University of Alberta

Digital Image Processing Based Semi-automatic Data Acquisition System for Ongoing Construction Progress Assessment

By

Yuhong Wu ©

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ABSTRACT

Advanced image processing can help substantially in promoting construction management automation and making timely decisions where traditional methods prove cost ineffective, time consuming, unsafe, or are even unfeasible. However, there has been limited use of image processing in monitoring and tracking ongoing construction operations to provide users with reliable, accurate, and timely information and analysis for project controls and assessments.

This thesis presents a research effort designed to produce a digital image processing based system to efficiently assess the level/status of ongoing construction progress. A prototype data acquisition system for reinforced concrete column construction progress assessment was developed, by means of applying various image processing methods and other related techniques, using semi-automatic building structural element detection and reconstruction. The system has also been tested and shown to be promising in a real project with the generated result being very close to that achieved by manual measurement.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

1 INTRODUCTION

1.1 Motivation

A construction project is a complex development that is typically undertaken in an outdoor environment and involves a variety of workers, a range of equipment, and diverse materials. To successfully complete a given project, numerous business decisions must be made by all levels of management; sound decisions are based on a well-developed project scope and project plan, and, most crucially, on the ongoing reassessment of the changing and dynamic conditions of the construction field. However, the complex, shifting nature of construction makes it extremely challenging to quickly and thoroughly assess the status of the construction field at any particular time. For example, it is a daunting task to track the progress made across a range of physical components during the construction of a facility, let alone to verify the quality of that construction on a regular basis.

In addition, there has been an increase in the number of huge projects performed in harsh conditions or constructed in remote or inaccessible areas. This has made it more difficult, or even at times impossible, to perform regular site investigations and/or inspections to ensure that performance measures such as quality, progress, and cost controls are in order. The need to perform site inspections on large projects of this nature is also time-consuming, costly, and poses a number of risks and safety concerns. For instance, there are hundreds of huge projects in Fort McMurray, Alberta, Canada, being performed a significant distance away from their headquarters, or even their local offices. Professionals there usually have to spend a great amount of time traveling between and inspecting these huge projects on site every workday. This situation shows a great demand for timely data (such as object and/or building descriptions) acquisition during the construction period for the use of various levels of construction management. This problem is not only limited to remote or inaccessible areas, but is also observed in urban environments.

The use of image processing applications is one way to overcome these problems. Image processing has great advantages and shows the potential to be a powerful tool since the resultant digitized, two-dimensional array format can be processed freely to provide data and information about the size, shape, texture, and location of objects that are of interest to professionals in construction management. These data are required and are always crucial for many applications, among others:

- Quantity survey: comparison of the planned activities and the activities that have actually been completed in a quantitative manner, as well as timely providing specific quantities which are essential for cost estimates, progress payments, etc.
- Scheduling: providing visualization tools for project scheduling, and a continuously updating basis for construction progress control and timely decision-making by means of calculating and analyzing the productivities of particular activities based on time-lapse image data.
- Equipment/resource planning: planning and optimizing the daily or weekly management of equipment such as machine distribution, placement, and shift adjustment, as well as resource utilization after calculating and verifying the

productivity of major equipment on site by analyzing equipment idle time, cycle time, etc. based on time-lapse image data throughout the construction period.

- Contract management: providing stakeholders/parties with supporting documents and data to help resolve claims and disputes. For example, the time of critical activities taking place on site such as the erection and stripping of concrete forms, the installation of certain structural components which are considered as milestones in contract can be pinpointed and demonstrated as evidential data.

Whether these data can be acquired semi-automatically/automatically or not greatly depends upon, and should start from, the successful extraction of objects of interest.

1.2 Problems and Challenges

The great demand for highly detailed 2D/3D data in construction management collides with the enormous costs of data acquisition for these purposes (Rottensteiner, 2001). This is why automation of these tasks is currently a very desirable, challenging, and often difficult task.

The first challenge in the research is successfully and effectively identifying and detecting the objects of interest, which, at this stage, are the reinforced concrete columns, in the primitive construction-site digital images (in other words, how to differentiate these structural components from the background). However, "it is not a simple task to identify an object in a picture, especially if the picture depicts an open-field scene" (Neto et al, 2002). It is challenging to identify the various components of structures (columns, beams, and slabs, for example) and machines in those digital images obtained on site.

One of the most difficult problems in processing these primitive construction-site images is the significant amount of background visual interference generated by various surface textures and colors, the shapes of materials and facilities, non-uniform illumination, and lighting/weather conditions (i.e., snow or rain); other visibility elements also affect visual representations, including occlusions among various structural components in densely built-up areas, the shooting angle and the position of the camera with which the pictures are taken, or even blockages of the line of sight caused by ambient facilities.

The next challenge is to accurately determine the locations or coordinates, and the size and shape parameters, of the objects of interest in the images. Another key task in this and/or future research efforts is to measure the progress made on specific work items related to the identified structural components by means of analyzing time-lapse pictures, and/or distinguishing the corresponding idle and/or working equipment on site based solely on the sequential pictures.

1.3 Research Objective

In conclusion, the most challenging task in this research is extracting the objects of interest from the digital images. According to Brunn (1998), automatic object extraction usually consists of two stages: object detection and object reconstruction. During the object detection stage, various image processing techniques and tools are employed to detect objects of interest in images, and the results are used for subsequent object reconstruction. During the object reconstruction stage, the geometrical parameters of an object located in a given region of interest are determined. These two stages cannot always be clearly differentiated because the first stage may already make use of implicit geometric model knowledge and thus will already perform some tasks which could be seen as belonging to the second one. In each stage of object extraction, any knowledge about the objects of interest is supposed to be used by means of implicit representation of the object (e.g. by applying certain rules in order to better detect concrete columns), or by explicitly providing object data processing models and so on, if necessary. Therefore, the main research objectives in this research are:

1) Identifying and detecting the objects of interest--the reinforced concrete columns in the images at this stage, and later on other major structure components (the girders, slabs, etc.), as well as some typical construction operations such painting, masonwork which use specific material or have particular texture and color --and differentiating them from the background;

2) Obtaining progress assessment data based on object reconstruction, into which image detection results and some professional common knowledge or even database of the objects of interest are to be integrated on the basis of that quantitative analysis and assessment of project progress status/level can be performed freely and dynamically.

1.4 Proposed Research Methodology

The main techniques and algorithms that are to be applied in this research include:

1. Image enhancement methods

At the first stage, some morphological image enhancement and adjustment routines will be used to correct non-uniform illumination and increase contrast in the primitive images taken from the construction site. If the images are taken under undesirable lighting conditions (such as cloudy or foggy weather conditions), an additional "lighting compensation technique," which will be introduced later in **Chapter 3**, is automatically applied prior to these morphological functions. Then, a median filter is used to effectively reduce some of the finer background noise. By using these image preprocessing techniques on the primitive images taken on site, better results can be obtained in the following object identification and extraction stage.

2. Canny edge detector and watershed transformation

Once the primitive images are preprocessed, the Canny edge detector and watershed transformation, along with other morphological transformation algorithms, are applied to effectively define the edges of the objects of interest (the reinforced concrete columns in the pictures taken on site), respectively. The first one of these algorithms is a standard edge detection algorithm that detects local changes; the second is region-based segmentation, which searches for pixel and region similarities (Beucher, 1990).

3. Image data filtering technique—3D perspective view image filtering mask

In order to significantly reduce background noise, an image data filtering technique, whereby a digital imaging mask (a filter model obtained from the 3D perspective view of the reinforced concrete columns in the AutoCAD drawings) is applied to the pictures within a certain period of time, is developed and integrated into both the Canny edge detector and the watershed transformation methods. This enhances both algorithms. The

3D perspective view imaging mask is employed as an effective explicit filter in the image segmentation process, and plays a crucial role in the overall approach.

4. Data fusion strategy

After separately obtaining the useful information through the Canny edge detector and watershed transformation methods (the AutoCAD perspective view filter model is integrated into both of them), this information is further combined by using the data fusion strategy to obtain a better result for progress assessment.

5. Object reconstruction

Once the objects of interest are detected, some assumptions, made with the help of professional knowledge/expertise, regarding object surface and shape will be integrated to obtain a more reasonable result in the object reconstruction stage. Based on these results, primitive project progress assessment data are obtained.

6. Priority based error correction algorithm (**PECA**)

To further enhance the overall quality (reliability and accuracy) of the primitive progress data generated from the image processing procedure, a priority based error correction algorithm is initiated and proposed in **Chapter 4** to logically reduce the data errors and to improve those values that are abnormal in terms of time order, so that the computed progress data better fit the actual values.

Additionally, many other morphological transformation algorithms are applied throughout the overall image segmentation procedure to obtain the objects of interest, as well as to measure their properties for further analysis and future use.

Figure 1.1 shows the flowchart of the methodology proposed in this research for semi-automatic project progress assessment:

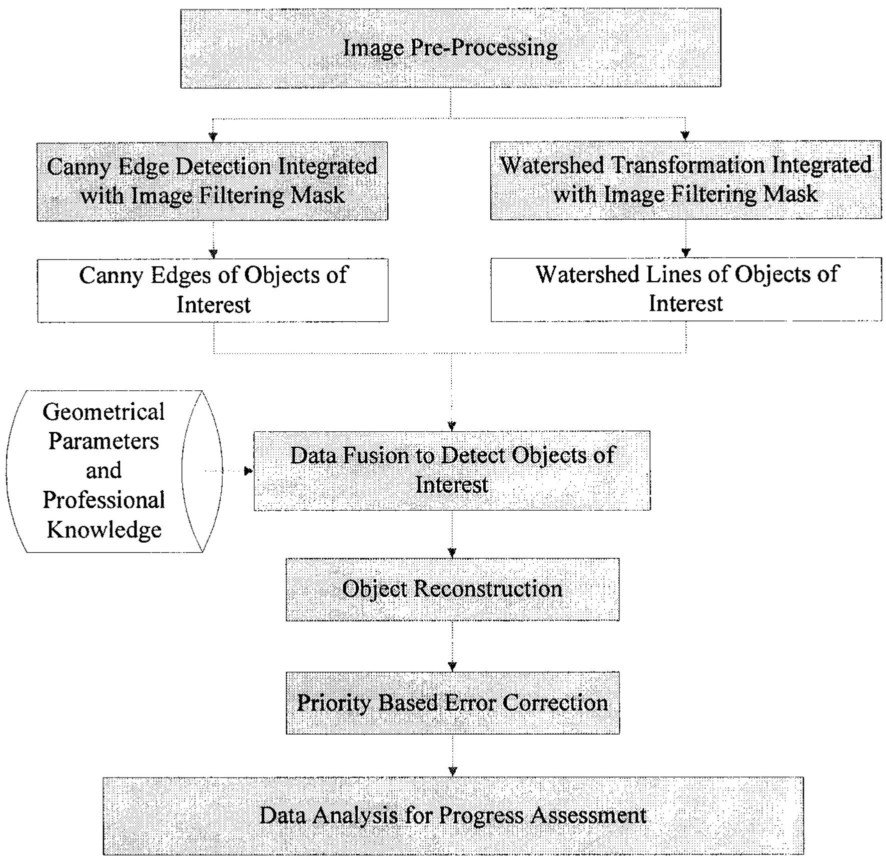


Figure 1.1: Proposed Methodology for Semi-automatic Project Progress Assessment

1.5 Outline of This Work

During the construction of the Natural Resources Engineering Facility (NREF building) at the University of Alberta in Edmonton, Canada, primitive RGB images with a resolution of 640×480 taken by a digital network camera (Axis 2100) installed on site (on the Southwest corner of the roof of ECERF building) were used to monitor the project; these images enabled the timely tracking of activities performed on site in order to study the potential capabilities, effects, and limitations of image processing in construction progress control.

Because these digital images were used as a real test project, a newly developed prototype system for semi-automatic object detection and reconstruction is proposed in this research as an effective means to enable the automated assessment of a construction project's progress, which may lead to advanced modes of project control. The main goal of the new method is to create a sound basis for an operational tool for the semi-automatic acquisition of data for the purpose of dynamic construction progress control. To fulfill this goal, three major tasks must be accomplished:

1. Give an overview of the theoretical foundations of all fields relevant to this research, in particular, Canny edge detecting, watershed transformation, normalized cross correlation, data fusion, and automatic object surface/shape reconstruction.
2. Describe the newly developed approach and all its components in the context of the theoretical foundations mentioned above.
3. Test the approach in a realistic construction project in order to evaluate its performance with respect to the reliability and accuracy of the results obtained throughout the overall process.

Chapter 1 describes the research motivation and the problems and challenges encountered in the research, and discusses the objectives of the research. Further, it details the research methodology applied to solve these problems, as well as to achieve the research objectives, and outlines the organization of this thesis.

Chapter 2 includes an extensive study of available literatures related to this research; different image segmentation techniques are also discussed and evaluated for their effectiveness in processing primitive construction-site images. The Canny edge detector and watershed transformation methods, as well as other image segmentation algorithms, are explored.

Chapter 3 presents the central technical issues of this work: the image preprocessing and segmentation techniques applied in this research, the image data filtering model (mask) generated from the 3D perspective view of the objects of interest, data fusion strategies, and the manner of object reconstruction. First, image preprocessing techniques used to better the inputs of segmentation are introduced, then the principles and unique features of the Canny edge detector method, watershed transformation method, and other morphological transformation functions are investigated and briefly presented. Next, the procedure for creating image filtering masks from AutoCAD drawings is described. As a robust data filter model, it is incorporated into the Canny edge detector and watershed transformation methods, respectively. After that, the data fusion concept is introduced and used to merge the information obtained from Canny edge detection and watershed transformation, as well as from some other morphological transformations integrated into the process. Finally, for the purpose of progress assessment, an object reconstruction based on the surface/shape characteristics of the objects of interest in combination with professional knowledge has to be applied. The chapter will be concluded with a consideration of some practical aspects of this approach.

In **Chapter 4**, an experiment conducted with the proposed image processing approach, along with the results from the test images, is presented. In order to evaluate the reliability and accuracy of this approach for semi-automatic progress data acquisition, an experiment was carried out using the original NREF construction-site images. The specific structural components (the reinforced concrete columns on the second basement floor, low level 2) of the NREF building are reconstructed in the sample images using the proposed approach. During the experiment, construction plan/schedule information was further merged to enhance the accuracy and reliability of the results. In addition, the progress data acquired from the image processing approach were to be modified by a priority based error correction algorithm. Statistic analysis was conducted to evaluate the proposed prototype system in the final section.

Finally, some conclusions and recommendations made regarding this research are presented in **Chapter 5**, and an outlook for future work is provided in order not only to improve this approach, but also to increase the degree of automation in object detection and reconstruction by integrating other methods.

2 LITERATURE REVIEW

2.1 Introduction

The field of image processing has been growing at a fast pace. This field has grown in both breadth and depth of concepts and techniques. The mainstream areas of image processing operation include: image capturing, image spaces and image representation, image compression, image enhancement in the spatial and frequency domains, image restoration, image segmentation/feature extraction for measurement, image description, and object recognition.

"Image segmentation is a fundamental step in most of the applications of image analysis" (Iannizzotto and Vita, 2000); "In computer vision, segmentation preludes the appropriate representation of the objects contained in an image and their classification according to specific features of interest" (Ballard, 1982). There are many kinds of image segmentation techniques available today, such as automatic and adaptive thresholding, light intensity based and spatial relationship based segmentation, discontinuity based and similarity based segmentation, and region growing, splitting, and merging, etc., which have been extensively and successfully applied to solve challenging and practical engineering and management problems. Also, there are many affiliated techniques and strategies, such as lighting compensation and correcting techniques, as well as various data processing strategies such as data filtering and data fusion, aimed at improving the reliability of the performance of image processing.

This chapter reviews state of the art literature covering image processing techniques and their current applications in the civil/construction engineering domain. Various points of view and concepts are discussed and compared. In addition, the various techniques and tools that are available to help establish an effective image segmentation approach for ongoing construction project progress assessment are discussed.

Furthermore, this review groups the available literature into two broad categories that focus primarily on state of the art knowledge developments in the following areas:

- State of the art image segmentation and associated techniques
- State of the art image processing applications in civil/construction engineering

2.2 Review of State of the Art Image Segmentation and Associated Techniques

2.2.1 Review of State of the Art Image Segmentation Strategy

John Hanks (1998) introduced common edge-detection software strategies for applications such as inspection for missing parts, measurement of critical part dimensions using gauging, and identification and verification of electronic user interface displays. He outlined nine steps for machine vision success and for developing a system. Following the recommended steps and strategies, the first step in this research is to determine all the objects of interest (for example, the concrete columns) for the development of the prototype system. The second step is to calculate the FOV (Field Of View, the area covered by the lens' angle of view) prior to taking images on site. By selecting the camera lens and shooting angles, the ongoing construction operations related to the determined objects of interest on site are to be monitored. The following step is to calibrate the lighting and camera system. In this research, since all of the objects of interest and related operations are performed outdoors and therefore under various natural lighting conditions, lighting compensation and/or correction for poor lighting should be considered in the system development process. According to Hanks, it might be helpful to identify a fiducial element (that is, select a unique feature that is not an object of interest, but is always present in the image) that can be used throughout the whole process. With these steps completed, a feature-locating technique based on the features and speed requirements should be selected for practical application. In regards to this, Hanks further suggested that "If the feature is of a known size and orientation, use grayscale pattern matching. In general, if the feature is of a known shape and unknown size, use binary shape matching. If the feature is of a known area and perimeter but with varying orientation, use blob analysis". Subsequently, the inspection or monitoring strategy needs to be tested with ideal images and then with images that show atypical objects of interest. The last step of the strategy is automation, which includes lighting and camera calibration for the automated inspection system.

Since the steps mentioned above are common practices in image segmentation software development, they are to be used as main guidelines in this research.

2.2.2 State of the Art Image Segmentation Techniques Review

In addition to the general strategy, many particular feature-based and raster-based image segmentation techniques were recommended and applied under different circumstances. Moga and Gabbouj (1998) introduced a parallel watershed transformation algorithm for grayscale image segmentation, which was augmented to perform with the aid of markers and to help calibrate a resilient algorithm to over-segmentation. They stated "the algorithm offered an efficient method for computing the catchment basins of a grayscale image in a distributed fashion and, at the same time, using a constrained Boruvka-like minimum spanning forest (MSF) operator for merging non-marked regions to marked ones". (MSF is a graph algorithm used to find a set of edges with minimum cost, prior to the application of which, all edges were placed in a priority queue. To learn more about MSF, please see the referred website). Image pixels were first clustered based on spatial proximity and gray-level homogeneity with the watershed transformation in a hybrid fashion. Boundary-based region merging was then employed to condense non-marked regions into marked catchment basins, in which the agglomeration strategy worked with a weighted neighborhood graph representation of the over-segmented image. They also mentioned that "In both stages, locality and concurrency were best exploited, while the amount of communication was reduced to the needed data set". According to them, one benefit of this parallel algorithm is that both the local detection of the catchment basins and the parallel computation of the Boruvka-like MSF modules, which merge partial regions and non-marked regions to marked basins, were designed with great concurrency, locality, and reduced software engineering cost, generating a scalable algorithm. Another benefit is the reduction in over-segmentation. Also, Ghalib and Hryciw (1999) presented a new method for obtaining soil grain size distribution curves from digital images of a soil specimen. This method greatly improved the existing methods by adapting mosaic imaging and watershed analysis. According to Ghalib and Hryciw (1999), "the mosaic imaging allows the grain size distribution to be developed using a single magnification level adjusted for the finest particles in the soil". In their paper, the earlier need for statistical correction of grains along image boundaries became unnecessary after taking successive images on a regular grid pattern and integrating them into one ''mosaic'' image. The watershed method for segmentation of the particles also made the prerequisite that all detached particles in the soil should be on the viewing table dispensable. A shape adjustment factor, λ_d, was further introduced by them to explain the difference between sieve-based grain size distributions and digital image based grain size distributions, which was found to be a function of the grain shape as expected. Wu and Yu (2003) proposed a two-level approach for image segmentation based on region and edge integration. Edges were first detected in the original image using a combination of intensity gradient based and texture discontinuities based algorithms (intensity edges were detected using the first and second Gaussian derivatives, while texture edges were obtained from the EdgeFlow algorithm). Wu and Yu (2003) further introduced that "to preserve the spatial coherence of the edges and their surrounding image regions, the detected edges were vectorized into connected line segments that served as the basis for a constrained Delaunay triangulation". Segmentation was then performed on the triangulation using graph cuts (this method favors segmentations that pass through more vectorized line segments). Finally, the obtained segmentation on the triangulation was projected onto the original image, and then the region boundaries were refined to increase pixel accuracy. Wu and Yu's (2003) experimental results showed that the two-level approach could achieve accurate edge localization, better spatial coherence, and improved efficiency. Iannizzotto and Vita (2000) proposed a novel and robust edge-based segmentation algorithm, Amoeba, which is built on a new type of active contour. According to them, the input of the system consists of a binary image, whose points are obtained through any algorithm of contour marking (edge extraction), based on the grayscale gradient. To obtain an accurate reconstruction of the contour, the Amoeba algorithm starts from the assumption that each contour should be represented by a closed chain consisting of the points of the contour itself, possibly interpolated if some holes appear. Then, it models the chain as a sequence of points, "each having its own capacity for movement in a manner similar to the way living tissue consists of a set of cells, which are independent, but strictly connected at the same time" (Iannizzotto and Vita, 2000). According to the biological approach, such points (MOVels, or MOVing ELements) on the chain reproduce, move, and die following some rules based on strictly local information, meeting the need for parallelizability of the algorithm and, at the same time, maintaining continuity and coherence in the movement. "In this algorithm, the chain needs all the objects that must be revealed to be on its inside. The MOVels it consists of always move in direction that they make the chain contract evenly in all directions. Once a MOVel finds a contour, it lies on the contour and stops moving." (Iannizzotto and Vita, 2000). If a chain does not find any object with significant dimensions at its inside, it closes in on itself and disappears. Following these sequence of steps, the chain adapts its shape and dimensions until it follows exactly those of the objects on its inside. Iannizzotto and Vita (2000) also highly recommended that "this algorithm is fast, has a low computational complexity, and does not introduce unwanted smoothing on the retrieved contours. The contours are always returned as closed chains of points, resulting in a very useful base for subsequent shape representation techniques". Tsai et al. (2003) studied the use of normalized cross correlation (NCC), which has been used extensively for industrial inspection to detect defects in complicated images in both gray-level and

RGB color. Their experimental results demonstrated that NCC in gray-level images could result in false alarms for two compared images containing uniform patterns, and that NCC derived from color images generated consistently high similarity values for two faultless images, potentially alleviating the false alarms that may occur in gray-level images. Through their experiment, a smoothing procedure applied to both reference and scene color-images could further improve the consistency and reliability of the NCC in color images. They also suggested that a small smoothing filter of size 3×3 was generally sufficient for providing with an effective and easily-implemented referential approach for industrial inspection of defects in complicated images.

2.2.3 State of the Art Image Segmentation Associated Techniques Review

In addition to these particular segmentation techniques, many associated techniques and tools were exploited and incorporated to enhance the reliability and accuracy of the performance of image processing in recent research studies. Hsu and Abdel-Mottaleb (2002) proposed a face detection algorithm for color images using a skin-tone color model and facial features in the presence of varying lighting conditions and complex backgrounds. The approach first corrected the color bias using a novel lighting compensation technique that automatically estimated the reference white pixels and then overcame the difficulty of detecting the low-luma and high-luma skin tones by employing a nonlinear transformation to the YC_bC_r color space. After that, skin regions were detected over the entire image using skin color detection, variance-based segmentation, and connected component and grouping methods. Face candidates were then generated based on the spatial arrangement of the skin patches. Finally, the algorithm constructed eye, mouth, and boundary maps to verify each face candidate. The experimental results also showed successful face detection over a wide range of facial variations in color, position, scale, orientation, 3D pose, and expression in images from several indoor and outdoor photo collections. This algorithm hints that lighting compensation techniques should be seriously considered when images taken under varying lighting conditions need to be processed. This is especially true for images of construction projects, which are always undertaken outdoors and last a long period of time, during which the weather and lighting conditions inevitably change. Valkenburg and McIvor (1998) developed an approach for obtaining accurate 3D measurements using a temporarily encoded structured light system which consisted of a projector together with a camera. The projector projected a coded stripe pattern on the scene and the camera captured an image. Hence, for each visible point in the image, there was a corresponding stripe number (stripe value) and image location (pixel coordinates). Lens distortion was also accounted for in the models for both camera and projector. In addition, a substripe estimator was used to estimate projector stripe values and a subpixel estimator was used to locate image features. The authors concluded that the geometry of the SLS configuration (particularly the triangulation angle) substantially affects system performance, which could be improved by using a better calibration reference and "multiple frame methods", though this would be time-consuming. Ruiz et al. (2003) used the idea of blobs in pre-attentive perception using color information as the basis for a simple classification of low resolution pictures taken with mobile phones. The blob-like representation of the image associated with other information involved in the creation of the image in the user's context, such as time or location (GPS information), was combined with a fast segmentation based on color categorization in the presented framework. It served as the basis for a new graphical interface for HCI (Human Computer Interaction) in a mobile phone terminal.

2.3 State of the Art Review of Image Processing Applications in Civil / Construction Engineering

2.3.1 Review of Image Processing Application in Civil Engineering

Image processing has been extensively and successfully used in many sub-areas of civil engineering, such as engineering document scanning, pavement distress assessment, site evaluation via satellite imagery, studies of crack propagation and microstructure in cement-based materials, and evaluation of soil fabric, etc. (Lee and Chou, 1993). It is a remarkably versatile tool that provides a means by which to augment existing methods of analysis and also opens up a large number of possibilities for significant advances in current civil engineering practices. For instance, the size and shape of features, or the amount of each phase in a microstructure, can be quantified and related to material properties such as the automated characterization of stone aggregate particles (Brown et al. 2001), strength and toughness, and also process variables (Prestridge, 1993). Several automated pavement distress measuring devices have been developed in the past (Chan et al. 1993; Klassen and Swindall, 1993). The development of machinery that uses image processing techniques for automated crack sealing has been pursued by Velinsky and Kirschke (1991) and Hedrickson et al. (1991). X-ray imaging of soil specimens in the laboratory is used to record the image of the detailed patterns of local deformation within the soil mass (Bourdeau, 1993).

Image processing techniques have also been used together with remote sensing and geographic information systems to aid civil engineers in environment impact assessments, land use planning, and resource management. The non-contact, non-destructive, and remote sensing techniques are used to detect buried hazardous waste sites such as underground storage tanks (Weil et al., 1993). Hirschberg and Streilein (1996) described DIPAD, a system for digital architectural photogrammetry, which brings together the functionality of three-dimensional computer aided architectural design (CAAD) and state-of-the-art photogrammetric computer measurement procedures, many possible applications of digital photogrammetry in CAAD related fields, and the main ideas and aspirations of the project. A modeler built on top of an existing CAAD system is designed to meet the special requirements of the photogrammetric computer measurement procedures. According to Hirschberg and Streilein (1996), within DIPAD, modeling weak forms ('objects with controllable deformability') becomes a very straightforward approach to guide computer measurement procedures qualitatively. Ameri (2000) introduced a novel method, Feature Based Model Verification (FBMV), for the modification and refinement of the reconstructed generic polyhedral-like building objects. This was accomplished by back projecting the 3D model onto the corresponding images taken from different viewpoints, treating the hypothesis model as evidence, which leads to a set of confidence intervals in image space that can be used as a search space to find the corresponding 2D image primitives, and performing a consistency verification of the reconstructed coarse model. The FBMV method was developed as part of an ongoing research project aimed at developing an automated method for the recognition and 3D reconstruction of generic building objects using aerial images. A boundary representation (b-rep) of a coarse building hypothesis was generated in a bottom-up, data-driven process from simple qualitative geometric primitives in image domain to more complex quantitative primitives in object domain. The proposed method was a model-based image analysis procedure where a priori knowledge of the shape and geometric appearance of an object was used during the process of interpretation. Subsequently, the reconstructed coarse building underwent a refinement process based on the FBMV concept. The verification process was performed by simultaneously fitting the reconstructed model primitives into the homologous two dimensional (2D) features of images taken from different viewpoints, while at the same time imposing the geometrical and topological model information onto the process as external and/or internal constraints. In his work, which is based on the integration of object parameter estimation into the photogrammetric process, Rottensteiner (2001) presented a new method for semi-automatic building extraction, together with a concept for storing building models, along with terrain and other topographic data, in a topographical information system (TIS). Elaksher et al. (2003) presented a valid technique for the extraction of 3D building wire-frames using a robust multi-image line-matching algorithm for building extraction in urban areas. The methodology in this paper gave an excellent example of how this kind of problem can be resolved in a practical and novel way - four images were used to extract the building wire-frames. First, through the use of the split-and-merge image segmentation technique, the images were segmented into regions and then classified into roof regions and non-roof regions based on their size, shape, and intensity values, together with a modified version of the Hough Transformation. Next, the roof region boundary pixels were located and used to find the region perimeters. Meanwhile, by using the Scott and Longuet-Higgins algorithm, together with the epipolar constraint, region size, region shape, and region intensity values, region correspondence was solved in a pair-wise mode over all images. Image lines within the corresponding regions were matched over all images simultaneously by first creating a plane for each region line. Planes were then intersected simultaneously and geometric consistency was used to determine acceptance or rejection. Finally, the results demonstrated the completeness and accuracy of this method for extracting complex urban buildings.

Treash and Amaratunga (2000) developed an automatic road detection system for applications on high-resolution grayscale aerial images. Road edges were extracted using a variation on the Nevatia-Babu edge detector, followed by an edge-thinning process and a new edge-linking algorithm that filled gaps in the extracted edge map. By using a zoned search technique, an improved edge-linking algorithm capable of closing both large gaps in long, low-curvature road edges and smaller gaps occurring at triple or intersection points, was designed. Subsequently, an edge-pairing algorithm was applied; taking advantage of the parallel edges of roads to locate the road centers. The results demonstrated that the proposed methodology formed a solid base for a more sophisticated map-generation system.

Wang (1998) proposed a new heuristic search algorithm for touching aggregates in a binary image. The algorithm first applied a polygonal approximation for every object, where several particles could touch each other, and then classified concave points on object boundaries into different classes based on the angle and lengths of 2-vertex lines.

Polygonal approximation and classification of concavities, based on polygons, substantially enhanced the robustness of the algorithm. Subsequently, candidates for start and end points, where the end point is not necessarily a concave point, were found. After that, a supplementary cost function was used to determine whether or not a split path could be accepted. In this split path variables such as the shortest distance, the shortest relative distance, minimum number of unmatched concave points, “opposite direction”, particle area, and the maximum ratio between two split parts in terms of areas would be applied. The algorithm can split not only simple cases of touching particles (two or three particles touching each other), but also large clusters of particles. Also, it includes a routine to treat the case of having one or more holes inside an object. The algorithm had been coded and tested in an on-line system for measuring crushed aggregates in a gravitational flow, and had also been tested for other different particle images in which particles touch in a complicated fashion. Desirable results were obtained in both tests. Brzezicki and Kasperkiewicz (1999) presented a new method for aggregate shape determination employing image analysis. This method enables automatic characterization of the shape of coarse aggregates through the use of novel measurements of aggregate shape, in which, two pairs of parameters characterizing average flakiness and elongation, as well as the homogeneity of aggregate shapes, are employed. Furthermore, with the appropriate hardware, this method could be modified to measure the aggregate grain shapes on-line (that is, measuring the moving grains during transportation of the aggregates). The proposed system would consist of a declined form on which aggregate grains delivered from a conveyor belt move or roll, and their instant image is acquired by a camera with a flash. Should it be implemented, this system would help with the quality control of aggregate production, as well as in concrete mix production. Kim et al. (2003) proposed a robust segmentation approach based on the fusion of data from the Canny edge detector and the watershed transformation. They also proposed a varying search window method for determining regional minima to process images of 3D particles acquired from laser profiling. First, the randomly spread particles are scanned and thresholded into a binary image. Next, Canny edges are detected in order to draw rough initial outlines for the connected particles on the binary image. Then, the edge outlined binary image is transformed into a distance map, on which regional minima are identified with a varying search window approach. After the regional minima are labeled, they grow to meet other regions by means of a binary dilation process and the border becomes a watershed. To check the validity of the watersheds and merge the over-segmented particle regions, Canny edges are detected again and compared with the watersheds. Subsequently, a particle void filling process is conducted to compensate for the data lost from self-occlusion in the data acquisition process. Finally, a particle splitting process is applied to separate the merged particles by creating borders where two different ROI (region of interest) meet. This method is an effective tool for segmenting 3D images of stone aggregates acquired from laser profiling. However, with a simple modification of the varying search window in the original definition of regional minima, the method can also be used in other 2D DIT segmentation applications.

2.3.2 Review of Image Processing Application in Construction Management

Although the geotechnical and transportation engineering sub-areas of civil engineering have taken the lead in applying image processing techniques to solve practical problems over last twenty years, the advancements in hardware and software developed for digital image processing and analysis provide promising opportunities for application in construction management and site investigation. Also, with the enormous decrease in the cost of both computational power and data storage capacities, fully 2D, and even 3D, representations of actual objects on construction sites are now feasible from an economic point of view (Rottensteiner, D. F.,2001). To assess construction progress based on image processing, first, the objectives of interest, components of the structure, and equipment on site should be identified using a robust applicable segmentation approach. According to Smith and Raynar (1993), Jayaram (1990) developed a conceptual system for digital image applications to produce as-built drawings. It is outlined as follows: 1) Establish a CAD system to supply models for all components of a facility; 2) Define the camera angle and optical axis; 3) Determine a method for controlling lighting in order to control shadow effects; 4) Develop a method of comparing the CAD model to the camera images; 5) Compare the shaded CAD model to camera images. Abeid (2000) developed a system, PHOTO-NET, to compare the last picture taken at the end of a given day with the last picture taken at the end of the previous day in order to automatically record and assess the progress of different activities. After that, Neto et al. (2002) described a method for recognizing the presence of structural components in a digital picture taken at a construction site. To detect and separate a component in a picture, an "edge-detector algorithm" was employed to identify the boundary of an object through its color and position, in which the edge was first traced by collecting the coordinates of each pixel on the edge in a stack of pointers pointing to records where the coordinates of one pixel were stored. Then, pictures with the same field of view on different dates were compared to identify and classify the "background" in the very first picture. By reviewing the picture from top to bottom, row by row, and comparing the RGB of the selected pixel with the RGB range of the material of the object pursued, the first pixel that fit in the RGB range pursued, excluded from the background, was determined to be the first edge element. The edge was then traced from the first edge element in a clockwise manner and the coordinates in the neighboring matrix were calculated for each edge element. After the edges were detected, all the internal pixels were browsed and their addresses were stored in a linked list with the edge elements. Finally, both edge and internal pixels were stored under an object name. This algorithm was successful in its application. However, it is a demanding procedure to build a library of RGB ranges for all types of construction materials. Furthermore, as Neto et al. (2002) mentioned, if the picture on site is taken from a significant distance, or the structural components are not large enough, the geometry of each object may not be recognized and distinguished using this algorithm alone, as sometimes various structural components can have the same surface texture and color. To significantly enhance the performance of image processing, advanced segmentation techniques and human knowledge are to be incorporated for feature extraction and comparison. Kim et al. (2004) proposed a 3D spatial-modeling approach to represent construction sites to be used in various safety-enhancement applications and for as-built data acquisition in project-control systems. By incorporating human perception and two general classes of geometric primitives (convex hulls and workspace partitions), bounding objects representing a wide range of construction-site scenes were created by the convex hull and workspace-partitioning algorithms. In order to merge data from different acquisition locations, the coordinates of bounding objects were transferred to a common coordinate system, in which the coordinates of range points for various types of objects were acquired in three dimensions by using a laser with pan-and-tilt kinematics. The equipment used for data acquisition and modeling consists of a laser rangefinder, a two-axis pan-and-tilt unit (PTU), the laser manufacturer's distance-data acquisition software, a tripod, a *C* program that continuously reads pan and tilt angles from the PTU, and modeling routines developed in *Matlab*^{TM} that display the models graphically via a graphical user interface (GUI). The algorithms used in this approach are computationally efficient and fast enough to be applied to safety enhancement in machine control. This was also investigated by running experiments in actual construction environments. AbdelRazig and Chang (2000) presented a hybrid intelligent computerized model for the surface quality assessment of constructed facilities. The model used computers to analyze digital images of the areas needing to be assessed in order to identify and measure defects. Moreover, neural networks were used to train the system to automate the process and replicate the experts' knowledge in identifying defects. This hybrid system applied concepts from the fields of artificial neural network (ANN), pattern recognition, and image processing, and overcame the subjectivity and inconsistency of human visual assessment by analyzing digital images with computers. By analyzing different parameters and characteristics for each pixel in any given image, the model recognizes defect patterns undetectable by humans. Furthermore, the system can measure the extent of the defect with reasonable accuracy. Nevertheless, human expertise can be integrated into the system. This is done specifically during threshold selection for image classification so as to accommodate external factors such as the image quality and the existence of dirt or other objects on the coating. Neural networks enable the system to learn from examples in order to automatically perform the recognition task after training. According to AbdelRazig and Chang (2000), the basic concept of recognizing defects is assigning all parts or pixels of an image to different classes according to their optical characteristics, and the number of classes varies according to the application. For the recognition of rust in a steel bridge coating, all of the images' pixels were classified into two classes: rust areas and non-rust areas. This system was expected to improve the surface quality assessment process by making the process more objective, quantitative, consistent, and accurate, and to reduce the assessment time. AbdelRazig and Chang (2000) also concluded that "although the steel bridge coating assessment was used as an implementation example, the model framework has the potential to be applied in other construction quality assessment applications, such as identifying cracks in sewer lines or pipe lines".

3 PROPOSED IMAGE PROCESSING APPROACH

To assess construction progress using image processing techniques, the first step is to distinguish the objects of interest (the reinforced concrete columns on the lower level 2 of the NREF building at the University of Alberta in Edmonton, Canada) from the original images. Object detection is the most challenging task in this research; the success of the overall process of this research is strongly dependent on the quality of this initial stage. According to Rottensteiner (2001), many problems or error sources, such as image noise, low contrast in the images, poor lighting conditions, shadows, occlusions, poor definition of object edges, small building features, and bad fit of the model to the actual object might impede the success of automatic object detection and fine measurement. Therefore, a robust image processing/segmentation approach will be investigated in this chapter to solve or significantly mitigate the influence of these problems in the objects of interest detection process.

3.1 Image Preprocessing Method

The aim of preprocessing is to improve the image data that suppresses unwanted distortions or enhances some image features important for further processing. To increase the probability of delivering satisfactory segmentation results with high reliability and accuracy under the impact of heavy background noise and poor lighting conditions, it is necessary to include as much useful information as possible and to exclude unnecessary information. At the image preprocessing stage, to meet this goal and facilitate the following image segmentation process, the original RGB images are converted to grayscale images. Then, two image enhancement approaches are combined to preprocess the images (to improve upon the results from the grayscale images), prior to the application of the major image segmentation techniques. In this research, one image preprocessing approach employs certain morphological transformations along with an image adjustment method to remove noise and enhance contrast in the input images, while another uses a proposed lighting compensation technique when necessary.

3.1.1 Morphological Transformations and Image Enhancement

According to the definition from *MathWorks*^{TM}, morphology is an image processing technique based on the shapes of objects in an image. Morphological transformations are some of the basic techniques which are usually used to extract and alter the structure of regions in an image for the purpose of quantitative analysis, observation of the geometry of regions, extraction of forms for modeling and identification purposes, and so forth (*IMAQ Vision User Manual*, 1999). In morphological transformations, the value of each pixel in the output image is based on a comparison of the corresponding pixel in the input image with its neighbors. By choosing the shape and size of the neighborhood, a morphological operation sensitive to specific shapes in the input image is constructed to perform common image processing tasks, such as contrast enhancement, noise removal, thinning, skeletonization, filling, and segmentation.

Usually, due to the complex lighting conditions on construction sites, the background illumination in most of the sample images is non-uniform. To tackle this problem at the image preprocessing stage, an initial morphological opening is employed to estimate the background illumination, as well as to remove some background noise. It is important to note that a morphological opening is an erosion operation followed by a dilation operation. The same structuring element is used for both steps. This produces the effect of removing from an image small objects that cannot completely contain the structuring element, while preserving the shape and size of larger objects in the image. Hence, the structuring element should be large enough to remove the small noise when eroding the image, but not large enough to remove the objects of interest. Once the background illumination is subtracted from the original grayscale image, a more uniform background is created.

To further enhance the contrast of the images, several image enhancement routines are investigated and compared by using some functions contained in the *Image Processing Toolbox* of *MATLAB*^{TM} software. By plotting the histograms of most of the grayscale sample images obtained from the previous step, it was found that most of pixels in them were concentrated in the center of the histograms. Since "*imadjust* function increases the contrast of the image by mapping the values of the input intensity image to new values, by default, 1% of the data is saturated at low and high intensities of the input data" (refer to the Website of *MATLAB*^{TM}), the *imadjust* function was then used to effectively improve the contrast of the input images. Subsequently, a median filter was applied to these images, as it simultaneously reduced noise and preserved the object edges. According to the *MATLAB*^{TM} Manual, median filtering is a nonlinear operation often used in image processing to reduce "salt and pepper" noise. It is more effective than convolution when the goal is to simultaneously reduce noise and preserve edges.

3.1.2 Lighting Compensation Technique

Since construction operations are usually performed outdoors, lighting conditions change from time to time. Poor weather and lighting conditions always cause low contrast and noise in the original images, and consequently make feature extraction and the detection of image edges corresponding to relevant structural components of the project difficult. Therefore, a lighting compensation technique was taken into account in the image preprocessing phase for those images taken under undesirable lighting conditions. In this research, a fiducial element, a reference window located at a predefined position, was selected for the purpose of detecting the overall lighting condition of each sample image. Meanwhile, an intensity threshold value was investigated and compared with the average intensity value of the pixels in the fiducial window on each image. Once the average intensity value of the fiducial window was less than the threshold value, the pixels in the image with their intensity values falling within a certain range around the threshold value were compensated for or corrected so that the objects of interest candidates in the image were enhanced and then could be more easily differentiated from the background. Another function of the threshold is that, if the average intensity value of the fiducial window in an image is greater than or equal to this threshold, then this image is considered to have desirable lighting conditions and will be assigned a high priority for future use.

Figure 3.1 shows the flowchart of the proposed image preprocessing procedure:

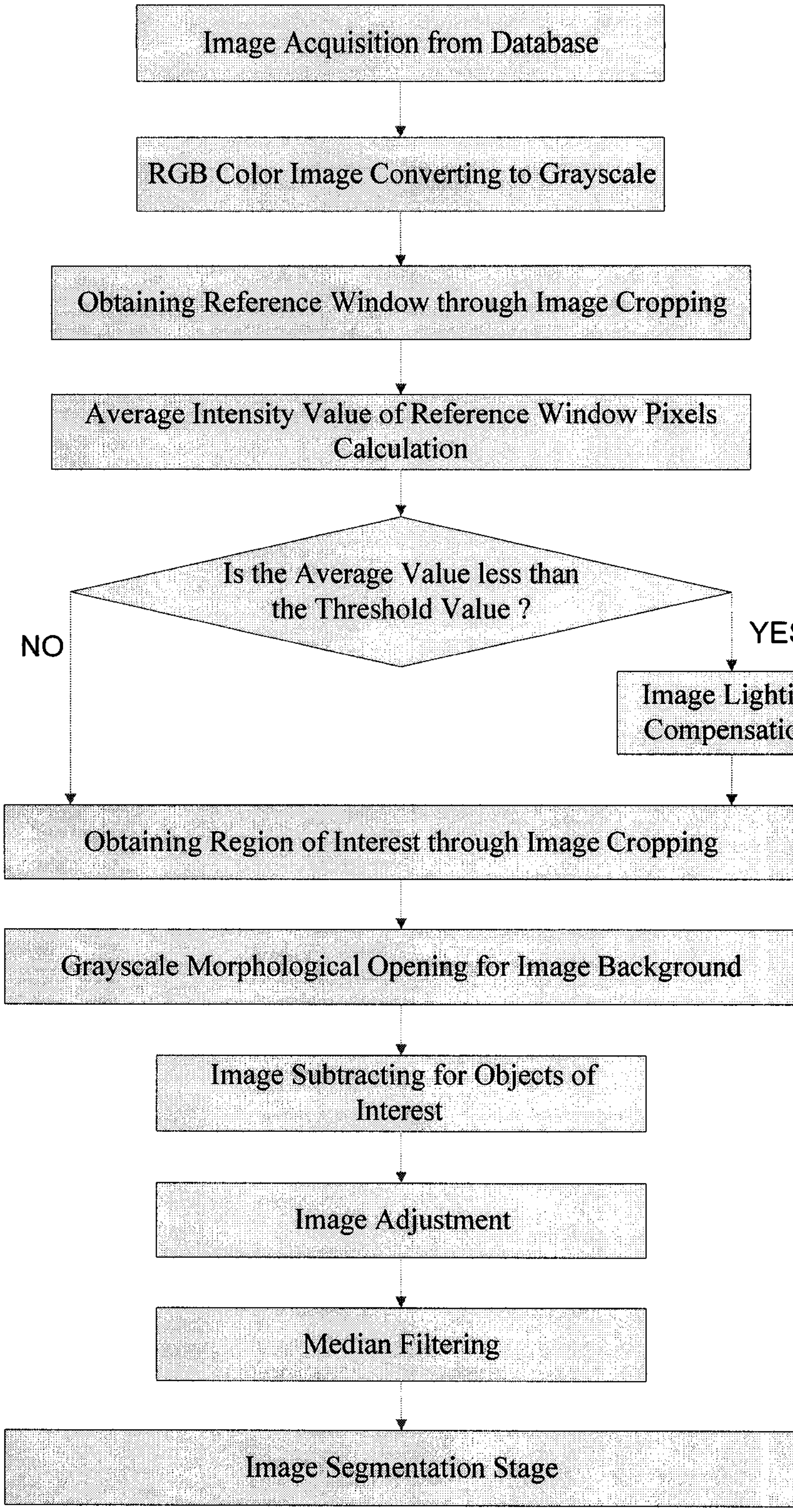
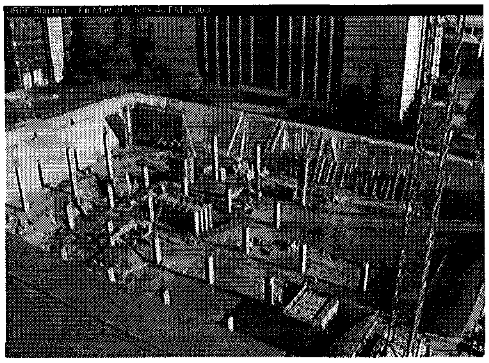


Figure 3.1: Proposed Image Preprocessing Method

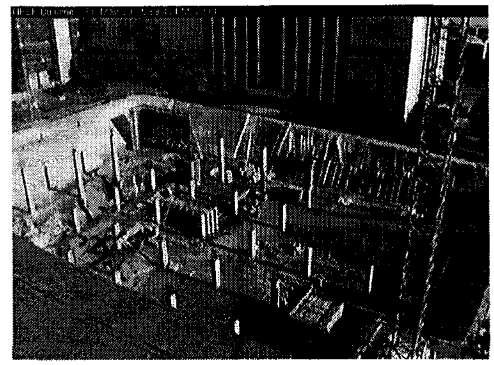
Initially, the original 640×480 RGB (Red Green Blue) color images taken on site were loaded as input data from the image database or image source, as shown in **Figure 3.2** (a). Then the loaded RGB color images were converted into grayscale (**Figure 3.2** (b)). To investigate the lighting conditions of each image, a 9×3 pixel reference window at the center of the top half of the first concrete column poured on site was automatically cropped using functions available in *MATLAB*^{TM} software. The average intensity value of the pixels in the reference window was calculated and compared with the threshold value, which was investigated and set at 240 for the purposes of this research. If the average light intensity value of the reference window was not less than 240, then the image was taken under desirable lighting conditions and the lighting compensation process was deemed to be dispensable. However, if the average light intensity of the reference window was less than the threshold value (for example 180), then lighting compensation was necessary for the pixels, of which the light intensities were within a specified correcting range (for example, [170 190]) in the image. The light intensities of those specified pixels were then corrected to 255 to enhance the contrast between the objects of interest candidates and the background, and to get a better result in the following image segmentation stage. The light-compensated image is also shown in **Figure 3.2** (c).

To save unnecessary computing time in the procedure, a region of interest (ROI) with size 500×340 in each image was cropped based on the FOV, as shown in **Figure 3.2** (d). After that, in order to correct the non-uniform illumination of this ROI grayscale image, grayscale morphological opening was applied to approximate the background illumination (**Figure 3.2** (e)). Here, the background illumination was estimated through grayscale morphological opening using a disk-shaped structuring element with a radius of 5 pixels. Following this step, the obtained background illumination image (**Figure 3.2** (e)) was subtracted from the grayscale image of interest (**Figure 3.2** (d)). In other words, each element of the background illumination image was arithmetically subtracted from the corresponding element of the resized grayscale image. The resulting output was an enhanced grayscale image with uniform illumination, as can be seen in **Figure 3.2** (f).

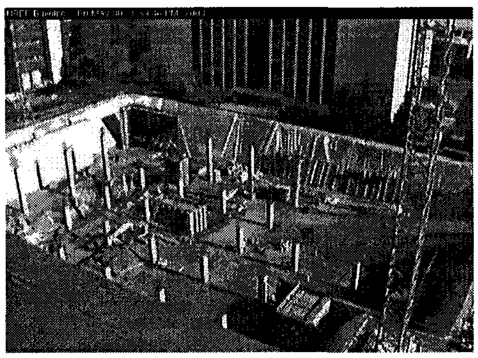
Next, image adjustment is conducted on the enhanced grayscale image of interest to increase the visibility of the objects of interest, as the original images taken outdoors from relatively far away are not very clear. Image adjustment increases the contrast of the image by mapping the intensity values of the input image to new values, as is shown in **Figure 3.2** (g). Once the grayscale image is adjusted, the median filtering is performed to simultaneously reduce noise and preserve the edges of objects; this is done by using a 10-by-3 vertically rectangular neighborhood, in which each output pixel contains the median value in the 10-by-3 neighborhood around the corresponding pixel in the input image (**Figure 3.2** (h)).



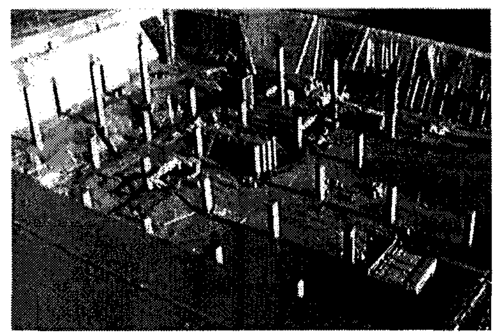
(a) Original RGB Color Image



(b) Original Grayscale Image

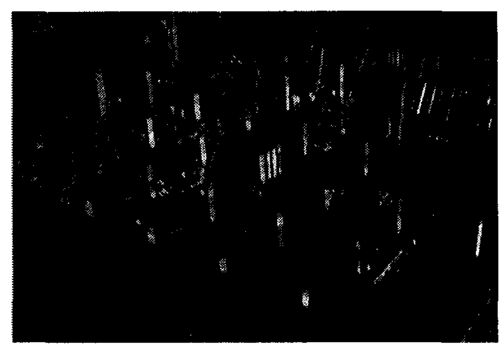


(c) Image with Light Compensated

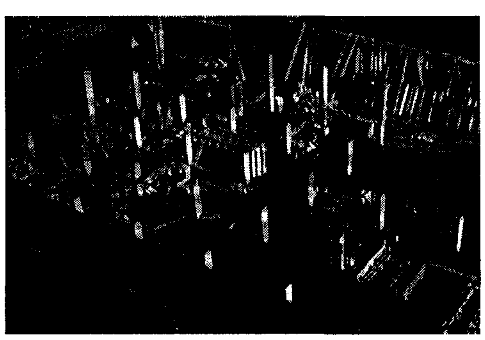


(d) Grayscale Image of Interest

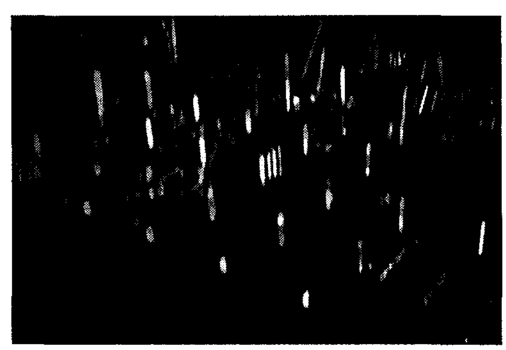
(e) Background Illumination Image



(f) Grayscale Image with Background Subtracted



(g) Adjusted Grayscale Image of Interest



(h) Median Filtered Grayscale Image of Interest

Figure 3.2: Images of Each Step of the Proposed Image Preprocessing Method

3.2 Canny Edge Detection and Watershed Transformation

3.2.1 Canny Edge Detection

As a classical feature detection method, Canny edge detection was designed to be an optimal edge detector for step edges corrupted by white noise (Beucher, 1982). The method exploits three performance criteria covering these elements: (1) Good detection (no missing edges); (2) Good localization (minimal distance between true and detected edge positions); and (3) One response (minimum multiple responses to a single edge), and has been extensively used in image segmentation. The reason that the Canny method is applied in this research is that it uses two thresholds to detect strong and weak edges. It also includes the weak edges in the output only if they are connected to strong edges. The Canny method is therefore less likely than the other edge detection methods to be fooled by noise, and more likely to detect true edges.

Usually, Canny edge detection takes a grayscale image as input and produces an image that shows the positions of tracked intensity discontinuities as output. The Canny operator works in a multi-stage process. First, the input image is smoothed by Gaussian convolution (convolve the image with a Gaussian of scale sigma). Then, a simple 2-D first derivative operator is applied to the smoothed image to highlight regions of the image with high first spatial derivatives. Edges give rise to ridges in the gradient magnitude image (compute gradient magnitude and direction). The algorithm then tracks along the top of these ridges and sets to zero all pixels that are not actually on the ridge top, thus producing a thin line in the output (a process known as non-maximal suppression). The tracking process exhibits hysteresis that is controlled by two thresholds: high threshold (T_H) and low threshold (T_L), where $T_H > T_L$. Tracking can only begin at a point on a ridge higher than T_H. Then, tracking continues out from that point in both directions until the height of the ridge falls below T_L (to eliminate spurious edges by hysteresis thresholding). This hysteresis helps to ensure that noisy edges are not broken up into multiple edge fragments.

3.2.2 Watershed Transformation

Watershed transformation has become a powerful image segmentation method and has been applied extensively in various research areas. As a region-based approach, the watershed transformation searches for pixel and region similarities by means of dividing lines to segmentation problems. A common technique for the watershed transformation is first to build a gradient magnitude or distance image, and then to find the watershed regions in this image. When the homogeneity of the grayscale values of the objects is the main criterion for segmentation, a gradient image is often used in the watershed transformation. But, when other criteria are related, especially when the segmentation is based on the shape of the objects, the distance function is favorable (Beucher, 1990). To find the watersheds, a digital image is considered as a topographic map with ridges dividing various drainage areas, in which the catch basins of the image and the watershed lines are defined by means of a flooding process. The "immersion simulation" technique suggested by Beucher (1990) vividly shows the process of locating the watersheds in a digital image. He concluded that "the watershed transformation provides closed contours by construction, and there is a good match between contours appear in the image and the divide lines in the gradient watershed". The major problem with watershed segmentation is that it usually over-segments the image (too many, too small regions). Because of this, most instances of watershed segmentation involve some form of post-processing step that attempts to merge over-segmented areas.

3.3 Image Filtering Mask Creation

Heavy background noise on the construction site always deteriorates the extraction of the objects of interest features in image segmentation. For instance, some images of long object edges might be broken into small discrete image edges or even disappear as a result of noise, which also agitates the positioning accuracy of the image features. The shadow areas appear very dark in the images, which causes low contrast and has a negative effect on feature extraction; some of the clearly defined shadow borders become candidates by mistake because their shapes are similar to those of the actual object edges to be detected. To minimize these kinds of problems, an image filtering concept was proposed to significantly enhance the results of the segmentation methods. This concept is based on common practices in photogrammetry and the building design and drawing processes.

Usually, the digital images taken on site are geometrically uncorrected because they include camera perspective, terrain and building relief, and internal (lens) distortions. Therefore, they do not have any particular alignment or registration with respect to the global coordinate system or user coordinate system in the engineering drawings, meaning that the data obtained from image processing are not authentic enough for direct use in quantity surveying and/or progress measurement. In addition, it is not easy to orthorectify (to remove camera, perspective, and relief distortions) the whole set of images via image transformation processes in order to obtain the corresponding definite geographic locations and size/shape parameters of the objects of interest.

However, all the related data and parameters of the objects of interest are available on the AutoCAD engineering drawings and can be freely obtained in advance. Furthermore, in practice, different structural elements are usually drawn on different layers or presented in different colors in an AutoCAD document. Once the FOV (field of view) and target are calculated and selected, and the network camera is calibrated and fixed on site, the spatial coordinates of the camera and the target are also obtained according to the reference points from the geodetic plans of the ECERF building and the NREF building (the target point is the point appearing in the center of the view; in this case, the northwest upper corner of the reinforced concrete column @D4 on low level 2 was employed as the target). Thus, the 3D perspective view of the objects of interest on site can be acquired using some built-in commands in AutoCAD or some third party add-ons for AutoCAD. According to Lockhart (2002), if the 3D northwest isometric view of all the reinforced concrete columns on the low level 2 of the NREF building (**Figure 3.4** (a)) were to be established in AutoCAD software in advance, then the 3D perspective view of the columns could be obtained following the command sequence outlined below:

- Command: DVIEW ↵
- Select objects: (pick all the reinforced columns on low level 2 in the 3D NW isometric view) ↵
- CAmera/TArget/Distance/POints/PAn/Zoom/TWist/CLip/Hide/Off/Undo/<exit>: PO (for the points option) ↵

- Enter target point <36787.5048,49282.1092,9033.7803>: input the XYZ values (the AutoCAD prompts you for the XYZ values of the chosen target point) ↵
- Enter camera point <36786.5048,49283.1092,9034.7803>: input the XYZ values of the camera point) ↵
- Camera/Target/Distance/Points/Pan/Zoom/Twist/Clip/Hide/Off/Undo/<exit>: D (for Distance) because the XYZ values for the target and camera were already input, just press *Enter* to input the default distance value automatically calculated by AutoCAD.
- ↵ The **DVIEW** command now displays a 3D perspective view from the Camera point. To complete the **DVIEW** sequence, hit ↵to exit the **DVIEW** command and the whole drawing will be regenerated in perspective. Also, the 3D perspective view can be saved using the **DDVIEW** command; details are provided in AutoCAD 2002.

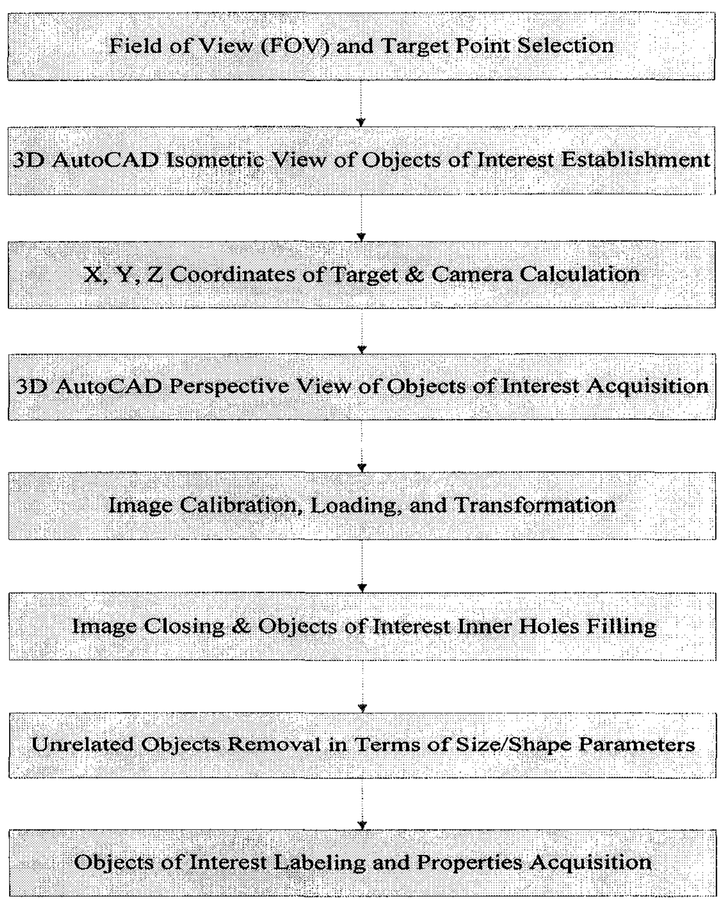
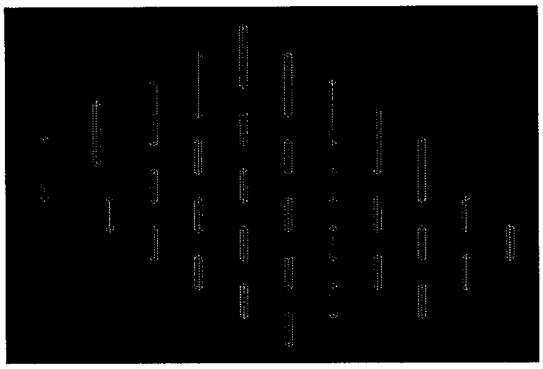
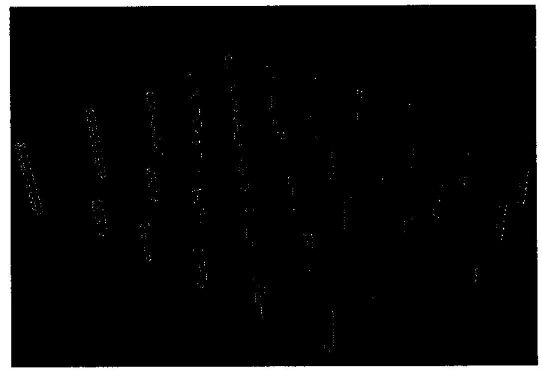


Figure 3.3: Imaging Mask Creation Process

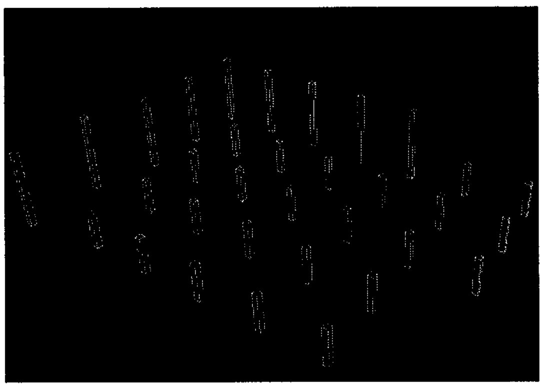
When the 3D perspective view is obtained in AutoCAD software, as shown in **Figure 3.4** (b), it is calibrated and loaded into *MATLAB*^{TM} software to create the imaging mask (model). In *MATLAB*^{TM} software, the 3D perspective view image of the reinforced concrete columns on low level 2 is first converted to grayscale, and then transformed to binary format (**Figure 3.4** (c)). After that, the tiny gaps in the objects of interest, the actual edges of the reinforced concrete columns, and the interior holes in them are filled using binary morphological closing and filling functions, successively. During this process, morphological closing (a dilation followed by an erosion) is applied first, using a disk-shaped structure element with a radius of 2 pixels, so that the tiny gaps of the outlined column edges are closed. Afterwards, a flood-fill operation is performed to fill the holes in the columns, resulting in **Figure 3.4** (e). If necessary, the sizes of objects of interest can be further increased by means of the image dilation function, using a disk-shape structure element with a bigger radius. Finally, all the reinforced concrete columns in this image (**Figure 3.4** (e)) are labeled to obtain some of their shape and size parameters for the purpose of future object reconstruction. Once an imaging mask (**Figure 3.4** (f)) is created with the same size as the preprocessed sample images, it is to be used as an imaging filter to enhance the image segmentation methods. The flowchart of the imaging mask creation procedure is shown in **Figure 3.3**.



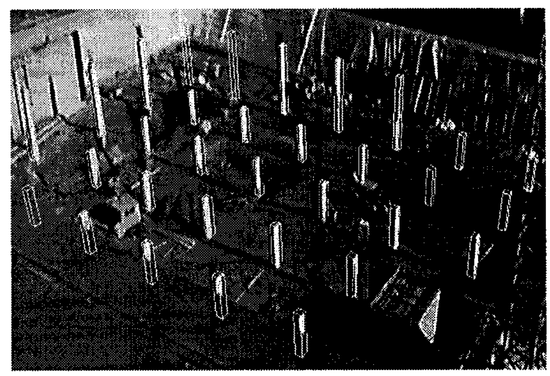
(a) 3D NW Isometric View of Objects of Interest



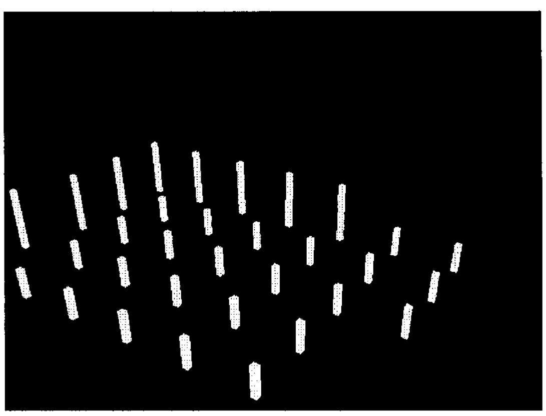
(b) 3D Perspective View of Objects of Interest



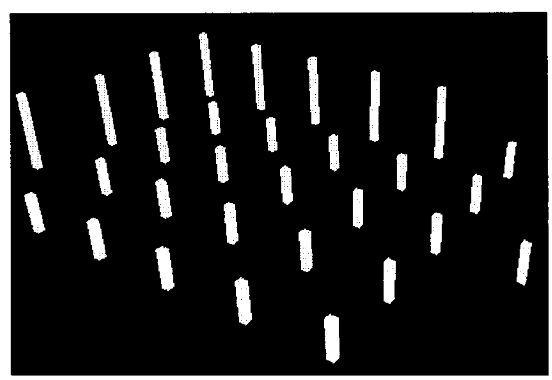
(c) Binary Image of Calibrated 3D Perspective View



(d) 3D Perspective View Compared with Grayscale Image of Interest



(e) 3D Perspective View Imaging Mask with Size 640×480



(f) 3D Perspective View Imaging Mask with Size 500×340

Figure 3.4: Images of Each Step of the 3D Imaging Filter Mask Creation Procedure

3.4 Proposed Image Segmentation Method Using Two-Step Data Fusion

Although Canny edge detection and watershed transformation are both powerful tools for image segmentation, there are also some drawbacks to each of them. For instance, in Canny edge detecting, the edges of the objects of interest obtained are always discontinuous due to low light contrast, shades, or other noise. Meanwhile, though Canny edge detection detects local changes, it is not so strongly related to the shape of objects. To some extent, this kind of data loss prevents this method from becoming a stable and universal tool in image segmentation. On the other hand, though watershed transformation supplies information about the shape of objects, it always leads to over-segmentation and sometimes provides false information.

The possibility of correct segmentation can be increased by excluding as much unnecessary information as possible and including as much useful information as possible (Kim, H. et al., 2003). Therefore, it is possible to combine the necessary information obtained from the edge-based segmentation method and the information obtained from the region-based method so as to improve the result. This data fusion concept has been widely used as a way of reducing error in robotic and automated sensing systems (Haas, 1990), and for 3D image segmentation of aggregates from laser profiling (Kim, 2003). Taking from these results, four criteria were also established in this research to develop a reliable and accurate segmentation method using a two-stage data fusion strategy:

1. Minimize redundancy: Minimize the redundant and unnecessary information in the Canny edge and watershed transformation images.

2. Minimize undersegmentation: Minimize the instances of multiple objects of interest being clustered as one.
3. Minimize missing edges: Minimize the number of situations in which some useful information is removed during Canny edge detecting and watershed transformation.
4. Avoid false matching: Avoid mistaking a different object or noise for an object of interest during the image segmentation process.

The first two criteria relate to identifying appropriate edges of objects of interest. The principle is to keep useful information related to the object of interest and to eliminate noise. To satisfy these two criteria, in Canny edge detecting, because strong and weak edges are detected using the high threshold value T_H and the low threshold value T_L, the optimal values of T_H and T_L should be applied. In addition, the created imaging mask is to be integrated into the Canny edge detector and watershed transformation based algorithms, respectively, during the first stage, so as to filter out most of the unnecessary information in each image. By doing this, both of these two segmentation algorithms can be significantly enhanced. Moreover, information related to the shape and/or size of the objects of interest should be integrated into both the Canny edge detector and watershed transformation based algorithms to reduce false-matches by means of sub-sequential morphological transformations.

To satisfy the third criterion and further improve the reliability and accuracy of the overall image segmentation approach, the useful information obtained from each segmentation algorithm needs to be further integrated in the second data fusion stage.

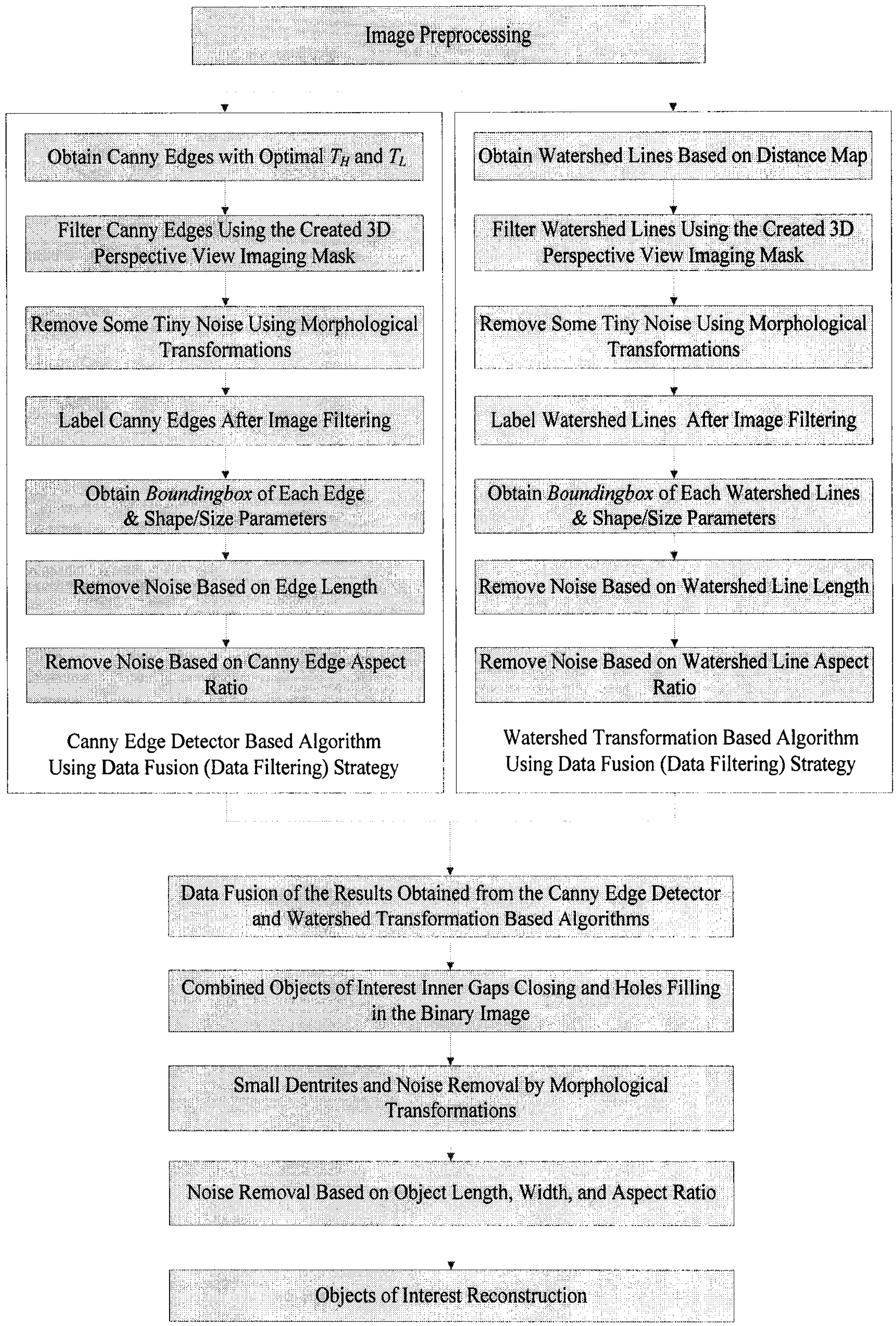


Figure 3.5: The Proposed Image Segmentation Approach Using the Data Fusion Strategy

Similarly, in order to meet the fourth criterion, the shape and size information of the objects of interest obtained from the AutoCAD drawings, along with some common knowledge in construction, can be employed in this stage (it is also important and helpful for the object reconstruction process that follows). **Figure 3.5** shows the work flow of the proposed image segmentation approach, using this two-stage data fusion strategy.

In order to identify reinforced concrete columns on the building construction site, as an example, **Figures 3.6 – 3.8** show a sequence of pictures that represent the steps outlined here: To make a further dimension of information accessible, first, in the Canny edge detector based segmentation algorithm, Canny edges are detected from the preprocessed grayscale image using a 5×5 Gaussian filter with optimal high threshold value T_H and low threshold value T_L, as shown in **Figure 3.6**(a). Once the Canny edge binary image is obtained, it is then filtered by the previously created imaging mask with most of the noise in the image removed (**Figure 3.6** (b)) by using "AND" operation. In other words, only those edges within the reinforced concrete column areas (the white regions) of the imaging mask are kept in the Canny edge binary image, and thus **Figure 3.6**(b) is acquired by means of first-stage data fusion. To save image processing time in the following stages, some tiny objects and noise on the filtered Canny edge images are removed using a binary area open algorithm in which the connected components in the binary image are labeled first. Then, the area of each component is computed and small objects that have less than a certain number of pixels are removed (**Figure 3.6**(c)). Following this step, the objects of interest candidates are labeled and the bounding box of each object of interest candidate is obtained. Subsequently, other kinds of noise are to be successively eliminated in terms of their lengths, widths, and/or aspect ratios, as shown in **Figure 3.6**(d).

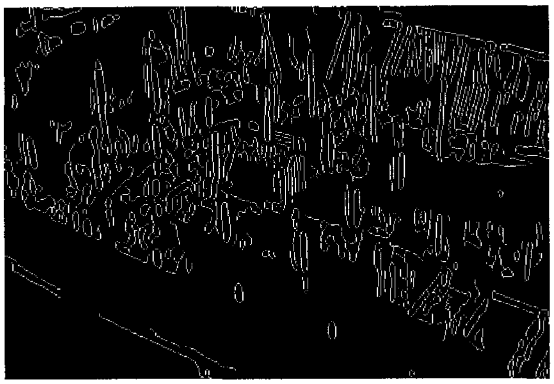


Figure 3.6 (a): Canny Edges Created by optimal T_H and T_L

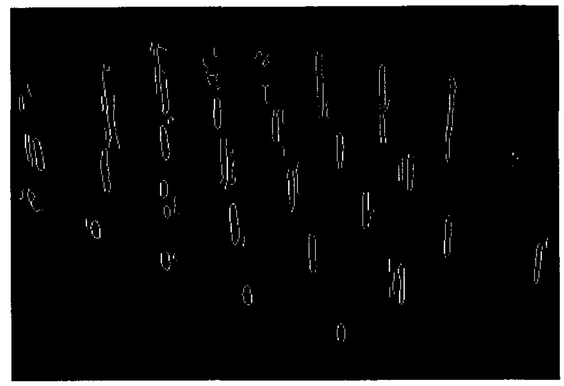


Figure 3.6 (b): Canny Edges Filtered by Imaging Mask

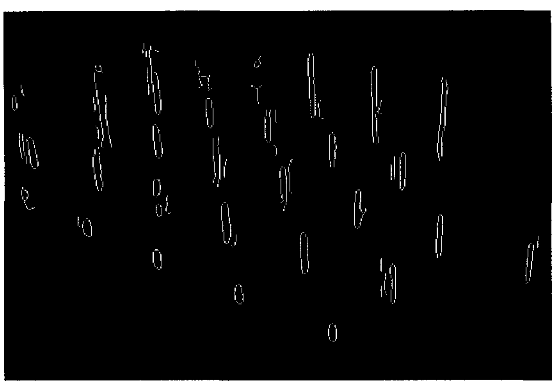


Figure 3.6 (c): Canny Edges with Small Noise Removed

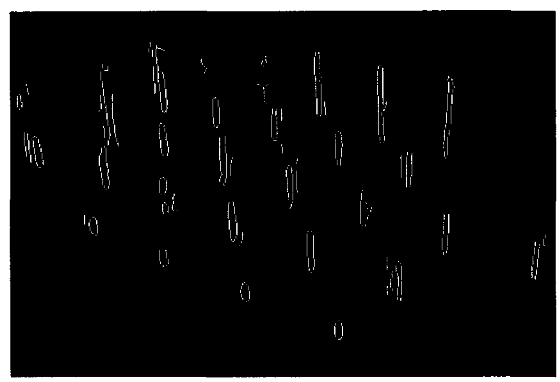


Figure 3.6 (d): Canny Edges Filtered Based on Size parameters

Figure 3.6: Canny Edge Detector Based Image Segmentation Algorithm

In the watershed transformation based algorithm, the preprocessed grayscale image is first converted into a binary version (**Figure 3.7**(a)). Next, the Euclidean distance transform of the complement of the binary image is computed and complemented; pixels that do not belong to the objects are forced to be at *-infinite*. After that, the watershed transform is computed using a variation on the Vincent and Soille algorithm, as described in Vincent et al. (1991). Results are shown in **Figure 3.7**(b). To facilitate the data fusion strategy, the watershed transform image is complemented and also filtered by the 3D perspective view image filtering mask. Therefore, a better result for object of interest candidates is obtained by following those steps adopted in the Canny edge detector based algorithm; these image steps are shown in **Figure 3.7**.

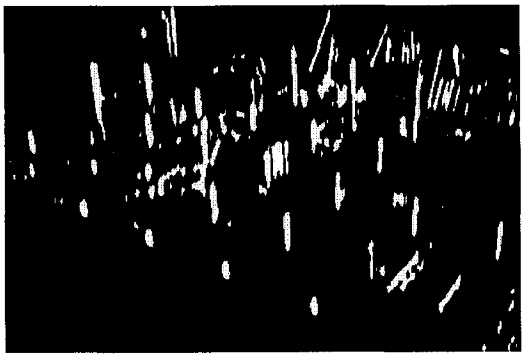


Figure 3.7 (a): Binary Version of the Preprocessed Grayscale Image

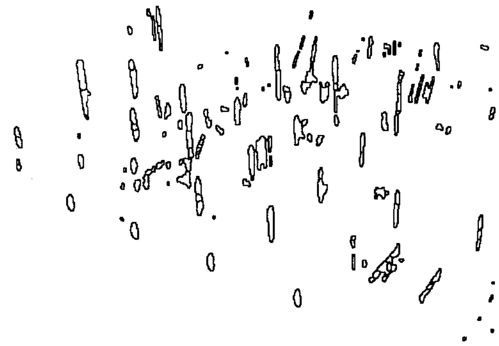


Figure 3.7 (b): Watershed Lines

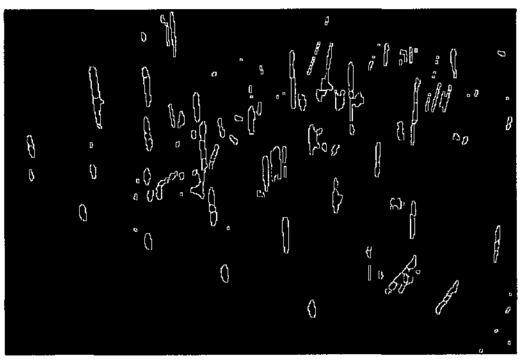


Figure 3.7 (c): Complemented Watershed Lines

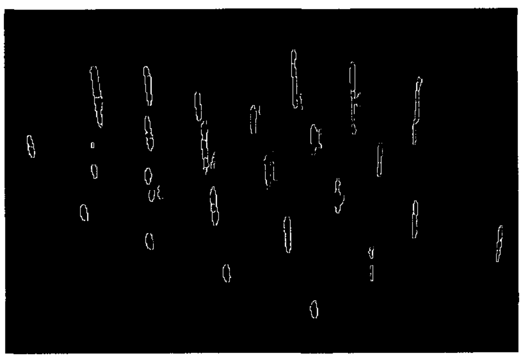


Figure 3.7 (d): Watershed Lines Filtered by Imaging Mask

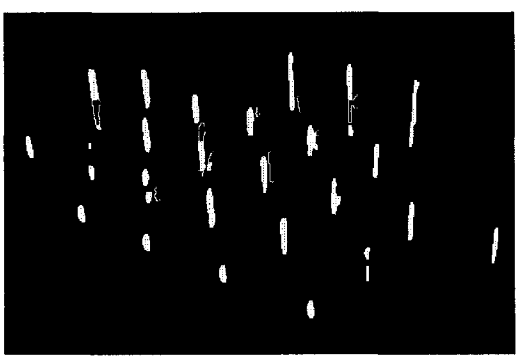


Figure 3.7 (e): Watershed Lines with Inner Holes Filled

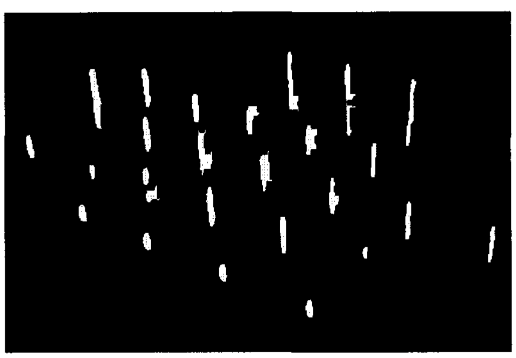


Figure 3.7 (f): Watershed Lines Filtered Based on Size Parameters

Figure 3.7: Watershed Transformation Based Image Segmentation Algorithm

As the program progresses, the data fusion strategy is performed again (by using "OR" operation this time) to combine the outputs from the Canny edge based segmentation algorithm and the watershed transformation based segmentation algorithm (called second-stage data fusion), the results of which are shown in **Figure 3.8**(a). Subsequently, the small gaps in object of interest candidates are filled through the use of binary morphological closing (**Figure 3.8**(b)), and the dentrites of these objects are also removed through successive image erosion and dilation using a disk-shaped structure element with a radius of 1 pixel. The results of this process are shown in **Figure 3.8**(c). After that, some morphological functions are used to remove pixels in the binary image that do not belong to the objects of interest; the basic steps of this stage include: (1) Determination of connected components; (2) Computation of the length, width, and area of each component; and (3) Removal of small and large objects that are significantly beyond the scope of the objects of interest based on the size and shape parameters of each object in the image. Some objects connected to the border are also removed using a morphological filter designed to exclude all the objects that touch the image border.

At the end of the operation, the objects of interest in the combined binary image are labeled, as can be seen in **Figure 3.8** (d), and their properties are measured for future analysis and application in progress assessment. Finally, a comparison between **Figure 3.2** (b) and **Figure 3.8** (d) indicates the promising results of the proposed segmentation approach.

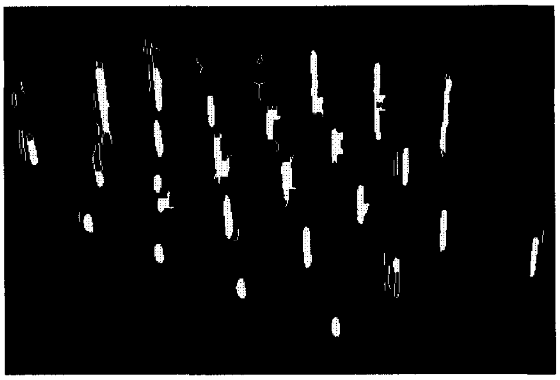


Figure 3.8 (a): Combined Result of Canny Edges and Watershed Lines

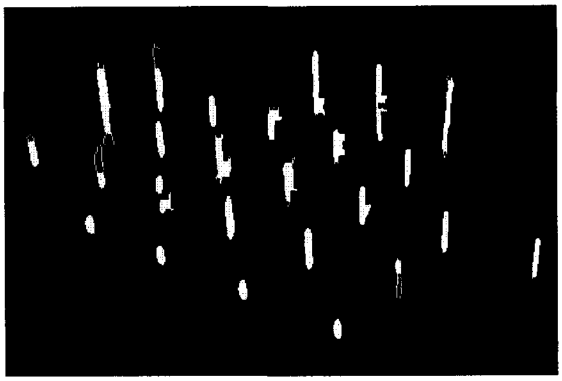


Figure 3.8 (b): Combined Image with Small Noise Removed

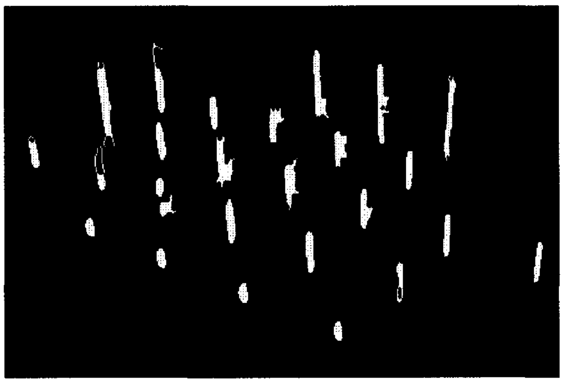


Figure 3.8 (c): Combined Image with Small Gaps Filled

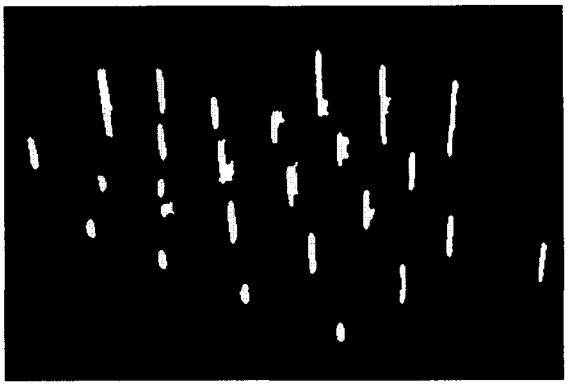


Figure 3.8 (d): Combined Image after Morphological Transformations

Figure 3.8: Object Detecting by Combining Information from Canny Edge Detector Based & Watershed Transformation Based Algorithms

3.5 Object Orientation and Reconstruction

The main goal of this research is the automation of project progress assessment, which is conducted by comparing the quantities of completed reinforced concrete columns at different points in time. As was previously mentioned, upon applying digital image processing and pattern analysis, the detected objects (reinforced concrete column candidates) in each image are acquired (as shown in **Figure 3.8** (d)). Therefore, the next critical task in this context is to quantify the predefined objects of interest (the number of columns) in each image so as to reflect the construction performance on site.

According to Lang and Förstner (1998), both the object location and object reconstruction problems need to be solved at this stage. To determine the relationship between each object, or between patches of an object, in the image(s) and the corresponding concrete column which was actually completed on site, the position and orientation parameters of each detected object in the digital image, or the set of digital images, are first obtained by some morphological functions available in *MATLAB™* software. For instance, in the labeled images obtained from the image segmentation approach, the centroid of each object detected in the image is computed and saved. At the same time, from the previously created imaging mask, all the columns that should be constructed on low level 2 are labeled to obtain their bounding boxes, as well as other location parameters. It is assumed here that if the centroid of an object in a digital image is within the bounding box of a column in the imaging mask, then this object is identified as that column or as a patch of that column. On the other hand, if there is no object in the digital image within a specific column's bounding box, then it is assumed that the corresponding column has not been constructed yet. Also, if multiple objects in a digital image are found to be located within the same bounding box, they are recognized as patches of the same column. Some typical situations are distinctly shown in **Figure 3.9** (a) as an example: (1) the columns which are wholly detected; (2) the columns which are partially detected; (3) the columns which are detected by separate object patches. Two possible situations are not covered here, those being, the cases where the objects are not successfully detected by the image segmentation approach and where objects are located by chance in some bounding boxes, and are therefore are mistaken to be columns.

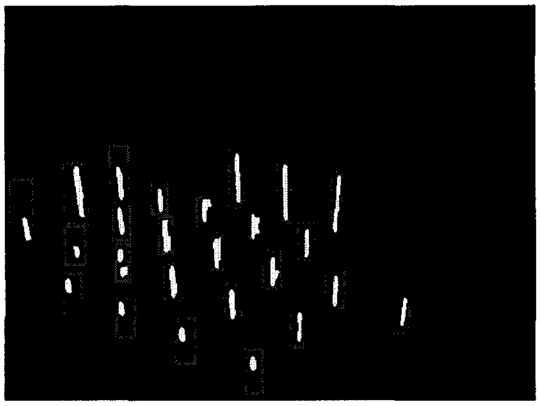


Figure 3.9 (a): Detected Objects of Interest Candidates and their Bounding Boxes

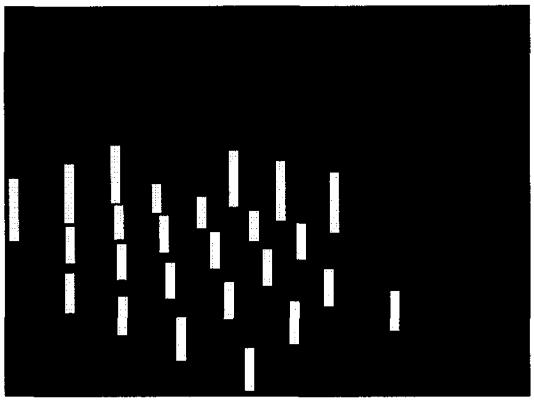


Figure 3.9 (b): Image with Objects of Interest Reconstructed

Figure 3.9: Detected and Reconstructed Objects of Interest

Another central issue here is object reconstruction: the determination of the shape and, eventually, the structure of the object. In fact, it is a typical correspondence problem, i.e. the establishment of a relationship between the shape of objects detected in the digital image and objects which are to be reconstructed or located (Rottensteiner, 2001). For this purpose, at least two images taken at different shooting angles (or another available data source) have to be used because a 3D object cannot be reconstructed from a single 2D image. Although explicit model knowledge about the reinforced concrete columns can be obtained in advance from the detailed drawings, and the procedure can be simplified by assuming some information related to these objects, at this stage, the automation of object reconstruction is only concentrated on 2D symbolic surface description, without trying to find a solution to the general case of automatic scene interpretation. In this step, the general procedure outlined by Haralick et al. (1992) is used to attach a unique label (identification number) to each separate region so that every region can be identified and processed individually. As an example, to quantify the reinforced concrete columns completed on site, the objects of interest in **Figure 3.8** (d) are labeled to determine their corresponding bounding boxes. Individually, we can obtain the length of each object according to the parameters of these bounding boxes. Though few errors occur during construction, the length of each column can be assumed to be fixed on the basis of the technical requirement that the control joint of the cast-in-place concrete column should be set right under the bottom of the upper girder(s) or beam(s). Based on this assumption, we can reconstruct the image by using the fixed length to replace the detected length of each column in the image. However, a possible simplification for the algorithm would be to set this value automatically through a quick statistical analysis of the input. In other words, if we only need the number of columns finished on site every workday, to improve the scene in the image, we can still use the length of each bounding box and a fixed width to simply represent each column. **Figure 3.9** (b) shows a picture that represents the simplest solution to identify reinforced concrete columns on the construction site. A comparison between **Figures 3.8** (d) and **Figures 3.9** (b) indicates the simplified results for the reconstructed columns detected by the proposed segmentation approach.

3.6 Overall Image Segmentation Approach Testing

After the principal framework of the image processing approach was developed, it was necessary for the overall approach to be trained and tested prior to its practical application. There are many factors influencing the reliability and accuracy of the overall approach at each stage. For instance, in the image preprocessing phase, the location and size of the reference window, as well as the threshold value and the correcting range span chosen on the basis of the average light intensity of the reference window, can greatly affect the lighting compensation process. Also, the effects of illumination adjustment and noise filtering on the original digital images at this stage strongly depend on the selection of the corresponding morphological structure elements. To obtain an optimal result for project progress assessment, all the parameters and factors at each stage of the overall image processing approach were trained at the beginning of the construction stage. In order to do this, several original images taken under both desirable and undesirable lighting conditions (which require lighting compensation in the preprocessing phase) were used. During this process, 3 sample images taken under sunny weather conditions and 3 taken under cloudy or foggy weather conditions were used separately in the training process. The major parameters/factors, along with their values, utilized in the image processing process are outlined in **Table 3.1** below:

Table 3.1: Parameters/Factors Trained in the Overall Image Processing Approach

Image Processing Phase	**Main Parameters/ Factors**	**Value**	
		Undesirable Lighting Conditions	Desirable Lighting Conditions
Image Preprocessing	Location of the Reference Window in the Original Images	[139 253 3 9]	[139 253 3 9]
	Threshold of the Average Light Intensity of Reference Window	240	240
	Correcting Range Span	±10	±10
	Structure Element	Disk-Shaped with Radius 5	Disk-Shaped with Radius 5
	m-by-n neighborhood in Median filtering	[10 3]	[10 3]
Canny Edge Detector Based Algorithm	The Quantity of Pixels in an Object	10	10
	The Length of Detected Canny Edges	10	15
	The Width of Detected Canny Edges	20	--
	Aspect Ratio	1.5	2
Watershed Transformation Based Algorithm	The Length of Detected Watershed Lines	10	15
	The Width of Detected Watershed Lines	20	--
	Aspect Ratio	1.5	2
	The Quantity of Pixels in an Object	50	50
Morphological Transformations after Second-Stage Data Fusion Strategy	The Quantity of Pixels in an Object	30	30
	Structure Element	Disk-Shaped with Radius 3	Disk-Shaped with Radius 3
	The Quantity of Pixels in an Object	50	50
	Structure Element	Disk-Shaped with Radius 1	Disk-Shaped with Radius 1

The following step was undertaken to test the reliability and accuracy of the trained image segmentation approach under various lighting conditions. Eleven original images taken in a specific period of reinforced concrete column construction were randomly selected to test the overall approach. The situations of the detected objects in the sample images, which are classified by the lighting conditions, were investigated and analyzed. From the data shown in **Table 3.2**, as these pictures were taken under desirable/sunny weather conditions, all the constructed columns on site were successfully detected by the proposed approach. The few exceptions are the pictures taken on April 22nd and May 1st, 2003. In each of these, an object was misunderstood to be a completed reinforced concrete column (mismatched), as shown in **Figure 3.10**. In this research, the accuracy or reliability of the results from the overall image processing approach is defined as the **Equation 3.1**:

$$Accuracy = \frac{Correctly\ Detected\ Columns - False\ Matches}{Actually\ Completed\ Columns} \quad \textbf{(3.1)}$$

Generally, the accuracy/reliability of the results from the image processing/segmentation approach for the 6 testing images with desirable lighting conditions is greater than 98%, which proves that this method is very reliable in this case.

Table 3.2: Testing Results from the Proposed Image Processing Approach for Sample Images Taken under Desirable Lighting Conditions

Sample Images	Date	Weather Condition	Detectable Columns in Original Images	Columns Correctly Detected by Overall Image Processing Approach	False Match (Mismatch)
image_030422_175938	April 22nd	Sunny	2	2	1
image_030501_175945	May 1st	Sunny	10	10	1
image_030512_175944	May 12th	Sunny	19	19	0
image_030513_175950	May 13th	Sunny	20	20	0
image_030529_175940	May 29th	Sunny	25	25	0
image_030530_175946	May 30th	Sunny	25	25	0

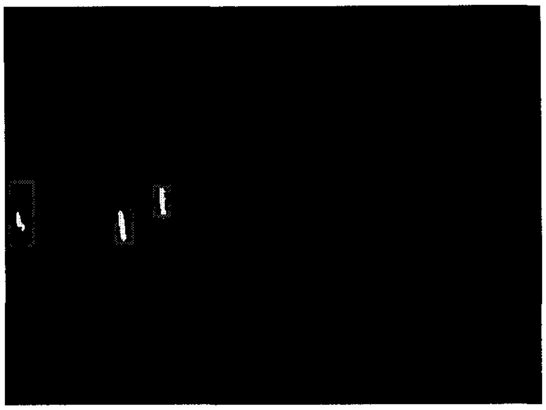


Figure 3.10 (a): Detected Objects of Interest and their Boundingboxes on April 22, 2003

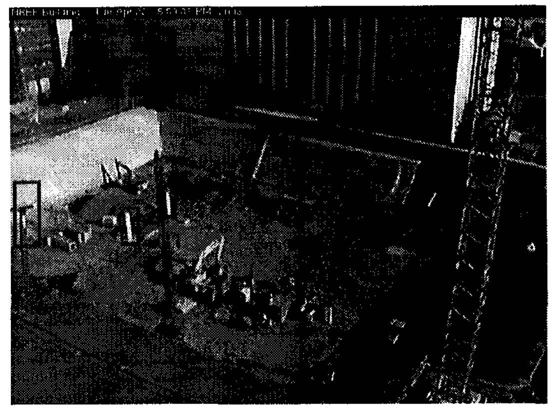


Figure 3.10 (b): Detected Objects of Interest in the Original Image on April 22, 2003

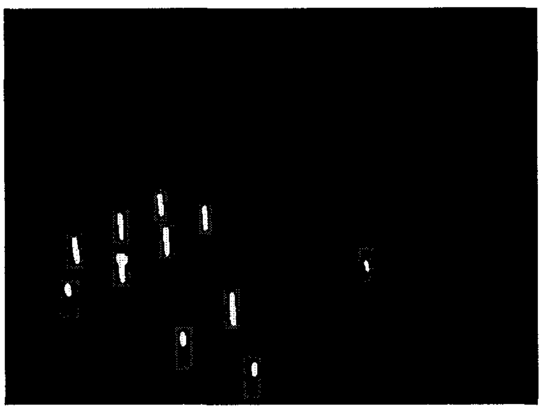


Figure 3.10 (c): Detected Objects of Interest and their Boundingboxes on May 1, 2003

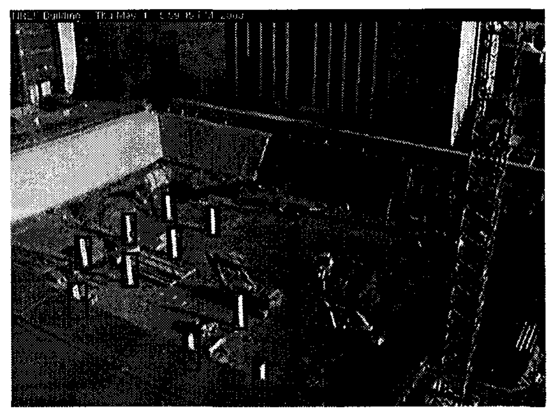


Figure 3.10 (d): Detected Objects of Interest in the Original Image on May 1, 2003

Figure 3.10: Detected Objects of Interest from Undesirable Original Images

In the images taken under cloudy or foggy weather conditions, as shown in **Table 3.3**, many completed columns on site were not successfully detected. This still poses a major challenge for the developed overall approach. Furthermore, there are some mismatches (false matches) in the results from some testing images (**Figure 3.11**). On the whole, the accuracy/reliability of the output of the overall approach for these low quality sample images is about 75%, which excludes the possibility of using them without additional information or user interaction.

Table 3.3: Testing Results of the Proposed Image Processing Approach for Sample Images Taken under Poor Lighting Conditions

Sample Images	Date	Weather Condition	Detectable Columns in Original Images	Columns Correctly Detected by Overall Image Processing Approach	Mismatch
image_030423_175945	April 23rd	Cloudy	2	2	1
image_030515_175953	May 15th	Cloudy	22	16	2
image_030519_175940	May 19th	Cloudy	22	16	1
image_030613_175953	July 13th	Foggy	15	13	0
image_030605_175941	June 5th	Cloudy	19	17	0

Figure 3.11 (a): Detected Objects of Interest and their Boundingboxes on April 25, 2003

Figure 3.11 (b): Detected Objects of Interest in the Original Image on April 25, 2003

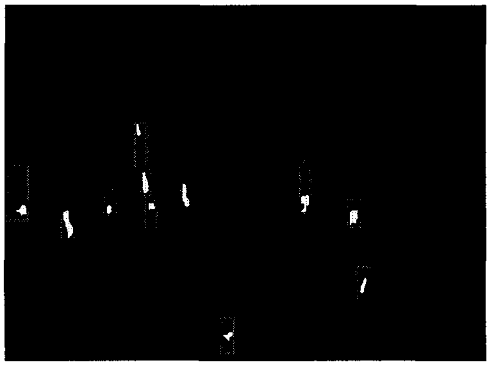


Figure 3.11 (c): Detected Objects of Interest and their Boundingboxes on May 2, 2003

Figure 3.11 (d): Detected Objects of Interest in the Original Image on May 2, 2003

Figure 3.11: Detected Objects of Interest and Mismatches in the Results, and Original Images under Poor Weather Conditions

In summary, the results from the overall image processing approach are still sensitive to the control parameters and factors. There is a particularly strong dependency on weather/lighting conditions at this stage. Inevitably, there are objects of interest, sometimes more, sometimes less, which can not be successfully detected. However, the better the lighting conditions in the original images, the more accurate and reliable are the results that can be obtained from them. In addition, due to heavy noise on site, it is still very difficult to exclude any mismatches in the results generated from either high or low quality images.

4 EXPERIMENT AND CASE STUDY

In this chapter, a test project which was carried out on the University of Alberta campus in Edmonton, Canada is presented. The pictures taken on site every 10 seconds using a network camera, which was installed with its pose (position and shooting angle) fixed during a specified period of time, were automatically stored in an image database. In this section, for the purpose of project progress assessment, only the last images taken every workday from April 22 to May 30, 2003 under various weather (sunny, cloudy, foggy and even snowy) conditions are selected from the image database and saved in a special directory as the image source. These are used in the experiment to reflect the differences in terms of time horizon, and also to demonstrate the applicability of the overall process by presenting the relevant figures and data observed in the test project.

4.1 Automatic Image Data Acquisition and Processing

To enhance the automation level and functionality of the system, once the program begins to run, "ImageNo" and "Number" first prompt the user to freely select an image data set (a number of images started from the appointed first image corresponding to the "ImageNo" with the total of the selected "Number") to be processed from an image folder. Then, it automatically displays a dialog box, which enables the user to browse through the directory structure and select a directory, the designated image folder, as the data source and current working directory. All the image files in this directory with a specific format (such as the *jpg* format used in this research) are listed to an m-by-1 structure with the fields of *name*, *dates*, *bytes,* and *isdir*. These selected sample images, along with their names, are then read into a concatenated data set in time order for image classification, as well as for the use of subsequent image preprocessing and image segmentation phases. The interactive prompts and interface for automatic data source selection are shown in **Figure 4.1:**

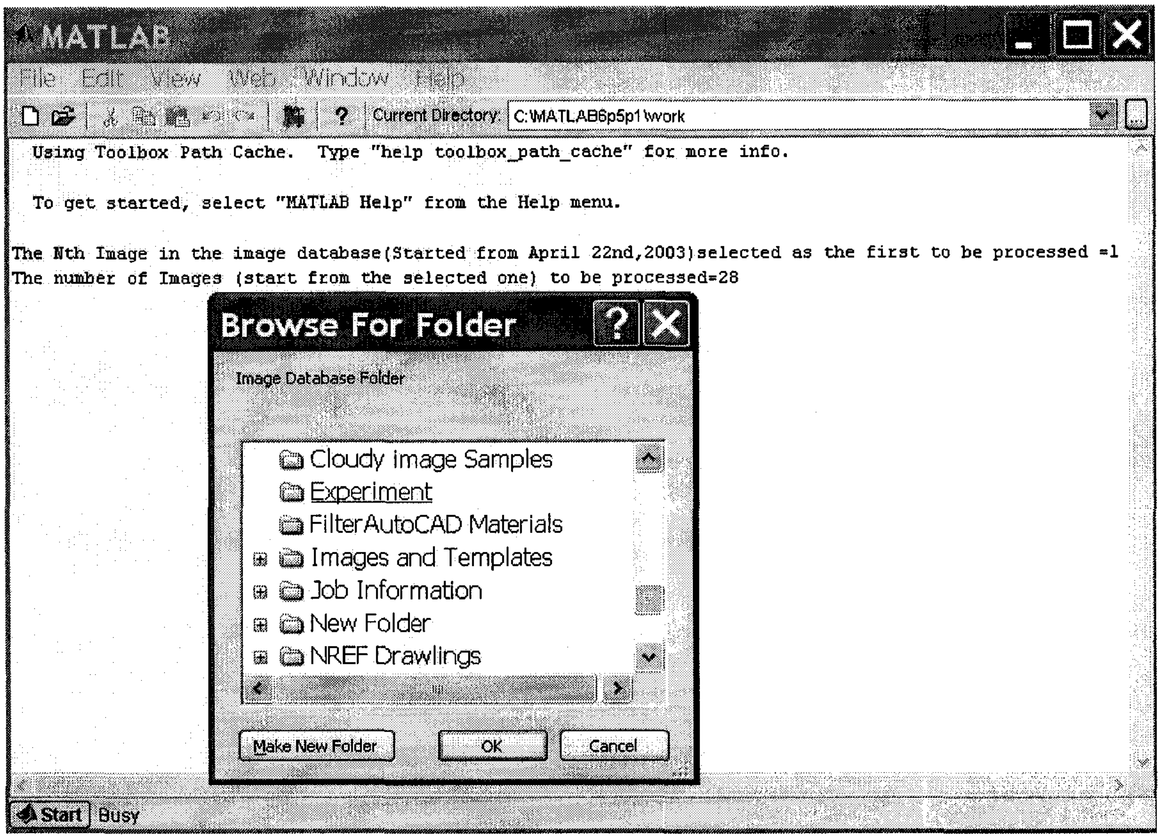


Figure 4.1: Interactive Prompts and Interface for Image Data Source Selection

As mentioned in **Chapter 3**, some of the original images taken under poor lighting conditions on site need to be sought out and compensated for prior to image segmentation. This process is also automatically performed by the developed program. All original sample images in the concatenated data set are scanned in sequence and classified on the basis of the average light intensity value of the reference window within each of them; priorities are then assigned. In other words, if the average light intensity value of the reference window is greater than or equal to 240, the lighting is considered to be desirable and the corresponding priority of the original image is designated as 2; otherwise, the image is considered to have been taken under poor lighting conditions and its priority is designated as 1. Therefore, once the quantity of the reinforced columns in an image is obtained through the following overall image segmentation approach, the corresponding priority and image sequence number are simultaneously presented to the user. The flowchart for the automatic process of image data acquisition and classification is shown as **Figure 4.2**:

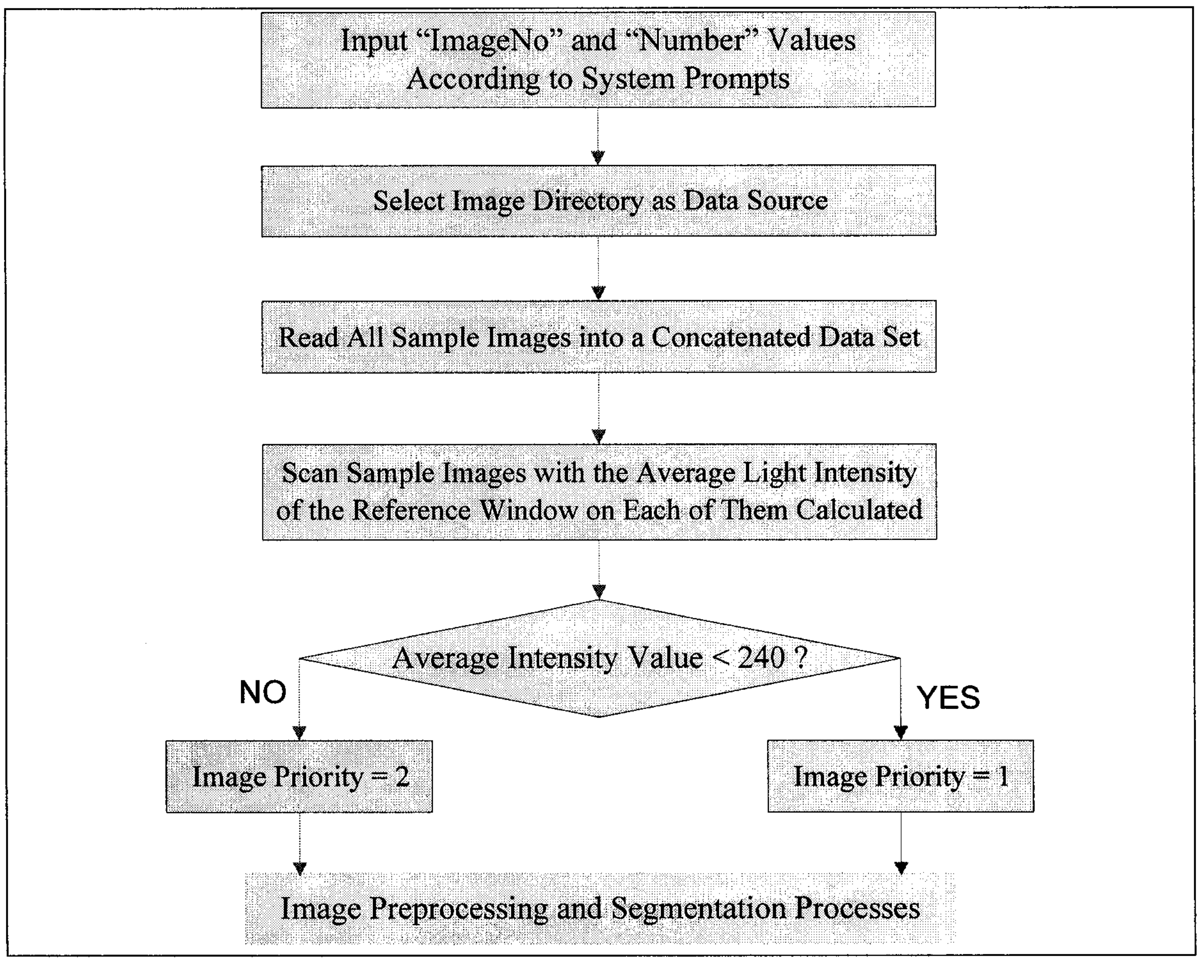


Figure 4.2: Automatic Image Data Acquisition and Classification

With the developed program, all sample images in a directory can be batch processed at once regardless of the memory capacity of the user's computer. In this experiment, a total of 28 successive workday images were automatically processed with the so-called "detected number of reinforced concrete columns" in each of them, as shown in the "Image Processing Output" column in **Table 4.1**. In fact, these numbers are nominal progress data for the practical construction operation of concrete work because of some bad fits (mismatches). For example, the progress number obtained from the program on April 22, 2003 is 3, however, the actual finished concrete on site is only 2, which means there is 1 unrelated instance of noise or an installed column formwork has been misunderstood to be a poured concrete column. Even worse, on April 25, the quantity of columns gained from the developed image processing approach, is 4, which happens to be exactly the same number as the actual finished columns on site. Comparison with the actual results reveals that there are only 3 real columns detected by the overall image segmentation approach and the remaining 1 is a mismatch resulting from extremely unfavorable lighting conditions. Generally, in the 28 images representing a total of 442 columns, 393 columns were successfully detected by the system. This means that 49 columns were not able to be successfully detected. Also, considering 33 mismatches (including 12 sets of column formworks misunderstood to be concrete columns), according to **Equation 3.1**, the overall accuracy of the output of the overall image processing approach is 81.45% (in other words, the error rate of the output of the image processing approach is 18.55%). Because the formworks were installed at the exact locations of columns with similar size/shape parameters, this kind of mismatch can not yet be effectively eliminated by the overall approach. If the mismatches could be deducted from the results by incorporating formwork installation information, a relatively higher accuracy of 84.16% could be acquired. Thus, it is very crucial to improve the reliability and accuracy of the progress data by using any associated methods.

Table 4.1: The Obtained Progress Data and Reliability Analysis

No.	Image Name	Actually Completed Columns	Image Processing Output	Correctly Detected Columns	False Matches (Mismatches)	Formwork Mismatched as Columns
1	image_030422_175938	**2**	3	2	1	0
2	image_030423_175945	**2**	3	2	1	0
3	image_030424_155912	**2**	4	2	2	2
4	image_030425_175935	**4**	4	3	1	0
5	image_030428_175945	**6**	8	5	3	0
6	image_030429_175946	**6**	8	6	2	2
7	image_030430_175946	**8**	9	7	2	1
8	image_030501_175945	**10**	11	10	1	0
9	image_030502_175942	**10**	11	6	5	1
10	image_030505_175952	**12**	7	6	1	1
11	image_030506_175955	**12**	10	9	1	0
12	image_030507_175957	**12**	9	7	2	0
13	image_030508_175947	**13**	9	8	1	0
14	image_030509_175936	**16**	20	16	4	3
15	image_030512_175944	**19**	19	19	0	0
16	image_030513_175950	**20**	20	20	0	0
17	image_030514_175946	**22**	23	22	1	0
18	image_030515_175953	**22**	18	16	2	0
19	image_030519_175940	**22**	17	16	1	0
20	image_030520_175931	**23**	23	22	1	1
21	image_030521_175955	**24**	24	23	1	1
22	image_030522_175945	**25**	23	23	0	0
23	image_030523_175946	**25**	24	24	0	0
24	image_030526_175945	**25**	25	25	0	0
25	image_030527_175944	**25**	25	25	0	0
26	image_030528_175931	**25**	19	19	0	0
27	image_030529_175940	**25**	25	25	0	0
28	image_030530_175946	**25**	25	25	0	0
	Sum of Columns	442		393	33	12
	Overall Error Rate (%)	**18.55%**	*(15.84%)*		7.5%	
	Overall Accuracy (%)	**81.45%**	*(84.16%)*			

4.2 Data Reliability Enhancement with Construction Plan Information Merged

The data in **Table 4.1** reveals that the undetected number of reinforced concrete columns accounts for about 11% of the overall error rate, while the mismatches account for the remaining 7.5% in the nominal progress data, the output of the overall image processing approach. Therefore, there are two methods to consider to improve the accuracy/reliability of the progress data gained from the developed approach: one is to increase the number of real columns detected by as much as possible, which requires further improvement to the image segmentation techniques, or enhancement of the outdoor lighting conditions when the weather conditions are undesirable. Another suitable method would be to decrease the number of mismatches. Although an image filtering mask has already been employed in the image segmentation approach and effectively reduced the noise, there are still many mismatches in the progress data, which seriously affect the reliability of these data in application.

In most construction practices, the project planner/scheduler in the contractor's project management group develops detailed construction plans and schedules ahead of construction operations, or even right after winning the contract. If the construction plan information is available in advance, that is, the detailed working items and schedules for the next stage are known, then some of the mismatches in the obtained progress data can be further reduced. Actually, this can be realized by means of the second-step-filtering operations. In this experiment, for example, the weekly detailed construction plans and schedules for the NREF building under optimal conditions were obtained in advance from the principal contractor, the PCL construction group. Specifically, in the first week (from April 22nd to April 25th, 2003), the 4 reinforced concrete columns on the gridlines of C7, D7, E7, and F3 on low level 2 were scheduled to be poured; in the second week (from April 28th to May 2nd, 2003), 6 columns on E4, F4, C6, D6, E6, F6 were to be finished on the basis of the first week's results; in the third week (from May 5th to May 9th, 2003), another 6 columns D2, D3, F5, E8A, E5, and D5 were to be completed in sequence. Subsequently, the tasks of the fourth week (from May 12th to May 16th, 2003) were D4, E3, D8, C5, C8, and C4; in the fifth week (from May 19th to May 23rd, 2003), 3 of the left columns, B6, B5, B4, were to be completed and there was a total of 25 columns expected to be successfully detected during this week. In the sixth week (from May 26th to May 30th, 2003), no more column concrete work was planned; all columns already poured were to be cured and some formworks for the upper level slabs and girders were to be prepared. Therefore, the total detectable number of columns was to remain the same. During the seventh week (June 2nd to June 6th, 2003), some of the formworks for the slabs and girders on low level 1 were installed. Although the number of reinforced concrete columns on low level 2 was not supposed to change, some of them, such as columns E4, F3, F4, F5, were undetectable by the network camera because they were to be cloaked by the upper level forms. Therefore, the detectable number of the columns was to be reduced instead and an updated imaging mismatch filtering mask should have been used for the images taken during this week. Also, as the formwork installation continued on site, the number of detectable columns (19 and 16 columns in the 8th and 9th weeks, respectively) in the images was to be less and less, which reflects the fact that the construction operations subsequently carried out during the concrete pouring work were performed step by step.

Based on the detailed plan information described above, as well as on the 3D perspective view image filtering mask previously created (**Figure 3.4** (e)), the filtering masks for the images taken during this period can be created piecewise (week by week in this experiment) and in advance. This allows mismatches to be filtered from the obtained image processing results of the next week, as shown in **Figure 4.3**.

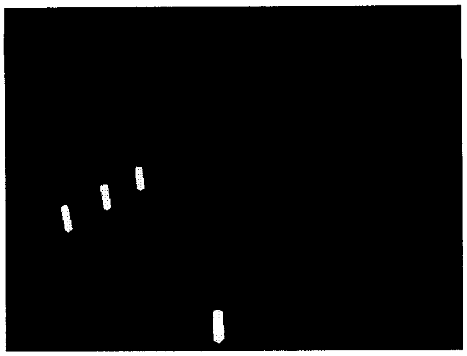


Figure 4.3 (a): Imaging Mask Created for the 1st Week

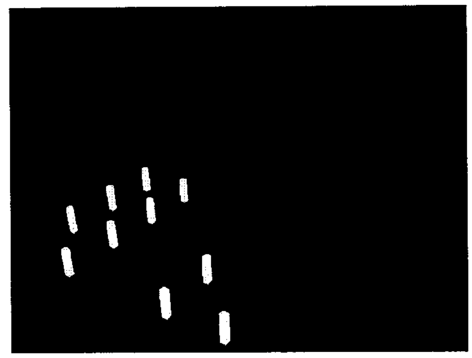


Figure 4.3 (b): Imaging Mask Created for the 2nd Week

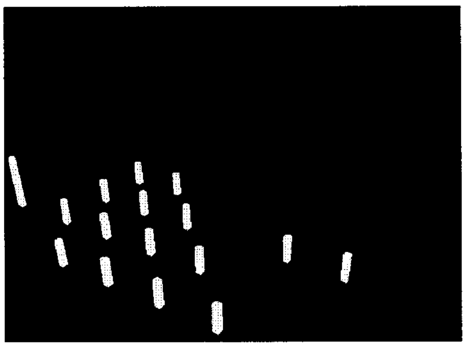


Figure 4.3 (c): Imaging Mask Created for the 3rd Week

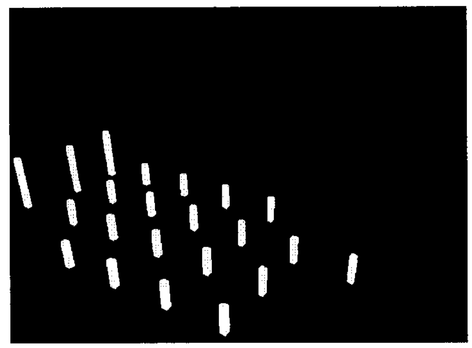


Figure 4.3 (d): Imaging Mask Created for the 4th Week

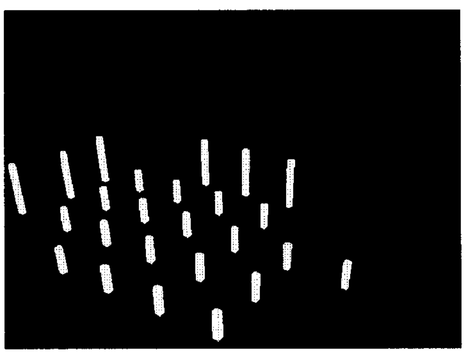


Figure 4.3 (e): Imaging Mask Created for the 5th & 6th Week

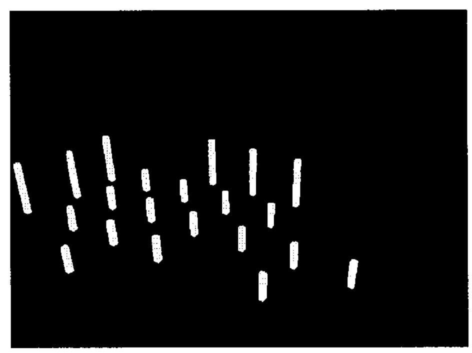


Figure 4.3 (f): Imaging Mask Created for the 7th Week

Figure 4.3: Imaging Masks for the Second-Stage Mismatch Filtering

Most of mismatches in the "Image Processing Output" listed in **Table 4.1** were successfully excluded through the use of the updated imaging masks as shown in **Figure 4.3**. For instance, in **Figure 4.4** (a), there are three object of interest candidates detected by the overall segmentation approach in the sample image taken on April 22nd, 2003; however, only two of them are real completed reinforced concrete columns. One of these is just an erect extension of an automobile crane on site which was successfully rejected by the imaging mask (**Figure 4.4** (a)). The actual results obtained are shown in **Figure 4.4** (b).

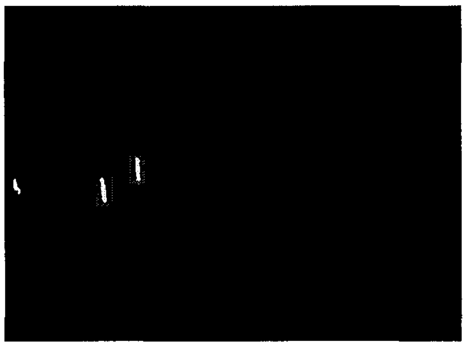


Figure 4.4 (a): Progress Data with Real Columns and Mismatch

Figure 4.4 (b): The Detected Real Columns in Original Image

Figure 4.4: Detected Objects of Interest with Construction Plan Information Merged

The obtained progress data after inserting the detailed construction plan information are listed in **Table 4.2**.

From the data listed in **Table 4.2**, the number of mismatches was significantly reduced from the former 33 in **Table 4.1** to 10, seven of which are corresponding formworks installed for the upcoming column concrete construction. Accordingly, with the reduction in mismatches, the overall reliability/accuracy was raised from 81.45% to 86.65%, which shows that mismatch filtering masks are necessary and helpful for the enhancement of the reliability/accuracy and applicability of the progress data produced by the overall image processing approach.

Table 4.2: Progress Data after Combining Construction Plan Information

No.	Image Name	Weather Condition	Actually Completed Columns	Image Processing Output	Correctly Detected Columns	False Matches (Mismatches)	Formwork Mismatched as Columns
1	image_030422_175938	Sunny	**2**	2	2	0	0
2	image_030423_175945	Cloudy	**2**	2	2	0	0
3	image_030424_155912	Sunny	**2**	3	2	1	1
4	image_030425_175935	Cloudy	**4**	3	3	0	0
5	image_030428_175945	Sunny	**6**	6	5	1	0
6	image_030429_175946	Sunny	**6**	8	6	2	2
7	image_030430_175946	Sunny	**8**	8	7	1	1
8	image_030501_175945	Sunny	**10**	10	10	0	0
9	image_030502_175942	Snow	**10**	6	6	0	0
10	image_030505_175952	Snow	**12**	7	6	1	1
11	image_030506_175955	Snow	**12**	9	9	0	0
12	image_030507_175957	Snow	**12**	7	7	1	0
13	image_030508_175947	Snow	**13**	8	8	0	0
14	image_030509_175936	Sunny	**16**	16	16	0	0
15	image_030512_175944	Sunny	**19**	19	19	0	0
16	image_030513_175950	Foggy	**20**	20	20	0	0
17	image_030514_175946	Sunny	**22**	22	22	0	0
18	image_030515_175953	Foggy	**22**	16	16	0	0
19	image_030519_175940	Foggy	**22**	17	16	1	0
20	image_030520_175931	Sunny	**23**	23	22	1	1
21	image_030521_175955	Sunny	**24**	24	23	1	1
22	image_030522_175945	Foggy	**25**	23	23	0	0
23	image_030523_175946	Sunny	**25**	24	24	0	0
24	image_030526_175945	Sunny	**25**	25	25	0	0
25	image_030527_175944	Sunny	**25**	25	25	0	0
26	image_030528_175931	Foggy	**25**	19	19	0	0
27	image_030529_175940	Sunny	**25**	25	25	0	0
28	image_030530_175946	Sunny	**25**	25	25	0	0
	Sum of Columns		**442**		**393**	10	7
	Overall Error Rate (%)		**13.35%**	*(11.76%)*			
	Overall Accuracy (%)		**86.65%**	*(88.24%)*			

4.3 Priority Based Error Correction Mechanism

The testing results of the sample images in last section demonstrated that the overall image processing approach is still very sensitive to variations in lighting conditions in the original images, and inevitably there are some errors in the data set. To correct some of the errors in the image processing results (the "nominal project progress data"), especially for those images taken under poor lighting conditions, an independent priority based error correction mechanism was established and the developed algorithm is also introduced in detail in this section.

In the priority based error correction procedure, first, the system, with user interaction, classes the priority of the image processing results (the quantity of reinforced columns detected in an image) into 3 levels, two of which are in terms of the corresponding lighting conditions in the original images, as mentioned in **Chapter 3**. In common practice, major construction operations are always monitored and inspected by professionals on site regularly, regardless of location or weather conditions. Accordingly, the developed system lets the user make decisions regarding when and how often site inspections/field surveys will be conducted and acquire the actual progress information. If the project progress data are obtained by site inspection, they have the highest priority and are to be used as benchmarks in the automatic error correction algorithm. Within this algorithm, the priority of the data obtained by site inspection is assigned 3 (high), and, as previously mentioned, the priorities corresponding to the results obtained from desirable and undesirable lighting conditions are assigned 2 (medium) and 1 (low), respectively. The error correction processes are then mainly guided by the following principles:

- All the images in a population of an experiment are to be processed in terms of time sequence;
- The higher the priority a progress result has, the more reliable and accurate it is;
- Once there are actual progress data available from construction sites, the corresponding results obtained from the image processing approach should be corrected using the real data value and assigned the highest priority 3;
- For all progress data obtained in a run (from one batch process), the value on each time point should not be less than any of those values on the previous time points;
- For all progress data obtained in a run, the value on each time point should not be greater than any of those values on the following time points.

To meet these basic principles, especially the fourth and the fifth, some situations were considered in the program to automatically correct the potential, but unreasonable, errors in those progress results directly obtained by means of the overall image processing approach. In the error correction mechanism, each progress result in a run is compared with all the others pairwise. When some abnormal situations emerge in the progress data after a run, the error correction mechanism is activated and the errors in the data set are automatically corrected in terms of their time sequences and priorities for the purpose of getting more reliable and accurate progress data. This is accomplished following these two assumptions/control criteria:

1. If a progress result with lower priority is found to be less than any previous result with higher priority, it should be replaced by that comparative value;

2. If a progress result with lower priority is found to be greater than any following result with higher priority, it should be replaced by that comparative value.

Based on the testing results, when there are errors in the generated progress data of the images with desirable lighting conditions, most of them are column mismatches instead of missing columns. On the contrary, when there are errors in the generated progress data for the images with poor lighting conditions, most are missing columns. Therefore, another two assumptions/criteria are also applied in the algorithm for progress data with the same priority level:

3. If a progress result with priority 2 (medium) is found to be greater than its following result, also with priority 2 (medium), it should be replaced by the following value;
4. If a progress result with priority 1 (low) is found to be less than its previous result, also with priority 1 (low), it should be replaced by the previous value.

The priority based error correction algorithm (**PECA**) developed in this research also allows the user to freely input any progress information obtained directly from regular field surveys through an interactive interface. The overall flowchart and the four individual processes of this algorithm are shown one by one in **Figures 4.5** to **4.7**.

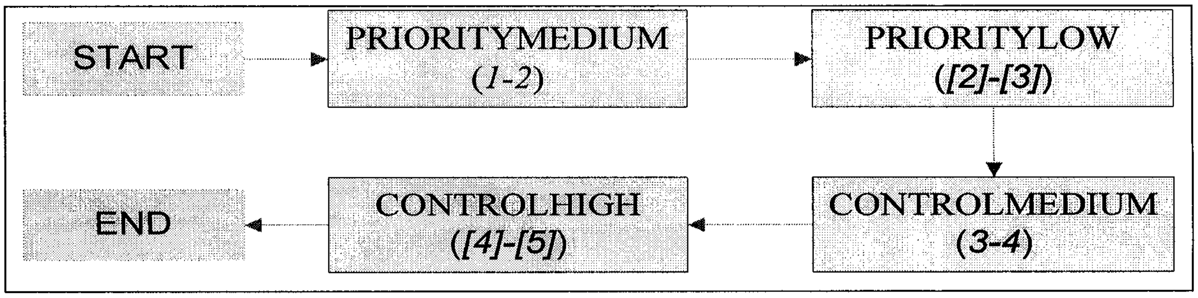


Figure 4.5: Overall Flowchart of the Error Correction Algorithm (PECA)

PRIORITYMEDIUM (from node 1 to node 2 in **Figure 4.6**) commands the program to browse all the images in the population, find those with priority 2, and save the corresponding image IDs (for example, sequence orders) and progress data generated from the image processing approach (concrete column numbers) into a temporary matrix in the first loop. Then, criterion 3 is coded in the second loop to backward sort the project data with priority 2 and make sure it is in ascending order in terms of image sequence. After that, those sorted project data are returned according to their image IDs.

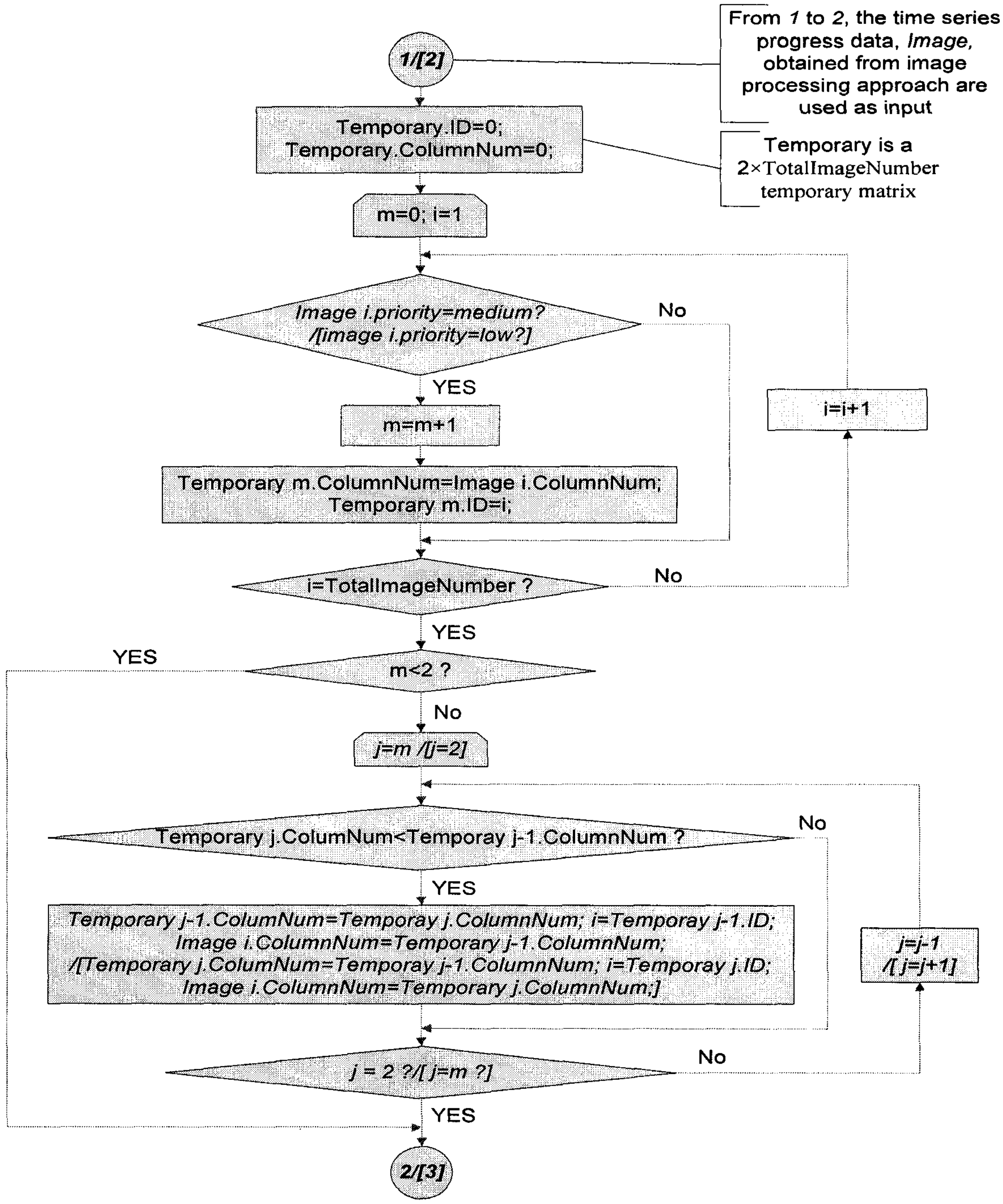
Similarly, PRIORITYLOW (from node *[2]* to node *[3]* in **Figure 4.6**) continues to handle the sample images with priority 1. After their project data and their IDs are saved in a temporary matrix in the first loop, the fourth criterion is used in the second loop to forward sort the project data in ascending order. Afterwards, the sorted data are returned in the same manner.

CONTROLMEDIUM (from node 3 to node 4 in **Figure 4.7**) first uses two loops to find the nearest progress data with priority 2 on both sides of each datum with priority 1. It uses these data as local minimum column number and local maximum column number. Then, if necessary, it applies the first and second criterion to correct the priority-1-datum/data within the data range divided by the priority-2-progress-data.

If there is related progress information available from regular field surveys, the progress data for these time points (dates) are replaced by the actual data first, with their priorities simultaneously changed to 3 (high). CONTROLHIGH (from node *[4]* to node *[5]* in

Figure 4.7) is then processed to correct the project data with priority less than 3 according to the priority-3-data on both sides, if necessary, using the first and second criterion again.

The **PECA** finally returns the corrected results, which are to be utilized for the purpose of future performance review and productivity analysis.



Note:

PRIORITYMEDIUM = *1* to *2*; **PRIORITYLOW = [2] to [3];**
Temporary = temporary matrix; ID = image sequence order; i, j, m = counter; low = priority 1; medium = priority 2; high = priority 3; ColumnNum = detected column number in an image;
TotalImageNumber = total number of sample images to be processed in a batch;
MinimumColumnNumber = local minimum column number with specific priority within a data range;
MaximumColumnNumber = local maximum column number with specific priority within a data range;

Figure 4.6: PRIORITYMEDIUM and PRIORITYLOW Process

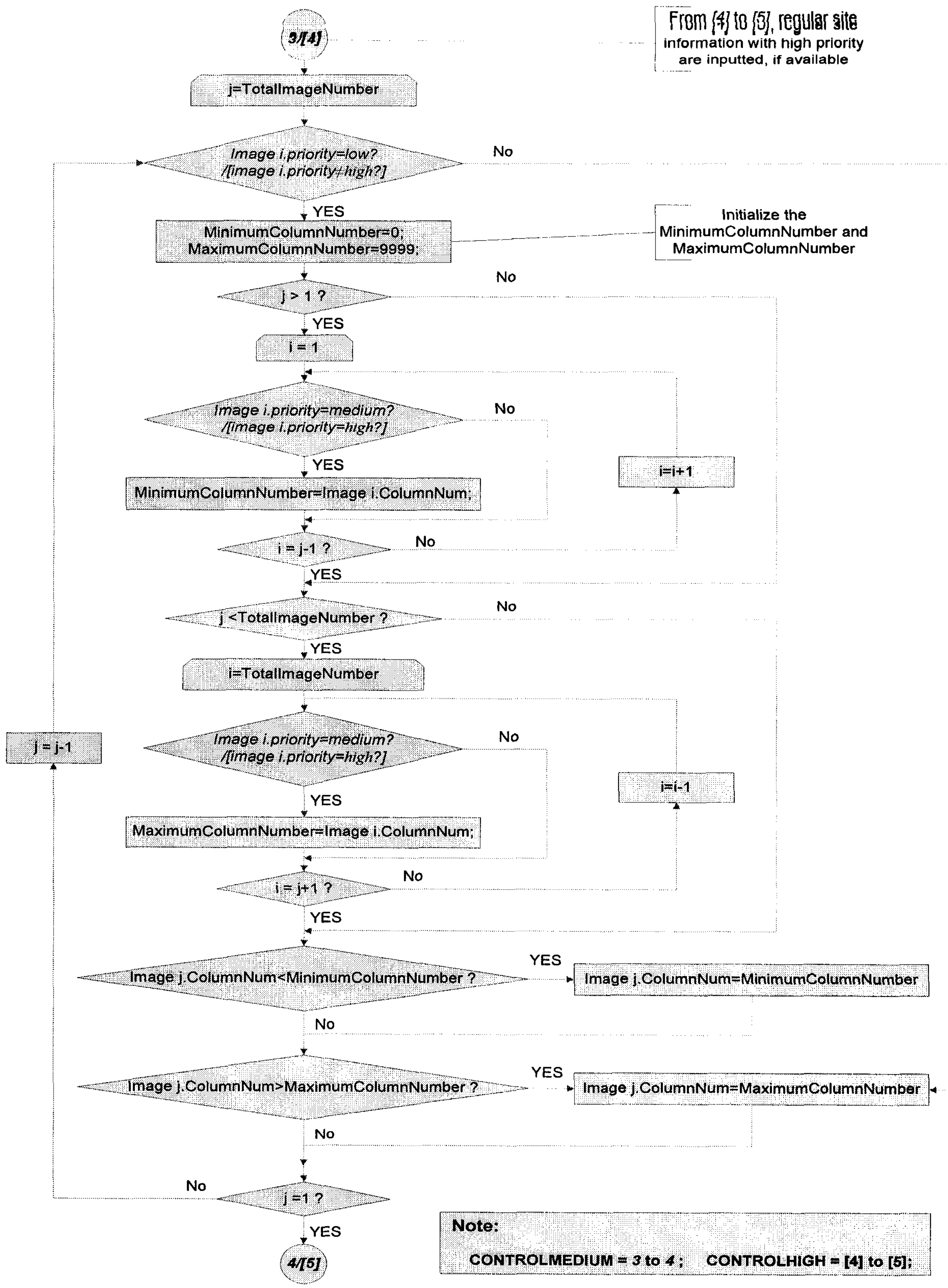


Figure 4.7: CONTROLMEDIUM and CONTROLHIGH Process

4.4 Statistical Analysis and Evaluation of the Performance of the Developed Semi-Automatic Progress Assessment System

At the final stage of the experiment, the progress data obtained from the 28 successive workday pictures after image processing and with construction plan information merged, as well as those corrected by means of the error correction mechanism and those corrected by both the error correction mechanism and the weekly inputting of some real project data from site inspection/field surveys, were automatically gained and listed in column (5), (6), and (7) of **Table 4.3**, respectively. For this case study, the real progress data, the accumulated numbers of the actual finished concrete columns on the 1st, 6th, 11th, 16th, 21st, and 26th days from April 22nd, 2003, were interactively inputted as site information. Unlike the uncorrected progress data, the output of the image processing approach with construction plan/schedule information incorporated, in column (5), there are no abnormalities in time sequence for the data sets listed in columns (6) and (7). This demonstrates that the automatic error correction mechanism successfully solved those potential problems in the generated progress data. The positive effects of this algorithm are not limited to the correction of errors; the overall quality of the progress data set was greatly enhanced, a fact reflected by the correlation coefficient between the computed progress data sets and the actual data.

The correlation coefficient is a concept from statistics; it is a quantity, a number between 0 and 1, which gives the quality of a least squares fitting to the original data. According to related "Correlation Coefficient Online References", it is used to determine the relationship between two properties, for instance, to measure how well the predicted/computed values from a forecast model "fit" with the real-life data. If there is no relationship between the predicted/computed values and the actual values, the correlation coefficient is 0 or very low, indicating that the predicted/computed values are no better than random numbers. As the strength of the relationship between the predicted/computed values and actual values increases, so does the correlation coefficient. A perfect fit gives a coefficient of 1.0. Thus, the higher the correlation coefficient, the better the predicted/computed values are. According to Microsoft online assistance (Excel 2003), the equation for the correlation coefficient is:

$$\mathit{Correlation\ Coefficient}(X,Y) = \frac{\sum (x-\bar{x})(y-\bar{y})}{\sqrt{\sum (x-\bar{x})^2 \sum (y-\bar{y})^2}} \qquad \textbf{(4.1)}$$

$\mathit{Correlation\ Coefficient}(X,Y) =$

Where:

X is an array of values (data set) and Y is a second array of values;

$\bar{x}$ and $\bar{y}$ are the sample means of X and Y, respectively.

In this experiment, to examine the relationship between each of the three sets of computed progress data and the actual one, the corresponding correlation coefficient was also calculated pairwise and is shown in **Table 4.3**. The ascending correlation coefficients, starting at 0.961, then increasing to 0.993, and finishing at 0.998, demonstrate that the generated progress data became more and more coincidental with the actual data set after step-by-step corrections. This means the final generated progress data in column (7) of **Table 4.3** could successfully replace the real-life data to reflect the construction performance on site and also be used for practical performance reviews, progress payments, and/or productivity analysis.

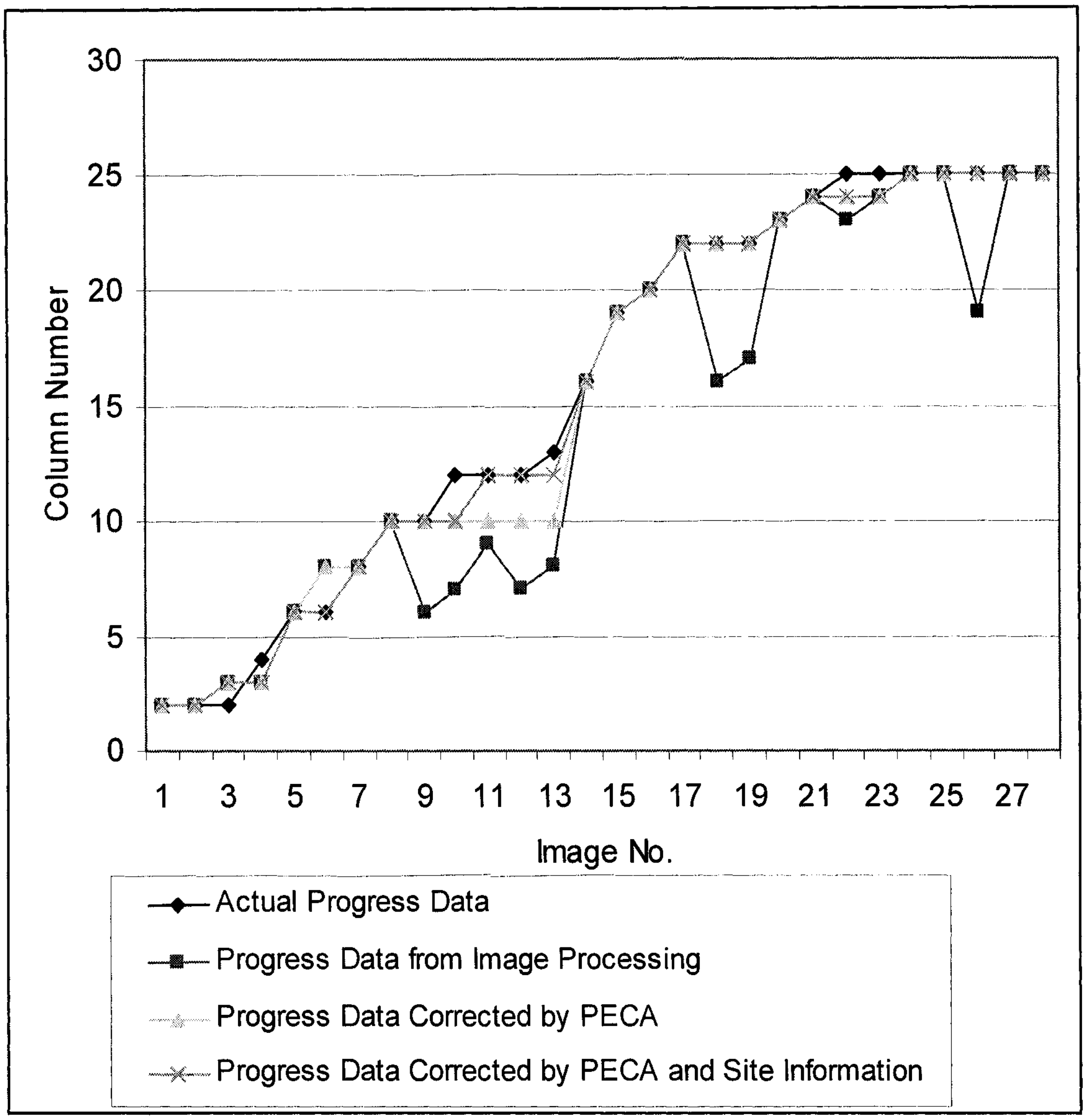


Figure 4.8: Progress Data Comparison Diagram

The advancements of the computed progress data sets can also be obtained from the visual illustration through comparison of the four cumulative progress data sets, the S-Curves, as shown in **Figure 4.8**.

In addition to the correlation coefficients, the differences among the three sets of computed progress data and the actual progress data set in column (4) of **Table 4.3** were calculated and are separately shown in columns (8), (9), and (10). The values of the sums, the first and second moments of the differences, and the differences themselves, show that the modification of the progress data improved approaching the actual progress data set.

Table 4.3: Priority Based Project Progress Data Correction and Analysis

No. (1)	Priority (3)	Actual Columns Completed (4)	Image Processing Output (With Construction Plan Merged) (5)	Corrected Progress Data (Without Site Information Merged) (6)	Corrected Progress Data (With Weekly Site Information Merged) (7)	D1 (8)= |(5)-(4)|	D2 (9)= |(6)-(4)|	D3 (10)= |(7)-(4)|
1	2	2	2	2	2	0	0	0
2	1	2	2	2	2	0	0	0
3	1	2	3	3	3	1	1	1
4	1	4	3	3	3	1	1	1
5	1	6	6	6	6	0	0	0
6	1	6	8	8	6	2	2	0
7	2	8	8	8	8	0	0	0
8	1	10	10	10	10	0	0	0
9	1	10	6	10	10	4	0	0
10	1	12	7	10	10	5	2	2
11	1	12	9	10	12	3	2	0
12	1	12	7	10	12	5	2	0
13	1	13	8	10	12	5	3	1
14	1	16	16	16	16	0	0	0
15	1	19	19	19	19	0	0	0
16	1	20	20	20	20	0	0	0
17	1	22	22	22	22	0	0	0
18	1	22	16	22	22	6	0	0
19	1	22	17	22	22	5	0	0
20	1	23	23	23	23	0	0	0
21	1	24	24	24	24	0	0	0
22	1	25	23	24	24	2	1	1
23	1	25	24	24	24	1	1	1
24	2	25	25	25	25	0	0	0
25	1	25	25	25	25	0	0	0
26	1	25	19	25	25	6	0	0
27	1	25	25	25	25	0	0	0
28	1	25	25	25	25	0	0	0
Sum		442				46	15	7
Standard Deviation						2.21	0.88	0.52
Average						1.64	0.54	0.25
Correlation Coefficient			**0.961**	**0.993**	**0.998**			

5 CONCLUSIONS AND RECOMMENDATIONS

5.1 Research Summary

In this research project, a new prototype system for semi-automatic building reinforced concrete column extraction and construction progress assessment was developed. It was designed to be one module of the program of an automatic/semi-automatic building construction progress assessment research project. This research was motivated mainly by the increasing demands for timely communication of information for ongoing project quality, cost, progress control, and safety management or performance review, and for productivity analysis for some specific projects constructed in remote areas. The general purpose of this study was to freely acquire useful data for project progress assessment by means of successfully and effectively identifying and detecting the objects of interest (the reinforced concrete columns at this stage) in the digital images taken on site, pushing the boundaries of conventional practice in the related research areas, and substantially decreasing dependence on frequent field surveys. To meet this goal, the article first presents the outcome of the overall image processing approach, the core of the system, which is a novel approach for detecting the reinforced concrete columns in primitive images taken on a construction site. It then proposes a priority based error correction algorithm to optimize the results obtained from the overall image processing approach. Finally, an experiment is carried out to investigate the applicability of the developed system in a real construction project practice.

The objective of the overall image processing approach is to significantly enhance the performance of image segmentation methods, thus minimizing the need for manual separation of objects of interest in an image and, ultimately, facilitating dynamic construction progress control. The work methodology utilized to accomplish this research objective basically consists of three phases. The first phase of the overall approach is image preprocessing, which involves morphological transformations, image enhancement, and the proposed lighting compensation technique. Initially, original images taken on site are browsed and classed by detecting the average light intensity of the specified reference window on each grayscale image to see whether it needs to be compensated for or not. After that, all grayscale images are enhanced by means of various morphological transformations and image enhancement methods, such as image adjustment and median filtering, to exclude as much unnecessary information as possible.

The second phase of the overall image processing approach involves image segmentation methods, data filtering/data fusion strategies, as well as some morphological transformations. The algorithms for segmenting objects of interest are developed based on the Canny edge detector and watershed transformation methods, and are incorporated with other information and morphological transformations. The Canny Edge detector and watershed transformation methods initially outline all the respective objects in the images based on the outputs from the first phase (image preprocessing). Then, the results from both methods are filtered by an imaging mask created from a 3D perspective view of the concrete columns in the AutoCAD drawings. This removes a significant amount of heavy background noise, and the bounding box of each column is also computed. This filtering process is called the first-step data fusion. On the basis of the results from the first-step, the second-step data fusion strategy is implemented to combine the results from both of the segmentation methods in order to obtain more useful column information. Also, some morphological transformations are employed to further reduce useless information according to the shape and size parameters of the reinforced concrete columns. These parameters, as well as other control factors, are trained and tested at the very beginning of construction, prior to application. This proposed procedure proved to be effective and successful as a means of segmenting the structural components in digital images taken from the NREF building construction site, especially under sunny weather conditions. Having acquired the columns and/or column patches in the images, the object reconstruction process was performed to represent the detected columns and obtain their quantity and locations by means of their bounding boxes and other previously obtained parameters, which are usually used as primitive or nominal progress data. To further modify the results, it is strongly recommended that the detailed construction plans and schedules related to the concrete column operation, if available, be merged in this overall approach to remove potential bad fits (mismatches) in a technical manner. This process can be simply accomplished by using a series of mismatch filtering masks created beforehand on the basis of the aforementioned image filtering mask and construction plan/schedule information. The work methodologies for each of the processes are documented, along with their corresponding flowcharts developed in context.

Along with the overall image processing approach for the acquisition of progress data for the reinforced concrete columns in building, a method for the logical modification of these data has been developed. The priority based error correction algorithm (**PECA**) is presented and utilized either to automatically eliminate or significantly reduce potential errors/abnormalities in the nominal progress data set, the progress results obtained from the overall image processing approach. It is based on four assumptions summarized from the testing results of the overall image processing approach, so as to better fit the actual construction performance on site in time series. The **PECA** also allows the user to further enhance the corrected progress data by interactively inputting actual site information obtained through regular field surveys. The overall procedure and detailed processes of the **PECA** are developed and represented in the form of flowchart. A correlation coefficient is introduced and employed as a principal parameter to evaluate the advancement of the progress data set after using this algorithm.

Having established the prototype system, an experiment was conducted using 28 primitive images continuously taken at the end of each workday to test its reliability and applicability, The computed progress data sets from the overall image processing approach, with or without construction plan information incorporated, were collected separately. After a pairwise comparison of each figure with the corresponding one from the original images, the overall accuracy / reliability values for each computed progress data set in this case were deemed to be 81.45% and 86.65%, respectively. This shows that the overall image processing approach developed in this research can successfully identify and segment most of the objects of interest in the digital images taken on the construction site, despite heavy background noise. However, the experimental results vary significantly with the weather/lighting conditions in the input images; the better the lighting conditions are for the input, the more real columns are likely to be detected, resulting in fewer mismatching cases. Also, with the related construction plan/schedule information integrated, a better result was achieved because most of the unrelated mismatches could be technically removed by the designed step-by-step filter. Based on this result, the **PECA** was employed to further enhance the progress data in the experiment. The variation in the correlation coefficients (from an initial value of 0.961 to 0.993 and finally to 0.998) reveals that the **PECA** is very effective at logically improving the overall quality of the progress data set, even though it is not expected to completely correct all the errors. With regular or occasional site information, even better modifications can be made. The final progress results generated demonstrate that they are very desirable and reliable for practical progress assessment applications. Further, the graphs were plotted to illustrate the variance between all the computed progress data sets and the actual data.

It should be noted that the prototype system developed for the semi-automatic progress assessment in this thesis was geared specifically towards the reinforced concrete columns. Due to the sensitive nature of this type of measurement technique, along with the time constraint, some parameters in the algorithms need to be adjusted to obtain a more desirable result before using the system for other projects. Also, the automatic degree of the overall system depends on the complexity of the task to be solved. At this stage, human interaction remains an important part of the work flow even though the amount of work to be done by the human operator can be reduced considerably.

5.2 Research Contributions

To fulfill the research objectives, a robust image segmentation method to effectively extract the objects of interest from a digital image was first investigated. After trying a large number of the image processing/segmentation methods available to date, the Canny Edge detector and watershed transformation methods were eventually selected as the core methods in the system due to their respective strength. On the other hand, to overcome the drawbacks of each, a data fusion strategy was considered as an inevitable part of this approach. The second major contribution was the idea for and creation of the 3D perspective view image filtering mask, which was a breakthrough in the research and provided a very solid base for the success of the whole system. Without this mask, it would be extremely difficult to successfully remove most of the heavy background noise from the primitive images. Again, based on this idea, to further reduce the potential mismatches in the primitive results, a series of 3D perspective view filters were created and employed to remove bad fits (mismatches) according to the available construction plans and schedules. The third contribution was the proposed lighting compensation technique, which greatly increased the accuracy of the results for images taken under poor weather/lighting conditions; there is still, however, ample opportunity for the improvement of this algorithm. Another key accomplishment was the application of the priority based error correction mechanism and the algorithm developed based on that, which brought forth the novel idea of logically modifying the progress data in way other than those previously mentioned.

In addition to those mentioned above, some efforts were made over the course of this research to enhance the input image data in the image preprocessing stage, and to upgrade the degree of automation of the prototype system throughout the whole procedure. These endeavors include the development of processes for image enhancements, automatic image data acquisition interface, and object reconstruction.

As a result of this research, it is anticipated that the overall system will be modified and used to increase the productivity of construction operations and management, and will likely result in cost savings for the companies involved. This work brought academic research to industry in order to solve real world problems, which indicates a promising future for automatic construction progress control based on image processing techniques. To some extent, it breaks new ground to solve one of the most crucial and challenging problems in the area of construction automation.

5.3 Recommendation and Future Work

According to the primitive progress data, the results from the developed image processing approach with construction plan information integrated, the overall accuracy/ reliability of the data is over 85%, despite poor lighting conditions in many of the original images. However, further studies are needed before this method is applied successfully in more practical cases. There are still a number of research opportunities to modify the segmentation algorithms to more successfully extract the objects of interest and more effectively exclude mismatches, especially in the case of digital images taken under poor weather/lighting conditions. According to the data analysis and statistics, there is more than 10% error due to data missing (some objects of interest were not successfully detected by the algorithms) and around 3% due to mismatches. There are possible solutions to mitigate these two problems. To tackle the problem of missing data, one could improve the quality of the input image data, for instance, by increasing the resolution of the original digital images taken on site, or improve the lighting conditions by using a flash or an infrared filter when the weather is not favorable. A second method of improvement would be to let the program search the image with the best lighting conditions at the end of each workday. This technique may better the results, but is not expected to fundamentally solve the problem. To prevent unrelated mismatches in the results, corresponding to construction plans and schedules, a series of filters could be created in advance and employed in the overall approach as mentioned before. If there are regular field surveys made during construction to avoid cumulative errors in the data set and, more importantly, to handle and solve some typical situations, such as columns being constructed on different stories at the same time, a better method would be to use an image filtering mask in which only columns slated for construction in the next period are included, and all completed columns are considered as background. In addition, for mismatches due to concrete column formwork being installed in the same positions, some ways and means based on the logical relationships between successive construction operations/activities need to be further considered. For instance, developing a subsystem to specifically detect the installed column formwork so as to remove this kind of mismatch would be a possible option.

Also, there are some potential opportunities to enhance the object reconstruction process. Because, in this system, some of the parameters of the 3D objects of interest are hard to obtain based solely on the 2D images, only the column numbers in the images are acquired as progress data at this stage. Thus, neither the size/shape parameters of the structural components nor the productivity of each activity derived for the purpose of progress control is satisfactorily precise. To further enhance the performance of this methodology (to render it more reasonable and practical), the true size/shape parameters of the objects of interest in each sample image are to be acquired beforehand through other approach. With the incorporation of advanced data correspondence techniques and professional knowledge, the results of the object reconstruction process will be more desirable. For example, the volume of concrete columns associated with their locations could be automatically and efficiently obtained using the aforementioned image processing procedure.

When many kinds of structural components need to be identified at the same time, or the structural components (objects of interest) are too small (because the pictures are taken from too great a distance), the system needs further modification and some additional modules created for other structural elements or construction operations. These developments are still underway and represent a major problem to be tackled in the future.

There are still some other limitations to this research so far. The degree of automation which can be achieved in digital image processing, the core process of the system, depends on the complexity of the task at hand and on information availability. In some cases, such as object reconstruction, the degree of automation can be high. However, in object detection, human input for tasks such as creating image filtering masks, integrating construction plan information, and testing control parameters in the adopted methods, remains an important part of the work flow, even though the amount of work to be done by the human operator could be reduced considerably.

There are also some possibilities for the improvement of prototype system operability which could be carried out in the future. The most important ones to be tackled are:

1. Image Filtering Mask Creation: In the prototype system, image filtering masks for eliminating background noise and removing mismatches in the object extraction process were interactively created. In future research, these image filtering masks are to be developed in advance by taking time-lapse pictures for the scheduled construction operations of the indoor downsized model according to construction plans/sequences. This could also be achieved through step-by-step construction operation visualizations, which could be saved in an imaging filter database so as to be readily available later in the program. By doing this, the automation level of the whole system could be greatly improved.
2. Correspondence in Object Reconstruction: Since only 2D digital images taken from one camera were available, the object reconstruction process was simplified and the progress data set was restricted to the measurement of the reinforced concrete column number in each image. There are some additional tools which might enhance the performance of this system:
   - Prior to construction, a database for the main structural elements/members or operations could be established, in which some basic information, such

as co-ordinates, shape/size parameters, types of resource to be used, etc. would be included. This database could be employed in the object reconstruction process so that the system could be applied not only for better progress assessment, but also for cost control, or even resource management.

- Increasing the number of cameras on site (especially in the densely built-up areas) would be desirable. This would make it possible to locate each of the objects of interest in the images and to obtain more size/shape information (3D information) for each of them.

In conclusion, despite the problems and limitations mentioned above, based on the 2D primitive digital images, the prototype system has produced very promising results and indicates remarkable opportunities for automatic progress control in the construction industry.

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