Risk assessment for work-related musculoskeletal injury using wearable sensors

By

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Abstract

Work-related musculoskeletal disorders are a worldwide problem that affects millions of people every year, and they have a cost of billions of dollars that keeps increasing over the years. One of the main causes of musculoskeletal disorders is fatigue. One of the most used and relievable methods to detect fatigue is with electromyography (EMG) signal, and even though the results obtained with this method are good enough for some applications, the use of these sensors can be time-consuming, expensive, and inconvenient. Currently, there is no objective and accurate measure of fatigue for long-term measurement in real-world working scenarios.

This thesis investigated the use of wearable inertial measurement units (IMU) for body posture, fatigue, and ergonomic risk assessments in long-term and real-world working conditions. To this end, we proposed to measure and detect fatigue in-field using only kinematic information with an established parameter, i.e., Rapid Entire Body Assessment (REBA), and a novel kinematic parameter, i.e., K-score introduced in this study. To investigate the validity of these two parameters for muscle fatigue detection, we performed an experimental study involving a material handling task with 10 able-bodied participants. The fatigue was measured with three methods: a Borg Rating of Perceived Exertion scale RPE, EMG signal, and the two kinematic parameters measured with IMUs. The results showed that REBA did not have a significant correlation ($p>0.05$) with the EMG signal amplitude affected by muscle fatigue. The lack of correlation between REBA and EMG amplitude could be related to the limited resolution of the REBA score. Our introduced kinematic parameter (K-score) is a function of body joint angles but has a higher resolution than REBA and could tackle this challenge. K-score showed a correlation coefficient of $\rho = 0.21$ ($p <0.05$) with EMG amplitude, which validated its use for fatigue detection in repetitive tasks.

Furthermore, we investigated the difference of muscle fatigue for three work-rest schedules: (1) a typical 30-min trial without any breaks, (2) adding two one-minute micro-breaks in between the trial, and (3) adding two breaks in between to perform specific stretching exercises. EMG signal and K-score were recorded for muscle fatigue characterization. Both parameters showed a significant difference among the trials using a multiple comparison test. We concluded that 1) micro-breaks can have a meaningful muscle fatigue reduction in working conditions, which may contribute to a reduced risk of WMSD, and 2) K-score has the potential to detect and characterize muscle fatigue, and their measurements using an IMU could be a substitute for EMG measurement that is challenging in the long-term.

Lastly, we present a validation for IMUs to properly measure ergonomic risk assessments compared to camera-based motion capture for five minutes and in a material handling task. We measured the accuracy of IMUs to measure 1) 3D joint angles, and 2) two kinematic parameters for ergonomic risk assessment: REBA and K-score. IMUs were able to measure the 3D joint angles of the shoulder, trunk, elbow, and knee with an RMSE of less than 4° and the neck joint angles with a mean RMSE of 6.2°. Furthermore, REBA and K-score based on joint angles measured with IMUs and motion capture were compared using Cohen's Kappa coefficient, and demonstrated to have a "substantial agreement".

In summary, these studies demonstrated the accuracy of wearable IMUs for the measurement of body joint angles, ergonomic scores, and muscle fatigue in long-term and real-world conditions.

Preface

This thesis is an original work by Karla Beltrán Martínez. The research project, of which this thesis is part, received research ethics approval from the University of Alberta Research Ethics Board, Project Name "Risk assessment for work-related musculoskeletal injury using wearable sensors" No. Pro00089234.

Parts of this thesis were presented as a presentation at the 21st Annual Alberta Biomedical Engineering Conference 2020 (Canada).

Dedicated to

My mom, Coral Martinez

And

My sister, Paola Beltran

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CHAPTER 1

INTRODUCTION

1.1 Overview

Musculoskeletal disorders (MSDs) are injuries that can affect the muscles, nerves, tendons, joints, cartilage, and or spinal discs [1]. When MSD is occurred or is significantly worsened in the work environment, it is known as work-related musculoskeletal disorder (WMSD) [1]. According to the Bureau of Labor Statistics, an MSD needs to be caused by the bodily reaction, overexertion (fatigue), or repetitive motion [1].

Most of the WMSDs have a direct or indirect effect on hands, wrists, elbows, neck, shoulders, legs, hips, ankles, and/or feet [2], and these can be caused due to awkward postures, repetitive or intense movements, and exposure to vibrations or low temperatures [3]. Any of these factors by itself does not represent any major danger, however, when they interact with each other, it can cause severe damage for both the short and long term. For example, if one's back is bent to reach something from the floor, it is completely harmless, however, if the back is bent to pick up boxes for long hours and without proper rest in between, it can cause chronic lower back pain [4].

Some of the dangers of WMSDs are that they present symptoms in the long term, and by the time they are detected, it can be too late to treat them [2]. Some of the symptoms that can be seen in an early stage include pain and fatigue during a regular work shift; if the patient is in an intermediate stage, pain and tiredness are not only during the work shift, but also afterward, and their productivity can be affected at this stage; finally, in a late-stage, the patient presents pain and fatigue during the whole day, and they are unable to perform all types of duties [2].

WMSDs are known to not only affect the injured person, but also have a great economic impact on the employer, the insurance company, and the government. A study in 1994 showed that the total cost (direct and indirect) for MSDs was 25.6 billion dollars which included the cost of hospitals, physicians, direct health expenditures, loss of productivity, etc. [5]; and according to a US report made in 2012, the cost of WMSDs have been continuing to steadily increase [6].

There are many methods to reduce the risk of WMSDs including engineering controls, such as changing the layout of the workstations, and the use of mechanical machines to reduce the load while lifting; administrative controls, such as rotating workers, training, and taking scheduled breaks; and lastly, the use of personal protective equipment such as earplugs, safety shoes and back belts [1]. Besides, there are several ergonomic assessments to make sure the tasks performed do not represent any significant risk for the worker, these assessments can include Rapid Entire Body Assessment (REBA) and Rapid Upper Limb Assessment (RULA) scores, which provide a numerical score to show if the task is a low, medium or high risk, or the National Institute of Occupational Safety and Health (NIOSH) lifting equation, which depending on the layout of the work station, provides a maximum load safe to be carried by the worker [7].

Musculoskeletal disorders represent a global health challenge. Between 20% and 33% of the people around the world suffer from some type of MSD [8], only in the US, there have been 126 million cases of MSD reported by 2012, which represents half of the adult population [6]. Despite all the medical advances and scientific efforts to reduce these numbers, MSDs are still the first cause of temporary and permanent disability in the workplace [9]. Although WMSDs cannot be eliminated, strategies can be proposed towards a significant reduction of the overall number of WMSDs, such as those caused by material handling.

Reducing the WMSDs helps to reduce costs for private companies, government, and insurance companies, and it improves productivity. In 2012, there was a loss of 290.8 million workdays due only to back and neck pain in Canada [6]. A study shows that the direct cost of MSDs in Canada was $7.5 billion, and the indirect cost was $18.1 billion [5] in 1998. The easiest and most efficient way to reduce these numbers is identifying the risks and preventing these MSDs. To this end, the development of easy, in-field, and cost-effective methods to detect any possible risk, and optimal work schedules is crucial, so that the workers can have enough rest during a work shift to avoid muscle fatigue.

1.2 Objective

The objective of this thesis is to propose accurate and reliable in-field measurement devices to assess the risk of WMSDs, specifically for material handling jobs, by detecting muscle fatigue while little affecting productivity during a work shift. To do this, we aim to find an objective and user-friendly technique to detect muscle fatigue in the workplace. The following is a list of specific goals needed to be achieved to this end:

1) Design experimental protocols to induce muscle fatigue and measure it using state-of-the-art techniques.
2) Propose novel parameters to detect muscle fatigue based on body kinematics in a non-invasive and inexpensive manner.
3) Investigate the accuracy of wearable inertial measurement units (IMUs) to detect such kinematic parameters.
4) Detect an optimal break schedule to minimize muscle fatigue during a work shift based on the proposed kinematics parameters as well as the state-of-the-art techniques.

1.3 Structure

This thesis is divided into six chapters, Chapter 1 presents an introduction of the motivations and objectives of this research project. Chapter 2 presents a literature review on the proposed research topic and illustrates the use and differences of the technology used and the existing methods to detect fatigue and reduce the risk of WMSDs. Chapter 3 introduces a novel kinematic parameter to detect fatigue in a stationary workplace. Chapter 4 describes a study to find an optimal work schedule to reduce fatigue in material handling jobs. Chapter 5 presents the methods used to investigate the accuracy of wearable IMUs to measure human body kinematics against that measured by the motion-capture cameras as the reference system. Chapter 6 includes a discussion of all the studies, conclusions for the conducted research, and future perspectives. Figure 1 represents the structure of this thesis.

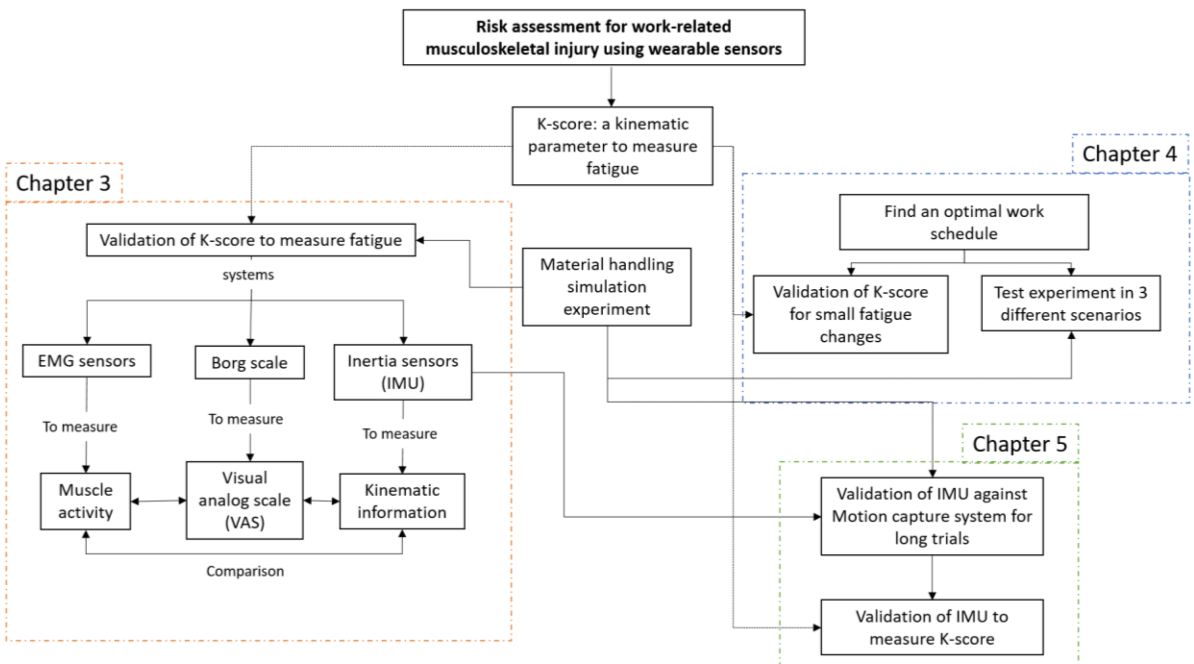


Figure 1 Thesis structure

CHAPTER 2

LITERATURE REVIEW

2.1 Risk reduction and assessments for WMSD

Several methods are used in the industry towards reducing the risk of WMSD, such as improving the store racks for easy reach, adding hoist cranes, roller conveyors, or carts for easier transportation; adapting the workstations, and rotating jobs within a work shift to avoid fatigue [10]. It has also been proved, that taking psychosocial hazards into account can reduce the risk of WMSD [11]. Major causes of WMSD are the manipulation of heavy loads, working with load for a long time, or in a high frequency; awkward postures, and being exposed to vibrations [1]. The manipulation of heavy loads can be harmful because it requires a high muscular activity, which over time produces muscular fatigue [12]. It also involves a high force applied to the joint cartilages, ligaments, and tendons, which can induce degenerative disorders over time [12]. It is recommended to avoid manual material handling as much as possible, otherwise, considering the following recommendations:

- Lift the load close to the body.
- Carry the load with two hands, and if possible by two people.
- Lift the load in an upright trunk and extended legs.
- Carry the load through clear paths (no obstacles).
- Do not handle any loads on uneven or slippery surfaces, or up and down the stairs.
- Avoid handling material manually frequently.
- Mark the heavy loads.
- Provide training [12].

When a task is being designed, or managed, it is important and recommended to use risk management tools to design new workstations like the NIOSH lifting equation, and to make regular risk assessments using the REBA or RULA scores, to make sure that the employees do not overpass their load capacity or frequency limit.

2.1.1 NIOSH LIFTING EQUATION

The NIOSH lifting equation is a tool that provides the maximum recommended load that a person can handle without being harmed. To calculate this maximum load, the following variables should be considered:

1. The horizontal distance of the load from the ankles.
2. The distance from the ground to where the load initially is located.
3. The vertical distance to where the load will be carried.
4. The lifting frequency.
5. The angle of the load from the initial to the final position.
6. The quality of the grasp (e.g., handles).

A multiplier factor is given to each of these variables from charts, and the recommended weight limit (RWL) is calculated as follows:

$$RWL = LC * HM * VM * DM * FM * AM * CM$$

Equation 1: NIOSH equation

Where LC is the load constant: 23 kg, established by NIOSH. This load, under ideal conditions, is safe for 75% of females and 90% of males. The rest of the variables are:

HM – Horizontal multiplier

VM – Vertical multiplier

DM – Distance multiplier

FM – Frequency multiplier

AM – Asymmetric multiplier

CM – Coupling multiplier

Figure 2, and Figure 3, Table 1, Table 2, Table 3, Table 4, Table 5, and Table 6 present how to obtain these multiplier factors based on the geometrical properties of the workstation according to [13].

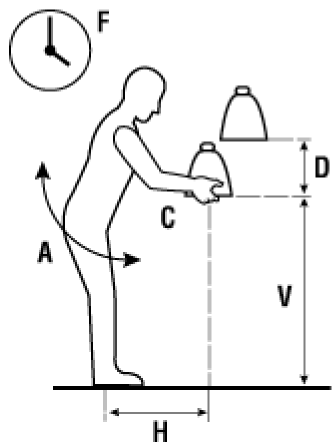


Figure 2 NIOSH equation variables, adapted from [13]

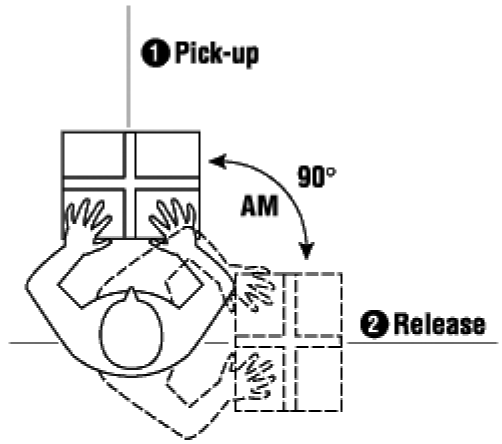


Figure 3 MIOSH equation AM variables, adapted from [13]

Table 1 Horizontal Multiplier, adapted from [13]

H = Horizontal Distance	HM Factor
25 or less	1.00
30	0.83
40	0.63
50	0.50
60	0.42

Table 2 Vertical Multiplier, adapted from [13]

V = Starting height	VM Factor
0	0.78
30	0.87
50	0.93
70	0.99
100	0.93
150	0.78
175	0.70
>175	0.00

Table 3 Distance Multiplier, adapted from [13]

D = Lifting Distance	DM Factor
25 or less	1.00
40	0.93
55	0.90
100	0.87
145	0.85
175	0.85
>175	0.00

Table 4 Angle Multiplier, adapted from [13]

A = Angle (degrees)	AM Factor
90°	0.71
60°	0.81
45°	0.86
30°	0.90
0°	1.00

Table 5 Frequency Multiplier, adapted from [13]

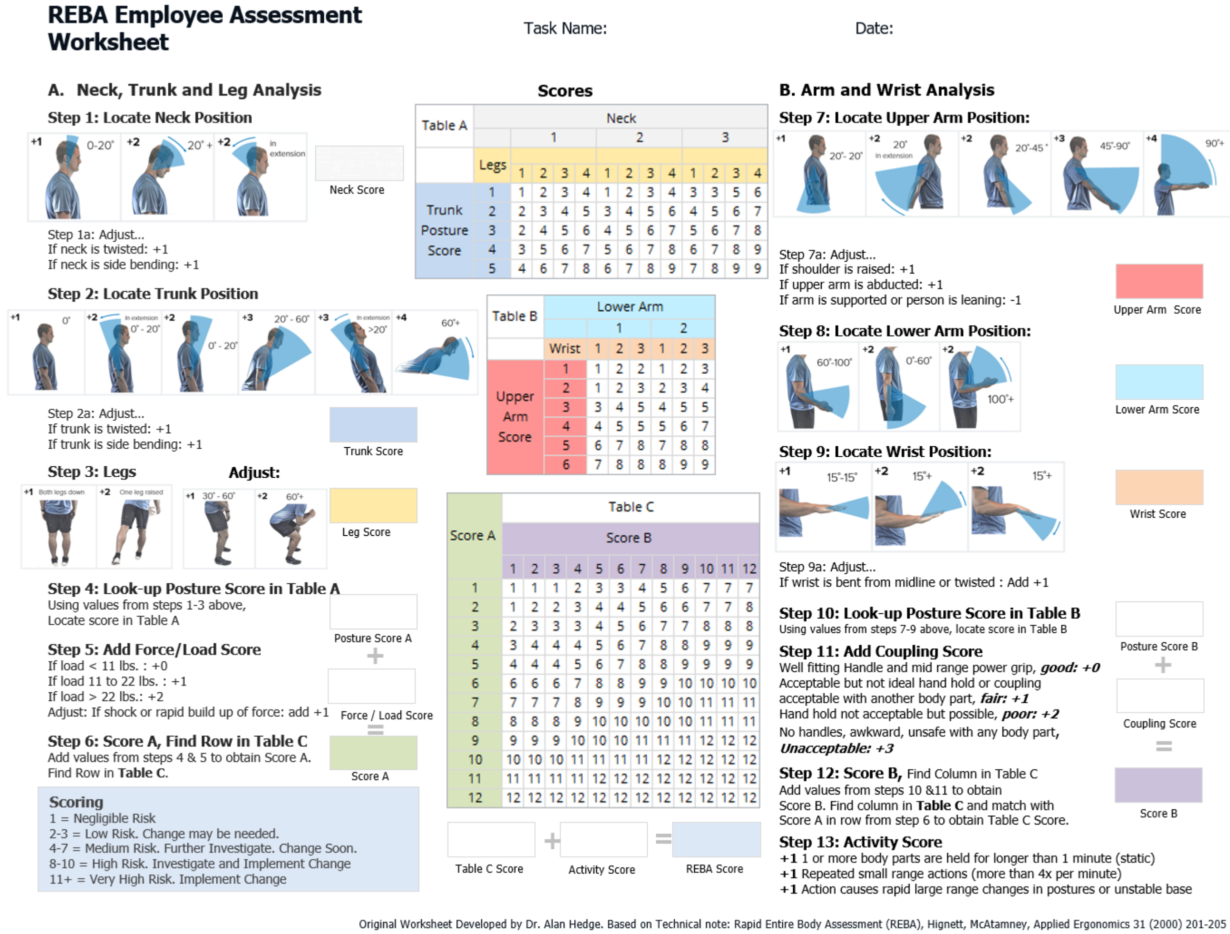
F = Time between lifts	FM Factor			
	Lifting while standing		OR Lifting while stooping	
	≤1 hr	**> 1 hr**	**≤ 1hr**	**> 1 hr**
5 min	1.00	0.85	1.00	0.85
1 min	0.94	0.75	0.94	0.75
30 sec	0.91	0.65	0.91	0.65
15 sec	0.84	0.45	0.84	0.45
10 sec	0.75	0.27	0.75	0.27
6 sec	0.45	0.13	0.45	-
5 sec	0.37	-	0.37	-

Table 6 Coupling Multiplier, adapted from [13]

C = Grasp	CM Factor	
	Standing	**Stooping**
Good (handles)	1.00	1.00
Fair	1.00	0.95
Poor	0.90	0.90

2.1.2 RAPID ENTIRE BODY ASSESSMENT (REBA)

The REBA is an ergonomic tool to assess the risk of certain WMSD through the evaluation of the whole body posture. It was invented as a low-cost method of risk assessment since it does not require an experienced professional to do the assessment. This method is based on a single-page worksheet (Figure 4) which provides a range of scores depending on the person's posture. The scores are given for each of the following joint angles: wrist, elbow, shoulder, neck, trunk, and knees. After the joint scores are collected, they will be used to calculate three sets of sub-scores, which are added together to obtain a single REBA score. The resulted score obtains the WMSD risk level of the operation, as shown in Table 7 [14].



REBA Employee Assessment Worksheet

Task Name: Date:

A. Neck, Trunk and Leg Analysis

Step 1: Locate Neck Position

+1 0-20° +2 20°+ +2 in extension

Neck Score

Step 1a: Adjust...
If neck is twisted: +1
If neck is side bending: +1

Step 2: Locate Trunk Position

+1 0° +2 in extension 0°-20° +2 0°-20° +3 20°-60° +3 in extension >20° +4 60°+

Step 2a: Adjust...
If trunk is twisted: +1
If trunk is side bending: +1

Trunk Score

Step 3: Legs **Adjust:**

+1 Both legs down +2 One leg raised +1 30°-60° +2 60°+

Leg Score

Step 4: Look-up Posture Score in Table A
Using values from steps 1-3 above,
Locate score in Table A

Posture Score A

Step 5: Add Force/Load Score
If load < 11 lbs. : +0
If load 11 to 22 lbs. : +1
If load > 22 lbs.: +2
Adjust: If shock or rapid build up of force: add +1

Force / Load Score

Step 6: Score A, Find Row in Table C
Add values from steps 4 & 5 to obtain Score A.
Find Row in **Table C.**

Score A

Scoring
1 = Negligible Risk
2-3 = Low Risk. Change may be needed.
4-7 = Medium Risk. Further Investigate. Change Soon.
8-10 = High Risk. Investigate and Implement Change
11+ = Very High Risk. Implement Change

Scores

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

Table B		Lower Arm					
		1			2		
	Wrist	1	2	3	1	2	3
Upper Arm Score	1	1	2	2	1	2	3
	2	1	2	3	2	3	4
	3	3	4	5	4	5	5
	4	4	5	5	5	6	7
	5	6	7	8	7	8	8
	6	7	8	8	8	9	9

Score A	Table C / Score B											
	1	2	3	4	5	6	7	8	9	10	11	12
1	1	1	1	2	3	3	4	5	6	7	7	7
2	1	2	2	3	4	4	5	6	6	7	7	8
3	2	3	3	3	4	5	6	7	7	8	8	8
4	3	4	4	4	5	6	7	8	8	9	9	9
5	4	4	4	5	6	7	8	8	9	9	9	9
6	6	6	6	7	8	8	9	9	10	10	10	10
7	7	7	7	8	9	9	9	10	10	11	11	11
8	8	8	8	9	10	10	10	10	10	11	11	11
9	9	9	9	10	10	10	11	11	11	12	12	12
10	10	10	10	11	11	11	11	12	12	12	12	12
11	11	11	11	11	12	12	12	12	12	12	12	12
12	12	12	12	12	12	12	12	12	12	12	12	12

Table C Score + Activity Score = REBA Score

B. Arm and Wrist Analysis

Step 7: Locate Upper Arm Position:

+1 20°-20° +2 20° in extension +2 20°-45° +3 45°-90° +4 90°+

Step 7a: Adjust...
If shoulder is raised: +1
If upper arm is abducted: +1
If arm is supported or person is leaning: -1

Upper Arm Score

Step 8: Locate Lower Arm Position:

+1 60°-100° +2 0°-60° +2 100°+

Lower Arm Score

Step 9: Locate Wrist Position:

+1 15°-15° +2 15°+ +2 15°+

Wrist Score

Step 9a: Adjust...
If wrist is bent from midline or twisted : Add +1

Step 10: Look-up Posture Score in Table B
Using values from steps 7-9 above, locate score in Table B

Posture Score B

Step 11: Add Coupling Score
Well fitting Handle and mid range power grip, ***good: +0***
Acceptable but not ideal hand hold or coupling
acceptable with another body part, ***fair: +1***
Hand hold not acceptable but possible, ***poor: +2***
No handles, awkward, unsafe with any body part,
Unacceptable: +3

Coupling Score

Step 12: Score B, Find Column in Table C
Add values from steps 10 &11 to obtain
Score B. Find column in **Table C** and match with
Score A in row from step 6 to obtain Table C Score.

Score B

Step 13: Activity Score
+1 1 or more body parts are held for longer than 1 minute (static)
+1 Repeated small range actions (more than 4x per minute)
+1 Action causes rapid large range changes in postures or unstable base

Original Worksheet Developed by Dr. Alan Hedge. Based on Technical note: Rapid Entire Body Assessment (REBA), Hignett, McAtamney, Applied Ergonomics 31 (2000) 201-205

Figure 4 REBA worksheet, adapted from [14]

Table 7 Risk level of REBA score, adapted from [14]

Score	Level of MSD Risk
1	Negligible risk, no action required
2-3	Low risk. Change may be needed
4-7	Medium risk, further investigation, change soon
8-10	High risk, investigate and implement change
11+	Very high risk, implement change

The REBA score was designed to be used as an inexpensive, and user-friendly technique to provide an assessment recommending an action level with an urgency indicator. Some of its limitations include the lack of consideration for the duration of the tasks, or time to recover in between, and the need to separately assess the left and right sides of the body [14].

2.1.3 RAPID UPPER LIMB ASSESSMENT (RULA)

The RULA, similar to the REBA, is a method to assess the ergonomic risk during a specific work task; however, RULA only assesses the risks associated with the upper extremities and trunk posture [15]. The RULA is a valuable tool to use when the evaluator can easily notice that the lower limbs do not have an awkward posture during the task. Figure 5 shows the RULA assessment worksheet, and Table 8 presents the risk levels depending on the obtained score.

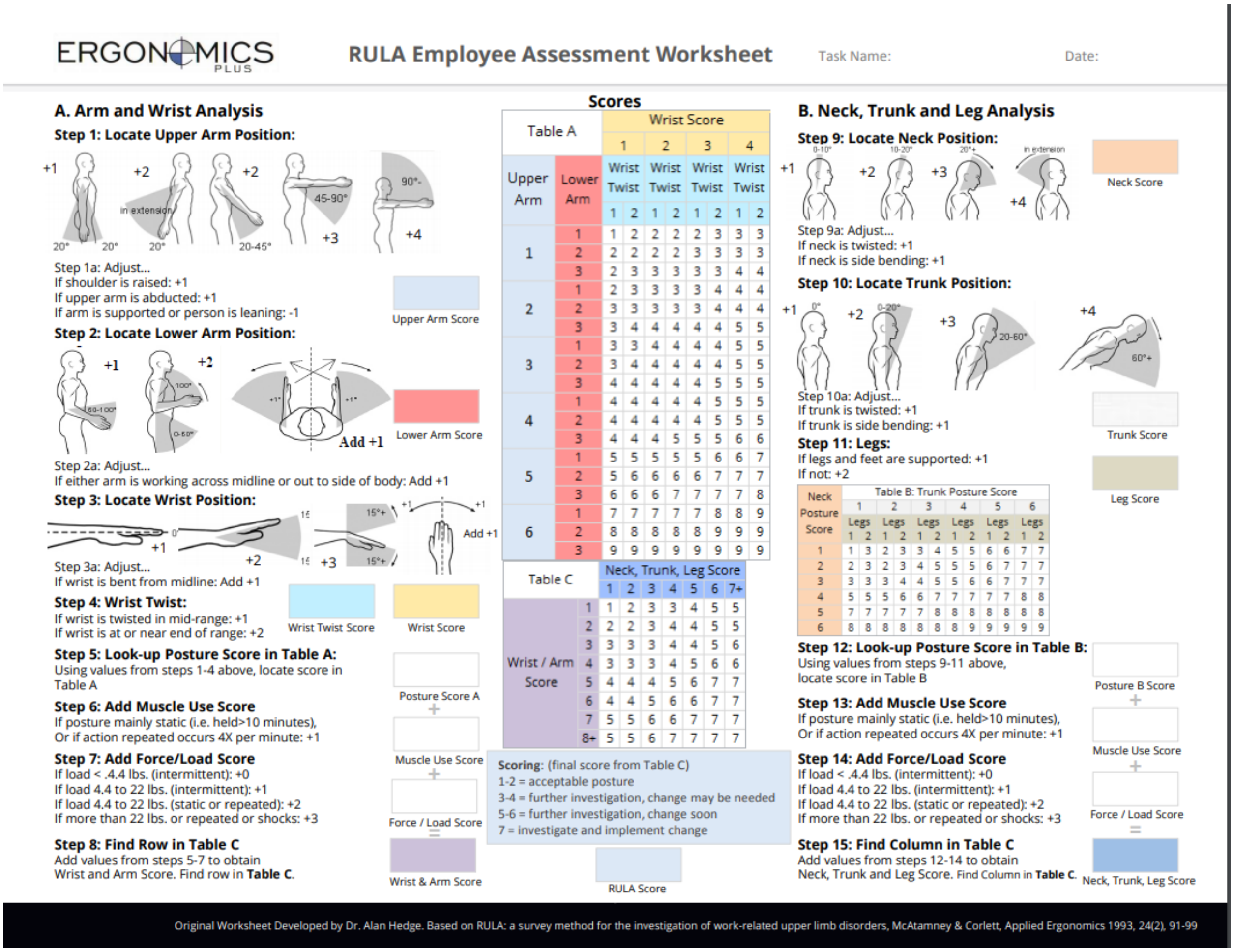


Figure 5 RULA worksheet, adapted from [15]

Table 8 Level of risk from RULA score, adapted from [15]

Score	Level of MSD Risk
1-2	Negligible risk, no action required
3-4	Low risk, change may be needed
5-6	Medium risk, further investigation, change soon
6+	Very high risk, implement change now

Even though REBA and RULA scores are user-friendly and low-cost, there is still the need for someone to complete the angle/posture measurements as accurately as possible. Some of the methods used to make the body joint angle measurement are mentioned in the following section.

2.2 Technology used to measure joint angles

The human body joint angles are measured for a variety of applications including sports kinematics, rehabilitation, risk assessment in the workplace, and many others. Because of its importance, the joint angle is obtained via several different methods; from observation, and simple mechanical devices like goniometers; to more complex systems like motion capture, and computer vision. And in the last years, there has been some research made to measure joint angles with inertial measurement units (IMUs). Such methods are further described in this section.

2.2.1 OBSERVATION

For the joint angles to be measured by observation, it is necessary to have an expert in ergonomics to acquire the data. There are many methods on how observation can take place. Some of these methods include a three-category scale, six-category scale, and visual analog scale. These refer to how many ranges the scale has in which the expert can select a value [16]. Table 9, Table 10, and Figure 6 show examples of how an expert obtains the joint angles for wrists with the observation method. Figure 7 shows the range of motion of the wrist. Obtaining angles through observation does not lead to an accurate representation of the real values, therefore, it cannot be used as a tool when exact values are needed. However, it can be a good tool as a first assessment.

Table 9 Three-category scale, adapted from [16]

Category	Flexion/extension	Supination/pronation	Radial/ulnar deviation
1	>20° flex	>40° sup	>10° radial
2	20° flex - 20° ext	40° sup - 40° pro	10° radial - 10° ulnar
3	>20° ext	>40° pro	>10° ulnar

Table 10 Six category scale, adapted from [16]

Category	Flexion/extension	Supination/pronation	Radial/ulnar deviation
1	>45° flex	>60° sup	>20° radial
2	20° - 45° flex	30° - 60° sup	10° - 20° radial
3	0° - 20° flex	0° - 30° sup	0° - 10° radial
4	0° - 20° ext	0° - 30° pro	0° - 10° ulnar
5	20° - 45° ext	30° - 60° pro	10° - 20° ulnar
6	>45° ext	>60° pro	>20° ulnar

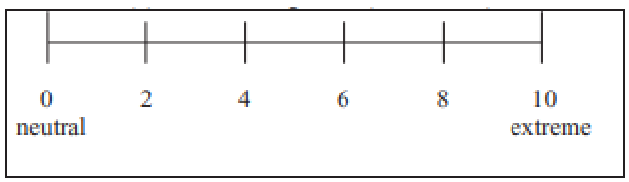


Figure 6 Visual analog scale, adapted from [16]

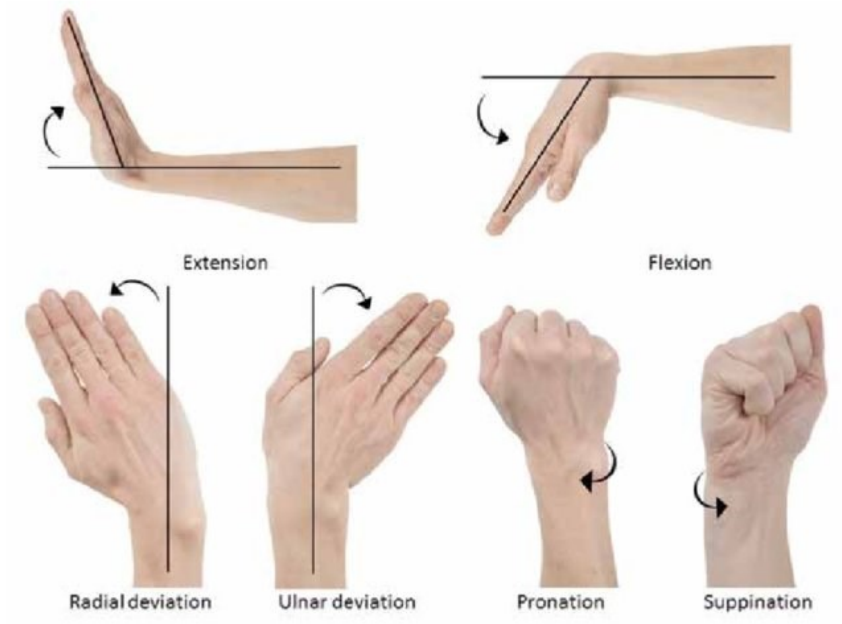


Figure 7 Wrist range of motions, adapted from [17]

2.2.2 GONIOMETER

A goniometer is composed of two arms: a static one, which is positioned in one of the limbs, and a dynamic one attached to the second limb that holds the measuring scale. The scale can vary depending on the type of device to either 360° or 180°. To calculate the joint angles with a goniometer, the person measures the angle between the stationary arm, and the end position of the moving arm [18]. There is no need for any expert professional to use this device. Goniometers, even though they are very commonly used, are not precise and reliable. Their measurements have shown to have a variation of ± 5° when measuring joint angles of the hand and wrist [19], and a minimum significant difference of 10° for measuring knee angles with a fixed position [20]. These variations depend on the type of goniometer being used, whether is mechanical or digital, long arm or short arm, but it provides an idea of their general accuracy. A goniometer is a good tool to use when a single 2D joint angle is desired, however, it cannot measure 3D joint angles, it lacks a standardized procedure, and its use can be considered cumbersome.

2.2.3 MOTION CAPTURE SYSTEMS

Motion capture systems are known to obtain the most accurate results in collecting kinematic information on the human body motion such as joint angles, and thus, are used as a gold standard for this purpose. It is based on a set of cameras located around the subject, and markers placed on anatomical landmarks of the subject's body, based on which he joint angles are defined in the literature. Most of the motion capture systems on the market use infrared light, together with passive or active markers [21]. Also, a multicamera system is usually used to 1) obtain a 3D trajectory of the marker-based on the combination of 2D images recorded by each camera, and 2) make sure that all the markers around the body are seen. Figure 8 shows a laboratory multicamera setup. As seen in Figure 8, a motion capture system requires a big space for setup and preparation, this can lead to this system being undesirable when talking about in-field measurements.

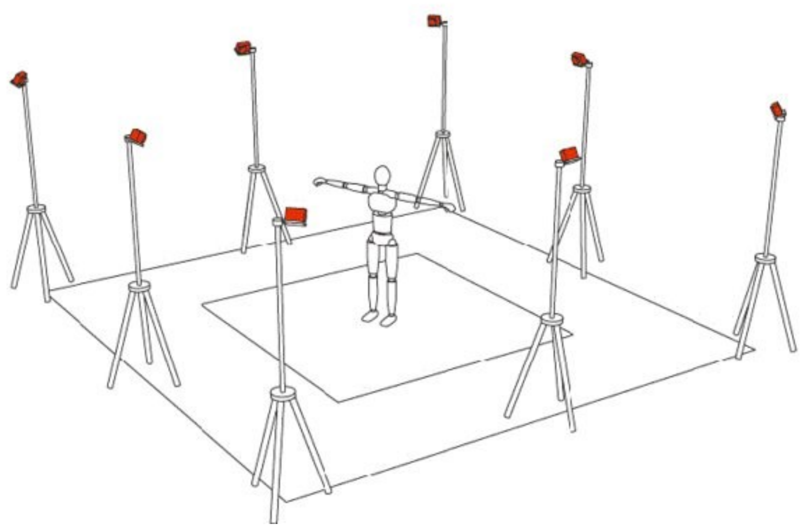


Figure 8 Example of multicamera laboratory setup, adapted from [22]

2.2.4 COMPUTER VISION SYSTEMS

As discussed in the previous section, the motion capture system is the most accurate device to measure human body joint angles. However, it can only be used in a controlled setting, most of the time in a laboratory and the preparation time can be quite long. These characteristics constrain the use of motion capture cameras in real-world settings. This has led to the need for obtaining human body kinematic parameters with the same accuracy but without the need for any markers or dedicated lab settings; which is why there has been much interest from researchers to calculate joint angles with either computer vision or wearable sensors like IMUs.

Detecting the joint angles using computer vision requires recording with at least two views of the settings, so the angles can be calculated in 3D instead of 2D. The first step is to use Histogram Orientation Gradient (HOG) to characterize the gradient orientation and convert the images into image features. Second, a 3D pose needs to be reconstructed for each frame, which is done with the Twin Gaussian Process (TGP) explained in [23]. Finally, once the 3D pose has been reconstructed, inverse kinematics is used to calculate the joint angles. The mean and standard deviation of the difference between a computer vision method and a motion capture measurement for joint angles is 2.31 ± 4.00 degrees [24]. The method described here is only one of many that can be used to obtain kinematic parameters from computer vision, other methods can be found in [25], [26], [27]. Computer vision can eventually become a good replacement for motion capture, but at the moment, it still contains many restrictions at the time of the recording e.g. the person being recorded needs to be by him/herself, and preferably with not so much background noise, it also requires a great deal of processing to get to accurate results, which makes it not very user friendly.

2.2.5 IMU

Over the last years, inertial sensors, also known as IMUs have been widely investigated for human motion measurement. These sensors can measure joint angles with low error, do not depend on any laboratory settings, and can be bought for a very low price. IMUs are composed sensors that can measure linear acceleration, angular acceleration, and magnetic field. With this information as input, the sensor's orientation can be estimated using a set of algorithms involving strap-down-integration that produces a drift of the obtained angles over time. A calibration process generally takes place during any trial with IMUs to detect the local coordinate system of the segment's axis [28]. The errors obtained with inertial sensors can depend on the quality of the sensor, the algorithm used, the calibration performed, among others, but some studies have elaborated experiments with good relatively results, and reported errors of less than 3°, e.g. [28], [29], [30].

2.3 Technology used to detect fatigue

Although there are many methods to measure joint angles, which can help us to detect when a work task can be an ergonomic hazard, even in the absence of awkward high-risk postures, if a task is performed in high frequency, or for long periods of time without breaks, it can also lead to a WMSD. Avoiding muscle fatigue is a way to prevent such risks. The technologies used to detect muscle fatigue are described in this section; however, detection of fatigue onset is inherently subjective, and there is no gold standard with 100% accuracy for fatigue onset detection.

2.3.1 BORG RATING OF PERCEIVED EXERTION SCALE (RPE)

This is the simplest representation of fatigue consists of a small table, or graph used as a visual representation for the user. Examples of these scales are shown in Figure 9 and Figure 10, where the person selects a number or position within the scale range depending on their fatigue state. This method is simple to use and does not require any equipment, which makes it perfect for situations that do not require great precision. However, this method would not be efficient for an accurate assessment of fatigue since fatigue also depends on the subject's perception.

Not at all fatigued	0	1	2	3	4	5	6	7	8	9	10	Extremely fatigued

Figure 9 Fatigue scale, adapted from [31]

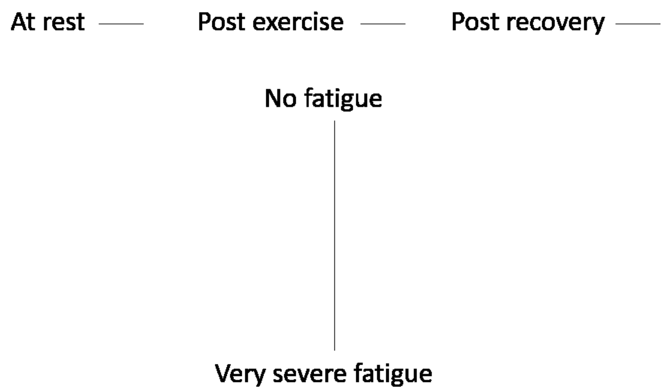


Figure 10 Fatigue scale, adapted from [32]

2.3.2 KINETIC ENERGY

A novel approach to the measurement of fatigue was introduced in 2019 [33]. This study quantified the kinetic energy through the mathematical model proposed by Southerland in [34] and the body postures before and after a fatiguing experimental protocol (Figure 11). The fatiguing protocol consisted of a running program for 180 s followed by a repeated-sprint exercise for 30 s, a step test for 30 s (0.2 m height platform that the subjects step onto), crunch + jump for 30 s, sit to stand up + push-ups for another 30 s. The body posture states were measured by inertial sensors during a Stair Climbing Test (SCT), and the data was modeled using a Gaussian mixture model. The fatigue score proposed in this study was calculated based on the difference of each parameter (i.e., kinetic energy and postural state) between the first and second SCT tests, and divided by its average. After obtaining each difference, an average of both parameters was calculated, and this was their objective fatigue score. The correlation between this score and the subjective score (a visual analog scale result) was 0.95 for males and 0.70 for females [33]. This method, although it can be appropriate for laboratory studies, it involves a great deal of preparation before and after the actual exercise period, which would not be ideal for a real work environment.

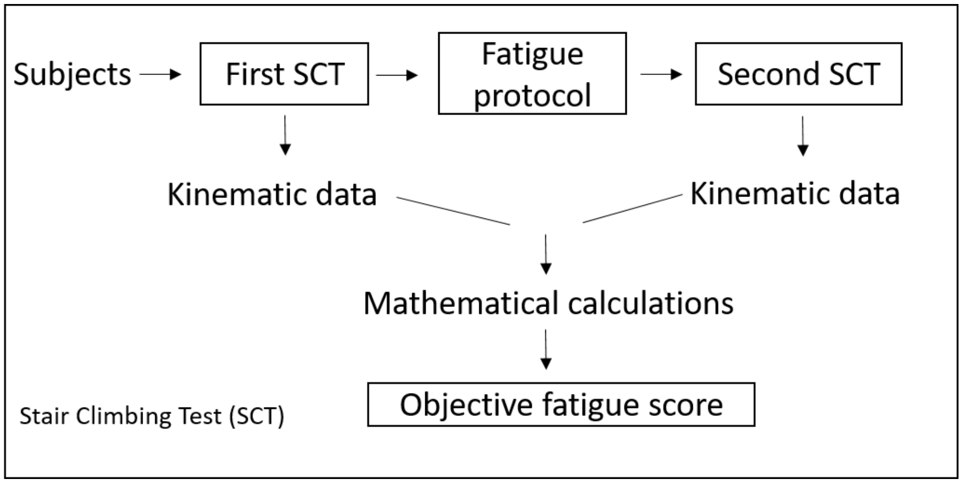


Figure 11 Method to obtain an objective fatigue score, adapted from [33]

2.3.3 EMG

Electromyography (EMG) directly measures the electrical activity of the muscle. The EMG sensors can be invasive (fine wire electrodes) or noninvasive (skin surface electrodes) [35]. Fatigue can be measured through EMG recording with two variables: amplitude of the EMG signal, and its frequency content. When a muscle starts fatiguing, the EMG signal amplitude increases, and its frequency decreases. Muscle fatigue can also be found in a reduction of Maximal Voluntary Contraction (MVC) after an induced exercise [36]. Figure 12 shows an example of how the EMG signal amplitude increases overtime during a fatigue experiment, adapted from [37].

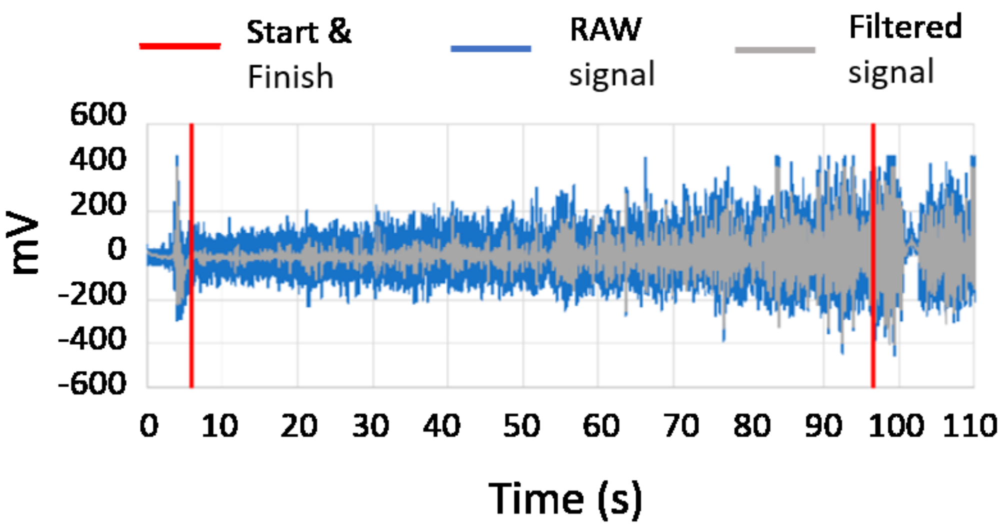


Figure 12 Raw and filtered EMG amplitude during an exercise experiment across time, adapted from [37]

Regardless of the good accuracy that can be provided by EMG signal when it comes to fatigue, the process of data collection and signal analysis can come to be rather long, expensive, and sometimes inconvenient or invasive to the subject. Challenges when working with EMG are listed below:

- The placement of the sensors needs to be precisely located in the targeted muscle, and the direction of the muscle fibers. It is recommended to place the sensors by a trained professional.
- If during the trial the participant sweats, it is likely that the sensor will be detached from the skin and needs to be reattached.
- EMG signal has a very small amplitude, and thus a small signal-to-noise ratio that would require elaborated signal processing.

This chapter reviewed the necessity and methodologies to properly design a work task and workstation, so a person's load capacity is not overpassed. It was also shown how to assess a work assignment to make sure the motions and postures are ergonomically safe. Yet, in addition to the posture and motions assessment, their frequency and duration also need to be considered for assessment and lowering the risk of WMSD. Therefore, an optimal schedule needs to be designed that can help employers and employees avoid fatigue and fatigue-related WMDs during the work shift. To maximize the practical use of suggested fatigue assessment and fatigue reduction strategies, the development of a non-invasive, low-cost method to measure fatigue, without the need for the presence of any experts is highly recommended. To this end, this project proposes 1) a novel non-invasive, inexpensive, convenient methodology to detect the onset of muscle fatigue based on the worker's body kinematics in the workplace, and 2) investigate if this novel methodology can distinguish the muscle fatigue variation in different work schedules toward proposing optimized work schedules for reducing fatigue and fatigue-related WMDs. For this purpose, we propose the application of low-cost IMU systems that do not require 1) much technical knowledge and expertise for implementation in the workplace and 2) modification of the tasks and workstation. To comply with the project proposals mentioned above, the following steps need to be taken:

1) Design an objective parameter to detect and quantify fatigue using purely kinematic information rather than EMG-based parameters.
2) Design and develop an experimental procedure to validate the new parameter against EMG signal and a Borg Rating of Perceived Extertion scale (RPE).
3) Experiment with various work condition scenarios to investigate the efficiency of the proposed kinematic parameter in muscle fatigue detection.
4) Validate the accuracy of the IMUs in collecting the proposed kinematic parameter against the camera-based motion capture system for a long-term material handling task.

CHAPTER 3

K-SCORE: A PRACTICAL NON-INVASIVE KINEMATIC PARAMETER FOR MUSCLE FATIGUE DETECTION

3.1 Introduction

Manual material handling jobs are considered to be of high risk because of their association with musculoskeletal disorders (MSD) [38]. One of the main causes of MSD is the overuse of the musculoskeletal system of the body, and it can be detected when there is a feeling of fatigue [39]. However, as mentioned in the previous chapter, the current methods to measure fatigue are expensive, invasive, not fully accurate, and subject to complicated analyses.

Analysis of EMG recordings is one of the most reliable methods to detect muscle fatigue; however, the signal obtained can be easily contaminated during the data collection by electrical artifacts, activity on adjacent muscles, or sweating [40]. The EMG electrodes are also difficult to be placed on the skin, which requires the involvement of an individual with technical expertise. At the same time, IMUs measure the angular velocity, linear acceleration, and magnetic field [41]. This information can help us estimate the joint angles of a person's posture over time, which may contribute to muscle fatigue detection. IMUs are non-invasive, light, small, non-expensive, wearable, and can be used in a large variety of environments [42].

The objective of this chapter is to propose kinematic parameters to measure muscle fatigue using IMU recordings in a user-friendly, inexpensive, and non-invasive way. For this purpose, we investigated the efficiency of two kinematic parameters in detecting muscle fatigue. The first one is the already established REBA score, and the second one is a novel parameter introduced in this chapter called K-score (Kinematic score). K-score is calculated based on REBA score but contains a higher resolution of body joint angles, which might, in turn, improve the sensitivity of body posture monitoring for muscle fatigue detection.

To investigate the efficiency of these kinematic scores, an experimental procedure was designed and experiments performed to induce fatigue in a material handling setting. The muscle fatigue was measured using EMG and RPE and the outcome was compared to that of the kinematic scores, i.e., REBA and K-score.

3.2 Methods

K-score was inspired by REBA, an ergonomic assessment tool that obtains a score based on the body joint angles and posture during any task. To calculate the REBA score, sub-scores are determined as a function of the ranges for each joint angle (neck, trunk, knee, shoulder, elbow, and wrist). For example in Figure 13, the sub-score for the neck flexion joint angle is +1 if the angle is between 0° and 20°, +2 if this angle is higher than 20°, and +2 if this angle is less than 0° (i.e., extension). The sub-score for the trunk position, as seen in Figure 14, is +1 if the joint angle is at 0°, +2 if it is between 0° and 20° or in extension direction, +3 if it is in the range of 20° and 60°, and +4 if it is more than 60°. Even though these ranges can help to provide a general idea of the risk of a certain task, they are not precise enough to characterize subtle changes of dynamic posture and ergonomic risk (e.g., due to fatigue) over time. For example, when a person picks up a box from the floor, the recommendation is to bend the knees instead of the trunk [4], when they do, the knee can have an angle of 30º, and the trunk an angle of 9º. When a person performs this same movement for many repetitions, it becomes natural that the legs begin to get tired (fatigued), and to compensate, the person starts incrementing their trunk bending little by little. This increase can be of as little as 5° over a period of 20 minutes, but its measurement may indicate that the person is fatiguing, is at risk of WMSD and action must be taken to avoid them.

Figure 13 Neck score for REBA, adapted from [14]

Figure 14 Trunk score for REBA, adapted from [14]

The ergonomic risk assessment tools such as RULA and REBA have a limited range and resolution (e.g., an integer between 1 and 15) and are determined between low-resolution thresholds of body joint angles (e.g., every 20 degrees). Therefore, they might not be sensitive enough for the detection of subtle changes in body posture due to fatigue. This might require a definition of revised kinematic scores to describe body postures.

The K-score contains a much larger range of values for every joint angle used. It assigns a value for it, and this value is then multiplied with other joint angles within the same limb (or the one closest to it). K-score obtains one score for upper limb posture and one for the lower limb to be added for obtaining the final score. A worksheet explaining how to obtain the K-score is shown in Figure 15. Is important to notice that the joint angles presented in this worksheet were selected specifically for the experimental task performed for its validation (presented in section **3.2.1 EXPERIMENTAL SETUP**), however, if K-score is used in a different task, the selected joint angles in 3D should be reconsidered accordingly.

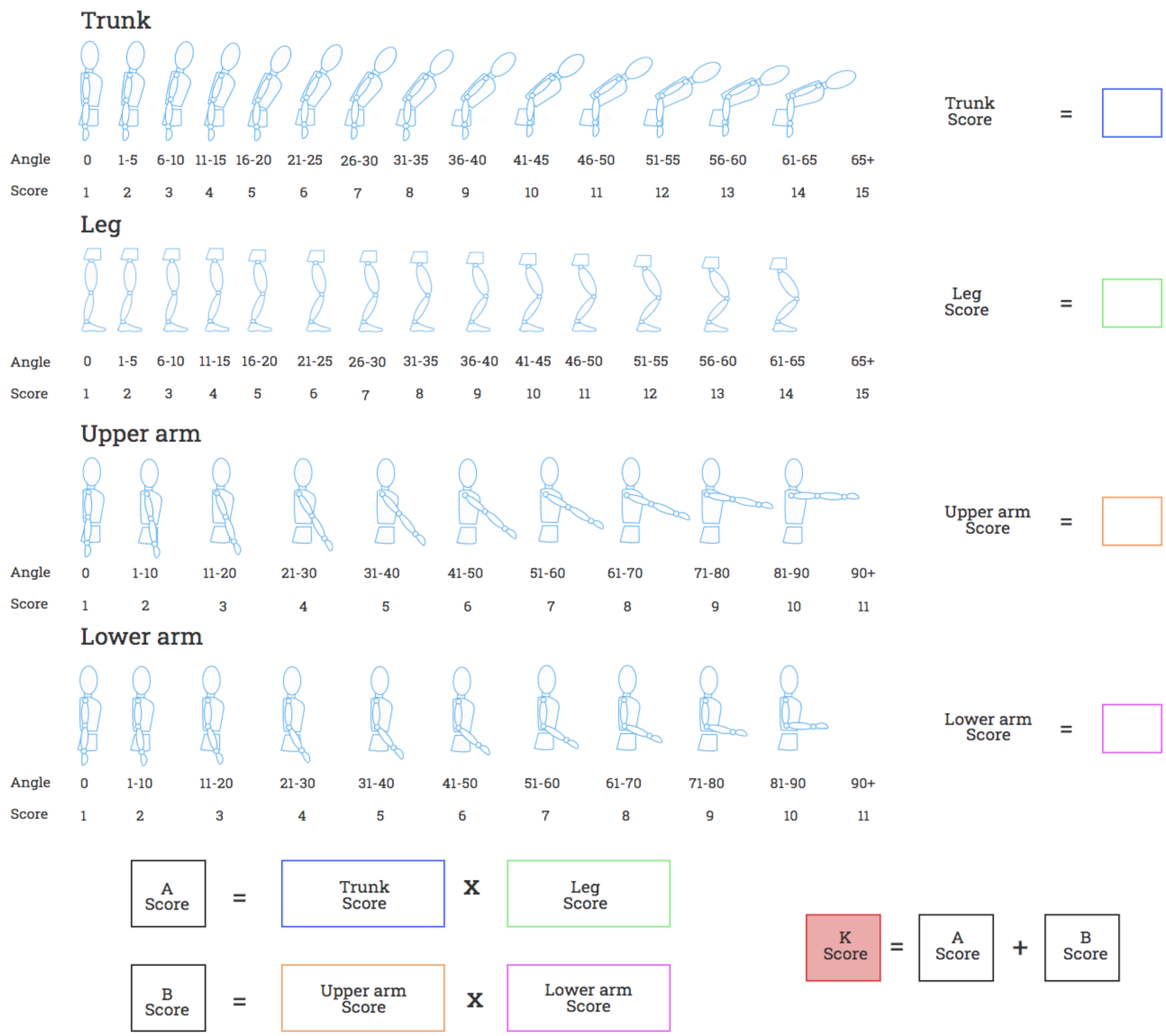


Figure 15 step by step worksheet to measure K-score

3.2.1 EXPERIMENTAL SETUP

To investigate the efficiency of the K-score in detecting fatigue, an experimental procedure was designed that would allow the participant to be fatigued during a material handling task. We assessed fatigue using three different techniques: RPE, EMG recording, and two kinematic parameters (REBA and K-score).

Ten able-bodied participants (all male, age: 24 ± 2, body mass: 73 ± 11 kg, body height: 179 ± 4 cm) performed an experiment designed to duplicate a material handling task. The experimental protocol was approved by the local research ethics board. Each experimental repetition consisted of lifting a box of 16 lbs. from a table of 15 cm height and placing it on the second table of 75 cm height, and vice versa. A diagram of the experimental process is shown in Figure 16. The participants were asked to perform this repetitive movement and report if fatigue was reached. To know when fatigue was reached, the participant was asked their level of tiredness every 2 minutes on a 0 to 10 scale using the Borg scale (Figure 17). When the participant reached level 9 or 10, the experiment stopped.

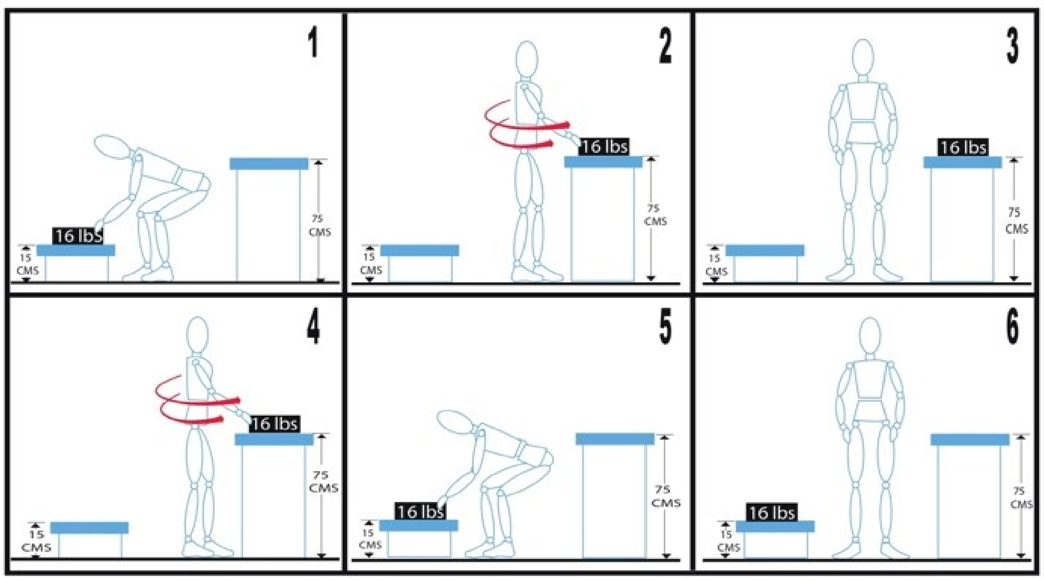


Figure 16 Experimental setup

1 – 10 Borg Rating of Perceived Exertion Scale	
0	Rest
1	Really Easy
2	Easy
3	Moderate
4	Sort of Hard
5	Hard
6	
7	Really Hard
8	
9	Really, Really Hard
10	Maximal: just like my hardest race

Figure 17 Borg scale, adapted from [43]

Muscle activity (EMG) was recorded to detect muscle fatigue. The muscle activity was recorded using a wireless EMG system (Trigno, Delsys, USA) at 1200 Hz from biceps, carpi radialis, rectus femoris, tibialis anterior, biceps femoris, lateral gastrocnemius, erector spinae, triceps, and trapezius as shown in Figure 19. To avoid any additional noise recorded by the electrodes, the electrode location was shaved and cleaned before its attachment. 9 IMUs (XSENS, NL) were used to calculate the body joint angles and subsequently REBA and K-score. The IMUs were placed on the forehead, sternum, sacrum, upper arm, forearm, hand, thigh, shank, and foot as seen in Figure 18.

We evaluated the accuracy of the IMUs in calculating the joint angles against joint angles measured by a motion capture system (Vicon, USA). To this end, a set of 28 reflective markers was placed on the anatomical locations shown in Figure 20 and described in

Table 11. The comparison between IMUs and motion capture system is presented in detail in Chapter 5.

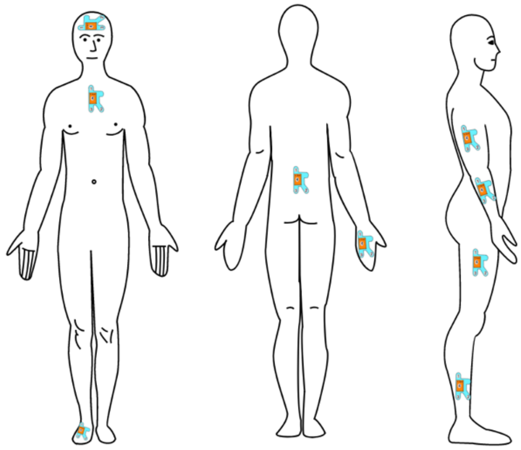


Figure 18 position of IMUs

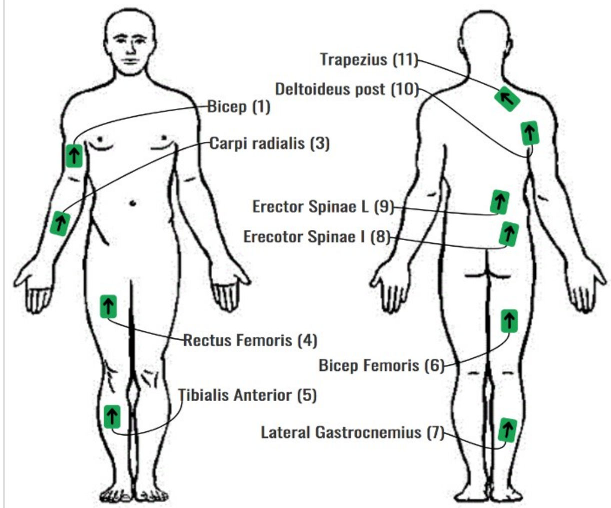


Figure 19 EMG muscle position

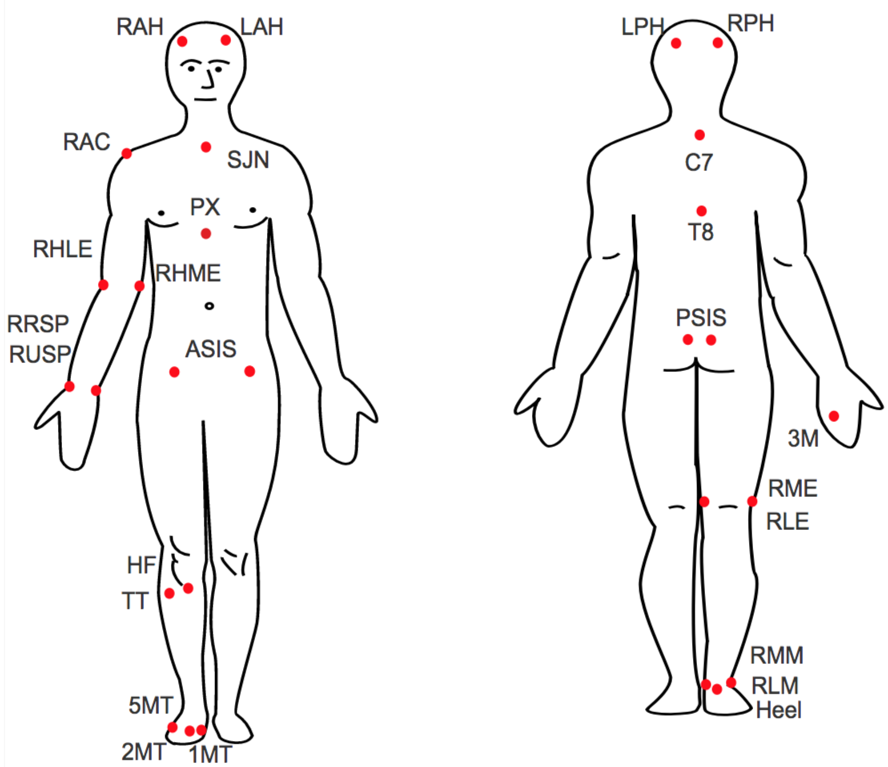


Figure 20 reflective markers position

Table 11 Reflective markers position

Abbreviation	Meaning
RAH	Right Anterior Head
LAH	Left Anterior Head
LPH	Left Posterior head
RPH	Right Posterior head
RAC	Right acromion
SJN	Incisura jugulars
C7	Seventh cervical
PX	Processus xiphoideus
T8	8^{th} thoracic vertebra
RASIS	Right anterior superior iliac spine
LASIS	Left anterior superior iliac spine
RPSIS	Right posterior superior iliac spine
LPSIS	Left posterior superior iliac spine
RHLE	Right humerus lateral epicondyle
RHME	Right humerus medial epicondyle
RRSP	Right radial styloid
RUSP	Right ulnar styloid
3M	3^{rd} phalange
HF	Head of fibula
TT	Tibial tuberosity
RME	Right medial epicondyle
RLE	Right lateral epicondyle
RMM	Right medial malleolus
RLM	Right lateral malleolus
HEEL	Right heel
5MT	5^{th} metatarsal
2MT	2^{nd} metatarsal
1MT	1^{st} metatarsal

3.3 Data analysis

3.3.1 EMG

EMG recordings were filtered with a 4^{th} order band-pass Butterworth filter, with cutoff frequencies of 10 Hz and 500 Hz. Then, the obtained time-series were rectified and smoothened with a moving average of a window of 200 samples described in Figure 21. Muscle fatigue can be detected using both frequency and amplitude characteristics of the EMG time-series; however, since the measurement trial were highly dynamic, the EMG time-series were not stationary and their frequency content could not be used for muscle fatigue detection. Therefore, we chose to detect muscle fatigue by finding the difference in the EMG amplitude following the recommendations in [35] and [21]. The EMG amplitude was attained as the RMS amplitude value of each repetition (each time the participant changes the box from one table to the other). This amplitude was compared between the first and last 10% of each measurement trial. If the amplitude increase was higher than 5% it was considered as muscle fatigue.

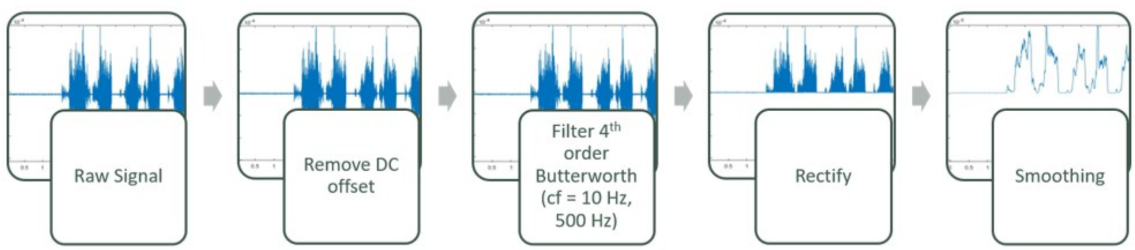


Figure 21 EMG signal processing

3.3.2. IMU

IMUs were used to measure joint angles and subsequently to obtain the K-score. The first step to this end was to calculate the reference frame of each IMU (based on the IMU's embedded sensor fusion algorithm) and multiply it by a sensor-to-body transformation matrix obtained through functional calibration. Functional calibration refers to aligning the sensor frame to its corresponding segment's anatomical frame, according to the ISB recommendation. The functional calibration was performed by 5 seconds of standing still, followed by 5 motions of flexion/extension in a single plane. This procedure was made for the right leg and arm, and the analysis was made following the steps described in [44].

Once the anatomical frame of each segment was calculated using the IMU recording, the 3D joint angles were obtained based on the joint coordinate system according to Grood & Suntay

[45]. Since the trial begins with a standing still period, it can be assumed that all joint angles at the beginning were equal to zero, and thereby the joint angle offsets were removed. Given that the IMUs' recordings present a drift over time, there was a standing still period of three seconds at the begging and end of every five minutes of the trial, this period was used to estimate and remove the drift. After calculating all joint angles, K-score is calculated following the steps described in Figure 15. Then, the RMS values of the K-score were obtained for each repetition. Muscle fatigue was detected similar to the criteria for the EMG sensors: by comparing the RMS value between the first and last 10% of the trial.

3.3.3 STATISTICAL ANALYSIS

Spearman's correlation coefficient was calculated to find the correlation between the EMG RMS amplitude in each repetition and the participant's fatigue expression in the form of a RPE value. The Spearman's correlation coefficient was also obtained to get the relation of EMG amplitude and the kinematic parameters, i.e., REBA and K-score.

3.4 Results

The mean ± standard deviation of Spearman's correlation coefficient (ρ) between the RMS of the EMG amplitude and fatigue expressed using the RPE was 0.49 ± 0.14 among all the participants. Table 12 shows the results of all 10 participants.

Once a significant relationship between the EMG amplitude and the RPE values given by the participants was identified, a correlation between the same EMG amplitude and the novel K-score was calculated. The mean ± standard deviation of Spearman's correlation coefficient (ρ) was 0.21 ± 0.06. The results obtained for all participants are shown in Table 14 and Figure 22. This significant relationship between fatigue and K-score proves that in fact, K-score is a good and reliable method to measure fatigue using only kinematic information.

Table 12 Spearman's correlation coefficient between EMG amplitude and RPE for all participants

Participant	Correlation coefficient (ρ)	p-value
1	0.45	<0.05
2	0.66	<0.05
3	0.48	<0.05
4	0.60	<0.05
5	0.60	<0.05
6	0.26	<0.05
7	0.62	<0.05
8	0.31	<0.05
9	0.55	<0.05
10	0.35	<0.05
Mean	0.49	
SD	0.14	

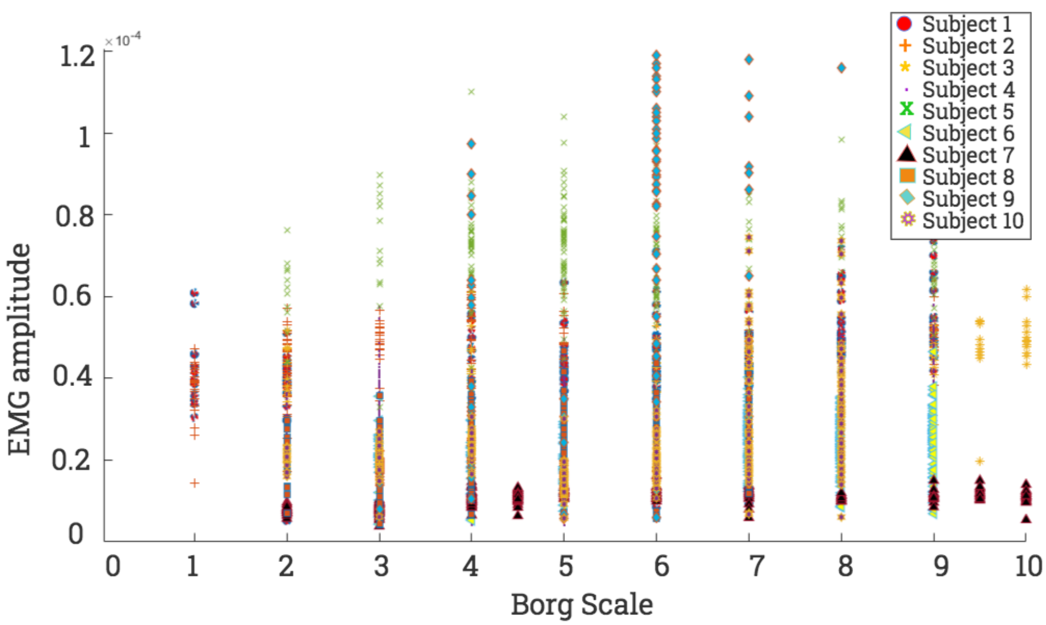


Figure 22 Fatigue results for EMG amplitude and Borg Scale (RPE) among all participants

The results showing the Spearman's correlation coefficient between REBA scores and EMG amplitude are shown in Figure 23 and Table 13 for all participants with a mean ± standard deviation of ρ = 0.10±0.07.

Table 13 Spearman's correlation coefficient between EMG amplitude and REBA score for all participants

Participant	Correlation coefficient (ρ)	p-value
1	0.15	0.04
2	0.06	0.50
3	0.05	0.55
4	0.14	0.04
5	0.05	0.42
6	0.12	0.01
7	0.02	0.13
8	0.05	0.25
9	0.09	0.08
10	0.27	0.00
Mean	0.10	
SD	0.07	

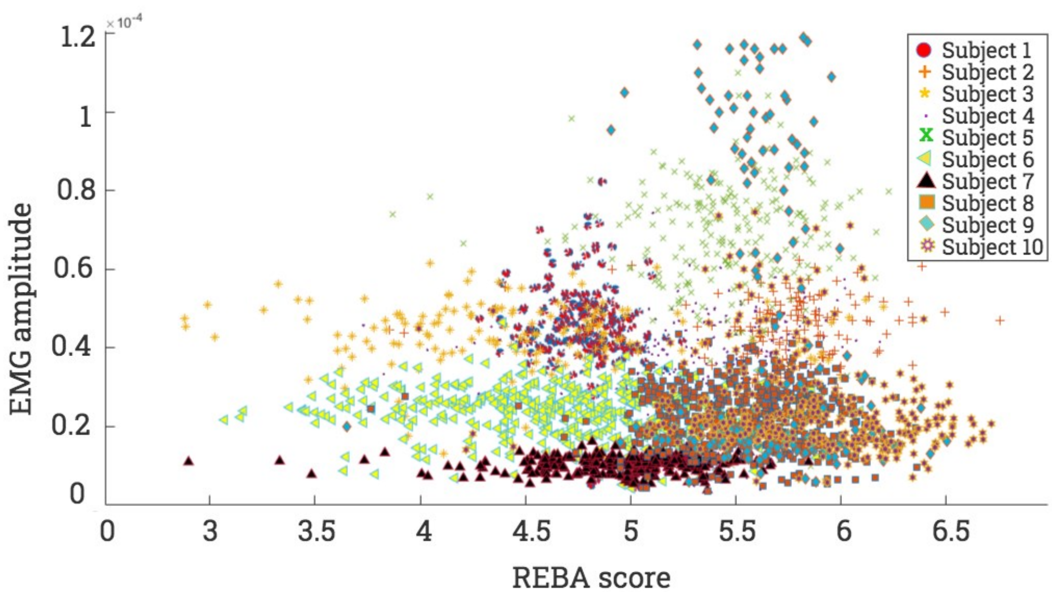


Figure 23 Fatigue results for EMG amplitude and REBA scores among all participants

The mean ± standard deviation of Spearman's correlation coefficient (ρ) between K-score and EMG amplitude was $\rho = 0.21 \pm 0.06$. The results obtained for all participants are shown in Table 14 and Figure 24.

Table 14 Spearman's correlation coefficient between EMG amplitude and K-score for all participant

Participant	Correlation coefficient (ρ)	p-value
1	0.19	<0.05
2	0.31	<0.05
3	0.23	<0.05
4	0.17	<0.05
5	0.14	<0.05
6	0.16	<0.05
7	0.27	<0.05
8	0.20	<0.05
9	0.14	<0.05
10	0.29	<0.05
Mean	0.21	
SD	0.06	

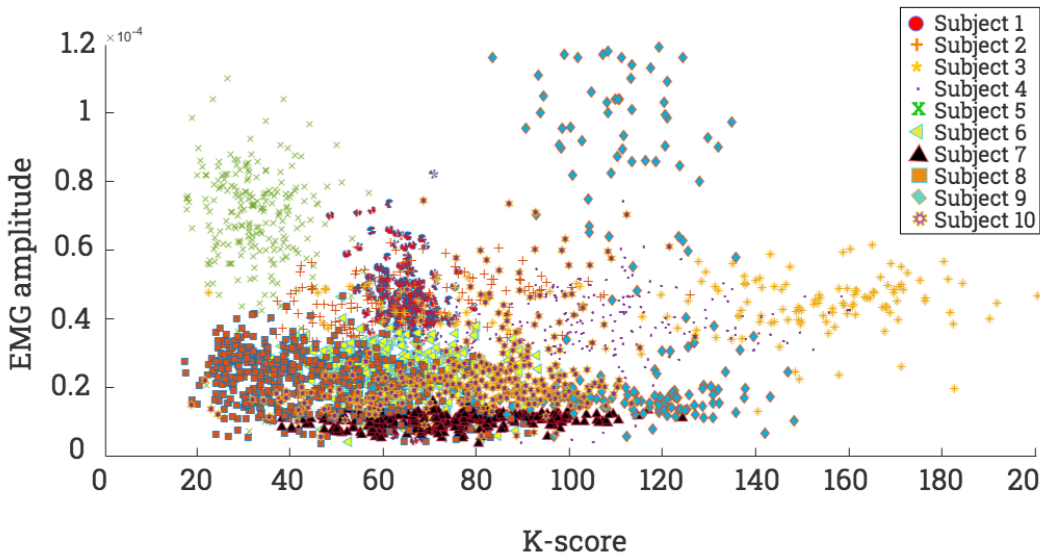


Figure 24 Fatigue results for EMG amplitude and K-score among all participants

3.5 Discussion

This study investigated the capability of kinematic scores measured by wearable IMUs (i.e., REBA and our proposed K-score) in muscle fatigue detection based on their correlation with EMG amplitude.

We investigated the efficiency of the REBA, an established kinematic score for ergonomic risk assessment, and particularly its change indicating the change of body posture for the detection of muscle fatigue. However, the results showed that there is no significant correlation between the changes of the REBA score during a long-term task and the change of EMG amplitude due to fatigue. The mean ± standard deviation of ρ between REBA and EMG amplitude was 0.10 ± 0.07 and a p-value > 0.05 for 6 out of the 10 participants. The reason might be a low resolution of the REBA score and its sub-scores, which might not is sufficient to detect small kinematic variants due to fatigue.

To address this shortcoming of the REBA score for fatigue detection, we introduced a new kinematic score (K-score). K-score was calculated based on similar joint angles used for REBA score calculation but had higher sensitivity to the joint angle change. K-score thus had the potential to detect small changes in the body posture during repetitive tasks, which can be related to fatigue. In the experiments duplicating a material handling task, K-score showed a significant correlation with EMG amplitude (changed because of muscle fatigue) measured with Spearman's correlation coefficient of 0.21 ± 0.06 (p-value <0.05 for all participants).

The results presented by the comparison between EMG amplitude and K-score support the assumption that K-score can be a reliable kinematic method for muscle fatigue detection. Given that it can be measured only with IMUs, K-score measurement can be a user-friendly, inexpensive, and non-invasive alternative to EMG measurement. In contrast with other studies that detected muscle fatigue using EMG sensors ([46], [47], [48]), K-score obtained with wearable IMUs provides an objective fatigue measurement tool for long-term measurements in the real world with minimal hindrance to the workers and without being affected by the objects in the work environment, sweating, or other sources of measurement error.

The limitations of this study are detailed in section **6.1.1 LIMITATIONS AND FUTURE WORKS** . Future work should include testing K-score in a different scenario including more or different joint angles to validate its functionality in measuring muscle fatigue in different work tasks. This will allow us to further evaluate the utility of K-score as an objective muscle fatigue measurement.

In this chapter, we have investigated and validated a new kinematic parameter (K-score) that could be a valuable tool for muscle fatigue detection. In chapter 4, we will further investigate this parameter, by using it to find a difference (if any) in muscle fatigue between three different work-rest scenarios, to suggest the most efficient work-rest schedule to prevent WMSD.

CHAPTER 4

VALIDATION OF AN OPTIMAL WORK SCHEDULE TO REDUCE MUSCLE FATIGUE FOR MATERIAL HANDLING JOBS

4.1 Introduction

As mentioned in previous chapters, being exposed to task repetition, forceful exertions, and sustained awkward postures for a long time, can fatigue a person, and eventually lead to an MSD [49]. To avoid this, it is important that if a person reaches a fatigued state, they have a recovery break to restore the muscles to their natural state [50]. Every person fatigues at a different pace, some of the individual factors that can affect this pace are fitness habits, health, and work practices [49]. One of the most popular methods to avoid fatigue in the workplace is job rotation; however, this method has several limitations, such as not being valid for workers with medical restrictions, it has proven to have a decrease in the quality of the product, and it often has a lack of tasks that can be rotated to [51]. Another method for fatigue prevention is the implementation of engineering controls such as redesigning the workstations. This has proven to be an effective technique to reduce WMSD; nevertheless, it involves a high level of investment and a complicated redesign process that industry companies are not always willing to perform [52]. Lastly, according to [53] work-rest schedules could have the ability to reduce WMSD, but the current studies lack scientific proof, which does not allow a definite conclusion. Researchers have suggested many different work-rest schedules to help the prevention of fatigue during a work shift [54] [55] [56]; however, none of these works have been proven other than by the participant's perception, which can be very subjective.

The first objective of this study is to characterize the impact of the work-rest schedule on the muscle fatigue detected for a person. To this end, we investigated three different work-rest schedules and measured muscle fatigue to quantify the effect of the work-rest schedule on the measured fatigue.

As previously mentioned, using EMG sensors for fatigue detection and measurement have a long list of limitations such as having (1) invasive procedures, (2) a long procedure for set-up and post-processing, (3) sensitivity to poor sensor to skin connection, and (4) the need for qualified personnel for its. Also, the use of RPE for fatigue detection lacks accuracy and sensitivity. To implement a kinematic score that can detect and measure fatigue with an objective score, the second objective for this study is to investigate if the proposed K-score introduced in chapter 3, is capable of detecting small changes in muscle fatigue. If so, the EMG electrodes could be replaced with IMUs; given that IMUs are non-invasive, easier to use, require little training, and can be placed on a person regardless of the working conditions (e.g., sweating). To this end, the muscle fatigue on each work-rest schedule scenario was measured with both EMG and K-score and compared against each other.

4.2 Methodology

The experimental setup and procedure are the same as described in section **3.2.1 EXPERIMENTAL SETUP**, but it is used in three different scenarios. The first scenario was done exactly as it is described, and it was used as a controlled trial. This first trial indicated the time that each subject could last doing the experiment before reaching fatigue, and it gives the fatigue values when there are no breaks involved. For the second and third scenarios, a micro-break was given every one-third of the trial; for example, if a subject lasted 30 minutes during the control trial, then the breaks for the second and third trials were given every 10 minutes. For the second trial, the micro-breaks lasted 1 minute each, in which the participant would sit still for one minute. For the third trial, a specific stretching routine was performed for the muscles that showed fatigue during the first trial. A description of each trial can be found in Table 15. To determine which muscles show fatigue, a preliminary study was made with 6 participants, and it showed that the muscles more prone to fatigue in this specific task were the bicep femoris, and erector spinae iliocostoalis, followed by biceps, carpis radialis, and triceps [57]. The stretching routine was selected according to those muscles, and it is composed of the three movements described in Figure 25. There was a waiting period of at least two days in between trials to allow muscle recovery.

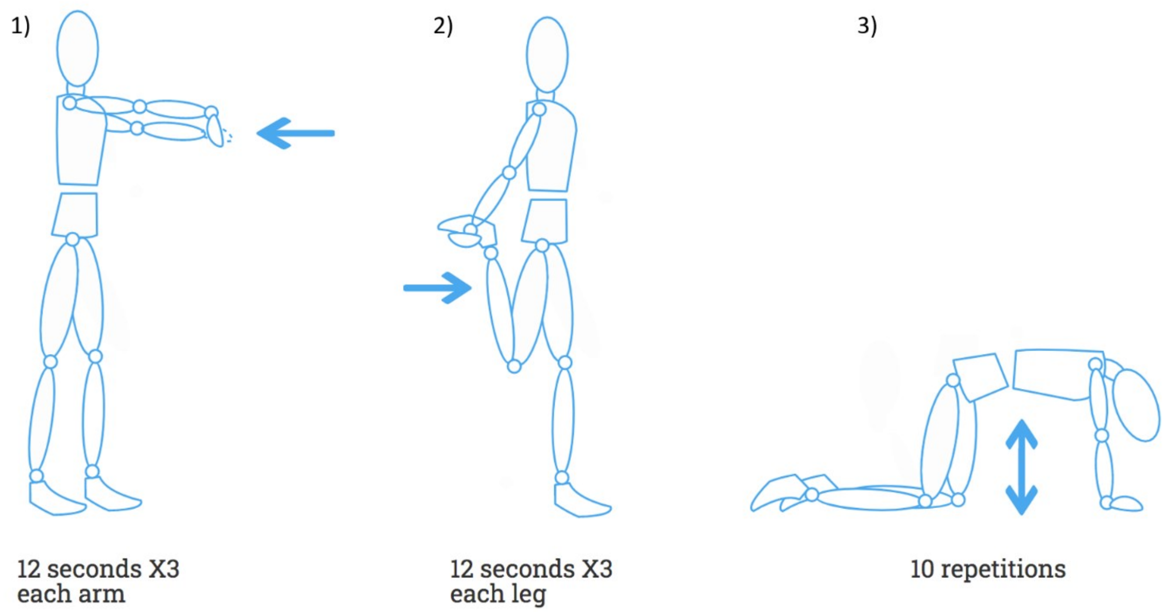


Figure 25 Stretching routine

Table 15 Description of each trial

Trial	Description
Trial 1	The trial was performed without any breaks in between
Trial 2	The trial was performed with a 1 min break every 1/3 of the trial
Trial 3	The stretching routine of Figure 25 was performed every 1/3 of the trial

The data analysis and fatigue calculations were done as described in section **3.3 Data analysis**. We detected fatigue in each muscle based on a threshold of a 5% increase in the EMG amplitude. Once we identified the muscles that were fatigued, and their percentage of EMG amplitude increase, we added these percentages for the fatigued muscles and obtained an accumulative fatigue measurement. For example, if the participant showed an increase of EMG amplitude of 26% in the bicep femoris, and an increase of EMG amplitude of 18% in the erector spinae, and did not show fatigue in any other muscle, then the accumulative fatigue was 44% =26%+18%.

4.2.1 STATISTICAL ANALYSIS

To verify if there was any significant difference in the detected muscle fatigue (characterized by EMG and IMU recordings) between the trials, a Kruskal Wallis test was performed between the three trials. If there was any difference found in the Kruskal Wallis test, we proceeded to run a Dunn's test to detect which of the trials presented a significant difference.

4.3 Results

The results of accumulative muscle fatigue measured with EMG are presented in

Table 16, and the difference in muscle fatigue between the trials are shown in Figure 26. Kruskal Wallis test showed that the work-rest schedule had a significant effect on muscle fatigue detected by EMG recordings ($p<0.01$). Dunn's test showed a significant difference between trials 1 and 2 ($p<0.05$).

The results of accumulative muscle fatigue measured with K-score are presented in Table 17, and the difference in muscle fatigue among the trials is shown in Figure 27. Kruskal Wallis showed that there is a significant effect on muscle fatigue detected by K-score ($p<0.01$). However, in this case, Dunn's test showed a significant difference between trials 1 and 3 ($p<0.05$).

Table 16 Difference in accumulative fatigue measured with EMG signal between the three trials. Measured in the percentage of EMG amplitude increase

Participants	Accumulative fatigue for trial 1 (%)	Accumulative fatigue for trial 2 (%)	Accumulative fatigue for trial 3 (%)
1	96.31	69.38	17.15
2	301.02	52.83	41.52
3	222.44	38.58	33.62
4	164.63	66.56	14.35
5	134.35	29.46	66.85
6	133.71	8.88	57.61
7	60.71	54.04	107.59
8	111.71	127.99	135.69
9	168.02	15.68	230.83
Mean	154.77	51.49	78.36
SD	71.78	35.63	69.96

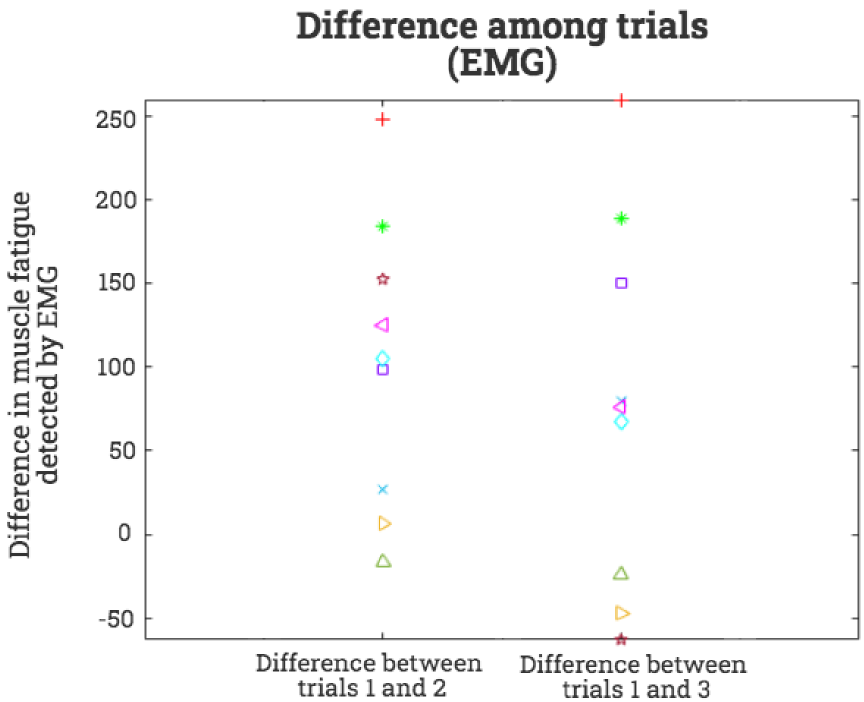


Figure 26 Difference of muscle fatigue detected between trials 1 and 2, and between trials 1 and 3 for all participants measured with EMG amplitude. The results for each participant are shown with a symbol and/or color different from others.

Table 17 Difference in muscle fatigue measured with K-score between the three trials

Participants	Fatigue for trial 1 (%)	Fatigue for trial 2 (%)	Fatigue for trial 3 (%)
1	87.46	26.94	11.76
2	43.85	19.28	32.89
3	11.36	26.34	1.52
4	42.71	14.28	2.77
5	40.09	25.57	8.46
6	40.78	38.62	4.93
7	30.72	19.89	29.76
8	54.60	35.06	15.64
9	29.89	6.47	19.20
Mean	42.39	23.61	14.10
SD	20.75	9.95	11.37

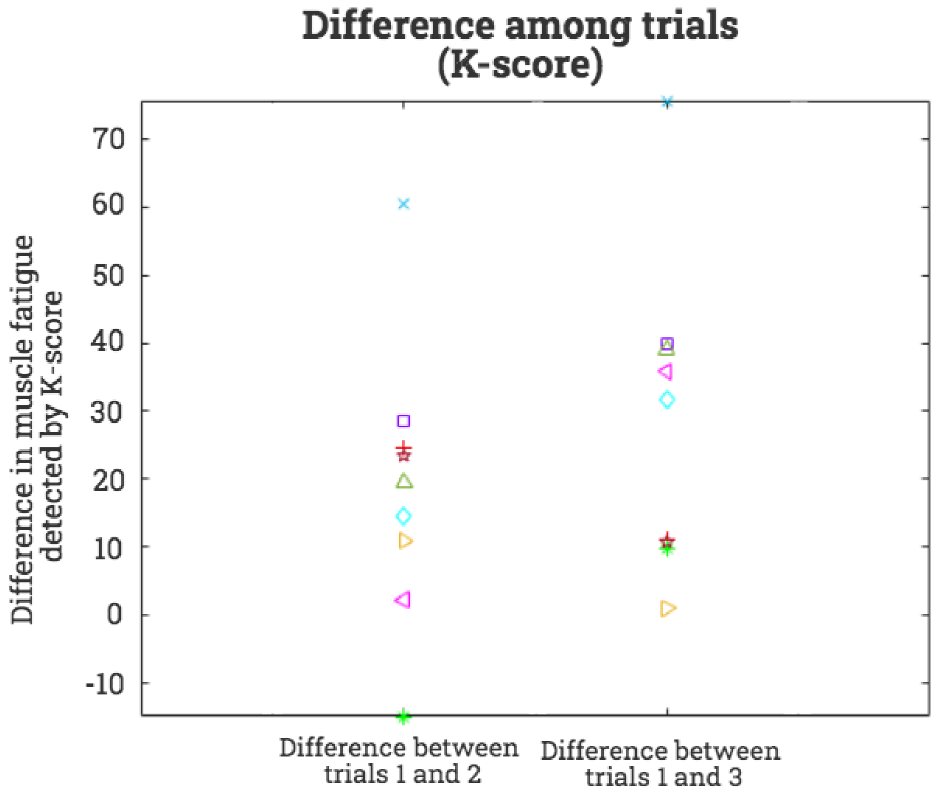


Figure 27 Difference of muscle fatigue detected between trials 1 and 2, and between trials 1 and 3 for all participants measured with K-score. The results for each participant are shown with a symbol and/or color different from others.

The productivity of each trial was also measured and shown in Table 18. The productivity was measured by counting the number of repetitions of each trial; one repetition is counted every time the participant moved the box from one table to the next one and back. The results of the Kruskal Wallis test (H (2) = 0) show no significant difference in the productivity of each trial.

Table 18 Difference in the number of repetitions made between the three trials.

Subject	# of repetitions made in trial 1	# of repetitions made in trial 2	# of repetitions made in trial 3
1	198.00	234.00	245.00
2	146.00	162.00	187.00
3	97.00	93.00	108.00
4	232.00	293.00	192.00
5	235.00	209.00	166.00
6	417.00	279.00	441.00
7	309.00	345.00	266.00
8	545.00	981.00	768.00
9	384.00	371.00	455.00
Mean	284.78	329.67	314.22
SD	142.72	259.31	207.53

4.4 Discussion

This study presented and compared three different work-rest schedules: a trial without any breaks, a trial with two 1-minute micro-breaks, and a trial with two micro-breaks to perform a short stretching routine. In contrast with other studies [54] [55] [56], this work compared the efficiency of work-rest schedules objectively by measuring the muscle fatigue presented in each trial with both EMG and a kinematic parameter (i.e., K-score). The schedule introduced in this chapter can be personalized to the individual's needs since it normalized the distribution of breaks according to their performance.

To characterize the impact that a work-rest schedule had over muscle fatigue, the Kruskal Wallis test was performed and showed that both parameters (EMG amplitude and K-score) presented a significant difference ($p<0.01$) in the muscle fatigue due to a work-rest schedule. Furthermore, a post hoc multiple comparison test (Dunn's test) was performed and indicated a significant difference ($p<0.05$) between trials 1 and 2 when measured with the EMG amplitude, and a significant difference ($p<0.05$) between trials 1 and 3 when measured with K-score. Notable, we expected to observe a significant muscle fatigue reduction after complete rest for the muscles during each break and thus the impact of the break on the EMG measurement can be justified.

On the other hand, stretching during the break can both reduce muscle fatigue and improve body posture. Since K-score measures body posture, and thus the impact of stretching on K-score might be justified.

There was no significant difference while measuring the productivity between trials. The results of this experiment indicate that even a small break can be considered as a preventive measure to reduce fatigue and in turn, the risk of WMSD, without affecting productivity.

The aim of this study was also to identify if the proposed K-score introduced in chapter 3 was able to detect small changes in muscle fatigue and capable of finding any difference in the three proposed work-rest scenarios. The muscle fatigue measured with K-score was able to show a significant difference among the three trials, and therefore, K-score might be a suitable parameter for muscle fatigue detection. This may indicate that IMUs are an appropriate tool to measure muscle fatigue through kinematic parameters in repetitive tasks, and can substitute EMG sensors for this purpose. The limitations and future work for this study can be seen in section **6.2.1 LIMITATIONS AND FUTURE WORKS**.

K-score, as a parameter to characterize body posture and muscle fatigue, is calculated through joint angles measured with IMUs. In the following chapter, we investigate the validity of IMUs to measure joint angles and kinematic parameters such as REBA and K-score against motion capture system.

CHAPTER 5

A VALIDATION OF IMU FOR ERGONOMIC RISK ASSESSMENT IN A FIVE-MINUTES MATERIAL HANDLING TASK

5.1 Introduction

If not treated, WMSD can potentially lead to serious and painful disabilities for the workers, and enforce elevated costs for employers, government, and insurance companies to pay [58]. The most accurate and cost-effective method to eliminate WMSD is to prevent them; however, to apply any preventive measurements, we first need to be able to accurately identify the jobs at risk [59]. The current process to assess the risk of the job is through subjective observation, whose accuracy is questionable [16] [60].

The current gold standard to measure kinematic parameters of body motion is the camera-based motion-capture system; however, this system is expensive, requires a dedicated area to be set up, and its set-up and post-processing procedure can be complex and time-consuming [61] [62]. Because of the high cost and large time consumption that the motion-capture system entitles, most clinicians or ergonomists do not have access to this technology [62]. IMUs can be an ideal substitute for the motion-capture systems because they are small, light, portable, and inexpensive, do not interfere with the person's natural movement and can be used in different environments (rather than only a laboratory) [63].

Previous works assessed IMU's accuracy and reliability for human motion and posture measurement in a variety of tasks, settings, and environments [65], [66], [67], [68]. Yet, most studies limited their investigation of the IMU measurement accuracy to short periods of time (less than a minute), in contrast to IMU's application on real-life situations, typically several minutes.

The objective of this study is to measure the accuracy of IMUs in capturing human body motions for ergonomic risk assessment during a material handling job for five consecutive minutes. To accomplish this goal, an experimental study was performed in which the body joint angles and kinematic scores (REBA score and K-score) were measured during a material handling job with a set of IMUs, and a camera-based motion-capture system and the results were compared together. After being validated as accurate and precise substitutes for a camera-based motion capture system, IMUs can allow industries to perform a more reliable, in-field risk assessment for a wide range of tasks, as the first step to prevent WMSD.

5.2 Methodology

We collected kinematic data to calculate the body joint angles along with the REBA score and K-score during a five-minute trial of a material handling job, as described in section **3.2.1 EXPERIMENTAL SETUP**, using both IMUs and camera-based motion-capture system. However, only the first five minutes of the full trial were used for this study to compare the parameters obtained by the two measurement systems.

The calculation of the joint angles with IMUs is described in detail in section **3.3.2. IMU**. To calculate the joint angles measured with the camera-based motion capture system we first placed 28 reflective markers as shown in Figure 20 and Table 11. The positions of these reflective markers and the calculation of the local coordinate system of each segment are according to the ISB recommendation [69] and [70]. The hip coordinate system cannot be calculated using only the position of the reflective markers, since it lacks anatomical landmarks for its centre calculation; therefore, the hip joint centre was obtained following the instructions in [71]. Also, the head segment is not defined by the ISB recommendations, therefore, its local coordinate system was calculated with the markers in the right anterior head (RAH), left anterior head (LAH), left posterior head (LPH), and right posterior head (RPH). After the calculation of the local coordinate system of each segment, the 3D joint angles were obtained through the joint coordinate system convention proposed in [45]. REBA score and K-score were obtained according to sections **2.1.2 Rapid Entire Body Assessment (REBA)** and **3.2 Methods** respectively.

To validate the use of IMUs for this particular task, two comparisons were made:

1) The joint angles for neck, trunk, shoulder, elbow, and knee measured with IMUs were compared against those measured with motion capture, and the root means square error (RMSE) was calculated and presented.
2) A comparison between the ergonomic scores (REBA and K-score) was made between the values obtained with IMUs and the motion–capture system. To compare these two values, we used the Cohen's Kappa coefficient and its interpretation.

5.3 Results

The 3D joint angles were measured for the trunk, neck, shoulder, elbow, and knee, and the results for a standing still period of 10 seconds and the first repetition of the trial are presented in Figure 28.

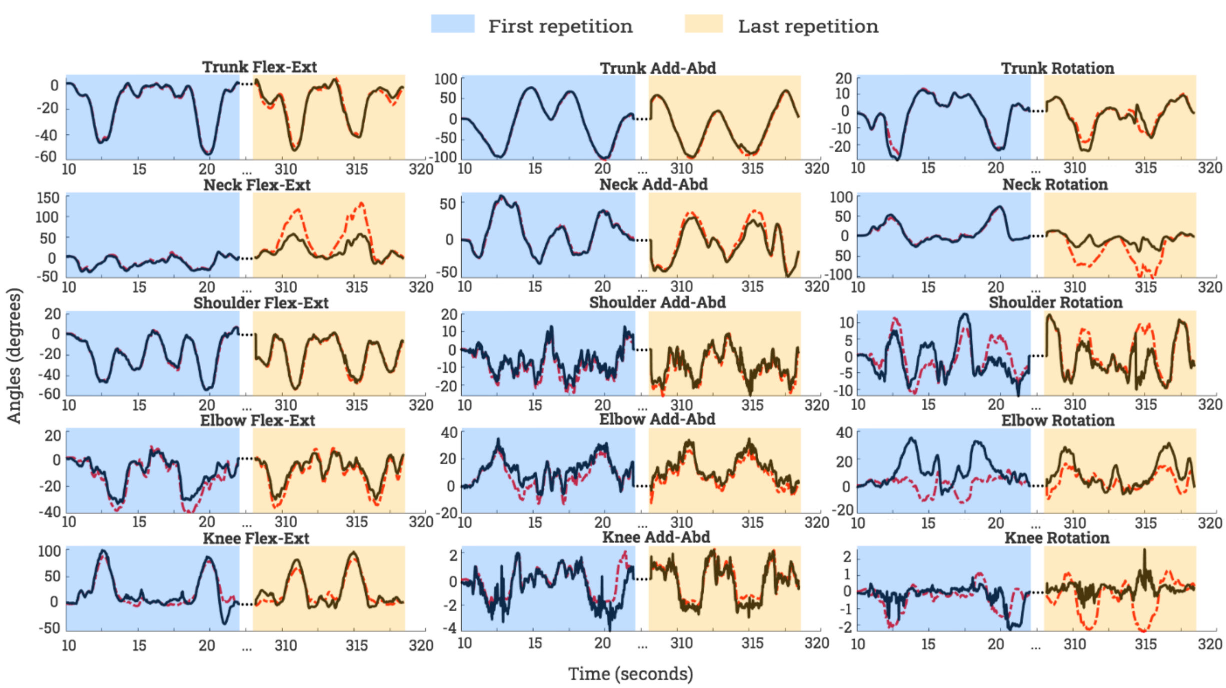


Figure 28 3D angles measured with IMUs (red dashed line) and motion capture (black continuous line) for the first repetition and last repetitions

The RMSE of the joint angles measured with IMUs against the motion-capture system are presented in Table 19, and Figure 29, Figure 30. For most joint angles, the obtained mean RMSE value was less than 4°, except for the neck joint angles, for which the mean RMSE values were 7.07°, 4.22°, and 7.31° for flexion-extension, adduction-abduction, and rotation respectively.

Table 19 RMSE of joint angles measured with IMUs and motion capture system. The results are presented in mean ± standard deviation among all the participants

Joint	Movement	RMSE (in degrees)
Elbow	Flex-Ext	3.18 ± 3.25
	Add-Abd	2.93 ± 2.97
	Rotation	3.49 ± 2.65
Shoulder	Flex-Ext	2.70 ± 3.26
	Add-Abd	3.36 ± 2.18
	Rotation	2.98 ± 2.28
Knee	Flex-Ext	1.09 ± 1.34
	Add-Abd	2.79 ± 2.73
	Rotation	2.18 ± 1.17
Trunk	Flex-Ext	1.42 ± 2.16
	Add-Abd	3.52 ± 1.88
	Rotation	1.34 ± 1.00
Neck	Flex-Ext	7.07 ± 4.28
	Add-Abd	4.22 ± 2.08
	Rotation	7.31 ± 3.97

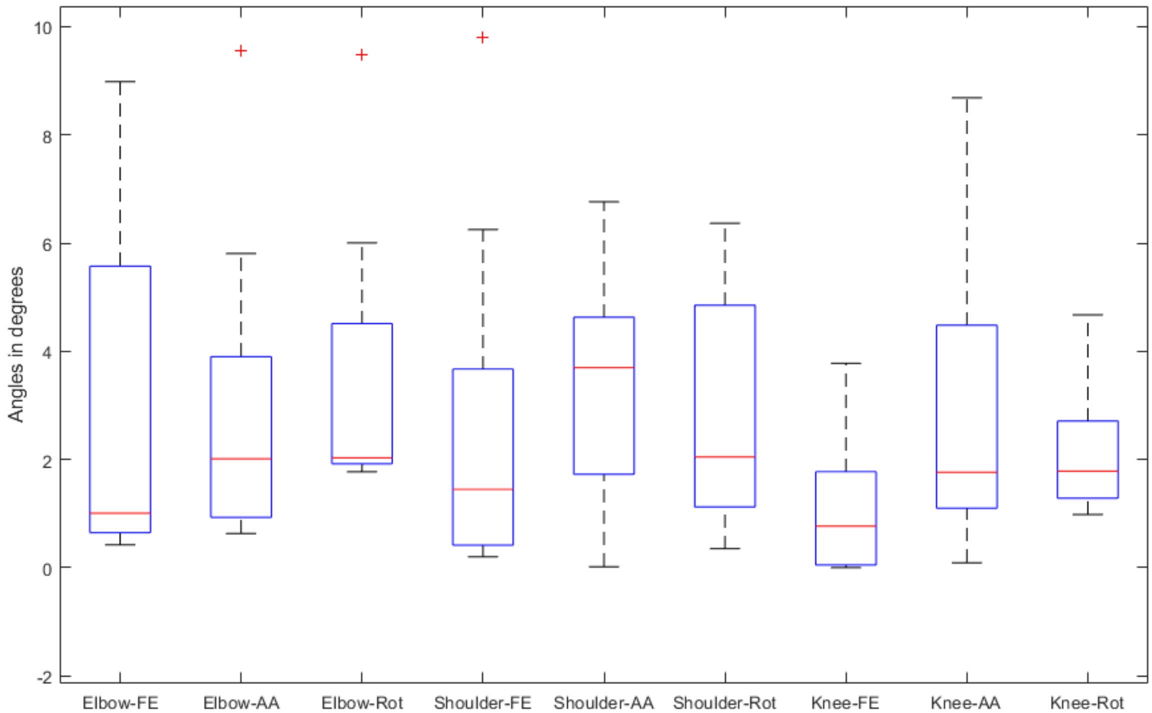


Figure 29 Root mean square error of the 3D joint angles (Elbow, Shoulder, and Knee) measured with IMU compared to those measured with motion capture, presented as boxplot among all participants

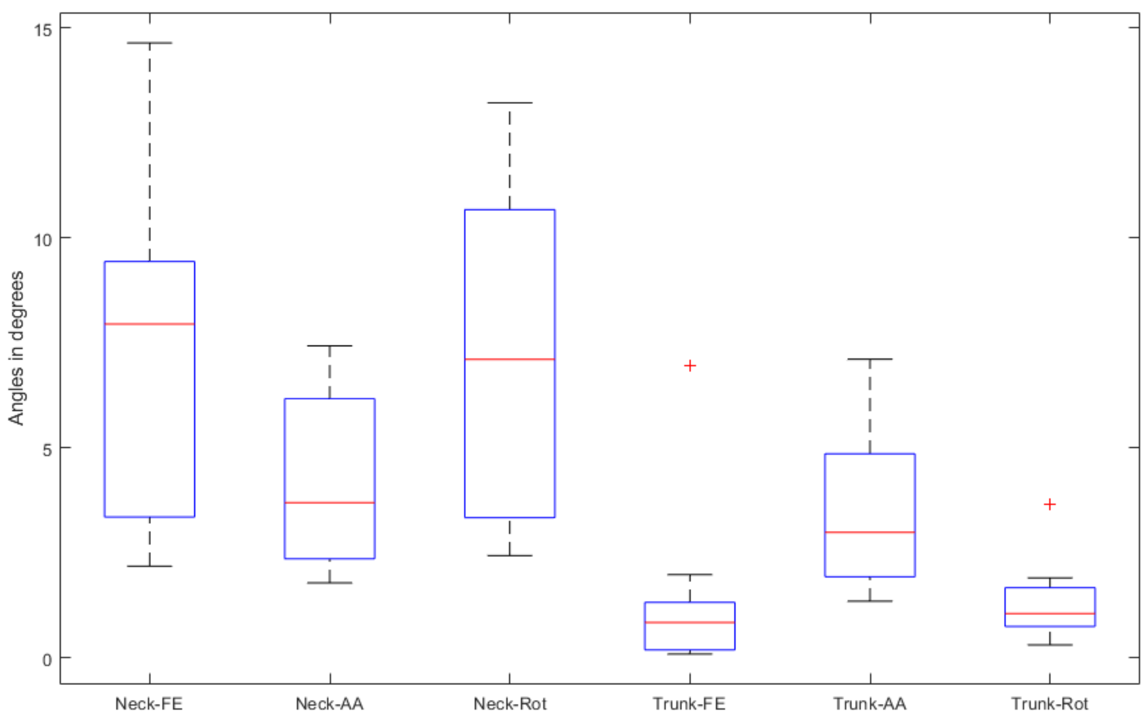


Figure 30 Root mean square error of the 3D joint angles (Neck and Trunk) measured with IMU compared to those measured with motion capture, presented as boxplot among all participants

The measurement of REBA score and K-score with IMUs and motion capture are presented in Figure 31 for comparison between the two measurement systems. The results showed a mean Cohen's Kappa coefficient of 0.67 and 0.68 for REBA score and K-score respectively, which, represents a "Substantial agreement" for both scores according to Lana and Koch in [72].

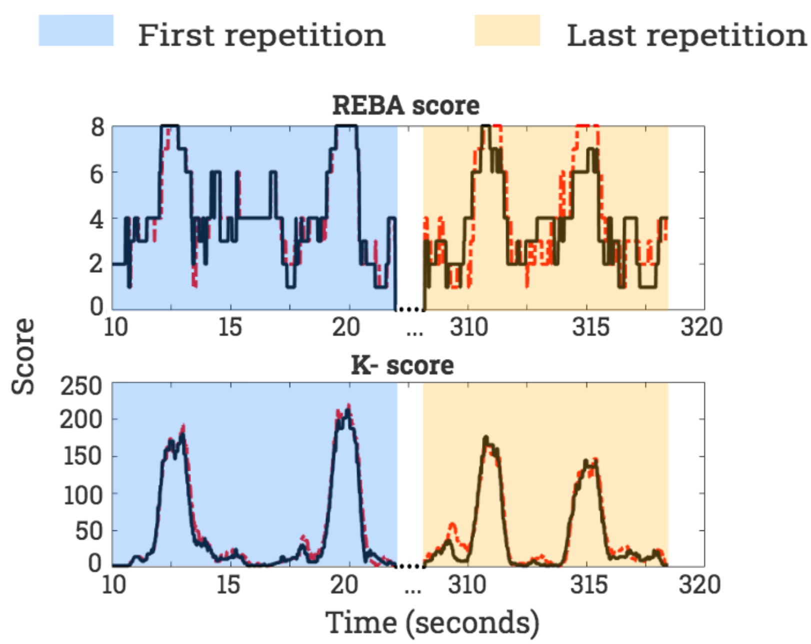


Figure 31 REBA score and K-score measured with IMUs (red dashed line) and motion capture system (black line) for the first repetition.

5.4 Discussion

This work investigated the validity of IMUs' accuracy for measuring joint angles and two kinematic scores (REBA and K-score) against the gold standard reference system: a camera-based motion capture system. In contrast with other studies ([65], [66], [67], and [68]), this study is not limited to a short period of time, since both systems measured the kinematic parameters during a material handling task for five consecutive minutes.

This study demonstrated that seven IMUs were able to measure body joint angles (except for the neck joint angles) with an RMSE of less than 4 degrees. The RMSE values for the neck joint angles were 7.07°, 4.22°, and 7.31° for flexion-extension, adduction-abduction, and rotation respectively. The IMU that was measuring the head segment was not attached directly to the head, instead, it was attached to a sport's headband that was worn by the participant. The use of this headband could have been the reason for the large error of the neck angles since it allowed more movement to the IMU, and it did not fit perfectly to all participants. The results obtained in this study are superior to the ones obtained by other technologies. For example, in [73] the authors presented an average error between 5.30° and 9.75° for joint angles measured with image processing and in [74] they authors presented RMSE values between 7.7° and 9.2° (depending on the task) for joint angles measured with Microsoft Kinect.

The IMUs obtained kinematic scores such as REBA and K-score with a "substantial agreement" (mean Cohen's Kappa coefficient of 0.67 or higher) compared to those obtained with the motion-capture system. This proves that 1) IMUs can be used for ergonomic risk assessment in the industry in the real-world condition and the long-term, at least for a material handling job, and therefore a better accuracy can be obtained compared to the current assessment method (i.e., observation); and 2) IMUs can measure K-score with good accuracy, which could enable the use of IMUs for fatigue detection. Limitations for this study can be seen in section **6.3.1 LIMITATIONS** .

The results of this study have confirmed the use of IMUs for longer trials, as long as there is a "standing still" period before and after the trial to reduce the drift effect. The outcome of this work contributes to an easier and less expensive method to measure any kinematic parameter without the need to be restricted in a laboratory setting.

C H A P T E R 6

DISCUSSIONS AND CONCLUSION

6.1 K-score: a practical non-invasive kinematic parameter for muscle fatigue detection

Muscle fatigue may interrupt the muscle's ability to function properly [75] which could lead to high-risk body posture and task execution. Therefore, muscle fatigue detection is an important factor in ergonomic risk assessment for demanding tasks such as material handling jobs, especially in the long-term. Muscle fatigue detection has the potential to identify if a person is at risk of developing WMSD in the future [39]. The current methods of fatigue detection tend to be subjective, invasive, complicated, expensive, or inaccurate. Two of the most common methods for muscle fatigue detections are EMG signals, and the RPE; however, both of these parameters have many limitations. Some of the limitations for using EMG sensors include: 1) the sensors need to be attached directly to the person's skin, and therefore, the area of contact needs to be shaved and cleaned before attaching the sensors, 2) the sensors are easily detached when the person sweats or performs any abrupt movement, 3) the EMG signal has a very small amplitude, and can be easily affected with external noise, 4) the EMG data analysis is a complicated process and needs to be done by a trained professional. At the same time, the RPE, is easy to perform, since it does not require any technology other than a RPE, but the results are very subjective, given that they only depend on the worker's feedback.

Therefore, this study aimed to investigate a fatigue detection method using only kinematic parameters. The use of purely kinematic parameters enables substituting the use of EMG sensors with IMUs, which are cost-effective, non-invasive, and require little training to be set up. To this aim, an experiment with 10 participants was performed that duplicated a material handling job. The participants were monitored with EMG and IMUs. To define a fatigue score with the EMG signal, we calculated the percentage increase in the RMS amplitude of the EMG signal between the first and last 10% of the trial. REBA is a widely used ergonomic risk assessment tool. In this study, we investigated the detection of small changes in the participant's posture due to fatigue. The muscle fatigue detected with EMG amplitude (changed because of fatigue) was compared against the REBA scores (affected by muscle fatigue), and the results for Spearman's correlation coefficient showed no significant correlation for 6 out of the 10 participants. Given that the REBA score is ranged from 1 to 15, it does not give enough range to detect these changes, therefore there was not a significant correlation with muscle fatigue. Since the already established parameter was not able to have the posture resolution we were looking for, we had to design and develop a new kinematic score with high resolution in the change of posture, this parameter was named K-score.

K-score calculates a number between 1 and 346 depending on the person's posture, this wide range allows us to differentiate between postures even if the change is small. The mean ± standard deviation of Spearman's correlation coefficient between K-score (affected by muscle fatigue) and EMG amplitude (changed because of fatigue) was $\rho = 0.21 \pm 0.06$ with a *p*-value of $p<0.05$ among all participants.

The study results showed the potential of the proposed kinematic parameter (K-score) for detecting muscle fatigue while doing repetitive tasks. The outcome of this study supports the fact that muscle fatigue can be measured in a non-invasive manner, with low-cost IMUs, in a variety of environments.

6.1.1 LIMITATIONS AND FUTURE WORKS

Some of the limitations of this study include: 1) when measuring the REBA scores, muscle use, weight, and repetitions were not taken into consideration, 2) the experiment took place in a laboratory setting, with controlled conditions, and 3) the EMG signal quality recorded in long periods of time was affected by movements artifact, sweating, and the skin-electrode interface. Because the results of this study showed that K-score does have the potential to measure fatigue, an additional investigation needs to be done with diverse trials involving different joint angles (i.e., neck and wrist) to further validate the use of our proposed K-score. In addition to K-score, in the future, the incorporation of jerk (the time-derivative of acceleration) can be investigated as a kinematic parameter to measure muscle fatigue.

6.2 Validation of an optimal work schedule to reduce muscle fatigue for material handling jobs

As seen in [49], muscle fatigue can potentially lead to the development of MSDs. Finding an optimized work-rest schedule can become an easy and inexpensive method to reduce muscle fatigue and subsequently the risk of WMSDs in the workplace. Previous studies ([54], [55], and [56]) presented work-rest schedules that seemed to reduce muscle fatigue in the individuals. However, they used the participant's feedback as the fatigue indicators which is inherently subjective and has limited sensitivity. In contrast, this study presents an approach toward 1) objective measurement of muscle fatigue in long-term trials not only based on the EMG recording but also using IMUs, and 2) suggests work-rest schedules reduce any muscle fatigue presented in an individual user.

To find the optimized work-rest schedule, a material handling task was performed in three different scenarios; one with no breaks in between, taken as the control trial, one with two one-minute breaks in between, and one with a specific stretching routine that was performed twice during the trial. We measured muscle fatigue using both EMG amplitude and K-score. Both parameters showed to have a significant difference in muscle fatigue among the trials ($p<0.01$). Furthermore, a post hoc multiple comparison test pointed to a significant reduction ($p<0.05$) in muscle fatigue between trials 1 and 2, when it was measured with EMG, and trials 1 and 3 when it was measured with K-score. It was expected to have a significant difference of different trials between the EMG measurements and K-score. Since EMG measures muscle activity, it could be natural that it showed a significant reduction of muscle fatigue after a complete rest that helps the muscles to relax. In the same manner, since K-score measures the body posture, the posture is expected to be more affected after a stretching routine.

The fact that both EMG amplitude and K-score detected a significant difference in muscle fatigue between the trials, indicate the potential of K-score as a reliable source for muscle fatigue detection even when the measurement of small changes in the body posture that might be an ergonomic risk indicator is required.

Furthermore, the number of repetitions performed in each trial was similarly measured and showed to have no significant difference between the trials. This shows that the implementation of micro-breaks between work shifts can help to significantly reduce muscle fatigue without affecting productivity.

6.2.1 LIMITATIONS AND FUTURE WORKS

A limitation in this study was that some of the participants were not able to finish the three trials consecutively, because each trial needed to be done on a different day, and the experimental schedule was interrupted due to COVID-19 and had to wait for three months before finishing. A lack of controlled lifestyle monitoring during these months could potentially have affected the results. Future work for this study includes the further investigation of the resulted work-rest schedule (one-minute micro-breaks) in an eight-hour shift, to have a better understanding of how a full work shift should look like.

6.3 A validation of IMU for ergonomic risk assessment in a five-minutes material handling task

The accuracy of risk assessment in the workplace is one of the main issues that need to be addressed to prevent WMSD [53]. Risk assessments usually depend on kinematic parameters, the current golden standard to measure kinematic parameters is the motion capture system; however, this method has several challenges including 1) the need for a dedicated laboratory setting, 2) long periods of time for setting up, 3) long periods of time for post-processing, and 4) required expensive equipment is needed. Because of these reasons, there have been many studies ([65], [66], [67], [68]) focusing on the use of IMUs as an alternative to the motion-capture system to measure kinematic parameters of the body motion. However, these studies were able to cover only short-term trials. The present study aimed to validate the use of IMUs for a five-minute trial, and during a material handling job. To do this, 10 participants performed a task duplicating a material handling job while their body movements were recorded by a motion-capture system and IMUs. The results showed an RMSE of less than 4° for all 3D joint angles except for the neck joint, which showed and RMSE of 7.07°, 4.22°, and 7.31° for flexion-extension, adduction-abduction, and rotation, respectively. The high error of the neck could be a result of not attaching the head IMU directly to the head but instead placing it in a headband.

The second objective of this study was to validate the use of IMUs to calculate kinematic parameters used for ergonomic risk assessment such as REBA and the newly introduced K-score. The measurements of both parameters showed to have a "substantial agreement" when compared with Cohen's Kappa coefficient (IMU against the motion-capture system) and interpreted based on [72].

The results presented in this study showed that IMUs could be an accurate tool for body joint angle measurement in material handling jobs and subsequently performing ergonomic risk assessments. By measuring a kinematic parameter such as K-score, IMUs could be a reliable and practical substitute for EMG for measuring muscle fatigue in repetitive tasks.

6.3.1 LIMITATIONS

The limitations in this study include: 1) typical inaccuracy of marker trajectory recording using the motion-capture system, especially in the presence of objects in the workplace duplicated in the laboratory, and 2) symmetry assumption for human body kinematics during the studied manual handling task.

6.4 Conclusion

This thesis research introduced a novel kinematic parameter (K-score) for ergonomic risk assessment, especially for fatigue detection. K-score proved to be a more efficient indicator of fatigue compared to the already established REBA score, at least in the studied material handling task. The results showed that a work-rest schedule with one-minute micro-breaks in between significantly reduced muscle fatigue without affecting work efficiency. Similar to EMG signal amplitude, K-score could be an accurate, sensitive, and practical good tool for the detection of even small changes in muscle fatigue when working with repetitive tasks. Finally, we investigated the accuracy of IMUs to measure joint angles and ergonomic scores such as REBA and K-score. The results demonstrated the accuracy of wearable IMUs for measurement of body joint angles and ergonomic scores, against those obtained by a camera-based motion-capture system.

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