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ScienceDirect

Procedia Manufacturing 34 (2019) 798–803

Procedia MANUFACTURING

www.elsevier.com/locate/procedia

47th SME North American Manufacturing Research Conference, Penn State Behrend Erie, Pennsylvania, 2019

Real-time visual detection and correction of automatic screw operations in dimpled light-gauge steel framing with pre-drilled pilot holes

Pablo MARTINEZ[a], Rafiq AHMAD[b*] and Mohamed AL-HUSSEIN[a]

[a] *University of Alberta, Department of Civil Engineering, 116 St. and 85 Ave., Edmonton, AB, T6G 2R3, Canada.*
[b] *University of Alberta, LIMDA Lab, Department of Mechanical Engineering, 116 St. and 85 Ave., Edmonton, AB, T6G 2R3, Canada.*

* Corresponding author. Tel.: +1 780-492-7180. *E-mail address:* rafiq.ahmad@ualberta.ca

Abstract

Modular and panelized construction have been promoted and recognized globally as advanced construction techniques for residential and commercial industries alike. Light-Gauge Steel (LGS) panels have become more popular for commercial buildings and high-rise residential buildings in the last decades. When constructing such panels, for ease of manufacturing and assembling, a common practice in the construction industry is the use of dimples and pre-drilled pilot holes. Current automatic LGS machinery, however, is not designed to operate with such constraints. In this study, a real-time vision-based approach is proposed to enable current machinery to use dimpled studs with pre-drilled pilot holes. An algorithm designed for hole detection inside the dimples on LGS steel studs, based on edge detection and ellipse fitting is proposed. Finally, an adaptive approach is proposed to adjust the screw driving manipulators to ensure that the drilling operation occurs accurately, avoiding any possible damage to the LGS studs or failure of the screwing operation. The proposed algorithm is validated on a real steel assembly and a comparison is provided with other well-known algorithms for ellipse detection to demonstrate the effectiveness of the proposed method. This real-time algorithm gives real-time results for pilot hole detection and screwing location estimation within 3 mm tolerance. When compared with other well-known approaches in the literature, the proposed approach is 59% more accurate than the fastest available algorithm.

Keywords: Industry 4.0; Panelized construction; Machine vision; Ellipse detection; Light-gauge steel framing; Smart drilling.

1. Introduction

1.1 Background

During the last decade, modular construction and the offsite production of steel framing assemblies has become increasingly popular in North America for commercial and mid-rise residential buildings. These recent changes to traditional construction brought the advantages of increased production rates, superior quality products, safer and less physical workloads, reduced waste and faster cycle times. Given those benefits and combined with stable factory environments, automated construction of steel structures is in high demand. To support the increased interest in pre-fabricated construction, the manufacturing process for steel frame assemblies was automated. Based on CAD shop drawings, the process was optimized to reduce cycle times and improve steel frame squaring [1]. However, such studies did not consider the variety of connections between steel members. Although other fastening processes can be found in industry, such as welding or bolting, light-gauge steel studs (LGS) are mostly connected using screws. Screw connections between LGS studs are performed by directly screwing through the steel profile or using pre-drilled pilot holes. Due to its ease of assembly, pre-drilled pilot holes are commonly used in industry. To support the research of automation in construction manufacturing, the University of Alberta designed and built a semi-automatic Steel Framing Machine Prototype (SFMP) as shown in Figure 1. This

10.1016/j.promfg.2019.06.204

prototype was originally designed solely for the purpose of building 'raw' steel profiles.

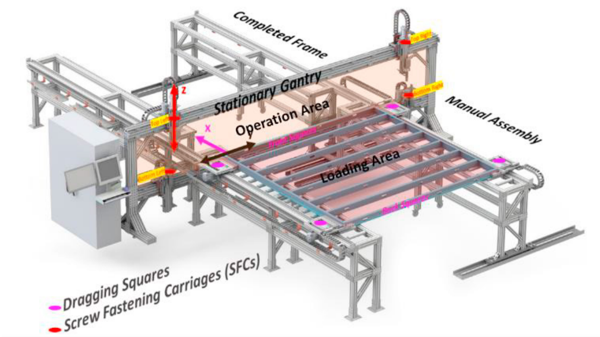

Figure 1. Steel Framing Machine Prototype (SFMP) Diagram.

With the rise of information technology and Industry 4.0 applications on manufacturing systems, intelligent manufacturing assembling is becoming more and more widely used. Machine vision, as one of the most important intelligent technologies, has been proven to greatly improve the flexibility and automation level of production lines due to its ease of integration and low cost. At present, machine vision has been widely used in the field of automation assembling, defect detection, and electronic manufacturing in place of human eyes; however, the construction industry has still to benefit from its numerous applications. Under ideal conditions of machine accuracy and manufacturing precision, the accuracy of screw operations would be dependent on the CAD models; however, global imperfections in cold-formed steel members used in manufacturing have been well documented [2]. Machine vision has been previously used to deal with steel assembly inspection processes and offer correction procedures in real-time due to CAD modeling not matching the real frame conditions [3]. Hence, machine vision can be used to enable the current prototype for automatic drilling of LGS studs with pre-drilled pilot holes by detection and correction of the screw manipulator positioning to accurately and safely perform screwing operations.

1.2 Literature Review

An important number of studies can be found in literature regarding the application of machine vision in industrial equipment for object recognition and computer-aided manufacturing. Very few of those studies refer to the use of machine vision for screwing manipulator positioning in industry. Wang et al. describe a method to solve the positioning of screw holes using an artificial LED red lighting to make the screw holes distinct even in low contrast environments such as dark background of work pieces [4]. The hole detection was achieved using a modified version of the Hough Transform, namely the Circle Hough Transform (CHT), and a template matching method based on the characteristics of the gradient histogram was used to estimate the position of the screw holes. Considering a stationary camera placed at a known location, global coordinates of the screw operations were estimated from the centroid of the circular detected holes. This methodology has proven itself more accurate and robust against obliqueness, distortion, and shadowing than a regular Hough Transform (HT). A similar approach was used by Chen et al. to develop a detection method for dual screw holes using iterative threshold segmentation and statistical pixel counts for the calculation of the screw tooth [5].

For both aforementioned approaches, the modeling of the detected screw holes is done by circular contours. This assumption forces the camera to be in line with the screwing operation; the use of artificial lighting and its accuracy depends entirely on the tilting angle of the surface of the product. This approach has several drawbacks precluding the possibility of any real-time inspection of the drilling operation. As the screw manipulator is working, the screw hole would be occluded. If the location of the camera were to be changed to a side position to have visual sight of the screwing, the circular model would be inaccurate. Thus, a more generalist model could be used to model the screw holes, such as an elliptic contour.

Real-time ellipse detection and modeling is a challenging task even for modern computers, since the estimation and evaluation of the five parameters of an ellipse, namely the center coordinates, the orientation, and the major and minor axes, require heavy computation. As many applications as there are of ellipse detection, there are also a great number of algorithms proposing solutions to this problem [6]. For each different industrial application, the trade-off between accuracy, efficiency, and limited computational resources must be accounted for. In most currently reported ellipse detection works, researchers try to compute the ellipse parameters by using less and less information and constructing simpler parameter spaces. They are commonly classified in three categories: least square based methods, HT based methods and the most recent approach known as edge contour following methods. However, most of the ellipse detection applications in industrial images or industrial environments use HT based methods or its hybridized versions [7].

The basic approach shared by most of the existing methods employs the HT space on edge points and then proposes techniques to reduce the parameter space to speed up the process [8-11]. For instance, a very common approach, due in part to its open-source nature, is proposed in a study by Xie and Ji [12]; this approach performs an exhaustive search of ellipses through iteration of each pair of pixels in the image that did not use the detection of edges or contour tangents. This approach almost guarantees a good average accuracy, but at the cost of a very high computational time. Its randomized version is much faster but loses accuracy [13]. In a more recent work, an ellipse detection method is proposed to reduce the number of edge points to compute by exploiting edge convexity and mutual edge position to reduce the initial number of points significantly [14]. Using this method, the computational requirements were lowered to a level where it could be used on an Android device, while maintaining a very decent level of accuracy.

Nonetheless, HT ellipse detection methods suffer greatly with noise, which includes background noise, but also superposition of ellipses. Presently, edge contour methods, i.e. arcs, are being researched with the aim to address those limitations. Many approaches to generate the arcs have been presented, such as linking short straight lines [15-19], splitting the edge contour [20,21], or, more recently, validating connected edge pixels [22,23]. Although these methodologies have proven to be successful on different common testing datasets, their implementation in industrial applications, and more specifically in manufacturing applications, are scarce and not as well documented in the literature. As such, this paper will focus on HT based methods for performance comparison purposes.

To summarize, current machine vision for screwing operations could benefit from a more generalist model that allows other camera locations. Applying machine vision, the current machine would be enabled to operate on a different type of LGS members with minimal changes. Ellipse detection methods are required to determine, in real-time, the location of each screwing position on the panel. However, existing ellipse detection algorithms must attain a delicate balance between accuracy and computational time, which limits their real-time integration in construction manufacturing processes. In this paper, a new model is proposed for real-time visual detection of pre-drilled pilot holes in dimpled LGS steel studs based on ellipse detection methods. From the model results, global coordinates of the pre-drilled pilot hole are obtained to allow real-time 2D corrections of the screw driving operations using feedback control over the screw driving manipulators. The proposed model will be then validated in a real steel assembly and compared to other well-known ellipse detection methods.

2. Vision-based model description

2.1 Mechanical model

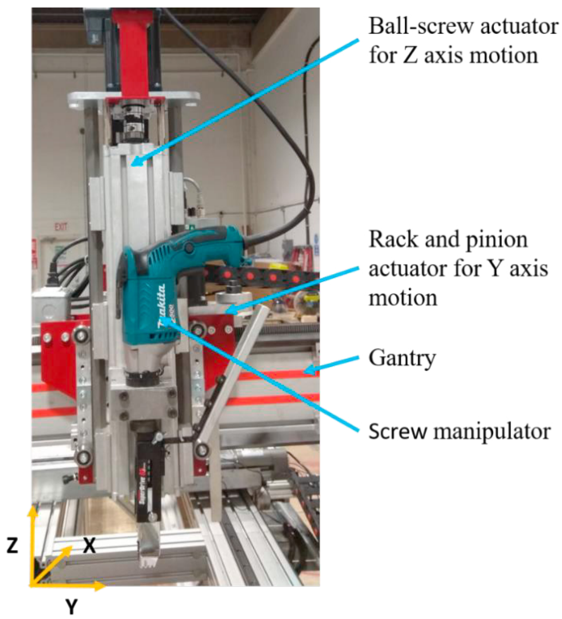

Figure 2. Screw fastening carriage in SFMP.

In this study, an automatic screw fastening carriage (SFC) is used to process the positioning, drilling operation, and screw locking without the help of workers. This system is identical to the one used in the Steel Framing Prototype Machine (SFMP), available at the University of Alberta (see Figure 2).

This machine was designed to automatically assemble LGS panels in offsite construction facilities. Some modifications were made to the actual SFC system: a camera was mounted on the lower end of the SFC and points toward the screwing locations. This strategy doesn't require complex coordinate frame transformations because the distance and angle between the camera and the pilot hole is fixed. Thus, the camera would capture the location of the pre-drilled pilot holes on the dimpled steel studs as the panel gets processed. Figure 3 shows the proposed model structure.

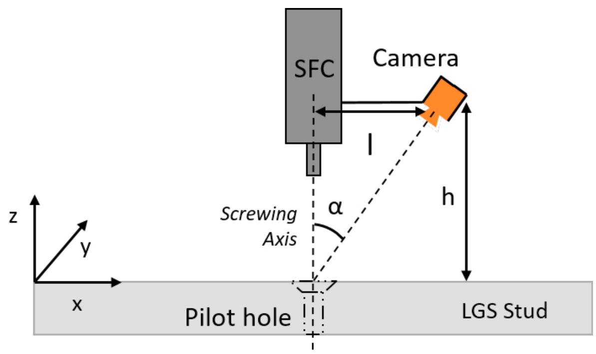

Figure 3. Proposed model schematic.

2.2 Pre-drilled pilot hole detection algorithm

To detect the pilot hole from the camera, four steps are needed to process the image to obtain the coordinates of the center of the pilot hole. Step (1): The image is first converted to grayscale to reduce its memory allocation, thus reducing computational requirements, and then the well-known Canny edge detector is applied. Step (2): Relevant contours are then defined from the resulting binary image as Suzuki and Abe [24] described on their first algorithm. As the order of magnitude of the pilot hole is well known, this step allows for the reduction of most of the unwanted edges obtained by the Canny edge detector, which can be quite numerous as shown in Figure 4a, by restricting the area of each contour to avoid detecting contours that are too large or too small. Step (3): The detected contours are checked for a "circular" shape. The circularity of a contour, φ, is defined in Equation 1.

$$\varphi = {P_c^2}\big/{4\pi A_c} \tag{1}$$

where P_c and A_c are the perimeter and the area of a contour respectively. The contour will be considered elliptical enough for this problem if the value of the circularity of a contour is between 0.8 and 1.2. Step (4): For the remaining contours, an ellipse fitting algorithm is used to define the center of the pilot hole that will be noted $[u, v]^T$. The ellipse is defined using the algebraic distance with quadratic constraint algorithm (B2AC) [25]. For a family of curves $C(\mathbf{a})$, the algorithm searches the value of $\mathbf{a}$ that minimizes the error function shown in Equation 2.

$$\epsilon^2 = \sum_{i=1}^{n} \delta(C(\boldsymbol{a}), \boldsymbol{x}) \quad (2)$$

where $\delta(\mathrm{C}(\mathbf{a}), \mathbf{x})$ represents the distance metric from a point $\mathbf{x}$ of the contour to the curve. An example of the results obtained at each step can be found in Figure 4.

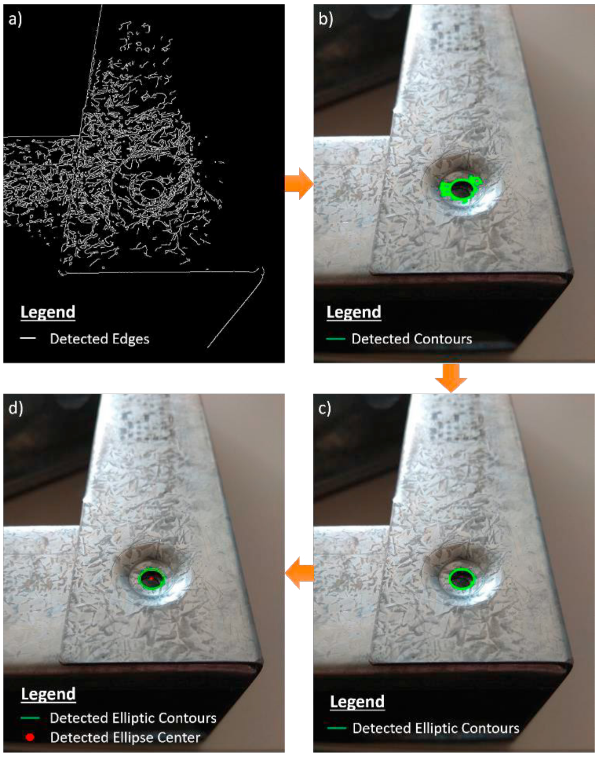

Figure 4. Results obtained for pre-drilled pilot hole detection in a dimpled LGS stud: (a) edge detection; (b) filtered contour detection; (c) 'circular' contour detection; and (d) ellipse fitting and screwing point estimation.

To associate the coordinates of the detected pilot hole with a correct location, they need to be converted to 3D coordinates in a global reference frame. We use $\tilde{x}$ to denote the augmented vector by adding 1 as the last element. Considering the camera as a pinhole, the relationship between a 3D point $\boldsymbol{M} = [X, Y, Z]^T$ and its image projection $\boldsymbol{m} = [u, v]^T$ is given by:

$$s\widetilde{\boldsymbol{m}} = \boldsymbol{A}[\boldsymbol{R}\ \boldsymbol{t}]\widetilde{\boldsymbol{M}}, \quad with\ \boldsymbol{A} = \begin{bmatrix} \alpha & \gamma & u_0 \\ 0 & \beta & v_0 \\ 0 & 0 & 1 \end{bmatrix} \quad (3)$$

where s is an arbitrary scale factor; ($\mathbf{R}\ \mathbf{t}$), called the extrinsic parameters, are the rotation and translation matrices respectively, which relates the global coordinate system to the camera coordinate system; and $\mathbf{A}$ is called the camera intrinsic matrix with (u_0, v_0) being the coordinates of the principal point, α and β the scale factors in the image on the u and v axes respectively and γ the parameter describing the skew of both image axes. The parameters above can be obtained using a well-known camera calibration method [26]. To simplify the estimation of the vector $\boldsymbol{M}$ and given that the depth estimation obtained from a single frame is usually not quite accurate, a 2D estimation of the screwing location, $[X, Y]$, will be given assuming that the screwing will occur at the surface of the steel stud, thus assuming the Z value constant at the frame width value.

3. Real-time visual detection results

To test the previously defined vision algorithm, a relatively small sized dimpled LGS panel is used (see Figure 5). The chosen LGS panel is used as a test bench due to its geometry, which includes all the most common connections in LGS panels: exterior frame, and horizontal and diagonal bracings. The experimental lighting conditions were set up as defined by Martinez et al. [3]: low-light conditions to minimize reflectance and high contrast.

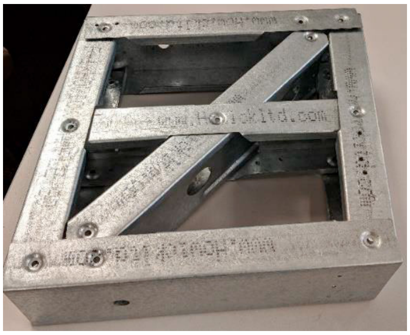

Figure 5. Dimpled LGS panel sample.

To prove its efficiency and accuracy, our method is compared against three methods for fast ellipse detection, namely the methods of Xie and Ji [9], its randomized version of Basca et al. [10], and the most recent algorithm of Fornacieri et al. [11]. These methods have been selected due to their diffusion, declared efficiency, and availability of source code. Since some methods do not provide a pre-processing step, to guarantee the fairness of the comparison, all methods start from the same edge mask. All the methods have been tested on the same dimpled LGS panel with 6 studs.

The results of the visual detection of the pre-drilled pilot holes on the panel are depicted in Table 1 for each different method in terms of accuracy and computational time. Computational time is the average elapsed time over 10 runs with 1000 loops each and has been computed on a PC with 16 GB of RAM and an Intel Core i7-6700 processor. The measurement error is the average absolute value of the error between the real center and the estimated center of the pilot hole. The real center was measured with a mechanical caliber (0.02 mm precision). Considering the model previously defined in Figure 1, our experimental validation settings are $\alpha = 39.5°$, $h = 550\ mm$ and $l = 350\ mm$.

Table 1. Accuracy and computational time results.

Method	Computational Time (mean ± std. dev.)	Average Measurement Error
Proposed Method	286.64 ± 42.39 ms	3.14 mm
Xie and Ji [12]	395612.87 ± 41632.27 ms	1.68 mm
Basca et al. [13]	32684.97 ± 8463.02 ms	25.38 mm

Fornacieri et al. [14]	71.21 ± 12.37 ms	7.36 mm

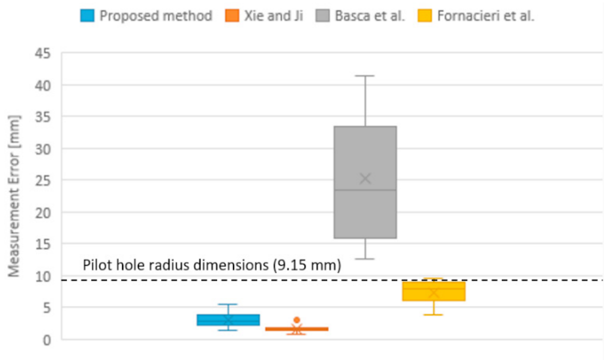

Figure 6. Accuracy box plot results per visual detection methodology.

As expected, the exhaustive search method of Xie and Ji guarantees good average accuracy at the cost of a very high computational time. Its randomized version (Basca et al.) is much faster but loses in accuracy. The point selection optimization in Fornacieri et al. method gives a considerably faster computational time but sacrifices some accuracy. Our method is computationally more demanding than the previous one but offers a slightly better accuracy.

Due to the problem constraints, the algorithm for pilot hole detection should be running in real-time and accurately determine the screwing location within the pilot hole diameter. From a computational perspective, a real-time operation is considered when no significant delay on the overall performance of the system is introduced. In this case, the deadline is set around one second. As a result, both Fornacieri's algorithm and our proposed method proved that they can perform under real-time constraints. From an accuracy perspective, only Basca et al. does not meet the minimum requirements of detecting the pilot hole center within the pilot hole dimensions. Such minimum requirements are necessary to ensure that the ellipse detection algorithm is accurate enough to define the screwing operation within the boundary of the pre-drilled pilot hole. When all things are considered, either our method or Fornacieri's method can be used for real-time detection of pre-drilled pilot holes.

4. Real-time corrected screwing operations

From the initial set of coordinates obtained from the CAD shop drawings, the correction approach aims to address possible errors in the position of the pre-drilled pilot hole. For each screw operation, three sets of coordinates are available: the original position set by the CAD model, $[X_{CAD}, Y_{CAD}]$, one set obtained from the vision-based system proposed based on the center of the detected ellipse, $[X_V, Y_V]$, and one set obtained from the motor encoders in the dragging squares and screw fastening carriage respectively, $[X_F, Y_F]$ that represent the real-time position of the screw manipulator relative to the position of the steel frame (see Figure 1). Assuming the minimum performance necessary of the vision-based algorithm discussed in Section 3, the screw manipulator needs to be aligned with the pre-drilled pilot hole to ensure a safe screw operation. The screwing operation, under these circumstances, needs to always satisfy Equation 4, where d is the diameter of the pilot hole, otherwise, the screwing operation may miss the pilot hole, hit the steel stud, and possibly cause damage to the frame and the screw manipulator.

$$(X_V - X_F)^2 + (Y_V - Y_F)^2 \leq {d^2}/{4} \tag{4}$$

Currently, the initial step for any screwing operation is to set the position of the screw manipulator satisfying $X_F = X_{CAD}$ and $Y_F = Y_{CAD}$. Then, machine vision gives its estimate on the real position. If Equation 4 is not satisfied, then motors engage on an extra corrective motion until $X_F = X_V$ and $Y_F = Y_V$. Finally, the algorithm runs again to check if the corrected position satisfies Equation 4. If that is not the case, the correction approach would restart with the most recent results of the machine vision algorithm. A flowchart representing the corrective approach steps can be found in Figure 7.

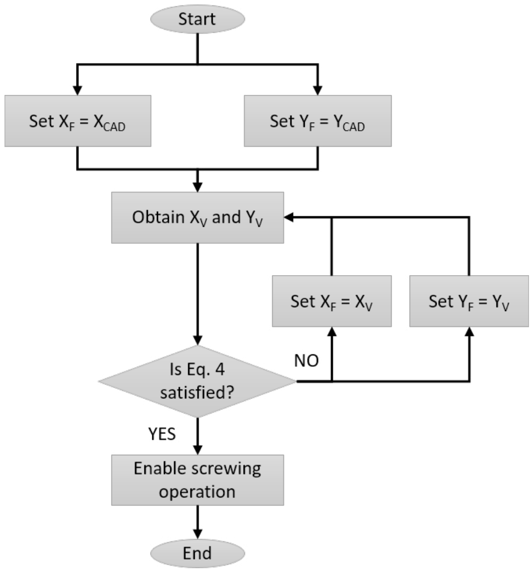

Figure 7. Complete screwing operation procedure flowchart.

5. Conclusions

Information technology and Industry 4.0 applications are getting more and more popular in manufacturing and intelligent manufacturing assembling is becoming more widely used. Through machine vision, the flexibility and automation level of production lines greatly improves due to its ease of integration and low cost. To enable automatic drilling operations on dimpled light-gauge steel assemblies in existing operating machinery, a new vision-based methodology is proposed in this paper. With a single monocular camera positioned on a tilted angle over the screwing axis, this system allows for inspection of the screwing operations without occlusion from the screwing manipulators. Based on edge contour detection and ellipse fitting, a novel model is proposed for real-time detection of pre-drilled pilot holes in dimpled light-gauge steel studs. The resulting image coordinates of the pilot hole are then transformed to the world coordinates for correction of the screwing position, if needed. The corrective approach ensures that the screwing operation is performed in a safe manner and ensures screwing quality. Experimental results demonstrate that the proposed approach can perform in real-time (300 milliseconds) and has high accuracy (approx. 3 millimeters error). Results show that the proposed machine vision approach is 59% more accurate than the other real-time algorithms tested.

6. Future Work

To implement the proposed algorithm in a machine environment, such as the Steel Framing Machine Prototype available at the University of Alberta, further research is necessary. Current tool paths are simulated, optimized, and pre-generated in an offline software and cannot be modified during the process [27]. Once the automatic process has started, the proposed approach modifies, if necessary, its current path to correct the screwing operation location. As the current path is modified and delayed, cycle time optimality is lost. Furthermore, the motion of the frame along the X axis is common to the four independent screw fastening carriages of the machine. However, the correction steps mentioned in Section 4 assume that the screw manipulator position can be modified independently. If corrective steps are taken by more than one screw manipulator at once, a conflict occurs when the system tries to move to two possible different locations in the X axis. Even though corrective steps could be scheduled one by one, such an approach is suboptimal and would increase unnecessarily the machine operation cycle times. Thus, a 1D integrated optimization can be done on such motion to minimize the number of independent operations and thus reduce product cycle times. Such an approach was previously used to optimize tool path trajectories in CNC machines and a similar approach could be used in this problem [28,29].

Acknowledgements

The authors gratefully acknowledge the financial support from the Natural Sciences and Engineering Research Council of Canada (NSERC).

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