice versa. First, a framework will be developed to observe and define the sequential work breakdown structure of ongoing operations at the motion level (e.g., grasp, move, position) based on existing PMTSs. This approach divides manual work into basic motion units and, therefore, enables the determination of reasonable cycle time, efficient work method, and workplace layout, from a given job description. A special purpose simulation (SPS) modeling template that facilitates the modeling of the required motions and their sequential flows in a hierarchical structure of operations will be developed. Integrating PMTSs into simulation will allow for (1) calculation of job efficiency (i.e., actual cycle time as a percentage of projected cycle time) solely based on human motions, (2) experimentation with various scenarios by modifying working conditions, and, ultimately, (3) assessment of each scenario in terms of safety and productivity. This task implements simulation modeling for actions performed in a cyclical manner during operations, which will serve to evaluate manual operations from the productivity perspective. Furthermore, this step of the research is the basis for the next stage, which aims to integrate safety and productivity analyses.

1.3.4 Integrated workplace design

This stage incorporates the biomechanical simulation models into the developed simulation platform to facilitate understanding of the mutual impact between production tasks and human behavior from a physical perspective. By linking these, the relationship between productivity and safety can be further studied by examining the impact of production task attributes (e.g., duration, frequency, posture) on both performance and safety. Furthermore, a framework is developed at this stage that allows for the linkage of individual components, such as simulation models, motion sensing, and visualization tools, to function as a whole. In this virtual environment, physical working environments and conditions (e.g., activity cycle time, workbench design) are changed within possible ranges to compare resulting outcomes of ergonomic and operation analysis (e.g., job efficiency, ergonomic risk levels), to identify the extent to which such changes influence productivity and safety. Consequently, this stage integrates two different simulation paradigms through which (1) researchers can understand the causal effect of production on safety and (2) practitioners can design and plan productive and safe workplaces and operations.

1.4 SCOPE OF RESEARCH

- To implement some of the proposed methods of this research, construction fabrication shops are selected to collect actual data. These fabrication shops encompass physically demanding labor operations, comparable to other types of construction, due to the similarity of the activities, which leads to high exposures of workers to ergonomic risks. The manufacturing setup of these job sites provides a controlled environment that enables the collection and experimentation with data of the same labor activity. On the other hand, the dynamic nature of construction job sites can also be observed due to the constantly changing products that must be fabricated.
- This study focuses on physical ergonomics, which considers human anthropometric, physiological, and biomechanical characteristics associated with physical work systems (Mehta 2016) as the main contributor to ergonomic risks in labor-intensive industries such as construction. Accordingly, it does not involve cognitive ergonomics where the impact of human cognitive abilities (e.g., perception, reasoning) on a system is studied.
- Various definitions of labor productivity are used in construction practice and research depending on the intended application. This study uses time as the basis of defining productivity when evaluating existing labor operations and focuses on the duration of a labor operation (man-hours in prevalent productivity definitions). Terms such as efficiency and performance are sometimes used interchangeably for similar definitions in the literature and in industry.

1.5 THESIS ORGANIZATION

The remainder of this thesis is organized into the following chapters. Chapter 2 reviews the existing literature and previous work carried out as it relates to this study. Chapter 3 discusses the motion data-driven framework for ergonomic analysis that automates the ergonomic and biomechanical analysis process. The proposed approach uses motion data from recordings or the virtual model of a jobsite to evaluate the risk factors that can produce excessive physical loads on the human body. Chapter 4 investigates the difficulties in visually estimating human postures (e.g., body joint angles) required for ergonomic analysis that have led to inconsistent results due to observer subjectiveness. Also, a fuzzy logic approach for posture-based ergonomic evaluation tools is introduced that produces more accurate results than traditional methods and, hence, helps minimize human errors in observation for reliable on-site ergonomic assessment. In Chapter 5, the reliability of ergonomic methods are investigated from the input measurement perspective, collected by a human observer or motion capture sensors, and the imprecision associated with acquiring the required inputs for ergonomic assessment and its impact on the final result of the analysis is examined. A stochastic approach is proposed to evaluate the impact of input errors on the final result of the ergonomic assessment. Chapter 6 investigates the use of PMTSs for modeling manual construction operations for cycle time estimation and efficiency evaluation and proposes a motion-level simulation approach by integrating PMTS into discrete-event simulation modeling, in turn, providing a reliable and simple-to-use method of analyzing manual tasks. In Chapter 7, an integrated, comprehensive framework that couples simulation modeling, PMTS, ergonomic and biomechanical assessment, and workplace visualization to incorporate both productivity and safety analysis into the design process is proposed. Chapter 8 builds on Chapter 7 by integrating sensing, action recognition, as-is workplace model generation, and human motion animation into the comprehensive framework.

Chapter 2 Literature Review

The main objective of this research is to investigate the integration of productivity and safety into workplace and operation design by examining the effect of design modifications on efficiency and ergonomic safety. Accordingly, prior work examining relationships between productivity and safety as well as existing challenges in ergonomic analysis in construction are reviewed. Due to their roles in achieving the objective of the research, simulation modeling in construction and the applications of PMTSs are also discussed.

2.1 RELATIONSHIP BETWEEN PRODUCTIVITY AND ERGONOMIC SAFETY

Previous construction studies have provided strong evidence that safety performance is correlated to productivity (Hallowell 2011). For example, production demands explicitly affect safety performance by generating work pressures that can adversely affect safety behavior (Mitropoulos and Cupido 2009; Hinze and Parker 1978; Goldenhar et al. 2003). Many advances have been made in accident causation modeling to better understanding the complex role of safety in a production system. A systems model (Mitropoulos et al. 2005) demonstrates how production can give rise to hazardous situations and unsafe behaviors, which combine to increase exposure to accidents. Causal loop diagrams (Rodrigues and Williams 1998; Love et al. 1999; Park and Pena-Mora 2003) and regression models (Wanberg et al. 2013) show that rework resulting from quality deviations can also cause production pressure, which negatively affects safety behavior. Simulation models have also been developed to understand safety behavior through scenario-based quantitative analysis (Shin et al. 2014; Jiang and Fang 2014). Accident causation models have provided valuable insight into the dynamics derived from the interactions between safety and production, particularly from psychological perspectives (e.g., pressure). In construction, however, the findings of studies focusing on the relationship between performance and safety are indecisive (Hallowell 2011). Some practitioners in the construction industry view safety management as an additional expense that hinders productivity, as compliance requires extensive amount of effort and resources, and argue that traditional safety management practices do not add value to production (Hallowell 2011). Thus, some studies have discussed the trade-off between performance and safety (Hinze and Parker 1978; Choudhry and Fang 2008; Evans et al. 2005; Probst and Brubaker 2007; Choi et al. 2006). For instance, Evans et al. (2005) investigated worker perception of productivity climate and concluded that workers who perceived a stronger climate for productivity reported higher number of accidents. They surveyed 526 individuals, where more than half of the participants responded that there was a negative association between productivity and safety since focusing on efficiency increases risky behavior. Furthermore, it has been shown that production demand explicitly affects safety performance by generating work pressure, which gives rise to hazardous situations that can adversely affect ergonomic behavior, together further increasing exposure to accidents (Mitropoulos and Cupido 2009; Goldenhar et al. 2003; Mitropoulos et al. 2005). Alternatively, others have demonstrated improvements in productivity resulting from safety management strategies, achieved through enhanced working conditions and better ergonomics (Hare et al. 2006; Hinze and Appelgate 1991; Shikdar and Sawaqed 2003; McLain and Jarrell 2007; Hinze 2006). For example, Hinze (2006) theorized the Distraction Theory, which asserts that a worker will have higher efficiency if the distraction of a known hazard is minimized and that efficiency is reduced when the focus on the distractions posed by the hazards are high. Furthermore, although improving working conditions through ergonomics can lead to improved efficiency due to higher level of comfort, some safety interventions, such as slower pace of work and more rest allowances, can result in lower productivity (Wells et al. 2007). This research, therefore, investigates the relationship between productivity and safety in workplace design and aims to propose an approach that enables the planning of efficient and safe operations concurrently. Despite the vast amount of research focusing on improving each of these elements of workplace design (i.e., productivity and safety) separately, less attention has been given to investigating the relationship between efficiency of manual tasks and ergonomic behavior at a detailed motion level.

2.2 CHALLENGES IN ERGONOMIC ANALYSIS IN CONSTRUCTION

In an effort to prevent WMSDs in construction, previous research has focused on identifying awkward postures that may contribute to the development of WMSDs. For example, Alwasel et al. (2011) applied magneto-resistive sensors to measure body joint angles and identify exposure to unsafe postures during construction tasks. Ray and Teizer (2012) suggested real-time analysis of construction workers' posture using a Kinect sensor to detect non-ergonomic activities. Li and Lee (2011) introduced a computer-vision-based approach to obtain construction workers' motion data from video and to recognize unsafe actions. The posture-based approaches in previous studies have provided valuable insight into the use of motion information for ergonomic analysis. However, taking into account that WMSDs occur as an interactive process of biomechanical and physiological internal responses of the human body to external physical stresses (e.g., posture, exertion, and vibration) (Kumar 2001), further research efforts are still required to assess internal loads on the human body during construction activities. More importantly, critical factors affecting WMSD development include production-related variables such as the level, duration, and frequency of loads imposed on tissues (Armstrong et al. 1996), which have seldom been studied in the existing body of research. There is thus a need to integrate production planning with ergonomic analysis to achieve optimum workplace design.

Despite previous efforts, the construction industry still faces the following challenges: (1) current practices rely heavily on manual observation that not only requires significant time and effort, but also involves the subjective judgment of observers; (2) the existing assessment methods (e.g., physical demand analysis) may not provide sufficient information to identify risk factors for the prevention of reoccurrences; and (3) it is difficult to forecast how risk mitigation measures and interventions (e.g., changes in tools or workbench configuration) may affect safety and productivity. This research aims to address these challenges by providing a means for automated data collection and simulation that allows for experimentation with various risk mitigation strategies in a virtual environment.

2.3 SIMULATION MODELING IN CONSTRUCTION

Simulation modeling is a very well-known and widely used approach for efficiency analysis and productivity improvements in construction (Wang and Halpin 2004). For construction projects to be successful, effective planning and scheduling is required, and simulation modeling is a valuable construction management tool that enables the analysis of construction operations to achieve efficient operations planning (Kamat and Martinez

2000). Simulation modeling provides production planners with the opportunity to evaluate various scenarios of work processes and to design productive workplaces. In particular, discrete-event simulation has proven to be a highly reliable approach for (re)designing and analyzing complex, dynamic, and collaborative construction systems (Lu 2003). Discrete-event simulation has been used for various applications in different phases of construction (e.g., Ozcan-Deniz and Zhu 2015; Zhou et al. 2009; Corona-Suárez et al. 2014; Yang et al. 2012). For over four decades, construction researchers have worked on developing simulation modeling tools that can appropriately describe the features of construction operations, including its dynamic and random nature. Some of the most commonly used simulation platforms include: STROBOSCOPE (Martinez 1996), which is a general purpose simulation system designed for the simulation of processes common to construction engineering; CYCLONE (Halpin 1977), which is a well-established and simple system that is easy to learn, is effective for modeling various simple construction operations, and is the basis for a number of construction simulation systems (Sawhney et al. 1998); and Simphony (AbouRizk and Hajjar 1998), which attempts to simplify and standardize the development and utilization of construction Special Purpose Simulation (SPS) tools. With advancements in construction simulation, researchers have increasingly focused on developing SPS templates. SPS modeling involves building a platform that can be used by construction practitioners that are familiar with a specific domain, but not with the methods and details of simulation modeling, to model an operation using simplified symbolic representations (AbouRizk and Hajjar 1998). Thus, SPS modeling targets a specific area (e.g., highway construction) and provides templates and modeling elements that enable convenient modeling of projects pertaining to that area. It enables precise modeling while requiring less time and effort compared to general purpose simulation due to its lower level of complexity and abstraction (Chua and Li 2002). Some examples of SPS applications include: tunneling (Ruwanpura et al. 2001), bridge construction (Marzouk et al. 2008), tower crane operation (Appleton et al. 2002), construction noise prediction (Gannoruwa and Ruwanpura 2007), and workflow analysis (Palaniappan et al. 2007).

Although many advances have been made in the use of simulation modeling for estimation of construction task duration, it has not been adapted to its full potential for modeling manual construction operations. In particular, discrete-event simulation can be useful for modeling manual tasks, as it enables modeling human operators as resources of the system and can be adjusted to generate appropriate information on time aspects of human work (e.g., active and idle time). Given that this type of information is not directly available from other pertinent modeling and analysis tools, discrete-event simulation can complement these methods to provide reliable analysis outputs without requiring detailed and extensive inputs. Furthermore, discrete-event simulation facilitates experimentation with and optimal selection of different methods for carrying out manual tasks. Furthermore, the flexibility of SPS modeling enables the integration of motion-time standards into simulation environments, and its ease-of-use enables the incorporation of manual tasks into models of construction operations. Thus, an SPS template containing modeling elements, which represent manual construction activities and provide standard duration for manual tasks based on available validated motion-time systems (i.e. PMTS), should be developed. Furthermore, integrating ergonomic assessment into the PMTS-based SPS can provide initial insight into both the efficiency and safety of an operation during its design phase.

2.4 THEORETICAL BACKGROUND ON PREDETERMINED MOTION TIME SYSTEMS

Different measurement techniques (e.g., time study, work sampling) have evolved to estimate the amount of time required to perform a manual task. Among these techniques, predetermined motion-time systems, also known as predetermined time systems, have gained increasing attention as they address the subjectiveness of time studies for setting standards. A PMTS is a structured set of data, procedures, methods, and motion times used to study manual tasks and is expressed by describing the motions used to perform a task and their previously established standard times (Institute of Industrial Engineers 1983). Large samples of various manual tasks have been studied and evaluated by researchers to develop a PMTS that can provide the standard time required to carry out a manual activity. PMTSs have been commonly used to examine and improve labor productivity (Kuhlang et al. 2011; Gupta and Chandrawat 2012; Thakre et al. 2009; Xu et al. 2013; Sun et al. 2009). The most commonly used PMTSs include: Modular Arrangement of Predetermined Time Standards (MODAPTS) (Heyde 1966), Methods-Time Measurement (MTM) (Maynard et al. 1948), and Maynard Operation Sequence Technique (MOST) (Zandin 1980). As an example of a simple PMTS, MODAPTS is developed based on the premise that the time required for any body movement can be expressed as a multiple of the time required to move a single finger. The time required to move a finger is called a MOD and is equal to 0.192 seconds. Basic alphanumeric codes (e.g., G=Get, M=Move), which describe the nature of the motions, are defined and are combined with an MOD value that represents the number of MODs required to perform the motion (e.g., G3, M4). Applying MODAPTS requires breaking down a manual activity into its basic motions (e.g., moving hand, grasping object, walking) and assigning MOD values to each motion. By adding the MOD values, the total number of MODs required is calculated and is converted to seconds to derive the standard time required to complete the operation.

While PMTSs have been successfully adopted for different applications in other industries, such as manufacturing, less attention has been given to their potential applications in the construction industry. By integrating PMTSs into simulation environments, it is possible to conveniently model various manual construction tasks and obtain standard durations for different scenarios of carrying out an operation. When simple design data are provided as input (e.g., walking distance, bending motion), the simulation engine calculates the corresponding standard duration automatically and uses the duration as required time data for the simulation model. Computerizing PMTS methods has advantages, such as faster application, simplicity of use, consistency of application, and update capabilities (Genaidy et al. 1990). Thus, the use and integration of PMTS into simulation can be highly useful for exploring manual operations at a motion level.

Chapter 3 An Automated Biomechanical Simulation Approach to Ergonomic Job Analysis for Workplace Design [1]

3.1 SUMMARY

One of the most effective approaches to preventing WMSDs is to evaluate ergonomics considerations early in the design and construction planning stage before the worker encounters the unsafe conditions. However, a lack of tools for identifying potential ergonomic risks in a proposed workplace design has led to difficulties in integrating safety and health into workplace design practice. In an effort to address this issue, this chapter discusses a motion data-driven framework for ergonomic analysis that automates and visualizes the evaluation process in a virtual workplace. This is accomplished by coupling ergonomic analysis with three-dimensional (3D) virtual visualization of the work environment. The proposed approach uses motion data from the 3D model of the jobsite to evaluate the risk factors that can produce excessive physical loads on the human body through biomechanical analysis. A global risk assessment of musculoskeletal disorders is performed on worker motions first, and biomechanical simulation is then used to further analyze unsafe motions by estimating internal loads on each selected body joint of the worker and redesigning the motion and workplace accordingly. As a case study, several tasks taking place in a construction prefabrication shop are modeled and analyzed to modify the workplace and ensure improved ergonomic safety.

3.2 INTRODUCTION

WMSDs are reported to be the leading cause of non-fatal occupational injuries that may lead to temporary or permanent disability (Bureau of Labor Statistics 2008). WMSDs account for about 34% of non-fatal injuries resulting in days away from work in the construction industry (CPWR 2013), and involve a median of 8 days per person per year away from work, compared with 6 days for all nonfatal injury and illness cases (NIOSH 2004). Despite technological advances in recent years, the construction industry is still

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labor-intensive, with workers frequently exposed to manual handling tasks involving forceful exertion and awkward postures. Furthermore, construction jobsites are generally more hazardous than other work environments (e.g., manufacturing) due to the presence of heavy equipment, physically demanding tools, hazardous materials, and rapidly changing work conditions, all of which increase the possibility of unsafe actions, human errors, and injuries (Abudayyeh et al. 2006). This leads to consistently high rates of work-related accidents, injuries and fatalities among construction workers (Lopez and Gilkey 2014). However, current practice in workplace design often focuses on productivity improvements rather than on enhancing health and safety (e.g., ergonomics) (Freivalds 2014). This phenomenon is frequently observed in off-site and modular construction, where production line design is mainly focused on improving productivity through better process flow, material handling, and factory layout. As mentioned before, when ergonomic precautions are not fully considered, the benefits of increased productivity are likely offset by the increased medical and workers' compensation costs resulting from WMSDs.

In addition, Prevention through Design (PtD) has been considered in construction as an important process that enables integrating safety considerations into the design stage and can potentially prevent up to half of construction accidents (Toole and Gambatese 2008). Adoption of PtD can also provide a great opportunity to mitigate occupational health risks such as WMSDs (Nussbaum et al. 2009; Gambatese et al. 2005; Weinstein et al. 2005; Hecker and Gambatese 2003). However, one of the challenging issues for the PtD approach to health issues is a lack of tools for identifying potential ergonomic risks prior to actual work during the design phase (Kim et al. 2008; Nussbaum et al. 2009). To address this issue, this chapter proposes an automated ergonomic analysis framework that identifies and evaluates the awkward worker postures and motions that can be expected to be involved in a proposed workplace design, in a 3D virtual model of the work environment. Integrating ergonomic analysis with visualization of the workplace (i) enables the assessment of clearance, reachability and visual requirements, as well as postural comfort (Feyen et al. 2000), and (ii) facilitates communication of ergonomic concerns and design alternatives early in the design and planning phases or during redesign for process improvement. The proposed framework visualizes and validates ergonomic risks as well as improvements in the digital environment that will later be applied on the jobsite. As a case study, manual tasks taking place in a construction prefabrication company are investigated for the purpose of modifying the workplace and ensuring improved ergonomic safety.

3.3 RELATED WORK

In recent decades, researchers and practitioners have focused on developing effective ergonomic assessment models, such as Rapid Entire Body Assessment (REBA) (Hignett and McAtamney 2000), Rapid Upper Limb Assessment (RULA) (McAtamney and Corlett 1993), and Ovako Working posture Assessment System (OWAS) (Karhu et al. 1997). However, these assessment models have not been fully adopted yet in construction due to the difficulties of practical implementation (Burns et al. 1997). This section thus reviews the current state of the literature on workplace design research to identify the challenges associated with existing ergonomic analysis methods.

3.3.1 Overview of Motion Studies in Construction

Various approaches (e.g., self-evaluations, observation-based methods, and direct measurements) have been developed to proactively assess risk factors associated with WMSDs (Li and Buckle 1999). Self-reports from workers are used to collect information on exposure to physical and psychosocial factors through worker diaries, interviews, and questionnaires (David 2005). Observational methods involve a job analyst observing working postures and movements in real time or from recorded video to identify hazardous actions and classify risk factors (NIOSH 2014). Different types of sensors and electrical devices (e.g., goniometric, optical, electromagnetic, and accelerometer-based systems) have also been developed and used to define body postures directly. Examples include magneto-resistive sensors (Alwasel et al. 2011), using a Kinect sensor (Ray and Teizer 2012) and applying computer-vision-based methods (Han and Lee 2013). These approaches have provided very useful means for using motion information for ergonomic analysis. However, the previous studies in construction have mainly focused on monitoring ongoing tasks that may cause WMSDs. Further research efforts are thus required to understand how laborers perform tasks in a given work environment and how the workplace can be improved to minimize awkward postures and motions. Applying ergonomic considerations in the early phases of designing a project and planning the tasks may help with risk mitigation and achieve proactive safety management that allows for the prevention of ergonomic injuries (Freivalds 2014).

3.3.2 Overview of Ergonomic Analysis Approaches

Two main approaches have been developed and implemented to identify and evaluate hazard risk factors: (i) ergonomic posture analysis, which is the scientific discipline to understand interactions among humans and other elements of a system (e.g., tools, equipment, machines and workspace layout) in order to optimize human well-being and overall system performance; and (ii) biomechanical analysis, which is the study of human motion as a function of body structure to identify causes of injuries and prevent them. Ergonomic posture analysis uses assessment models and checklists (e.g., REBA and RULA) to evaluate the risks involved in human actions by calculating overall scores indicating the level of risk associated with a manual task. This approach typically considers external risk factors such as task frequency and duration as well as human postures to provide the global risk assessment (i.e. ergonomic risks imposed on the whole body) associated with a posture. Biomechanical analysis is performed to assess the internal loads on the worker's joints and analyze musculoskeletal stresses on the joints at risk (Armstrong et al. 1996). Biomechanical models help estimate internal forces and moments that cannot easily be measured directly by describing the complex musculoskeletal systems of the human body (Chaffin et al. 1996). They also provide a quantitative assessment of musculoskeletal loads during occupational tasks, which help to identify body parts with hazardous loading conditions (Marras and Radwin 2005). Since WMSDs occur as an interactive process of biomechanical and physiological internal responses of the human body to external physical stresses (Kumar 2001), biomechanical models have been developed and utilized to understand and reduce the risk of WMSDs in the work environment (Marras and Radwin 2005). Recently, several simulation and analysis tools (e.g., 3D SSPP and OpenSim) have been developed based on 3D biomechanical modeling to assess the ergonomic risks associated with a motion. These tools provide both proactive and reactive analyses of work tasks (Seo et al. 2013).

Nonetheless, only a few studies in construction have applied both approaches simultaneously. Each approach considers different types of factors (e.g., frequency, duration, and posture by posture-based ergonomic analysis, and motions by biomechanical models) and provides different analysis outcomes (e.g., overall risk levels by ergonomic tools, and quantitative risk levels at a body joint level by means of biomechanical models). Taking into account that all these factors are determined by production activities, a systematic and comprehensive assessment encompassing both approaches can provide valuable information to evaluate the risks involved in manual operations and enable effective workplace design and task planning.

3.3.3 Overview of Ergonomic Workplace Design Tools in Other industries

In other industries (e.g., automobile and manufacturing), computer-aided methods have been developed to evaluate the performance of human operators in work environments. One approach has been to develop computer-aided design (CAD) platforms with built-in ergonomic assessment capabilities, also known as Digital Human Modeling (DHM) (Chaffin 2008). Examples include 3DSSPP/AutoCAD (Feyen et al. 2000), SAMMIE (Porter et al. 1995), APOLIN (Grobelny et al. 1992), CAAA (Hoekstra 1993), Deneb/ERGO (Nayar 1995), ERGOMAN (Mollard et al. 1992), and JACK (Badler et al. 1995). Also, the prospect of developing complementary ergonomic software for CAD systems has been investigated; examples include MINTAC (Kuusito and Mattila 1990), ErgoSHAPE (Launis and Lehtela 1992), HUMAN (Sengupta and Das 1997), RAMSIS (Seidl 1997), and ANYBODY (Porter et al. 1995).

Challenges have been identified in applying these platforms to construction, including the following: (i) the use of these systems in construction practice requires additional learning of terminology, command structures, and modeling techniques differing from those employed in the the CAD systems widely used in the construction industry; (ii) only a few of them produce a detail-level of ergonomic risk (e.g., static strength capabilities or back compression forces) for the modeled postures and loads, which can play a key role in assessing and re-modeling the workplace (Feyen et al. 2000); and (iii) when assessing postural comfort, the capabilities of most existing systems appear limited to a designer's subjective judgment regarding awkward postures. In this regard, robust and compatible methods are required to carry out objective ergonomic analysis in construction.

3.4 RESEARCH FRAMEWORK

This chapter presents a 3D virtual model-based framework for ergonomic job analysis which provides a designer with quantitative information regarding the potential ergonomic risk involved in current and proposed workplace designs. The 3D modeling of work environments is a powerful tool for recreating the complexity of the real jobsite and observing workplace evolution over time to detect ergonomic risks that would otherwise be difficult to foresee (Cimino et al. 2009). In particular, the increasing prevalence of building information modeling (BIM) in the construction industry brings with it the potential to use 3D modeling for ergonomic analysis purposes. Accordingly, 3D visualization could be an effective observation method by which to obtain required information such as motion data, job sequences, and process flow without on-site visits. To exploit this opportunity, this chapter specifically (1) utilizes motion data built in a 3D environment representing the jobsite, (2) employs ergonomic analysis to identify tasks posing injury risks, (3) evaluates the risk factors that can produce excessive physical loads on the human body through biomechanical analysis, and (4) mitigates the risk factors associated with given tasks to improve safety and productivity. As described in Fig. 3-1, the proposed framework is established by coupling ergonomic and biomechanical analyses with the 3D virtual model of the work environment. The inputs include information pertaining to both operations and the physical environment (e.g., workflow, dimensions of materials and tools, worker information, and site layout). These inputs are used to develop an accurate 3D virtual representation of the work environment. Notably, the data collection process is critical as the resulting 3D model contains geometry data which serves as a basis to produce motion information for ergonomic analysis. The motion datasets extracted from the virtual models are then used for ergonomic and biomechanical analyses. The ergonomic analysis helps to identify which workers potentially encounter the given unsafe workplace conditions, and eventually to determine whether a task is ergonomically safe or requires further modification. For the unsafe tasks requiring further improvement, biomechanical analysis is then executed to estimate internal loads on each body joint. The results of the biomechanical analysis are used to improve the motion and redesign the workplace to ensure safe and effective design of jobsite components, such as workstations, tools, and machines, corresponding to the task requirements. As a result, the linking of ergonomic analysis and 3D virtual modeling enables one to analyze and improve human motions in an interactive manner.

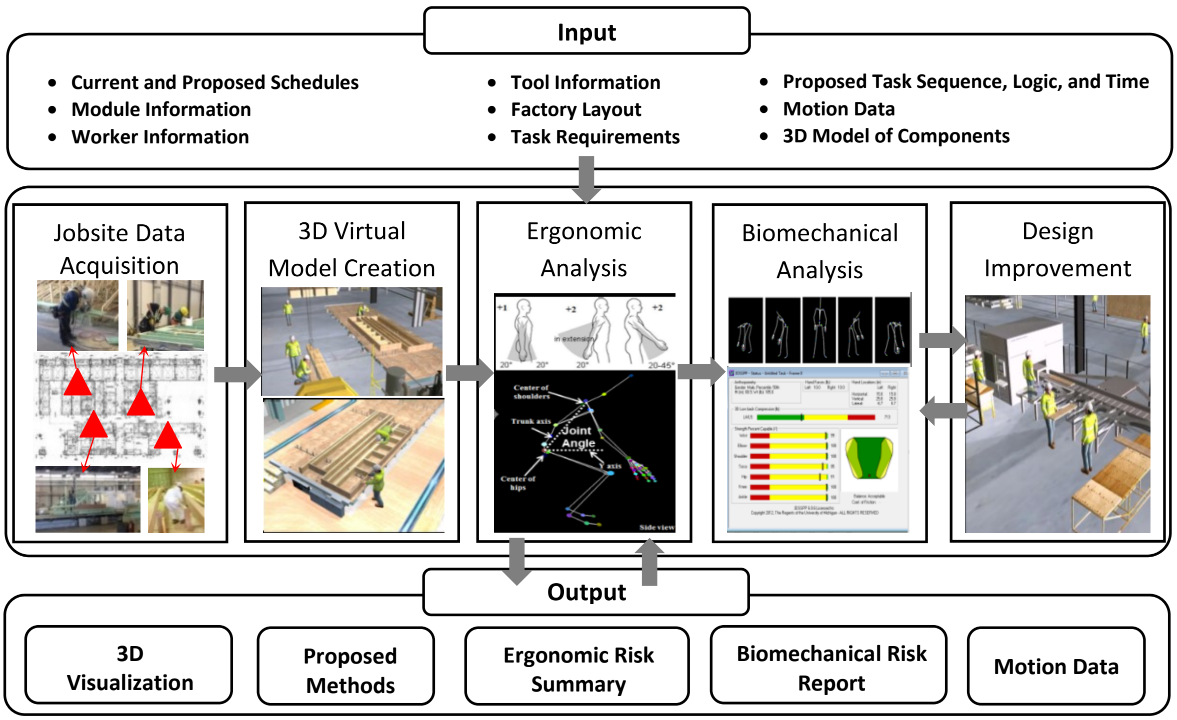


Figure 3-1 Automated ergonomic analysis framework for workplace design

3.4.1 Data Acquisition

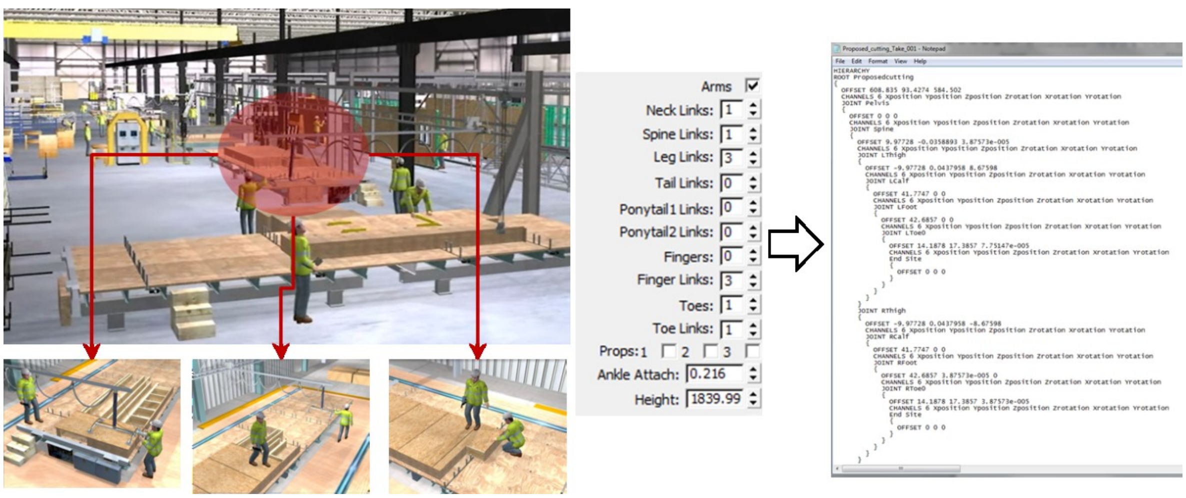
Data acquisition is required to gather all the required information describing the work environment. The inputs consist of: (1) job sequences and process times of the tasks taking place at the site; (2) module information such as dimensions (e.g., length, width, and height) of all the components (e.g., equipment) and materials (e.g., sheathing and timbers); (3) worker anthropometry data (e.g., sex, height, and weight); (4) tool information (e.g., weight of tools to be handled); and (5) physical site layouts of the jobsite. The layout of the site, process times of the different tasks, and dimensions of the material and objects are required for the 3D model building process, while the worker attributes and weights of tools and materials are required to ensure precise creation of the worker models and motions for ergonomic and biomechanical analyses. The data is gathered by acquiring all available blueprints and specifications from the company's management and observing the workplace to ensure an accurate representation of the real system is created in the 3D virtual environment.

3.4.2 3D Virtual Model Creation

Human actions and postures employed to perform a task are affected by the work environment. For example, walking distances to carry an object are determined by the distance between the initial location of the object and the end position where it is to be placed. The height of an object, as another example, determines moving trajectories and postures required to hold and carry an object. In this regard, the design of workplaces plays a key role in gaining understanding of human movements to prevent ergonomically unsafe actions at a jobsite.

In building accurate models of work environments, the data collected from a job site provides necessary information such as geometries of the environment as well as sequential order of the tasks. The development of the 3D virtual model thus consists of two procedures: (1) creating the 3D geometric model of the jobsite representing the site's physical layout, equipment, tools, and material; and (2) simulating the operation's procedure to represent the sequence of events at the real jobsite. The 3D modeling processes involve not only building and visualizing 3D geometric models of the work environment, but also developing the motions of 3D workers with tools and material to satisfy task requirements according to the modeled workplace (Fig. 3-2a). This motion inference can be the result of a post-simulation visualization approach that creates motions through simulation (Han et al. 2012), or it can be built independently. The present chapter uses Autodesk 3ds Max as the modeling platform due to its visualization capabilities. The 3D models of the workers are built considering the characteristics of the operators (e.g., sex, height, and weight) to represent the real jobsite conditions as accurately as possible.

After developing the 3D virtual model of the jobsite (Fig. 3-2a), each worker's motion data is extracted in a motion capture data format such as a Biovision Hierarchy (BVH) file (Fig. 3-2b). The BVH format is a standard ASCII file used to flexibly define body configurations and describe rotational joint data from various motion capture systems to animate bipedal characters (see Appendix A). In this process, a human skeleton with information on joint angles at each time frame is extracted which can be used to track the movements of the skeleton, reflecting the actions of the real character in the jobsite. However, 3ds Max does not support the direct extraction of this file type for further analysis. Hence, each 3D worker motion is transferred into Autodesk Motion Builder after matching the body structures of 3D workers with the body configurations defined for the ergonomic analysis. To automate this matching process, a customized system, called ergoSupport, is used in MAXScript, which is the built-in scripting language of 3ds Max. Then, the BVH file for each 3D worker is automatically generated in Motion Builder. This motion file is used for the developed analysis algorithm, as described in the following section.



(a) (b)

Figure 3-2 Motion data extraction, (a) 3D virtual model of workplace and (b) sample BVH file

3.4.3 Ergonomic Analysis

This research uses motion capture data extracted from the virtual model for ergonomic risk assessment based on existing ergonomic evaluation methods, such as RULA (McAtamney and Corlett 1993). Researchers and practitioners have developed various ergonomic assessment methods that provide a standard approach for evaluating the risks involved in human actions. These assessment tools are used to calculate overall scores that indicate the level of risk associated with the task, based on manual observation. These assessment guidelines typically require the user to input the angles between body joints, which are the main inputs for the evaluation. However, it is time-consuming and error-prone for a human observer to record angles of many body joints for ongoing work. For example, common practice is to record videos of workers and then repeatedly rewind and re-view the video to calculate all the required angles. The process is also subject to the evaluator's understanding of the task. This chapter thus focuses on the automation of this manual process by using motion capture data.

The motion data (i.e., BVH files) extracted from 3ds Max characterizes human poses using 3D Euler rotation angles at each body joint. The rotation angles, however, cannot be directly input to ergonomic assessment models, since each assessment model may define the input data (e.g., joint angles) differently for the analysis. The research presented herein thus initially computes 3D positions of body joints simply by calculating a transformation matrix composed of the rotation angles and translations available from the BVH format (Meredith and Maddock 2001). Then, the position data allows for the calculations of other types of data required for a particular ergonomic assessment method in order to provide the analysis results, such as overall ergonomic scores. The calculated score implies the final recommendation that determines, for example, whether action is safe, further investigation required, or action is unsafe. In this research, the motion data is extracted from the virtual model; however, motion files (e.g., BVH) extracted from different type of sensors also can be analyzed in a similar way, simply by computing 3D positions of joints and inputting them into the ergonomic assessment tool. The RULA evaluation method is implemented for the case study of this research.

The RULA system examines biomechanical and postural loading on the whole body with particular attention to the neck, trunk and upper limbs (McAtamney and Corlett 1993). The result of evaluating a task using an ergonomic analysis method such as RULA is determined by calculating a score for each ergonomic risk factor related to a body part and combining these scores to obtain a final score. Different body segment positions (e.g., trunk, upper arm, and neck) are divided into posture categories, and the corresponding score is defined by assigning the body segment to one of these categories. Each posture category represents a certain portion of the range of motion. The number of posture categories into which the posture range is partitioned for different body parts in the RULA method is shown in Table 3-1.

Table 3-1 Number of posture categories for the RULA system

Upper arm			**Lower arm**		**Wrist**	
Flexion	Abduction	Raised	Flexion	Lateral bend	Flexion	Radial/ulnar deviation
5	2	2	2	2	3	2
Neck			**Trunk**			**Leg**
Flexion	Twist	Lateral bend	Flexion	Twist	Lateral bend	Supported/unsupported
5	2	2	4	2	2	2

For example, to determine the score for the flexion of the upper arm, the posture has to be classified in one of the five categories shown in Fig. 3-3. Each of these categories corresponds to a score that is used to achieve the total score for the upper arm. By calculating the corresponding joint angle, the posture category for all the different body segments can be identified and scores can be determined.

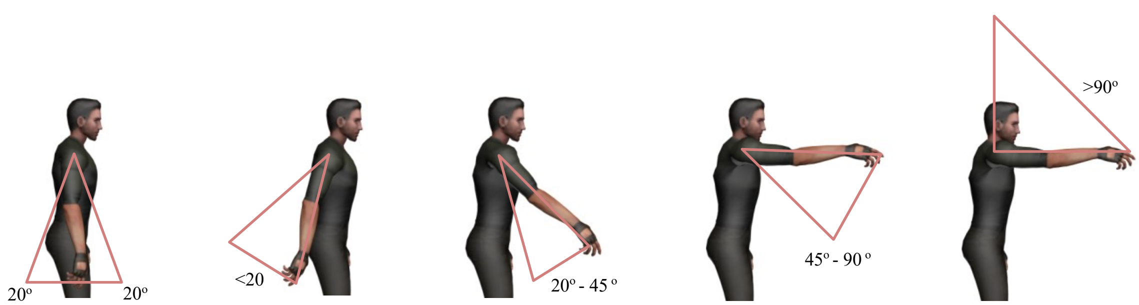


Figure 3-3 Posture categories for upper arm flexion using RULA

For instance, to calculate the score of the upper arm using the proposed approach, the motion data is used to calculate the angle between the shoulder and the vertical axis. This is achieved by defining two vectors: the first vector connects the upper arm joint to the elbow joint, and the second vector defines the vertical axis. The coordinates of the first vector are calculated by subtracting the coordinates of the destination of the vector (i.e., the 3D coordinates of the shoulder joint) from its origin (i.e., 3D coordinates of the forearm joint).

The angle is then calculated in the algorithm based on the dot product theory (Arfken 1985) as in Equation 3-1:

$$X.Y = |X|\ |Y| \cos \theta \tag{3-1}$$

Where X and Y are the vectors described above; then, the angle between them, θ, is calculated using Equation 3-2:

$$\theta = \cos^{-1} X.Y \ / \ |X|\ |Y| \tag{3-2}$$

The same process is carried out for all the different body segments and joint positions. The resulting scores are combined to obtain a final score ranging from 1 to 8. A total score of 1 or 2 indicates that the posture is ergonomically acceptable and the worker is working in a safe posture with no risk of injury, while 3 or 4 specifies that further investigation is needed since the worker is performing the task in a posture that could present some risk of injury. This score is most likely the result of one part of the body being in a deviated and awkward position, so the task should be modified to prevent the risk. A score of 5 or 6 indicates that investigation and changes are required soon, and 7 or higher means that the worker is exposed to immediate risk and investigation and changes are required promptly. Two other inputs for the RULA method are muscle use score and force score. The muscle use score variable describes the frequency of the task being performed (e.g., mainly static or repeated often) and the force score defines the load associated with the task. Since these two variables are recorded based on observation of the tasks, they are simply input into the computation as known variables.

Since other practical ergonomic evaluation systems, such as REBA (Hignett and McAtamney 2000), Strain Index (Moore and Garg 1995), and Occupational Repetitive Actions Index (OCRA) (Occhipinti 1998), require the same inputs (e.g., joint angles) as the RULA system and only differ in the number of posture categories and their emphasis on different body parts, they can be conveniently incorporated into the proposed approach. The user will have the option to choose the one that most precisely corresponds to the task under investigation.

3.4.4 Biomechanical Analysis

Different computerized simulation and analysis tools have been developed to analyze human motions based on 3D biomechanical modeling. In this research, the 3D SSPP software (Chaffin et al. 2006) developed by the Center of Ergonomics at the University of Michigan is used to assess the risk factors that can produce excessive physical loads on the worker's body through a biomechanical analysis using the motion data created previously. Fig. 3-4 shows a snapshot of the 3D SSPP environment, which includes the human model and its skeletal system, as well as information regarding the forces imposed on the human model's joints based on its posture.

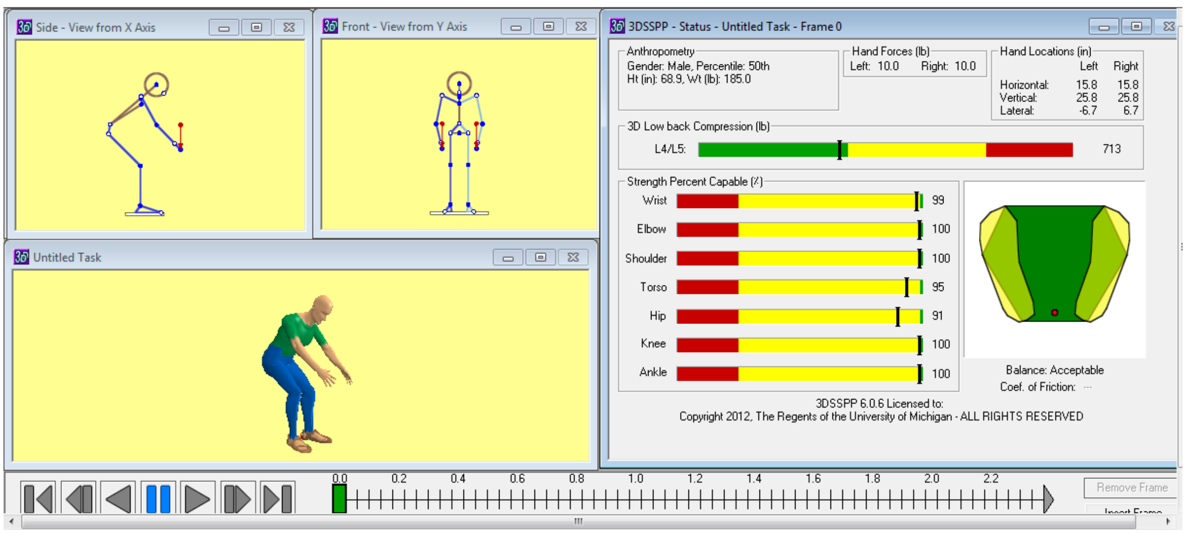


Figure 3-4 3D SSPP motion modeling environment

For the worker motions that the ergonomic analysis has reported to be ergonomically unsafe, a biomechanical analysis is performed to identify body joints with excessive loads. In this case, the developed application automatically creates a batch file that can be input into 3D SSPP for further analysis (Seo et al. 2014). Biomechanical analysis using a simulation tool such as 3D SSPP requires three types of inputs: joint angles, external loads, and anthropometry. The latter two inputs can be obtained by observing the task (e.g., weight of objects when lifting, and sex and height of human subject), while the body configuration of the motion file (in this case from the virtual model) can be slightly different from the body configuration that 3D SSPP uses. Since the proposed approach uses the motion data to calculate joint angles, this difference can cause inaccuracy. To address this issue, linear estimation of joint positions is applied to map and estimate corresponding body joints of these two body types to ensure that the created motion is an accurate representation of the original motion. For example, the body joint configuration used in 3D SSPP requires location input for the *Chest* joint located between the *Neck* joint and the *Spine* joint. However, the body configuration of the motion file extracted previously does not include the *Chest* joint. Since this joint is essentially located on a straight line connecting the *Neck* and the *Spine* joints, and since its linear distance from these two joints does not change, the 3D coordinates of its location can be calculated using linear interpolation. Once all three required inputs are calculated, a batch file is created to run 3D SSPP that computes loads exerted on each body joint over all the frames. This enables precise detection of the movements that cause excessive stress on a joint for the whole motion and of the body joint at risk. The motion can then be modified by redesigning the task and its surrounding workplace until it is ergonomically safe and all forces are below the allowable limit.

3.4.5 Improved Workplace Design

After modifying all the unsafe worker motions to create ergonomically acceptable motions, these are presented in the 3ds Max model of the workplace. These motions replace the corresponding unsafe ones to complete the final 3D virtual model for representation to the owner and facility managers. This model includes design data regarding the physical layout of the jobsite as well as worker motion data for each activity which can be used for visualization purposes, managerial decision making, communication, and training. For the case of workplace redesign, the modifications of the work environment and motions can be conveniently communicated with all different levels of staff, from managers and supervisors to workers, which facilitates implementation of the adjustments. These adjustments usually include alterations such as rearranging a work station, increasing/decreasing the height of a worktable, or providing more comfortable worker postures.

3.5 IMPLEMENTATION: CASE STUDY

The proposed approach is implemented in a production line of a construction modular prefabrication company, to investigate the ergonomic risk associated with its operations and to propose a new design that minimizes safety risks to workers. Off-site construction methods such as modular and prepanelized construction are among the residential construction methods used in Edmonton, Canada. There is a high market demand for off-site construction methods since they offer the advantages of an environmentally-friendly process, shorter completion time, and predictable quality and cost. To meet these requirements, construction manufacturing companies continually redesign their production lines to improve the efficiency of their operations. However, due to the lack of effective approaches, in many cases ergonomic considerations are not being applied to workplace design and redesign. Despite technological advances, workers in off-site construction still perform labor-intensive and physically demanding tasks, including cleaning, assembling, loading/unloading material, and operating machines, which results in high rates of work-related accidents and injuries among these workers. Thus, although the study presented in this chapter implements the developed framework in a construction fabrication shop setting, it can be similarly applied to any other construction jobsite.

For the purpose of this research, the process of building floor panels in a fabrication shop is modeled and analyzed (Fig. 3-5). The production line consists of four stations where the first station involves material preparation and the other three are assembly stations. Two of the assembly stations are operated primarily by machines, and the workers' manual tasks involve operating the machines. However, most of the tasks taking place in the last assembly station are operated manually and are physically challenging for the workers; thus, this chapter mainly focuses on the last assembly station. All the required information is collected from the jobsite to build the virtual 3D model of the floor line in 3ds Max. This information includes the layout of the facility and equipment, the processing times of different tasks, and information pertaining to the materials used. Table 3-2 shows the collected information regarding the sheathing and timber used in the production line. Each row provides specifications of the given building component handled by the workers at this station. Information about the tools used by the workers is also collected which is used to determine the loads imposed on workers while operating them. The main tools used in the observed tasks are a nail gun and a cutting tool, which weigh approximately 3.4 kg (7.5 lb) and 3.8 kg (8.4 lb), respectively.

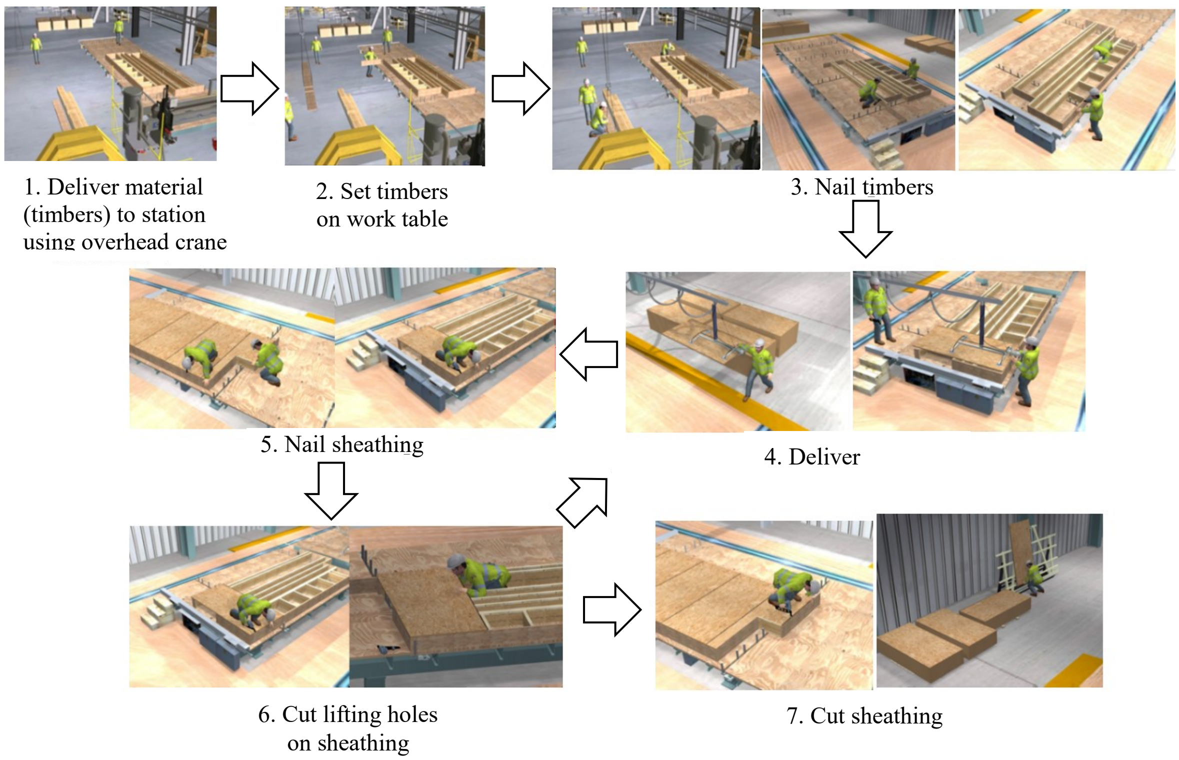


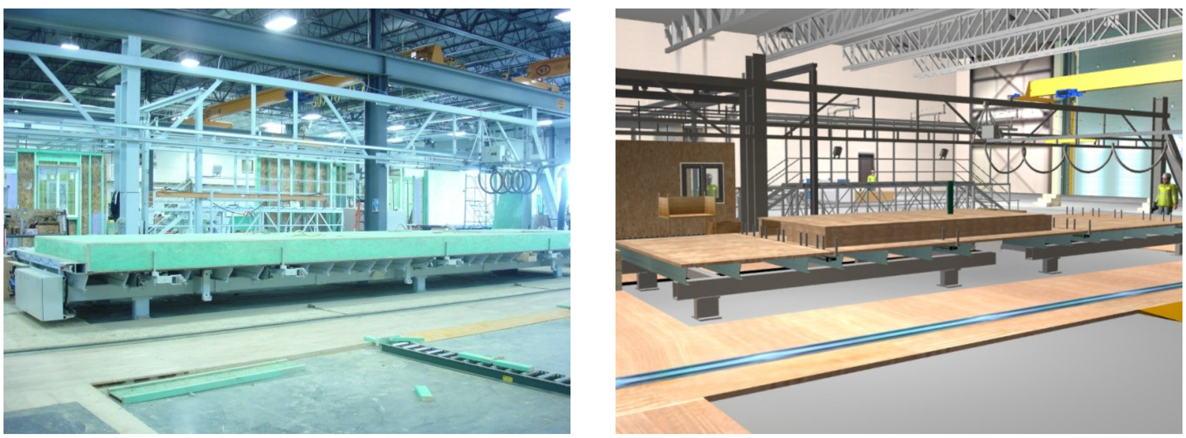
Figure 3-5 Sequence of tasks for floor panel production line

Table 3-2 Specifications of materials used in the production line

Sheathing List			
Number of Pieces	Width (mm)	Height (mm)	Length (mm)
1	1,219.2	22.2	1,593.1
1	609.6	22.2	535.8
2	609.6	22.2	1,487.0
6	1,219.2	22.2	1,593.0
5	1,219.2	22.2	1,487.0
Timber List			
Number of Pieces	Length (mm)	Number of Pieces	Length (mm)
1	1,070.0	1	425.4

1	2,975.0	3	368.3
1	1,593.1	1	149.2
1	1,486.9	2	9,080.5
1	609.6	3	7,239.0
1	504.0	2	7,848.6

After collecting all the required data, the 3D model of the production line is built in the 3ds Max environment by carrying out measurements in the jobsite and using blueprints provided by the facility managers in a detailed level. The models are built through thorough visual inspection of the as-built conditions, and the models were also reviewed and verified by facility management personnel. Fig. 3-6 shows a picture of the real jobsite and a screenshot of the virtual environment from the same perspective. The result of this process is a 3D model of the jobsite including simulated animation data showing production operation.



(a) (b)

Figure 3-6 (a) Picture of jobsite and (b) screenshot of virtual model from same perspective

The sequence of the activities on the floor assembly station is illustrated in Fig. 3-5, which also gives snapshots of the virtual model. The sequence starts when the timbers are delivered to the station and set on the designated table. While the timbers are being nailed together, the sheathing is also delivered. The timbers and sheathing are then assembled and nailed to each other to form the floor panel and are transferred to the next workstation for cutting.

The seven work processes shown in Fig. 3-5 include twelve different manual tasks in total. After the 3D model of the production line has been built, the motions of the workers are added as described above. At this point, visual inspection on the modeled animations is performed to confirm that the virtual model constitutes an accurate representation of the work environment which can be used for different workplace visualization applications. The next step involves extracting these worker motions and performing ergonomic analysis. The motions are input into the developed application and the RULA method is used to analyze the ergonomic risks in the motions. Table 3-3 reports the results of the ergonomic analysis for the twelve manual tasks at the fabrication shop. We also manually analyze the risk to compare the proposed motion data-driven approach with human observation. The results of the two methods of analysis are found to differ with respect to tasks *Nailing 4* and *Timber Setting*. These tasks are further examined to investigate the cause of these errors. It is found out that the reason behind the discrepancy for the nailing task is that the application has calculated a joint angle of more than 100 degrees for the lower arm from the motion data, whereas this angle is considered to be less than 100 degrees in the manual analysis. For the timber setting task, the manual analysis has assumed a joint angle greater than 20 degrees for the neck joint while the application has calculated the same joint angle to be less than 20 degrees. These variations in joint angles lead to slightly different RULA final scores. The thorough error analysis reveals that the discrepancy between the automated and manual analyses is the result of human error in observing at-risk postures and estimating the joint angles. The proposed automated method is thus more accurate and robust since it uses precise calculation of joint angles for each time frame of the motion data to determine the most awkward posture.

Table 3-3 RULA results of the automated ergonomic analysis compared with manual assessment

Task	Motion Data-driven Approach	Manual Analysis
Nailing 1	Investigate and implement change	Investigate and implement change
Nailing 2	Investigate and implement change	Investigate and implement change
Nailing 3	Investigate and implement change	Investigate and implement change
Nailing 4	Further investigation, change soon	Investigate and implement change
Nailing 5	Investigate and implement change	Investigate and implement change

Hole cutting	Further investigation, change soon	Further investigation, change soon
Frame delivery	Further investigation, change may be needed	Further investigation, change may be needed
Panel delivery	Acceptable posture	Acceptable posture
Timber setting	Investigate and implement change	Further investigation, change soon
Cutting 1	Further investigation, change may be needed	Further investigation, change may be needed
Cutting 2	Further investigation, change soon	Further investigation, change soon
Gluing	Investigate and implement change	Investigate and implement change

For the tasks for which the automated method reports a RULA result other than ‘acceptable posture’ (RULA score higher than 2), further biomechanical analysis is performed to investigate the amount of exerted forces on different body joints. This analysis provides information on body joints at risk and provides insight for redesigning the workplace to achieve ergonomically safe motions. After the proposed method generates the required batch file for 3D SSPP analysis, each of these motions are loaded into 3D SSPP and the forces and moments on the different body joints are extracted. The back compression load and also the percentage of workers capable of performing the task (i.e., strength design limit) based on different body joints are plotted on a chart in order to compare the exerted loads with the allowable limits. As a result, the time frames when the imposed loads exceed the allowable limit can be detected and necessary modifications can be made. Fig. 3-7a shows examples of such charts, which represent the biomechanical analysis of the nailing task. The chart on the left represents the load on the worker’s back over time and the chart on the right represents the Strength Design Limit (SDL) data.

For this task, the result of the biomechanical analysis indicates a potential risk of back and torso injury which is the result of excessive force on the worker’s L5/S1 disc and hip due to awkward posture while nailing the timbers (i.e., 3D avatar model in Fig. 3-7a). The worker’s knees and ankles are also at risk of injury. To address this unsafe task, the workplace is redesigned and the motion reanalyzed to assess the potential risk. The workplace adjustments include providing a gap between two adjacent workstations, which enables the worker to perform the task while standing. This measure serves to greatly reduce the loads on the worker’s body joints. The updated motion results in acceptable forces, as shown in the charts in Fig. 3-7b. Fig. 3-7 also shows the workplace redesign in the 3D virtual environment before and after modification.

The same process is carried out for all the other unsafe motions; the summary is presented in Table 3-4. The suggested modifications include (1) training, (2) workstation adjustment, (3) equipment change, and (4) work methods (i.e., team work). Specifically, for the tasks for which the ergonomic risk is the result of the worker's awkward posture, worker training is proposed which involves informing the worker about the risks associated with the task and educating them about the correct posture by performing it in the workplace visualization (i.e., Nailing 1, Nailing 3, and Gluing). Workstation adjustments and equipment changes include changes to the jobsite such as increasing the height of a work table for picking up pieces (i.e., Timber setting), rotating the panels to a vertical position for nailing (i.e., Nailing 4 and Nailing 5), and picking a piece of material and moving it with a forklift instead of handling it manually (i.e., Cutting 2). In cases where the task is too challenging for the worker to perform alone, adding another member of the crew to help with handling the task is proposed (i.e., Frame delivery and Cutting 1).

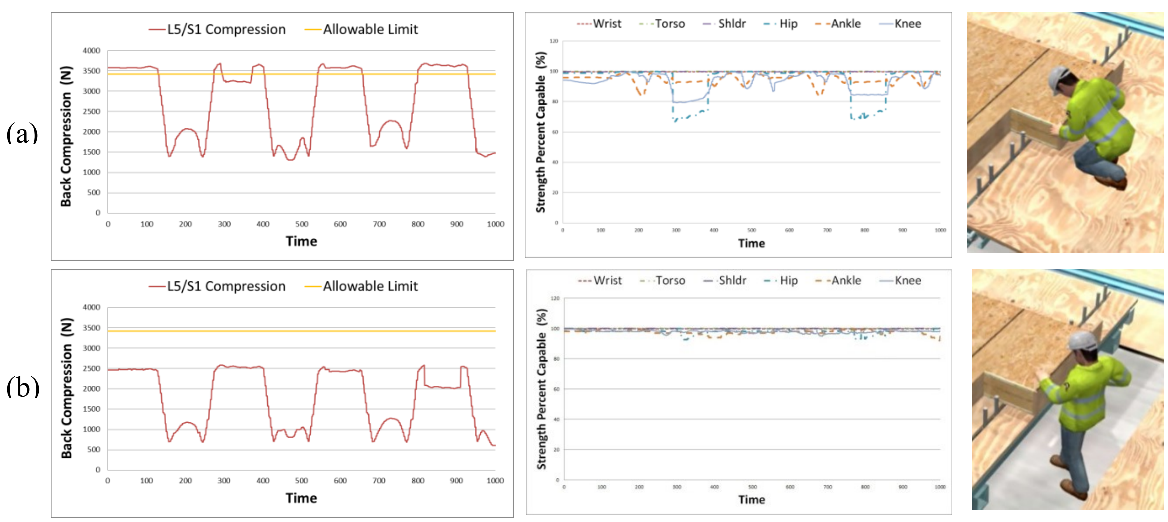


Figure 3-7 Back compression chart, SDL chart, and workplace visualization of the nailing task, (a) before modification and (b) after modification

Table 3-4 Summary of results of biomechanical analysis for unsafe tasks

Task	Before Modification	After Modification	Type of Modification

	RULA Score	Back Compression* (N)	Body Joint at Risk	Strength Percent Capable (%)	RULA Score	Back Compression (N)	Strength Percent Capable (%)	
Nailing 1	7	3,996	Knee	58	3	2,743	91	Training
Nailing 2	7	3,614	Hip	77	2	2,594	92	Workstation adjustment
Nailing 3	7	3,795	Knee	72	3	2,477	94	Training
Nailing 4	6	3,394	Ankle	69	2	2,296	92	Workstation adjustment
Nailing 5	7	3,457	Hip	77	2	2,304	95	Workstation adjustment
Hole cutting	5	2,184	Hip	82	2	1,932	94	Equipment change
Frame delivery	3	2,420	Shoulder	81	1	1,971	96	Team work
Timber setting	7	2,735	Knee	63	2	2,608	93	Workstation adjustment
Cutting 1	3	2,129	Hip	75	1	2,430	96	Team work
Cutting 2	6	2,526	Torso	71	2	2,096	95	Workstation adjustment
Gluing	7	3,562	Hip	73	2	2,682	93	Training

* Allowable limit for back compression is 3,400 N (Waters et al. 1993).

3.6 DISCUSSION

The ergonomic analysis approach described in this chapter provides a quantitative evaluation of behavioral risks which is used to ensure ergonomically safe workplace design. The biomechanical analysis (e.g., capable strength at body joints in Fig. 3-4, and back compression and SDL charts in Fig. 3-7) provides detailed information regarding the specific body parts at risk, the exerted forces on the worker's joints over time, and the allowable human capacity. This enables not only identifying the postures that impose the highest risk, but also modifying the motion or working environment accordingly. As a result of the modification, the RULA score, back compression, and strength percent capable for the tasks can be kept within acceptable limits after the re-designing, as shown in Table 3-4. The proposed approach can thus provide precise information to identify ergonomic risks associated with a proposed design to prevent WMSDs before the worker is exposed to unsafe conditions. The magnitude, duration, and frequency of the musculoskeletal loads exerted on the worker's joints are the main factors leading to WMSDs (Kilbom et al. 1996), and thus the quantitative assessment of forces exerted on body joints is critical in reducing the risks of these disorders.

This chapter has focused on human motion analysis in a virtual environment to evaluate and minimize the ergonomic risks associated with workplace designs. In this chapter, the ergonomic analysis has been carried out on motion data created in the 3D visualization environment of the jobsite. However, motion datasets (e.g., BVH format) extracted from any types of sensors can also be utilized for the proposed analysis, particularly when assessing human motions in existing operations. With the ongoing advancements in sensing technologies, analysts will be able to accurately record existing motions in different working conditions (e.g., outdoor), and such motion capture data can be used in the framework developed in this chapter to identify body joints at risk and improve worker motions accordingly. Future work can investigate the use of sensing devices to extract motion information from existing operations as well as estimating human motions (i.e., motion planning) for design alternatives, where motion data is not available.

It should be noted that this chapter focuses on identifying and preventing ergonomic risk factors associated with worker motions and does not consider other types of jobsite safety risks. Analyzing jobsite accidents is a complex process as many various factors are involved in it. Thus, to perform a complete safety analysis, the framework proposed in this chapter should be used in conjunction with analysis of other type of jobsite hazards such as fall and struck-by hazards.

The development of the 3D virtual model of the work environment as described in this chapter may necessitate significant time and effort for collecting site information and building the 3D model. In today's construction industry, however, the use of these 3D models is increasingly prominent and is becoming a common practice for the design process. In particular, building information models, which are being used in major construction projects, can be conveniently converted to formats suitable for platforms such as 3ds Max. This chapter has attempted to leverage this by developing a specialized approach that uses these models as a basis for ergonomic evaluation of the work environment. Using virtual visualization of the work environment enables efficient comparisons between operational alternatives and convenient implementation of the proposed modifications to evaluate and confirm the safety improvements before applying the changes to the real jobsite. The 3D models used in this chapter are created through visual inspection of the as-built conditions and are verified by the facility management personnel. However, laser scanners and 3D sensing technologies (e.g., 3D reconstruction) can be used as well to provide higher geometrical accuracy.

The application of the proposed approach to on-site construction can also be further investigated. The frequent changes of working environments over time in on-site construction require a considerable amount of time to update the virtual visualization of the worksite, including the 3D model and motion datasets. The use of advanced motion sensing technologies and computer vision techniques (e.g., laser scanners, image-based 3D reconstruction) can be potential solutions that can automate such modeling processes. As combined with the sensing technologies, the framework presented in this chapter may facilitate the on-site ergonomic risk assessment that can be adapted to the changing conditions of construction sites.

3.7 CONCLUSION

This chapter presents an automated approach to jobsite ergonomic safety analysis for effective and proactive design of construction jobsites. The proposed framework integrates ergonomic analysis with 3D visualization of the workplace to provide production planners and designers with the potential ergonomic risk and safety concerns associated with a potential design. Particularly, this chapter has: (1) investigated a risk intervention means to reduce workers' at-risk movements in the planning phase that goes beyond the observational monitoring of worker motions; (2) presented comprehensive uses of ergonomic and biomechanical analyses in conjunction to perform a global risk assessment as well as to calculate the forces exerted on body joints to ensure efficient worker safety evaluation; and (3) proposed computerized methods using motion capture data, which can minimize the involvement of designer's subjective judgments in determining postural comfort. Consequently, this chapter may assist practitioners in considering ergonomic risk in their design and planning tasks, and assist researchers to further explore the relationship between workplace design and safety performance. Taking the significance of design-related accidents into account, this PtD approach to safety may in turn contribute to a significant reduction of WMSDs in construction workplaces.

3.8 ACKNOWLEDGMENTS

We would like to thank graduate students at the University of Alberta, as well as the staff at Landmark Group of Builders for their help in data collection. The work presented in this chapter has been supported financially by the Natural Sciences and Engineering Research Council of Canada (NSERC) Industrial Research Chairs (IRC) program, the National Science Foundation (NSF), as well as by the Center for Construction Research and Training (CPWR) through the National Institute for Occupational Safety and Health (NIOSH) cooperative agreement. Any opinions, findings, and conclusions or recommendations expressed in this chapter are those of the authors and do not necessarily reflect the views of NSERC, NSF, CPWR, or NIOSH.

Chapter 4 A Fuzzy Logic Approach to Posture-based Ergonomic Analysis for Field Observation and Assessment of Construction Manual Operations [2]

4.1 SUMMARY

To prevent ergonomic injuries, proper assessment of ergonomic risk is a key to identifying risk factors and modifying work practice in a timely manner, as shown in the previous chapter. In field observation, however, difficulties in visually estimating human postures (e.g., body joint angles) required for ergonomic analysis have led to inconsistent results due to the subjectiveness of observers. This chapter introduces a fuzzy logic approach to posture-based ergonomic evaluation tools to address this issue. RULA is selected as a case study to describe the fuzzy logic modeling of RULA scoring systems and discuss the application to modular construction shops. The results of validation comparing correlations with biomechanical analysis—used as a ground truth—reveal that the proposed system can produce more accurate results than traditional methods and hence help minimize human errors in observation for reliable on-site ergonomic assessment.

4.2 INTRODUCTION

Appropriate and efficient ergonomic assessment is critical in efforts to mitigate the ergonomic risks involved in worker movements and eventually to reduce the rate of WMSDs. To enable proactive risk assessment and control in a jobsite, practitioners and researchers have developed different approaches: self-evaluation, observation-based methods, and direct measurements (Li and Buckle 1999). Among the three ergonomic risk analysis approaches, observation-based methods (i.e., manual observation using ergonomic assessment tools) have been the most widely implemented in practice due to their simplicity, validity, accessibility, and cost- and time-efficiency (NIOSH 2014; Chiasson et al. 2012; Bao et al. 2007; Takala et al. 2010; Kee and Karwowski 2007). Self-evaluation methods are generally less accurate and reliable compared to the other methods (David

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[2] A version of this chapter is published as Golabchi, A., Han, S., and Fayek, A. Robinson (2016). "A Fuzzy Logic Approach to Posture-based Ergonomic Analysis for Field Observation and Assessment of Construction Manual Operations." *Canadian Journal of Civil Engineering*, 43: 294–303.

2005). On the other hand, despite the potentially higher accuracy of the direct measurement techniques, their use still remains challenging due to technology and resource limitations; for example, they are usually applied to small population samples, where postures with only limited number of joints can be measured simultaneously (Bao et al. 2007). Furthermore, the accuracy of these technologies is highly affected by the jobsite conditions (e.g., outdoor construction), and some types of sensors (e.g., wearable sensors) limit the worker's ability to freely perform their regular tasks and may result in discomfort. Furthermore, direct measurement techniques are generally used to obtain joint angle values describing a posture that would later be analyzed using existing ergonomic assessment tools. In this regard, ergonomic assessment tools serve as a key to properly identifying and evaluating onsite ergonomic risks associated with human postures. Observational methods are applied through ergonomic assessment tools which assign scores to manual tasks based on body posture, task repetitiveness, and duration. Examples of widely-used tools include RULA (McAtamney and Corlett 1993), REBA (Hignett and McAtamney 2000), NIOSH lifting guideline (Waters et al. 1993), and Strain Index (SI) (Moore and Garg 1995).

In field observation, however, the reliability of ergonomic evaluation results is contingent upon manual measurement of inputs required for the assessment tools (e.g., body joint angles, moving distances). The visual ambiguity in estimating those inputs often makes it difficult for a human observer to obtain accurate inputs, leading to inaccurate analysis outcomes. Consequently, the accuracy of evaluation results and derived risk intervention plans is inherently affected by the subjectiveness towards the evaluator's inputs. In an effort to address this issue, this chapter presents a fuzzy logic-based framework to deal with the imprecision of ergonomic assessment inputs caused by human intuition in field observation. This framework involves re-modeling the scoring systems of an ergonomic tool. This chapter first reviews existing ergonomic assessment tools and discusses the issues pertaining to the impact of input errors on analysis results. Then, the proposed ergonomic model is presented and validated by comparing the results of the existing tool and proposed model with the results obtained from biomechanical analysis. As discussed in Chapter 3, biomechanical analysis enables the identification of ergonomic risks by evaluating the internal loads imposed on the human body's joints and is thus regarded as an objective assessment method. A case study in which the proposed model is applied to modular construction is also carried out, and the contributions and limitations of the study are discussed based on the results.

4.2.1 Traditional Ergonomic Assessment Tools

Ergonomic posture analysis is performed using assessment models and checklists in order to evaluate the safety risks involved in human actions by calculating overall scores indicating the level of risk associated with a manual task. This approach considers human postures as well as external risk factors such as task frequency and duration to provide a global risk assessment (i.e., ergonomic risks imposed on the human body) associated with a posture. The assessment systems typically require inputs pertaining to the posture of the worker (e.g., body joint angles), the load being handled by the worker (e.g., weight of object being carried), and the frequency of the task (e.g., static, repeated). Using this set of inputs, the level of ergonomic risks associated with a manual task is estimated. These assessment tools typically define discrete boundaries between ranges of input variables (e.g., body joint angle), where inaccurate human perception can lead to discrepancies in the analysis results when an observer fails to clearly distinguish the input values close to boundaries. Considering the imprecision of the inputs, this discrepancy can yield unreliable ergonomic evaluation results. Table 4-1 shows six of the widely used posture-based ergonomic assessment tools, as well as the inputs with discrete boundaries for each.

Table 4-1 Example of inputs with discrete boundaries in ergonomic assessment tools

Method	**Inputs with discrete boundaries**	**Range of input values**	**Number of input ranges**
RULA (McAtamney and Corlett 1993)	Upper arm	[-90° 180°]	5
	Lower arm	[0° 180°]	3
	Wrist	[-90° 90°]	4
	Neck	[-45° 90°]	4
	Trunk	[60° 120°]	4
	Load	0 lb - 22^{+} lb	3
REBA (Hignett and McAtamney 2000)	Neck	[-45° 90°]	3
	Trunk	[60° 120°]	5
	Leg (adjustment)	[0° 180°]	3
	Upper arm	[-90° 180°]	5
	Lower arm	[0° 180°]	3
	Wrist	[-90° 90°]	3
	Load	0 lb - 22^{+} lb	3
The Strain Index	Duration of exertion	0% - 100%	5

(Moore and Garg 1995)	Efforts per minute	0 - 20$^+$ min	5
	Duration of task per day	0 - 8$^+$ hours	5
NIOSH Lifting Equation (Waters et al. 1993)	Horizontal multiplier	0 in - 25$^+$ in	17
	Vertical multiplier	0 in - 70$^+$ in	16
	Distance multiplier	0 in - 70$^+$ in	13
	Asymmetric multiplier	[0° 135°]	10
	Frequency multiplier	0 - 8 hours	6
OCRA (Occhipinti 1998)	Force multiplier factor	0 – 1	10
	Posture multiplier factor	0 – 1	5
	Recovery multiplier factor	0 – 1	8
LUBA (Kee and Karwowski 2001)	Wrist	0° - 60°$^+$	3
	Elbow	0° - 120°$^+$	3
	Shoulder	0° - 150°$^+$	4
	Neck	0° - 45°$^+$	3
	Back	0° - 60°$^+$	4

One of the cases with the highest imprecision of inputs in field observation occurs in estimating body joint angles, as required for posture-based ergonomic assessment tools (e.g., RULA, REBA, LUBA). Since joint angles are the main inputs for such assessment methods, the perception issue on angles close to border ranges can highly affect the accuracy and reliability of the final results. This chapter focuses on the RULA method as a case study based upon which to discuss the human perception issue with respect to posture estimation, as well as to describe the proposed fuzzy logic approach to ergonomic analysis.

4.2.2 Rapid Upper Limb Assessment (RULA)

As discussed in the previous chapter, RULA is widely accepted as an effective ergonomic assessment method due to its simplicity and precision in assessing posture-related loads (Levanon et al. 2014; Kee and Karwowski 2007). In RULA, each body segment is considered independently and a corresponding score is calculated for the body part based on its posture. For each body segment (i.e., upper arm, lower arm, wrist, neck, and trunk), the ergonomist assigns the posture to one of the categories proposed by RULA and obtains the corresponding score for that body part. The final score, which represents the level of risk, is then obtained by combining the scores of different body segments. RULA also considers the frequency of the task (i.e., muscle use) and the force exerted on the worker's body. The scores of different body segments are combined with the muscle use and force scores and a final score between 1 and 8 is obtained. Lower scores represent ergonomically acceptable postures with very low risk of injury and higher scores indicate exposure to immediate risk and the need for prompt investigation and modifications.

4.2.3 Human Perception Issue in RULA

The RULA method has been validated by McAtamney and Corlett (1993), who conducted an experiment in an ergonomics laboratory environment by analyzing subjects performing a data entry operation. The experiment aimed to investigate whether RULA scores appropriately reflect the musculoskeletal loads corresponding to the test subjects' reports of pain, ache, or discomfort in the relevant body part. The Chi-Square (X^2) statistical test was used to determine the association between RULA score and any reported pain, ache, or discomfort, and a highly significant association ($P < 0.01$) was reported. To test RULA's reliability, over 120 ergonomists and engineers were trained to assess motions of operators and workers using RULA. A high consistency in RULA scores was found among the subjects.

However, discrepancies occurred in cases where the posture consisted of a body part being located at a border between two ranges (McAtamney and Corlett 1993). Although the ranges of lower arm were modified from the original version to mitigate this discrepancy, the issue still remains for any posture with body segments close to the border of ranges. While observing a worker motion to evaluate it using an ergonomic assessment tool such as RULA, the evaluator inputs the body segment angles based on approximate estimates rather than precise values. However, the RULA system proposes discrete boundaries between the angle ranges for the different body parts. This results in discrepancies in the RULA results for postures involving body segments close to the angle borders.

For example, three different postures are created for comparison in a 3D modeling environment with exact values of joint angles (Fig. 4-1). Table 4-2 shows the three sets of inputs for the RULA method and the resulting RULA score for each. Considering posture I and posture II, it can be observed that, although many of the angles and also the exerted force are considerably different, the final RULA score is the same. On the other hand, inputs of posture II and posture III have very close values, making it difficult for an observer to choose between the two, while the RULA score is substantially different. The sharp boundary between the upper arm angle ranges of 20° to 45° and 45° to 90° in Fig. 4-2 indicates that an upper arm angle of 44° will result in an upper arm score of +2, while an upper arm angle of 46° results in an upper arm score of +3. Consequently, the total RULA score and corrective plan of action will be different for these two postures. This discrepancy occurs due to the inputs selected being close to the border of angle ranges.

Figure 4-1 Postures corresponding to data in Table 4-2

Table 4-2 RULA scores for three sets of inputs

Posture Case	Upper Arm	Lower Arm	Wrist	Wrist Twist	Neck	Trunk	Leg	Muscle Use	Force	**RULA score**
Posture I	22°	65°	4°	2	11°	18°	2	0	5 lb	**4**
Posture II	44°	98°	14°	2	19°	18°	2	0	21 lb	**4**
Posture III	46°	102°	16°	2	21°	22°	2	0	23 lb	**7**

For further analysis, Fig. 4-2 shows the change in the RULA Arm & Wrist score, when lower arm and wrist angles remain fixed and the upper arm angle changes from -90° to 180°. As shown in the chart, the discrete boundaries between angle ranges results in sudden change of score at border angles (e.g., -20°, 20°). Considering the imprecision of inputs caused by human perception, a gradual transition between the scores, rather than an abrupt change, will improve the accuracy of the method. Since RULA is being widely used as an efficient ergonomic assessment tool, this chapter aims to improve its reliability by addressing the issue of discrepancy at postures with inputs close to borders of ranges.

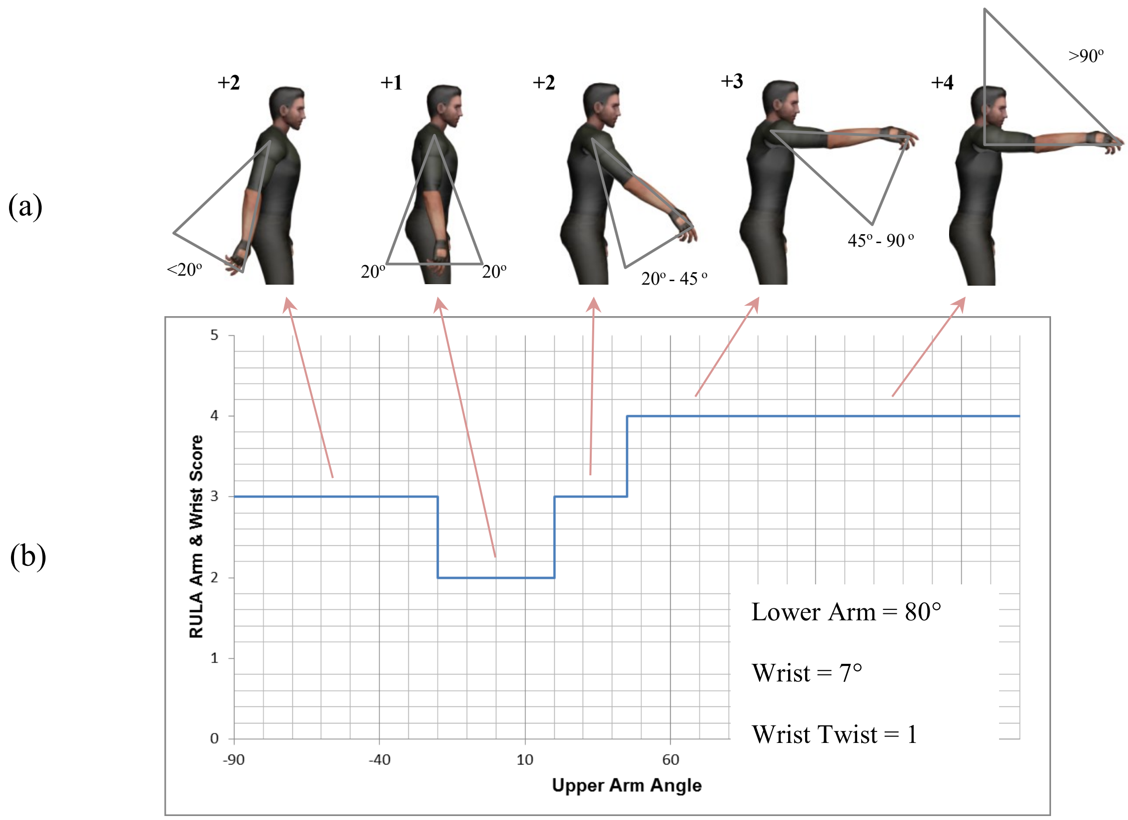

Figure 4-2 The impact of upper arm posture categories on intermediate results of Arm & Wrist score: (a) Upper arm posture categories of RULA (adapted from McAtamney and Corlett (1993)), and (b) abrupt change in RULA Arm & Wrist score corresponding to change in upper arm angle

4.3 RESEARCH FRAMEWORK

This chapter leverages fuzzy logic techniques to model ergonomic assessment tools as fuzzy expert systems. Fuzzy logic is an effective way to deal with imprecise and uncertain information and reason with ambiguous concepts, as it enables gradual transition between different classes of continuous variables with unsharp boundaries (Zadeh 1975). Thus, the imprecision of the inputs of ergonomic assessment systems (i.e., body joint angles) and the sharp boundary between the posture classifications (i.e., angle ranges) can be incorporated into fuzzy logic modeling processes to minimize the human perception issue in estimating joint angles. In the case of posture-based assessment systems, the use of fuzzy logic thus enables a steady transition between the scores of different angle ranges of body joints, which results in gradual transition of corresponding scores. This approach improves the reliability of ergonomic assessment methods by overcoming the limitation of abrupt changes in scores. A fuzzy expert system, Fuzzy RULA, is developed based on RULA. Fuzzy RULA requires the same set of inputs as RULA (e.g., body joint angles, load) and outputs a total assessment score. The performance of the model is assessed by investigating its correlation with RULA as well as with biomechanical analysis results, used as a ground truth in this research. The correlation between RULA and biomechanical analysis is also calculated to compare the performance between Fuzzy RULA and RULA. A sensitivity analysis is then carried out to find the system configuration resulting in the highest accuracy. The proposed approach is implemented in a construction jobsite to further examine its effectiveness and applicability.

4.3.1 Fuzzy RULA Model Development

Fuzzy logic is a mathematical tool developed to deal with reasoning that is approximate rather than precise (Zadeh 1965). Due to the subjective uncertainty inherit in construction operations and decision making processes, fuzzy logic techniques have been increasingly used in many applications such as construction knowledge discovery systems (Elwakil and Zayed 2014), benchmarking knowledge management of construction firms (Kale and Karaman 2011), contractor default prediction (Awad and Fayek 2012), risk assessment (Li et al. 2013; Nasirzadeh et al. 2008), and quality assessment of infrastructure projects (Fayek and Rodriguez Flores 2010). For the modeling of subjectiveness, a fuzzy expert system uses a collection of fuzzy membership functions and if-then rules to imitate the thinking process of an expert and reason about data. The rule's antecedent defines the extent to which the rule applies using membership functions, and the conclusion assigns a membership function to the output variables. The inference process starts with assigning membership grades to the inputs based on the premises of the rules, known as fuzzification. The membership degrees in the rule's premise are then combined, typically using minimum or product operators, which is known as inference. The fuzzy subsets assigned to each output variable are then combined, usually using s-norm operators, to form a single fuzzy subset in a process known as aggregation. Finally, the fuzzy output set is converted to a crisp number through defuzzification. The basic configuration of a fuzzy logic system is shown in Fig. 4-3.

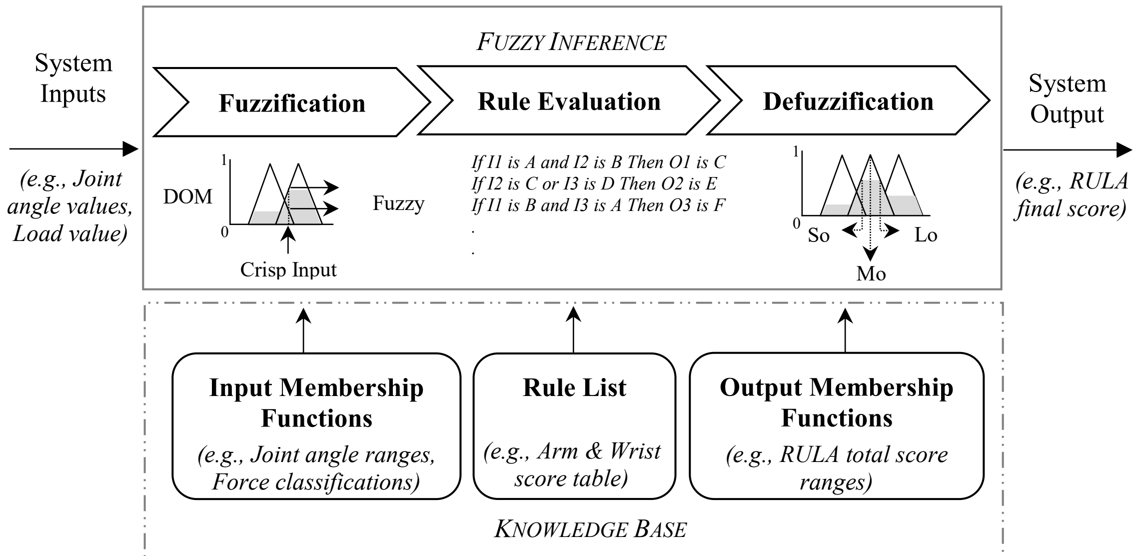

Figure 4-3 Configuration of a fuzzy logic system

The RULA-based fuzzy model developed in this chapter consists of a fuzzy expert system with 9 inputs, 4 intermediate variables, 1 final output, 5 rule blocks, 114 membership functions, and 371 if-then rules. The structure of the model is shown in Fig. 4-4.

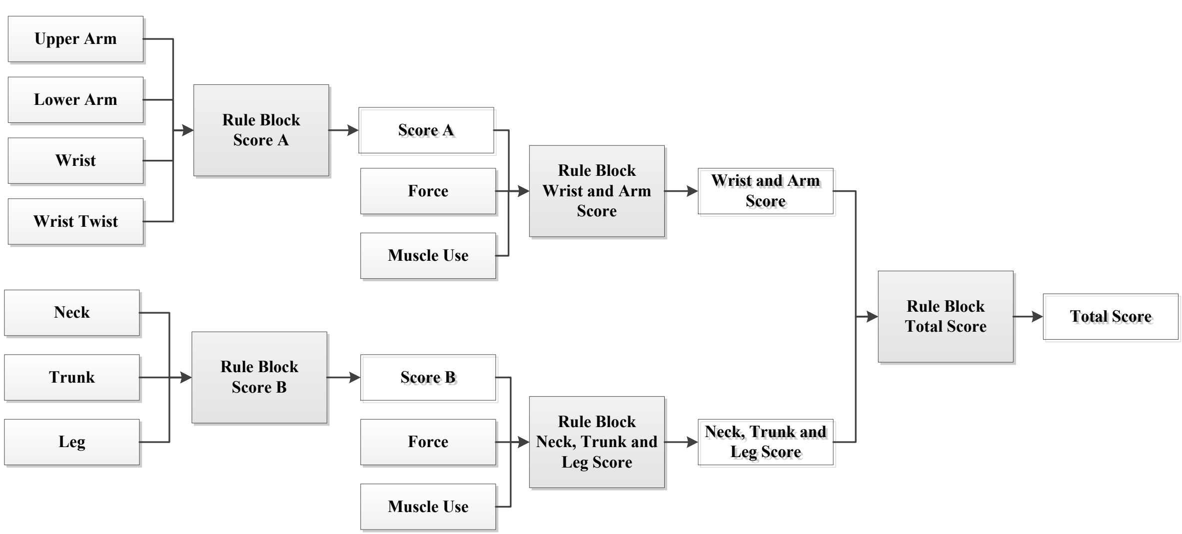

Figure 4-4 Structure of the Fuzzy RULA expert system

In Fuzzification (Fig. 4-3), membership functions are curves that describe the evaluation criteria for inputs and outputs of the fuzzy expert system. They are used to map input values to a degree of membership in the fuzzy set. Membership degrees indicate the degree of belonging of a value to different terms and range from 0 to 1, with 0 representing non-membership and 1 representing full membership. Developing membership functions is a crucial but also challenging step in developing a fuzzy expert system. Membership functions can be developed using different techniques that can be categorized as discrete representation and continuous functional form representation (Dissanayake and Fayek 2007). Examples of discrete representation include pairwise comparison, direct assignment, and exemplification. Examples of continuous functional form representation consist of heuristically-based, statistically-based, and cluster-based methods (Poveda and Fayek 2009).

In this chapter, a heuristic method is used to develop the membership functions for the input and output variables. As a base case, trapezoidal membership functions are used to represent the angle ranges of the inputs as well as the force imposed on the worker, and triangular membership functions are used for intermediate variables which represent the RULA intermediate scores. The final output variable, RULA total score, is also represented by triangular membership functions. Triangular and trapezoidal membership functions are used due to efficiency of the computation involved, simplicity of application and understanding for different users, and high frequency of use in fuzzy logic modeling (Poveda and Fayek 2009). The overlap between adjacent membership functions is designed such that the point of intersection has a membership degree of 0.5, which enables gradual transition between variables. The point of intersection for the input variables is the border angle between two angle ranges for joint angle inputs and the border force for the load/force input variable, as shown in Fig. 4-5. For intermediate and output variables, the core point of each membership function corresponds to the score that the curve represents.

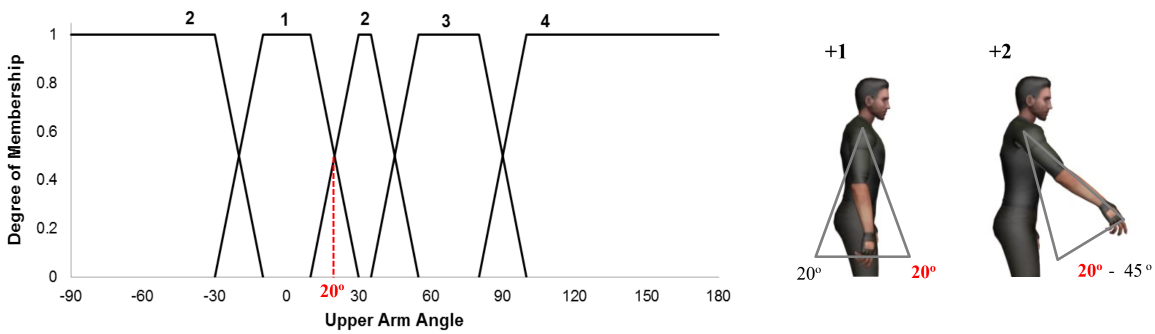

Figure 4-5 Example of point of intersection for upper arm input variable

In Rule Evaluation (Fig. 4-3), fuzzy expert systems contain a set of if-then rules which define the logical reasoning that relates the input variables to the output variables. The condition part of a rule is represented by membership functions of the input variables, and the conclusion part is represented by membership functions of the output or intermediate variables. The basis of the if-then rules for the Fuzzy RULA model are the three scoring tables of the RULA system. Fig. 4-6 shows the scoring table for neck, trunk, and leg score (McAtamney and Corlett 1993), as well as an example of a rule derived from the table.

After rule aggregation and as the final step (Defuzzification in Fig. 4-3), membership functions of the output (i.e., RULA total score) are used to obtain a crisp value representing the final score. Defuzzification is the inverse process of fuzzification, where, based on the given fuzzy sets of the output and calculated degrees of membership, a defuzzification method (e.g., centroid, bisector, smallest of maximum) is used to select the most accurate quantifiable representation of the output. The total Fuzzy RULA score obtained from this step defines the level of ergonomic risk associated with the input posture based on the RULA interpretation of final scores.

Neck Posture Score	Trunk Posture Score 1		2		3		4		5		6	
	Legs		Legs		Legs		Legs		Legs		Legs	
	1	2	1	2	1	2	1	2	1	2	1	2
1	1	3	2	3	3	4	5	5	6	6	7	7
2	2	3	2	3	4	5	5	5	6	7	7	7
3	3	3	3	4	4	5	5	6	6	7	7	7
4	5	5	5	6	6	7	7	7	7	7	8	8
5	7	7	7	7	7	8	8	8	8	8	8	8
6	8	8	8	8	8	8	8	9	9	9	9	9

If
(NeckScore) is 2 and
(TrunkScore) is 4 and
(LegScore) is 2
Then
(NeckTrunkLeg) is 5

Figure 4-6 Neck, Trunk, & Leg score table and example of an if-then rule

4.4 RESULTS AND VALIDATION

To validate the Fuzzy RULA model, a two-step validation process is carried out. The first step is to ensure that Fuzzy RULA has a high correlation with the RULA method. The second step involves validating that Fuzzy RULA is a more accurate representation of the loads exerted on the worker's body than is RULA. The base case of the Fuzzy RULA expert system is developed using triangular and trapezoidal membership function shapes, the minimum t-norm operator for combining the input variables, the product operator for implication of the combined input to the output in each rule, the maximum s-norm operator for the aggregation of the rules, and the Center of Maximum (CoM) method as the defuzzification method.

4.4.1 Correlation between RULA and Fuzzy RULA

To study the correlation between RULA and Fuzzy RULA, a correlation analysis is performed using the Spearman's rank correlation coefficient (Spearman 1904). The Spearman's rank correlation coefficient, also known as Spearman's rho (ρ), is a nonparametric measure of statistical dependence between two variables. It is a measure of the dependence between two variables, giving a value between +1 and -1, where 1 is total positive correlation, 0 is no correlation, and -1 is total negative correlation. To detect a simple correlation ($r = 0.5$) of N observations with a 5% significance level ($\alpha = 0.05$) test and 80% power ($\beta = 0.2$), the required sample size is 29 (Lachin 1981). Thus, 29 random input data sets (joint angles, muscle use, and force) are generated, and the RULA score and Fuzzy RULA score are calculated for each data set. As a result, a Spearman's rank correlation coefficient of 0.833 is calculated between the two sets of scores, which indicates strong correlation (Mukaka 2012) between the RULA system and Fuzzy RULA.

4.4.2 Correlation between Fuzzy RULA and biomechanical analysis

Since biomechanical analysis provides an objective assessment of ergonomic risks associated with a posture, the correlation between the Fuzzy RULA model and biomechanical analysis is investigated to further study the Fuzzy RULA model's reliability. This correlation is compared with the correlation between the RULA method and biomechanical analysis to compare the accuracy of the Fuzzy RULA model with RULA. To this end, the 3DSSPP software (Chaffin et al. 2006) is used to assess the loads imposed on the body joints, and the compression load on the human's back is selected to reflect the biomechanical forces associated with a posture. The 3DSSPP software enables evaluating postures by inputting angle values for the different body segments as well as forces exerted on the hands into the analysis environment.

To perform correlation analysis, the low back compression for each of the 29 postures is extracted from 3DSSPP. Spearman's correlation analysis is performed between the low back compression and the corresponding Fuzzy RULA scores, and a correlation coefficient of 0.710 is calculated. Furthermore, a correlation coefficient of 0.508 is calculated between the low back compression and posture scores obtained from the RULA method. The results indicate that RULA holds a moderate correlation with the result of biomechanical analysis (i.e., low back compression), while there is a strong correlation between Fuzzy RULA and biomechanical analysis.

4.4.3 Sensitivity Analysis

A sensitivity analysis is carried out by varying the parameters of the base case model in order to determine the configuration yielding the highest accuracy. The parameters changed during the analysis include shape of membership functions (linear and s-shape), input aggregation methods (minimum, product, minimum/maximum, and minimum/average), rule aggregation methods (maximum and bounded sum), and defuzzification methods (center of maximum, middle of maximum, fast center of area, and hyper center of maximum). In total, 64 cases are developed, and for each case the Spearman's correlation coefficient between Fuzzy RULA and biomechanical analysis is calculated for the 29 random postures. The most accurate configuration consists of triangular and trapezoidal shaped membership functions, minimum operator for input aggregation, product operator for rule implication, bounded sum operator for rule aggregation, and fast center of area for defuzzification method. A Spearman correlation coefficient of 0.713 is calculated for this configuration. Table 4-3 shows the result of the sensitivity analysis for the 32 cases of linear membership function.

Table 4-3 System configurations for sensitivity analysis

Scenario #	**MF shape**	**Fuzzy operator**	**Inference method**	**Aggregation method**	**Defuzzification method**	**Spearman's coefficient**
Base	Linear	MIN	PROD	MAX	COM	0.709
1	Linear	PROD	PROD	MAX	COM	0.651
2	Linear	MIN	PROD	BSUM	COM	0.712
3	Linear	PROD	PROD	BSUM	COM	0.711
4	Linear	MIN	PROD	MAX	MOM	0.483
5	Linear	PROD	PROD	MAX	MOM	0.483
6	Linear	MIN	PROD	BSUM	MOM	0.579
7	Linear	PROD	PROD	BSUM	MOM	0.628
8	Linear	MIN	PROD	MAX	Fast COA	0.710
9	Linear	PROD	PROD	MAX	Fast COA	0.651
10	Linear	MIN	PROD	BSUM	Fast COA	0.713
11	Linear	PROD	PROD	BSUM	Fast COA	0.711
12	Linear	MIN	PROD	MAX	Hyper COM	0.710
13	Linear	PROD	PROD	MAX	Hyper COM	0.651
14	Linear	MIN	PROD	BSUM	Hyper COM	0.712
15	Linear	PROD	PROD	BSUM	Hyper COM	0.711
16	Linear	MIN/MAX	PROD	MAX	COM	0.424
17	Linear	MIN/AVG	PROD	MAX	COM	0.596
18	Linear	MIN/MAX	PROD	BSUM	COM	0.320
19	Linear	MIN/AVG	PROD	BSUM	COM	0.523
20	Linear	MIN/MAX	PROD	MAX	MOM	0.477
21	Linear	MIN/AVG	PROD	MAX	MOM	0.483
22	Linear	MIN/MAX	PROD	BSUM	MOM	0.290
23	Linear	MIN/AVG	PROD	BSUM	MOM	0.290
24	Linear	MIN/MAX	PROD	MAX	Fast COA	0.424
25	Linear	MIN/AVG	PROD	MAX	Fast COA	0.596
26	Linear	MIN/MAX	PROD	BSUM	Fast COA	0.320
27	Linear	MIN/AVG	PROD	BSUM	Fast COA	0.523
28	Linear	MIN/MAX	PROD	MAX	Hyper COM	0.424
29	Linear	MIN/AVG	PROD	MAX	Hyper COM	0.596
30	Linear	MIN/MAX	PROD	BSUM	Hyper COM	0.320
31	Linear	MIN/AVG	PROD	BSUM	Hyper COM	0.523

* MF=membership function, MIN=minimum, MAX=maximum, PROD=product, AVG=average, BSUM=bounded sum, COM=center of maximum, COA=center of area.

4.5 CASE STUDY: APPLICATION IN MODULAR CONSTRUCTION

A case study is carried out to illustrate the application of these procedures in practice to further validate the fuzzy system with motion datasets obtained from an actual site. This case study also provides a context for discussing the motivation for this study from a practical perspective. In this case study, the developed fuzzy expert system is used to assess the ergonomic risks associated with manual activities in a production line of a construction modular prefabrication company. Data regarding manual handling tasks are collected from the jobsite to perform RULA and Fuzzy RULA assessments as well as biomechanical analysis. The Spearman's correlation is then used to investigate the association between the results.

Off-site modular construction is considered an efficient construction method which is environmentally-friendly, entails a shorter completion time, and effectively facilitates quality and cost control. Despite technological advances in the construction and manufacturing industries, workers in off-site construction perform labor-intensive and physically demanding tasks, resulting in high rates of work-related accidents and injuries (see Chapter 3). This chapter implements the developed framework in a construction fabrication shop setting; it can be similarly applied to other types of construction jobsites. In this case study, the manual tasks involved in the process of building floor panels in the fabrication shop are investigated; this study builds on the case study of the previous chapter. The sequence of the activities starts with delivering timbers to the nailing workstation where they are nailed together. The pieces are then nailed to sheathing to form the floor panels. These floor panels are transferred to the cutting workstation where openings are added. This process consists of twelve different manual tasks in total. Motion data of these manual tasks are collected in order to obtain the required input for the RULA, Fuzzy RULA, and biomechanical analysis. Specifically, videos of each of the manual activities are recorded from the jobsite and analyzed to build the corresponding motion data for each activity in a 3D environment representing the jobsite. This process is carried out to link ergonomic analysis with 3D virtual modeling, which enables analyzing and improving human motions in an interactive manner. To build the 3D virtual model, data pertaining to the layout of the jobsite, dimensions of the different material and equipment involved, and processing times of the tasks are collected from the jobsite (see Chapter 3). Also, worker anthropometry data and weights of tools and materials are collected to ensure accurate representation of the worker models and motions for ergonomic analysis purposes. For example, data regarding the tools used by the workers (e.g., nail gun) are collected to compute the loads imposed on the workers during the manual tasks. The data are gathered by obtaining all available blueprints and specifications of the production line as well as visual inspection of the jobsite to ensure the accuracy of the 3D virtual environment, which is also reviewed and verified by the facility management personnel. After creating the 3D virtual model in Autodesk 3ds Max, each worker's motion data are extracted in a motion capture data format, such as the BVH format. From the motion datasets extracted from the virtual model, awkward postures are identified, and the joint angle values for each posture are obtained automatically by computing the body joint angles at each time frame from the BVH format datasets. These angle values are then used as inputs to perform RULA, Fuzzy RULA, and biomechanical analysis as described above. Table 4-4 shows the twelve tasks and the results of the RULA and Fuzzy RULA analysis, as well as the back compression associated with each task from the biomechanical analysis.

Table 4-4 Results of ergonomic analysis of manual activities in the production line

Task	RULA Score	Fuzzy RULA Score	Back compression from biomechanical analysis (N)
Timber setting	7	6.04	2829
Nailing 1	7	6.56	3521
Nailing 2	7	6.04	3446
Nailing 3	7	6.30	3479
Nailing 4	7	5.93	1995
Nailing 5	7	6.30	3528
Lifting hole	6	4.88	2470
Glue	7	6.63	3548
Frame delivery	4	4.12	1501
Panel delivery	2	2.22	565
Cutting 1	3	4.45	1196
Cutting 2	7	6.20	2145

A Spearman correlation coefficient of 0.930 is calculated between the Fuzzy RULA results of the twelve tasks and the corresponding back compressions, while a Spearman coefficient of 0.765 is calculated between the RULA results and the results of biomechanical analysis.

A correlation coefficient of 0.832 is also calculated between the RULA and Fuzzy RULA results. The results of the case study are consistent with the results of the validation section, confirming the higher reliability of the Fuzzy RULA system in analyzing worker motions from actual jobsites.

For biomechanical analysis, significant time and effort are required to build motion models of workers, compared to observation-based ergonomic assessment tools such as RULA. Unlike the observation-based methods, biomechanical analysis systems are not generally used in a field setting to observe and analyze a worker in real time, since detailed posture information (e.g., angles at most critical body joints) is required. The high correlation between Fuzzy RULA and biomechanical analysis (i.e., 0.930) indicates that occupational health and safety practitioners can rely on the results of the Fuzzy RULA model without the need to go through further biomechanical analysis to verify the results of ergonomic analysis. This facilitates incorporation of ergonomic analysis by construction practitioners in the daily operations, which will result in lower rates of WMSDs.

4.6 DISCUSSION

The Fuzzy RULA model as proposed in this chapter achieves a correlation of 0.713 with biomechanical analysis results through validation with random postures, and a correlation of 0.930 in using worker postures collected from a construction jobsite. These correlations are higher than the corresponding correlations of traditional RULA (0.508 for random postures and 0.765 for jobsite postures). These results imply that the fuzzy logic approach to ergonomic analysis is capable of dealing robustly with human perception issues, particularly those occurring at close-to-border angles in ergonomic methods. Thus, the proposed fuzzy expert system addresses the issue of discrepancy of ergonomic analysis results when analyzing body postures with body joint angles close to borders of angle ranges defined by the ergonomic assessment tools. Since workers in the construction industry perform various manual activities involving unique postures, this chapter provides a precise, reliable, and efficient ergonomic assessment method that can be used to analyze ergonomic risk in a field setting.

There are several potential limitations which further investigation is required to address. First, it should be noted that this chapter focuses solely on RULA. The proposed fuzzy expert system can be applied in a similar manner to other types of posture-based ergonomic evaluation methods (e.g., REBA, LUBA), as they require similar types of inputs to RULA but only differ in the number of posture categories or in the body parts to be observed. Nevertheless, the membership functions and model parameters selected in this chapter may differ from other tools that define the varying input boundaries. The boundaries set differently may affect human cognitive systems in recognizing and distinguishing human postures. Thus, understanding of human perception is required to properly determine fuzzy logic parameters and membership functions.

Second, other types of ergonomic assessment methods require different inputs (e.g., horizontal multiplier in NIOSH lifting equation in Table 4-1) rather than human postures. In this case, each boundary of inputs can range narrowly, thereby resulting in a large number of membership functions being set. Other types of inputs, such as frequency and duration, may not have linear relationships with the final score. Such cases require further investigation of the impact of input variances on the output and thorough verification of fuzzy logic modeling through the comparison with objective measures of ergonomic risk (e.g., biomechanical analysis).

Third, this chapter uses low back compression imposed on the human body as the measure of level of ergonomic risks from the results of biomechanical analysis. Although the back is the most commonly injured body part in ergonomic injuries (Work Safe Alberta 2012), it should be noted that an increase in the RULA or Fuzzy RULA score does not always result in a corresponding increase in the lower back compression. This is due to the fact that the methodology for identifying the level of risks is different in the two approaches, and the results of the ergonomic evaluation methods also focus on the loads exerted on other body joints. This chapter only used the back compression from biomechanical analysis as it more appropriately reflects the ergonomic risks compared to other body parts. In future research, additional results of biomechanical analysis, including forces exerted on other body joints, can be extracted and used for correlation analysis to achieve more comprehensive results.

In addition, the Fuzzy RULA expert system, in its current format, requires discrete angle and force values as inputs and produces a final RULA score in a deterministic form. Although the imprecision inherit in estimating body angles of a posture is considered in the proposed model, the user still needs to select only one distinct value for each input (e.g., upper arm angle). Since ergonomists use approximate values as the joint angles in observation, inputting a range of angles instead of one discrete value may make the evaluation process more reliable by providing users with possible variations of the final scores. Ranges of the final output may represent the effect of potential human errors, thus assisting in appropriate decision making pertaining to the evaluation and mitigation of ergonomic risks. This approach can be further investigated in future studies.

Future work can also include application of fuzzy logic techniques to linguistic types of input variables for ergonomic analysis. For instance, Physical Demands Analysis (PDA) is another type of ergonomic assessment tools which enables quantifying the physical, psychological, and environmental demands of a manual task for proactive management of injury prevention or for retroactive assessment of injured workers in returning to work (IAPA 2009). This type of analysis is frequently used in practice and involves similar types of inputs such as frequency, force, and distance, which may cause the same imprecision of input estimation. This method utilizes linguistic variables to describe the severity of a physical activity in the observation processes. Thus, fuzzy logic approaches can be studied to better address the description of job conditions and requirements in evaluating the demands of a physical activity.

4.7 CONCLUSION

The continuous improvement of construction safety and health depends on the early identification of potential risk and timely mitigation of such at-risk conditions. Reliable assessment of ergonomic risk is essential in preventing WMSDs as ergonomic injuries are gradually developed over time. Toward this goal, this chapter presents a fuzzy logic approach to ergonomic assessment to incorporate perception gaps in differentiating human postures into the evaluation mechanism of ergonomic methods. Case study results show that a fuzzy expert system for ergonomic evaluation outperforms the traditional method by addressing the issue of discrepancy of the results of traditional tools, caused by human perception with respect to discrete input boundaries. This chapter thus provides a more reliable field tool to identify and prevent unsafe worker postures in manual operations, and consequently reduce the rate of WMSDs in construction.

4.8 ACKNOWLEDGMENTS

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Chapter 5 Stochastic Modeling for Assessment of Human Perception and Motion Sensing Errors in Ergonomic Analysis [3]

5.1 SUMMARY

As shown in the previous chapter, despite the wide use of posture-based ergonomic evaluation methods, their reliability has not been fully investigated from the input measurement perspective, collected by a human observer or motion capture sensors—which may inevitably contain measurement errors (e.g., human perception errors and sensing errors in estimating human postures). Thus, this chapter examines the imprecision associated with acquiring the required inputs for ergonomic assessment and investigates its impact on the final result of the analysis. The two main methods of obtaining the inputs of posture-based evaluation tools, i.e., human observation and recordings of motion sensing devices, are examined, and a stochastic approach is proposed to evaluate the impact of the input errors on the final result of the ergonomic assessment. Such approach allows practitioners and researchers to understand possible ranges of outputs that can be caused by observation and measurement errors and to determine allowable tolerance of sensing errors required for ergonomic evaluation.

5.2 INTRODUCTION

As one of the most effective and widely-used approaches to preventing WMSDs is to evaluate and identify ergonomic risk factors at workstations and reduce the exposure to these factors through intervention plans, various tools and systems (e.g., posture analysis, and motion capture sensors) have been developed and used as guidelines to enable the assessment of different manual tasks. One of the main contributing risk factors of WMSDs is the human body posture (Takala et al. 2010; Punnett and Wegman 2004; Li and Buckle 1999), and as mentioned in the previous chapter, many evaluation methods require inputs describing posture (e.g., body joint angle values) as part of the analysis. To obtain the required inputs for a posture-based ergonomic evaluation, ergonomists can either (1)

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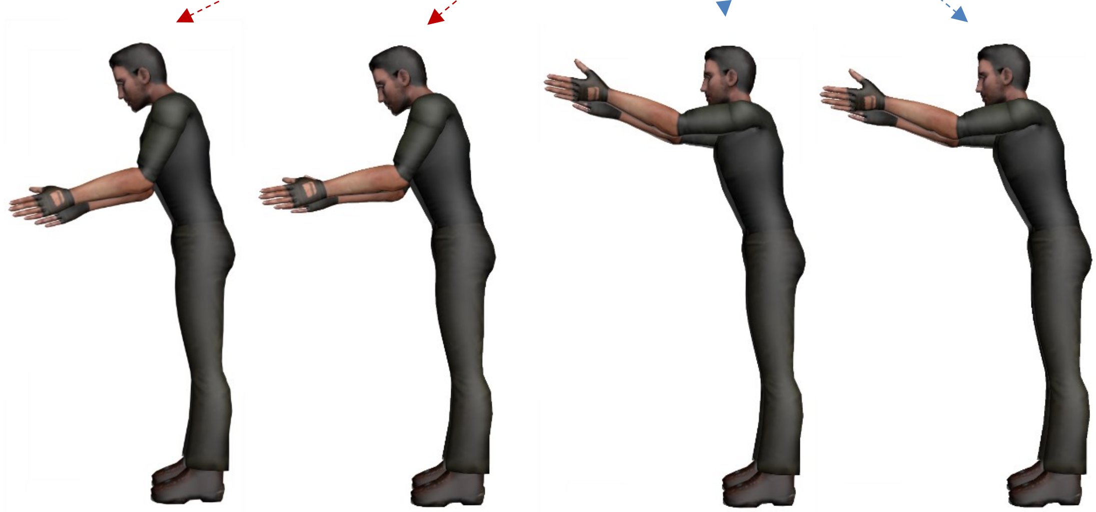
visually observe the worker's motions and postures and use their personal judgement for estimation of the inputs, or (2) use sensing devices and technologies (e.g., range camera, RGB-D sensor) that can automatically extract the inputs from sensor recordings. Observing postures for ergonomic evaluation, in real-time or from video recordings, is more prevalent in practice as it is simple to implement, flexible, cost-efficient, and does not require disruption to the workforce (Li and Buckle 1999). Motion capture technologies have also been studied as a method to automate this process and improve its accuracy by directly measuring the human postures with a sensor (Ray and Teizer 2012). In any case, the reliability of the results of the ergonomic assessment depends on the precision of the inputs used for the analysis. In the case of observational approaches, the inputs are prone to human error in estimation (e.g., joint angles between body parts), while in the case of using sensing devices, instrument errors can lead to unreliability of evaluation results. Thus, this chapter investigates the imprecision associated with the inputs of ergonomic evaluation tools in estimating human body postures and its impact on the ergonomic analysis output, and proposes a stochastic approach to quantify the impact of the input errors on the analysis results.

5.3 PROBLEMS IN POSTURE ESTIMATION

Ergonomic assessment tools based on observation (e.g., RULA) are frequently used in practice as they require limited time and resources, and appropriately fit the needs of occupational safety and health practitioners in providing a basis for prioritizing intervention plans (David 2005). However, one of the main concerns in using these methods is their lack of reliability due to the imprecision of the inputs, which result either from human perception errors and the subjectivity towards observer inputs (Burdorf 2010), or from instrument errors associated with sensing devices (Li and Buckle 1999). As discussed in the previous chapter, the subjectiveness of the assessment methods towards the inputs results from the sharp boundaries that these methods consider between the posture classifications (i.e., joint angle ranges) for the various body joints. Due to the design of these systems using sharp boundaries between posture categories, there can be a sudden jump or drop in the assessment results with a small change in the joint angle values used as inputs (Fig. 5-1).

Total RULA Score		Neck, Trunk, Leg Score						
		1	2	3	4	5	6	7+
	1	1	2	3	3	4	5	5
	2	2	2	3	4	4	5	5
Wrist and Arm Score	3	3	3	3	4	4	5	6
	4	3	3	3	4	5	6	6
	5	4	4	4	5	6	7	7
	6	4	4	5	6	6	7	7
	7	5	5	6	6	7	7	7
	8+	5	5	6	7	7	7	7



(a) (b) (c) (d)

Figure 5-1 Final RULA scores of four postures

Thus, the reliability of the output of posture-based ergonomic evaluation tools (e.g., RULA, REBA, OCRA, etc.) highly depends on the accuracy of the inputs used. The potential amount of error associated with acquiring the inputs using visual observation as well as motion sensing devices is examined in this chapter, and the impact of the errors on the output of ergonomic assessment is also studied.

5.3.1 Human Errors

While using posture-based observational ergonomic assessment methods, the ergonomist classifies different body joints based on predefined posture categories (NIOSH 2014). These body joint positions are usually partitioned into different portions of range of motions based on the angles between the body segments. Thus, accurate estimation of the body joint angles is crucial in achieving reliable assessment results. However, this estimation typically involves human error as it is difficult to visually measure accurate joint angle values while observing a worker carrying out a task. Consequently, the result of the evaluation is highly subject to the user inputs (Bhise 2011; David 2005; Lau 2011; Li and Buckle 1999; Spielholz et al. 2001).

An experiment was carried out to further study the imprecision of the estimated joint angle values and its impact on the result of ergonomic analysis and risk intervention plans. Fifty engineering students were trained on how to use the RULA method and asked to provide the inputs for performing a RULA analysis on the three distinct postures shown in Fig. 5-2. In this experiment, virtual posture models were created and the exact values for the different body joint angles were measured inside the virtual environment.

Posture 1	Posture 2	Posture 3

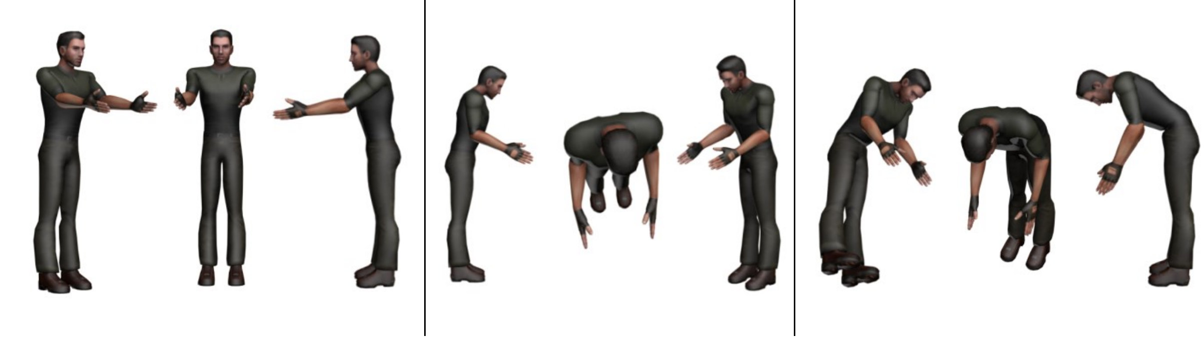


Figure 5-2 Postures used for experimentation

Fig. 5-3 shows the required inputs for a RULA analysis, which include joint angle values describing the human posture. Table 5-1 shows the correct values of the joint angles for the three postures of Fig. 5-2, as well as the average and standard deviation of the inputs provided by the participants. As shown in Table 5-1, the average of standard deviations for all joints in the three postures are 7.16°, 8.91°, and 10.15°, with maximum standard deviations of 10.69°, 12.92°, and 15.45°. These figures imply that the imprecision associated with the input values is substantial. Table 5-2 shows the impact of this imprecision on the result of the RULA analysis (i.e., total RULA score).

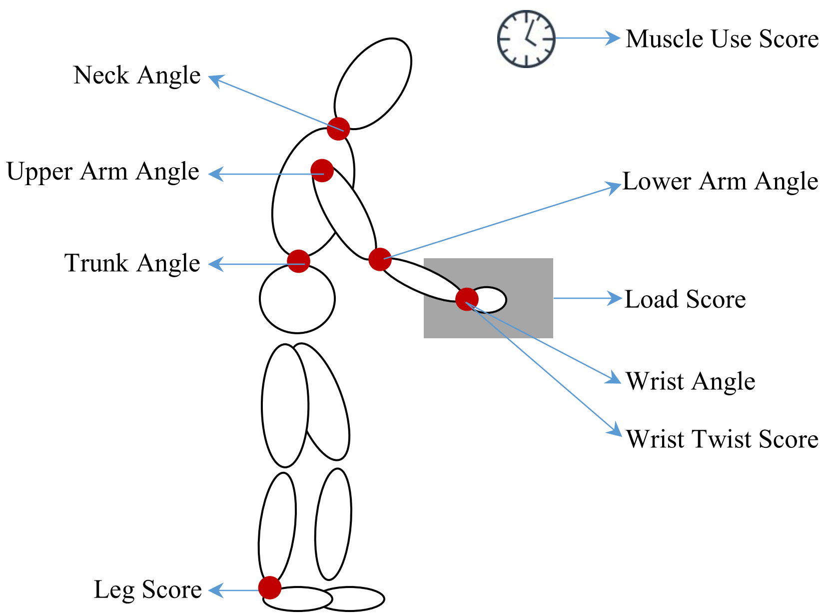


Figure 5-3 Inputs required for RULA analysis

Table 5-1 Parameters of the inputs of the experiment

Posture	Parameter	Upper Arm Angle	Lower Arm Angle	Wrist Angle	Neck Angle	Trunk Angle	Mean
1	Correct angle	60°	30°	0°	0°	10°	-
	Average	54.12°	32.10°	1.63°	6.66°	9.49°	-
	Standard deviation	9.82°	10.69°	3.77°	6.97°	4.54°	7.16°
2	Correct angle	21°	62°	14°	19°	19°	-
	Average	9.80°	63.22°	3.76°	24.20°	18.83°	-
	Standard deviation	8.77°	12.92°	5.32°	9.03°	8.53°	8.91°
3	Correct angle	−15°	50°	0°	23°	65°	-
	Average	−1.64°	48.07°	0.55°	31.73°	54.11°	-
	Standard deviation	13.51°	15.45°	2.08°	12.98°	6.72°	10.15°

As Table 5-2 indicates, the impact of the scatter of the inputs on the final results of the analysis is substantial. As shown in the table, 76% of the results achieved the correct RULA score for posture 1 and only 49% and 46% of the datasets obtained the correct

RULA score for postures 2 and 3, respectively. The reason behind the higher discrepancies of posture 2 and posture 3 is that more joint angle values for these two postures are located close to the angle boundaries than in the case of posture 1. The results imply that a small deviation from the correct angle can result in selection of the wrong input category and, consequently, the wrong final score.

Table 5-2 Percentage of participants calculating each RULA score

Posture	Correct RULA score	RULA Score			
		4	5	6	7
1	4	76%	16%	8%	0%
2	5	15%	49%	28%	8%
3	5	13%	46%	37%	4%

5.3.2 Instrument Errors

Motion sensing technologies can be effectively used to obtain the required inputs for ergonomic analysis by recording movements of the worker and automatically extracting the inputs. This approach eliminates the human error associated with estimating the inputs. However, the instrument error and its impact on the result of the analysis can still result in discrepancy of the results. Different motion sensing systems have been used to generate motion capture data for various applications. In construction, the use of RGB-D sensors has gained attention due to its simplicity of use and cost effectiveness (Khosrowpour et al. 2014; Han et al. 2013; Weerasinghe et al. 2012; Ray and Teizer 2012; Escorcia et al. 2012). Thus, this chapter explores the accuracy of an RGB-D sensor, the Microsoft Kinect™ (Microsoft; Redmond, Washington), as an example of a widely-used motion sensing device, and its impact on the results of ergonomic analysis.

The origin of the instrument error of the Kinect sensor might be from the sensor (e.g., lack of calibration), from the environment (e.g., poor lighting), or from the target (e.g., reflection from the target's surface) (Khoshelham 2011). Researchers have examined the accuracy of the Kinect by conducting various experiments such as investigating its consistency with laser scanner outputs and more precise sensors. A summary of some related studies is shown in Table 5-3.

Table 5-3 Previous research on the precision of Kinect

Topic	Study	Result
Evaluation of depth discrepancy between pairs of point clouds generated by a Kinect and a high-end laser scanner.	Khoshelham and Elberink (2012)	Less than 3 cm discrepancy for 84% of the point pairs. The point spacing in the depth direction is about 2, 2.5, and 7 cm at the 1, 3, and 5 m distance.
	Rafibakhsh et al. (2012)	Average distance error between the point pairs is 3.49 cm, and the resolution of the Kinect is about 4 times less than that of a laser scanner at 1.7 to 3.4 m distances.
	Stoyanov et al. (2011)	Kinect's performance is acceptable within 3.5 m distances.
Investigation of the accuracy of motion capture data obtained using Kinect.	Livingston et al. (2012)	Maximum error of 2.7 cm at 4 m distance from sensor.
	Fernández-Baena et al. (2012)	Difference in rotation angles of body parts between Kinect and Vicon range from 6.78 to 8.98 degrees for knee, from 5.53 to 9.92 degrees for hip, and from 7 to 13 degrees for shoulder.
	Han et al. (2013)	The average and standard deviation of the 3D position error for all body joints are 10.7 cm and 5.3 cm, compared to Vicon. The average and standard deviation of rotation angles are 16.2 and 18 degrees.

As shown in Table 5-3, different studies have suggested different measurement errors for the Kinect. This may be because of different experimental settings (e.g., distances between a sensor and a human subject) and different body postures (e.g., postures with higher or lower levels of self-occlusions). These errors could be potentially higher if the effect of occlusion, shadowing, and different lighting conditions were also considered. In this chapter, the results obtained by Han et al. (2013) are used because: (1) the study provides specific average and standard deviation of motion sensing errors for the different body joints, (2) the values are obtained by experimenting with motion capture data focused on construction activities, (3) and the suggested values are more conservative compared to other studies. Han et al. (2013) evaluated the performance of Kinect by comparing its recordings with motions recorded by a high accuracy marker-based motion capture system (VICON) for a ladder climbing task. Results were reported based on comparison of 3D locations of body joints tracked, 3D rotation angles of joints, and impact of sensor accuracy on motion analysis. The impact of the suggested error values on the results of ergonomic assessment is examined later.

5.4 STOCHASTIC APPROACH TO ERROR EVALUATION

The subjectiveness of the ergonomic evaluation systems towards the inputs affects the accuracy and reliability of these systems, which is due to the use of sharp boundaries between posture categories of inputs. As the final results of the analysis are also discrete scores, the imprecision of the inputs results in discrepancy in the outcome of the analysis. Thus, an advanced method with less sensitivity to the inputs is needed to reduce the issues on sharp boundaries for posture classifications. The measurement error and its impact on the output also have to be taken into account when using these tools for assessment of postures. To achieve this, the amount of errors associated with different methods of acquiring the inputs (i.e., human observation and motion sensing) are first obtained, and the effect of these errors on the results of the analysis is then examined using a stochastic approach. This is accomplished by generating random errors for body joint locations and angles, which enables generation of random postures representative of inputs obtained in actual assessments, conducting ergonomic assessment on these postures, and analyzing the distribution of the results. The different steps of the study are shown in Fig. 5-4. For the case of using inputs from human observation, the error values of the different joint angles are obtained through experimentation, as described in the second section of this chapter. These values are used to generate random body joint angles and, for each set of generated joint angles, the assessment score of the new posture is calculated. This process is repeated to ensure generation of sufficient samples for the analysis. Similarly, for the case of motion sensing errors, the error values used for different body joints are drawn from prior studies on the accuracy of motion capture data, and the results are used to generate new 3D locations of different body joints. These 3D positions are then used to calculate the required body joint angles and for each set of joint angles the assessment score is computed. Furthermore, the fuzzy logic-based approach elaborated in the previous chapter is used to examine the distribution of the final assessment scores, as it enables a more accurate analysis of the impact of the input errors on the evaluation results compared to the discrete scores resulting from traditional methods. The final result of the analysis enables quantifying the subjectiveness of the ergonomic evaluation systems towards the inputs.

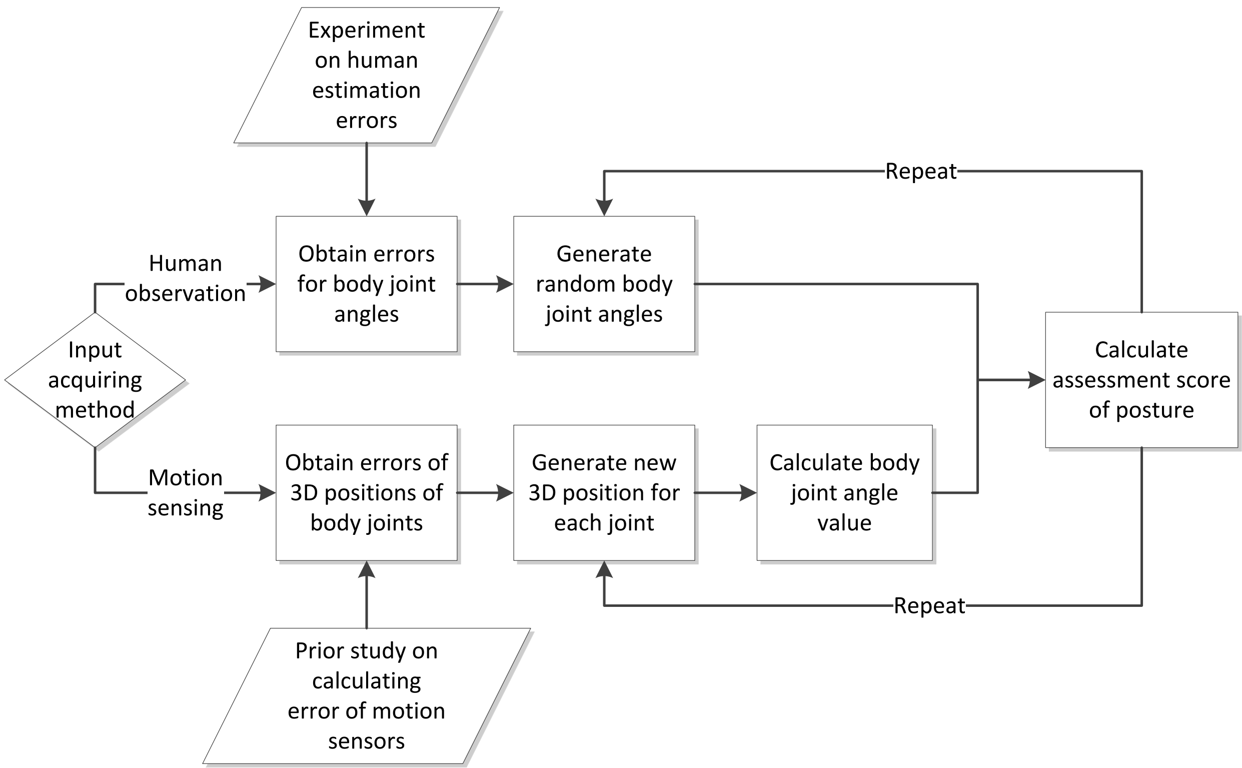


Figure 5-4 Steps of examining the impact of input errors on result of analysis

5.4.1 Human Observation Errors

To examine the imprecision associated with human observation for ergonomic evaluation, first an experiment was carried out, as described in the second section. Fifty senior undergraduate engineering students were trained for an hour on how to use RULA and asked to provide the joint angle values that should be used to carry out a RULA analysis. The results of this experiment enable acquiring the deviation of the inputs obtained by human observers from actual values. To ensure the errors were the result of the participants' inaccurate estimations of the joint angles for the provided postures, and not of other factors such as not knowing how to use RULA or a mistake in calculating the final score, all of the intermediate and final scores are recalculated and verified. Thus, the standard deviation of the results of the experiment for each body joint can be an indication of the potential errors involved in human judgement of the inputs, as the standard deviations are a reliable measure of the variability of the joint angle values (Fraenkel et al. 1993). After obtaining the error values, the impact of the errors on a RULA and Fuzzy RULA analysis is studied by generating ten thousand random joint angle values for each body joint, by using the actual value for the joint angles as the average and the standard deviations obtained by the experiment (Table 5-1), as conceptually represented in Fig. 5-5. This approach ensures that the joint angle values of the random postures represent a reliable distribution of the actual inputs obtained by human observers. Posture 3 is selected for the analysis as this posture has the highest discrepancy of results among the three postures. For each set of the ten thousand inputs, the corresponding RULA and Fuzzy RULA scores are then calculated and the result is used to quantify the impact of the errors on the analysis outcome by examining the percentage of the correct final scores. The results of the two systems (i.e., RULA and Fuzzy RULA) are also compared to study the improved reliability associated with applying fuzzy logic techniques.

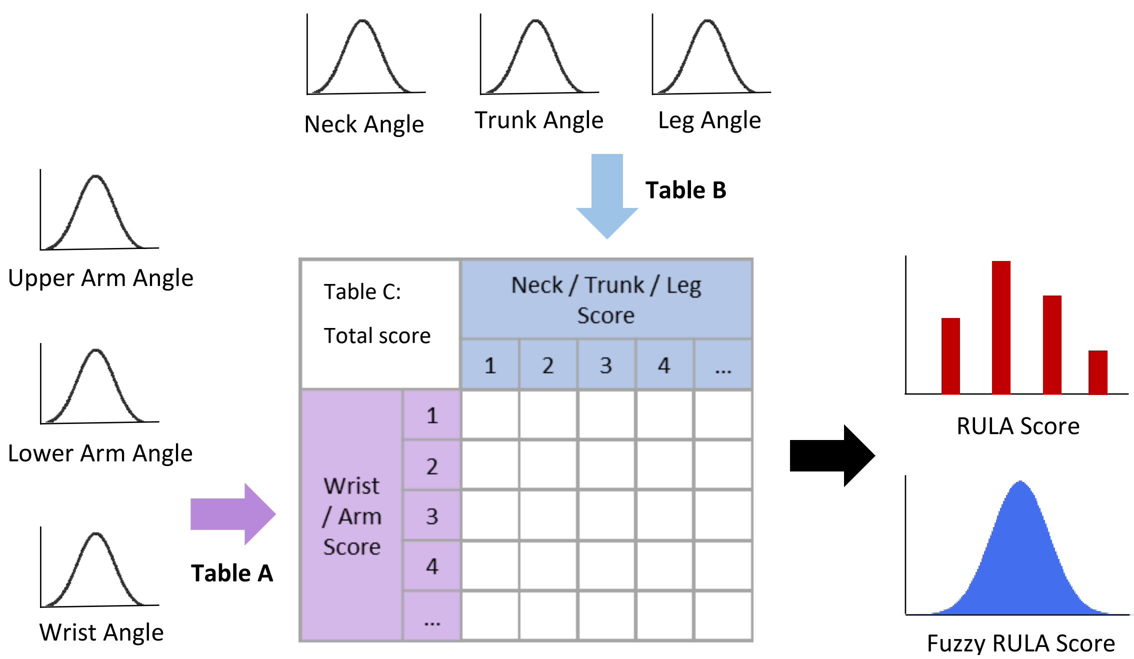


Figure 5-5 Distribution of inputs are used for a RULA and Fuzzy RULA analysis of ten thousand randomly generated postures

5.4.2 Motion Sensing Errors

To study the impact of instrument errors of motion sensing devices on ergonomic assessment, the amount of error associated with using these devices is first obtained from prior studies, as shown in Table 5-3. The Kinect sensor is used as an example of a commonly used motion sensing device, and the error values shown in Table 5-4 (Han et al. 2013) are selected as the potential errors of the Kinect in estimating the 3D positions of the different body joints.

Table 5-4 Error values used for different body joints (extracted from Han et al. (2013))

Error parameter	Body Part							
	Hand	Shoulder	Forearm	Neck	Head	Chest[a]	Middle Spine[a]	Lower Spine[b]
Average (cm)	24.3	6.8	12.4	19.0	7.7	10.7	10.7	2.9
Standard deviation (cm)	12.0	2.3	4.9	1.2	2.3	5.3	5.3	0.5

[a] Since the error values for these joints are not provided, the average error value is used.

[b] Since the error value for this joint is not provided, the mean error of left and right upper legs are used.

After selecting the amount of errors associated with the motion capture data extracted from the Kinect sensor, these error values are used to examine the impact of the errors on the result of ergonomic evaluation. To do so, a Kinect recording of the motions of a masonry task is used and a random posture is selected from the motion data. From this motion capture file, the 3D positions of the different body joints are calculated by using the rotation angles and joint offset values of the motion data. These 3D positions are then used to calculate new positions for each joint for ten thousand samples.

To obtain the new 3D position of each joint with a corresponding error value as shown in Table 5-4, the spherical coordinate system of each joint is considered. The spherical coordinate system is selected since all potential new positions of a joint with a specified random error value are located on a sphere around the joint, where the center of the sphere is the original location of the joint, and the radius of the sphere is the amount of error. The amount of error for each joint is calculated by generating a random error value using the average and standard deviations shown in Table 5-4. This is shown in Fig. 5-6, where the global coordinate system for the whole body is shown in red with capital axis labels, and the hand's local spherical coordinate system is shown as an example in green with small axis labels. In the figure, r, θ and φ are the radius, polar angle, and azimuthal angle, respectively. In generating the new joint positions, the polar and azimuthal angles can take any random value between 0 and π and 0 and 2π, respectively.

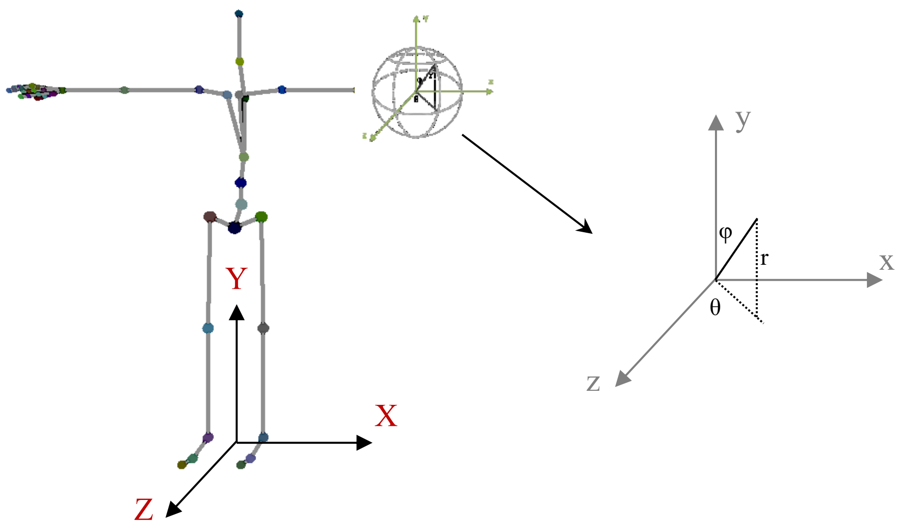


Figure 5-6 Global and local coordinate systems for error generation

Once the parameters of the spherical coordinate system for each error point have been calculated, the Cartesian coordinates of the joint are calculated using Equations 5-1 to 5-3. The new location of the joint for each error is then calculated as the addition of its Cartesian coordinates to the coordinates of the origin of the local coordinate system with respect to the global coordinate system.

$$x = r \sin\varphi \sin\theta \tag{5-1}$$

$$y = r \cos\theta \tag{5-2}$$

$$z = r \cos\varphi \sin\theta \tag{5-3}$$

Since the RULA and Fuzzy RULA methods require body joint angles as inputs, the calculated 3D positions of the body joints for each posture are used to obtain the required body joint angles. Fig. 5-7 shows the calculation for the lower arm angle as an example. The same process is carried out to calculate all the required joint angles, by defining the appropriate corresponding vectors. This process is carried out to calculate the joint angle values for the 10,000 generated postures to carry out a RULA and Fuzzy RULA analysis.

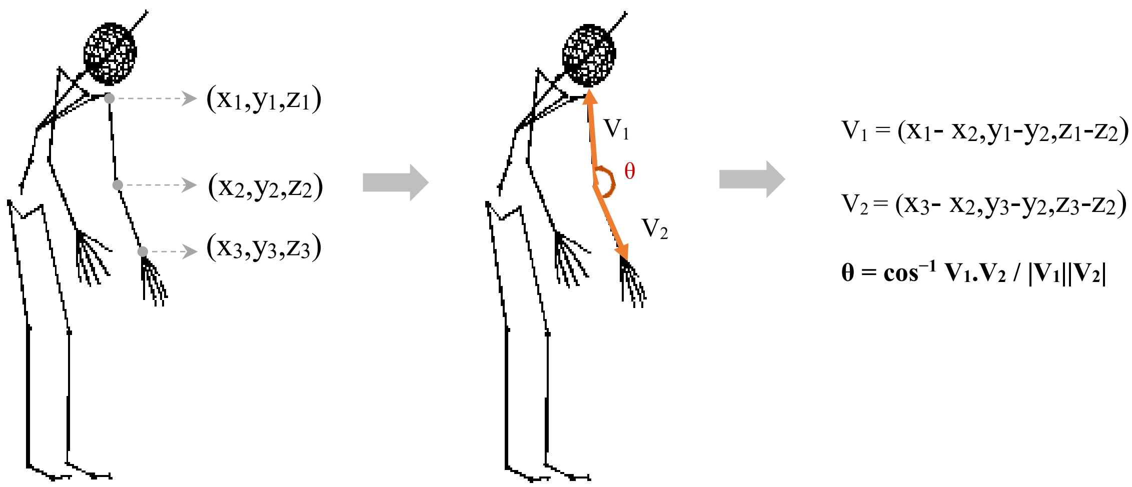


Figure 5-7 Steps of calculating lower arm angle from 3D coordinates of body joints

5.5 RESULTS AND DISCUSSION

The result of RULA and Fuzzy RULA analysis for the ten thousand postures generated for the two cases of human observation errors and motion sensing errors are shown in Figures 5-8 and 5-9 respectively. For convenient understanding and comparison of the results, the scores are provided in charts, with the x axis representing the range of scores and the y axis representing the percentage of results in that range. For the RULA analysis, the columns represent the distribution of results for discrete scores (i.e., 4, 5, 6, and 7), and for the Fuzzy RULA analysis, as the scores have continuous values, the columns indicate the distribution of results within the specified range. Fig. 5-8 shows the results of analysis for posture 3 (from Fig. 5-2), with an actual RULA score of 5, while Fig. 5-9 shows the result of the analysis for the random posture of a masonry task with a RULA score of 5 for the base posture selected. Furthermore, to examine the impact of lower error values (in case of higher accuracy of human estimates or motion sensors) and to further explore allowable error ranges for ergonomic evaluation, the analysis process for a RULA assessment is repeated for error values equal to half (case 1) and also one-fifth (case 2) of the error values used as the base case. This is achieved by changing the standard deviation of the body joint angles obtained from the experiment for the human observation errors (Table 5-1) to half and one-fifth, then generating 10,000 random postures for each case and conducting a RULA assessment. In case of motion sensing errors, both the average and standard deviation of the error values (Table 5-4) are changed to half and one-fifth and a RULA evaluation is carried out on each set of the randomly generated 10,000 postures. The results are summarized in Table 5-5 and also visualized in Fig. 5-10.

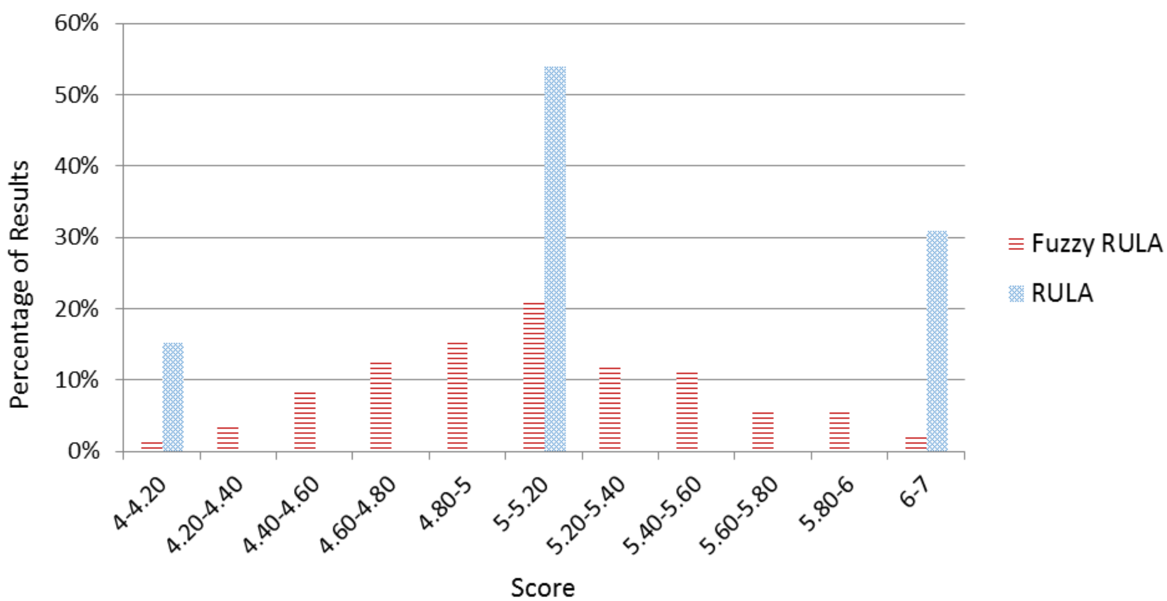


Figure 5-8 Distribution of RULA and Fuzzy RULA scores for the case of human observation errors

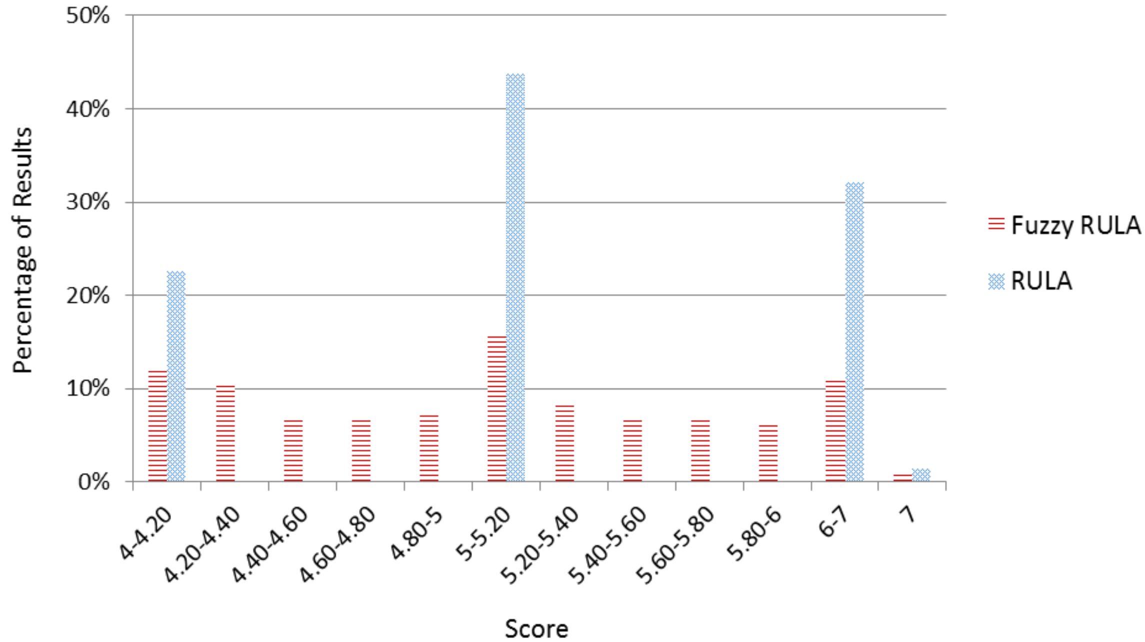
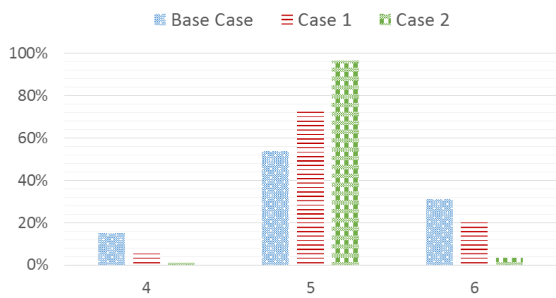


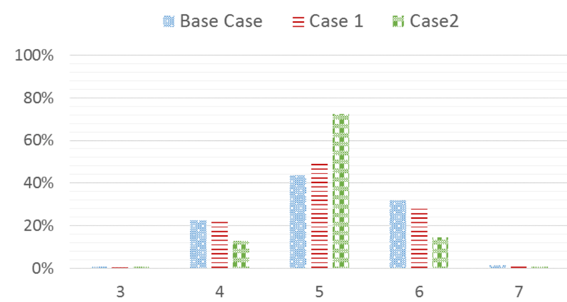
Figure 5-9 Distribution of RULA and Fuzzy RULA scores for the case of motion sensing errors

Table 5-5 Result of RULA assessment for different error values

Score	Human Observation Error			Motion Sensing Errors		
	Base Case: errors from experiment	Case 1: Error = 1/2 of base case	Case 2: Error = 1/5 of base case	Base Case: errors from literature	Case 1: Error = 1/2 of base case	Case 2: Error = 1/5 of base case
3	-	-	-	<1%	1%	<1%
4	15%	5%	<1%	23%	22%	13%
5 (correct score)	54%	73%	97%	44%	49%	72%
6	31%	21%	3%	32%	29%	15%
7	-	-	-	1%	<1%	<1%



(a)



(b)

Figure 5-10 Distribution of RULA scores for (a) human observation errors, and (b) motion sensing errors

The results show the impact of errors associated with human observation and motion sensors on the results of ergonomic analysis using RULA and Fuzzy RULA. Considering the distribution of the results shown in the figures, the following can be concluded:

(1) As shown in Figures 5-8 and 5-9, Fuzzy RULA is less sensitive to the imprecision of the inputs than is RULA. Thus, the subjectiveness of the inputs has a smaller impact on the result of a Fuzzy RULA analysis compared to RULA, and therefore the result is more reliable. The average of the scores obtained by Fuzzy RULA in case of human error is 5.05 with a standard deviation of 0.67, which compared to the RULA results of 54% with a score of 5, 31% with a score of 6, and 15% with a score of 4, shows the lower subjectiveness of Fuzzy RULA towards the deviation of the inputs from the actual values.

(2) In case of human errors, the percentage of the Fuzzy RULA results is the highest at the correct RULA score of the posture (i.e., 5) and decreases as the scores get close to 4 and 6 (Fig. 5-8). In case of motion sensing errors, the highest percentage of the Fuzzy RULA results is the highest at the RULA score of the base posture (i.e., 5), but the percentage also increases at scores 4 and 6 (Fig. 5-9). This is due to the fact that considering the large error values used, a high portion of the ten thousand random postures has input values that correspond to scores closer to 4 and 6 instead of 5 (i.e., combinations of errors in x-, y-, and z-axis directions at each body joint). In both cases, the results indicate that Fuzzy RULA analysis results in continuous score values that increase as the posture gets closer to discrete RULA scores (e.g., 4, 5, 6), and smoothly decrease as the joint angles become closer to

border values. This function addresses the issue of discrepancy of the results at angle values close to the borders of posture categories.

(3) The results of investigating human observation errors and motion sensing errors show that the potential inaccuracy of the results of a RULA analysis using both human observation and also the Kinect sensor is significant. As Fig. 5-8 shows, the results of the analysis imply that there is a 46% chance that the use of human observation for acquiring inputs of posture-based ergonomic assessment methods can result in an incorrect RULA score. Thus, the correct estimation of inputs by the observer is very important when using RULA. Similarly, Fig. 5-9 shows that there is a 56% chance that the use of the Kinect sensor for acquiring inputs can result in an incorrect RULA score.

(4) Table 5-5 and Fig. 5-10 show the results of the RULA analysis using error values less than the base case to further examine the subjectiveness of the ergonomic assessment results towards the inputs. In case of human motion errors, the results are found to have considerably improved for the first case, with the percentage of correct scores increasing from 54% to 73%. For the second case, the results can be considered highly reliable, as the final scores for 97% of the error cases are estimated correctly. In case of motion sensing errors, the results are found not to have improved significantly for the first case, with the percentage of correctly estimated results only increasing to 49%. The results of the assessment for the second case are more acceptable, as 72% of the final scores are found to be correct. While this chapter uses the error values of the Kinect sensor for the base case of motion sensing errors, the distribution of the results, shown in Fig. 5-10, provides insight into the reliability of the results of ergonomic assessments that use motion sensing devices with different accuracy ranges. When using other motion sensing technologies, the associated instrument error must similarly be taken into account. The proposed stochastic approach thus can help not only with understanding the ranges of errors that can be caused by the sensing device, but also with determining the required accuracy of motion sensing for certain types of ergonomic assessment.

Overall, the impact of the errors on available posture-based ergonomic assessment methods such as RULA are substantial for both methods of obtaining the inputs, as only approximately half of the generated inputs resulted in the correct RULA scores for the base case. This indicates that ergonomic assessments in the construction industry can yield unreliable outputs and demonstrates the high potential for misidentifying unsafe postures, resulting in elevated rates of WMSDs. To address this issue, evaluation tools with reduced sensitivity to the inputs, such as Fuzzy RULA, need to be developed and used in industry. Also, ergonomists should consider the subjectivity of these tools in their assessment, ensuring that results of the tools are used as rough estimates and guidelines rather than as definitive outputs and also, that these tools are used in conjunction with different evaluation tools and systems. By quantifying the probability of errors occurring in the ergonomic analysis, this chapter brings attention to the importance of accurate measurements and the use of high precision motion sensors. The distribution of results, shown in Figures 5-8, 5-9, and 5-10, contributes to the understanding of the ranges of score values that are caused by input errors and thus allows for defining acceptable precision tolerances for acquiring the inputs. Using the proposed approach, safety practitioners can identify the required precision for motion sensing technologies for different types of analysis, as well as the body joints that have higher impact on the accuracy of the results, and thus achieve acceptable overall accuracy through focusing on improving the accuracy of the inputs for particular body parts, using other types of sensors (e.g., Inertial Measurement Units (IMUs) for hands), data fusion, and etc.

5.6 CONCLUSION

This chapter examined the imprecision associated with the inputs used for ergonomic evaluation systems, in two cases of human perception errors and motion sensing errors, and also explored the impact of this imprecision on the results of ergonomic analysis. The findings show that the impact of the inaccuracy of the inputs on the outputs is significant and thus emphasize the importance of considering the inaccuracy of the inputs in using any ergonomic assessment method. Furthermore, the use of a fuzzy logic-based ergonomic evaluation tool and its subjectiveness towards the inputs is studied. The results indicate that compared to RULA, Fuzzy RULA is less sensitive to the imprecision of the used inputs and is therefore more reliable. Thus, despite the effectiveness of the posture-based ergonomic assessment methods, there is a need for tools that are less sensitive to the imprecision of the inputs, as this chapter showed that there is a high probability that the inputs contain substantial human observation error or instrument error. The contribution of this chapter is in quantifying the effect of these errors on the analysis results using a stochastic approach, which enables incorporating the impact of imprecise inputs into the evaluation. This understanding is critical in ergonomic risk assessment, as it allows for considering the worst case (i.e., requiring immediate mitigation), which could be potentially ignored because of the incorrect posture measurement.

5.7 ACKNOWLEDGMENTS

The authors would like to thank the survey participants for the human observation errors experiment. The work presented in this chapter was supported financially by the Natural Sciences and Engineering Research Council of Canada (NSERC) and Hanyang University (HY-2016). Any opinions, findings, and conclusions or recommendations expressed in this chapter are those of the authors and do not necessarily reflect the views of NSERC.

Chapter 6 Micro-Motion Level Simulation for Efficiency Analysis and Duration Estimation of Manual Operations [4]

6.1 SUMMARY

Due to the labor-intensiveness of the construction industry, accurate estimation of cycle time of manual activities is essential for reliable planning and scheduling of operations. Labor productivity study is used in current practice to obtain the required cycle time of manual tasks. However, the reliability of labor productivity study in estimating durations of manual activities is inhibited by its dependence on various factors which change with the different working conditions of construction jobsites and the difficulties associated with measuring productivity. This chapter thus investigates the use of a PMTS for modeling manual construction operations for cycle time estimation and efficiency evaluation. A motion-level simulation approach is developed by integrating PMTS into discrete-event simulation modeling, providing an automated and simple-to-use method of analyzing manual tasks. As a case study, manual construction operations from a construction jobsite with different levels of repetitiveness are modelled, and the actual and simulated cycle times are compared and analysed.

6.2 INTRODUCTION

Considering the labor-intensive nature of construction activities, the efficiency of the manual tasks carried out by workers has a significant impact on the success of projects (El-Gohary and Aziz 2014). Previous research has also shown that labor can account for more than half of the total cost of a project (Gomar et al. 2002), and owners and contractors lose billions of dollars every year as a result of inefficiencies related to the deployment of labor resources (Horner et al. 1989). Given that labor is considered to have the highest risk among the main project cost components of construction operations (Hanna et al. 2005), accurate estimation of cycle time of manual activities is essential for reliable planning and scheduling of processes (Genaidy et al. 1990). Furthermore, in the case of ongoing

[4] A version of this chapter is published as Golabchi, A., Han, S., and AbouRizk, S. M. (2016). "Micro-Motion Level Simulation for Efficiency Analysis and Duration Estimation of Manual Operations." *Automation in Construction*, 71: 443–452.

operations, reliable evaluation of the efficiency of the involved manual tasks is important in assessing and potentially improving productivity.

In current practice, labor productivity is commonly used in the construction industry in order to obtain the required cycle time of manual tasks for production planning and operational design. However, labor productivity may not always provide a precise estimation of duration of manual activities, as it depends on various factors that change based on the given working conditions (Dai et al. 2009; Rojas and Aramvareekul 2003; Maloney 1983). Since there is no common productivity measurement standard due to the difficulties associated with quantifying it (Goodrum and Haas 2004), productivity rates of the same activity are measured by different people using different methods, which results in incomparable values as well as in difficulty in defining and estimating productivity (Song and AbouRizk 2008). Furthermore, in the case of assessing the efficiency of ongoing manual operations, labor productivity cannot be reliably used as a benchmark for evaluation, since it merely represents an average figure and does not reflect the physical attributes of the manual tasks and the working environment. Due to the abovementioned reasons, using labor productivity for obtaining the duration of manual tasks might not result in accurate and reliable cycle time estimation and efficiency analysis. On the other hand, PMTSs have been developed to provide a standard duration for manual activities by characterizing the working method in which a task is carried out. Thus, this chapter investigates the use of PMTS for estimating duration of non-existing manual construction tasks as well as for evaluating the efficiency of ongoing manual operations.

To investigate the effectiveness of a PMTS-based approach to estimating cycle time of manual construction activities, this chapter uses a motion-level simulation approach that integrates PMTS into discrete-event simulation modeling. By doing so, various manual activities can be modelled with minimal time and effort and with higher reliability compared to manual analysis. After developing the motion-level simulation platform, this approach is implemented to model manual operations from an actual construction jobsite, in order to study the suitability of the proposed approach in modeling construction tasks for cycle time estimation and efficiency evaluation. Manual tasks with different degrees of repetitiveness are selected to examine the reliability of this approach for different types of construction activities.

6.3 RELATED WORK

This section reviews the challenges inherent in estimating the cycle time of manual activities using labor productivity to evaluate its reliability and effectiveness and investigate the potential need for a more accurate and efficient approach. The techniques currently used in the construction industry for evaluating duration of manual tasks are also introduced. Issues related to measuring labor productivity and using it for estimation of activity durations, as well as the effectiveness of traditional estimation approaches, are discussed as informed by the existing literature on the subject.

6.3.1 Challenges in Activity Duration Estimation by Labor Productivity

In estimating the duration of activities, productivity performance from ongoing or past projects is a key input commonly used in practice, allowing for predicting the amount of resources (e.g., man-hours) needed to complete a given task (Hinze 1998). This relationship can be intuitively explained using Equation 6-1, which expresses the most common and widely accepted definition of labor productivity in construction (Thomas 2014; Vogl and Abdel-Wahab 2014).

$$\text{Labor Productivity} = \frac{\text{Total Output}}{\text{Total Man-hours}} \tag{6-1}$$

In this equation, the total man-hours can be calculated simply when total output (e.g., amount of work) and labor productivity are known, and thus the activity durations can be estimated by determining the number of laborers to input. In practice, however, accurate measurement and estimation of labor productivity is not easily achieved, since the efficiency of manual tasks performed by laborers is affected by various factors. For instance, Hwang and Soh (2013) introduced the common challenges of measuring productivity in the construction industry and categorized them as industry-related challenges, firm-related challenges, and trade-related challenges. Some of the challenges include absence of standard productivity measurement method, lack of clear definition of productivity, difficulty in obtaining accurate benchmarks for productivity comparisons, low reliability of data recorded, and difficulty in measuring work hours. Previous studies have also attempted to identify the different productivity-influencing factors. For example, Dai et al. (2009) examined 83 factors affecting productivity and found that those involving tools and consumables, material, engineering drawing management, and construction equipment are the factors which contribute most to productivity, based on craft workers' perception of productivity. Jarkas and Bitar (2012) identified 45 factors, including clarity of technical specifications, labor supervision, design complexity, and construction manager's leadership. Kheirieh and Heravi (2010) sorted various factors into four main categories (i.e., external, management, human, and technical), and concluded that weather, management, motivation and incentives, tools, planning, and materials are the factors which exert the greatest influence on labor productivity. Song and AbouRizk (2008) proposed 17 productivity-influencing factors, including project type, work scope, draftsperson qualification, and overall complexity of work. Previous studies and the diversity of the identified factors provide insight into the complexity involved in the estimation of labor productivity in construction. Despite the various factors affecting labor productivity, it can provide an acceptable estimate for many construction planning applications, especially during the early phases such as preliminary design. However, it may not be able to provide reliable estimates for the purpose of cycle time calculation and efficiency evaluation for manual operation analysis.

An issue pertaining to determining the amount of work to be done—the datum to be used in the productivity calculation (i.e., *Total Output* in Equation 6-1)—also arises from the fact that, in construction, the product to be produced is generally unique, working environments are continuously changing, and different workers can be assigned to tasks over time or over projects. For example, we cannot assume that the production rate of masonry work in a small residential house is equal to that in a high-rise building, even if the tasks are performed by the same crew. Even in fabrication shops, where similar tasks are repeatedly performed, the production rates for different products can vary based on the slightly different amount of work and the work methods required. In this respect, how to quantify the output of work can be another issue in the estimation of labor productivity and activity duration. Thus, a cycle time estimation approach is required that considers the physical conditions of the jobsite and the details related to carrying out the different manual activities involved.

6.3.2 Traditional Approaches to Determining Activity Durations

The traditional methods currently used to estimate the duration of manual activities include the following: (1) Personal judgment: previous research shows that more than 20% of contractors use personal judgment and opinion of estimators for their estimates of productivity (Motwani et al. 1995). However, using the estimator's perception of the time required to carry out a manual task renders the results highly subjective and unreliable. In many cases, estimators are not sufficiently familiar with work items on projects to enable them to provide reliable estimates. In such cases, they can inquire about durations of particular tasks from personnel who are more familiar with the given task, such as job superintendents. However, job superintendents are often overly optimistic about the time required to accomplish tasks (Hinze 1998). Thus, there is a very high degree of uncertainty involved in using personal judgment for estimating duration of activities. (2) Published productivity data: standard published productivity data, such as RSMeans (2007), can also be used as a reference for productivity estimates when there are no other resources available. However, the productivity values obtained from these reference guides only provide average figures from the industry (Song and AbouRizk 2008), which can vary substantially based on the specific working conditions of different projects. (3) Company's historical data: companies can use existing data as the basis for the estimation and evaluation of new processes. However, construction companies in most cases lack a formal and systematic process for monitoring and recording detailed project data, the result being insufficient information for making reliable estimates (Chan and Kaka 2004). This is partly due to the fact that monitoring construction productivity is time-consuming and costly (Motwani et al. 1995). Furthermore, considering the dynamic nature of construction jobsites, using prior data may not result in realistic estimates, as the working methods and physical settings of the new operation and workplace are not incorporated into the estimate. (4) Productivity estimation models: many researchers have focused on developing productivity models that aim to analyse the impact of factors affecting labor productivity on productivity rates using historical data (Sonmez and Rowings 1998). Examples include the use of techniques such as neural networks (Ezeldin and Sharara 2006; AbouRizk et al. 2001; Chao and Skibniewski 1994), regression models (Smith 1999), expert systems (Christian and Hachey 1995), fuzzy logic (Fayek and Oduba 2005), and statistical analysis (Halligan et al. 1994). Despite the effectiveness of previous studies in developing productivity models for particular cases, due to the inability to deal with the various productivity-influencing factors and their complex relationships the majority of previous work has focused on the impact of a single factor, with only a few studies, limited to masonry construction, having considered multiple factors (Yi and Chan 2014; Nasirzadeh and Nojedehi 2013). Furthermore, the subjectivity of the estimation has an impact on the results of many of the productivity models, and most models are limited in their ability to adapt to different conditions in new projects (Fayek and Oduba 2005). Finally, the lack of reliable, consistent, and comprehensive historical data limits the use of many of the advanced productivity estimation techniques (Sonmez and Rowings 1998).

Despite the value of labor productivity study in applications such as preliminary planning, cost allocation, and bidding, this metric may not provide a reliable estimate of the cycle time of manual activities for scheduling of operations due to the aforementioned limitations. Furthermore, considering the approximation involved in labor productivity as well as the different working methods involved in each project, using productivity estimates as a benchmark for evaluating the efficiency of ongoing operations may result in an unrealistic analysis. Considering the unreliability involved in using labor productivity for analysis of manual operations, this chapter investigates the effectiveness of using PMTS for modeling manual construction operations for cycle time estimation and efficiency evaluation.

6.4 RESEARCH BACKGROUND

Due to the importance of the amount of time required to carry out a manual task for applications such as production planning and scheduling, assessing different alternatives, and efficiency analysis and improvement, measurement techniques (e.g., time study, work sampling) have evolved over time to enable estimation of the required durations of manual tasks. Among these techniques, predetermined motion-time systems, also known as predetermined time systems, have garnered increasing attention due to their effectiveness, as well as to the subjectivity of time studies in setting standards (Genaidy et al. 1990). A PMTS is defined as a structured set of data, procedures, methods, and motion times used to study manual tasks, and is expressed by describing the motions used to perform a task and their previously established standard times (Institute of Industrial Engineers 1983). Large samples of various manual tasks have been studied and evaluated by researchers to develop a PMTS that can provide the standard time required to carry out a manual activity.

Despite the wide applications of PMTS in other industries (Kuhlang et al. 2011; Gupta and Chandrawat 2012; Thakre et al. 2009; Xu et al. 2013; Sun et al. 2009), they have seldom been applied in the construction industry. This is primarily due to the fact that time-and-motion studies have generally originated in industrial engineering, where production is typically carried out in a steady-state environment (Thomas et al. 1990), as opposed to the dynamic nature of construction jobsites. While it is true that these systems perform better in situations with highly repetitive operations, their effectiveness for estimating the cycle time of manual construction operations still needs to be proven. Among the most widely used PMTSs (e.g., MODAPTS, MTM, MOST), this chapter uses MODAPTS as an example of a simple, effective, and quick approach; however, the proposed approach can also be implemented using other available PMTSs.

MODAPTS is developed based on the premise that the time required for any body movement can be expressed as a multiple of the time required to move a single finger. The time required to move a finger is called a MOD, and is equal to 0.129 seconds. Basic alphanumeric codes (e.g., G = Get, M = Move) are defined which describe the nature of the motions and are combined with a MOD value representing the number of MODs required to perform the motion (e.g., G3, M4). Applying MODAPTS necessitates breaking down a manual activity into its basic motions (e.g., moving hand, grasping object, walking) and assigning MOD values to each motion. By adding the MOD values, the total number of MODs required is calculated and then converted to seconds. MODAPTS also enables consideration of rest allowances, which can be very useful in designing safe work practices. Table 6-1 shows the process of obtaining the MODAPTS code and duration of a sample manual task. As shown in the table, the task is broken down into its basic motions, and, for each basic motion, the corresponding MODAPTS class and code are identified.

Table 6-1 MODAPTS code and duration for a sample task

Action	**Attribute**	**MODAPTS motion**	**MODAPTS code**
Move hand to reach a concrete block	Hand is moved 30 cm	move	M4
Grasp the concrete block	Grasp requires visual feedback	get	G3
Walk while holding the block	Distance is 2 steps	walk	W10
Put concrete block on table	Put requires visual feedback	put	P2
Handle block	Block weighs 5 kg	load	L1
		MODAPTS code:	M4G3W10P2L1
		Total MODs:	20
		Total duration:	20 * 0.129 = 2.58 seconds

6.5 MICRO-LEVEL MOTION SIMULATION

To enable simple and effective modeling of manual tasks based on PMTS, a micro-level motion simulation approach is proposed. In particular, a Special Purpose Simulation (SPS) template is developed which integrates MODAPTS into discrete-event simulation modeling. This approach enables automation of the MODAPTS analysis and offers advantages such as quick application, high reliability, simplicity of use, and consistency of application (Genaidy et al. 1990). Simulation modeling is a very well-known and widely used approach for efficiency analysis and productivity improvements (Wang and Halpin 2004), and, with advancements in construction simulation, researchers have increasingly targeted development of SPS templates (see Chapter 2).

The flexibility of SPS modeling enables integration of PMTS standards into simulation environments for more convenient analysis of manual operations. The present study uses Simphony (Hajjar and AbouRizk 1999) for this purpose, as it provides a structured approach to developing user-friendly SPS templates. Fig. 6-1 shows different sections of Simphony's user interface. An SPS template is developed for the purpose of this study which contains modeling elements that represent manual construction activities and provides standard durations of manual tasks based on an available validated motion-time system (i.e., MODAPTS). It is also compatible with Simphony's general-purpose simulation interface, which supports the use of these elements in any other simulation model of construction processes.

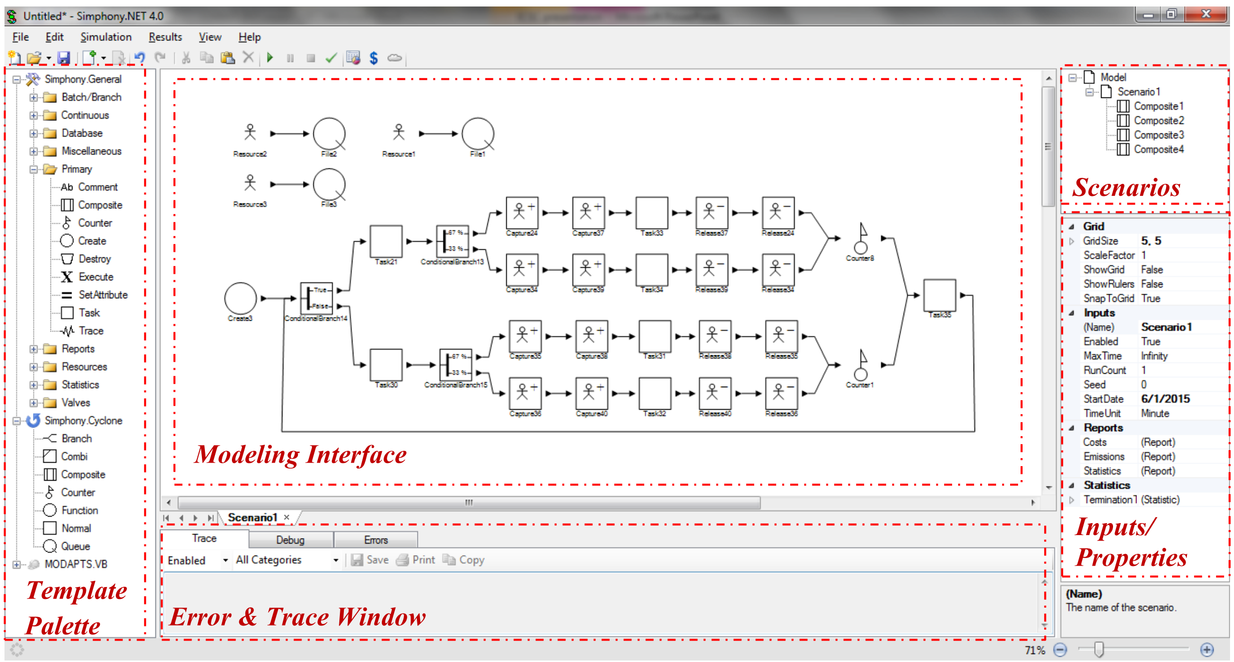


Figure 6-1 Simphony's user interface

The steps required in developing a motion-level SPS template are shown in Fig. 6-2. To develop the SPS template, the modeling elements of the template are first designed based on MODAPTS, and the required inputs and properties of each element are identified. The main MODAPTS classes are shown in Table 6-2, along with a description of each. Each class has a corresponding modeling element in the developed SPS template which, using the input provided by the user (shown in Table 6-2), calculates the corresponding MODAPTS duration and uses it as the duration of that manual task. The developed SPS template and its modeling elements are designed such that they can be used to represent manual tasks without the need for prior knowledge of MODAPTS and the details of its implementation.

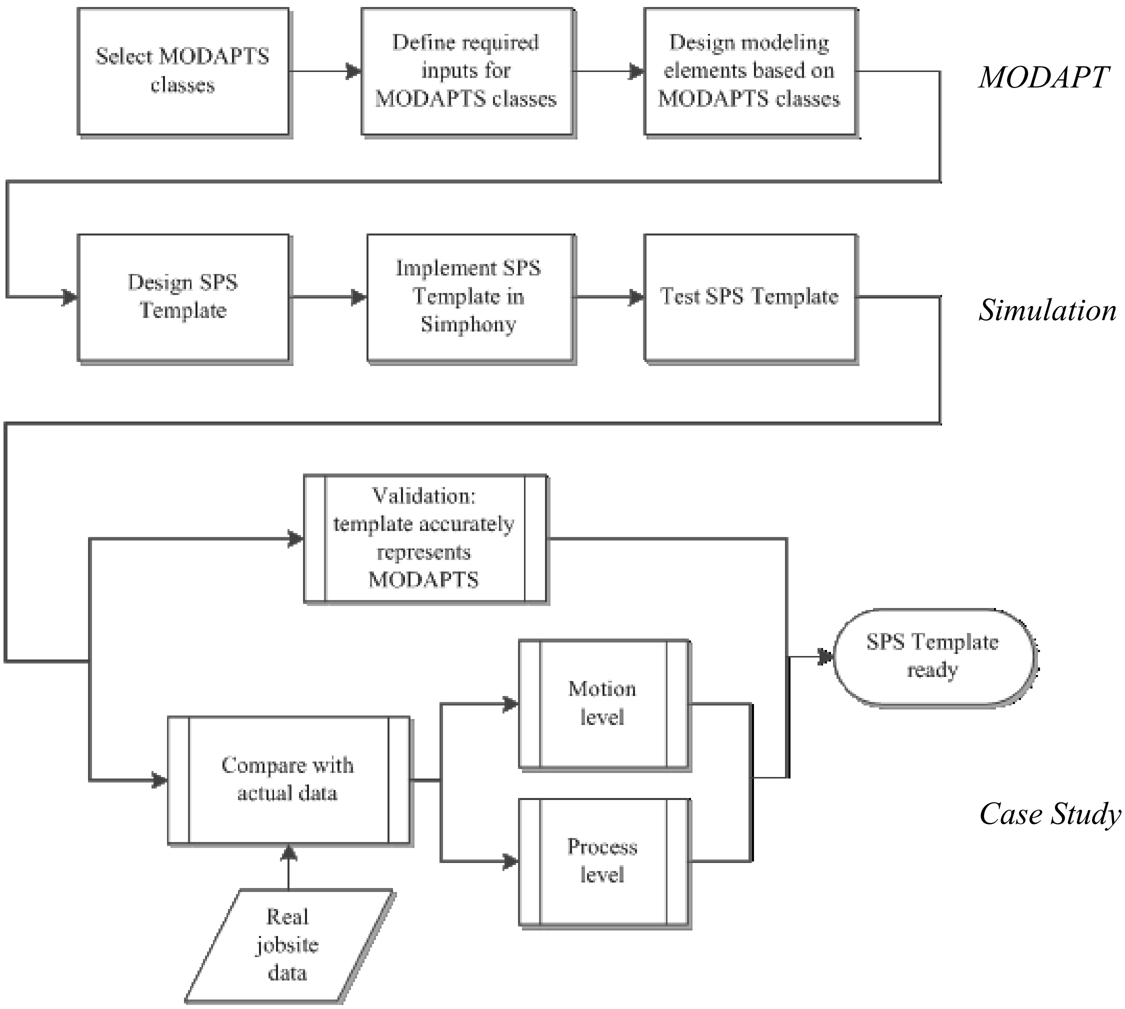


Figure 6-2 Process of developing micro-motion-level simulation

Table 6-2 Main MODAPTS classes used for SPS template

Class	**Description**	**Input**
Move (M)	Movement of a finger	Moving distance
Get (G)	Grasping an object	Ease of grasp
Put (P)	Placing an object	Sensory feedback required
Walk (W)	Act of walking	Walking distance
Load (L)	Incorporating weight of objects	Weight of object
Read (R)	Act of reading	Length of reading material
Handwrite (H)	Act of writing	Number of words written
Bend and Arise (B)	Act of bending and arising	Number of times

Sit and Stand (S)	Act of siting and standing	Number of times

Furthermore, elements representing combined tasks which consist of several basic motions are designed to make the template more flexible. An example of a combined task is the act of carrying an object, which consists of moving a hand to reach the object (MOVE), grasping the object (GET), walking with the object (WALK), moving a hand to place the object (MOVE), and placing the object at its destination (PUT). The modeling element representing this task and the required inputs are shown in Fig. 6-3. Once the components of the template have been designed, it is implemented using object-oriented programming to define the simulation behaviour of each element (e.g., calculating the corresponding MODAPTS duration for each task).

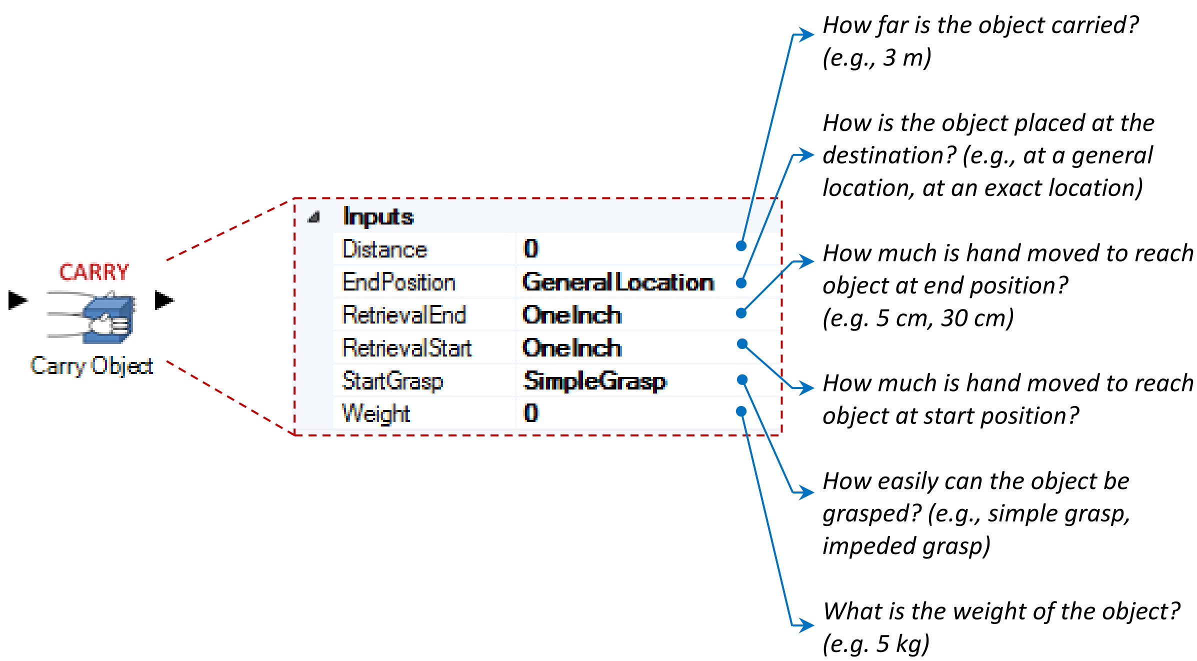


Figure 6-3 Required inputs for carrying task modeling element

As an example of the simulation behaviour of the modeling elements, the pseudo code that defines the behaviour of the carrying task element is shown in Fig. 6-4. As this task combines the basic motions of the WALK, PUT, MOVE, GET, and LOAD classes, the corresponding MOD value for the motion corresponding to each of these classes is calculated based on the inputs, and the final duration is calculated by converting the total

MOD value to seconds. Finally, the calculated duration is used as the duration of the modeling element in the simulation model. The same process is repeated for the other modeling elements (e.g., GET, PUT) of the template.

```
MOD = 0
1. WALK class
Based on the provided distance value, add corresponding MOD value:
        MOD = MOD + 5 × ((Me.Distance × 100) ÷ 64.5)
2. PUT class
Based on the input provided for end position, add corresponding MOD value:
        If EndPosition = GeneralLocation/WithTidiness/ExactLocation Then
                MOD = MOD + 0/2/5
3. MOVE class
Based on the input provided for revrieval start and end, add corresponding MOD value:
        If RetrievalStart(or End) = OneInch/TwoInches/…/ThirtyInches Then
                MOD = MOD + 1/2/…/7
4. GET class
Based on the input provided for start grasp, caclulate MOD value:
        If StartGrasp = SimpleGrasp/ImpededGrasp Then
                MOD = MOD + 1/3
5. LOAD class
Based on the provided weight value, add corresponding MOD value:
        If weight<2 / 2<weight<6 / 6<weight<8 / … Then
                MOD = MOD + 1/2/3/…
Convert MOD value to seconds:
Duration = MTU * 0.129
Set calculated duration as the duration of the task
Engine.ScheduleEvent(entity, TransferOut, Duration)
```

Figure 6-4 Pseudo code for calculating duration of a carrying task element

To use the modeling elements of the developed template, the elements describing a manual activity are added to the modeling interface in the same sequence in which they are carried out, and the required inputs for each element are assigned. After adding an element and running the model, the simulation engine calculates the required time for that task based on MODAPTS each time an entity passes through it, and uses this value as its duration. Fig. 6-5 shows a sequence of motions for a simple manual task and the corresponding modeling elements used in the developed template.

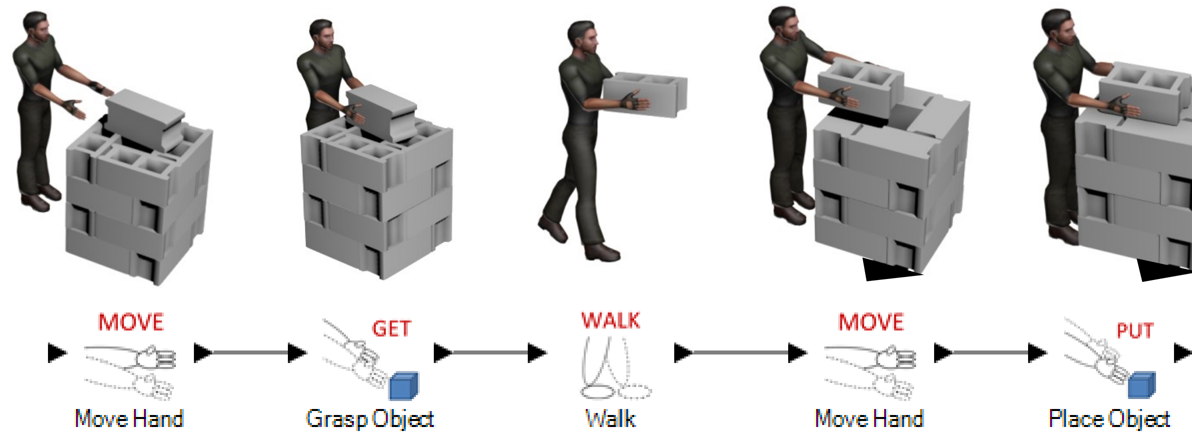


Figure 6-5 A manual task and its representation using the developed modeling elements

6.6 CASE STUDY

The developed SPS modeling template is used to model manual construction tasks from an actual steel fabrication construction jobsite to examine the effectiveness of using PMTS for cycle time estimation and efficiency evaluation of manual operations. These tasks include handling steel plates, handling steel beams, and handling steel ladders. A steel fabrication jobsite is selected for the case study since it enables observation and videotaping of the tasks with more control over the conditions of the work environment. The tasks mentioned above are specifically selected to represent manual construction tasks with three different levels of repetitiveness (i.e., highly cyclic, moderately cyclic, and non-cyclic). The workstations of the three tasks selected for the case study are shown in Fig. 6-6, and a summary of information pertaining to the tasks is shown in Table 6-3. In Table 6-3, the main activities carried out by the workers include the actions that are repeated the most during a full cycle and can be considered as the main tasks the worker must carry out to complete the job. The steel plate handling task mainly involves removing steel plates from a cutting machine and carrying them to a work table. The steel beam handling task is carried out by a steel worker known as a "steel fitter". The duty of a fitter is to fit steel plates into beams to prepare them for final welding, and this involves various physically challenging manual tasks. The task of building steel ladders also involves various manual activities such as welding and hammering, as well as working with various tools.

(a) (b) (c)

Figure 6-6 Workstations for (a) steel plate handling, (b) steel beam handling, and (c) steel ladder handling

For each task, the motions of the worker are observed and videotaped for a full cycle, and the durations of all the basic motions are extracted from the video recordings. The number of basic motions in Table 6-3 corresponds to the basic classes as defined by MODAPTS. For example, a walking action is considered one basic motion irrespective of the number of steps taken by the worker, and a carrying element is considered to contain several basic motions (including MOVE, GET, PUT, and WALK), although it can be represented by the developed simulation template using one modeling element. Other examples of these basic motions include grasping a hammer, moving hands to remove welding mask, and placing a steel plate on a beam.

Table 6-3 Summary of information for the observed manual tasks

Task	Main activities	Level of repetitiveness	Duration of full cycle (second)	Number of basic motions
Steel plate handling	Carrying steel plates	High	774	210
Steel beam handling	Measuring, hammering, carrying, grinding, and welding	Medium	989	593
Steel ladder handling	Welding, measuring, and hammering	Low	630	389

For each basic motion, the duration is recorded in addition to the conditions of the jobsite. The type and order of the basic motions carried out are used to obtain the sequence of actions that a worker must complete in performing the job in order to ensure a realistic simulation model is built. The jobsite conditions also serve as inputs for the simulation modeling elements of the developed template as described above. The duration of each basic motion is extracted from video recordings to investigate, using the Spearman's rank correlation coefficient (Spearman 1904), the correlation between the actual dataset from the jobsite and the corresponding dataset from the simulation. For each of the manual tasks of the case study, the Spearman's correlation coefficient between the actual and MODAPTS times is calculated to study the association between the actual durations of basic motions and the MODAPTS durations. As an example of the information extracted from the video recordings, Table 6-4 shows the data obtained for the plate handling task for three instances of plate-carrying, where the first six columns represent the inputs required for the MODAPTS analysis and the seventh column shows the resulting MODAPTS duration. The MODAPTS code is also obtained manually for random instances of the motions, and the corresponding duration is calculated from the code. This validation step is carried out to ensure that the manually obtained duration is the same as the duration computed by the simulation to confirm that the simulation engine is correctly calculating MODAPTS durations. Finally, the last column represents the actual duration at the jobsite. Similar inputs are extracted for the basic motions of the other tasks as well.

Table 6-4 Required information for each instance of plate handling task

Weight of plate (kg)	Walking distance (m)	Start Grasp	End Position	Retrieval Start	Retrieval End	**MODAPTS duration (simulation)**	**MODAPTS Code (manual)**	**Actual duration (jobsite)**
9	4.2	Impeded Grasp	General Location	Six	Eighteen	**6.063**	**M3G3L3W33 M5P0**	**6.59**
3	2.6	Impeded Grasp	With Tidiness	Twelve	Six	**4.257**	**M4G3L1W20 M3P2**	**4.91**
9	3.8	Impeded Grasp	General Location	Six	Twelve	**5.418**	**M3G3L3W29 M4P0**	**5.75**

For each task in the case study, two simulation models of the entire cycle are created which represent two levels of detail. The first model is built exactly based on the sequence of activities that the worker carries out to complete the full cycle. This model is created to examine the difference between the calculated cycle time using MODAPTS and the actual cycle time from the jobsite to evaluate the reliability of using PMTS for duration estimation. The resulting simulation time is used to calculate the efficiency of the modeling process (reflecting the efficiency of the manual operation) using Equation 6-2. Although it is beyond the scope of this chapter, this model can be used to identify the inefficiencies of the manual operation and to test different scenarios to improve worker productivity. Using this model facilitates the efficiency analysis process and can effectively replace manual analysis of operations.

$$\text{Efficiency} = (\text{actual time} - \text{simulation time}) / \text{actual time} \qquad (6\text{-}2)$$

The second simulation model aims to simplify the representation of the task as much as possible using cyclic representations of the activities. Such a model represents the simple model that would be created and used for a non-existing instance of a similar task. The resulting simulation time is compared with the actual time as well as with the simulation time of the first model to examine the effectiveness of using PMTS approaches to represent existing and non-existing manual tasks, and also to compare the use of the proposed simulation approach in modeling tasks with different levels of repetitiveness. As an example, Fig. 6-7 shows six instances of the plate-carrying activity as part of the steel plate handling simulation model. The model on the left shows the six activities from the high detail model and their main attributes (i.e., inputs), which consist of distinct values. The same process can be modelled using a cycle which is repeated six times (low detail model). In this case, the attributes of the modeling elements represent the average of the attributes of the elements of the high detail model. This difference between the values used for the inputs of the elements of the models and the approximation used in representing the sequence of activities in the low detail model is the cause of the discrepancy between corresponding simulation times. A smaller difference between the simulation times of the two models is expected in the case of more cyclic activities.

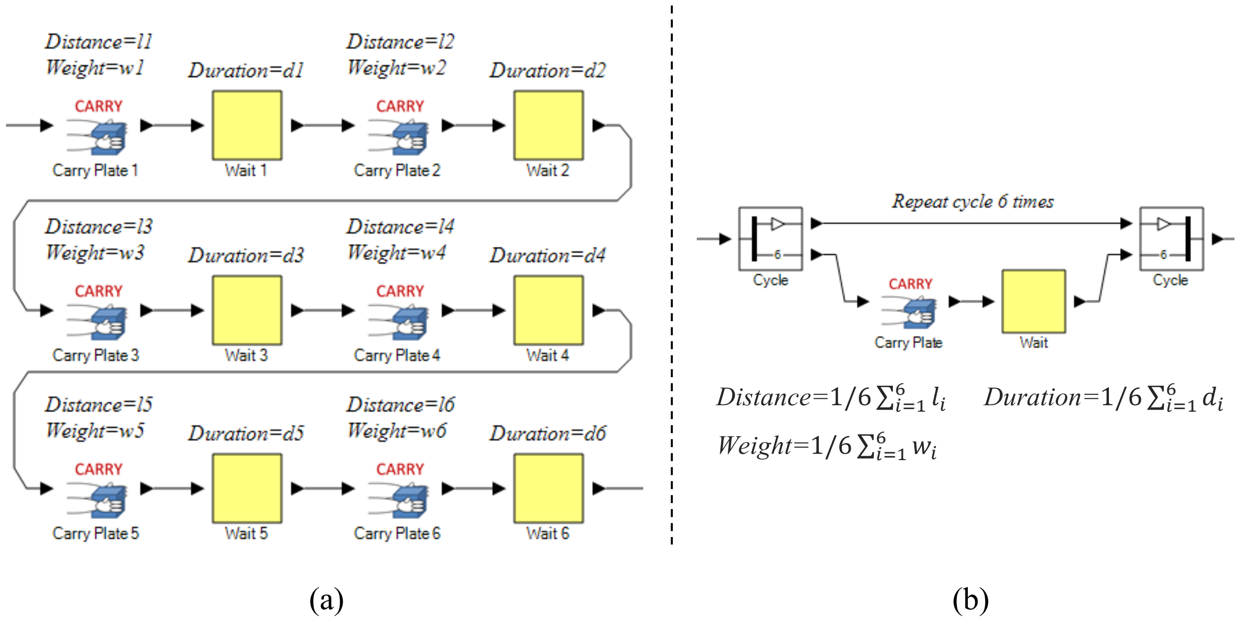


Figure 6-7 Representation of six instances of plate-carrying task in (a) high detail model, (b) low detail model

6.7 RESULTS

Table 6-5 shows a summary of the results both of extracting the required data from video recordings and of running the simulation models for each task. The Spearman's correlation coefficients for each task are shown, representing the correlation between the actual and MODAPTS durations for time datasets of basic motions. The efficiency values of each task (calculated using Equation 6-2) enable comparisons of the total actual and simulation cycle time of the tasks in cases of both high detail and low detail models. The number of MODAPTS elements corresponds to the number of different modeling elements used in the simulation model representing the task. As the number of modeling elements implies, the high detail models are created using the same sequence of motions that the worker carries out in the jobsite, whereas the low detail models are created to represent a simple cyclic representation of the task for new instances of the operations. To enable better understanding and comparison of the high detail and low detail models of each task, Table 6-6 provides more detailed information about the number of times each modeling element is used in the simulation models. The number of times the different modeling elements representing the MODAPTS basic motions are used also assists in understanding the frequency at which each manual activity is performed for a task. Furthermore, this information can be used to compare other types of manual tasks with the ones examined in this chapter, based on the working methods, to evaluate the applicability of the proposed approach to other manual construction operations.

Table 6-5 Summary of results of case study

Task	**Correlation Coefficient**	**Efficiency**		**Number of MODAPTS elements**	
		High detail	**Low detail**	**High detail**	**Low detail**
Steel plate handling	0.91	9.3%	10.59%	53	7
Steel beam handling	0.94	7.79%	15.47%	443	46
Steel ladder handling	0.90	5.24%	20.32%	364	34

Table 6-6 Number of different modeling elements used in each simulation model

Task	**Modeling elements and number of times used in (high detail model, low detail model)**
Steel plate handling	CARRY (26,3) – WALK (6,1) – other* (21,3)
Steel beam handling	GET (65,5) – PUT (47,1) – MOVE (196,17) – CARRY (25,6) – WALK (23,8) – other (87,9)
Steel ladder handling	GET (39,4) – PUT (27,3) – MOVE (212,20) – CARRY (3,0) – WALK (31,3) – other (52,4)

* “Other” includes non-MODAPTS elements such as idling and welding

Fig. 6-8 illustrates the difference between the efficiency values obtained by the high detail and low detail simulation models of each task. The dashed arrows in Fig. 6-8 show the difference between the efficiency values of the models, which can be used to interpret the approximation involved in using the simplified low detail model for non-existing tasks. Fig. 6-9 also shows the changes in the total actual and simulation times of each task as the task proceeds. The final difference between the actual and simulation time of each task represents the variance of the total simulation time from the total cycle time recorded at the jobsite.

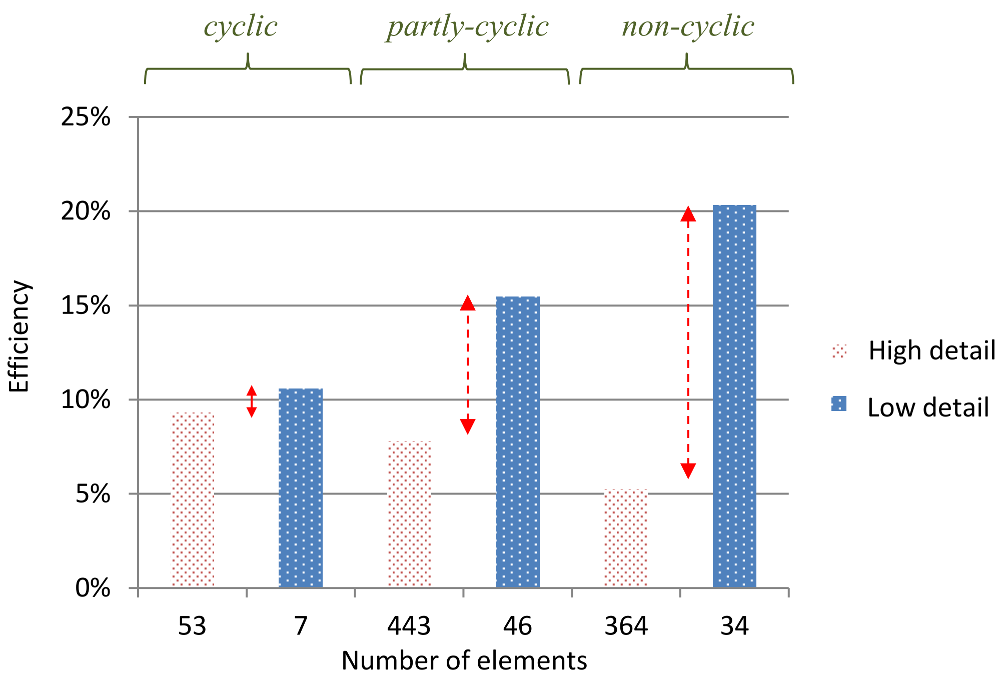


Figure 6-8 Efficiency values of the high detail and low detail models of each task in case study

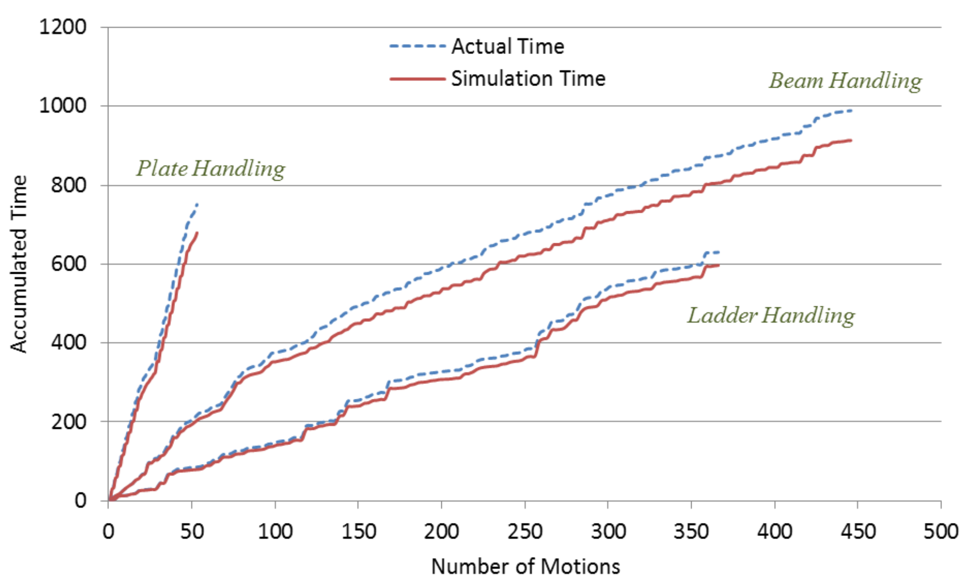


Figure 6-9 Changes in actual and simulation time for the three tasks of case study

6.8 DISCUSSION

The results of the case study indicate that the proposed PMTS-based simulation approach can provide an effective means of modeling manual operations. The proposed methodology can potentially be used for reliable duration estimation and efficiency assessment of manual tasks, as well as for safety analysis. The implications of the results for each of these areas, as well as the limitations of this chapter, are discussed below.

6.8.1 Implications for Duration Estimation and Efficiency Evaluation

The results show that the proposed approach can provide reliable estimates for the durations of manual construction activities, especially in the case of cyclic activities. As shown in Table 6-5, in the case of highly repetitive tasks there is about a 10% difference in the duration of the low detail simulation model and the actual cycle time from the jobsite. It should be noted that the efficiency values are calculated before applying rest allowances, such that the obtained cycle times will be closer to the actual cycle times after applying appropriate allowances. Thus, the low detail model can effectively reflect the manual operation, and the resulting cycle time can be reliably used as the duration of the task. The small difference between the efficiency of the low detail and high detail models (about 1%) also confirms that the simple cyclic representation of repetitive manual operations based on PMTS can be used to obtain durations of operations. Furthermore, considering the small number of modeling elements required for the low detail models (which indicates the small amount of time required to create the models), the difference between the efficiency values of the two simulation models of both the moderately repetitive and less repetitive tasks (dashed arrows in Fig. 6-8) indicates the suitability of the PMTS-based approach for modeling manual operations for most scheduling applications. The approximation of the cycle times seems acceptable for most cases of scheduling where there is only general information available regarding the conditions of the jobsite and how the tasks will be carried out. The high correlation between the datasets of actual and MODAPTS durations for all tasks of the case study also points to a strong association between the two datasets (Mukaka 2012). The high correlation also implies that available PMTSs provide a means to associate estimated durations with the actual durations of manual activities, which in turn enables more accurate planning and scheduling of manual operations.

Furthermore, by integrating PMTS into simulation modeling, existing manual tasks can be conveniently modelled, and the efficiency of the manual operations can be estimated to modify and potentially improve the productivity of the operations by testing different scenarios. The values obtained using PTMS not only provide a benchmark to which to compare the efficiency of manual operations, but also can serve as a basis to modify work methods and compare the use of different methods to achieve maximum productivity. As a future study, the effectiveness of the proposed approach for improving labor efficiency can be examined by assessing various scenarios of operations, and the incorporation of different motion and time study techniques (e.g., work-methods study, crew-balance analysis) into the analysis can be investigated.

6.8.2 Potential Implications for Ergonomic Safety Analysis

As any operation consists of work processes with specific tasks and steps required to complete it (Russell and Skibniewski 1990), analysis of manual operations using PMTS can provide useful information for ergonomic assessment. Previous studies have shown that integrating ergonomic evaluation into PMTS can provide an effective means of accounting for ergonomic safety considerations during the design and planning of operations (Laring et al. 2002). Considering the detailed analysis of both ongoing and non-existing manual tasks which the developed PMTS-based simulation approach enables, incorporating ergonomic assessment into the simulation can potentially associate production tasks with ergonomic behaviour. This, in turn, permits examination of the relationship between productivity of operations and ergonomic safety, which can be highly effective considering the prevalence of WMSDs in construction (Inyang 2016). Consequently, manual activities can be designed to attain the highest achievable efficiency and safety simultaneously, by testing various scenarios of operations in a simple, quick, and reliable manner.

6.8.3 Limitations

This chapter has used MODAPTS as an example of an efficient and simple-to-use PMTS to model manual construction operations. Despite obtaining promising results by applying MODAPTS, the use of other well-known PMTSs (e.g., MTM, MOST) for modeling of manual construction tasks need to be investigated. Given that manual construction activities differ significantly in their degree of repetitiveness, comparing the suitability of these systems for modeling construction tasks enables selection of the most appropriate system based on the working methods and conditions of the jobsite. Since less attention has been directed toward the use of these systems in construction, such a comparison has not been carried out in previous studies and can be performed as part of a future study. Furthermore, this chapter tested the applicability of the proposed approach by implementing it on three manual operations with low, medium, and high degrees of repetitiveness. However, further verification can be achieved through a more detailed analysis which applies the methodology to more diverse construction tasks from different trades and examines the reliability of the proposed approach for each task. Finally, given that one of the main functions of PMTSs is to improve the productivity of manual tasks, the feasibility of the proposed PMTS-based simulation approach in providing an effective automated approach to improvement of the efficiency of manual operations can be examined.

6.9 CONCLUSION

This chapter has investigated the effectiveness of using PMTSs for modeling manual construction operations for cycle time estimation and efficiency evaluation. By developing an SPS template, manual tasks with different levels of repetitiveness are modelled from a construction jobsite to examine the suitability of the proposed approach in representing construction tasks. The findings indicate that a PMTS-based approach can provide reliable estimates of the durations of non-existing manual construction activities, and can also be used to effectively evaluate the efficiency of ongoing manual tasks to make improvements to existing operations. The results show that, in the case of highly repetitive tasks, a simplified cyclic model representing the task can provide accurate estimates of durations; in the case of less repetitive activities, the approximation involved in the estimates can be considered acceptable for most scheduling applications. Furthermore, correlating actual durations of manual tasks with PMTS time sets enables deriving realistic cycle times, merely based on inputs describing the general conditions of the jobsite.

6.10 ACKNOWLEDGMENTS

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Chapter 7 A Simulation and Visualization-based Framework of Labor Efficiency and Safety Analysis for Prevention through Design and Planning [5]

7.1 SUMMARY

Considering the physically demanding nature of manual tasks in the construction industry, an effective approach to mitigating ergonomic risks is to prevent the unsafe working conditions proactively during design and planning (i.e. prevention through design), as discussed in the Chapter 3. However, there is a lack of approaches for identifying the potential ergonomic risks of a proposed design that can effectively address designers' lack of familiarity with ergonomic risks and understanding of the PtD concept and its implementation. Furthermore, it is difficult to evaluate the impact of ergonomic interventions on productivity and vice versa using the available tools. Thus, an integrated approach to PtD is proposed in this chapter by developing a comprehensive framework that uses simulation modeling, coupled with PMTSs and ergonomic and biomechanical assessment, as well as workplace visualization, to incorporate both productivity and safety analysis into the design process.

7.2 INTRODUCTION

The construction industry is identified as one of the most unsafe industries around the world (Gangolells et al. 2010). Statistics indicate that the construction industry accounts for an average of 20% of all workplace fatalities in Canada (Sharpe and Hardt 2006) and 20.5% of all fatalities in the US (OSHA 2014). Considering the high rate of fatalities and injuries in the construction industry, one of the most effective approaches to improving the safety of construction workplaces is preventing these injuries proactively from the early design stage (Weinstein et al. 2005). Previous studies have linked 42% of fatalities to the design for safety concept (Behm 2005). Accordingly, the prevention through design

[5] A version of this chapter is submitted as Golabchi, A., Han, S., and AbouRizk, S. M. (2017). "A Simulation and Visualization-based Framework of Labor Efficiency and Safety Analysis for Prevention through Design and Planning." Automation in Construction.

initiative was implemented by NIOSH, which aims to identify workplace hazards and risks during design to prevent and reduce injuries, illnesses and fatalities (Schulte et al. 2008).

The concept of PtD can be highly effective in mitigating the occupational risks leading to WMSDs (Nussbaum et al. 2009). Despite the prevalence of WMSDs in the construction industry and the potential of PtD-based approaches to mitigate WMSDs, less attention has been given to integrating ergonomic and biomechanical analysis into the design process, due to the lack of tools and approaches for identifying and evaluating the potential ergonomic risks of a proposed design that can effectively address designers' lack of familiarity with ergonomic risks (Wang et al. 2015; Hecker et al. 2006; Weinstein et al. 2005) and understanding of the PtD concept and its implementation (Kim et al. 2008; Gangolells et al. 2010). It is difficult to assess the biomechanics of a task which is not yet observable and without the existence of a physical workplace with the tools available in the construction industry. As the literature on PtD has been slow in addressing the technical principles of PtD (Toole and Gambatese 2008), more tools and approaches are required to enable designers to effectively incorporate ergonomic evaluations into the workplace and process design (Gambatese 2008). Furthermore, safety performance is highly correlated to productivity (Hallowell 2011) and ergonomic behaviour in particular results primarily from physical conditions (e.g., human postures, repetitive movements, duration, forceful exertion) determined by production tasks (e.g., production rate, job procedures, and workplace layout) (Mitropoulos et al. 2005; Freivalds and Niebel 2014). However, current approaches used in construction lack the concurrent integration of both production and safety into workplace and operation design and do not fully consider the high association between the two, especially in terms of ergonomic risks.

Thus, due to the lack of effective tools for incorporating ergonomic assessment into the design phase of construction operations, and the potentially high impact of actions of workplace and production designers on biomechanical exposure (Wells et al. 2007), this chapter explores an integrated approach to PtD that incorporates both productivity and safety into the design process. The scope of these PtD interventions includes design of workplaces (e.g., jobsite layout), operations (e.g., sequence of tasks), equipment and tools (e.g., height of workbench), material (e.g., shape and size of concrete blocks), human actions (e.g., body posture) and etc. The trade-off between ergonomic risk and the duration of manual activities, as the main element of productivity of manual operations, is also examined in this chapter. The proposed micro-level motion simulation approach combines discrete-event simulation modeling of manual operations with ergonomic and biomechanical modeling of motions, which provides an effective means of evaluating various human motions potentially taking place in jobsites. PMTSs are integrated into simulation which enables calculating reliable job efficiency, experimenting with different scenarios of manual operations, and evaluating each scenario in terms of safety and productivity. Visualization of the workplace is also used to enable accurate and convenient extraction of the required inputs, facilitate the communication and execution of the design, assist with managerial decision-making, and promote training of workers and personnel. The proposed framework aims to enable an effective implementation of the safety in design concept in conjunction with efficiency analysis, in a simplified and user-friendly manner, which can be used by designers, without requiring extensive prior knowledge about the technical details of the different components of the system.

7.3 BACKGROUND

The concept of design for safety, defined as considering construction safety during the design of a project (Behm 2005), is accepted as a critical intervention to enhancing the safety of construction workers (Gambatese 2003). The concept dates back to 1985, where the International Labor Office (ILO) acknowledged the need for designers to consider construction safety in workplace and operation design (ILO 1985). The need for such intervention has been increasingly recognized since then (Gambatese et al. 2008). For example, 60% of fatal accidents in the construction industry were found to be the results of shortcomings in early design and organization of work (Eurofound 1991). Although many studies have tried to apply the concept of design for safety, which has recently led to the PtD initiative, in different aspects of construction (Zhang et al. 2013; Cooke et al. 2008; Gambatese et al. 1997), not many studies have focused on incorporating principles of ergonomic safety into construction workplace design. Some researchers in the construction industry have worked on adapting ergonomic analysis for improving worker safety and preventing injuries using different approaches such as motion sensing and tracking (Chen et al. 2014; Ray and Teizer 2012; Alwasel et al. 2011; Han et al. 2014), assessment tools (Buchholz et al. 1996), and participatory ergonomics (Molen et al. 2005; Hess et al. 2004). Despite the effectiveness of the previous studies in evaluating ergonomic risks, more research is required to investigate the correlation between ergonomic safety and productivity of operations from a design perspective, which is critical for effective implementation of ergonomic considerations in PtD and taking into account the impact of ergonomic interventions on efficiency and vice versa.

As discussed in Chapter 2, previous research on the correlation between construction productivity and safety has shown to be indecisive as some studies have indicated a positive correlation between safety and productivity (McLain and Jarrell 2007; Hare et al. 2006; Shikdar and Sawaqed 2003) and some have found out a negative correlation between the two (Probst and Brubaker 2007; Choudhry and Fang 2008; Choi et al. 2006). In terms of ergonomic safety, although improving the working conditions that result in less ergonomic risks can lead to improved efficiency due to higher level of comfort, some safety interventions suggested by ergonomists and safety practitioners, such as slower pace of work and more rest allowances, can also result in lower productivity (Wells et al. 2007). Furthermore, production demand affects safety performance as generating work pressure that can cause hazardous situations and impact ergonomic behavior. Thus, there is a need for tools and approaches that not only incorporate ergonomic considerations into the design phase to enable effective and convenient implementation of PtD, but also enable examining the impact of modifications in production and ergonomic design on both safety and productivity. Therefore, this chapter aims to examine the integration of ergonomics and efficiency analysis into the design process and provide a framework for planning efficient and safe operations concurrently.

7.4 RESEARCH FRAMEWORK

To enable concurrent analysis of the safety and efficiency of operations, this chapter suggests a micro-level motion modeling and simulation approach. The proposed framework is shown in Fig. 7-1. A proposed design is first visualized to enable reliable measurement and observation of the required inputs for the simulation, in addition to enabling effective communication and implementation of the design once it is finalized. Discrete event simulation modeling is then used to model the manual operations in a motion level (Chapter 6). PMTSs in conjunction with ergonomic assessment methods are incorporated into the modeling elements of the developed simulation template, which enables inputting data regarding the method of carrying out the manual task and its attributes (e.g., walking distance, difficulty of grasping an object) as well as the physical exertion on the body (e.g., weight of object, position of arms). The system is developed such that any designer can conveniently model manual operations, even without detailed knowledge about the mechanics of PMTSs and ergonomic evaluation methods, using simple design data (e.g., location of material, shape of equipment, job sequence). The design is then evaluated in terms of efficiency and safety and is modified to examine the impact of the various attributes and compare different designs and scenarios. Biomechanical analysis is also used for the ergonomic safety evaluation to provide a more accurate and reliable analysis of the ergonomic risks and facilitate achieving safe motions. Among the different scenarios, the optimal design in terms of both safety and efficiency is selected and the visualization of the design is used for perception, communication, and implementation of the design. This chapter focuses on the integration of the efficiency and safety analysis through simulation and visualization, and builds upon previous studies and existing literature for some components of the comprehensive framework. The different elements of the system and their role in the proposed approach are described in the following sections.

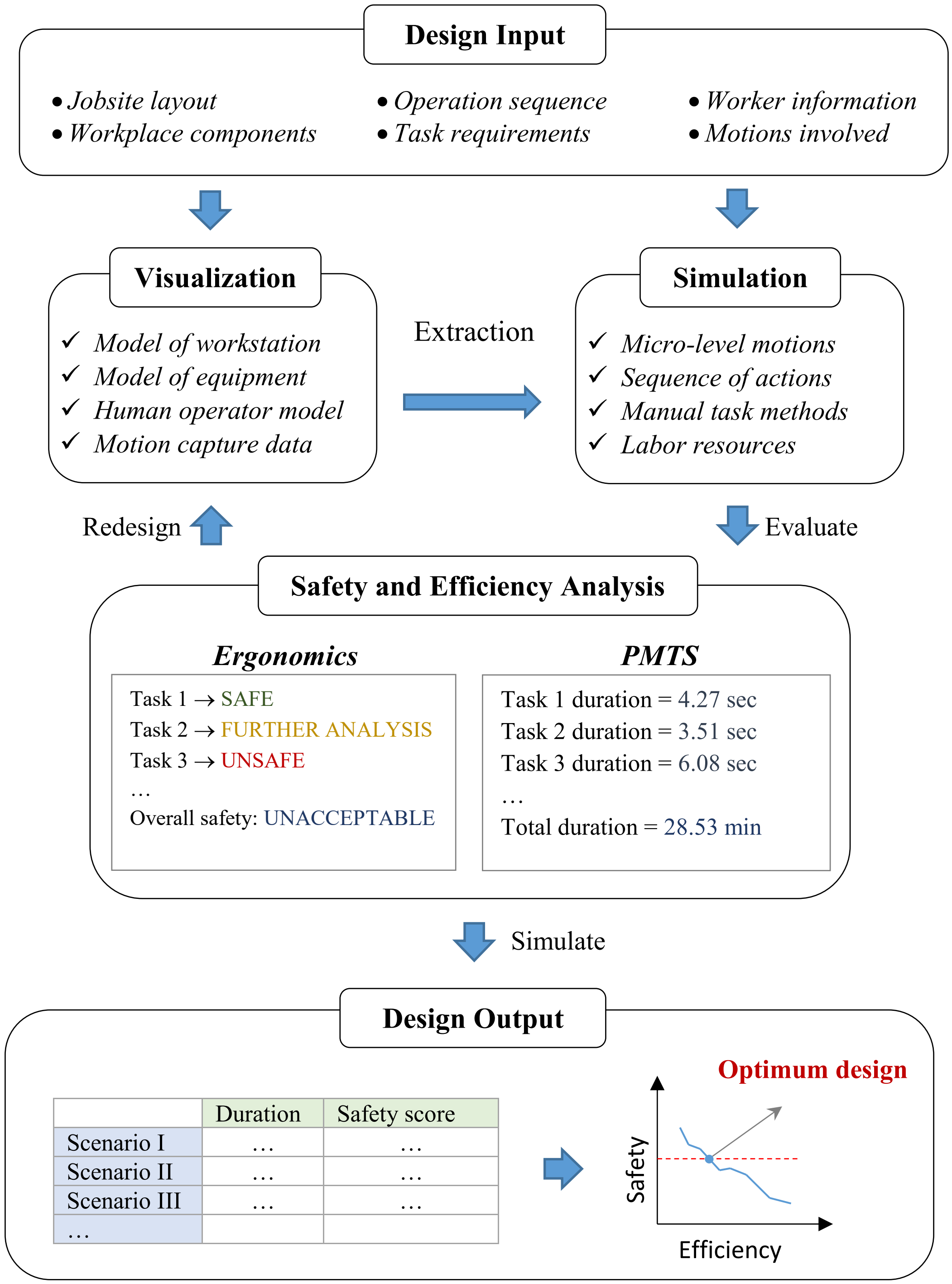


Figure 7-1 Framework of motion-level simulation-based workplace design

7.4.1 Workplace Visualization

Obtaining reliable data regarding the physical attributes of a jobsite is essential for effective analysis of manual operations, as the dimensions and geometry of different elements of the workplace has a major impact on both the efficiency and safety of a manual task. Acquiring these inputs in case of existing workplaces requires significant amount of time and effort, and in case of non-existing workplaces, which are still in the design stage, it is difficult to carry out the analysis without any reference, as it is challenging to perceive the design of a non-existing workplace and assess different possible scenarios. Thus, a visual representation of the workplace can facilitate extracting the required inputs for analyzing the design and also improves the reliability of the inputs. The virtual model can be used for obtaining the analysis inputs through direct measurements of quantitative attributes such as distances (e.g., walking distance to pick up an object), as well as observation of different jobsite components for obtaining qualitative attributes (e.g., body motion required to carry out a manual activity) (Guo et al. 2016) and enabling accurate perception of the design (see Chapter 3). The 3D representation can also be highly useful in evaluating ergonomic factors such as clearance, reach, and visibility. Some advanced tools that can be highly useful in the visualization process and have gained attention in the construction industry include BIM, for modeling non-existing operations, point cloud models, for modeling existing workplaces, and motion capture data, for modeling human motions. These tools, especially when used in conjunction, can increase the accuracy and simplify creation of the virtual model as well as the analysis process. The proposed comprehensive framework of visualization of the design is shown in Fig. 7-2.

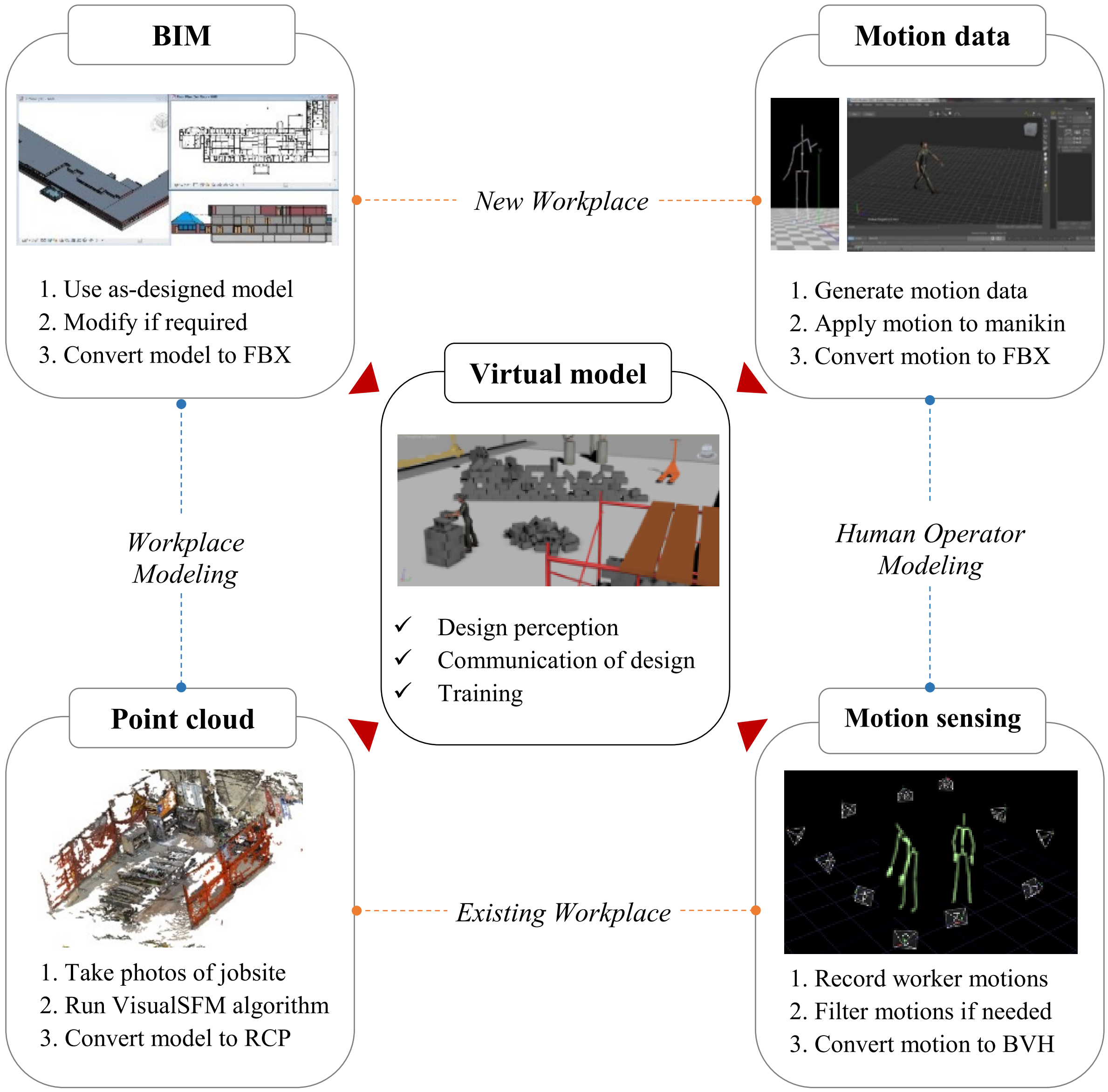


Figure 7-2 Workplace visualization framework

7.4.1.1 Building Information Models

Considering the advancements in using BIM for effective visualization of workplaces and the prevalence of using it during different phases of a project, leveraging BIM models for evaluation and design of manual operations can be highly beneficial, especially in case of non-existing operations. As-designed BIM models can provide accurate information regarding the dimensions, geometry, shapes, and locations of different elements of the jobsite, which can be used to extract the safety and efficiency analysis inputs. Current BIM software platforms enable convenient measurement of distances and the 3D visualization capabilities enable virtual observation of the workplace for obtaining the qualitative inputs required. Furthermore, these models can be transferred into 3D modeling and visualization platforms and game engines (e.g., 3ds Max, Unity) for further visualization applications and to combine them with human operator models, motion data, and 3D models of other objects not existing in the BIM (e.g., equipment, material). The proposed framework suggests using Autodesk Revit as the BIM environment and 3ds Max for the final virtual representation as examples of effective modeling and visualization platforms, although other BIM and visualization environments can be similarly used. To enable the transfer of data, the as-designed BIM model is extracted from the BIM platform into the FBX format, which is a proprietary file format that enables data exchange and interoperability between different digital modeling platforms, and then imported into the 3D virtual environment.

7.4.1.2 Point Cloud Models

In case of existing jobsites, the proposed approach to jobsite visualization is to generate point cloud representations of the workplace and use it for design improvements, in conjunction with BIM and other 3D models. Research in the construction industry has been active in developing and using point cloud data (Dimitrov et al. 2016; Han et al. 2015; El-Omari and Moselhi 2008) and transforming point clouds into 3D models (Tang et al. 2010; Perez-Perez et al. 2016; Bosche and Haas 2008). A simple, yet effective, approach is the implementation of an image-based 3D reconstruction method that uses simple photographs of the jobsite to generate a point cloud model (Fathi and Brilakis 2011; Koutsoudis et al. 2014; Yang et al. 2013; Remondino and El-Hakim 2006; Dellaert et al. 2000; Debevec 1996), which can also be used to facilitate extraction of inputs of efficiency and safety analysis. Considering the dynamic nature of construction jobsites and the frequent changes in the physical settings of workplaces, this approach ensures that the virtual model is an accurate reflection of the current conditions of the jobsite. In this approach, photographs are taken from the jobsite and using a structure-from-motion algorithm, which utilizes the relationship between the locations of key points in different images to recover the 3D shape of an object, the 3D reconstruction of the point cloud model is obtained (Guo et al. 2016). After creating the point cloud model, it needs to be converted into the file format readable by the 3D visualization environment. By using the VisualSFM (Wu 2011) structure-from-motion algorithm, a point cloud with PLY format is created, which is a file format for storing graphical objects by describing them as a collection of polygons. This file is first converted to the XYZ format, which contains information regarding the location of each point through its coordinate, by MeshLab (2011) or other similar applications, and imported into Autodesk ReCap to apply any modifications desired. It is then exported as an RCP file that is supported by both Autodesk Revit and Autodesk 3ds Max and can be used as part of the virtual model.

7.4.1.3 Motion Capture Data

Since human motions encompass critical information regarding how a manual operation is carried out (e.g., posture, duration, frequency), using motion capture data as part of the framework not only can increase the accuracy of the analysis but can also be highly useful for visualization purposes. In case of existing workplaces, the motion data can be recorded using different available sensors. Despite the precision of high-end motion sensors (e.g., VICON), they usually cost more and require extensive setup and training. The use of the Microsoft Kinect sensor as an example of a cost effective and simple-to-use motion sensor (Han et al. 2013) is proposed in the current framework. As recording motions in construction jobsites directly can be difficult due to effects of occlusion, lighting conditions, shadowing, and distance from subject, and can also interrupt workers' duties, the worker motions can be imitated and recorded in a controlled laboratory environment. The resulting motion capture data is in the BVH file format, which is a standard ASCII format that defines body configurations and rotations of body joints for each time frame and enables animating bipedal characters. After creating the BVH motion file, it is imported directly into 3ds Max and attached to the biped model of the worker to animate it. In case of non-existing workplaces, the motions can be built either using the same process in a laboratory setup or directly inside the 3D modeling environment. This is achieved by defining the posture and position of the worker model at different time frames inside the virtual model (as described in Chapter 3). In addition to increasing the reliability of the efficiency and safety analysis, visualizing the human operator along with motions inside the 3D virtual representation of the workplace helps the designer substantially in assessing clearance, fit, reach, visibility, and comfort, and can also be used for communication of design and training of workers.

7.4.2 Ergonomic and Biomechanical Analysis

Mitigating the ergonomic risks of an operation during design and before the workers encounter the unsafe conditions is the most effective way of preventing WMSDs. However, tools and approaches are required that enable identifying ergonomic risks by a designer not familiar with the principles and techniques of ergonomics, on a task not yet observable. Thus, this chapter proposes integration of available ergonomic assessment tools into discrete-event simulation modeling, that not only provides the designer with a feedback on the level of ergonomic risks associated with the design, but also connects the ergonomic evaluation with productivity analysis. In particular, the Ovako Working Posture Analysing System (OWAS) (Karhu et al. 1977) is used as an example of an effective and prevalent ergonomic evaluation system, as it provides a general feedback on the level of safety of a task as well as the level of safety for different body joints and also incorporates posture, force, and frequency into the evaluation. Other types of ergonomic assessment tools (e.g., RULA, REBA, PATH, PEO) can also be similarly used. While evaluating a manual operation using OWAS, the designer provides design data for each individual manual task that the worker performs. Fig. 7-3 shows the required inputs and the values for a sample posture as well as the outputs of an OWAS assessment. A special purpose simulation platform is developed inside the Simphony (Hajjar and AbouRizk 1999) simulation modeling environment, due to its structured approach to developing easy-to-use templates, to integrate ergonomic assessment into the discrete-event simulation. The simulation template is developed by designing and creating modeling elements that can represent manual construction activities within the simulation environment. The elements are programmed through scripts in the C# language such that each manual task is represented by a modeling element inside the simulation platform and the designer selects the appropriate inputs (shown in Fig. 7-3) for each task. After running the simulation, the algorithm behind the simulation engine uses the inputs to calculate the corresponding OWAS score and reports on the level of risks for each task as well as the entire operation, both for the whole body and for different body joints. This data can be conveniently used to change the manual tasks and examine the impact on ergonomic safety of the workers to ensure that the operation is within the acceptable level of risk.

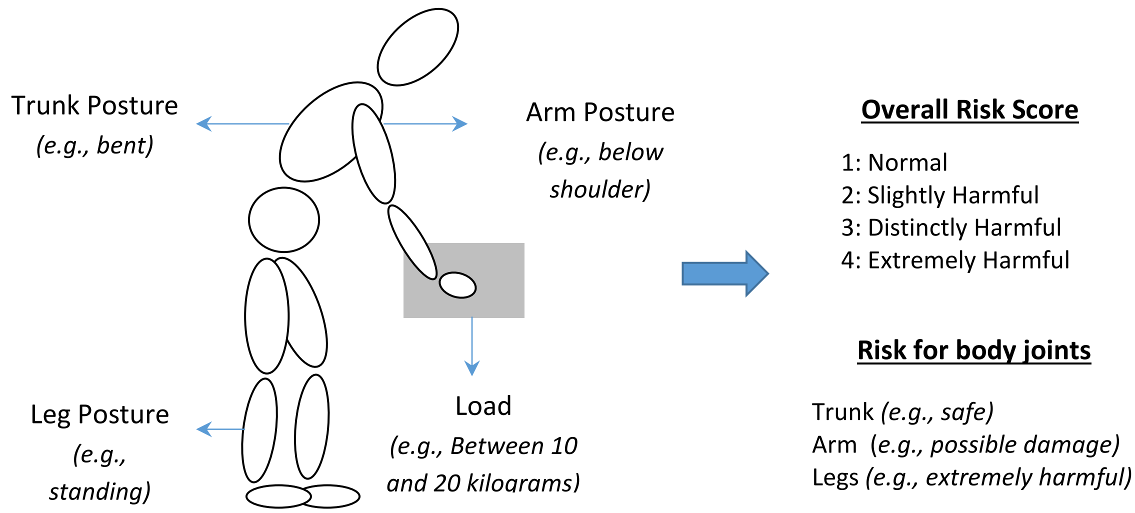


Figure 7-3 Inputs and outputs of an OWAS assessment

In addition to ergonomic evaluation tools, biomechanical analysis can be used to provide a more detailed and objective assessment of the ergonomic risks by estimating the loads and moments on the human body joints as a function of external exposure data (Chaffin et al. 2006). The approach of biomechanical analysis can be particularly useful for comparing different methods of carrying out a manual task and selecting the safest for workplace and operation design. As an example, Fig. 7-4 shows two different methods of lifting an object weighing 20 lbs and the compression on the back obtained from biomechanical analysis (3DSSPP 2014). By comparing these values with the allowable limits (3,400 N in case of low back compression (Waters et al. 1993)), the safe method of manual handling tasks can be determined. Biomechanical analysis can be carried out using mathematical models (Alexander 2003) or more conveniently using the available software platforms (e.g., 3DSSPP, OpenSim). These software platforms enable inserting the values for the angles between body joints or simply modifying the 3D model of a manikin to achieve the desired posture. Further information, such as loads on the hands and worker's anthropometry data, is also inputted. The load on the worker's body joints, especially lower back, and the level of risk for different body joints are example of the obtained outputs. This chapter uses 3DSSPP (3DSSPP 2014) due to its simplicity as well as precision in calculating the biomechanical loads (see Chapter 3). After running the simulation model, unsafe motions are modeled inside 3DSSPP to modify and achieve safe motions. The results are then used to change the design and the simulation model. 3DSSPP also enables loading motion capture data to observe the level of risks for the whole manual task which is especially useful in case of existing motions. This is achieved by converting a motion capture BVH file into a batch file readable by 3DSSPP, which contains data regarding the joint angles, external loads, and worker's anthropometry and loading this file into 3DSSPP (Seo et al. 2014). After running the model, the loads on different body joints are reported for all time frames of the motion file. This output is used to identify postures that cause excessive stress on a body joint and modify the motion by redesigning the task until it is ergonomically safe (i.e., all loads are within acceptable limit).

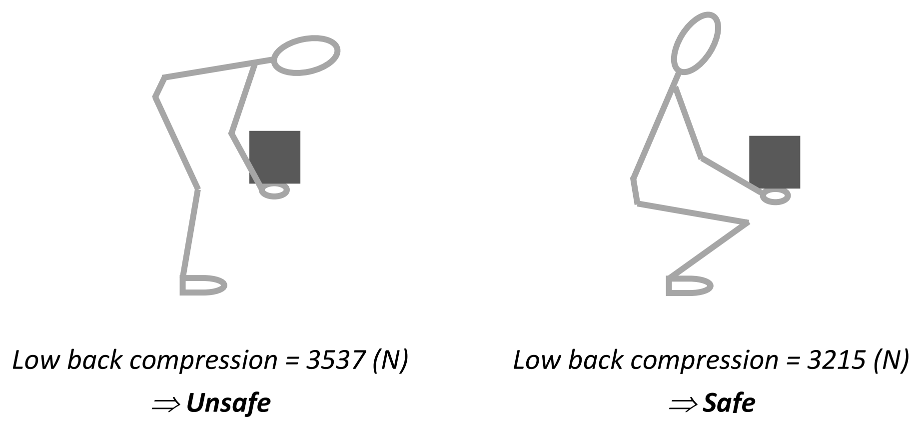


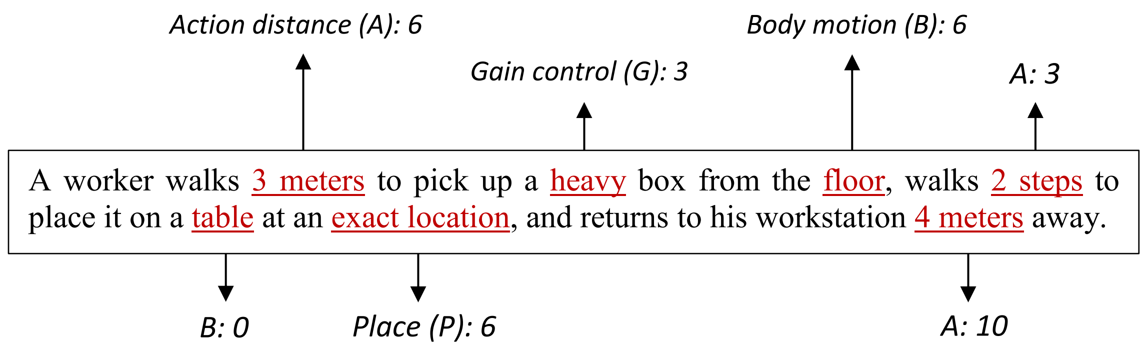
Figure 7-4 Sample results of biomechanical analysis for two lifting postures

7.4.3 Productivity Analysis

As the actions of designers, while focusing on improving the safety of operations, might have a negative impact on productivity, the design and planning process should enable concurrent evaluation of both the safety and efficiency. The contradiction between productivity and safety improvement arises when time-related aspects of work are modified (Wells et al. 2007). The proposed design approach of this chapter uses discrete-event simulation as it enables modeling human operators as resources of the system and generating useful time data for comparison of different scenarios of production and selecting the most feasible. Furthermore, to model manual operations effectively, the use of

PMTSs is proposed, as they provide a standard duration of a manual task based on the motions carried out and enable reliable estimation of the efficiency of a task that does not yet exist. Considering the effectiveness of PMTSs in evaluating manual construction operations (as described in Chapter 6), this chapter proposes integrating these systems into discrete-event simulation and assessing the efficiency of a proposed design, in conjunction with safety.

Among the available PMTSs, the MOST (Zandin 1980) system is used in this chapter to experiment with another example of a simple, effective, quick, and reliable approach (Tuan et al. 2014; Patil et al. 2004) (see Chapter 6 for implementation of MODAPTS). Fig. 7-5 shows an example of the MOST inputs required for a simple activity that will represent one manual task along with the corresponding output. As described before, a special purpose simulation template is developed which contains modeling elements than can represent manual activities. In addition to the ergonomic assessment inputs described before, the modeling element requires inputs pertaining to how a manual task is carried out (Fig. 7-5). These inputs enable carrying out a MOST analysis on the task and after running the simulation model, the MOST duration for each task is computed and reported. As the level of ergonomic risks and the duration for the different tasks and the whole operation is reported by the simulation engine, the designer can modify the design to achieve the optimum level of both efficiency and safety. As mentioned before, the visualization of the workplace will be highly useful in obtaining the correct inputs for the productivity analysis. Among the inputs shown in Fig. 7-5, the action distance variable is an example of an input that can be obtained through direct measurements inside the virtual model, and body motion, gain control, and placement are examples of inputs that can be conveniently obtained by observation of the virtual representation of the design. The simulation platform is designed such that the designer only needs to select from a list of descriptive inputs for each task without requiring extensive knowledge about the principles and components of MOST (e.g., general move activity sequence model). Furthermore, incorporating PMTSs into simulation enables a quick and reliable efficiency analysis and the design can be conveniently modified to examine the impact on efficiency. Furthermore, uncertainty associated with inputs can also be incorporated into the design process.



Duration for the General Move sequence model (ABGABPA):
$A_6B_6G_3A_3B_0P_6A_{10}$ = (6+6+3+3+0+6+10) * 10 = 340 TMU = **12.24 seconds**

Figure 7-5 Inputs and output of a simple manual task using MOST

7.4.4 Concurrent Safety and Productivity Analysis

The developed special purpose simulation template contains modeling elements that can be used to represent manual construction activities. As mentioned before, after creating a simulation model of an operation and running it, the standard duration of each activity based on MOST as well as the level of ergonomic risks associated with the activity and the whole operation based on OWAS are reported. The use of PMTSs in conjunction with ergonomic assessment enables evaluating risk factors early during the design stage before unsafe working conditions are encountered. PMTS data also constitutes important mechanical exposure information as it deals with types of motions, travel distances, loads exerted, etc. On the other hand, discrete-event simulation enables adding time patterns (e.g., idle time) to the exposure variables used in PMTSs. As data pertaining to the duration and ergonomic safety of the operation is reported concurrently, this information can be used to compare the impact of modifications in the design on productivity and safety and observe the trade-off between the two. In particular, simulation models of different scenarios of carrying out the operation are created by modifying the attributes pertaining to how a task is carried out and the result of both productivity and safety analysis are observed. These attributes and the required interventions can be categorized as related to: (1) worker training (e.g., awkward posture), (2) workplace arrangement (e.g., steel plates too far from workstation), (3) tools and equipment (e.g., tools without extension handles), (4) material (e.g., handling objects with unusual shapes), and (5) administrative (e.g., job rotation). To enable an effective and systematic approach to developing and evaluating various scenarios and designs, the framework represented in Fig. 7-6 is proposed. After developing a potential design (i.e. scenario of operations), ergonomic evaluation is carried out by using the visualization and simulation model of the operation, as described before. By identifying the body joint at risk and the cause of the unsafe conditions, the appropriate intervention is determined, and the design is modified accordingly. Biomechanical analysis is also carried out to ensure that the new postures are within acceptable limits. This process is repeated until all feasible modifications are applied. Using the simulation model, the duration and level of ergonomic risks for each design is extracted and compared with other scenarios to select the most optimum. In this study, the optimum scenario is selected as the scenario with the least total duration that has a safety score above the acceptable limit. The virtual model is also updated to reflect the modification of the design. The implementation of the analysis is further explained in the case study section.

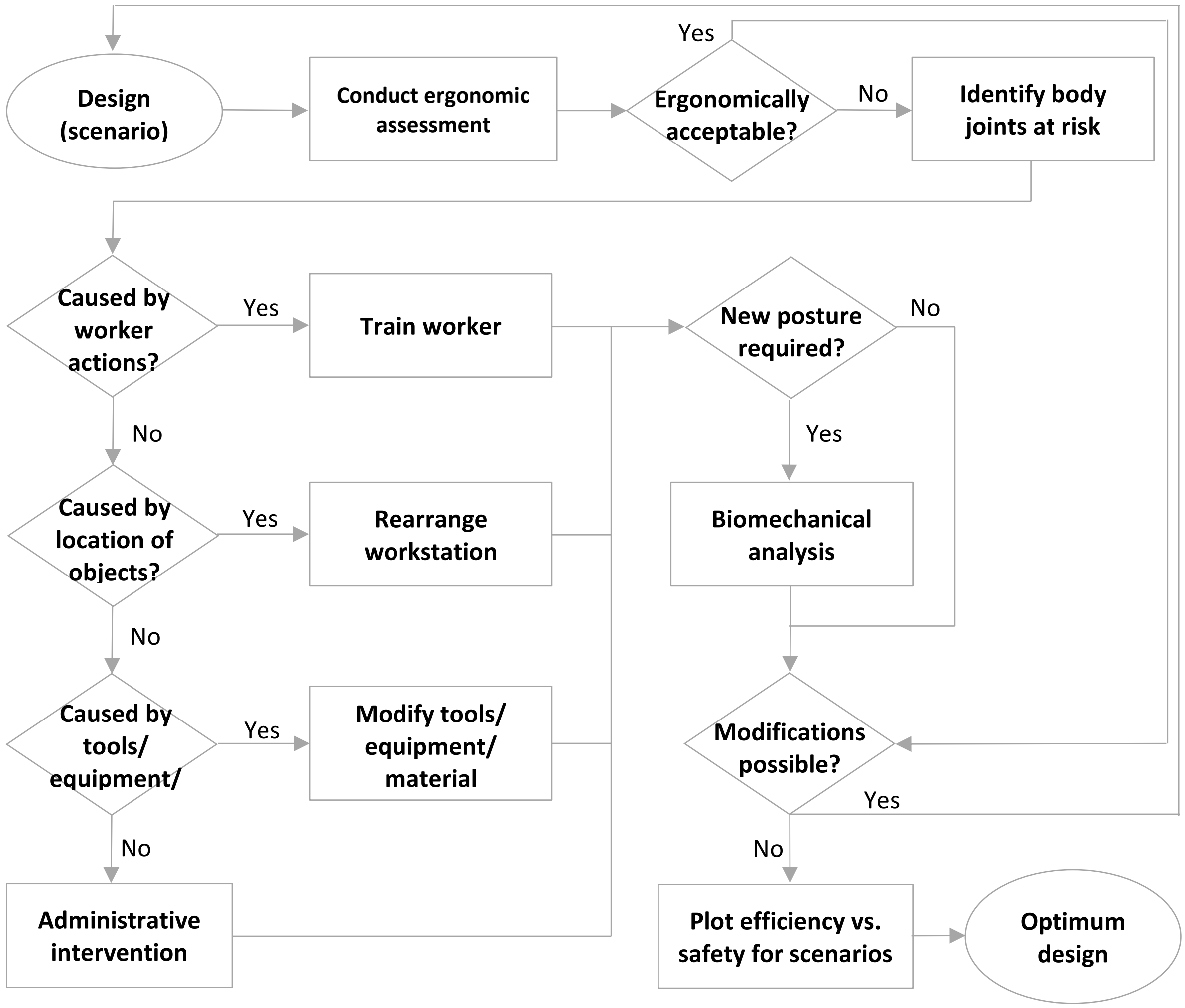


Figure 7-6 Framework for ergonomic evaluation of potential designs

7.5 IMPLEMENTATION: CASE STUDY

The proposed framework is applied to model a masonry operation, due to the prevalence of this type of manual operation and its impact on the productivity of construction operations, as well as the physically challenging nature of its tasks. The activity of a masonry worker laying concrete masonry units (CMU) is observed and videotaped (Fig. 7-7a) to extract the required inputs for the workplace modeling and analysis. The task includes applying mortar, carrying CMUs, and placing CMUs on the floor or on top of other units. In order to visualize the workplace, as the first step, the existing conditions of the jobsite are observed and the corresponding virtual model is created in Autodesk 3ds Max. Since the size and weight of CMUs are standard, by acquiring the required dimensions of the wall from the blueprints of the jobsite, the virtual model of a masonry operation can be created accurately even in case of non-existing operations. The existence of BIM models can also further improve the accuracy of the final model and facilitate the visualization process. For the purpose of this case study, since the as-designed BIM model does not exist, a BIM model containing columns and the floor are created inside Autodesk Revit, using the appropriate materials and dimensions, and exported as an FBX file and imported into 3ds Max. After importing the BIM model, 3D models of CMUs are created and positioned in the designated locations, based on the existing workplace conditions. The 3D model of the worker can also be created by adding a biped character, appropriately scaled, inside 3ds Max. Any desired skin can be created in 3ds Max and linked to the biped of the worker as a mesh. A BVH motion capture data can also be imported and directly linked to this human manikin inside 3ds Max. The process of creating the biped character, applying the skin, and adding the motion data can also be carried out inside Autodesk Motion Builder, and the resulting animated character can be imported into 3ds Max as an FBX model. As Motion Builder is specifically designed for working with motions and provides higher flexibility for the motion matching process, it is used in this study. Fig. 7-7 shows a snapshot of the jobsite as well the corresponding virtual model in 3ds Max. The worker that is observed for the case study is shown with a dashed circle.

(a) (b)

Figure 7-7 Masonry operation: (a) actual jobsite and (b) virtual representation

After creating the primary virtual representation of the jobsite, it is used to obtain the inputs required for developing the simulation model of the operation. The cyclic nature of the masonry tasks enables a simple and precise representation of the operation in the simulation environment. The main tasks represented by the developed modeling element include applying mortars between CMUs and moving to pick, carry and place CMUs in appropriate locations. Table 7-1 shows the inputs of the modeling element representing a CMU carrying task along with the list of possible options, as well as the attributes selected to model the task of carrying a 13 kg CMU unit from 2 steps away and bending to place it on the floor, as an example. As shown in the table, the appropriate inputs, used for the MOST and OWAS assessments, are selected from a list of descriptive attributes.

Table 7-1 Inputs of the manual handling task modeling element

Attribute	**Options**	**Input for "Carry CMU Task #2"**
Distance traveled to grasp object	Less than 5 cm; Within reach; 1-2 steps; 3-4 steps; 5-7 steps; 8-10 steps	Within reach
Distance traveled while carrying the object		1-2 steps
Distance traveled to return after completing task		1-2 steps
Body motion required to grasp object	Bend/arise; Bend and arise; Sit/stand; Pass door/climb	Bend/arise
Body motion required to place object		Bend/arise
Weight of object	Less than 10 kg; Between 10 kg and 20 kg; More than 20 kg	Between 10 kg and 20 kg
Posture of trunk	Straight; Bent; Twisted; Bent and twisted	Bent
Posture of arms	Arms below shoulder; One arm above shoulder; Both arms above shoulder	Arms below shoulder
Posture of legs	Sitting; Standing; Standing knees bent; Squatting; Squatting knees bent; Kneeling; Walking	Standing knees bent

The masonry operation for building two rows of a CMU wall is observed and the corresponding simulation model is created. The total duration of the operation from the video recordings and the simulation model (i.e., based on MOST) are 578.5 and 549.9 seconds respectively, which shows the reliability of the simulation model in representing actual operations as there is less than 5% difference between the two durations. Besides the duration of each manual activity and the whole operation, the simulation engine also reports on the level of ergonomic risks for each activity through the OWAS score. This information is represented in Fig. 7-8, where at different time frames, the OWAS score of the ongoing manual activity is reported. The acceptable limit for the OWAS score (i.e., a score of 2) is also denoted by a dashed line. This graph provides an overview of how safe the operation is in general, and enables convenient discovery of unsafe tasks. The average OWAS score for the base case is 2.40, which is beyond the allowable limit.

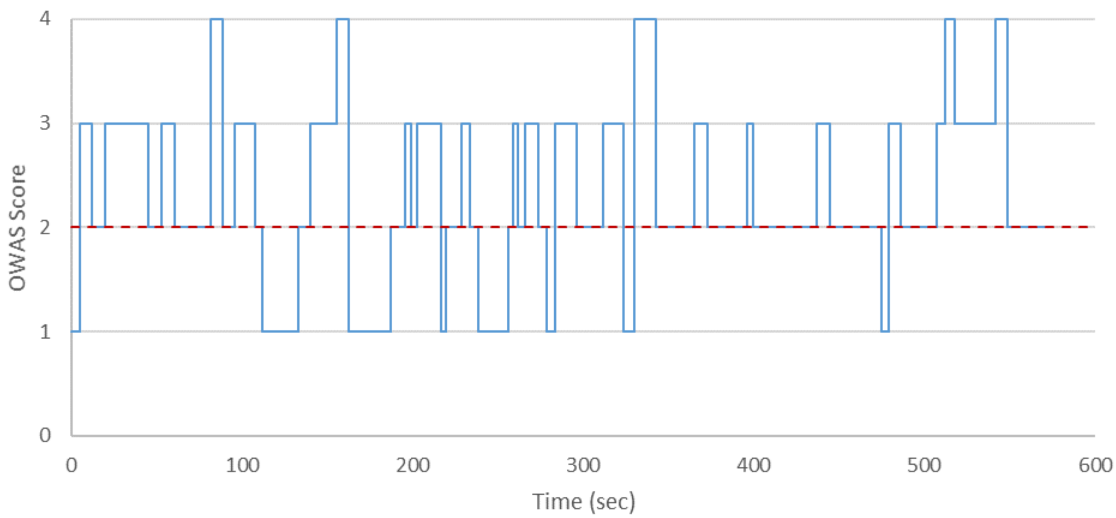


Figure 7-8 Level of ergonomic risks at different time frames for masonry operation

To further analyze the ergonomic risks of the operation, the simulation engine also reports on the safety of the operation for different body joints, by considering the frequency of the ergonomic risks in the OWAS computations. This output is presented in Fig. 7-9, where for the trunk, arms, and legs, the percentage of time spent at each posture as well as the share of each task in each posture is shown. This information can be highly useful in evaluating the current design of operation as well as designing new scenarios based on the safety risks associated with the current design. For example, the results show that the worker spends a lot of time bending or twisting which imposes high stress on his back.

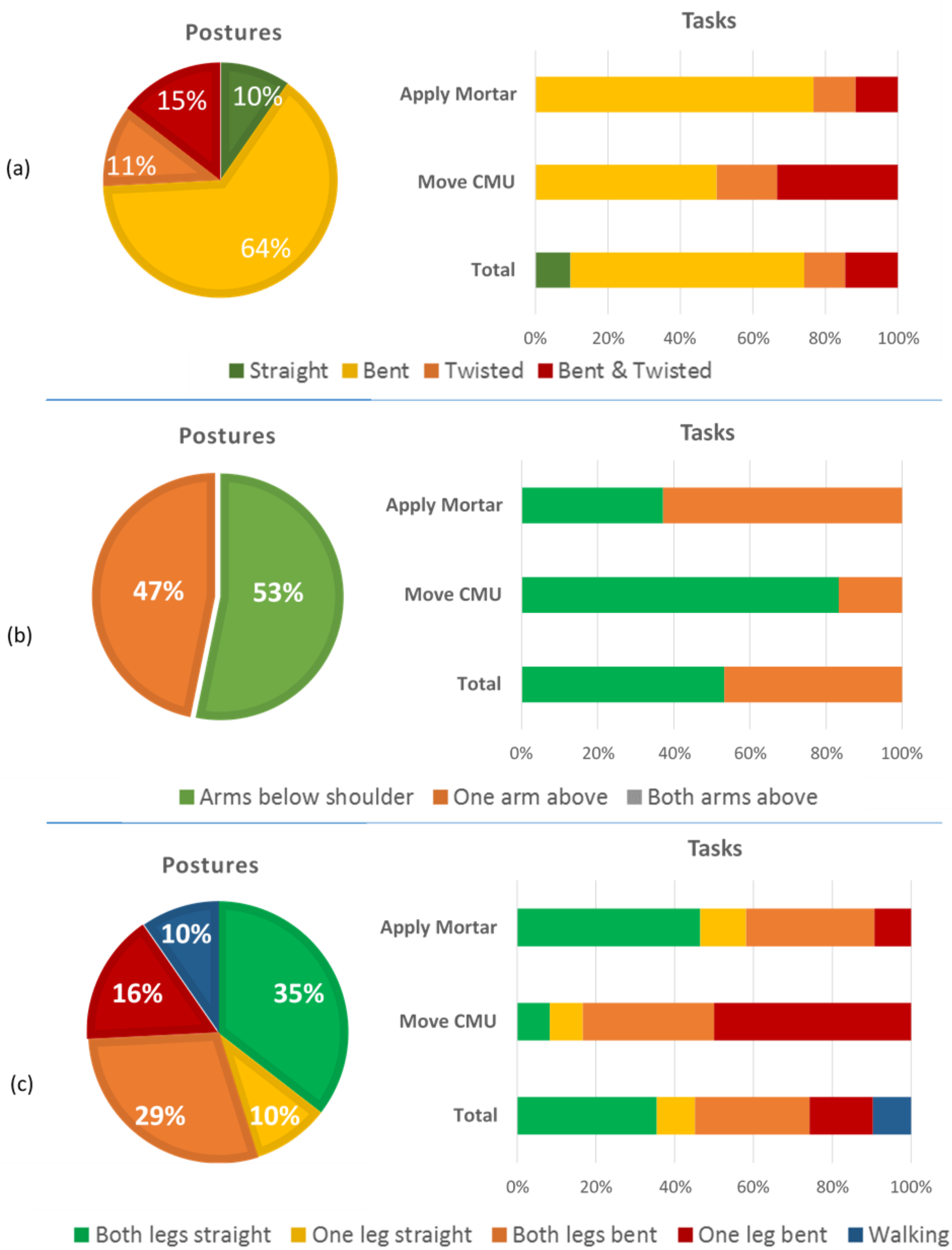
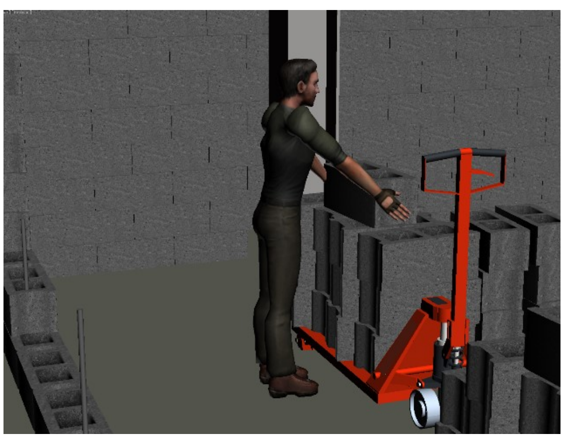


Figure 7-9 Distribution of ergonomic risks for (a) trunk, (b) arms, and (c) legs

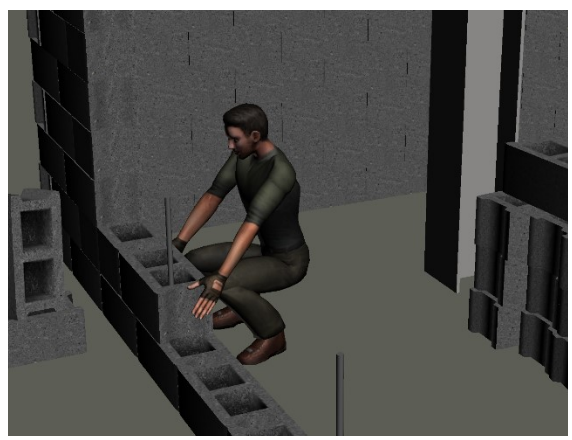
To evaluate the impact of different contributing factors and find the optimum design of the workplace and operation, different scenarios of the operation have to be assessed. The different proposed scenarios are shown in Fig. 7-10 and the results of ergonomic assessment for the whole operation is shown in Table 7-2, indicating the percentage of time each OWAS score is obtained during the whole operation as well as the average score of the operation.

Base case: Worker twists to get CMU since CMUs are close to wall.

Scenario 1: CMUs are moved a step away to prevent worker from twisting his back.



Scenario 2: CMUs are placed on lifting pallet to prevent bending.



Scenario 3: Squatting is proposed instead of bending to improve posture.

Figure 7-10 Scenarios of masonry operation design

Table 7-2 Results of ergonomic assessment for different scenarios

OWAS Score		**1**	**2**	**3**	**4**	**Average score**
Percentage of score	**Base Case**	15.87%	36.51%	39.68%	7.94%	1.4
	Scenario 1	15.87%	46.03%	36.51%	1.59%	2.2
	Scenario 2	30.16%	44.44%	23.81%	1.59%	1.9
	Scenario 3	31.75%	68.25%	0.00%	0.00%	1.6

As twisting of the trunk is imposing high risk of injury in the base case (i.e., current design), the first scenario aims to eliminate the possibility of twisting while picking up and placing CMUs. As the twisting occurs due to the small distance between the CMU pile and the wall that is being built, the concrete blocks are moved one step further from the wall so that the worker has to make complete turns to pick up and place CMUs and cannot twist his back. The results of the ergonomic assessment indicate that despite the improvements of the first scenario, it is still harmful to the worker's back due to the high number of bending motions while picking up CMUs. To address this issue, the use of a lift pallet or lift table is proposed, so that the worker can pick up CMUs at an appropriate height while keeping his trunk in a straight posture. As the worker has to place the CMUs at low heights during placement of first few rows of the wall, the third scenario suggests a posture modification while placing CMUs. To achieve the safest posture to carry out the CMU placement task, a biomechanical analysis is carried out, as shown in Fig. 7-11. From biomechanical assessment, the low back compression in the current posture is 3,609 N, which is above the acceptable limit (3,400 N). After modifying the posture to squatting instead of bending, the low back compression is reduced to 2,341 N. Furthermore, the strength percent capable, which is an indicator of the biomechanical stress on a particular body joint, for the torso and hip joints are improved substantially, as shown in Fig. 7-11. This analysis can be highly useful in training the workers on how to carry out different tasks as well.

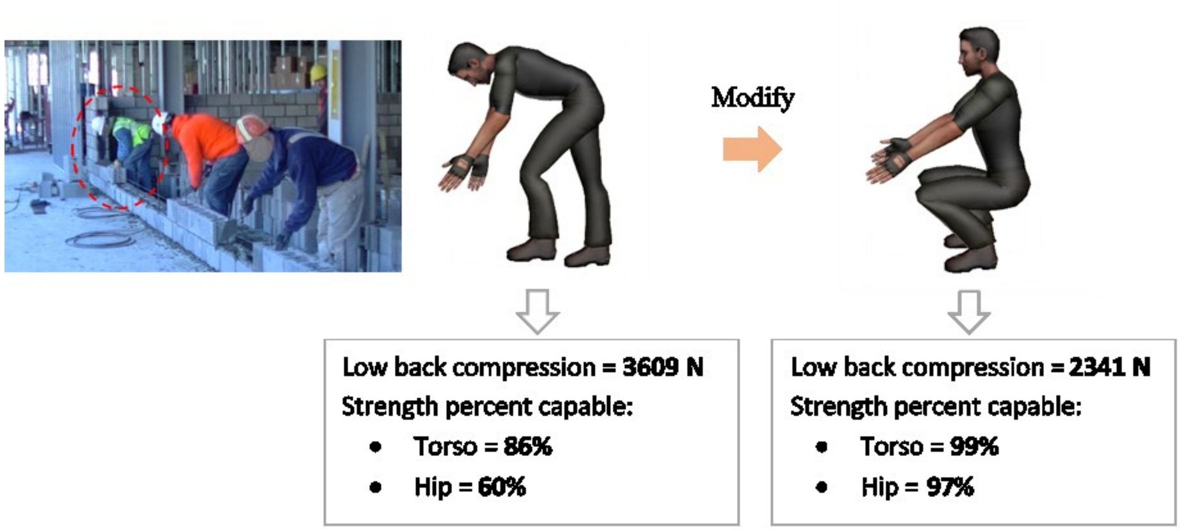


Figure 7-11 Biomechanical analysis on CMU lifting, before and after modification

The simulation model is adjusted to reflect the modifications in the design and represent the new scenarios. The result is shown in Fig. 7-12. As shown in the graph, the duration for the three modified designs increases compared to the base case. However, the overall safety of the operation is improved. As scenario 1 has an OWAS score above the acceptable limit, its implementation is not recommended. Scenario 2 and 3 both have an acceptable level of ergonomic risks, but scenario 2 has a lower duration which implies higher efficiency. In cases similar to scenarios 2 and 3, the decision regarding selecting between the two scenarios depends on the particular case and counts as a managerial decision. Although implementing scenario 2 will result in higher productivity, scenario 3 involves lower levels of risk and thus the decision should be made based on considering other factors such as schedule, cost, availability of resources, etc. In this particular case, as the results of ergonomic assessment for the third scenario indicate that there is some stress imposed on the worker's legs, alternating between bending and squatting can potentially be the most effective approach from an ergonomic point of view.

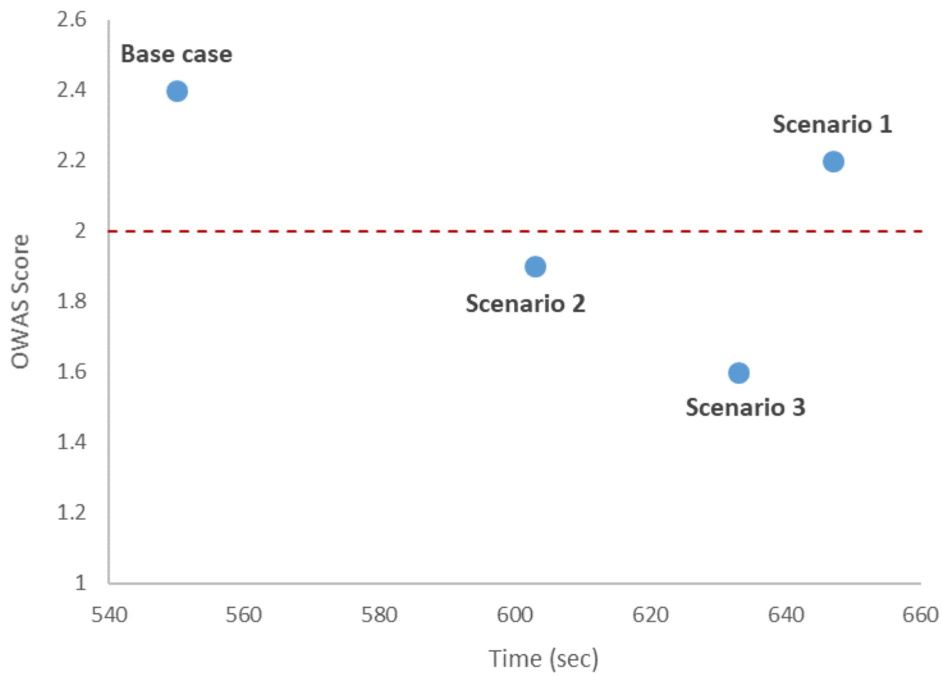


Figure 7-12 Efficiency vs. safety for different scenarios of masonry operation

7.6 DISCUSSION

The results of comparing different scenarios of the masonry operation are shown in Fig 7-12. As shown in the figure, the proposed approach enables evaluating different scenarios of an operation in terms of both productivity and safety. The results show that by modeling construction operations in a simulation environment, the efficiency of an operation as well as the ergonomic risks associated with it can be evaluated, which is critical in achieving highest productivity possible while remaining ergonomically acceptable. The developed framework intends to enable modeling and assessing manual operations without requiring high levels of expertise in production planning or ergonomics, to facilitate implementation of PtD in the construction industry and to provide the means to concurrently assess performance and safety. It also provides a new method of examining the trade-off between these two important indicators of success of construction projects, and enables researchers to formulize the impact of different contributing factors on efficiency and safety of different type of manual operations, which can be adapted as practical guidelines in actual jobsites.

While previous studies on the relationship between productivity and safety have made different conclusions regarding the trade-off between the two, depending on the factors evaluated and the methodology, the proposed approach of this chapter enables examining this association from a physical perspective. The results demonstrate that applying ergonomic interventions can both increase and decrease the efficiency of operations based on the type of intervention. Thus, different design of workplaces and operations need to be assessed to incorporate the impact of physical features related to the workplace and operational features related to tasks on ergonomic safety.

While this chapter uses modeling elements inside a simulation platform to model manual operations through PMTSs and ergonomic assessment tools, conducting the simultaneous productivity and safety evaluation directly on motion capture data and in an automated manner, can further simplify and increase the accuracy of the assessment in case of existing manual tasks. This automated analysis can also potentially be linked to the virtual representation to reliably reflect the design and will be highly useful for communication of design as well as training of workers. While the realistic human motion data created inside the virtual model can be highly beneficial for visualization purposes, it can also be effectively coupled with more detailed analyses such as human motion planning. Considering the ongoing research efforts to capture motion data in construction jobsites (Han and Lee 2013; Liu et al. 2016), using motion sensing techniques for real-time feedback can also highly increase the applicability of the approach and provide an effective means for evaluation and training of construction workers' performance. Furthermore, integrating the impact of fatigue, as an important contributor to the productivity and safety of construction operations (Chan 2011), into the simulation framework (Seo et al. 2016) can further enhance the accuracy of the analysis.

7.7 CONCLUSION

This chapter proposed an integrated approach to prevention through design that evaluates the ergonomic safety and efficiency of manual operations concurrently. The developed comprehensive framework incorporates PMTSs and ergonomic assessment into simulation modeling for efficiency and safety analysis and uses visualization of jobsites to facilitate communication and implementation of workplace design. It also enables integrating building information models, point cloud models, motion capture data, and biomechanical analysis into the design process to achieve an accurate and effective design. The results of implementing the approach to redesign a masonry operation show the effectiveness of coupling PMTSs and ergonomic assessment in exploring the trade-off between productivity and safety and evaluating different scenarios of operations. The proposed approach enables designers and construction practitioners to consider ergonomics in the design process to ensure that a proposed design is safe, while also achieving optimum productivity of the manual operations involved.

7.8 ACKNOWLEDGMENTS

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Chapter 8 An Integrated Ergonomics Framework for Evaluation and Design of Construction Operations [6]

8.1 SUMMARY

Labor is one of the most critical resources in the construction industry due to its impact on the productivity, safety, quality, and cost of a construction project. Ergonomic assessment, as a tool and method for analyzing human activities and their interactions with the surrounding environment, is thus crucial for designing operations and workplaces that achieve both high productivity and safety. In construction, however, the constantly changing work environments and laborious tasks cause traditional approaches to ergonomic analysis, such as manual observations and measurements, to require substantial time and effort to yield reliable results. Therefore, to simplify and automate the assessment processes, this chapter explores the adaptation and integration of various existing methods for data collection, analysis, and output representation potentially available for comprehensive ergonomic analysis. The proposed framework integrates sensing for data collection, action recognition and simulation modeling for productivity and ergonomic analysis, and point cloud model generation and human motion animation for output visualization. The proposed framework is demonstrated through a case study using data from an actual job site. The results indicate that integrating the various techniques can facilitate the assessment of manual operations and thereby enhance the implementation of ergonomic practices during a construction project by reducing the time, effort, and complexity required to apply the techniques.

8.2 INTRODUCTION

Because the construction industry is labor-intensive, worker activities can significantly affect the success of construction operations. Labor is one of the most crucial and flexible resources (Jarkas and Bitar 2011; Muqeem et al. 2012) and has the highest direct impact on the outcomes of a project, including time, cost, and quality (Leung et al. 2012). Labor can

[6] A version of this chapter is submitted as Golabchi, A., Guo, X., Liu, M., Han, S., Lee, S., and AbouRizk, S. M. (2017). "An Integrated Ergonomics Framework for Evaluation and Design of Construction Operations." *Advanced Engineering Informatics*.

account for nearly half the overall costs of a project (El-Gohary and Aziz 2013) and is highly associated with construction productivity, which is one of the most important and frequently used performance indicators in the industry (CII 2006). Furthermore, labor operations in construction involve physically demanding motions and tasks that frequently expose workers to risk in their working environments, leading to a rate of injuries and fatalities that are among the highest of any industry (Behm 2005; OHS 2017; Zhou et al. 2015).

As an approach to human-oriented work design, ergonomics is the study of human interactions with the surrounding environment with the intent to improve human safety and well-being, as well as productivity (IEA 2017; Dul and Neumann 2009; van Deursen et al. 2005; Hedge and Sakr 2005). An effective and comprehensive ergonomic analysis involves evaluating ongoing operations and proposing modifications and new designs that fit jobs and work environments to worker capabilities and limitations. Accordingly, the implementation of ergonomic principles can contribute to the success of a construction project by providing workers with comfortable working environments in which work procedures and tools are designed for safe and productive use. However, conducting an ergonomic analysis often requires extensive time and effort to yield reliable results as the data collection and evaluation involve human observations and measurements. This is particularly true in the dynamic environment of construction job sites, which involve many physically demanding manual tasks that create vast amounts of data to collect, analyse, and represent (Tak et al. 2011). Furthermore, the variety of tasks and postures required of workers necessitates methods for collecting and analyzing data that can address human error; the resulting low reliability of the analysis inputs and outputs make completing a meaningful ergonomic evaluation difficult (Kadefors and Forsman 2000; David 2005). Reliable and detailed visual representations of the analysis outputs can greatly improve the implementation of interventions or new workplace designs. Accordingly, the development and use of methods to automate, simplify, and increase the accuracy of data collection, analysis, and output representation could enable effective and comprehensive ergonomic evaluations. Furthermore, integrating such methods into an overall framework would potentially enhance the implementation of ergonomic practices at actual construction job sites by minimizing the need for experts, decreasing the time and effort required for analysis, and reducing the complexity of applying the various methods.

Therefore, this chapter proposes a framework to integrate different methods used for evaluating and designing manual construction operations to achieve a more unified and reliable ergonomic analysis. The framework and its modules are presented with a focus on linking the different components together. A manual operation at an actual job site is then used to implement the proposed approach and evaluate its effectiveness.

8.3 BACKGROUND

8.3.1 Limitations of Manual Observation–based Ergonomic Analyses

A complete ergonomic analysis involves evaluating the motions and postures of workers and the physical attributes of a job site to assess current work conditions and propose new designs for manual operations (e.g., safe motions) and workplaces (e.g., workstation dimensions). To carry out such an assessment, an ergonomist generally needs to complete three stages: (i) data collection, (ii) data analysis, and (iii) representation of results.

For data collection, the ergonomist traditionally observes the subjects (e.g., anthropometry, posture), their motions while working (e.g., leaning, bending), and the attributes of the work environment (e.g., workbench, tools, equipment). The inputs of an ergonomic assessment thus include various types of data, such as the distance between a worker and a necessary tool or material or the joint angles between different body joints, which are often challenging to observe simultaneously. Typically, an ergonomist visits a job site and collects the required data in real-time or uses video recordings to extract the inputs later (David 2005). In both cases, such a procedure results in subjectivity in the collected inputs introduced by the ergonomist's personal judgement (see Chapters 4 and 5). Although the traditional approach can work effectively in static workplaces, such as offices and manufacturing assembly lines, it can produce unreliable data at construction job sites because of the variety of manual tasks performed, complexity of exposures, and constantly changing work environment (Kadefors and Forsman 2000).

After data collection is complete, the ergonomist uses the gathered data to conduct an ergonomic evaluation using tools such as ergonomic assessment checklists (e.g., RULA, ROSA) and time and motion studies (e.g., MTM2, MOST). To complete this step, the ergonomist inputs the data into the tools, which use a set of predefined rules to produce the output of the analysis. For example, inputting a worker's posture (i.e., joint angles) along with the frequency and duration of exposure allows posture-based tools to report on the level of ergonomic risk associated with a task. Also, using inputs that describe working conditions (e.g., walking distance, motions involved), time and motion systems provide the standard duration for a task. However, similar to the challenges presented to data collection, manual analysis of construction tasks is inefficient because job sites and the motions required change every day.

Following data analysis, the ergonomist represents the gathered data and analysis results to illustrate how any modifications should be implemented and address any discovered risks. Traditionally, this involves reports that reflect the ergonomist's conclusions from the analysis and state any modifications suggested by the outputs from the checklists and tools used. Typically, those reports include only whether the level of ergonomic risk associated with a task is acceptable, moderate, or unacceptable based on the inputs provided. Such reports are thus limited data representations that do not allow re-evaluation of the proposed changes and designs because of the difficulty of assessing a non-observable task on a job site that does not yet exist (Laring et al. 2002). Furthermore, the traditional report-based approach does not offer managers a tool for practical decision-making, nor does it provide an effective means to accurately implement the proposed modifications or train the personnel involved. This approach also makes it difficult to effectively assess other ergonomic variables (e.g., clearance, vision) when modifying the design of a workplace.

Thus, the three stages of a thorough ergonomic analysis could be improved by adapting and integrating existing methods through automation to enhance different aspects of the analysis and connect them to provide a more reliable and simplified assessment. The different stages of an evaluation, including data acquisition through sensing, productivity and safety analysis of the obtained data, and representation of the results through visualization, are shown in Table 8-1. For each stage, the research areas that could be beneficial for manual operation evaluation and workplace design are identified as components of the framework, and both the input used for each component and its output are shown. The inputs and outputs show the connections among the different elements and indicate how data can be transitioned through the different components for an accurate and automated analysis.

Table 8-1 Research areas, inputs, and outputs for different stages of manual operation evaluation and design

Stage	Research area	Input	Output	Example references in research area
Data acquisition (sensing)	Action recognition	Video/sensor recordings	Type and sequence of actions	Akhavian and Behzadan (2016), Cheng et al. (2013), Joshua and Varghese (2011)
	Motion capture	Worker motion recordings	Worker motion-capture data	Han and Lee (2013), Starbuck et al. (2014), Ray and Teizer (2012)
	3D reconstruction	Photo/video of job site	As-is point cloud model	Rashidi et al. (2015), Fathi and Brilakis (2011), Guo et al. (2016)
Analysis	Simulation modeling	Action recognition	Operation efficiency	Seo et al. (2016), see Chapter 6
			Motion generation	Golabchi et al. (2016), Golabchi et al. (2015)
	Biomechanical analysis	Motion capture	Level of safety	Seo et al. (2014), Mehta and Agnew (2010), see Chapter 3
Representation (visualization)	Motion generation	Simulation modeling	Worker motions	Wei et al. (2011), Taylor et al. (2007)
	Path planning	Start and end location of motion	Animation of worker motions	Yao et al. (2010), Wu et al. (2007), Pettré et al. (2002)
	Visualization	3D reconstruction	Complete virtual model	Al-Hussein et al. (2006),

		Motion generation		Budziszewski et al. (2011), see Chapter 3

As shown in Table 8-1, many researchers have worked on different elements that can contribute to an ergonomic evaluation of labor operations and workplace design. However, many of the previous studies have focused on methods developed for a different purpose (e.g., 3D reconstruction for progress monitoring, action recognition for productivity measurements). Thus, further investigation is required to understand the inputs and outputs of the existing methods and the potential transition of data among them to enable their integration and achieve a comprehensive ergonomic analysis framework.

8.3.2 Integrated Ergonomic Analysis

To carry out a thorough ergonomic analysis, information about the effects of physical activities on a worker's body needs to be available. Main contributors to those effects are the type, duration, and sequence of manual tasks. Although that information can be collected through time studies, they are time-consuming and challenging to conduct for many manual construction operations. Furthermore, those data are difficult to gather when designing non-existing operations for new or prospective workplaces. As a result, ergonomists rely on human judgment and estimates in acquiring data, which can lead to unreliable information. This issue can be addressed through linking simulation modeling with action recognition. The use of video cameras for action recognition can automatically identify the type, duration, and sequence of activities. The results can then be used to create a simulation model for the operation that can be used to test any required modifications to the operation design. Furthermore, integrating PMTSs into the simulation environment allows not-yet-existing scenarios to be conveniently modeled and explored (see Chapter 6). Previous research has used sensing devices to identify different types of activities and tasks for applications such as operation analysis, work rate measurement, and productivity monitoring (Gong et al. 2011; Kim and Caldas 2013; Escorcia et al. 2012). Furthermore, simulation modeling has been used extensively in different phases of construction for planning, budgeting, design, maintenance, etc. (Ozcan-Deniz and Zhu 2015; Corona-Suárez et al. 2014; Yang et al. 2012). However, linking video-based action recognition to PMTS-based simulation modeling to enable the reliable and automated creation of simulation models for ergonomic analysis has not yet been fully explored.

Another main contributor to an operation's level of safety is the posture and motions of the workers. While ergonomic and biomechanical tools rely on that information for their evaluations, watching a worker carry out the tasks to obtain the required inputs (e.g., body joint angles) is time-consuming and produces low-reliability results. The use of motion-capture data, recorded using sensing devices (e.g., depth sensors), can greatly simplify data capture and improve data accuracy (Seo et al. 2014; Han and Lee 2013; Ray and Teizer 2012). Motion data can also be used in conjunction with 3D models of the work environment (Chapter 3) to visualize an operation and provide a virtual platform for managerial decision-making, implementation of designs, training, etc. Furthermore, connecting motion data with a simulation model of operations can generate the motions of proposed operations for the assessment of ergonomic variables such as clearance, visibility, fit, and reach.

Creating an effective and complete virtual model to represent the results of an analysis requires 3D models of the different components representing the current conditions of a job site. However, given the dynamic nature of construction sites, creating and updating as-is models using only 3D modeling tools and software is unfeasible. Therefore, previous work has focused on generating point-cloud models of work environments (Golparvar-Fard et al. 2011; Fathi and Brilakis 2011; El-Omari and Moselhi 2008). Cameras can be simply and inexpensively used to create as-is point cloud models of the work environment, replacing the need to manually create complicated models. Integrating such a model into a visualization environment that includes other components, such as BIM elements and worker motions, can provide a robust, reliable, and complete virtual model. Furthermore, worker models need to be connected to the other 3D elements in the virtual model to enable animating the worker motions along a path that does not collide with other objects and is also a realistic representation of worker motions and paths on an actual job site. Thus, there is a need to implement an automated path-planning algorithm inside the visualization to enable accurate animation of worker models and motions.

As there is a high correlation between safety and productivity (Hallowell 2011) and an ergonomic analysis works to improve both health and productivity, the effects of safety interventions on productivity and vice versa have to be considered for an analysis and design to be effective. Integrating methods that can measure productivity (e.g., PMTS-based simulation modeling) with methods that evaluate safety (e.g., motion capture-based ergonomic and biomechanical assessments) and representing them using inclusive virtual models (i.e. point cloud models in conjunction with worker motions) will thus enable the analysis of different scenarios in terms of both productivity and safety to select the best option.

8.4 METHODS

This chapter proposes and tests an integrated framework that couples data acquisition and visualization with analysis of manual operations to enable an effective evaluation of those manual operations for a comprehensive ergonomic analysis. Specifically, the objectives are: (1) exploring the data associated with the various sensing, analysis, and visualization methods, (2) examining the possibility and applicability of sharing data among those different methods, and (3) testing the feasibility and effectiveness of integrating the various methods.

The proposed framework and its components are shown in Fig. 8-1. As shown in the figure, the framework is composed of three main modules: simulation, as-is modeling, and safety assessment. The analysis starts by gathering information about current conditions of the work environment through sensing. Videos of worker activities are recorded, and an action recognition process extracts the type, sequence, and duration of tasks and creates a simulation model of the operation. The simulation model evaluates the productivity of the operation, as well as generating worker motions for animation in the final virtual model. Photos or videos of the job site are also used to create an as-is point cloud model of the work environment. Other 3D modeling elements are added to that model, and it is used to run a path planning algorithm that enables a realistic representation of worker motions in the virtual environment. Worker motion data are also captured and used for a precise, automated, biomechanical assessment, and worker motions and workplace design are updated based on the results. The outputs of the modules are used to create a complete virtual model of the manual operations, which can be used for various visualization applications (e.g., communication and implementation of design, decision making, and training).

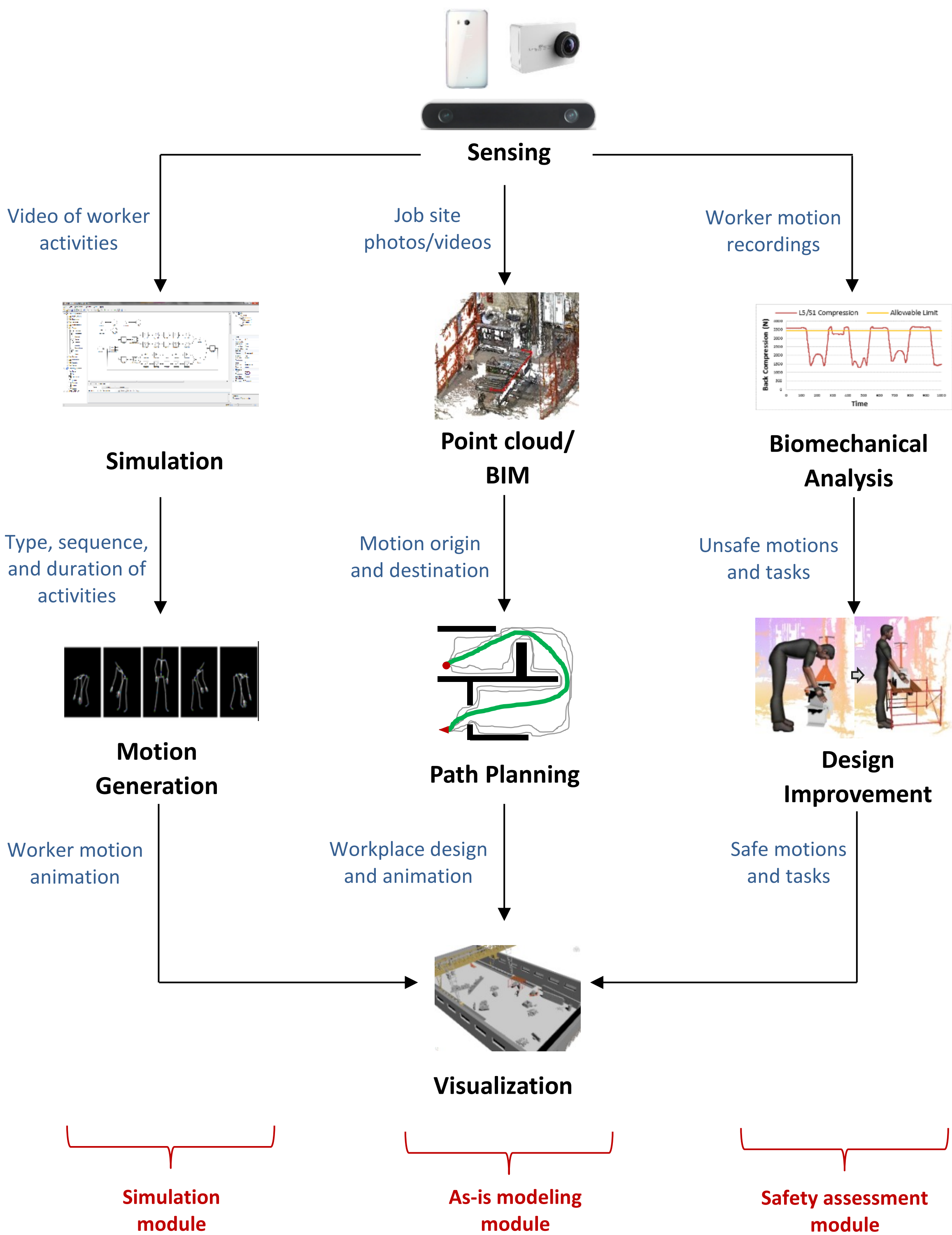

Figure 8-1 Framework of integrated analysis of manual operations

8.4.1 Simulation Module

To create a simulation model of a manual operation and analyze its operational efficiency, either human observation or sensing methods have to be used to gather the required inputs (e.g., types of tasks, activity durations). Human observation typically requires time, effort, and expertise and can be subjective. On the other hand, most sensing methods require high-end sensors that can work only within a specialized infrastructure under the guidance of a human expert. To address this issue, the action recognition approach in this chapter uses video recordings from ordinary cameras to identify the type, sequence, and duration of different manual tasks. The developed action recognition method predicts the activity type for each frame (Fig. 8-2) using a feature vector and classifies the vectors to specific activity types based on their distance from examples in a training dataset. The feature vector is primarily derived from the extracted human silhouette and the pixel-wise direction and magnitude (i.e., optical flow) of its movements (Tran and Sorokin 2008). With an initial estimate for every frame, the activity sequence is optimized by an enforced temporal constraint minimizing the duration of an activity. The duration of each task is also calculated using the number of frames and the video's frame rate.

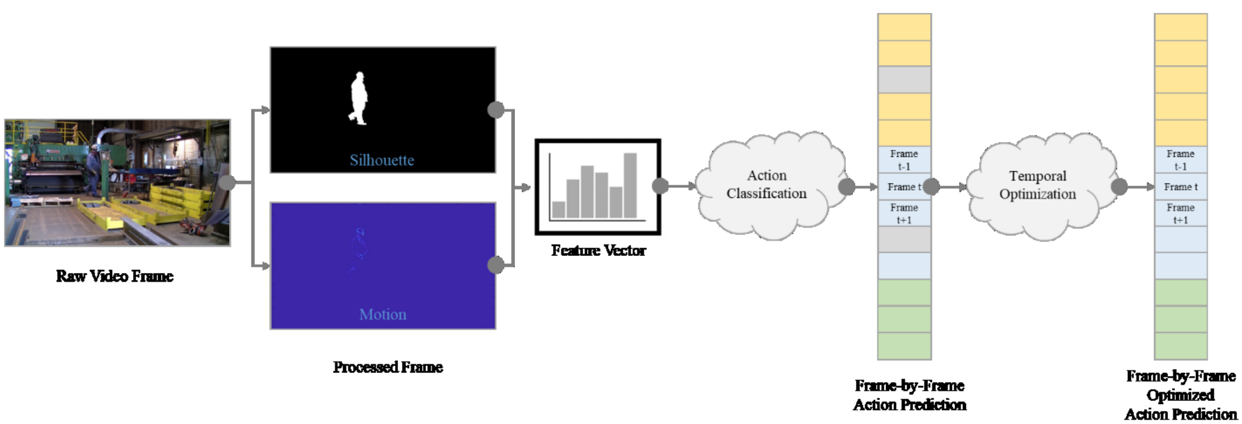

Figure 8-2 Action recognition from video recordings

The result of the action recognition process is linked to a discrete-event simulation modeling environment called Symphony (Hajjar and AbouRizk 1999). This is achieved by first extracting the activity types, their sequence, and their duration and then creating a simulation model based on those data, including different modeling elements to represent different tasks, as shown in Fig. 8-3. For cyclic operations, the simulation model includes a cycle of the motions and determines the duration of each activity using the average of the cyclic durations of each task type from the action recognition. The developed simulation model represents the current status of an ongoing operation and is used for two purposes. First, it serves as a base model to evaluate different scenarios for an operation (including the current practice) in terms of productivity and safety to find the most desirable. This process is greatly improved by integrating PMTSs into the simulation environment to accurately model potential scenarios (see Chapter 6). Second, it is linked to the motion generation component, which creates the complete motion of a worker by pulling from a database of captured motions and combining them (Golabchi et al. 2017). This is achieved by first generating a trace message based on the simulation, which contains information regarding the different motions carried out. This information is then used as input for an algorithm that queries basic motions (e.g., get, put, walk) from a database of motion-capture data and creates the complete motion.

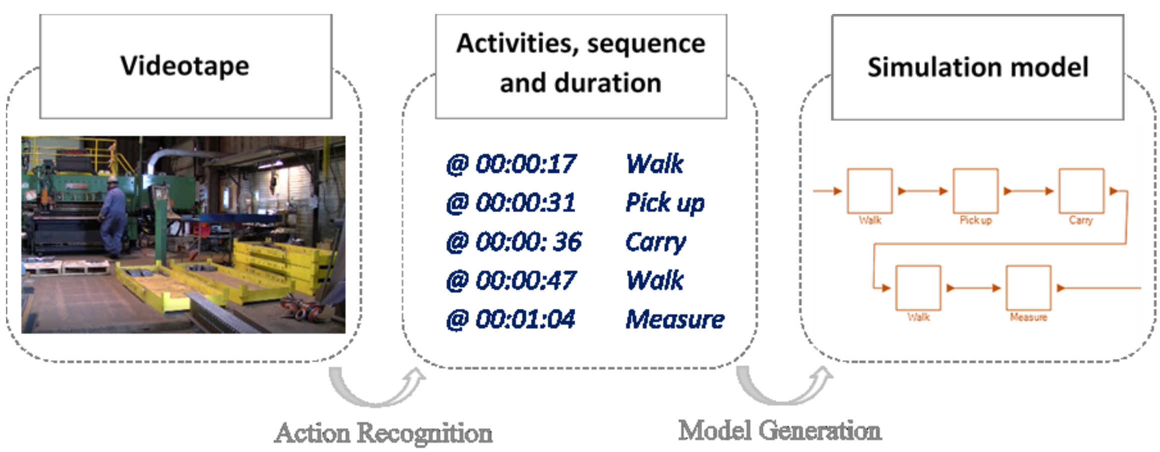

Figure 8-3 Simulation model generation from action recognition results

8.4.2 As-is Modeling Module

The as-is modeling module includes two main components. First, the current conditions of the existing workplace (structure and objects) have to be modeled. Second, the path that each worker's 3D animation will use in the virtual representation is identified through path planning. The two components are further described below.

8.4.2.1 Point cloud generation

The virtual representation of a job site needs to reflect current conditions, including the shape, size, and location of building components, equipment, and materials. Since as-designed CAD and BIM models might not accurately reflect the current, ongoing status of the surrounding work environment or temporary structures and objects, point cloud data models have emerged as a solution. These models can later be converted into 3D models, such as BIM (Hichri et al. 2013). Different tools and approaches can be used for point cloud model creation, including image-based approaches, video-based approaches, and laser scanners. The use of laser scanners has been thoroughly studied in construction (Akinci et al. 2006; Tang et al. 2010; El-Omari and Moselhi 2008). Despite the high accuracy of models created using laser scanners, the cost of the scanners and the need for experts to implement them can limit their use in practice. Image-based approaches, in which a structure from motion algorithm is used to generate a point cloud from ordinary photographs (Golparvar-Fard et al. 2011; Fathi and Brilakis 2011; Guo et al. 2016), can be used as an alternative approach as they carry no need for special equipment or expertise. However, such approaches involve high processing time and require images with high overlap to ensure the reliability of the output. Therefore, this chapter uses a video-based approach, which can address the issues with both the prior methods.

To create a point cloud model using the video-based approach, a stereo vision camera is used to generate depth data for objects. In other words, every point of an object is recorded through the left and right lenses at the same time, and then the videos are rectified (Fusiello et al. 2000). Rectification is a transformation process in which two or more images are projected onto the same image plane to find the matching points between them. After this process, the images from every frame of the recorded videos will be appropriately aligned. In Fig. 8-4, if A is the point being analyzed, the projections of point A from the left and right views are called A1 and A2, respectively. In the left view, A is described as A1 (x1, y1), and in the right view, A is described as A2 (x2, y2). In the original frames, the heights of A, A1, and A2 are different (i.e., they are not in same pixel row). Therefore, the epipolar plane (the plane containing A, A1, and A2) is not horizontal but triangular. When the rectified distance is eliminated, the epipolar plane becomes horizontal. In other words, the

3D plane containing A, A1′, and A2′ is transformed into a straight line. Then, the disparity between A1 and A2 can be described as (x1-x2, y1-y2). As the distance between the two lenses is known, the depth of each point can be calculated based on the proportional relationship, and the entire object can be rebuilt as a point cloud model.

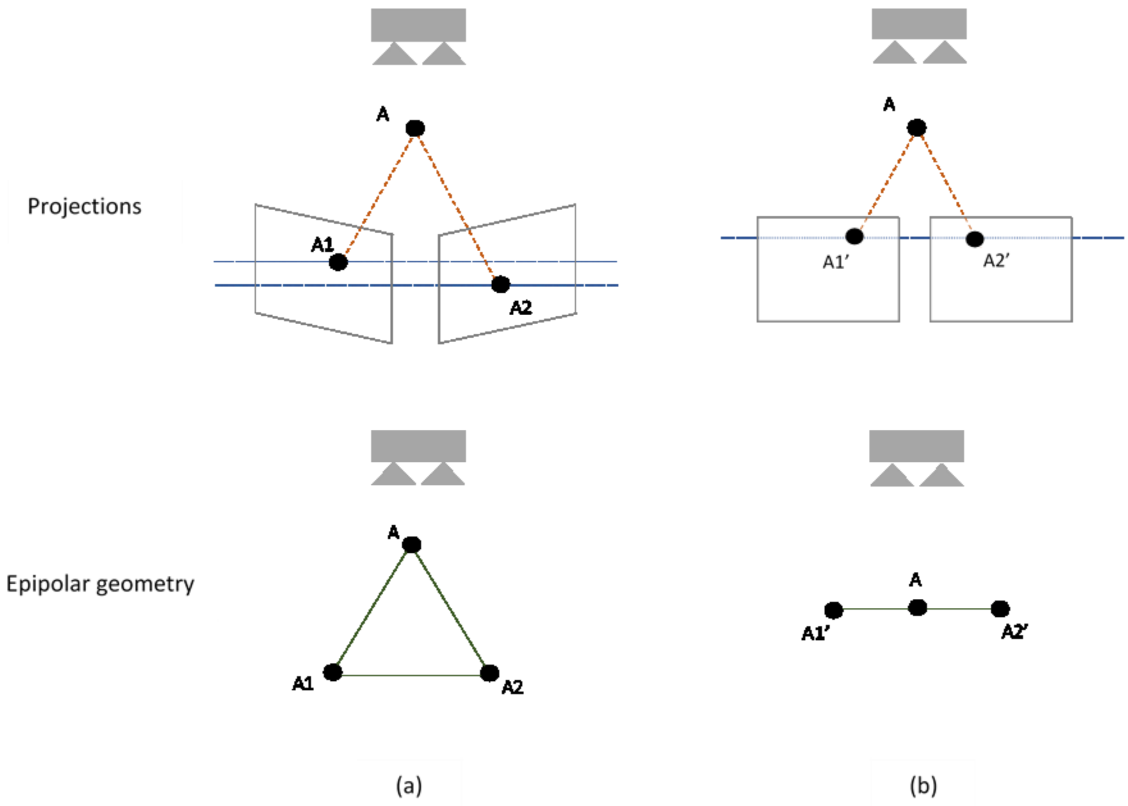

Figure 8-4 Image projections and epipolar geometry (a) before and (b) after rectification

The point cloud generation process is implemented using the procedure described above, which requires a video of a job site as input and generates the point cloud model as output. Through this simple process, the generated point cloud model reflects the existing conditions at a job site. When evaluating different scenarios and representing new designs, 3D models of other elements, including building components, equipment, material, tools, etc., are added by importing the point cloud model, potential BIM elements, and other 3D objects into the final visualization platform and positioning them in the correct locations. Human models and motions are added to the virtual model at a later stage.

8.4.2.2 Worker path planning for virtual modeling

To realistically represent a human model in a virtual environment, the anthropometric properties of the model, an animation of the motions the human carries out, and the path that they take inside the 3D model all need to be reflected reliably. The anthropometric attributes are considered while creating the skeleton of the 3D model of the human by choosing appropriate values for the joint lengths and body-part ratios. The motion is created from the sequence of activities and durations in the simulation model and by querying a database of motions, as explained above. The path that each worker will take to complete a motion also needs to be acquired to provide a reliable representation of activities. Thus, path planning needs to be used to predict the paths that workers will take on an actual job site and animate them in the virtual model.

For this purpose, the A* (Yao et al. 2010; Hart et al. 1968) path planning algorithm is adapted for its speed and reliability (see Appendix B). In this technique, the start and end nodes of the path and the locations of obstacles are the inputs, and the algorithm chooses the shortest path from start to finish. It selects the path that minimizes the f(n) function in Equation 8-1, where n is the last node on the path, g(n) is the exact cost of the path from the starting node to n, and h(n) represents a heuristic estimated cost from n to the final node.

$$f(n) = g(n) + h(n) \tag{8-1}$$

After the 3D model (point cloud or BIM) is created, it is analyzed to extract the coordinates of all objects in the model by recording their X and Y coordinates for all points on the Z axis, as shown in Fig. 8-5. The size of the matrices with the X and Y coordinates is determined by finding the largest distance in each of the X and Y directions among all the Z planes and using those values for the corresponding axis.

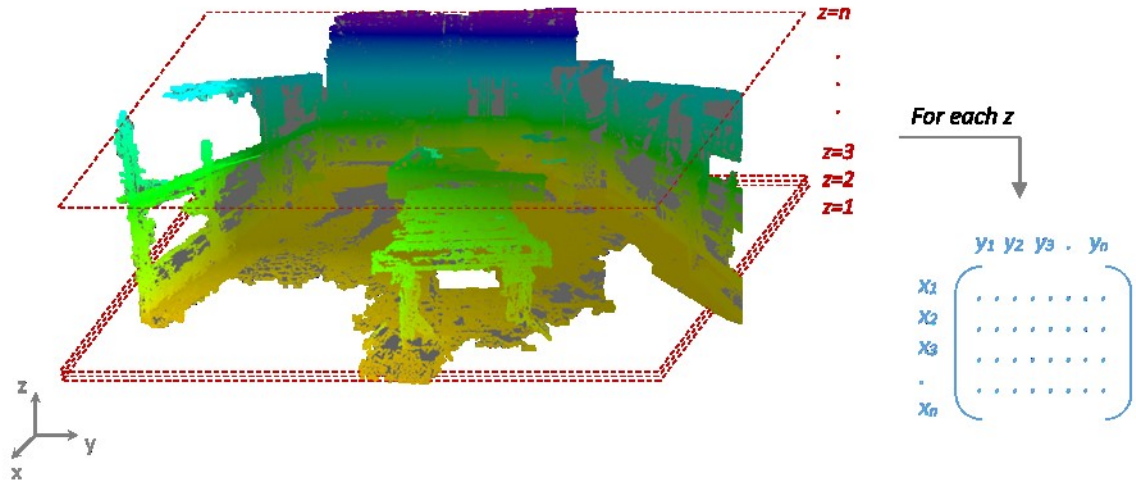

Figure 8-5 Registering the coordinates of all the objects of the 3D model in different planes

Next, the start and end locations in the virtual model are selected to extract the coordinates. Also, based on the Z coordinate of the start and end nodes, the object coordinates need to be filtered to find any obstacles in the worker's path. Thus, the coordinates of obstacles that could block the worker's path, defined by having a Z value between the worker's foot and head, are extracted. Then, the X and Y values of all nodes that represent an obstacle that the worker cannot pass (i.e., for the same X and Y, a Z range larger than the height of a step) are registered as obstacles. The start, end, and obstacle nodes are then fed into the A* algorithm, and the coordinates of the path are extracted. This path is then used to animate a human animation in the virtual model by feeding the coordinates into the visualization environment, along with the basic motions already attached to the animation.

8.4.3 Safety Assessment Module

The biomechanical analysis component of the framework enables the evaluation of an operation by examining the loads exerted on the human joints and comparing them to safe limits. The results can be used along with the productivity analysis output to improve the operation and select an optimal design (see Chapter 7). To carry out an automated ergonomic analysis, worker motions need to be extracted from either video recordings (Han and Lee 2013) or sensing devices (Han et al. 2013), and then the motion data can be used to automatically identify unsafe actions through ergonomic and biomechanical assessments (see Chapter 3). Those results are used to modify the design elements that cause the unsafe conditions and ensure representation of safe motions. The captured motions are also used to animate the worker model in the final virtual environment to accurately represent current conditions. When improving prospective operational scenarios, the motion generation element uses pre-recorded motions of ergonomically safe actions to visualize worker activities, enabling the use of the virtual representation for safety training applications. The safety analysis component and detailed descriptions pertaining to it can be found in Chapter 3 as well as Golabchi et al. (2016) and Golabchi et al. (2015).

8.5 CASE STUDY: ILLUSTRATION OF FRAMEWORK IMPLEMENTATION

The application of the proposed framework and its components is demonstrated by implementing it using data from an actual job site. A steel fabrication shop is selected as the work environment due to the existence of many manual operations and their importance in ensuring safe and productive processes. In particular, the task of handling steel plates is observed, recorded, modeled, and analyzed using the proposed integrated approach since its productivity is critical in the whole operation and it also involves physically demanding activities (e.g., carrying steel plates). This task involves picking up steel plates from a cutting machine, carrying them to a worktable, measuring and sorting them, and carrying them to storage bins. As the first step, the workstation is recorded using a video camera to extract time stamps and activity types using the action recognition component. This data is used to create a simulation model representing the existing, ongoing operation. Fig. 8-6 shows the work setup and samples of the identified worker tasks.

Walk | Pick up | Carry | Measure

Figure 8-6 Sample actions identified through action recognition

From the video recording of the operation, 32 tasks are identified in the four categories of walking, picking up, carrying, and measuring (see Appendix C). Since the operation is cyclic, after running the action recognition, the most repeated cycle is found and used as the correct sequence of activities. Activities not following the correct identified sequence are distinguished as outliers and removed. The simulation model of the cycle is then built using the average durations for each task, as derived from the action recognition results. Based on the 32 tasks identified from the video recording, which includes 4010 data points reflecting the video frames from the recording, the error in finding the correct sequence is 7.14%, and the error in calculating the correct durations is 8.48%. Fig. 8-7 shows the ground truth and predicted activities for the different aspects of the steel plate handling task.

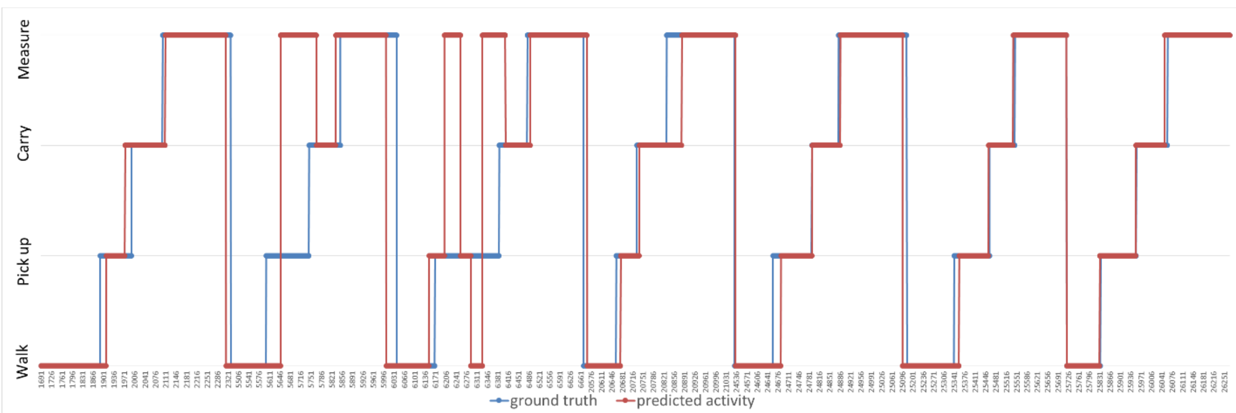

Figure 8-7 Comparison of the ground truth and predicted activity for steel plate handling

The results of the action recognition are used to create the simulation model that represents the current status of the operation. This is achieved with a script that describes the type and sequence of activities with timestamps from the action recognition. This simulation model serves as the basis for modifying the operation and evaluating different scenarios for potential improvement. As described in Chapter 7, integrating PMTSs into the simulation environment enables representation of manual activities that do not currently exist. This modeling process can be used to analyze the productivity of the current activities and improve it by assessing different methods for carrying out the process (e.g., different task sequence, more labor resources). Furthermore, the sequence of activities and task durations from the simulation model are used to generate motions from a pre-recorded motion-capture database. As shown in Fig. 8-8, models using PMTSs such as MODAPTS, MTM2, and MOST can be developed and tested from the base simulation model. These three systems are widely used and differ in their level of focus (cycle duration, repetitiveness of motions, complexity of movements, etc.). As these systems originated in industries other than construction, all three are used here to further validate the proposed simulation approach. Table 8-2 shows the result of running the simulation model for one cycle of the task. The durations are derived from running the simulation models shown in Fig. 8-8, using inputs collected from the actual job site. As shown in the figure, the modeling elements developed and used for the different PMTSs depend on the system design. For example, MODAPTS has a GET element to represent grasping an object, for which the input is the complexity of the grasp, and MTM2 has a step element representing a walking activity, for which the input is the number of steps taken. Next, the BVH motion of the operation is attached to a human model based on the sequence of the tasks from the simulation, making it ready for the path planning and visualization phase.

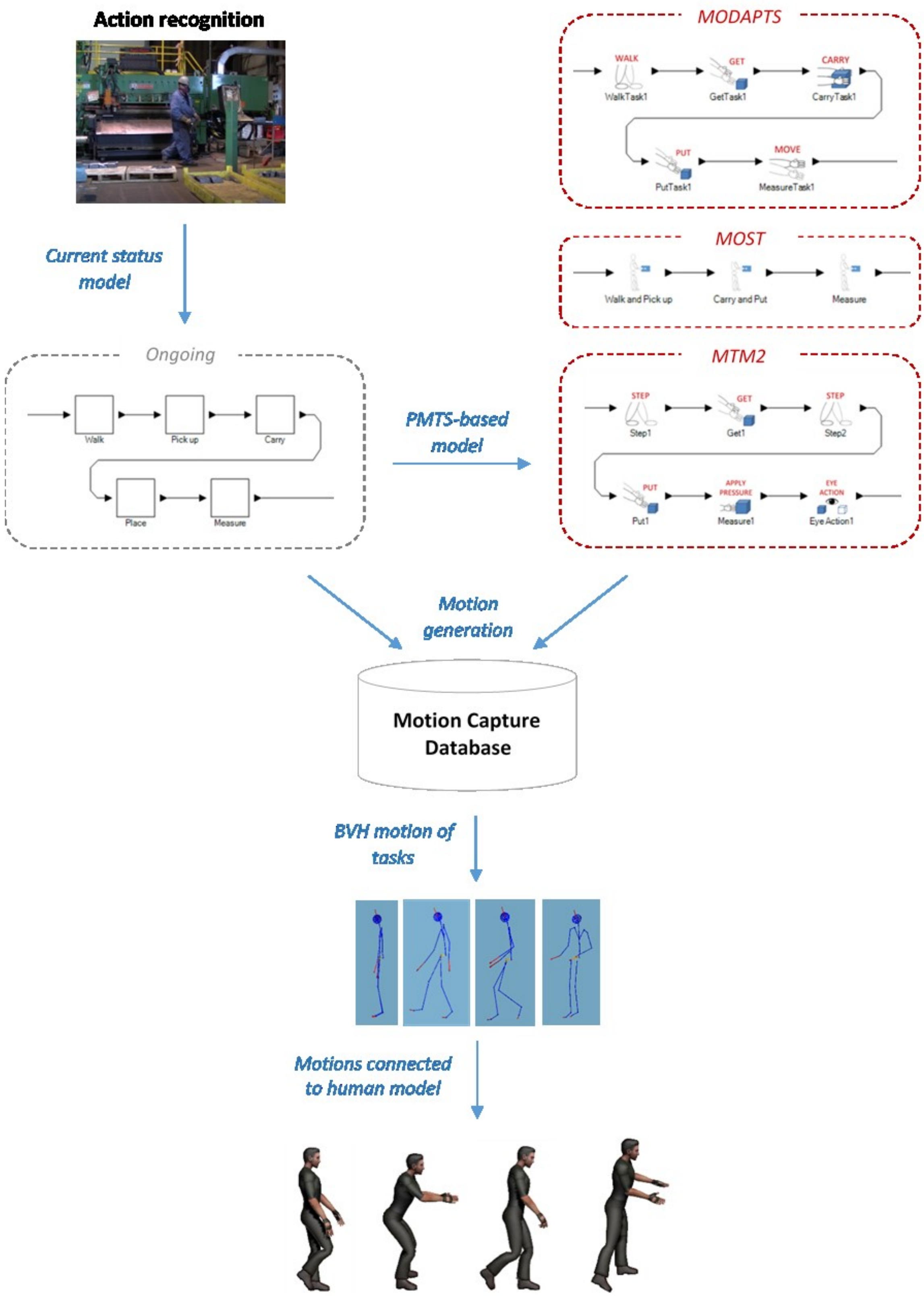

Figure 8-8 Simulation model and motion generation using action recognition

Table 8-2 Actual vs simulation durations for one cycle of the steel plate handling task

Average duration from job site (seconds)	PMTS-based simulation			Average difference between actual and PMTS-based
	MODAPS duration (seconds)	MTM2 duration (seconds)	MOST duration (seconds)	
8.66	8.06	8.42	8.28	4.70%

To create the 3D representation of the workstation, a 34-second video (1020 frames) of the job site is recorded. Using the described process, the point cloud model representing the as-is conditions is then generated. A snapshot of the point cloud model of the steel plate handling workstation is shown in Fig. 8-9.

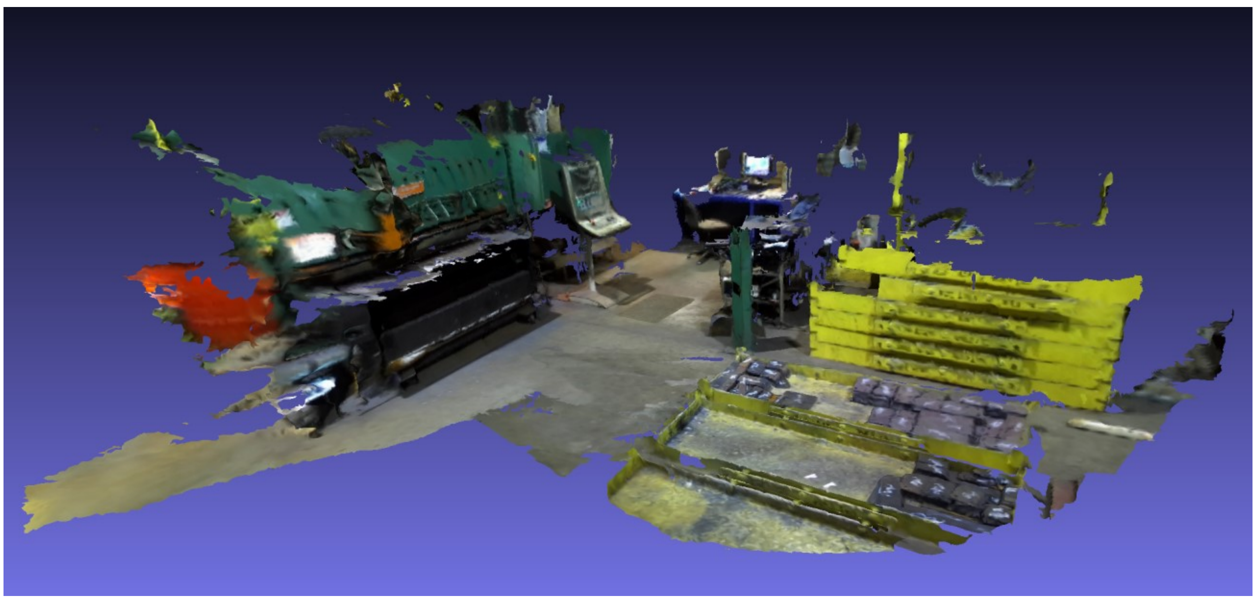

Figure 8-9 Point cloud model of the steel plate handling workstation

As an example of the ergonomic and biomechanical analysis for safety evaluation, the process of picking up the plates from the machine is demonstrated. As shown in Fig. 8-10, this analysis begins by modeling the worker's posture at any given point during the operation and using biomechanical models (Chaffin et al. 2006) to calculate the forces on different body joints and compare them to allowable limits (see Chapter 3). Any ergonomic concerns can be addressed during this modeling, and the worker's posture and workplace design can be changed, if required, to ensure the tasks are acceptably safe. This process can be carried out using any of several available biomechanical analysis tools and software, such as 3DSSPP, openSim, SIMM, or Visual 3D. The 3DSSPP software is used in this chapter as it can examine variables such as back compression (load on lower back) and the strength-percent capability of different body joints that are useful for assessing the steel plate handling task (see Chapter 3). Furthermore, it can effectively visualize and export posture modifications and their effects on biomechanical loads.

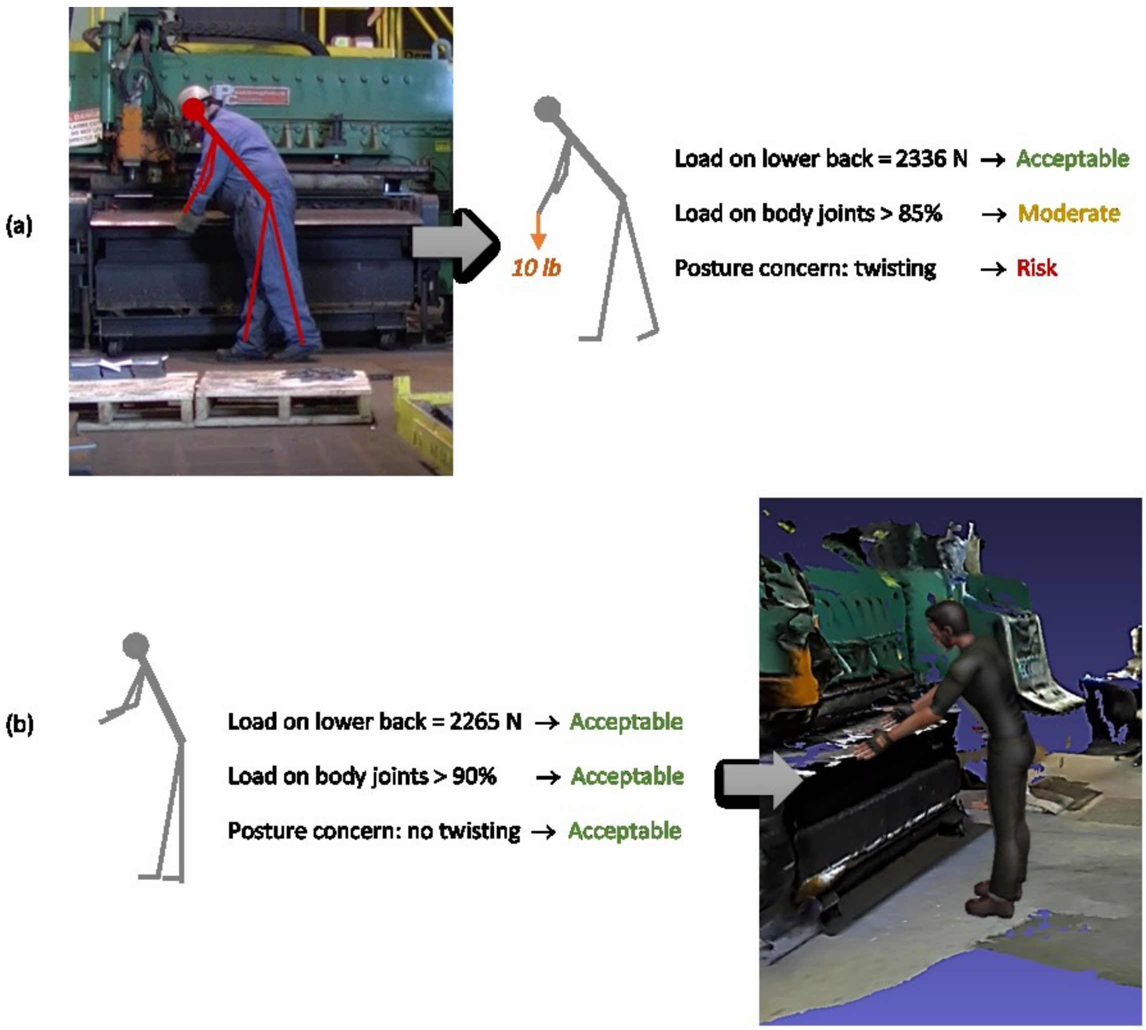

Figure 8-10 Biomechanical analysis of plate grasping task, (a) current conditions, (b) modified posture, added to the point cloud model after improvements

After creating the point cloud model, it is inserted into the platform for the final virtual representation. Autodesk 3ds Max is used as the final platform in this chapter. The point cloud can be used in conjunction with any 3D model (such as BIM) to evaluate ongoing operations and alternative scenarios. The human model and the motions attached to it from previous steps are also inserted into the visualization and manually aligned at the correct locations, along with other 3D models. The path planning algorithm is then used to find the best walking path for the worker model. Fig. 8-11 shows a snapshot of part of the virtual model with the point cloud, the human model, and other 3D models of equipment and material. The figure also shows the sequence for the path planning: by selecting the start and end locations, the obstacles are detected, and the shortest path is chosen and used to animate the human model. Different scenarios for the steel plate handling operation can include using a different cutting machine, adjusting the height of the worktable, relocating the bins for the cut plates, and changing the number of plates carried to the bins. The final output of the visualization is a complete virtual model representing the physical layout of the job site, building elements (e.g., walls, doors), 3D models of equipment, material, tools, and human models animating the motions of workers. This virtual model can be used in practice to further evaluate the design (e.g., assessing clearance and reach), improve the communication and implementation of new designs, train personnel, and more effectively manage decision-making.

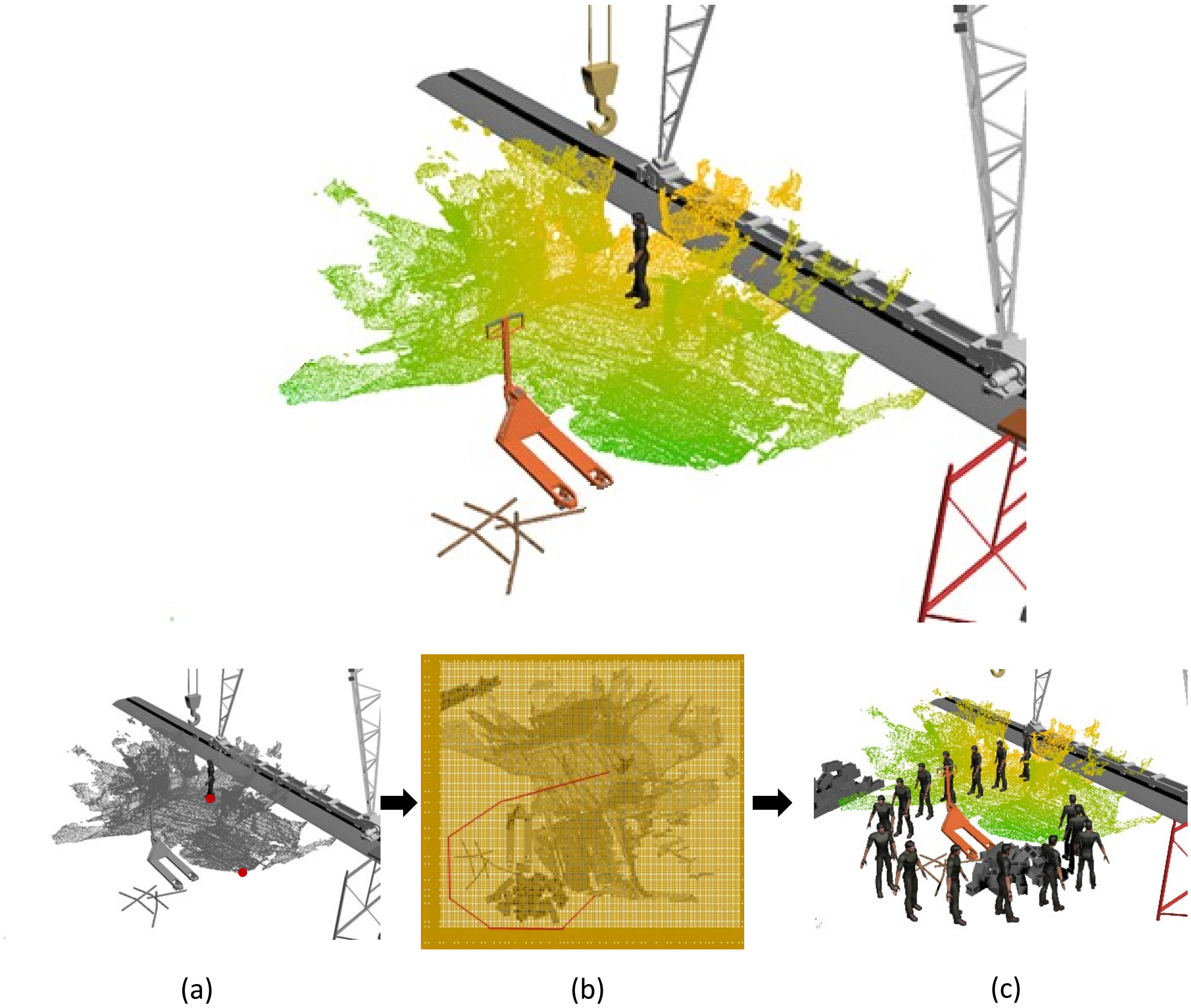

Figure 8-11 Top: virtual model of job site, bottom: path planning, (a) start and end locations selected, (b) A* algorithm detects shortest path, (c) worker motions are animated along the selected path

8.6 DISCUSSION

The implementation of the framework enables an examination of the effectiveness of the different components and their strengths and weaknesses and serves as a basis for further improvements to the framework. Based on the results, the following implications can be drawn.

(1) The results of implementing the action recognition process are promising. It saves time and effort in evaluating ongoing manual operations and improves the accuracy of the

evaluation. Furthermore, it eliminates the need for an expert in creating and analyzing simulation models of manual tasks because the only input is a video recording of the manual activity. The error values for the steel plate handling operation are 7.14% and 8.48% for finding the correct sequence and calculating the correct durations, respectively. The accuracy of the action recognition component could potentially be improved by extracting refined motion features (e.g., human silhouette with a more accurate contour) and training a more robust action classifier (e.g., fed data with a wider distribution over motions). The action recognition process is probably most practical when modeling cyclic operations, first because a short video of the process can be used to identify the correct sequence of activities and average durations (minimizing processing time). Second, as noncyclic operations do not contain a fixed sequence, outliers cannot be identified, which reduces the reliability of the system. In the proposed framework, the action recognition component serves as the basis for the simulation model used for productivity analysis and motion generation. However, it could also be used to integrate other applications into the framework, such as safety evaluations and worker training.

(2) The case study shows that the simulation model of the existing operation, created from video recordings using action recognition and used alongside a PMTS-based modeling platform, enables simple, accurate, and quick evaluation of ongoing activities. The action recognition–based simulation model represents the current operations, and the PMTS-based model represents the standard time for the operation. As shown in Table 8-2, the actual average duration for a cycle of the steel plate handling task is 8.66 seconds, and the simulation duration using MODAPTS, MTM2, and MOST is 8.06, 8.42, and 8.28 seconds respectively. The difference between the two durations can be used to represent the efficiency of the ongoing operation. Furthermore, the PMTS-based simulation enables convenient and accurate modeling of alternative scenarios for the operation to find the optimal process. Experiments with PMTSs in representing manual tasks, the simplicity of adopting them, and the amount of error associated with them indicate the importance of such systems in modeling construction operations.

(3) The generation of point cloud models from a video recording of a job site is a quick and simple method for obtaining a reliable 3D representation of current conditions. Since

construction sites are dynamic and the status of the work environment changes frequently, this method ensures that the 3D virtual model accurately represents the as-is state of the job site. It should be noted that the stereo vison system used in this chapter works reliably only for a certain size of workstation as the distance between the two lenses is fixed and relatively short. With a longer distance between the lenses, the perception level increases, and thus the depth perception ability will be higher. One potential solution to the boundedness limitation would be building a stereo vision camera with adjustable lenses.

Considering the conversion and import/export capabilities of existing software, the point cloud model connects smoothly to the final visualization model. However, manual manipulation is still required, along with scaling, to align the model in its correct position. The accuracy and labor-intensity of this process could be improved in further studies by using universal coordinate and unit systems and creating a method to automatically register different models in the final platform. Overall, the integration of point cloud data, human model and motions, and 3D models of equipment, tools, material, etc., resulted in a data-rich virtual model that could be effectively used for various potential visualization applications in construction.

(4) The path planning component, in conjunction with motion generation, enables an automated animation of worker motions, which is important in visualization of manual operations. The path planning algorithm eliminated the time and effort required to manually set up the animation of the human models and represented the motions in an acceptable and realistic scenario of worker activities in prospective work environments. This can be particularly useful when considering the existence of more than one worker in a single workstation, for which collision avoidance algorithms should also be incorporated. It should be noted that this process uses the shortest path between two points, and although it is generally safe to assume that workers will usually take the shortest path, this approach can be most useful for modeling prospective operations. If an exact representation of worker paths is required for an existing operation, it must be observed and recorded at the actual job site. Although that information might not be required for most applications, it is possible to automate this process using location-aware sensors and devices. This chapter used the A* path planning algorithm because of its popularity and accuracy. However,

implementing other algorithms and evaluating their effectiveness could be carried out in future studies.

Overall, the results indicate that integrating different sensing, analysis, and visualization methods can facilitate the linking of data required for an ergonomic analysis and streamline the evaluation and design of safe and productive workplaces. The first benefit is the automation and simplicity of the analysis process, which can result in higher adoption of ergonomic methods in practice. Second, because the same data is used by several components and the initial inputs are gathered using sensing approaches, the results provide high reliability and minimal subjectivity.

8.7 CONCLUSION

This chapter explores the adaptation and integration of methods to improve different stages of ergonomic analyses: data collection, data analysis, and representation of results. Improvements are achieved by proposing an overall framework to provide an automated, simple, and reliable analysis of manual operations. Specifically, the following framework components are investigated: (1) sensing to collect information about job site conditions, worker tasks and activities, and human motions; (2) action recognition from video recordings for simulation model creation; (3) predetermined motion time systems for efficiency evaluation; (4) biomechanical analysis for safety analysis; (4) motion generation and worker path planning for realistic animation of worker actions; (5) comprehensive virtual visualization for effective representation and implementation of the analysis and results. The results from implementing the framework indicate that integrating available methods of data collection, analysis, and visualization for labor operations can facilitate an inclusive ergonomic analysis. Such integration addresses challenges in traditional approaches to ergonomic evaluation: labor-intensity, unreliable results, and time-intensity. Considering the physically demanding nature of the manual tasks in the construction industry, this integration could result in a higher adoption of ergonomic methods in practice, as well as better reliability and reduced subjectivity in analysis results, which will lead to safer and more productive construction job sites.

8.8 ACKNOWLEDGMENTS

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Chapter 9 Conclusion

9.1 RESEARCH SUMMARY AND CONCLUSION

This research proposes an integrated approach for the evaluation and design of construction workplaces and labor operations to enable the simultaneous assessment of process productivity and safety and to explore the impact of production tasks and their physical demands on worker health and well-being. This is achieved by developing a framework that encompasses data acquisition through sensing and 3D modeling, analysis of data by means of simulation modeling and biomechanical analysis, and representation of data through inclusive visualization. Through this framework, the process of assessing ergonomic risks is automated, analysis reliability is improved, efficiency of labor operation is analysed, various scenarios of design are evaluated and compared, and the analysis process is simplified by linking different contributing components.

The developed motion data-driven framework for ergonomic evaluation, presented in Chapter 3, enables the automation of the ergonomic and biomechanical analysis process using motion capture data from existing job sites or virtual models of non-existing operations. This approach enables the mitigation of ergonomic workplace risks, proactively, to prevent injuries. This is in contrast to the traditional corrective (reactive) approach that is most prevalent on construction job sites. The results of implementing the framework on a prefabrication shop production line, which included twelve labor tasks, indicate that the approach can be effectively used to evaluate risk factors producing excessive physical loads on the human body and to propose workplace designs that can mitigate risks.

Common ergonomic assessment tools used in construction rely on human posture estimation for the evaluation of ergonomic risks associated with a task. However, estimating human postures using visual observation or sensing devices can lead to unreliable results due to human and instrument error. Accordingly, a fuzzy logic approach for ergonomic evaluation is proposed, in Chapter 4, to address input imprecision. Results of the correlation analysis between the developed fuzzy-based method and traditional approaches as well as biomechanical analysis demonstrate that the proposed approach produces more accurate results than traditional methods and can, therefore, help minimize errors. This correlation is further confirmed by applying the approach on actual manual activities from a modular construction shop. Furthermore, a stochastic approach is proposed, in Chapter 5, to evaluate the amount and impact of input errors on ergonomic assessment results and to enable the incorporation of this impact into the analysis. Results of analyzing ten thousand postures generated from a masonry task for cases of human observation errors as well as motion sensing errors are used to calculate and compare the amount of errors associated with both traditional and proposed methods.

To evaluate the productivity and ergonomic safety of labor operations from a physical perspective, motion level modeling of these operations is proposed. This task is enabled by the integration of PMTSs into simulation modeling, examined in Chapter 6. The results of implementing the proposed approach on manual tasks of a steel fabrication construction job site indicate that integration enables cycle time estimation and efficiency evaluation of labor activities in reliable and simple-to-use method. A framework is also proposed in Chapter 7 that links simulation modeling, PMTS, ergonomic and biomechanical assessment, and workplace visualization, to incorporate both productivity and safety analysis into the design process. Implementing the framework on data from a masonry operation demonstrates that the integrated framework provides a basis to evaluate and compare various labor operations scenarios in terms of both performance and safety, allowing for the selection of the most desirable scenario. More components such as sensing, action recognition, as-is workplace model generation, and human motion animation are added into the framework for further reliability and automation in Chapter 8. Experimenting with data from a steel plate handling task indicates that integration of different sensing, analysis, and visualization methods can potentially improve the ergonomic analysis of manual operations to effectively design efficient and safe workplaces.

Although safety and productivity are an integral part of project management, they have rarely been managed concomitantly in practice. This research emphasizes the importance of the interactive relationship between safety and productivity in operation planning and workplace design. The findings of this research enable an integrated approach to workplace design that ensures both increased productivity and safety by establishing the relationship between production tasks and physical demands of tasks and human capacity and well-being. The developed approach thus enables effective design and planning of workplaces and operations by providing reliable feedback regarding the impact of design on safety and productivity. In particular, these research results help reveal how production scenarios and working environments physically influence the development of WMSDs. This relation has often been ignored in daily safety and scheduling management practice, which are typically separated on a jobsite. Furthermore, coupling ergonomic analysis with simulation and virtual models of operational processes enables application of ergonomic safety considerations early in the planning phase or in ongoing operations for continuous improvement. The proposed approach not only brings attention to this critical issue from a practical perspective but also presents a motion-based simulation framework for the integration of ergonomic and productivity analysis from a scientific perspective. The findings of this research can contribute to knowledge advancement in safety science by articulating the causal relationship between production tasks and ergonomic behavior in construction operations. The integrated framework explores an emerging research area where already well-established fields (e.g. ergonomics, simulation, and visualization) can be integrated for safe and productive task planning and workplace design. Ultimately, this research aims to enhance understanding of safety in conjunction with work environments and production plans in the interest of human well-being in the workplace. The construction industry has some of the highest rates of injuries and WMSDs, and this study aims to address the challenge of reducing the rate of WMSDs by focusing on effective and accurate automated approaches of ergonomic analysis while ensuring the achievement of the highest productivity rate possible. By reducing the number of these injuries and the costs associated with them, the construction industry can focus on improving the quality of operations and final products.

9.2 RESEARCH CONTRIBUTION

The contributions of this research can be summarized as follows:

1. Development of a motion data approach for ergonomic and biomechanical evaluation that uses recordings of human motion, obtained from sensing devices, as input to carry out an assessment using available ergonomic checklists and biomechanical models in conjunction with 3D models of a workplace. By eliminating the need for human observation, this approach reduces the time and effort required to collect and analyze motion information for ergonomic evaluation and improves reliability of the results by removing human judgment errors and observer subjectivity. Furthermore, the proposed method enables the identification and mitigation of ergonomic risks, proactively, during design and planning phases.

2. Quantification of the impact of errors associated with collecting inputs for ergonomic analysis, using human observation or sensing devices, on outputs. Since collection of the required data for ergonomic evaluation (e.g., body joint angles) inevitably introduces human or instrument errors, quantifying the amount of this error, as well as its effect on analysis results, enables incorporation of this impact into the analysis, which, ultimately, leads to higher reliability of the evaluation process.

3. Implementation of a fuzzy-based approach to ergonomic assessment on widely-used ergonomic assessment tools. The developed fuzzy-based method improves the reliability of the analysis, compared to traditional methods, by reducing the impact of input errors on results. This approach addresses input imprecision as well as the discrete boundaries between posture-based ergonomic assessment tools.

4. Integration of PMTSs into simulation modeling for measurement and improvement of labor productivity from a physical perspective. This integration enables a reliable and efficient method for assessment of labor performance, both for existing and non-existing operations. The developed approach enables the modeling of labor activities to estimate the amount of time required to carry out labor operations, in a simple and automated manner, without requiring extensive prior knowledge regarding the details of PMTSs.

5. Development of an integrated framework that enables the examination of different labor operations scenarios and the selection of the most feasible in terms of both performance and safety. This framework enables the incorporation of different methods and tools of productivity and safety analysis for a unified, automated, reliable, and easy-to-use evaluation and design of labor operations. It leverages sensing for data acquisition, simulation modeling, action recognition, and biomechanical assessment for efficiency and safety analysis as well as virtual visualization for output representation. Through this integration, the relationship between productivity and ergonomic safety can be explored, which enables further understanding of the impact of production on biomechanical exposure and vice versa.

9.3 FUTURE WORK

Based on the findings of this research, the following areas have the potential to be explored in further detail:

- This research has experimented with the use of video recordings for extraction of type, sequence, and duration of worker activities through action recognition. With the advancements in the field of computer vision, this approach can be extended to include a comprehensive analysis of labor operations using merely video recordings. The potential system will use video recordings of an operation as input and will employ action recognition and machine learning algorithms to automatically report on the level of efficiency and safety of the operation. The efficiency analysis can be carried out by comparing the activities to standard motion time durations (e.g., PMTSs) or a preset benchmark (e.g., a skilled worker) and report on the deviations. The safety analysis can also be carried out using a skeleton extraction and biomechanical analysis directly from the video recordings, which is performed in this research using recordings of motion capture devices (e.g., depth sensors). Such system can be extremely useful for evaluation of ongoing operations as well as training of new workers.

- The proposed framework in Chapter 8 links different tools and methods of data acquisition, analysis, and output representation to improve the overall process of labor operation evaluation and design in construction. As shown before, such linkage can improve the analysis process through automation, increased simplicity, and improved reliability when compared to using the systems independently. However, the different tools and systems are not implemented in a single platform and are merely linked. Potentially, a single, virtual visualization platform, which has the simulation engine integrated into it enabling the acquisition of inputs of the simulation through manipulation the 3D model, can be developed. The 3D model itself could support the use of point cloud models, with automated and accurate registration at correct locations inside the virtual model. Furthermore, it could support animating human models with actual (i.e., recorded) motions for existing operations as well as generated motions for non-existing operations. The output of such visualization and simulation environment is not only the efficiency and safety status of different scenarios and designs of operations and workplaces but also a comprehensive visual model that can be used for various visualization applications (e.g., communication and implementation of design, decision-making, training of personnel).

- This research has used PMTSs for efficiency evaluation of labor operations. As these systems are originated in the manufacturing industry, further research is required to experiment with the different available systems (e.g., MTM, MOST, MODAPTS) and to evaluate the level of suitability of each for different labor activities in the construction industry. Furthermore, research efforts should focus on developing potential replacements of existing PMTSs for analyzing non-cyclic construction operations using newly customized methods.

- The ergonomic evaluation is conducted in this research using available ergonomic assessment tools (e.g., RULA) as well as biomechanical analysis. Since this research has also integrated this evaluation into simulation modeling, adding the contribution of fatigue into the analysis process can provide a highly effective tool for investigating the impact of fatigue on both performance and safety in different working conditions.

References

3DSSPP (3D Static Strength Prediction Program) [computer program]. Version 6.0.6. Ann Arbor, MI: The University of Michigan, Center for Ergonomics; 2014. Copyright 1990 The Regents of the University of Michigan. <http://umich.edu/~ioe/3DSSPP/index.html>.

AbouRizk, S. M., and Hajjar, D. (1998). "A framework for applying simulation in construction." *Canadian Journal of Civil Engineering*, 10.1139/l97-123, 25(3), 604-617.

AbouRizk, S., Knowles, P., and Hermann, U. (2001). "Estimating labor production rates for industrial construction activities." *Journal of Construction Engineering and Management*, 10.1061/(ASCE)0733-9364(2001)127:6(502), 502-511.

Abudayyeh, O., Fredericks, T. K., Butt, S. E., and Shaar, A. (2006). "An investigation of management's commitment to construction safety." *International Journal of Project Management*, 24(2), 167-174.

Akhavian, R., and Behzadan, A. H. (2016). "Smartphone-based construction workers' activity recognition and classification." *Automation in Construction*, 71, 198-209.

Akinci, B., Boukamp, F., Gordon, C., Huber, D., Lyons, C., and Park, K. (2006). "A formalism for utilization of sensor systems and integrated project models for active construction quality control." *Automation in construction*, 15(2), 124-138.

Alexander, R. M. (2003). "Modeling approaches in biomechanics." *Philosophical Transactions of the Royal Society of London B: Biological Sciences*, 358(1437), 1429-1435.

Al-Hussein, M., Niaz, M. A., Yu, H., and Kim, H. (2006). "Integrating 3D visualization and simulation for tower crane operations on construction sites." *Automation in Construction*, 15(5), 554-562.

Alwasel, A., Elrayes, K., Abdel-Rahman, E. M., and Haas, C. (2011). "Sensing construction work-related musculoskeletal disorders (WMSDs)." *Proceedings of the 28th International Symposium on Automation and Robotics in Construction (ISARC)*, Seoul, Korea, pp. 164–169.

Appleton, B. J., Patra, J., Mohamed, Y., and AbouRizk, S. (2002). "Special purpose simulation modeling of tower cranes." *Proceedings of the Winter Simulation Conference*, San Diego, CA, USA, Dec. 8-11, 10.1109/WSC.2002.1166455, pp. 1709-1715.

Arfken, G. (1985). "Scalar or dot product." *Proceedings of Mathematical Methods for Physicists*, pp. 13–18. Orlando, FL: Academic Press.

Armstrong, T., Buckle, P., Fine, L., Hagberg, M., Haring-Sweeney, M., Martin, B., and Viikari-Juntura, E. (1996). "Musculoskeletal disorders: Work-related risk factors and prevention." *International Journal of Occupational and Environmental Health*, 2(3), 239-246.

Awad, A., and Fayek, A. Robinson. (2012). "Contractor default prediction model for surety bonding." *Canadian Journal of Civil Engineering*, 39(9): 1027-1042

Badler, N. I., Becket, W. M., Webber, B. L. (1995). "Simulation and analysis of complex human tasks for manufacturing." *Proceedings of SPIE - the International Society for Optical Engineering*, 2596, 225–233.

Bao, S., Howard, N., Spielholz, P., and Silverstein, B. (2007). "Two posture analysis approaches and their application in a modified Rapid Upper Limb Assessment evaluation." *Ergonomics*, 50(12): 2118-2136.

Behm, M. (2005). "Linking construction fatalities to the design for construction safety concept." *Safety science*, 43(8), 589-611.

Bhise, V. D. (2011). *Ergonomics in the automotive design process*. CRC Press, ISBN: 1439842108.

Bosche, F., and C. T. Haas. (2008). "Automated Retrieval of 3D CAD Model Objects in Construction Range Images." *Automation in Construction*, 17(4):499-512.

Buchholz, B., Paquet, V., Punnett, L., Lee, D., and Moir, S. (1996). "PATH: a work sampling-based approach to ergonomic job analysis for construction and other non-repetitive work." *Applied ergonomics*, 27(3), 177-187.

Budziszewski, P., Grabowski, A., Milanowicz, M., Jankowski, J., and Dzwiarek, M. (2011). "Designing a workplace for workers with motion disability with computer simulation and virtual reality techniques." *International Journal on Disability and Human Development*, 10(4), 355-358.

Burdorf, A. (2010). "The role of assessment of biomechanical exposure at the workplace in the prevention of musculoskeletal disorders." *Scandinavian Journal of Work, Environment & Health*, 36(1), 1-2.

Bureau of Labor Statistics (2008). *Nonfatal Occupational Injuries and Illnesses Requiring Days Away from Work*. U.S. Department of Labor, Washington, DC.

Bureau of Labor Statistics. (2016). *Nonfatal occupational injuries and illnesses requiring days away from work*. U.S. Department of Labor, Washington, DC.

Burns, C. M., Vicente, K. J., Christoffersen, K., Pawlak, W. S. (1997). "Towards viable, useful, and usable human factors design guidance." *Applied Ergonomics,* 28(5), 311–322.

Canadian Centre for Occupational Health and Safety (CCOHS). (2014). *What are work-related musculoskeletal disorders (WMSDs)* [online]. Available from http://www.ccohs.ca/oshanswers/diseases/rmirsi.html [accessed 25 February 2015].

Chaffin, D. B. (2008). “Digital human models for workspace design.” *Reviews of Human Factors and Ergonomics*, 4(1), 41-74.

Chaffin, D.B., Andersson, G.B., and Martin, B.J. (2006). *Occupational Biomechanics*, Fourth Edition, John Wiley & Sons, Inc., Hoboken, NJ, USA.

Chan, M. (2011). “Fatigue: the most critical accident risk in oil and gas construction.” *Construction Management and Economics*, 29(4), 341-353.

Chan, P. and Kaka, A. (2004). “Construction productivity measurement: A comparison of two case studies.” In: Khosrowshahi, F (Ed.), *Proceedings 20th Annual ARCOM Conference*, 1-3 September, Edinburgh, UK. Association of Researchers in Construction Management, Vol. 1, 3-12.

Chao, L. C. and Skibniewski, M. J. (1994). “Estimating construction productivity: Neural-network-based approach.” *Journal of Computing in Civil Engineering*, 10.1061/(ASCE)0887-3801(1994)8:2(234), 234-251.

Chen, J., Ahn, C. R., and Han, S. (2014). “Detecting the hazards of lifting and carrying in construction through a coupled 3D sensing and IMUs sensing system.” *Proceedings of the International Conference on Computing in Civil and Building Engineering*, pp. 1110-1117, ASCE.

Cheng, T., Teizer, J., Migliaccio, G. C., and Gatti, U. C. (2013). “Automated task-level activity analysis through fusion of real time location sensors and worker's thoracic posture data.” *Automation in Construction*, 29, 24-39.

Chiasson, M.È., Imbeau, D., Aubry, K., and Delisle, A. (2012). “Comparing the results of eight methods used to evaluate risk factors associated with musculoskeletal disorders.” *International Journal of Industrial Ergonomics*, 42(5): 478-488.

Choi, S.D., Griinke, D. and Lederer, M. (2006). “Fall protection equipment effects on productivity and safety in residential roofing construction.” *Journal of Construction Research*, 7(1&2), 149-157.

Choudhry, R. and Fang, D. (2008). “Why operatives engage in unsafe work behavior: Investigating factors on construction sites.” *Safety Science*, 46(1), 566-584.

Christian, J. and Hachey, D. (1995). “Effects of delay times on production rates in construction.” *Journal of construction engineering and management*, 10.1061/(ASCE)0733-9364(1995)121:1(20), 20-26.

Chua, D. K., and Li, G. M. (2002). “RISim: Resource-interacted simulation modeling in construction.” *Journal of construction engineering and management*, 128(3), 195-202.

Cimino, A., Longo, F., and Mirabelli, G. (2009). “A multimeasure-based methodology for the ergonomic effective design of manufacturing system workstations.” *International Journal of Industrial Ergonomics*, 39, 447–455.

Construction Industry Institute (CII). (2006). *Work force view of construction labor productivity*. RR215-11, Austin, TX.

Cooke, T., Lingard, H., Blismas, N., and Stranieri, A. (2008). “ToolSHeDTM: the development and evaluation of a decision support tool for health and safety in construction design.” *Engineering, Construction and Architectural Management*, 15(4), 336-351.

Corona-Suárez, G., AbouRizk, S., and Karapetrovic, S. (2014). “Simulation-based Fuzzy Logic Approach to Assessing the Effect of Project Quality Management on Construction Performance.” *Journal of Quality and Reliability Engineering* 10.1155/2014/203427:1-18.

CPWR. (2013). *The construction chart book*, 5th Ed., CPWR, Silver Spring, MD.

Dai, J., Goodrum, P., and Maloney, W. (2009). “Construction craft workers' perceptions of the factors affecting their productivity.” *Journal of Construction Engineering and Management*, 10.1061/(ASCE)0733-9364(2009)135:3(217), 217-226.

David, G.C. (2005). “Ergonomic methods for assessing exposure to risk factors for work-related musculoskeletal disorders.” *Occupational Medicine*, 55(3): 190–199.

Debevec, P. E. (1996). Modeling and Rendering Architecture from Photographs. Doctor of Philosophy dissertation, University of California at Berkeley.

Dellaert, F., Seitz, S. M., Thorpe, C. E., and Thrun, S. (2000). “Structure from motion without correspondence.” *Proceedings of IEEE Conference on Computer Vision and Pattern Recognition*, Vol. 2, pp. 557-564.

Dimitrov, A., Gu, R., and Golparvar-Fard, M. (2016). “Non-Uniform B-Spline Surface Fitting from Unordered 3D Point Clouds for As-Built Modeling.” *Computer-Aided Civil and Infrastructure Engineering* 31, pp. 483–498.

Dissanayake, M., and Fayek, A. Robinson. (2007). “Assigning membership in fuzzy set analysis for construction management applications.” *Proceedings of the ASCE Construction Research Congress*, Grand Bahamas Island, The Bahamas, 6–8 May 2007. American Society of Civil Engineers (ASCE), New York, NY, USA.

Dul, J., and Neumann, W. P. (2009). “Ergonomics contributions to company strategies.” *Applied ergonomics*, 40(4), 745-752.

El-Gohary, K. M., and Aziz, R. F. (2013). “Factors influencing construction labor productivity in Egypt.” *Journal of Management in Engineering*, 30(1), 1-9.

El-Omari, S., and O. Moselhi. (2008). “Integrating 3D Laser Scanning and Photogrammetry for Progress Measurement of Construction Work.” *Automation in Construction*, 18(1):1-9.

Elwakil, E., and Zayed, T. (2014). “Construction knowledge discovery system using fuzzy approach.” *Canadian Journal of Civil Engineering*, 42(1): 22-32.

Escorcia, V., Dávila, M. A., Golparvar-Fard, M., and Niebles, J. C. (2012). “Automated vision-based recognition of construction worker actions for building interior construction operations using RGBD cameras.” *Proceedings of 2012 Construction Research Congress (CRC)*, West Lafayette, IN, USA, May 21-23, pp. 879-888.

Eurofound (1991). *From Drawing Board to Building Site* (EF/88/17/FR). European Foundation for the Improvement of Living and Working Conditions (Eurofound), Dublin.

Evans, D.D., Michael, J.H., Wiedenbeck, J.K. and Ray, C.D. (2005). “Relationship between organizational climates and safety-related events at four wood manufacturers.” *Forest Products Journal*, 25(6), 23-28.

Ezeldin, A. S. and Sharara, L. M. (2006). “Neural networks for estimating the productivity of concreting activities.” *Journal of Construction Engineering and Management*, 10.1061/(ASCE)0733-9364(2006)132:6(650), 650-656.

Fathi, H., and I. Brilakis. (2011). “Automated Sparse 3D Point Cloud Generation of Infrastructure Using its Distinctive Visual Features.” *Advanced Engineering Informatics*, 25(4), 760-770.

Fayek, A. and Oduba, A. (2005). “Predicting industrial construction labor productivity using fuzzy expert systems.” *Journal of Construction Engineering and Management*, 10.1061/(ASCE)0733-9364(2005)131:8(938), 938-941.

Fayek, A. Robinson, and Rodriguez Flores, J.R. (2010). “Application of fuzzy logic to quality assessment of infrastructure projects at conceptual cost estimating stage.” *Canadian Journal of Civil Engineering*, 37(8), 1137-1147.

Fernández-Baena, A., Susín, A., and Lligadas, X. (2012). “Biomechanical validation of upper-body and lower-body joint movements of kinect motion capture data for rehabilitation treatments.” *Proceedings of 4th international conference on intelligent networking and collaborative systems*, Bucharest, Romania, September 19-21, 656-661.

Feyen, R., Liu, Y., Chaffin, D., Jimmerson, G., and Joseph, B. (2000). “Computer-aided ergonomics: a case study of incorporating ergonomics analyses into workplace design.” *Applied Ergonomics*, 31, 291-300.

Fraenkel, J. R., Wallen, N. E., and Hyun, H. H. (1993). *How to design and evaluate research in education* (Vol. 7). New York: McGraw-Hill.

Freivalds, A. (2014). *Niebel's Methods, Standards, and Work Design*, 13th Edition. McGraw-Hill.

Fusiello, A., Trucco, E., and Verri, A. (2000). "A compact algorithm for rectification of stereo pairs." *Machine Vision and Applications*, 12(1), 16-22.

Gambatese, J. (2003). *Investigation of the viability of designing for safety*. The Center to Protect Workers' Rights, Rockville, MD, USA.

Gambatese, J. A. (2008). "Research issues in Prevention through Design." *Journal of Safety Research*, 39(2), 153−156.

Gambatese, J. A., Behm, M., and Rajendran, S. (2008). "Design's role in construction accident causality and prevention: Perspectives from an expert panel." *Safety Science*, 46(4), 675−691.

Gambatese, J. A., Hinze, J. W., and Haas, C. T. (1997). "Tool to design for construction worker safety." *Journal of Architectural Engineering*, 3(1), 32-41.

Gambatese, J.A., Behm, M., and Hinze, J.M. (2005). "Viability of designing for construction worker safety." *Journal of Construction Engineering and Management*, 131, 1029–1036.

Gangolells, M., Casals, M., Forcada, N., Roca, X., and Fuertes, A. (2010). "Mitigating construction safety risks using prevention through design." *Journal of safety research*, 41(2), 107-122.

Gannoruwa, A. and Ruwanpura, J. Y. (2007). "Construction noise prediction and barrier optimization using special purpose simulation." *Proceedings of the Winter Simulation Conference*, Washington, DC, USA, Dec. 9-12, pp. 2073-2081.

Gatti, U., Migliaccio, G., and Schneider, S. (2011). "Wearable physiological status monitors for measuring and evaluating workers' physical strain: Preliminary validation." *Computing in Civil Engineering*, 194-201.

Genaidy, A. M., Agrawal, A., and Mital, A. (1990). "Computerized predetermined motion-time systems in manufacturing industries." *Computers & Industrial Engineering*, 18(4), 571-584.

Golabchi, A., Han, S., and AbouRizk, S. (2017). "Post-simulation Visualization of Construction Manual Operations Using Motion Capture Data." *Proceedings of the ASCE International Workshop on Computing in Civil Engineering (IWCCE)*, Seattle, WA, USA, June 25-27.

Golabchi, A., Han, S., AbouRizk, S., and Kanerva, J. (2016). "Simulation-based analysis of operational efficiency and safety in a virtual environment." *Proceedings of the 2016 Winter Simulation Conference*, pp. 3325-3336, IEEE Press.

Golabchi, A., Han, S., and AbouRizk, S. (2015). “Integration of ergonomic analysis into simulation modeling of manual operations.” *Proceedings of the 16th ASIM Dedicated Conference on Simulation in Production and Logistics*, Dortmund, Germany, September 23-25, pp. 491-501.

Goldenhar, L. M., Williams, L. J., and Swanson, N. G. (2003). “Modeling relationships between job stressors and injury and near-miss outcomes for construction laborers.” *Work & Stress*, 17(3), 218-240.

Golparvar-Fard, M., Bohn, J., Teizer, J., Savarese, S., and Peña-Mora, F. (2011). “Evaluation of image-based modeling and laser scanning accuracy for emerging automated performance monitoring techniques.” *Automation in Construction*, 20(8), 1143-1155.

Gomar, J., Haas, C., and Morton, D. (2002). “Assignment and allocation optimization of partially multiskilled workforce.” *Journal of Construction Engineering and Management*, 10.1061/(ASCE)0733-9364(2002)128:2(103), 103-109.

Gong, J., Caldas, C. H., and Gordon, C. (2011). “Learning and classifying actions of construction workers and equipment using Bag-of-Video-Feature-Words and Bayesian network models.” *Advanced Engineering Informatics*, 25(4), 771-782.

Goodrum, P. M., and Haas, C. T. (2004). “Long-term impact of equipment technology on labor productivity in the US construction industry at the activity level.” *Journal of Construction Engineering and Management*, 10.1061/(ASCE)0733-9364(2004)130:1(124), 124-133.

Grobelny, J., Cysewski, P., Karkowski, W., and Zurada, J. (1992). “APOLIN: A 3-dimensional ergonomic design and analysis system.” *Proceedings of Computer Applications in Ergonomics, Occupational Safety and Health*. Elsevier, Amsterdam, Netherlands, pp. 129–135.

Guo, X., Golabchi, A., Han, S., and Kanerva, J. (2016). “3D Modeling of Workplaces for Time and Motion Study of Construction Labor.” *Proceedings of the 16th International Conference on Computing in Civil and Building Engineering (ICCCBE)*, July 6-8, Osaka, Japan, pp. 1516-1523.

Gupta, M. P. K. and Chandrawat, M. S. S. (2012). “To improve work force productivity in a medium size manufacturing enterprise by MOST Technique.” *IOSR Journal of Engineering (IOSRJEN)*, e-ISSN: 2250-3021, p-ISSN: 2278-8719, 2(10), 8-15.

Hajjar, D., and AbouRizk, S. (1999). “Simphony: an environment for building special purpose construction simulation tools.” *Proceedings of the Winter Simulation Conference*, Phoenix, AZ, USA, December 5-8, pp. 998–1006.

Halligan, D. W., Demsetz, L. A., and Brown, J. D. (1994). “Action response model and loss of productivity in construction.” *Journal of Construction Engineering and Management*, 10.1061/(ASCE)0733-9364(1994)120:1(47), 47-64.

Hallowell, M. (2011). “Understanding the link between construction safety & productivity: An active learning simulation exercise.” *Journal of Safety, Health & Environmental Research*, 7 (1), 1-9.

Halpin, D. W. (1977). “CYCLONE: method for modeling of job site processes.” *Journal of the Construction Division*, Vol. 103, No. 3, 489-499, ASCE.

Han, K. K., Cline, D., and Golparvar-Fard, M. (2015). “Formalized knowledge of construction sequencing for visual monitoring of work-in-progress via incomplete point clouds and low-LoD 4D BIMs.” *Advanced Engineering Informatics*, 29(4), 889-901.

Han, S. and Lee, S. (2013). “A vision-based motion capture and recognition framework for behavior-based safety management.” *Automation in Construction*, 35, 131–141.

Han, S. H., Al-Hussein, M., Al-Jibouri, S., and Yu, H. (2012). “Automated post-simulation visualization of modular building production assembly line.” *Automation in Construction*, 21, 229-236.

Han, S., Achar, M., Lee, S., and Peña-Mora, F. (2013). “Empirical assessment of a RGB-D sensor on motion capture and action recognition for construction worker monitoring.” *Visualization in Engineering*, 1(1), 1-13.

Han, S., Lee, S., and Pena-Mora, F. (2014). “Comparative Study of Motion Features for Similarity-based Modeling and Classification of Unsafe Actions in Construction.” *Journal of Computing in Civil Engineering*, 28 (5), A4014005.

Hanna, A., Taylor, C., and Sullivan, K. (2005). “Impact of extended overtime on construction labor productivity.” *Journal of Construction Engineering and Management*, 10.1061/(ASCE)0733-9364(2005)131:6(734), 734-739.

Hare, B., Cameron, I. and Duff, A.R. (2006). “Exploring the integration of health and safety with preconstruction planning.” *Engineering Construction and Architectural Management*, 13(5), 438-50.

Hart, P. E., Nilsson, N. J., Raphael, B. (1968). “A Formal Basis for the Heuristic Determination of Minimum Cost Paths.” *IEEE Transactions on Systems Science and Cybernetics (SSC)* 4(2): 100–107. doi:10.1109/TSSC.1968.300136.

Hecker, S. and Gambatese, J.A. (2003). “Safety in design: a proactive approach to construction worker safety and health.” *Applied Occupational and Environmental Hygiene*, 18, 339–342.

Hecker, S.F., Gambatese, J.A., and Weinstein, M. (2006). “Designing for construction safety in the US: Progress, needs, and future directions.” *Proceedings of the 16th Triennial Congress of the International Ergonomics Association*, Maastricht, The Netherlands, 10-14 July 2006.

Hedge, A., and Sakr, W. (2005). “Workplace effects on office productivity: A macroergonomic framework.” *Human factors in Organizational Design and Management – VIII*, IEA Press, Santa Monica, pp. 75-80.

Hess, J. A., Hecker, S., Weinstein, M., and Lunger, M. (2004). “A participatory ergonomics intervention to reduce risk factors for low-back disorders in concrete laborers.” *Applied Ergonomics*, 35(5), 427-441.

Heyde, G.C. (1966). *Modapts*. Industrial Engineering, 11-15.

Hichri, N., Stefani, C., De Luca, L., Veron, P., and Hamon, G. (2013). “From point cloud to BIM: a survey of existing approaches.” *Proceedings of the XXIV International CIPA Symposium*, September 2-6, Strasbourg, France.

Hignett, S. and McAtamney, L. (2000). “Rapid Entire Body Assessment (REBA).” *Applied Ergonomics*, 31, 201–205.

Hinze, J. (2006). *Construction safety*. Englewood Cliffs, NJ: Prentice Hall.

Hinze, J. and Appelgate, L.L. (1991). “Costs of construction injuries.” *Journal of Construction Engineering and Management*, 117(3), 537-550.

Hinze, J. W. (1998). *Construction planning and scheduling*. Pearson Higher Ed. ISBN: 0132473984.

Hinze, J., and Parker, H. W. (1978). “Safety: productivity and job pressures.” *Journal of the Construction Division*, 104(1), 27-34.

Hoekstra, P. N. (1993). “Some uses of ‘active viewing’ in computer aided anthropometric assessment.” *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, Seattle, WA, Oct. 11-15, 494–498.

Horner, R. M. W., Talhouni, B. T., and Thomas, H. R. (1989). “Preliminary results of major labor productivity monitoring programme.” *Proceedings of the 3rd Yugoslavian Symposium on Construction Management*, Cavtat, pp. 18-28.

Hwang, B., and Soh, C. (2013). “Trade-level productivity measurement: Critical challenges and solutions.” *Journal of Construction Engineering and Management*, 10.1061/(ASCE)CO.1943-7862.0000761, 04013013.

IAPA. (2009). *Performing a physical demands analysis.* Industrial Accident Prevention Association [online]. Available from http://www.iapa.ca/main/documents/pdf/freedownloads _pda_intro.pdf [accessed 6 March 2015].

IEA (2017). Definition and Domains of Ergonomics, International Ergonomics Association (IEA). Online < http://www.iea.cc/whats/index.html> (accessed: May 2017)

ILO (1985). *Safety and health in building and civil engineering work*. International Labor Office (ILO), Geneva.

Institute of Industrial Engineers (1983). *Industrial Engineering Terminology*, Institute of Industrial Engineers, Industrial Engineering and Management Press, Norcross, GA, USA, ISBN: 0898061059.

Inyang, N. (2016). "Ergonomic Assessment of Residential Construction Tasks Using System Dynamics." *Proceedings of 33rd International Symposium on Automation and Robotics in Construction (ISARC)*, Auburn, Alabama, USA, July 18th - July 21st.

Jarkas, A. M., and Bitar, C. G. (2011). "Factors affecting construction labor productivity in Kuwait." *Journal of Construction Engineering and Management*, 138(7), 811-820.

Jiang, Z., and Fang, D. (2014). "Confidence Building of a System Dynamics Model on the Causation of Construction Workers' Unsafe Behaviors." *Proceedings of the Construction Research Congress (CRC)*, pp. 80-89.

Joshua, L., and Varghese, K. (2011). "Accelerometer-based activity recognition in construction." *Journal of computing in civil engineering*, 25(5), 370-379.

Kadefors, R., and Forsman, M. (2000). "Ergonomic evaluation of complex work: a participative approach employing video–computer interaction, exemplified in a study of order picking." *International Journal of Industrial Ergonomics*, 25(4), 435-445.

Kale, S., and Karaman, E.A. (2011). "A fuzzy logic model for benchmarking the knowledge management performance of construction firms." *Canadian Journal of Civil Engineering*, 38(4), 464-475.

Kamat, V. R., and Martinez, J. C. (2000). "3D Visualization of Construction Processes and Products." *Proceedings of International Conference on Construction Information Technology*, Reykjavik, Iceland, pp. 506-512.

Karhu, O., Härkönen, R., Sorvali, P., and Vepsäläinen, P. (1981) "Observing working postures in industry: Examples of OWAS application." *Applied Ergonomics,* 12, 13–17.

Karhu, O., P. Kansi, and I. Kuorinka. (1977). "Correcting Working Postures in Industry: a Practical Method for Analysis." *Applied Ergonomics*, 8(4):199-201.

Kee, D. and Karwowski, W. (2007). "A comparison of three observational techniques for assessing postural loads in industry." *International Journal of Occupational Safety and Ergonomics*, 13(1), 3-14.

Kee, D., and Karwowski, W. (2001). "LUBA: an assessment technique for postural loading on the upper body based on joint motion discomfort and maximum holding time." *Applied Ergonomics*, 32(4), 357–366.

Kheirieh, S. P. and Heravi, G. (2010). “Effective labors’ productivity factors in industrial construction projects: A case study of South Pars gas field.” *Proceedings of the 24th International Project Management Association World Congress*, Amsterdam, Netherlands.

Khoshelham, K. (2011). “Accuracy analysis of kinect depth data.” *Proceedings of ISPRS Workshop, International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, Volume XXXVIII-5/W12, 133-138.

Khoshelham, K., and Elberink, S. O. (2012). “Accuracy and resolution of kinect depth data for indoor mapping applications.” *Sensors*, 12(2), 1437-1454.

Khosrowpour, A., Fedorov, I., Holynski, A., Niebles, J. C., and Golparvar-Fard, M. (2014). “Automated worker activity analysis in indoor environments for direct-work rate improvement from long sequences of RGB-D images.” *Proceedings of 2014 Construction Research Congress (CRC)*, Atlanta, GA, USA, May 19-21, 729-738.

Kilbom, A., Armstrong, T., Buckle, P., Fine, L., Hagberg, M., Haring-Sweeney, M., Martin, B., Punnett, L., and Silverstein, B. (1996). “Musculoskeletal disorders: Work-related risk factors and prevention.” *International Journal of Occupational and Environmental Health*, 2(3), 239–246.

Kim, J. Y., and Caldas, C. H. (2013). “Vision-based action recognition in the internal construction site using interactions between worker actions and construction objects.” *Proceedings of the International Symposium on Automation and Robotics in Construction and Mining*, pp. 661-668.

Kim, S., Seol, H., Ikuma, L. H., and Nussbaum, M. A. (2008). “Knowledge and opinions of designers of industrialized wall panels regarding incorporating ergonomics in design.” *International Journal of Industrial Ergonomics*, 38(2), 150-157.

Koutsoudis, A., Vidmar, B., Ioannakis, G., Arnaoutoglou, F., Pavlidis, G., and Chamzas, C. (2014). “Multi-image 3D reconstruction data evaluation.” *Journal of Cultural Heritage*, 15(1), 73-79.

Kuhlang, P., Edtmayr, T., and Sihn, W. (2011). “Methodical approach to increase productivity and reduce lead time in assembly and production-logistic processes.” *CIRP Journal of Manufacturing Science and Technology*, 10.1016/j.cirpj.2011.02.001, 4(1), 24-32.

Kumar, S. (2001). “Theories of musculoskeletal injury causation.” *Ergonomics*, 44(1), 17–47.

Kuusito, A. and Mattila, M. (1990).” Anthropometric and biomechanical man models in computer-aided ergonomic design structure and experiences of some programs.” In: *Computer-Aided Ergonomics*. Taylor & Francis, London, UK, pp. 104–114.

Lachin, J. (1981). “Introduction to Sample Size Determination and Power Analysis for Clinical Trials.” *Controlled Clinical Trials*, 2, 93-113.

Laring, J., Forsman, M., Kadefors, R., and Örtengren, R. (2002). “MTM-based ergonomic workload analysis.” *International Journal of Industrial Ergonomics*, 10.1016/S0169-8141(02)00091-4, 30(3), 135-148.

Lau, M. H. (2011). *An Investigation of Factors that Affect Subjective Assessment of Wrist Posture and Applied Hand Force* (Doctoral dissertation), The University of Michigan, Ann Arbor, MI, USA.

Launis, M. and Lehtela, J. (1992). “ergoSHAPE - a design oriented ergonomic tool for AutoCAD.” In: Mattila, M., Karkowski, W. (Eds.), *Computer Applications in Ergonomics, Occupational Safety and Health*. Elsevier, Amsterdam, Netherlands, pp. 121–128.

Leung, M. Y., Chan, I. Y. S., and Yu, J. (2012). “Preventing construction worker injury incidents through the management of personal stress and organizational stressors.” *Accident Analysis & Prevention*, 48, 156-166.

Levanon, Y., Lerman, Y., Gefen, A., and Ratzon, N.Z. (2014). “Validity of the modified RULA for computer workers and reliability of one observation compared to six.” *Ergonomics*, 57(12), 1856-1863.

Li, C. and Lee, S. (2011). “Computer vision techniques for worker motion analysis to reduce musculoskeletal disorders in construction.” *Proceeding of 2011 ASCE International Workshop on Computing in Civil Engineering*, Florida, USA, June 19–22, pp. 380–387.

Li, G., and Buckle, P. (1999). “Current techniques for assessing physical exposure to work-related musculoskeletal risks, with emphasis on posture-based methods.” *Ergonomics*, 42(5), 674-695.

Li, H.X., Al-Hussein, M., Lei, Z., and Ajweh, Z. (2013). “Risk identification and assessment of modular construction utilizing fuzzy analytic hierarchy process (AHP) and simulation.” *Canadian Journal of Civil Engineering*, 40(12), 1184-1195.

Liu, M., Han, S. and Lee, S. (2016). “Tracking-based 3D Human Skeleton Extraction from Stereo Video Camera toward an On-site Safety and Ergonomic Analysis.” *Construction Innovation*, 16 (3), 348-367.

Livingston, M. A., Sebastian, J., Ai, Z., & Decker, J. W. (2012). “Performance measurements for the Microsoft Kinect skeleton.” *Proceedings of the 2012 IEEE Virtual Reality Workshops (VRW)*, Costa Mesa, CA, USA, March 4-8, 119-120.

Lopez, C. and Gilkey, D. (2014). “Injuries among construction workers: An exploratory study.” *Proceedings of the 50th ASC Annual International Conference*.

Love, P. E., Mandal, P., and Li, H. (1999). “Determining the causal structure of rework influences in construction.” *Construction Management & Economics*, 17(4), 505-517.

Lu, M. (2003). “Simplified Discrete-event Simulation Approach for Construction Simulation.” *Journal of Construction Engineering and Management*, 129(5), 537-546.

Maloney, W. F. (1983). “Productivity improvement: The influence of labor.” Journal of Construction Engineering and Management, 10.1061/(ASCE)0733-9364(1983)109:3(321), 321-334.

Marras, W. S. and Radwin, R. G. (2005). “Biomechanical modeling.” *Reviews of Human Factors and Ergonomics*, 1(1), 1–88.

Martin, C. C., Burkert, D. C., Choi, K. R., Wieczorek, N. B., McGregor, P. M., R. A. Herrmann, and Beling, P. A. (2012). “A real-time ergonomic monitoring system using the Microsoft Kinect.” *Proceedings of the IEEE Systems and Information Engineering Design Symposium*, Charlottesville, VA, Apr. 27, 50–55.

Martinez, J. C. (1996). *STROBOSCOPE – State and resource based simulation of construction processes* (Doctoral dissertation). University of Michigan, Ann Arbor, MI.

Marzouk, M., Said, H., and El-Said, M. (2008). “Special-purpose simulation model for balanced cantilever bridges.” Journal of Bridge Engineering, 10.1061/(ASCE)1084-0702(2008)13:2(122), 122-131.

Maynard, H. B., Stegemerten, G. J. and Schwab, J. L. (1948). *Methods-time measurement*. McGraw-Hill, New York, NY, USA.

McAtamney, L., and Corlett, E.N. (1993). “RULA: A survey method for the investigation of work-related upper limb disorders.” *Applied Ergonomics*, 24, 91–99.

McGee, R., Bevan, S., and Quadrello, T. (2011). Fit for work? Musculoskeletal disorders and the Canadian labor market (Report 2). Ottawa: The Work Foundation, Conference Board of Canada.

McLain, D.L. and Jarrell, K.A. (2007). “The perceived compatibility of safety and production expectations in hazardous occupations.” *Journal of Safety Research*, 38(3), 299-309.

Mehta, R. K. (2016). “Integrating Physical and Cognitive Ergonomics”, *IIE Transactions on Occupational Ergonomics and Human Factors*, Vol. 4 , Iss. 2-3, pp 83-87.

Mehta, R. K., and Agnew, M. J. (2010). “Analysis of individual and occupational risk factors on task performance and biomechanical demands for a simulated drilling task.” *International Journal of Industrial Ergonomics*, 40(5), 584-591.

Meredith, M. and Maddock, S. (2001). *Motion capture file formats explained*. Department of Computer Science, University of Sheffield.

MeshLab (2011). Visual Computing Lab - ISTI – CNR. <http://meshlab.sourceforge.net/>

Mitropoulos, P., Abdelhamid, T. S., and Howell, G. A. (2005). "Systems model of construction accident causation." *Journal of Construction Engineering and Management*, 131(7), 816-825.

Mitropoulos, P., and Cupido, G. (2009). "Safety as an emergent property: investigation into the work practices of high-reliability framing crews." *Journal of Construction Engineering and Management*, 135(5), 407-415.

Molen, H. F. van der, Sluiter, J. K., Hulshof, C. T., Vink, P., Duivenbooden, C. van, Holman, R., and Frings-Dresen, M. H. (2005). "Implementation of participatory ergonomics intervention in construction companies." *Scandinavian journal of work, environment & health*, 191-204.

Mollard, R., Ledunois, S., Ignazi, G., and Coblentz, A. (1992). "Researches and developments on postures and movements using CAD techniques and ERGODATA." In: Mattila, M., Karkowski, W. (Eds.), *Computer Applications in Ergonomics, Occupational Safety and Health*. Elsevier, Amsterdam, Netherlands, pp. 337–343.

Moore, S.J., and Garg, A. (1995). "The strain index: a proposed method to analyze jobs for risk of distal upper extremity disorders." *American Industrial Hygiene Association Journal*, 56(5), 443-458.

Motwani, J., Kumar, A., and Novakoski, M. (1995). "Measuring construction productivity: A practical approach." International Journal of Productivity and Performance Management, 10.1108/00438029510103310, 44(8), 18–20.

Mukaka, M. (2012). "A guide to appropriate use of correlation coefficient in medical research." Malawi Medical Journal, 24(3), 69–71.

Muqeem, S., Idrus, A., Khamidi, M. F., Ahmad, J. B., and Zakaria, S. B. (2012). "Construction labor production rates modeling using artificial neural network." *Journal of Information Technology in Construction (ITcon)*, 16(42), 713-726.

Nasirzadeh, F. and Nojedehi, P. (2013). "Dynamic modeling of labor productivity in construction projects." International Journal of Project Management, 10.1016/j.ijproman.2012.11.003, 31(6), 903-911.

Nasirzadeh, F., Afshar, A., Khanzadi, M., and Howick, S. (2008). "Integrating system dynamics and fuzzy logic modeling for construction risk management." *Construction Management and Economics*, 26(11), 1197-1212.

Nayar, N. (1995). "Deneb/ERGO: A simulation based human factors tool." *Proceedings of the Winter Simulation Conference*, Arlington, VA, Dec. 3-6, 427–431.

NIOSH (1997). *Musculoskeletal disorders and workplace factors: A critical review of epidemiologic evidence for work-related musculoskeletal disorders of the neck, upper extremity, and lower back*. Bernard B. P., editor, U.S. Department of Health and Human Services, Centers for Disease control and Prevention, National Institute of Occupational Safety and Health. July 1997. DHHS Publication No. 97-141.

NIOSH (2004). *Workers health chart book*. NIOSH Publication No. 2004-146. Washington, D.C.

NIOSH (2014). *Observation-based posture assessment: review of current practice and recommendations for improvement*. By Lowe BD, Weir PL, Andrews DM. Cincinnati, OH: U.S. Department of Health and Human Services, Centers for Disease Control and Prevention, National Institute for Occupational Safety and Health, DHHS (NIOSH) Publication No. 2014–131.

NIOSH. (2014). *Observation-based posture assessment: review of current practice and recommendations for improvement*. By Lowe BD, Weir PL, Andrews DM. Cincinnati, OH: U.S. Department of Health and Human Services, Centers for Disease Control and Prevention, National Institute for Occupational Safety and Health, DHHS (NIOSH) Publication No. 2014–131.

NRCIM (2001). *Musculoskeletal disorders and the workplace: low back and upper extremities. Panel on Musculoskeletal Disorders and the Workplace.* National Research Council and the Institute of Medicine (NRCIM). Commission on Behavioral and Social Sciences and Education. Washington, DC: National Academy Press.

Nussbaum, M. A., Shewchuk, J. P., Kim, S., Seol, H., and Guo, C. (2009). "Development of a decision support system for residential construction using panellised walls: Approach and preliminary results." *Ergonomics*, 52(1), 87–103.

Occhipinti, E. (1998). "OCRA: A concise index for assessment of exposure to repetitive movements of the upper limbs." *Ergonomics*, 41(9), 1290–1311.

OHS. (2017). *2016 Workplace Injury, Disease and Fatality Statistics Provincial Summary*. Occupational Health and Safety (OHS), Ministry of Labor, Government of Alberta.

OHS. (2012). *Occupational injuries and diseases in Alberta: Lost-time claims, disabling injury claims and claim rates*. Occupational Health and Safety (OHS), Human Services, Government of Alberta.

Oleske, D.M., Lavender, S.A., Andersson, G.B., Morrissey, M.J., Zold-Kilbourn, P., Allen, C., and Taylor, E. (2006). "Risk factors for recurrent episodes of work-related low back disorders in an industrial population." *Spine* 31, 789-798.

OSHA. (2014). *Fatal occupational injuries by selected characteristics 2003-2014*, Occupational Safety & Health Administration (OSHA), United States Department of Labor. <http://www.bls.gov/iif/oshwc/cfoi/all_worker.pdf> (accessed 27 July 2016).

Ozcan-Deniz, G., and Y. Zhu. (2015). "A Multi-objective Decision-support Model for Selecting Environmentally Conscious Highway Construction Methods." *Journal of Civil Engineering and Management*, 21(6):733-747.

Palaniappan, S., Sawhney, A., Bashford, H. H., and Walsh, K. D. (2007). "Special purpose simulation template for workflow analysis in construction." *Proceedings of the Winter Simulation Conference*, pp. 2090-2098.

Park, M., and Peña-Mora, F. (2003). "Dynamic change management for construction: introducing the change cycle into model-based project management." *System Dynamics Review*, 19(3), 213-242.

Patil, S. S., B. M. Shinde, R. S. Katikar, and M. V. Kavade. (2004). "MOST an Advanced Technique to Improve Productivity." *Proceedings of the National Conference on Recent Trends in CAD/CAM/CAE (NCRTC-2004)*. R.I.T., Rajaramnagar.

Perez-Perez, Y., Golparvar-Fard, M., and El-Rayes, K. (2016). "Semantic and Geometric Labeling for Enhanced 3D Point Cloud Segmentation." *Proceedings of the 2016 Construction Research Congress (CRC)*, San Juan, Puerto Rico, May 31 – June 2, pp. 2542-2552.

Pettré, J., Siméon, T., and Laumond, J. P. (2002). "Planning human walk in virtual environments." *Proceedings of the International Conference on Intelligent Robots and Systems*, Vol. 3, pp. 3048-3053.

Porter, J. M., Freer, M., Case, K., and Bonney, M. C. (1995). "Computer aided ergonomics and workspace design." In: Wilson, J. R., Corlett, E. N. (Eds.), *Evaluation of Human Work: A Practical Ergonomics Methodology*, 2nd Edition. Taylor and Francis, London, UK, pp. 574–620.

Poveda, C.A., and Fayek, A. Robinson. (2009). "Predicting and evaluating construction trades foremen performance: Fuzzy logic approach." *Journal of Construction Engineering and Management*, 135(9), 920-929.

Probst, T. and Brubaker, T. (2007). "Organizational safety climate and supervisory layoff decisions: Preferences versus predictions." *Journal of Applied Social Psychology*, 37(7), 1630-1648.

Punnett, L., and Wegman, D. H. (2004). "Work-related musculoskeletal disorders: the epidemiologic evidence and the debate." *Journal of electromyography and kinesiology*, 14(1), 13-23.

Rafibakhsh, N., Gong, J., Siddiqui, M. K., Gordon, C., and Lee, H. F. (2012). “Analysis of xbox kinect sensor data for use on construction sites: depth accuracy and sensor interference assessment.” *Proceedings of 2012 Construction Research Congress (CRC)*, West Lafayette, IN, USA, May 21-23, 848–857.

Rashidi, A., Brilakis, I., and Vela, P. (2015). “Generating absolute-scale point cloud data of built infrastructure scenes using a monocular camera setting.” *Journal of Computing in Civil Engineering*, 29(6), 04014089.

Ray, S.J. and Teizer, J. (2012). “Real-time construction worker posture analysis for ergonomics training.” *Advanced Engineering Informatics*, 26(2), 439–456.

Remondino, F., and El-Hakim, S. (2006). “Image-based 3D modeling: A review.” *The Photogrammetric Record*, 21(115), 269-291.

Rodrigues, A. G., and Williams, T. M. (1998). “System dynamics in project management: assessing the impacts of client behaviour on project performance.” *Journal of the Operational Research Society*, 2-15.

Rojas, E. M., and Aramvareekul, P. (2003). “Labor productivity drivers and opportunities in the construction industry.” *Journal of Management in Engineering*, 10.1061/(ASCE)0742-597X(2003)19:2(78), 78-82.

RS Means (2007). *About RS Means*. <http://www.rsmeans.com/index.asp> (December 2015).

Russell, J. S., and Skibniewski, M. J. (1990). “An ergonomic analysis framework for construction tasks.” *Construction management and economics*, 10.1080/01446199000000027, 8(3), 329-338.

Ruwanpura, J. Y., AbouRizk, S. M., Er, K. C., and Fernando, S. (2001). “Special purpose simulation templates for tunnel construction operations.” *Canadian Journal of Civil Engineering*, 10.1139/l00-101, 28(2), 222-237.

Rwamamara, R., Norberg, H., Olofsson, T., and Lagerqvist, O. (2010). “Using visualization technologies for design and planning of a healthy construction workplace.” *Construction Innovation*, 10(3), 248–266

Sawhney, A., AbouRizk, S. M., and Halpin, D. W. (1998). “Construction project simulation using CYCLONE.” *Canadian Journal of Civil Engineering*, Vol. 25, No. 1, 16-25.

Schneider, S. P. (2001). “Musculoskeletal injuries in construction: a review of the literature.” *Applied Occupational and Environmental Hygiene*, 16(11), 1056–1064.

Schulte, P. A., Rinehart, R., Okun, A., Geraci, C. L., and Heidel, D. S. (2008). “National prevention through design (PtD) initiative.” *Journal of safety research*, 39(2), 115-121.

Seidl, A. (1997). “RAMSIS: A new CAD-tool for ergonomic analysis of vehicles developed for the German automotive industry.” *Automotive Concurrent/Simultaneous Engineering SAE Special Publications*, Vol. 1233, 51–57.

Sengupta, A. K., and Das, B. (1997). “Human: An AutoCAD based three dimensional anthropometric human model for workstation design.” *International Journal of Industrial Ergonomics*, 19(5), 345–352.

Seo, J., Lee, S., and Seo, J. (2016). “Simulation-Based Assessment of Workers’ Muscle Fatigue and Its Impact on Construction Operations.” *Journal of Construction Engineering and Management*, 10.1061/(ASCE)CO.1943-7862.0001182, 04016063.

Seo, J., Lee, S., Armstrong, T. J., and Han, S. (2013). “Dynamic biomechanical simulation for identifying risk factors for work-related musculoskeletal disorders during construction tasks.” *Proceedings of the International Symposium on Automation and Robotics in Construction and Mining (ISARC)*, Montréal, Canada, Aug. 11-15, 1074-1084.

Seo, J., Starbuck, R., Han, S., Lee, S., and Armstrong, T. J. (2014). “Motion data-driven biomechanical analysis during construction tasks on sites.” *Journal of Computing in Civil Engineering*, 29(4), 10.1061/(ASCE)CP.1943-5487.0000400, B4014005.

Sharpe, A., and Hardt, J. (2006). *Five Deaths a Day: Workplace Fatalities in Canada, 1993-2005*, CSLS Research Paper, Center for the Study of Living Standards.

Shikdar, A.A., and Sawaqed, N.M. (2003). “Worker productivity and occupational health and safety issues in selected industries.” *Computers & Industrial Engineering*, 45(4), 563-72.

Shin, M., Lee, H. S., Park, M., Moon, M., and Han, S. (2014). “A system dynamics approach for modeling construction workers’ safety attitudes and behaviors.” *Accident Analysis & Prevention*, Vol. 68, 95-105.

Smith, S. D. (1999). “Earthmoving productivity estimation using linear regression techniques.” *Journal of Construction Engineering and Management*, 10.1061/(ASCE)0733-9364(1999)125:3(133), 133-141.

Song, L. and AbouRizk, S. (2008). “Measuring and modeling labor productivity using historical data.” *Journal of Construction Engineering and Management*, 10.1061/(ASCE)0733-9364(2008)134:10(786), 786-794.

Sonmez, R. and Rowings, J. E. (1998). “Construction labor productivity modeling with neural networks.” *Journal of Construction Engineering and Management*, 10.1061/(ASCE)0733-9364(1998)124:6(498), 498-504.

Spearman, C. (1904). “The proof and measurement of association between two things.” *American Journal of Psychology*, 10.2307/1412159, 15(1), 72–101.

Spielholz, P., Silverstein, B., Morgan, M., Checkoway, H., and Kaufman, J. (2001). “Comparison of self-report, video observation and direct measurement methods for upper extremity musculoskeletal disorder physical risk factors.” *Ergonomics*, 44(6), 588-613.

Starbuck, R., Seo, J., Han, S., and Lee, S. (2014). “A stereo vision-based approach to marker-less motion capture for on-site kinematic modeling of construction worker tasks.” *Proceedings of Computing in Civil and Building Engineering*, pp. 1094-1101.

Stoyanov, T., Louloudi, A., Andreasson, H., and Lilienthal, A. J. (2011). “Comparative evaluation of range sensor accuracy in indoor environments.” *Proceedings of 5th European Conference on Mobile Robots (ECMR)*, September 7-9, 2011, Örebro, Sweden, 19-24.

Sun, X. F., Cheng, G., and Li, W. (2009). “Study on work improvement in a packaging machine manufacturing company.” *Proceedings of the 16th International Conference on Industrial Engineering and Engineering Management*, 10.1109/ICIEEM.2009.5344458, pp. 1155-1159.

Tak, S., Buchholz, B., Punnett, L., Moir, S., Paquet, V., Fulmer, S., Marucci-Wellman, H. and Wegman, D. (2011). “Physical ergonomic hazards in highway tunnel construction: overview from the Construction Occupational Health Program.” *Applied ergonomics*, 42(5), 665-671.

Takala, E.P., Pehkonen, I., Forsman, M., Hansson, G.Å., Mathiassen, S.E., Neumann, W. P., Sjøgaard, G., Veiersted, K.B., Westgaard, R.H., and Winkel, J. (2010). “Systematic evaluation of observational methods assessing biomechanical exposures at work.” *Scandinavian Journal of Work, Environment & Health*, 36(1), 3-24.

Tang, P., D. Huber, B. Akinci, R. Lipman, and A. Lytle. (2010). “Automatic Reconstruction of As-built Building Information Models from Laser-scanned Point Clouds: A Review of Related Techniques.” *Automation in Construction*, 19(7):829-843.

Taylor, G. W., Hinton, G. E., and Roweis, S. T. (2007). “Modeling human motion using binary latent variables.” *Advances in neural information processing systems*, 19, 1345.

Thakre, A. R., Jolhe, D., and Gawande, A. C. (2009). “Minimization of engine assembly time by elimination of unproductive activities through ‘MOST’.” *Proceedings of the 2nd International Conference on Emerging Trends in Engineering and Technology (ICETET)*, 10.1109/ICETET.2009.149, pp. 785-789.

Thomas, H. (2014). “Benchmarking construction labor productivity.” *Practice Periodical on Structural Design and Construction*, 20(4), 10.1061/(ASCE)SC.1943-5576.0000141, 04014048.

Thomas, H. R., Maloney, W. F., Horner, R. M. W., Smith, G. R., Handa, V. K., and Sanders, S. R. (1990). “Modeling construction labor productivity.” *Journal of Construction Engineering and Management*, 10.1061/(ASCE)0733-9364(1990)116:4(705), 705-726.

Toole, T. M., and Gambatese, J. (2008). “The trajectories of prevention through design in construction*.” Journal of Safety Research*, 39(2), 225-230.

Tran D., and Sorokin, A. (2008). “Human Activity Recognition with Metric Learning.” *Computer Vision–ECCV*, 548-561.

Tuan, S. T., A. N. M. Karim, H. E. Kays, A. K. M. N. Amin, and M. H. Hasan. (2014). “Improvement of Workflow and Productivity through Application of Maynard Operation Sequence Technique (MOST).” *Proceedings of the 2014 International Conference on Industrial Engineering and Operations Management*, Bali, Indonesia, January 7-9.

Valsangkar, S., and Sai, K. S. (2012). “Impact of musculoskeletal disorders and social determinants on health in construction workers.” *International Journal Of Biological and Medical Research*, 3(2), 1727–1730.

van Deursen, J., de Looze, M. P., van Rhijn, J. W., van der Grinten, M. P., and Schoenmaker, N. (2005). *Productivity and discomfort in assembly work: the effect of an ergonomic workplace adjustment at Philips DAP. Comfort and design: principles and good practice*, CRC Press.

Vogl, B. and Abdel-Wahab, M. (2014). “Measuring the construction industry’s productivity performance: Critique of International Productivity Comparisons at Industry Level.” *Journal of Construction Engineering and Management*, 10.1061/(ASCE)CO.1943-7862.0000944, 04014085.

Wanberg, J., Harper, C., Hallowell, M. R., and Rajendran, S. (2013). “Relationship between construction safety and quality performance.” *Journal of Construction Engineering and Management*, 139(10), 04013003.

Wang, D., Dai, F., and Ning, X. (2015). “Risk assessment of work-related musculoskeletal disorders in construction: state-of-the-art review.” *Journal of Construction Engineering and management*, 141(6), 04015008.

Wang, S. and Halpin, D. W. (2004). “Simulation experiment for improving construction processes.” *Proceedings of the Winter Simulation Conference*, Washington, DC, USA, Dec. 5-8, pp. 1252-1259.

Waters, T. R., Putz-Anderson, V., Garg, A., and Fine, L. J. (1993). “Revised NIOSH equation for the design and evaluation of manual lifting tasks.” *Ergonomics*, 36(7), 749-776.

Waters, T., Putz-Anderson, V., Garg, A., Fine, L. (1993). “Revised NIOSH equation for the design and evaluation of manual lifting tasks.” *Ergonomics*, 36, 749–766.

Weerasinghe, I. T., Ruwanpura, J. Y., Boyd, J. E., and Habib, A. F. (2012). “Application of Microsoft Kinect sensor for tracking construction workers.” *Proceedings of 2012 Construction Research Congress (CRC)*, West Lafayette, IN, USA, May 21-23, 858-867.

Wei, X., Min, J., and Chai, J. (2011). Physically valid statistical models for human motion generation. *ACM Transactions on Graphics (TOG)*, 30(3), 19.

Weinstein, M., Gambatese, J., and Hecker, S. (2005). “Can design improve construction safety? Assessing the impact of a collaborative safety-in-design process.” *Journal of Construction Engineering and Management*, 131(10), 1125-1134.

Wells, R., Mathiassen, S. E., Medbo, L., and Winkel, J. (2007). “Time—a Key Issue for Musculoskeletal Health and Manufacturing.” *Applied Ergonomics*, 38(6):733-744.

WHO. (2003). *The Burden of Musculoskeletal Conditions at the Start of the New Millennium*, World Health Organization (WHO) Scientific Group, Geneva. < http://apps.who.int/iris/bitstream/10665/42721/1/WHO_TRS_919.pdf > (July 8, 2016).

Work Safe Alberta. (2012). *Occupational Injuries and Diseases in Alberta, Lost-Time Claims, Disabling Injury Claims and Claim Rates, 2011 Summary*. Alberta Human Services [online]. Available from https://work.alberta.ca/documents/2011-Occupational-Injuries-Diseases-Alberta-Summary.pdf [accessed 10 October 2015].

WSIB. (2014). *By the Numbers: 2013 WSIB Statistical Report-Schedule 1*. Workplace Safety & Insurance Board (WSIB).

Wu, C. (2011). Visualsfm: A Visual Structure from Motion System. <http://www.cs.washington.edu/homes/ccwu/vsfm.>

Wu, H., Marshall, A., and Yu, W. (2007). “Path planning and following algorithms in an indoor navigation model for visually impaired.” *Proceedings of the* Sec*ond International Conference on Internet Monitoring and Protection*, 10.1109/ICIMP.2007.31.

Xu, R. Y., Sun, Z. L., Gao, H. W., Wang, R., Liu, X. J., and Wang, L. H. (2013). “The discussion on the application of Modapts about improving the pipeline of plastic enterprise.” *Proceedings of the 20th International Conference on Industrial Engineering and Engineering Management*, 10.1007/978-3-642-40063-6_9, pp. 91-97, Springer.

Yang, I., Hsieh, Y., and Kung, L. (2012). “Parallel Computing Platform for Multiobjective Simulation Optimization of Bridge Maintenance Planning.” *Journal of Construction Engineering and Management*, 138(2):215-226.

Yang, M. D., Chao, C. F., Huang, K. S., Lu, L. Y., and Chen, Y. P. (2013). “Image-based 3D scene reconstruction and exploration in augmented reality.” *Automation in Construction*, 33, 48-60.

Yao, J., Lin, C., Xie, X., Wang, A. J., and Hung, C. C. (2010). “Path planning for virtual human motion using improved A* star algorithm.” *Proceedings of the Seventh International Conference on Information Technology: New Generations (ITNG)*, April 12-14, Las Vegas, Nevada, USA, pp. 1154-1158. IEEE.

Yi, W. and Chan, A. (2014). “Critical review of labor productivity research in construction journals.” *Journal of Management in Engineering*, 10.1061/(ASCE)ME.1943-5479.0000194, 214-225.

Zadeh, L. A. (1975). “The concept of a linguistic variable and its application to approximate reasoning-II.” *Information Sciences*, 8(4), 301-357.

Zadeh, L.A. (1965). “Fuzzy sets”. *Information and control*, 8(3), 338-353.

Zandin. K. (1980). *MOST: Work Measurement Systems*. Dekker, New York, NY, USA.

Zhang, S., Teizer, J., Lee, J. K., Eastman, C. M., and Venugopal, M. (2013). “Building information modeling (BIM) and safety: Automatic safety checking of construction models and schedules.” *Automation in Construction*, 29, 183-195.

Zhou, Z., Goh, Y. M., and Li, Q. (2015). Overview and analysis of safety management studies in the construction industry. *Safety science*, 72, 337-350.

Zhou, F., S. M. AbouRizk, and H. Al-Battaineh. (2009). “Optimisation of Construction Site Layout using a Hybrid Simulation-based System.” *Simulation Modeling Practice and Theory*, 17(2), 348-363.

Zhu, Z., and Donia, S. (2013). “Potentials of RGB-D Cameras in As-Built Indoor Environment Modeling.” *Proceedings of the International Workshop on Computing in Civil Engineering*, pp. 605-612, ASCE.

Appendix A Sample Motion Capture Data of a Masonry Task

The following shows the first 10 frames of a masonry operation in the BVH format, captured using a Kinect sensor.

```
HIERARCHY
ROOT Hip
{
OFFSET    0.0000    0.0000    0.0000
CHANNELS 6 Xposition Yposition Zposition Xrotation Yrotation Zrotation
JOINT LowerSpine
{
OFFSET    0.0000    9.7640    -5.2837
CHANNELS 3 Xrotation Yrotation Zrotation
JOINT MiddleSpine
{
OFFSET    0.0000    8.9104    0.4655
CHANNELS 3 Xrotation Yrotation Zrotation
JOINT Chest
{
OFFSET    0.0000    11.0255   -2.4542
CHANNELS 3 Xrotation Yrotation Zrotation
JOINT Neck
{
OFFSET    0.0000    24.8457   -0.5167
CHANNELS 3 Xrotation Yrotation Zrotation
JOINT Head
{
OFFSET    -0.0001   14.0307   3.8164
CHANNELS 3 Xrotation Yrotation Zrotation
End Site
{
OFFSET    0.0001    19.6043   0.5853
}}}
JOINT LClavicle
{
OFFSET    2.5084    23.9774   8.2148
CHANNELS 3 Xrotation Yrotation Zrotation
JOINT LShoulder
```

```
{
OFFSET    14.6543   3.4392     -5.5650
CHANNELS 3 Xrotation Yrotation Zrotation
JOINT LForearm
{
OFFSET    31.1286   -0.1104    -0.2698
CHANNELS 3 Xrotation Yrotation Zrotation
JOINT LHand
{
OFFSET    25.9679   0.0753     -0.1556
CHANNELS 3 Xrotation Yrotation Zrotation
JOINT LFinger1
{
OFFSET    10.0644   0.8802     2.7954
CHANNELS 3 Xrotation Yrotation Zrotation
JOINT LFinger11
{
OFFSET    3.7646    -0.9180    0.6633
CHANNELS 3 Xrotation Yrotation Zrotation
JOINT LFinger12
{
OFFSET    2.5700    -0.6268    0.4530
CHANNELS 3 Xrotation Yrotation Zrotation
End Site
{
OFFSET    1.8288    -0.5459    0.2966
}}}}
JOINT LFinger2
{
OFFSET    10.2146   1.0165     0.2434
CHANNELS 3 Xrotation Yrotation Zrotation
JOINT LFinger21
{
OFFSET    4.6547    0.0130     -0.0275
CHANNELS 3 Xrotation Yrotation Zrotation
JOINT LFinger22
{
OFFSET    2.5801    0.0079     -0.0157
CHANNELS 3 Xrotation Yrotation Zrotation
```

```
End Site
{
OFFSET    2.3174    -0.1636   0.0031
}}}}
JOINT LFinger3
{
OFFSET    9.6805    0.6784    -2.2902
CHANNELS 3 Xrotation Yrotation Zrotation
JOINT LFinger31
{
OFFSET    4.2237    -0.2138   -0.2644
CHANNELS 3 Xrotation Yrotation Zrotation
JOINT LFinger32
{
OFFSET    2.4069    -0.1211   -0.1512
CHANNELS 3 Xrotation Yrotation Zrotation
End Site
{
OFFSET    2.1281    -0.2616   -0.1006
}}}}
JOINT LFinger4
{
OFFSET    8.9831    -0.6826   -3.9552
CHANNELS 3 Xrotation Yrotation Zrotation
JOINT LFinger41
{
OFFSET    2.5980    -0.5418   -0.7172
CHANNELS 3 Xrotation Yrotation Zrotation
JOINT LFinger42
{
OFFSET    1.9051    -0.3967   -0.5262
CHANNELS 3 Xrotation Yrotation Zrotation
End Site
{
OFFSET    1.6909    -0.4646   -0.3879
}}}}
JOINT LFinger0
{
OFFSET    2.0820    -1.5758   1.5784
```

```
CHANNELS 3 Xrotation Yrotation Zrotation
JOINT LFinger01
{
OFFSET 3.8763 -1.2730 2.9225
CHANNELS 3 Xrotation Yrotation Zrotation
JOINT LFinger02
{
OFFSET 2.5525 -0.9134 1.8390
CHANNELS 3 Xrotation Yrotation Zrotation
End Site
{
OFFSET 1.8770 -0.6461 1.2853
}}}}}}}}
JOINT RClavicle
{
OFFSET -2.5084 23.9774 8.2148
CHANNELS 3 Xrotation Yrotation Zrotation
JOINT RShoulder
{
OFFSET -14.6569 3.4398 -5.5659
CHANNELS 3 Xrotation Yrotation Zrotation
JOINT RForearm
{
OFFSET -31.1286 -0.1103 -0.2697
CHANNELS 3 Xrotation Yrotation Zrotation
JOINT RHand
{
OFFSET -25.9679 0.0753 -0.1555
CHANNELS 3 Xrotation Yrotation Zrotation
JOINT RFinger1
{
OFFSET -10.0645 0.8803 2.7954
CHANNELS 3 Xrotation Yrotation Zrotation
JOINT RFinger11
{
OFFSET -3.7646 -0.9180 0.6633
CHANNELS 3 Xrotation Yrotation Zrotation
JOINT RFinger12
{
```

```
OFFSET	-2.5700	-0.6270	0.4530
CHANNELS 3 Xrotation Yrotation Zrotation
End Site
{
OFFSET	-1.8288	-0.5459	0.2966
}}}}
JOINT RFinger2
{
OFFSET	-10.2146 1.0165	0.2434
CHANNELS 3 Xrotation Yrotation Zrotation
JOINT RFinger21
{
OFFSET	-4.6547	0.0130	-0.0275
CHANNELS 3 Xrotation Yrotation Zrotation
JOINT RFinger22
{
OFFSET	-2.5801	0.0079	-0.0158
CHANNELS 3 Xrotation Yrotation Zrotation
End Site
{
OFFSET	-2.3174	-0.1636	0.0031
}}}}
JOINT RFinger3
{
OFFSET	-9.6805	0.6784	-2.2903
CHANNELS 3 Xrotation Yrotation Zrotation
JOINT RFinger31
{
OFFSET	-4.2237	-0.2138	-0.2644
CHANNELS 3 Xrotation Yrotation Zrotation
JOINT RFinger32
{
OFFSET	-2.4069	-0.1211	-0.1512
CHANNELS 3 Xrotation Yrotation Zrotation
End Site
{
OFFSET	-2.1281	-0.2617	-0.1006
}}}}
JOINT RFinger4
```

```
{
OFFSET    -8.9831    -0.6826    -3.9552
CHANNELS 3 Xrotation Yrotation Zrotation
JOINT RFinger41
{
OFFSET    -2.5980    -0.5418    -0.7172
CHANNELS 3 Xrotation Yrotation Zrotation
JOINT RFinger42
{
OFFSET    -1.9051    -0.3966    -0.5262
CHANNELS 3 Xrotation Yrotation Zrotation
End Site
{
OFFSET    -1.6909    -0.4646    -0.3879
}}}}
JOINT RFinger0
{
OFFSET    -2.0820    -1.5757    1.5782
CHANNELS 3 Xrotation Yrotation Zrotation
JOINT RFinger01
{
OFFSET    -3.8762    -1.2732    2.9226
CHANNELS 3 Xrotation Yrotation Zrotation
JOINT RFinger02
{
OFFSET    -2.5524    -0.9132    1.8389
CHANNELS 3 Xrotation Yrotation Zrotation
End Site
{
OFFSET    -1.8770    -0.6461    1.2853
}}}}}}}}}}}
JOINT RThigh
{
OFFSET    -10.4451  4.4136     -0.8609
CHANNELS 3 Xrotation Yrotation Zrotation
JOINT RShin
{
OFFSET    -0.8358    -45.4312  0.0000
CHANNELS 3 Xrotation Yrotation Zrotation
```

```
JOINT RFoot
{
OFFSET	0.0000	-44.6107	0.0000
CHANNELS 3 Xrotation Yrotation Zrotation
JOINT RToe
{
OFFSET	0.0000	-4.9031	10.2531
CHANNELS 3 Xrotation Yrotation Zrotation
End Site
{
OFFSET	0.0000	0.0000	6.8784
}}}}}
JOINT LThigh
{
OFFSET	10.4449	4.4139	-0.8609
CHANNELS 3 Xrotation Yrotation Zrotation
JOINT LShin
{
OFFSET	0.8359	-45.4315	0.0000
CHANNELS 3 Xrotation Yrotation Zrotation
JOINT LFoot
{
OFFSET	0.0000	-44.6107	0.0000
CHANNELS 3 Xrotation Yrotation Zrotation
JOINT LToe
{
OFFSET	0.0000	-4.9031	10.2531
CHANNELS 3 Xrotation Yrotation Zrotation
End Site
{
OFFSET	0.0000	0.0000	6.8784
}}}}}}
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Frame Time: 0.0333333000
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Appendix B Implementation of the A* Algorithm

The following is an algorithm to implement the A* algorithm in MATLAB.

```
%START
%DEFINE MAP ARRAY
MAX_X=10;
MAX_Y=10;
MAX_VAL=10;
MAP=2*(ones(MAX_X,MAX_Y));

% Obtain Obstacle, Target and Robot Position
% Initialize the MAP with input values
% Obstacle=-1,Target=0,Robot=1,Space=2
j=0;
x_val = 1;
y_val = 1;
axis([1 MAX_X+1 1 MAX_Y+1])
grid on;
hold on;
n=0;%Number of Obstacles

% BEGIN Interactive Obstacle, Target, Start Location selection
pause(1);
h=msgbox('Please Select the Target using the Left Mouse button');
uiwait(h,5);
if ishandle(h) == 1
   delete(h);
end
xlabel('Please Select the Target using the Left Mouse button','Color','black');
but=0;
while (but ~= 1) %Repeat until the Left button is not clicked
   [xval,yval,but]=ginput(1);
end
xval=floor(xval);
yval=floor(yval);
```

```
xTarget=xval;%X Coordinate of the Target
yTarget=yval;%Y Coordinate of the Target

MAP(xval,yval)=0;%Initialize MAP with location of the target
plot(xval+.5,yval+.5,'gd');
text(xval+1,yval+.5,'Target')

pause(2);
h=msgbox('Select Obstacles using the Left Mouse button,to select the last obstacle use the Right button');
 xlabel('Select Obstacles using the Left Mouse button,to select the last obstacle use the Right button','Color','blue');
uiwait(h,10);
if ishandle(h) == 1
   delete(h);
end
while but == 1
   [xval,yval,but] = ginput(1);
   xval=floor(xval);
   yval=floor(yval);
   MAP(xval,yval)=-1;%Put on the closed list as well
   plot(xval+.5,yval+.5,'ro');
 end%End of While loop

pause(1);

h=msgbox('Please Select the Vehicle initial position using the Left Mouse button');
uiwait(h,5);
if ishandle(h) == 1
   delete(h);
end
xlabel('Please Select the Vehicle initial position ','Color','black');
but=0;
while (but ~= 1) %Repeat until the Left button is not clicked
   [xval,yval,but]=ginput(1);
   xval=floor(xval);
```

```
  yval=floor(yval);
end
xStart=xval;%Starting Position
yStart=yval;%Starting Position
MAP(xval,yval)=1;
 plot(xval+.5,yval+.5,'bo');
%End of obstacle-Target pickup

%LISTS USED FOR ALGORITHM
%OPEN LIST STRUCTURE
%--------------------------------------------------------------------------
%IS ON LIST 1/0 |X val |Y val |Parent X val |Parent Y val |h(n) |g(n)|f(n)|
%--------------------------------------------------------------------------
OPEN=[];
%CLOSED LIST STRUCTURE
%--------------
%X val | Y val |
%--------------
% CLOSED=zeros(MAX_VAL,2);
CLOSED=[];

%Put all obstacles on the Closed list
k=1;%Dummy counter
for i=1:MAX_X
  for j=1:MAX_Y
    if(MAP(i,j) == -1)
      CLOSED(k,1)=i;
      CLOSED(k,2)=j;
      k=k+1;
    end
  end
end
CLOSED_COUNT=size(CLOSED,1);
%set the starting node as the first node
xNode=xval;
```

```
yNode=yval;
OPEN_COUNT=1;
path_cost=0;
goal_distance=distance(xNode,yNode,xTarget,yTarget);
OPEN(OPEN_COUNT,:)=insert_open(xNode,yNode,xNode,yNode,path_cost,goal_distance,goal_distance);
OPEN(OPEN_COUNT,1)=0;
CLOSED_COUNT=CLOSED_COUNT+1;
CLOSED(CLOSED_COUNT,1)=xNode;
CLOSED(CLOSED_COUNT,2)=yNode;
NoPath=1;
% START ALGORITHM
while((xNode ~= xTarget || yNode ~= yTarget) && NoPath == 1)
%  plot(xNode+.5,yNode+.5,'go');
 exp_array=expand_array(xNode,yNode,path_cost,xTarget,yTarget,CLOSED,MAX_X,MAX_Y);
 exp_count=size(exp_array,1);
 %UPDATE LIST OPEN WITH THE SUCCESSOR NODES
 %OPEN LIST FORMAT
 %--------------------------------------------------------------------------
 %IS ON LIST 1/0 |X val |Y val |Parent X val |Parent Y val |h(n)|g(n)|f(n)|
 %--------------------------------------------------------------------------
 %EXPANDED ARRAY FORMAT
 %--------------------------------
 %|X val |Y val ||h(n) |g(n)|f(n)|
 %--------------------------------
 for i=1:exp_count
    flag=0;
    for j=1:OPEN_COUNT
        if(exp_array(i,1) == OPEN(j,2) && exp_array(i,2) == OPEN(j,3) )
            OPEN(j,8)=min(OPEN(j,8),exp_array(i,5));
            if OPEN(j,8)== exp_array(i,5)
                %UPDATE PARENTS,gn,hn
                OPEN(j,4)=xNode;
                OPEN(j,5)=yNode;
                OPEN(j,6)=exp_array(i,3);
                OPEN(j,7)=exp_array(i,4);
```

```
        end;%End of minimum fn check
        flag=1;
      end;%End of node check
%       if flag == 1
%           break;
    end;%End of j for
    if flag == 0
      OPEN_COUNT = OPEN_COUNT+1;

OPEN(OPEN_COUNT,:)=insert_open(exp_array(i,1),exp_array(i,2),xNode,yNode,exp_array(i,3),exp_array(i,4
),exp_array(i,5));
     end;%End of insert new element into the OPEN list
 end;%End of i for
 %END OF WHILE LOOP
 %Find out the node with the smallest fn
  index_min_node = min_fn(OPEN,OPEN_COUNT,xTarget,yTarget);
  if (index_min_node ~= -1)
   %Set xNode and yNode to the node with minimum fn
   xNode=OPEN(index_min_node,2);
   yNode=OPEN(index_min_node,3);
   path_cost=OPEN(index_min_node,6);%Update the cost of reaching the parent node
  %Move the Node to list CLOSED
  CLOSED_COUNT=CLOSED_COUNT+1;
  CLOSED(CLOSED_COUNT,1)=xNode;
  CLOSED(CLOSED_COUNT,2)=yNode;
  OPEN(index_min_node,1)=0;
  else
     %No path exists to the Target!!
     NoPath=0;%Exits the loop!
  end;%End of index_min_node check
end;%End of While Loop
%Once algorithm has run The optimal path is generated by starting of at the
%last node(if it is the target node) and then identifying its parent node
%until it reaches the start node. This is the optimal path
```

```
i=size(CLOSED,1);
Optimal_path=[];
xval=CLOSED(i,1);
yval=CLOSED(i,2);
i=1;
Optimal_path(i,1)=xval;
Optimal_path(i,2)=yval;
i=i+1;

if ( (xval == xTarget) && (yval == yTarget))
    inode=0;
   %Traverse OPEN and determine the parent nodes
   parent_x=OPEN(node_index(OPEN,xval,yval),4);%node_index returns the index of the node
   parent_y=OPEN(node_index(OPEN,xval,yval),5);

   while( parent_x ~= xStart || parent_y ~= yStart)
           Optimal_path(i,1) = parent_x;
           Optimal_path(i,2) = parent_y;
           %Get the grandparents:-)
           inode=node_index(OPEN,parent_x,parent_y);
           parent_x=OPEN(inode,4);%node_index returns the index of the node
           parent_y=OPEN(inode,5);
           i=i+1;
    end;
 j=size(Optimal_path,1);
 %Plot the Optimal Path!
 p=plot(Optimal_path(j,1)+.5,Optimal_path(j,2)+.5,'bo');
 j=j-1;
 for i=j:-1:1
  pause(.25);
  set(p,'XData',Optimal_path(i,1)+.5,'YData',Optimal_path(i,2)+.5);
 drawnow ;
 end;
 plot(Optimal_path(:,1)+.5,Optimal_path(:,2)+.5);
else
```

```
 pause(1);
 h=msgbox('Sorry, No path exists to the Target!','warn');
 uiwait(h,5);
end
```

Appendix C Action Recognition Dataset for the Steel Plate Handling Task

The following shows the results of action recognition from video recordings for one cycle of the steel plate handling task.

Ground truth	Predicted action	Correctness indicator	Frame id	Time stamp (min)	Time stamp (sec)
1	1	1	1691	0.0	56.4
1	1	1	1692	0.0	56.4
1	1	1	1693	0.0	56.4
1	1	1	1694	0.0	56.5
1	1	1	1695	0.0	56.5
1	1	1	1696	0.0	56.5
1	1	1	1697	0.0	56.6
1	1	1	1698	0.0	56.6
1	1	1	1699	0.0	56.6
1	1	1	1700	0.0	56.7
1	1	1	1701	0.0	56.7
1	1	1	1702	0.0	56.7
1	1	1	1703	0.0	56.8
1	1	1	1704	0.0	56.8
1	1	1	1705	0.0	56.8
1	1	1	1706	0.0	56.9
1	1	1	1707	0.0	56.9
1	1	1	1708	0.0	56.9
1	1	1	1709	0.0	57.0
1	1	1	1710	0.0	57.0
1	1	1	1711	0.0	57.0
1	1	1	1712	0.0	57.1
1	1	1	1713	0.0	57.1
1	1	1	1714	0.0	57.1
1	1	1	1715	0.0	57.2
1	1	1	1716	0.0	57.2
1	1	1	1717	0.0	57.2
1	1	1	1718	0.0	57.3
1	1	1	1719	0.0	57.3
1	1	1	1720	0.0	57.3
1	1	1	1721	0.0	57.4
1	1	1	1722	0.0	57.4
1	1	1	1723	0.0	57.4
1	1	1	1724	0.0	57.5
1	1	1	1725	0.0	57.5
1	1	1	1726	0.0	57.5

1	1	1	1727	0.0	57.6
1	1	1	1728	0.0	57.6
1	1	1	1729	0.0	57.6
1	1	1	1730	0.0	57.7
1	1	1	1731	0.0	57.7
1	1	1	1732	0.0	57.7
1	1	1	1733	0.0	57.8
1	1	1	1734	0.0	57.8
1	1	1	1735	0.0	57.8
1	1	1	1736	0.0	57.9
1	1	1	1737	0.0	57.9
1	1	1	1738	0.0	57.9
1	1	1	1739	0.0	58.0
1	1	1	1740	0.0	58.0
1	1	1	1741	0.0	58.0
1	1	1	1742	0.0	58.1
1	1	1	1743	0.0	58.1
1	1	1	1744	0.0	58.1
1	1	1	1745	0.0	58.2
1	1	1	1746	0.0	58.2
1	1	1	1747	0.0	58.2
1	1	1	1748	0.0	58.3
1	1	1	1749	0.0	58.3
1	1	1	1750	0.0	58.3
1	1	1	1751	0.0	58.4
1	1	1	1752	0.0	58.4
1	1	1	1753	0.0	58.4
1	1	1	1754	0.0	58.5
1	1	1	1755	0.0	58.5
1	1	1	1756	0.0	58.5
1	1	1	1757	0.0	58.6
1	1	1	1758	0.0	58.6
1	1	1	1759	0.0	58.6
1	1	1	1760	0.0	58.7
1	1	1	1761	0.0	58.7
1	1	1	1762	0.0	58.7
1	1	1	1763	0.0	58.8
1	1	1	1764	0.0	58.8
1	1	1	1765	0.0	58.8
1	1	1	1766	0.0	58.9
1	1	1	1767	0.0	58.9
1	1	1	1768	0.0	58.9
1	1	1	1769	0.0	59.0
1	1	1	1770	0.0	59.0

1	1	1	1771	0.0	59.0
1	1	1	1772	0.0	59.1
1	1	1	1773	0.0	59.1
1	1	1	1774	0.0	59.1
1	1	1	1775	0.0	59.2
1	1	1	1776	0.0	59.2
1	1	1	1777	0.0	59.2
1	1	1	1778	0.0	59.3
1	1	1	1779	0.0	59.3
1	1	1	1780	0.0	59.3
1	1	1	1781	0.0	59.4
1	1	1	1782	0.0	59.4
1	1	1	1783	0.0	59.4
1	1	1	1784	0.0	59.5
1	1	1	1785	0.0	59.5
1	1	1	1786	0.0	59.5
1	1	1	1787	0.0	59.6
1	1	1	1788	0.0	59.6
1	1	1	1789	0.0	59.6
1	1	1	1790	0.0	59.7
1	1	1	1791	0.0	59.7
1	1	1	1792	0.0	59.7
1	1	1	1793	0.0	59.8
1	1	1	1794	0.0	59.8
1	1	1	1795	0.0	59.8
1	1	1	1796	0.0	59.9
1	1	1	1797	0.0	59.9
1	1	1	1798	0.0	59.9
1	1	1	1799	0.0	60.0
1	1	1	1800	1.0	0.0
1	1	1	1801	1.0	0.0
1	1	1	1802	1.0	0.1
1	1	1	1803	1.0	0.1
1	1	1	1804	1.0	0.1
1	1	1	1805	1.0	0.2
1	1	1	1806	1.0	0.2
1	1	1	1807	1.0	0.2
1	1	1	1808	1.0	0.3
1	1	1	1809	1.0	0.3
1	1	1	1810	1.0	0.3
1	1	1	1811	1.0	0.4
1	1	1	1812	1.0	0.4
1	1	1	1813	1.0	0.4
1	1	1	1814	1.0	0.5

1	1	1	1815	1.0	0.5
1	1	1	1816	1.0	0.5
1	1	1	1817	1.0	0.6
1	1	1	1818	1.0	0.6
1	1	1	1819	1.0	0.6
1	1	1	1820	1.0	0.7
1	1	1	1821	1.0	0.7
1	1	1	1822	1.0	0.7
1	1	1	1823	1.0	0.8
1	1	1	1824	1.0	0.8
1	1	1	1825	1.0	0.8
1	1	1	1826	1.0	0.9
1	1	1	1827	1.0	0.9
1	1	1	1828	1.0	0.9
1	1	1	1829	1.0	1.0
1	1	1	1830	1.0	1.0
1	1	1	1831	1.0	1.0
1	1	1	1832	1.0	1.1
1	1	1	1833	1.0	1.1
1	1	1	1834	1.0	1.1
1	1	1	1835	1.0	1.2
1	1	1	1836	1.0	1.2
1	1	1	1837	1.0	1.2
1	1	1	1838	1.0	1.3
1	1	1	1839	1.0	1.3
1	1	1	1840	1.0	1.3
1	1	1	1841	1.0	1.4
1	1	1	1842	1.0	1.4
1	1	1	1843	1.0	1.4
1	1	1	1844	1.0	1.5
1	1	1	1845	1.0	1.5
1	1	1	1846	1.0	1.5
1	1	1	1847	1.0	1.6
1	1	1	1848	1.0	1.6
1	1	1	1849	1.0	1.6
1	1	1	1850	1.0	1.7
1	1	1	1851	1.0	1.7
1	1	1	1852	1.0	1.7
1	1	1	1853	1.0	1.8
1	1	1	1854	1.0	1.8
1	1	1	1855	1.0	1.8
1	1	1	1856	1.0	1.9
1	1	1	1857	1.0	1.9
1	1	1	1858	1.0	1.9

1	1	1	1859	1.0	2.0
1	1	1	1860	1.0	2.0
1	1	1	1861	1.0	2.0
1	1	1	1862	1.0	2.1
1	1	1	1863	1.0	2.1
1	1	1	1864	1.0	2.1
1	1	1	1865	1.0	2.2
1	1	1	1866	1.0	2.2
1	1	1	1867	1.0	2.2
1	1	1	1868	1.0	2.3
1	1	1	1869	1.0	2.3
1	1	1	1870	1.0	2.3
1	1	1	1871	1.0	2.4
1	1	1	1872	1.0	2.4
1	1	1	1873	1.0	2.4
1	1	1	1874	1.0	2.5
1	1	1	1875	1.0	2.5
1	1	1	1876	1.0	2.5
1	1	1	1877	1.0	2.6
1	1	1	1878	1.0	2.6
1	1	1	1879	1.0	2.6
1	1	1	1880	1.0	2.7
1	1	1	1881	1.0	2.7
1	1	1	1882	1.0	2.7
1	1	1	1883	1.0	2.8
1	1	1	1884	1.0	2.8
1	1	1	1885	1.0	2.8
1	1	1	1886	1.0	2.9
1	1	1	1887	1.0	2.9
1	1	1	1888	1.0	2.9
1	1	1	1889	1.0	3.0
1	1	1	1890	1.0	3.0
2	1	0	1891	1.0	3.0
2	1	0	1892	1.0	3.1
2	1	0	1893	1.0	3.1
2	1	0	1894	1.0	3.1
2	1	0	1895	1.0	3.2
2	1	0	1896	1.0	3.2
2	1	0	1897	1.0	3.2
2	1	0	1898	1.0	3.3
2	1	0	1899	1.0	3.3
2	1	0	1900	1.0	3.3
2	1	0	1901	1.0	3.4
2	1	0	1902	1.0	3.4

2	1	0	1903	1.0	3.4
2	1	0	1904	1.0	3.5
2	1	0	1905	1.0	3.5
2	1	0	1906	1.0	3.5
2	1	0	1907	1.0	3.6
2	1	0	1908	1.0	3.6
2	1	0	1909	1.0	3.6
2	1	0	1910	1.0	3.7
2	2	1	1911	1.0	3.7
2	2	1	1912	1.0	3.7
2	2	1	1913	1.0	3.8
2	2	1	1914	1.0	3.8
2	2	1	1915	1.0	3.8
2	2	1	1916	1.0	3.9
2	2	1	1917	1.0	3.9
2	2	1	1918	1.0	3.9
2	2	1	1919	1.0	4.0
2	2	1	1920	1.0	4.0
2	2	1	1921	1.0	4.0
2	2	1	1922	1.0	4.1
2	2	1	1923	1.0	4.1
2	2	1	1924	1.0	4.1
2	2	1	1925	1.0	4.2
2	2	1	1926	1.0	4.2
2	2	1	1927	1.0	4.2
2	2	1	1928	1.0	4.3
2	2	1	1929	1.0	4.3
2	2	1	1930	1.0	4.3
2	2	1	1931	1.0	4.4
2	2	1	1932	1.0	4.4
2	2	1	1933	1.0	4.4
2	2	1	1934	1.0	4.5
2	2	1	1935	1.0	4.5
2	2	1	1936	1.0	4.5
2	2	1	1937	1.0	4.6
2	2	1	1938	1.0	4.6
2	2	1	1939	1.0	4.6
2	2	1	1940	1.0	4.7
2	2	1	1941	1.0	4.7
2	2	1	1942	1.0	4.7
2	2	1	1943	1.0	4.8
2	2	1	1944	1.0	4.8
2	2	1	1945	1.0	4.8
2	2	1	1946	1.0	4.9

2	2	1	1947	1.0	4.9
2	2	1	1948	1.0	4.9
2	2	1	1949	1.0	5.0
2	2	1	1950	1.0	5.0
2	2	1	1951	1.0	5.0
2	2	1	1952	1.0	5.1
2	2	1	1953	1.0	5.1
2	2	1	1954	1.0	5.1
2	2	1	1955	1.0	5.2
2	2	1	1956	1.0	5.2
2	2	1	1957	1.0	5.2
2	2	1	1958	1.0	5.3
2	2	1	1959	1.0	5.3
2	2	1	1960	1.0	5.3
2	2	1	1961	1.0	5.4
2	2	1	1962	1.0	5.4
2	2	1	1963	1.0	5.4
2	2	1	1964	1.0	5.5
2	2	1	1965	1.0	5.5
2	2	1	1966	1.0	5.5
2	2	1	1967	1.0	5.6
2	2	1	1968	1.0	5.6
2	2	1	1969	1.0	5.6
2	2	1	1970	1.0	5.7
2	2	1	1971	1.0	5.7
2	2	1	1972	1.0	5.7
2	2	1	1973	1.0	5.8
2	3	0	1974	1.0	5.8
2	3	0	1975	1.0	5.8
2	3	0	1976	1.0	5.9
2	3	0	1977	1.0	5.9
2	3	0	1978	1.0	5.9
2	3	0	1979	1.0	6.0
2	3	0	1980	1.0	6.0
2	3	0	1981	1.0	6.0
2	3	0	1982	1.0	6.1
2	3	0	1983	1.0	6.1
2	3	0	1984	1.0	6.1
2	3	0	1985	1.0	6.2
2	3	0	1986	1.0	6.2
2	3	0	1987	1.0	6.2
2	3	0	1988	1.0	6.3
2	3	0	1989	1.0	6.3
2	3	0	1990	1.0	6.3

2	3	0	1991	1.0	6.4
2	3	0	1992	1.0	6.4
2	3	0	1993	1.0	6.4
2	3	0	1994	1.0	6.5
2	3	0	1995	1.0	6.5
3	3	1	1996	1.0	6.5
3	3	1	1997	1.0	6.6
3	3	1	1998	1.0	6.6
3	3	1	1999	1.0	6.6
3	3	1	2000	1.0	6.7
3	3	1	2001	1.0	6.7
3	3	1	2002	1.0	6.7
3	3	1	2003	1.0	6.8
3	3	1	2004	1.0	6.8
3	3	1	2005	1.0	6.8
3	3	1	2006	1.0	6.9
3	3	1	2007	1.0	6.9
3	3	1	2008	1.0	6.9
3	3	1	2009	1.0	7.0
3	3	1	2010	1.0	7.0
3	3	1	2011	1.0	7.0
3	3	1	2012	1.0	7.1
3	3	1	2013	1.0	7.1
3	3	1	2014	1.0	7.1
3	3	1	2015	1.0	7.2
3	3	1	2016	1.0	7.2
3	3	1	2017	1.0	7.2
3	3	1	2018	1.0	7.3
3	3	1	2019	1.0	7.3
3	3	1	2020	1.0	7.3
3	3	1	2021	1.0	7.4
3	3	1	2022	1.0	7.4
3	3	1	2023	1.0	7.4
3	3	1	2024	1.0	7.5
3	3	1	2025	1.0	7.5
3	3	1	2026	1.0	7.5
3	3	1	2027	1.0	7.6
3	3	1	2028	1.0	7.6
3	3	1	2029	1.0	7.6
3	3	1	2030	1.0	7.7
3	3	1	2031	1.0	7.7
3	3	1	2032	1.0	7.7
3	3	1	2033	1.0	7.8
3	3	1	2034	1.0	7.8

3	3	1	2035	1.0	7.8
3	3	1	2036	1.0	7.9
3	3	1	2037	1.0	7.9
3	3	1	2038	1.0	7.9
3	3	1	2039	1.0	8.0
3	3	1	2040	1.0	8.0
3	3	1	2041	1.0	8.0
3	3	1	2042	1.0	8.1
3	3	1	2043	1.0	8.1
3	3	1	2044	1.0	8.1
3	3	1	2045	1.0	8.2
3	3	1	2046	1.0	8.2
3	3	1	2047	1.0	8.2
3	3	1	2048	1.0	8.3
3	3	1	2049	1.0	8.3
3	3	1	2050	1.0	8.3
3	3	1	2051	1.0	8.4
3	3	1	2052	1.0	8.4
3	3	1	2053	1.0	8.4
3	3	1	2054	1.0	8.5
3	3	1	2055	1.0	8.5
3	3	1	2056	1.0	8.5
3	3	1	2057	1.0	8.6
3	3	1	2058	1.0	8.6
3	3	1	2059	1.0	8.6
3	3	1	2060	1.0	8.7
3	3	1	2061	1.0	8.7
3	3	1	2062	1.0	8.7
3	3	1	2063	1.0	8.8
3	3	1	2064	1.0	8.8
3	3	1	2065	1.0	8.8
3	3	1	2066	1.0	8.9
3	3	1	2067	1.0	8.9
3	3	1	2068	1.0	8.9
3	3	1	2069	1.0	9.0
3	3	1	2070	1.0	9.0
3	3	1	2071	1.0	9.0
3	3	1	2072	1.0	9.1
3	3	1	2073	1.0	9.1
3	3	1	2074	1.0	9.1
3	3	1	2075	1.0	9.2
3	3	1	2076	1.0	9.2
3	3	1	2077	1.0	9.2
3	3	1	2078	1.0	9.3

3	3	1	2079	1.0	9.3
3	3	1	2080	1.0	9.3
3	3	1	2081	1.0	9.4
3	3	1	2082	1.0	9.4
3	3	1	2083	1.0	9.4
3	3	1	2084	1.0	9.5
3	3	1	2085	1.0	9.5
3	3	1	2086	1.0	9.5
3	3	1	2087	1.0	9.6
3	3	1	2088	1.0	9.6
3	3	1	2089	1.0	9.6
3	3	1	2090	1.0	9.7
3	3	1	2091	1.0	9.7
3	3	1	2092	1.0	9.7
3	3	1	2093	1.0	9.8
3	3	1	2094	1.0	9.8
3	3	1	2095	1.0	9.8
3	3	1	2096	1.0	9.9
3	3	1	2097	1.0	9.9
3	3	1	2098	1.0	9.9
3	3	1	2099	1.0	10.0
3	3	1	2100	1.0	10.0
4	3	0	2101	1.0	10.0
4	3	0	2102	1.0	10.1
4	3	0	2103	1.0	10.1
4	3	0	2104	1.0	10.1
4	3	0	2105	1.0	10.2
4	3	0	2106	1.0	10.2
4	3	0	2107	1.0	10.2
4	3	0	2108	1.0	10.3
4	3	0	2109	1.0	10.3
4	4	1	2110	1.0	10.3
4	4	1	2111	1.0	10.4
4	4	1	2112	1.0	10.4
4	4	1	2113	1.0	10.4
4	4	1	2114	1.0	10.5
4	4	1	2115	1.0	10.5
4	4	1	2116	1.0	10.5
4	4	1	2117	1.0	10.6
4	4	1	2118	1.0	10.6
4	4	1	2119	1.0	10.6
4	4	1	2120	1.0	10.7
4	4	1	2121	1.0	10.7
4	4	1	2122	1.0	10.7

4	4	1	2123	1.0	10.8
4	4	1	2124	1.0	10.8
4	4	1	2125	1.0	10.8
4	4	1	2126	1.0	10.9
4	4	1	2127	1.0	10.9
4	4	1	2128	1.0	10.9
4	4	1	2129	1.0	11.0
4	4	1	2130	1.0	11.0
4	4	1	2131	1.0	11.0
4	4	1	2132	1.0	11.1
4	4	1	2133	1.0	11.1
4	4	1	2134	1.0	11.1
4	4	1	2135	1.0	11.2
4	4	1	2136	1.0	11.2
4	4	1	2137	1.0	11.2
4	4	1	2138	1.0	11.3
4	4	1	2139	1.0	11.3
4	4	1	2140	1.0	11.3
4	4	1	2141	1.0	11.4
4	4	1	2142	1.0	11.4
4	4	1	2143	1.0	11.4
4	4	1	2144	1.0	11.5
4	4	1	2145	1.0	11.5
4	4	1	2146	1.0	11.5
4	4	1	2147	1.0	11.6
4	4	1	2148	1.0	11.6
4	4	1	2149	1.0	11.6
4	4	1	2150	1.0	11.7
4	4	1	2151	1.0	11.7
4	4	1	2152	1.0	11.7
4	4	1	2153	1.0	11.8
4	4	1	2154	1.0	11.8
4	4	1	2155	1.0	11.8
4	4	1	2156	1.0	11.9
4	4	1	2157	1.0	11.9
4	4	1	2158	1.0	11.9
4	4	1	2159	1.0	12.0
4	4	1	2160	1.0	12.0
4	4	1	2161	1.0	12.0
4	4	1	2162	1.0	12.1
4	4	1	2163	1.0	12.1
4	4	1	2164	1.0	12.1
4	4	1	2165	1.0	12.2
4	4	1	2166	1.0	12.2

4	4	1	2167	1.0	12.2
4	4	1	2168	1.0	12.3
4	4	1	2169	1.0	12.3
4	4	1	2170	1.0	12.3
4	4	1	2171	1.0	12.4
4	4	1	2172	1.0	12.4
4	4	1	2173	1.0	12.4
4	4	1	2174	1.0	12.5
4	4	1	2175	1.0	12.5
4	4	1	2176	1.0	12.5
4	4	1	2177	1.0	12.6
4	4	1	2178	1.0	12.6
4	4	1	2179	1.0	12.6
4	4	1	2180	1.0	12.7
4	4	1	2181	1.0	12.7
4	4	1	2182	1.0	12.7
4	4	1	2183	1.0	12.8
4	4	1	2184	1.0	12.8
4	4	1	2185	1.0	12.8
4	4	1	2186	1.0	12.9
4	4	1	2187	1.0	12.9
4	4	1	2188	1.0	12.9
4	4	1	2189	1.0	13.0
4	4	1	2190	1.0	13.0
4	4	1	2191	1.0	13.0
4	4	1	2192	1.0	13.1
4	4	1	2193	1.0	13.1
4	4	1	2194	1.0	13.1
4	4	1	2195	1.0	13.2
4	4	1	2196	1.0	13.2
4	4	1	2197	1.0	13.2
4	4	1	2198	1.0	13.3
4	4	1	2199	1.0	13.3
4	4	1	2200	1.0	13.3
4	4	1	2201	1.0	13.4
4	4	1	2202	1.0	13.4
4	4	1	2203	1.0	13.4
4	4	1	2204	1.0	13.5
4	4	1	2205	1.0	13.5
4	4	1	2206	1.0	13.5
4	4	1	2207	1.0	13.6
4	4	1	2208	1.0	13.6
4	4	1	2209	1.0	13.6
4	4	1	2210	1.0	13.7

4	4	1	2211	1.0	13.7
4	4	1	2212	1.0	13.7
4	4	1	2213	1.0	13.8
4	4	1	2214	1.0	13.8
4	4	1	2215	1.0	13.8
4	4	1	2216	1.0	13.9
4	4	1	2217	1.0	13.9
4	4	1	2218	1.0	13.9
4	4	1	2219	1.0	14.0
4	4	1	2220	1.0	14.0
4	4	1	2221	1.0	14.0
4	4	1	2222	1.0	14.1
4	4	1	2223	1.0	14.1
4	4	1	2224	1.0	14.1
4	4	1	2225	1.0	14.2
4	4	1	2226	1.0	14.2
4	4	1	2227	1.0	14.2
4	4	1	2228	1.0	14.3
4	4	1	2229	1.0	14.3
4	4	1	2230	1.0	14.3
4	4	1	2231	1.0	14.4
4	4	1	2232	1.0	14.4
4	4	1	2233	1.0	14.4
4	4	1	2234	1.0	14.5
4	4	1	2235	1.0	14.5
4	4	1	2236	1.0	14.5
4	4	1	2237	1.0	14.6
4	4	1	2238	1.0	14.6
4	4	1	2239	1.0	14.6
4	4	1	2240	1.0	14.7
4	4	1	2241	1.0	14.7
4	4	1	2242	1.0	14.7
4	4	1	2243	1.0	14.8
4	4	1	2244	1.0	14.8
4	4	1	2245	1.0	14.8
4	4	1	2246	1.0	14.9
4	4	1	2247	1.0	14.9
4	4	1	2248	1.0	14.9
4	4	1	2249	1.0	15.0
4	4	1	2250	1.0	15.0
4	4	1	2251	1.0	15.0
4	4	1	2252	1.0	15.1
4	4	1	2253	1.0	15.1
4	4	1	2254	1.0	15.1

4	4	1	2255	1.0	15.2
4	4	1	2256	1.0	15.2
4	4	1	2257	1.0	15.2
4	4	1	2258	1.0	15.3
4	4	1	2259	1.0	15.3
4	4	1	2260	1.0	15.3
4	4	1	2261	1.0	15.4
4	4	1	2262	1.0	15.4
4	4	1	2263	1.0	15.4
4	4	1	2264	1.0	15.5
4	4	1	2265	1.0	15.5
4	4	1	2266	1.0	15.5
4	4	1	2267	1.0	15.6
4	4	1	2268	1.0	15.6
4	4	1	2269	1.0	15.6
4	4	1	2270	1.0	15.7
4	4	1	2271	1.0	15.7
4	4	1	2272	1.0	15.7
4	4	1	2273	1.0	15.8
4	4	1	2274	1.0	15.8
4	4	1	2275	1.0	15.8
4	4	1	2276	1.0	15.9
4	4	1	2277	1.0	15.9
4	4	1	2278	1.0	15.9
4	4	1	2279	1.0	16.0
4	4	1	2280	1.0	16.0
4	4	1	2281	1.0	16.0
4	4	1	2282	1.0	16.1
4	4	1	2283	1.0	16.1
4	4	1	2284	1.0	16.1
4	4	1	2285	1.0	16.2
4	4	1	2286	1.0	16.2
4	4	1	2287	1.0	16.2
4	4	1	2288	1.0	16.3
4	4	1	2289	1.0	16.3
4	4	1	2290	1.0	16.3
4	4	1	2291	1.0	16.4
4	4	1	2292	1.0	16.4
4	4	1	2293	1.0	16.4
4	4	1	2294	1.0	16.5
4	4	1	2295	1.0	16.5
4	4	1	2296	1.0	16.5
4	4	1	2297	1.0	16.6
4	4	1	2298	1.0	16.6

4	4	1	2299	1.0	16.6
4	4	1	2300	1.0	16.7
4	4	1	2301	1.0	16.7
4	4	1	2302	1.0	16.7
4	4	1	2303	1.0	16.8
4	4	1	2304	1.0	16.8
4	4	1	2305	1.0	16.8
4	4	1	2306	1.0	16.9
4	4	1	2307	1.0	16.9
4	4	1	2308	1.0	16.9
4	4	1	2309	1.0	17.0
4	4	1	2310	1.0	17.0
4	4	1	2311	1.0	17.0
4	4	1	2312	1.0	17.1
4	4	1	2313	1.0	17.1
4	4	1	2314	1.0	17.1
4	1	0	2315	1.0	17.2
4	1	0	2316	1.0	17.2
4	1	0	2317	1.0	17.2
4	1	0	2318	1.0	17.3
4	1	0	2319	1.0	17.3
4	1	0	2320	1.0	17.3
4	1	0	2321	1.0	17.4
4	1	0	2322	1.0	17.4
4	1	0	2323	1.0	17.4
4	1	0	2324	1.0	17.5
4	1	0	2325	1.0	17.5
4	1	0	2326	1.0	17.5
4	1	0	2327	1.0	17.6
4	1	0	2328	1.0	17.6
4	1	0	2329	1.0	17.6
4	1	0	2330	1.0	17.7