A Preliminary Investigation into Automated Identification of Structural Steel Without A Priori Knowledge

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Abstract -

One of the most prohibiting factors when attempting to reuse structural steel members or systems of members is the time and labour required to accurately determine dimensions. Current practices dictate that all required measurements are recorded by hand using tape measures and calipers which adds a significant cost to reused steel. To mitigate this cost, a semi-automated method for identifying structural steel components and systems is proposed that uses data acquired in the form of a 3D point cloud. Current research in the field of automated object recognition currently has two major limitations: (1) a priori knowledge, such as a building information model (BIM) is required, or (2) only simple, flat surfaces can be identified. The purpose of this study is to preliminarily investigate the possibility of automating the process of (1) cross section identification, (2) end connection geometry of bolted connections, and (3) relative component position of multi-component, planar structural systems such as trusses. Cross section identification is performed by creating filters that match standard structural sections and then convolving them over images of the cross section data. The end connection geometry is identified using Hough algorithms to detect lines and circles representing the limits of the component and the bolt holes, respectively. Planar structural systems are identified using Hough algorithms to detect lines which represent the components of the system. The results from the proposed methods show a strong potential for fully automated processes to be able to identify structural steel components and systems without a priori knowledge.

Keywords -

Steel Reuse, Object Identification, 3D Imaging, Automation

1 Introduction

Steel reuse has long been an underutilized method for reducing the life cycle cost of structural steel construction. It is believed that steel reuse could be increased by up to 150% of current reuse rates if there was a greater economic incentive to reuse steel [1]. This was found by performing an extensive survey of members of the steel construction industry. These members included steel service centers, demolition companies, scrap steel dealers, steel fabricators, and engineers and designers. A common concern among these groups was the economic benefit, or cost, of reusing structural steel because of the low cost of new steel components and the high value of scrap steel.

A common method of reducing the cost of specific activities is to automate that activity, or part of that activity. In the field of civil engineer, a number of research endeavours have been undertaken with the goal of automating the identification process of physical objects. The automation process begins with data acquisition. A number of 3D sensing methods have been developed to reduce the cost associated with data acquisition. These methods can be divided into two categories: image based systems, and time-of-flight based systems. An image based system records many digital images of a scene and then registers these images together using the principles of collinearity and coplanarity [2]. This process is often referred to as photogrammetry or videogrammetry, depending on whether digital photographs or frames from digital video recordings are used. Alternatively, time-of-flight based systems, which are typically referred to as laser scanners, measure the time required for a signal to travel from the base unit to the object and back. The main advantage of using image based systems is the speed of data collection [3]. Image based systems can perform 3D mapping in real time [4]. The benefit of using a time-of-flight based system is the higher accuracy that is achieved. Regardless of the collection method, the result of this type of data collection is a 3D point cloud of the structure's surface geometry. This point cloud will normally contain millions of individual data points.

After the physical geometry of the structure has been recorded, automated object recognition can be performed. Automated recognition of civil engineering components is not a new field of research. Bosché [5] presented a means of detecting construction objects for the purpose of automated progress tracking as well as determining dimensions for dimensional control of steel structures. This built on the original method developed by Bosché and Haas [6] which compared 3D point cloud data to 3D building information models (BIMs) to determine the presence of a component. Dimensional control of concrete structures, specifically the flatness of concrete slabs, was investigated by Tang, Huber, and Akinci [7]. Marble façade panels have also been analyzed for flatness using 3D point cloud data as well [8]. A common limitation of this line of research is that a priori knowledge is required, whether it be through a BIM or the knowledge that the object in question should be perfectly flat.

The field of machine vision attempts to automate detection, often without a priori knowledge. One of the cornerstones of machine vision is known as the Hough Transformation. The Hough Transform is used to identify shapes in 2D or 3D images. While the theory and underlying objectives of the Hough Transform remain the same, the implementation, and effectiveness of the implementation, can vary greatly [9]. This detection method is commonly employed for the automated detection of planar elements in binary images [10]. For 3D applications, automated edge and surface reconstruction has been performed from point cloud data [11] [12]. Providing edges and surfaces with semantic information has only been performed for very simple surfaces, such as ceilings, floors, and walls [13]. Throughout all of this research, the ability to automatically identify complex objects, such as those that would be found in a structural steel building, has not been established.

Automating the process of identifying existing structural steel components would significantly reduce the cost of reusing such materials, thereby making steel reuse a more economically viable alternative to new steel. It is forecast that this sort of economic improvement to the steel reuse industry would facilitate a significant increase in the reuse rate [1].

2 Methodology

2.1 Overview

The research method was separated into three preliminary studies: (1) cross section identification, (2) end connection geometry identification, and (3) joint location identification. The goal of these studies was to demonstrate the possibility of automating the identification process of structural steel components without a priori knowledge. As this was a preliminary study, the employed research method was semi-automated and limited in its applicability.

The cross section identification was performed on standard wide flange beam cross sections, but the developed algorithms were applicable to any standard cross section. The end connection geometry identification was performed on a plate containing holes. The intent of this study was to simulate the end of a beam with bolt holes located in the beam’s web. The joint location identification algorithm was performed on a planar truss. The developed algorithms were based on the assumption that all members of interest would be aligned along a common plane

2.2 Data Collection

The data collection for each research area was conducted in the same manner but on different structures. Data collection was carried out using a terrestrial 3D laser scanner. This laser scanner records geometric data as a list of x,y,z coordinates from objects within line-of-sight of the base unit. This meant that the laser scanner recorded the geometry of the desired structure as well as any nearby objects such as trees or other structures. The accuracy of the particular laser scanner used in this study is ±3 mm at 25 m [14].

The geometric data from one structure was recorded for each of the research methods presented. The cross section identification used data from a structural steel teaching aid (Figure 1a). This structure consists of a number of different standard steel cross sections, including wide flange beams, hollow structural sections, and channel sections. The end connection geometry identification was performed on data collected from a steel plate containing eight bolt holes (Figure 1b). The joint location identification was performed on data collected from an exposed truss supporting the roof of an arena (Figure 1c). Each of these data sets was comprised of multiple instances of laser scanner data that have been merged into a common coordinate system using commercial software.

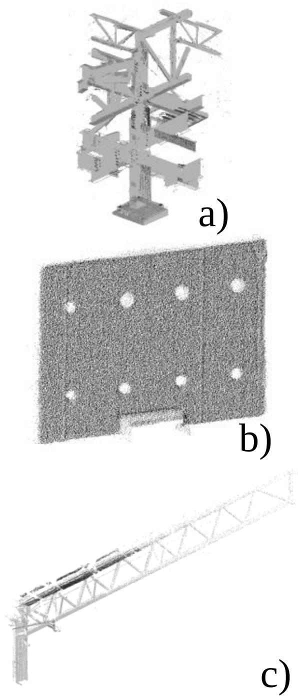

Figure 1 - Point cloud data used for cross section identification (a), end connection geometry identification (b), and joint location geometry (c)

2.3 Cross Section Identification

The process of cross section identification began by pre-processing the point cloud data. In this step, members that were to be analyzed were isolated from the rest of the point cloud and aligned such that the principle axis of the member was aligned with the z-axis and the strong axis of the cross section was aligned with the x-axis. This step was performed manually in 3D computer-aided design (CAD) software.

This separated and aligned point cloud is then sliced orthogonally to its principle axis with the purpose of creating binary images that represent the cross section geometry of the scanned member (Figure 2a). These images were created by first projecting the points contained in a single slice onto a plane that was parallel to the slice. This plane was then pixelated and pixels containing a point were marked as being filled. A varying number of the binary images were created based on the slice thickness and length of the member's point cloud. The slice thickness and pixel size of the resulting binary image were user defined parameters. These binary images then needed to be compared to equivalent binary images that represent the geometry of known structural steel sections. For this purpose, a database was created that contained a filter for each standard structural steel cross section. These filters were designed based on simplified geometry, where components of the cross section were always treated as rectangular (Figure 2b).

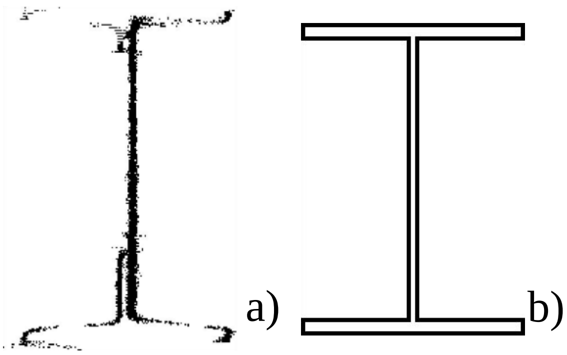

Figure 2 - The binary image of sliced point cloud (a), and a filter (b)

A convolution algorithm was implemented to compare the binary image of the scanned data with the binary image of the filter. Each filter was compared to each slice's binary image, and a match was established based on the number of corresponding pixels from both images. The matches for each filter and each slice were recorded and the highest match value from all slices was selected as the match for that particular member.

2.4 End Connection Geometry Identification

End connection geometry identification began with pre-processing the point cloud by trimming any points not associated with the plate and by aligning the plate with the yz-plane. The aligned point cloud was then converted into a binary image (Figure 3a) by projecting the data points onto a parallel plane, pixelating the plane, and then marking pixels that contain at least one data point as filled. With a smaller pixel size, and therefore more detail, it was likely that this binary image would contain many empty pixels that should be filled based on the assumption that data points are taken across the entire plate's surface. To fill these pixels, an expansion and contraction algorithm was implemented. This algorithm began by filling each pixel that neighbors a filled pixel. Alone, this method would alter the size of the plate and holes by expanding the region that was classified as the plate's surface. To remedy this, the filled pixels are contracted whereby each filled pixel that neighbors an empty pixel was marked as empty. The resulting image is one that represented the plate's surface as filled pixels (Figure 3b). Finally, all non-edge points were marked as empty (Figure 3c) because the detection algorithms used for the geometry identification required that only edge points be present in the binary image.

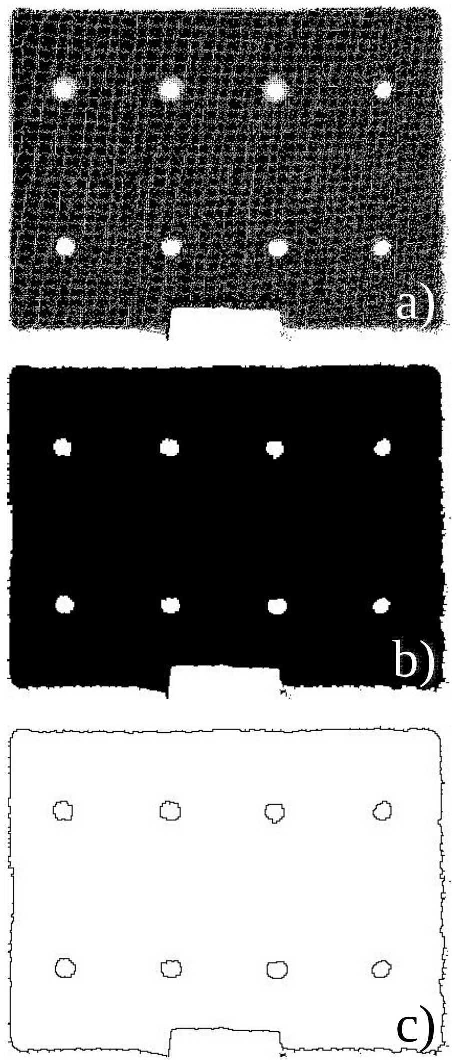

Figure 3 - The binary image of a steel plate with bolt holes after creation (a), filling (b), and edge detection (c)

The detection of important features, namely the edges of the plate and the size and location of bolt holes, was completed using Hough algorithms. The algorithms used for this particular study were pre-built, commercially available implementations of the Hough transform for line detection and the Hough transform for circle detection. The particular Hough algorithms that were implemented returned the start and end locations of detected lines and the center and radius of detected circles.

Post-processing of the detected lines and circles began by extending and/or trimming detected lines such that their ends met at a common point. This was performed so that the detected lines would properly represent the edges of the plate. Further, and optional, post-processing was performed based on two assumptions: (1) the plate is expected to be rectangular, and (2) the holes are expected to be arranged in a grid pattern. The detected lines and circles were adjusted to meet these assumptions. First, each line was rotated about its center so that it ended in a horizontal or vertical alignment. The lines were then extended and/or trimmed, as before. Next, the center locations of holes were aligned such that holes in a common row would have a vertical position equal to their average vertical position before adjustment and holes in a common column would have a horizontal position equal to their average horizontal position before adjustment.

2.5 Joint Location Identification

The pre-processing for the joint location identification algorithm began in a similar manner to the end connection geometry identification. The point cloud was first trimmed to only include the points of interest; specifically, the truss to be analyzed. The truss was then aligned such that the plane of the truss was parallel to the xy-plane. As before, a binary image was then created by projecting the data points onto a parallel and pixelated plane, where the pixels containing a point were marked as filled (Figure 4a).

The analysis phase began with an implementation of the Hough transform to detect lines in the image of the truss. These lines were detected iteratively by detecting a single line and then clearing pixels that are in close proximity to that line. Figure 4b and Figure 4c show this progression for the first two detected lines. Figure 4d shows a later stage in the iterative process where the first line representing a web member has been detected. This process results in a number of detected lines that is much greater than the number of truss elements that exist (Figure 5a). The elimination of redundant lines was performed during post-processing.

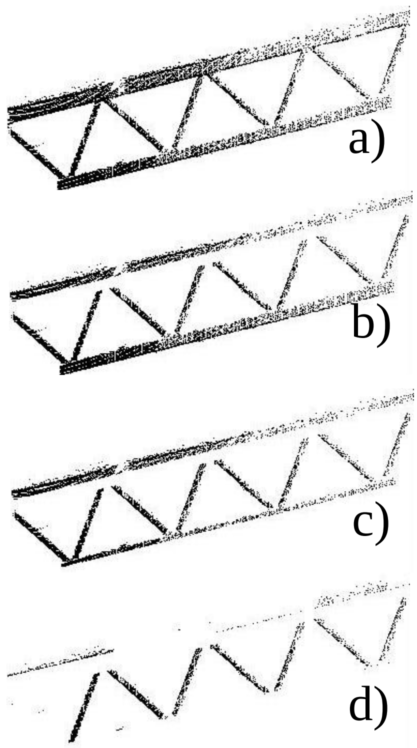

Figure 4 - Binary image of a truss before line detection (a), after the first line has been detected (b), after the second line has been detected (c), and after the first line representing a web member has been detected

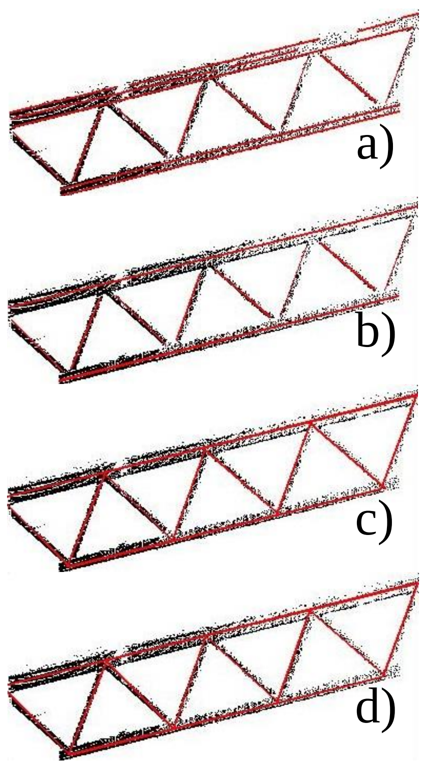

Figure 5 - Detected lines before post-processing (a), after merging (b), after trimming and extending (c), and after end point adjustment (d)

Post-processing of the detected lines was carried out in a three step method. The first step was to eliminate redundant lines to produce results where the number of detected lines matched the number of members in the planar structure (Figure 5b). This step was performed by determining groups of lines that had similar slopes and close proximities. Each group of lines was then merged into a single line in an average position based on the group. The limits of the line were determined based on the extreme limits from the lines in the group. The next post-processing step was to trim and/or extend each line so that lines met at common points (Figure 5c). For the case where more than two lines were approximately intersecting, an adjustment was made to force this intersection to a single point (Figure 5d).

3 Results

3.1 Cross Section Identification

The cross section identification process resulted in a match between the scanned member and a standard structural steel section. In total, nine members were analyzed that varied in size and proportion. These members were also hand measured to determine their true cross section.

When determining the capacity of structural steel members, three properties are important: (1) section modulus, (2) web area, and (3) cross sectional area. The section modulus, web area, and cross sectional area can be used as a very simplified and relative measure of bending capacity, shear capacity, and axial capacity, respectively. The measured and predicted, based on the identification process, value for each of these strength metrics were compared (Figure 6).

It was found that the cross section identification algorithm presented in this work had errors of between 15% overestimate to 41% underestimation. For the web area, the error was between 16% overestimation and 23% underestimation. Similarly for cross sectional area, the error was between 21% overestimation and 36% underestimation. This particular sample set had two members that were correctly predicted.

3.2 End Connection Geometry Identification

The predicted values for the plate dimensions were quite accurate when compared to measured results. The height of the plate had an average error of 1.5 mm and the width had average error of 4.5 mm. The overall plate dimensions were approximately 400 mm x 300 mm. These errors are within the expected amount of error from the scan data alone. The holes radii experienced significantly more error. The average error for hole radius was 6.3 mm but the error was very uniform for all the holes. The minimum error was 6.0 mm and the maximum error was 6.6 mm.

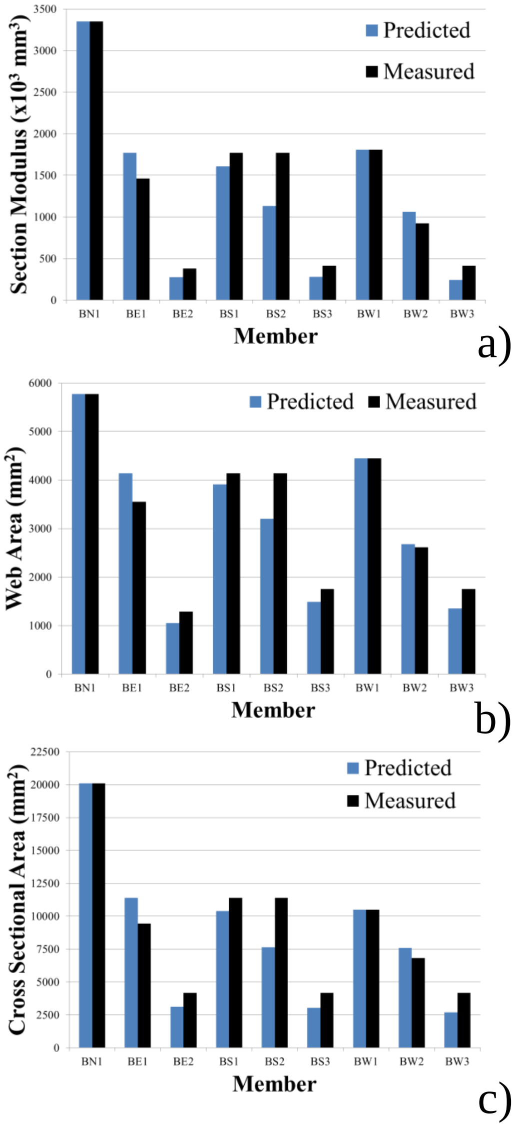

Figure 6 – Comparison of predicted and measured section modulus (a), web area (b), and cross sectional area (c)

The location of bolt holes is an important measurement to have accurate knowledge about when incorporating a used component into new design. The measured, predicted, and adjusted bolt hole locations were calculated (Figure 7). The hole locations shown in Figure 7 are relative to the lower left corner of the plate. In this relative position, the error in hole center before post-processing alignment was between 1.0 mm and 3.6 mm. After post-processing alignment, this error was reduced to between 0.0 mm and 3.1 mm. The error can be reduced if the relative position of the plates is translated to minimize the error in bolt hole center locations. After translation the error was between 0.6 mm and 2.4 mm. After translation and adjustment, the error was further reduced to between 0.4 mm and 1.5 mm. These errors are within the expected accuracy of the laser scan data and the fabrication tolerances.

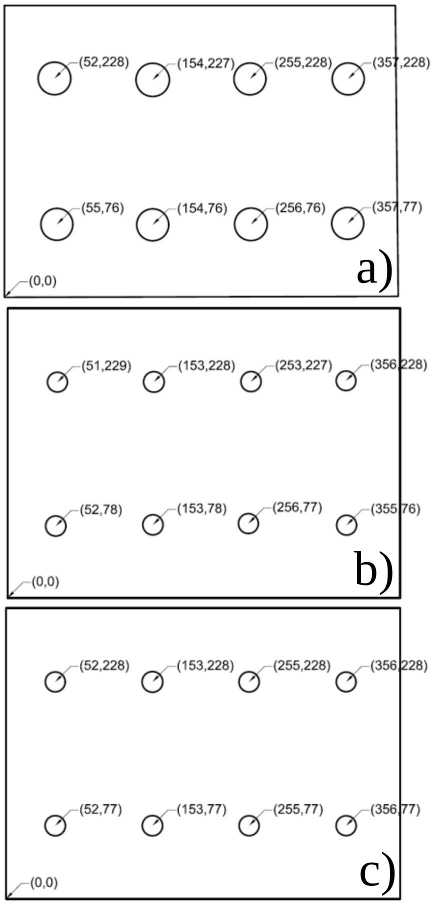

Figure 7 – Measured (a), predicted (b), and predicted and adjusted (c) hole center locations

3.3 Joint Location Identification

Physical access was not available for the truss used in this preliminary study due to safety concerns regarding its location in the building. As such, a measured length for each of member was determined by manually tracing the scan data of the truss in 3D CAD software and measuring these lines. Table 1 shows and compares the calculated and measured lengths, where the web members have been labeled sequentially from right to left (i.e. the rightmost web member is Web 1 and the leftmost web member is Web 8).

Table 1 – Comparison of calculated and measured truss member lengths

	Calculated	**Measured**	**Error**	
Top Chord	8.14 m	8.00 m	0.14 m	1.7%
Bottom Chord	6.09 m	6.60 m	0.51 m	7.8%
Web 1	1.89 m	1.85 m	0.04 m	2.4%
Web 2	1.93 m	1.85 m	0.08 m	4.1%
Web 3	1.89 m	1.85 m	0.04 m	2.0%
Web 4	1.89 m	1.85 m	0.04 m	2.3%
Web 5	1.89 m	1.85 m	0.04 m	2.0%
Web 6	1.83 m	1.85 m	0.02 m	1.0%
Web 7	1.95 m	1.85 m	0.10 m	5.5%
Web 8	1.83 m	1.57 m	0.26 m	16.4%

Excluding the large errors associated with the top chord, the bottom chord, and Web 8, the error for each member was not greater than 0.1m. This translates to less than 6% error in the length measurement for these members. Larger errors for the three aforementioned members can be explained by the trimming and/or extending step of the identification procedure. This step would result in the top chord and Web 8 being artificially lengthened to meet at a common location. Also, the bottom chord would be trimmed to end at the intersection of the outermost web members.

4 Conclusions

The three methods for identification of structural steel components demonstrate the possibility of accurately automating this process. The cross section identification procedure was able to predict the capacity of the cross section within ±50%. Given the simplified and preliminary nature of this study, this shows promise for future developments. The joint geometry identification method predicted the plate dimensions and bolt hole locations with acceptable accuracy, but the radius of each hole was predicted with significant but predictable error. The joint location identification technique obtained accurate results for most members of the analyzed truss. Invalid assumptions resulted in significant error for some individual members. Regardless, these three preliminary studies demonstrate the possibility for future developments resulting in the automated identification of structural steel components without a priori knowledge.

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