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Dimensional Quality Assessment of Steel H-Beams Using Terrestrial Laser Scan Data

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Abstract: In the construction industry, steel structures are prominent due to their exceptional strength and high bearing capacity, making them resilient against natural calamities. However, the stability and overall structural integrity of these steel structures depend significantly on the precision of the individual steel members used. Presently, the dimensions of these steel members are typically measured manually using mechanical instruments such as steel tape and vernier calipers. This conventional approach is not only time-consuming but also highly vulnerable to human error. Consequently, there is a growing need for more accurate and reliable methods for assessing the dimensions of steel members. This paper aims to measure the dimensions of key checklists of the cross-section surface of the steel H-beams using Terrestrial Laser Scan (TLS) data. This study involves the automatic extraction of scan points associated with the cross-section surface of the H-beam members using RANSAC. By the end, an algorithm was developed to predict the actual edge points belonging to the boundary of the extracted surface and introduced an edge loss compensation model to compensate the losses occurred due to uncertainties. Experimental evaluations were conducted using various scan data collected from steel H-beam and the measured dimensions were subsequently compared with manual measurements and dimensions obtained through the previously proposed method, demonstrating that the measurements meet 1mm accuracy and are within the allowable tolerance range followed in industry. This research underscores the efficiency and reliability of the introduced approach, offering a promising solution to enhance the dimensional quality assessment of steel H-beams in the construction industry.

Key words: Laser scan data, Dimension inspection, Steel structure, H-beam cross-section, Feature point extraction

1. INTRODUCTION

In construction, it is crucial to carefully check the prefabricated components before placing them in place in the main building. This means looking at their size, surface, and shape to ensure that they are made of good quality. If these checks are not done before assembly on site, it can lead to serious issues over ages, making buildings not last long and costing much more to fix the defective components.

Currently, 3D laser scanners are in trend to develop point cloud data of real-world structures, which helps to measure the dimensions of different components.

Several studies have focused on measuring the dimensions of prefabricated components, especially in the context of concrete and spatial structures. For instance, M.-K. Kim et al. conducted extensive research on precast concrete panels, formworks, and rebars, using terrestrial laser scanning for dimension assessment [1,2,3,4,5]. Another study by Q. Wang et al. proposed a non-contact automatic DQA technique for irregular precast concrete panels [6].

In recent years, researchers have expanded their focus to assess the quality of steel components. L. Fu et al. concentrated on space frame components, introducing feature-based algorithms for measuring spherical joints and cylindrical tubes [7]. J. Liu et al. assessed dimensional accuracy and structural performance of spatial structure components, introducing the Microrectangle traversing algorithm [8]. Geometric quality inspection of prefabricated MEP modules using 3D laser scanning was explored by J. Guo et al., who proposed a convex hull-based coordinate transformation algorithm [9].

When it comes to structural steel member assessment, various methods have been proposed. F. Bosche utilized Iterative Closest Point (ICP) for steel column position estimation [10], while K. Mirzaei proposed an end-to-end method for measuring the overall dimensions of structural steel members [11]. Other studies focused on measuring geometric imperfections in beams and columns, including deflection and slope [12]. D.F. Laefer and L. Troung-Hong developed an algorithm for generating 3D steel structures for building information modeling [13]. Z. Zhang et al. explored geometric dimension and imperfection measurements of box-T section columns using hand-held 3D laser scanning [14].

However, there is a noticeable research gap in the assessment of cross-sectional dimensions of structural steel members, directly related to the load-bearing capacity of structures. Despite studies on overall dimensions and geometric imperfections, a dedicated method for assessing cross-sectional dimensions is crucial for ensuring structural integrity of the building.

This study also emphasizes the importance of edge point detection in the dimension assessment process. Extracting edge points from 2D point cloud data is a fundamental step, and researchers have developed various techniques for this purpose. S. Pu and G. Vosselman proposed a triangulation-based method for 3D point cloud data [15], while E. Che and M.J. Olsen utilized normal variation analysis for 3D edge detection [16]. M.-K. Kim et al. developed a vector-sum algorithm for 2D flat surface data [1], and P. Tang et al. quantified edge loss in scan data [17]. Q. Wang and J.C.P. Cheng proposed edge line estimation algorithms for organized point clouds [18]. D. Bazazian et al. and H. Ni et al. developed edge detection algorithms for unorganized 3D point clouds [19] [20]. However, there is a notable gap in edge detection algorithms for unorganized 2D-point cloud data, emphasizing the need for further research in this area.

To overcome these limitations, the current study focuses on,

1. Measuring the cross-sectional dimensions (Figure 1) of structural steel members using terrestrial laser scan data and check the dimensions are within the allowable tolerance range given in Japanese Industrial Standards [21] (Table 1).
2. Develop an edge point extraction algorithm for the unorganized 2D-point cloud data with an edge loss compensation model.

Table 1. Japanese Industrial Standards

No.	Checklists	Tolerance
1	Depth	Length < 400 mm: ±2.0 mm
2	Flange Width	Length <=400 mm: ±2.0 mm
3	Web Thickness	Length <= 16 mm: ± 0.7 mm
4	Flange Thickness	Length < 16 mm: ± 1.0 mm

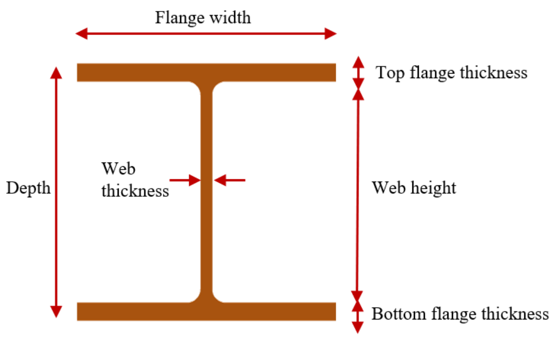

Figure 1. Cross-sectional Dimension Checklists

2. EDGE POINTS EXTRACTION

The raw scan data obtained from the 3D laser scanner usually contains some unwanted scan points such as noises, which are removed by the RANSAC plane fitting on the cross-section surface (Figure 2a) and extract only the scan points belonging to the fitted plane. The extracted cross-section surface is shown in Figure 2b. Then, edge points located on the boundary of the cross-section data need to be extracted for further dimension measurement. Here, it is assumed that the scan points obtained are unorganized and not arranged in a usual grid pattern (not equally spaced between scan points).

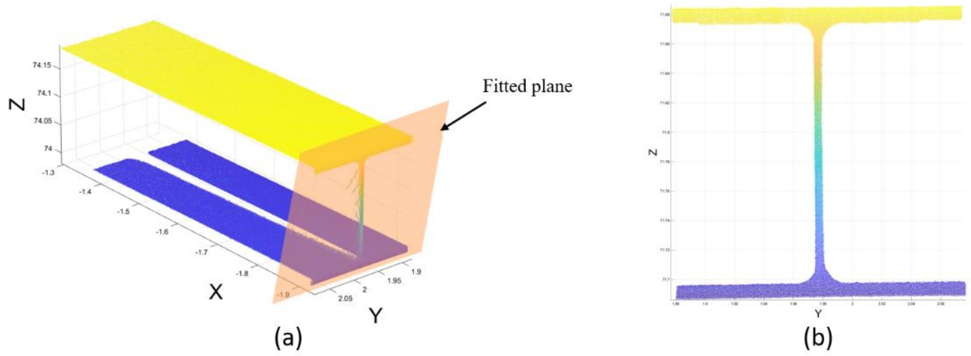

Figure 2. Extraction of cross-section surface

To extract the edge points from the unorganized 2D scan data, a novel grid-based edge point extraction algorithm is proposed in this study. This iterative algorithm employs a grid of 16 cells consisting of 4 rows and columns (Figure 3a). For each iteration, the grid's center is placed over a reference point and evaluates whether the current reference point is the edge point or the inner surface point. The proposed edge point extraction algorithm works by the following three steps,

2.1 Calculate cell size

Because the scan data is unorganized, the spacing between points is not uniform throughout the cross-section data. In this case, following the constant cell size will cause incorrect results, so the cell size for the grid is calculated for each iteration using the eight nearest neighbor points of the reference point. For each iteration, it selects the eight nearest neighbor points for the current reference point and calculates the Euclidean distance between the reference point to each neighbor point. The maximum distance between points is then used as the distance between the center of the grid to the outermost side of the grid. Therefore, the total grid size is 2*maximum distance. Adopting the maximum distance ensures that most of the neighboring points around the reference point are being covered by the grid. Each cell size is taken as ¼*grid size because a grid is subdivided into 4 cells of rows and columns.

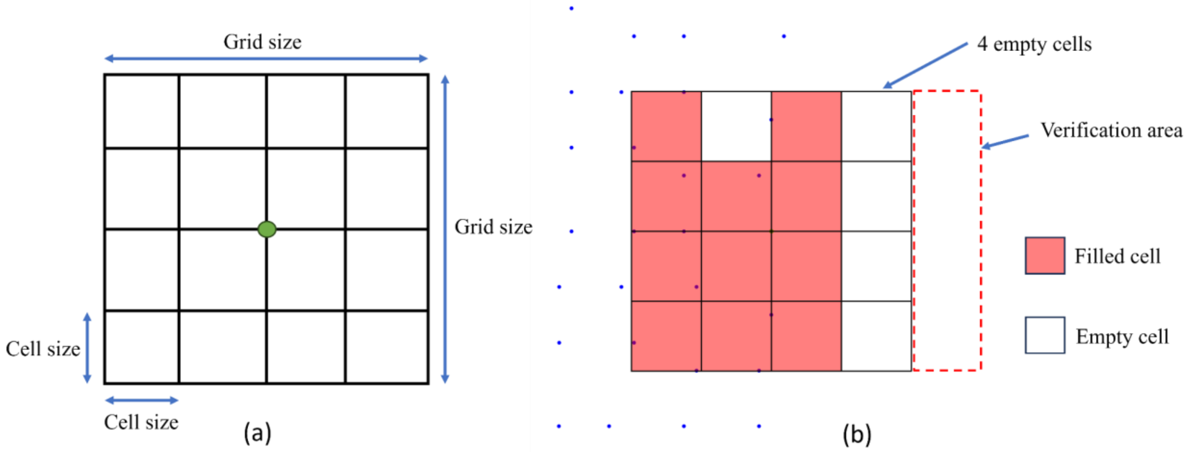

Figure 3. Grid-based edge point extraction

2.2 Cell evaluation and labeling

In this step, all the cells in the grid are evaluated and labeled either as 'empty cell' or 'filled cell' (Figure 3b). If the cell has at least one scan point inside it, then the cell is labeled as a 'filled cell'. If the cell has no scan points inside, then it is labeled as an 'empty cell'. It is worth noting that the four cells around the reference point are always labeled as 'filled cells' because these four cells always share a common point 'reference point'.

2.3 Edge point identification

Once all the cells are evaluated and labeled, then the reference point is categorized as either the 'Edge point' or 'Inner point'. An edge point refers to a scan point located on the boundary of the cross-section surface and an inner point refers to a scan point located inside the surface. If the reference point is categorized as an 'Edge point' it should satisfy the following two criteria.
1) The grid must have at least four consecutive empty cells in a row or column.
2) There must be no scan points present inside the verification area next to the 4 consecutive empty cells.
If the reference point doesn't satisfy both of the above criteria, then it will be categorized as an 'Inner point'. The size of the verification area is equal to the size of the four consecutive empty cells nearby. The categorized edge points and inner points are shown in Figure 4.

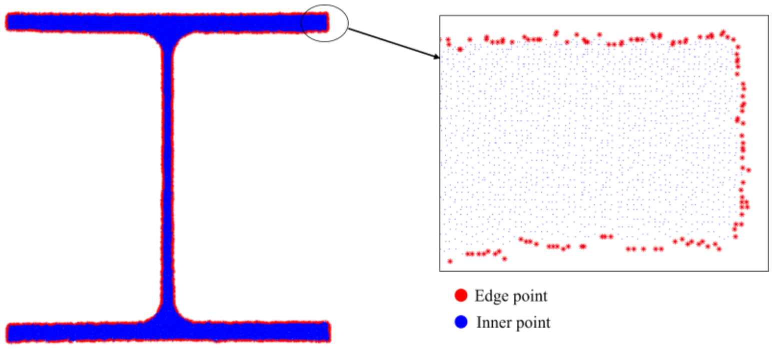

Figure 4. Extracted edge points

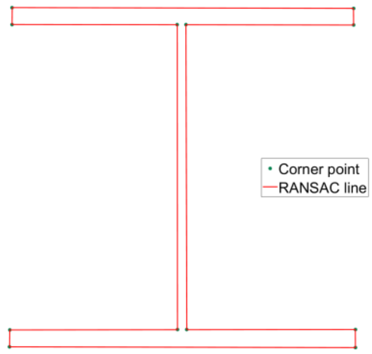

Figure 5. Fitted lines and corners

3. DIMENSION MEASUREMENT

After extracting the edge points from the cross-section data, cross-sectional dimensions are measured through the following steps,

3.1. Edge segmentation

Here, each edge from the obtained edge points is segmented for the RANSAC line fitting. To achieve this, edge points are separated into five sets as top flange, bottom flange, web, left edge, and right edge by employing five boundary boxes. The region for the boundary boxes is given manually based on the minimum and maximum x-axis values, minimum and maximum y-axis values, and the mean values of x and y-axis. After the separation of edge points into five sets, edges are segmented based on the normal vector. For each scan point in each set, it selects four neighbor points followed by fitting a line and calculates the normal vector of the fitted line. Based on the normal vector's alignment with the x or y-axis within the user-defined tolerance angle, each scan point in a set is further divided into horizontal and vertical edges. Once all the edges are segmented, the corner points of the cross-section surface are predicted by fitting a RANSAC line on each segmented edge (Figure 5). The intersection points of the fitted lines are taken as the corner points, which are used to measure the preliminary cross-section dimensions.

3.2. Edge loss compensation

Edge data loss always affects the preliminary dimensions measured from the raw cross-section data. Edge data loss happens mainly due to the following reasons,

1) During laser scanning, it is not always possible for laser rays to hit the actual edges of the cross-section surface and acquire edge data.

2) During the post-processing noise or mixed-pixel removal process, some of the valid edge points might be removed accidentally.

One of these leads to erroneous measurements at the end. To compensate this edge loss, a new edge loss compensation model is proposed in this study. This model uses the advantages of corner points predicted before and virtual scan points. For each corner point, two virtual scan points (Figure 6) are plotted next to it with the spacing 'sp'. The farthest endpoint in virtual points from the corner point is identified and a midpoint between those two farthest endpoints is assumed to be located very near to the actual true corner of the surface. The midpoint between the two farthest endpoints is considered as the new corner point.

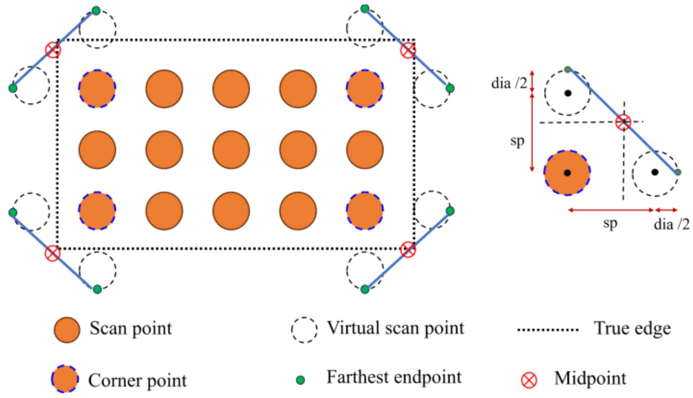

Figure 6. Edge loss compensation

Figure 7. Experimental setup

In mathematical terms, the above edge loss compensation model can be written in the equation (1) as follows,

$$\mathrm{EL} = 2*\left(\frac{sp+(dia/2)}{2}\right) \tag{1}$$

Spacing between scan points ‘sp’ and the diameter of the laser spot ‘dia’ on the surface can be obtained by using equations in [17] (P. Tang et al., 2009). The edge loss compensated cross-sectional dimensions can be obtained by adding or subtracting the edge loss value ‘EL’ to the calculated preliminary dimensions.

4. EXPERIMENTAL RESULTS

The proposed DQA method is validated using different laser scan datasets collected from a steel H-beam specimen. The ground-truth dimensions of the specimen in mm are given in Table 2 which was measured manually adopting conventional methods. Cross-sectional depth, flange width, and web height are measured using steel tape, and flange and web thicknesses are measured using a vernier caliper. In this study, the FARO Focus S70 terrestrial laser scanner was used. The straight distance between the scanner’s center to the specimen was 1.5m and the scanner’s head was elevated to the same level as the cross-section surface (Figure 7). Scans were taken from incident angles of 0°,10°,20°,30°, and 45° and for each incident angle, three angular resolution scan data 0.009°, 0.018°, and 0.036° were collected to validate the efficiency of the proposed method when the scan data quality differs. Results acquired by the currently proposed method are compared with the results obtained by the preliminary dimensions with no edge loss compensation measured in step 3.1 and with the results of the LSR2 algorithm proposed in [18]. Cross-sectional dimensions (Figure 1) are measured with three methods and the average absolute errors are compared in Figure 8.

Table 2. Ground-truth dimensions of specimen

Name	Depth		Flange Width		Flange Thickness				Web Thickness		Web Height	
					Top Flange		Bottom Flange					
	Left	Right	Top	Bottom	Left	Right	Left	Right	Top	Bottom	Left	Right
Specimen 1	248	247.5	250	250	14	13.7	13.5	14.25	9.1	9.1	219	219

As the incident angle rises from 0° to 45°, the error value increases in all three methods and angular resolutions. In the scan data obtained by 0.036° angular resolution at 45° incident angle, the error reaches its maximum of 4.66, 1.86, and 1.81 mm in the no compensation technique, current method, and LSR2 method, respectively. Regardless of angular resolutions, in all cases, the current method provides an error of <1mm from the incident angle of 0° to 30°, consequently LSR2 provides an error of >1mm. Comparatively, ‘No compensation’ errors are much larger than the other two methods because of the edge loss occurrence, followed by LSR2 and the current method. Also, the comparison shows that the average of errors in LSR2 is 1.42 mm, and the current edge extraction + edge loss compensation method shows an average of errors of 0.85 mm which is most accurate towards the ground-truth measurements.

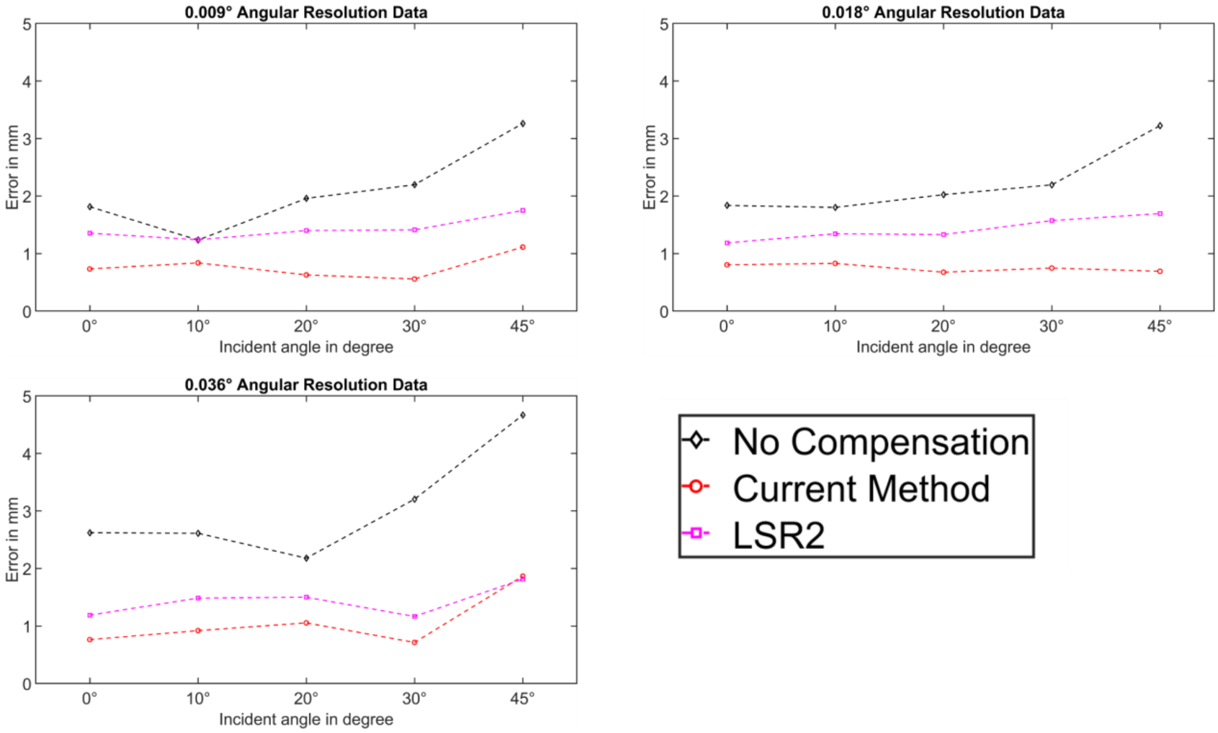

Figure 8. Accuracy of the cross-sectional dimension measurement

CONCLUSION

This study proposed a new approach for extracting the edge points from the 2D-point cloud data using a 4x4 grid and a new edge loss compensation model that utilizes only the corner points to reduce the dimension error caused due to uncontrollable circumstances while scanning. Both methods here are developed specifically for 2D unorganized point cloud data, which still can work well in organized point cloud data too. The results obtained from the scan data shows that the proposed method is highly efficient in extracting edge points and achieves an accuracy of less than 1mm by compensating edge loss and the measurements are mostly within the allowable tolerance range, offering a promising solution to enhance the dimensional quality assessment of steel H-beams. Nevertheless, the efficiency of the proposed method is only evaluated using one H-beam specimen, so an extended study is needed for evaluation with steel H-beams of different sizes. Furthermore, during the experiment, a phenomenon was noticed that the scan data was heavily affected by the specimen's material and surface finish. So, a detailed study of the relationship between the laser and material properties is needed.

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