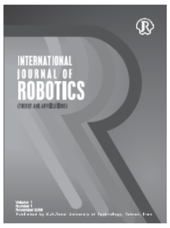

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Automatic Path Planning for GMAW Welding on Locomotive Bogie in Low Contrast by Welding Robot

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ABSTRACT

A locomotive is a rail vehicle that provides the driving power for a train. Railway vehicles consist of multiple components, among which *bogies* play a critical role as key load-bearing parts. They support the weight of the vehicle body and mitigate the impact of track irregularities to ensure smooth and safe operation. To achieve a lightweight assembly, bogie frames are typically constructed using welded structures. Welding is one of the most crucial methods in modern industrial manufacturing and is widely employed in the design of lightweight structures. However, during the welding process, major defects such as weld deformation and residual stresses are inevitable, which can affect assembly accuracy and increase production costs. Traditionally, this welding process is carried out manually, requiring high operator expertise and significant time to execute. This paper presents a welding path planning algorithm aimed at achieving higher welding quality, reducing the overall welding process time, eliminating the production process's dependence on the skills of specific operators, and enhancing the precision in manufacturing various structures used in the rail industry, such as locomotive bogies. The use of image processing for the identification and path planning of welding joints reduces the high costs associated with procuring online laser tracking devices. Moreover, this paper introduces a comprehensive method for processing the entire image and providing the welding path for offline robot programming without any prior knowledge of the joint location. Automatically and accurately determining the seam locations via the robot represents a significant advancement toward automating the arc welding process. The proposed methods have been tested and validated using a laboratory prototype of a 2DOF planar welding robot. The results confirm an accuracy of 2 mm for *parabolic* joints and 3 mm for *straight* joints, meeting the precision requirements of small and medium-sized industries.

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1.Introduction

Locomotives, as the backbone of any country's rail transportation system, are essential in providing the main driving force for trains. These vehicles primarily consist of an engine and control system mounted on a chassis, which rests on two *bogies* [1]. Bogies, also known as wheel carriages, include the frame that carries the wheels and connects to the vehicle (Fig. 1). The bogie frame, acting as the main structure, is responsible for supporting and transferring loads. Typically, bogie frames are constructed by welding metal sheets together, and various designs are available for them, [1].

Straight bogies are conventional, which are used in most rail vehicles, provide the necessary dynamic stability due to their rigid connection to the bogie frame, [2]. In the design of high-speed European trains, bogie frames are often constructed in an *H-shaped* configuration, comprising two longitudinal beams and a welded crossbeam. This design offers several advantages, such as reducing bogie weight, decreasing the moment of inertia, and lowering the torsional stiffness of the frame, which is crucial for preventing derailment on curved tracks.

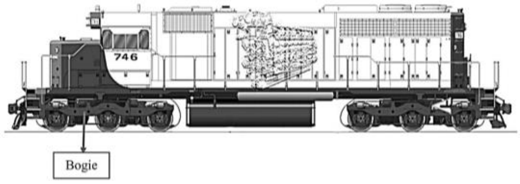


Fig.1. Bogie location on a locomotive

However, these design benefits also influence stress distribution at the joints, where higher torsional stiffness can reduce stress but may compromise dynamic performance on curved tracks, [3]. In China's high-speed *Electric Multiple Units* (EMUs), welded bogie frames play a critical role in transmitting fatigue loads between the wheel axles and the train body, [4].

The structural lightness of railway vehicle components is primarily achieved through welded connections. The welding process used to manufacture bogie frames, however, presents significant challenges. Welding defects, such as weld deformation and residual stresses, can affect assembly accuracy and increase production costs. These defects may lead to the formation of fatigue cracks, negatively impacting the fatigue life of the bogies and the overall safety of the vehicle, [5][6][7][8]. Given the critical need for precision and defect-free welding in bogie construction, employing welding robots and image processing techniques is strongly recommended. These advanced solutions can effectively minimize human errors, reduce welding defects, and ensure the safety and reliability of rail vehicles.

The integration of robotic systems into industrial processes has become increasingly crucial for enhancing productivity and ensuring consistent quality. While the adoption of robots in large-scale factories is now commonplace, small and medium-sized industries have yet to fully embrace this technological shift. In the context of welding, robots offer substantial benefits, such as increased speed, precision, and operator safety. However, the implementation of welding robots in smaller industries faces significant challenges, primarily due to the complexities of programming and the variability in production demands. One of the major obstacles is the lack of automated programming systems tailored to *Small and Medium-sized Enterprises* (SMEs), which often produce a diverse range of products in limited quantities. In large factories, robots are typically programmed using pre-defined paths that are rigidly applied to mass-produced parts. This programming often involves multiple manual trials on a sample workpiece, a process that is impractical and costly for SMEs that do not engage in mass production. Consequently, the need for automation in the robotic welding process is evident, especially in industries such as automotive, shipbuilding, and rail manufacturing, where precision and efficiency are paramount. Automating the programming of welding robots is not just beneficial but essential for enabling SMEs to leverage the full potential of robotic technology.

1.2. Arc Welding (GMAW) Process Automation

Gas Metal Arc Welding (GMAW), also known as *Metal Inert Gas* (MIG) welding, is a widely used welding process that requires careful selection and adjustment of welding parameters. Often, this is still done optimally by a skilled human operator based on the existing boundary conditions. In this research, it is intended to point out the importance of the welding automation process in the rail industry by presenting and developing algorithms for the vision system of industrial robots and using them in the rail industry, and specifically finding the path of weld seams of a bogie, as a complex and curved path.

The purpose of using the vision system is to take an image of the operating point and automatically detect the features of the joint. Automatic detection of these features will make the robot more intelligent in determining the path of the welding nozzle and adjusting the welding parameters more accurately and appropriately.

1.3. Robot Vision System

The use of computer vision in the robotic welding automation and seam detection process requires the creation or development of specific algorithms.

One of the related algorithms is the use of a *median filter* and *smoothing techniques* along with binary thresholding to segment the image so that only the weld seam is visible, [9][10][11]. The results are suitable for aluminum welding, as the high contrast difference between the light workpiece and the dark background makes segmentation easier than in the case of steel on steel (steel workpiece and steel worktable). The use of chamfers on the edges of the joints helps to make them more visible. In practice, most joints are not of this type and, on the other hand, thin, angled sheets are pressed together very tightly and are more difficult to identify. Identifying these joints is particularly challenging when steel is used, compared to when aluminum or stainless steel (iron, chromium, nickel alloy with carbon content less than one percent) is used. Various control logics, such as *fuzzy logic*, have been proposed to control the speed of the welding robot, [12]. Improvements have also been made to the robot's performance in noisy environments, [13].

A method for simultaneous segmentation and seam detection has been introduced, [14]. In this method, two images are taken: one with the workpiece and one without the workpiece from the worktable. The image without the workpiece is used for comparison and ultimately for background segmentation. Filters are then used to remove the effects of background removal. Then, using image processing, a method is presented that can automatically detect the weld seam in the *butt joint* configuration. This method is an improvement over the existing *K-Cosine* algorithm. The three-dimensional position of the weld points is determined using a *Eye-in-Hand* robot stereo vision system, [15]. One of the drawbacks of this method is the need to take multiple pictures of each workpiece. For the automation of the welding process, it is preferable to take one picture to reduce the setup time and the required time interval.

Another common method for seam detection is the use of *Region of Interest* (ROI). By introducing an ROI, the algorithm focuses on the welding area and ignores the background. In this context, an ROI has been defined in the center of the image, [16]. The intensity of the brightness of the pixels in the center is used to define a threshold value for background segmentation. In another study, the ROI is also assumed to be in the middle of the image and the surrounding parts are segmented, so that background objects are ignored, [17]. The results of this method show that it is also suitable for use in various environments. However, it is worth noting that for many welding applications, the center of the weld (due to the shape of the workpiece or the singularities of the welding robot) is not true. Various studies have been conducted on the effect of changing control parameters, [18][19].

Lasers are also used in automatic weld seam identification. Leading industrial automation companies, such as *Servo Robot*, have developed sensors for weld joint identification and path tracking, [20]. These systems are typically expensive. Additionally, due to their large size and placement on the welding torch, they can restrict the welding of various types of welds, which is not a limitation of image processing systems. In order to perform online weld path tracking, a stereo-based laser beam system has been used. In this system, a laser beam is projected onto the joints, and the resulting image is captured by cameras and the refracted angles of the beam are processed, [21]. Fig. 2 presents the conceptual framework for a machine vision system utilizing a laser and a video camera, [22]. Laser-based systems are generally considered a viable solution for online weld path tracking in industrial applications. However, these systems are limited in their applicability and are not suitable for general image processing tasks. Additionally, they cannot be used for offline weld joint identification and path tracking across the entire workpiece.

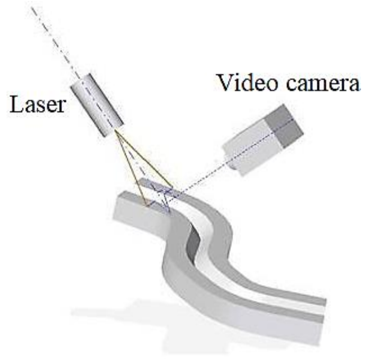


Fig.2.Vision system conceptual scheme: laser and video camera are focused on the joint gap, [22].

This paper aims to detect welding joints using a simple vision system by capturing a single image of the workpiece. The proposed method is capable of detecting all desired welding joints in the image and enables offline robot path planning for longer paths in the image. Supervised and automatic robot path detection has been investigated using research findings from the last decade, [23][24].

2.Railway Manufacturing Industrial Case Study

This industrial case study from the rail manufacturing industry focuses on the implementation of an automated welding process for joining the *platband* and *core* parts of a bogie side frame. Traditionally, this welding process is carried out manually, requiring skilled labor and resulting in extended production times. Automating this process would offer significant advantages in terms of enhanced productivity and improved weld quality consistency. However, it presents challenges due to the following aspects:

1. **Complex Welding Path:** The two parts to be welded (platband and core) exhibit curved profiles, necessitating a complex welding path (depicted by the yellow curves in Fig. 3. Developing an automated system capable of precisely following this intricate path is a key hurdle.
2. **Variable Joint Gap Width:** The width of the joint gap between the two parts varies along the welding path. This variability makes it difficult to pre-determine the optimal settings for consistent and high-quality welds. The automated system will need to adapt to these variations in real-time.

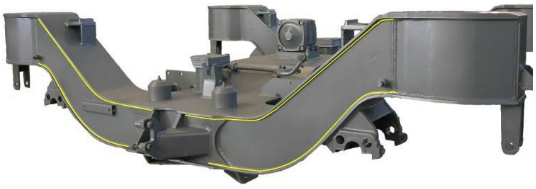


Fig. 3. Bogie: the welding path is highlighted in yellow.

Non-Aligned Profiles

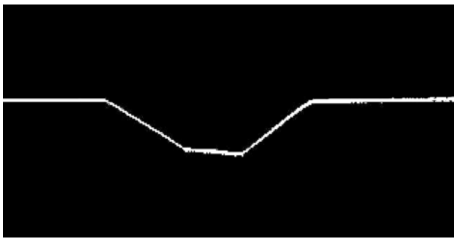
In this process, the two profiles (core and platband) are not perfectly aligned. This misalignment arises from the different manufacturing methods employed for each component. The curved contour of the core is obtained by cutting a metal sheet according to the desired profile, while the platband shape is created by bending a metal sheet. Consequently, the resulting gap between these two curved profiles is not uniform along the welding path, and the exact joint gap width cannot be accurately predicted beforehand.

Image Processing for Joint Detection

To address the challenges posed by non-aligned profiles, an image processing approach was employed to detect and characterize the joints prior to welding. The filtered digital image obtained after this process is shown in Fig. 4 (a), and its grayscale filter is presented in Fig. 4 (b).

Application in Robotic Welding

In this paper, we present a step-by-step approach for detecting joints on a locomotive bogie, which serves as a target for robotic welding in the railway industry.



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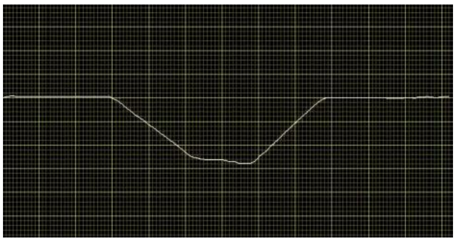


(b)

Fig.4. (a) Non-aligned profiles after digital filtering
(b) Non-aligned profiles after grayscale filtering

Welding Robot Path Planning Using Vision-Based Image Processing

Robots employ various systems to interact with their surroundings. These systems include visual perception systems, such as cameras or lasers. Since 3D laser estimation systems are expensive, using a simple camera and image processing algorithms can significantly reduce the overall cost. This paper aims to develop algorithms for processing images acquired by a camera attached to a welding robot using existing algorithms to provide an appropriate solution for determining the welding robot's path.

Pinhole cameras are commonly used in welding robots due to their infinite depth of field, which ensures that the entire image is in focus. This section discusses the image acquisition process and the application of image processing algorithms. Fig. 5 presents the flowchart of the proposed approach.

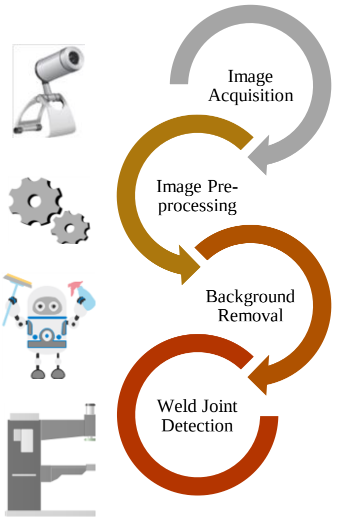


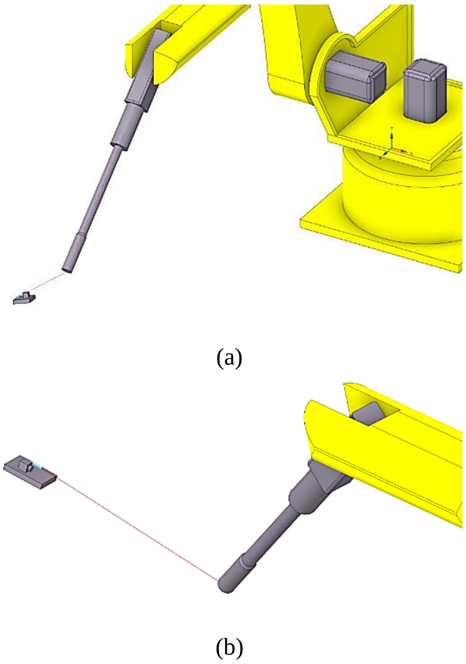
Fig 5. Flowchart and Research Process

3-1 Image Acquisition

Image acquisition in welding robots typically employs two common approaches:

a. Fixed Camera Approach:

In this method, the camera is mounted in the robot's workspace and remains stationary. The camera captures images of the workpiece and surrounding environment as the robot moves along its path, that shows in Fig. 6 This approach is suitable for applications where the workpiece is relatively stationary and the robot's movements are predictable.



(a)

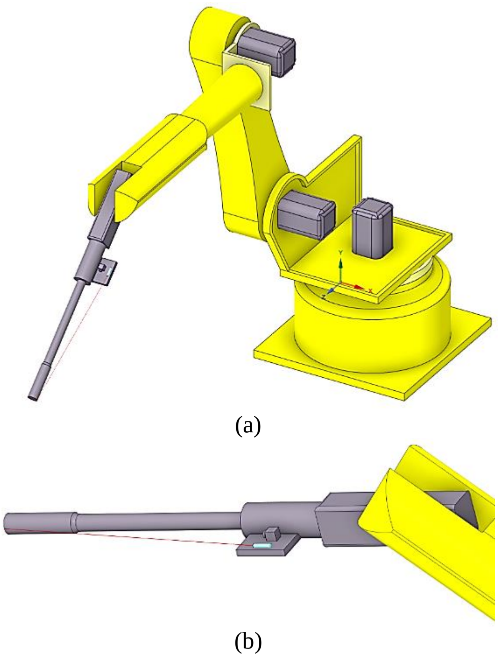
(b)

Fig. 6. Fixed Camera Approach; (a) 3D schematic of a welding robot. (b) Welding robot viewed from the side.

b. Mobile Camera Approach (Hand-Eye Camera):

In this approach, the camera is attached to the end of the robot's arm and moves along with the robot, that shows in Fig.7 This allows the camera to capture close-up images of the workpiece and weld joints from various angles. The mobile camera approach is particularly useful for applications where the workpiece is complex or irregularly shaped and the robot's movements are less predictable.

Both fixed and mobile camera approaches require image processing of the acquired images. The process of obtaining the robot's kinematic relationships, estimating the camera's intrinsic and extrinsic parameters, calibrating the robot, and preparing and planning the robot's path to follow it, involves various specialized topics that are beyond the scope of this paper. This paper focuses on providing algorithms for determining the correct path for welding joint detection.



(a)

(b)

Fig. 7. Mobile Camera Approach; (a) 3D schematic of a welding robot. (b) Welding robot viewed from the side.

3-2 Image Pre-processing

Welding metal parts in workshop environments presents significant challenges for vision systems. Factors such as poor workshop lighting, the workpiece being the same color and material as the worktable, scratches on the parts, rust, and the cleanliness of the part can affect the correct detection of joints using processing algorithms.

3-2-1 Image Conversion:

The first step in segmenting the weld pieces and background image (as shown in Fig. 8) is to convert the acquired color image into a grayscale image. This can be achieved using the following equation:

$$I_{Gray} = \begin{bmatrix} 0.3 & 0.6 & 0.1 \end{bmatrix} \begin{bmatrix} I_{RGB}\{R\}(u,v) \\ I_{RGB}\{G\}(u,v) \\ I_{RGB}\{B\}(u,v) \end{bmatrix} \quad (1)$$

where (u,v) are the pixel coordinates, $I_{RGB}\{\mathrm{R}\}$, $I_{RGB}\{\mathrm{G}\}$ and $I_{RGB}\{\mathrm{B}\}$ represent the *Red*, *Green* and *Blue* components of the *RGB* image, respectively.

Studies have shown that capturing an initial color image provides more information for subsequent processing steps compared to a grayscale image.

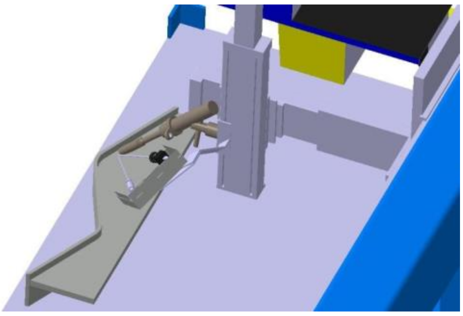


Fig. 8. Schematic diagram of joint detection on the bogie

3-2-2 Median Filter

The second step is to use a median filter to smooth the background. This filter reduces the effects of scratches that are connected to the workpiece boundary, which can interfere with edge detection. When the median filter is applied multiple times in succession, the effects of noise and scratches are significantly reduced.

In this study, we applied a 10*10 median filter twice to obtain an image suitable for subsequent processing.

3-2-3 Edge Detection

In order for the *Hough* transform to be able to detect the outer boundary of the weld piece, it is first necessary to define the edges. In this paper, the *Sobel* edge detection algorithm is used for this purpose.

The grayscale image is then converted into a black and white binary image using an adaptive thresholding algorithm. To ensure that the created boundary lines have no discontinuities, *dilation* and then *erosion* are applied to the resulting image. In this way, all thin discontinuous lines are connected to each other without changing the dimensions of the image, and lines with a width of one pixel are obtained. The resulting image is shown in Fig. 9.

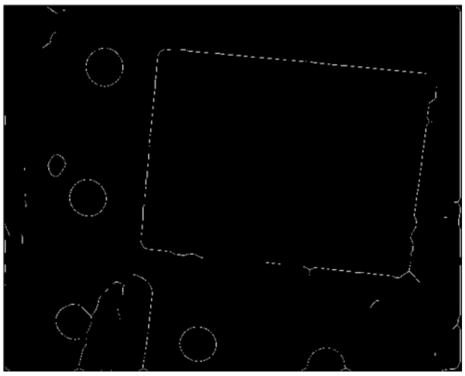


Fig. 9. First Stage of Edge Detection, Sobel Edge Detector

3-3 Background Removal

After applying the Sobel filter and applying dilation and erosion, the Hough transform can be used to identify the boundary lines of the workpiece and its surroundings. The Hough transform is used to find straight lines in binary images.

In this paper, the Hough transform is used to find the boundary lines of the workpiece, and then the background is removed by obtaining the normalized brightness intensity on both sides of the lines. The method for obtaining and removing the background will be described in detail below.

What is used in this paper about the Hough transform is as follows. The Hough transform can be defined by the following equations:

$$\rho = u\cos\theta + v\sin\theta \qquad \theta \in [0 \quad 2\pi] \qquad (2)$$

where ρ is the distance between the origin of the image and a point on the edge of the image, and θ is the angle between ρ and the x-axis. ρ and θ are grouped together, and only the more effective lines remain using the following thresholding:

$$T_1 = \beta H_{\max} \qquad (3)$$

where T_1 is the desired threshold value, β is a thresholding factor that indicates what percentage of the maximum volume of the detected bins $H_{\max}$ is used. Increasing the value of β leads to a decrease in the number of lines detected by the Hough transform, and conversely, decreasing the value of β will detect more lines.

Existing background removal methods typically use kernel in the desired regions, which requires prior knowledge of the workpiece. The method presented in this paper provides a comprehensive solution for use with a variety of workpieces.

Once the Hough lines have been correctly detected, we try to obtain the workpiece boundary lines from the detected lines. For this purpose, two separate lines are considered for each detected Hough line. We call the normalized average of each of these intensities I_n. For example, for the first detected line, two more lines on either side of it are obtained, and their brightness intensities are called I_{1n} and I_{2n}, respectively. The normalization of values in grayscale images is as follows:

$$I_n = \frac{I_{avg}}{255} \tag{4}$$

where I_{avg} is the average brightness intensity of the pixels on the virtual line on one side of the detected Hough lines. The magnitude of the difference in these brightness intensities is then considered as follows:

$$d = \left| I_{1n} - I_{2n} \right| \tag{5}$$

where I_{1n} and I_{2n} are the brightness intensities of the lines on either side of the detected Hough line. By considering an appropriate threshold, it can be determined which of the detected Hough lines lie on the workpiece boundary, and thus the regions outside the workpiece can be removed from the image.

$$edge = \begin{cases} True & d > T_2 \\ False & \text{other} \end{cases} \tag{6}$$

where *edge* represents the Hough lines that are correctly positioned on the workpiece boundary lines, and T_2 is the threshold value used to better detect these edges.

3-4 Weld Joint Detection

Once the boundary lines have been correctly detected and the workpiece has been properly separated from the background image, it is time to detect the main joint in the object. The resulting image from background segmentation is first smoothed using uniform filters; because after removing the background, pixels in the border regions may have a significant difference in brightness intensity, which can lead to improper joint detection at this stage. Therefore, in this paper, the median filter is proposed and used as needed, and the result is shown in Fig. 10.

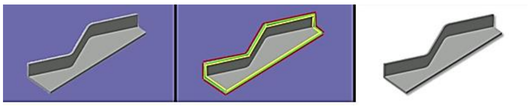


Fig. 10. Background removal from the bogie operating area

The Sobel filter is then used to find the joints. Finally, morphology is used to find the joint body. The found joints are estimated with a uniform polynomial. Fig. 11 shows the detection of joints.

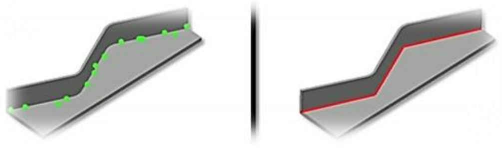
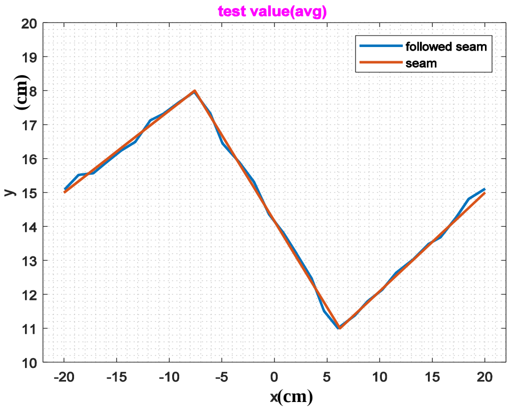


Fig. 11. Joint detection and approximation from the resulting connection points

4- Results and Discussion

To implement the innovative GMAW system for welding the locomotive bogie, experimental testing is required. This section presents the experimental results obtained using a laboratory prototype of a planar mobile robot. The results were obtained for two types of joints: *straight-line* and *parabolic*, each with four tests. The experimental results show that the algorithm used is capable of achieving an accuracy of 3 millimeters for straight-line joints and 2 millimeters for parabolic joints in Figs. 12 &13.

The comparison of results obtained in the x-y coordinate plane for the straight-line path shows a 0.951 mm reduction in error compared to the results of the 3D model described in, [22] as represented in the x-y plane. Additionally, in order to emphasize and confirm the accuracy of the welding, the results for the parabolic path are presented for the first time in this study.



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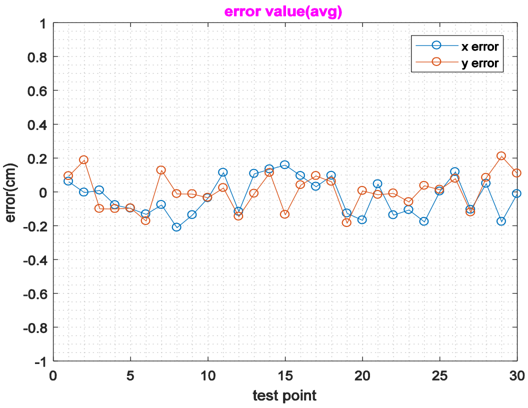
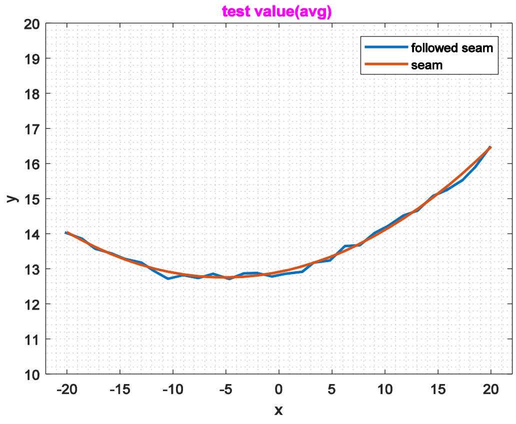
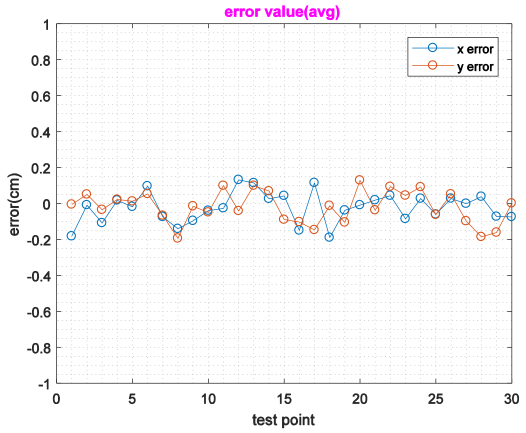


(b)

Fig. 12. (a) Test results of a planar robot for a straight-line joint. (b) Error in two dimensions



(a) (cm)



(b)

Fig. 12. (a) Test results of a planar robot for a parabolic joint, and (b) Error in two dimensions

5-Conclusion

In this paper, an image processing method for automatic seam detection in robotic welding was presented. The proposed method consisted of two main steps: *background removal* and *seam identification*.

In the first step, the background was removed from the image using a set of operations. This was done by using auxiliary lines to separate the background from the foreground. The steps involved in this process were shown schematically in Fig. 10.

Once the background had been removed, the seam was identified. This was done by first applying filters and masks to smooth out the edges resulting from the background segmentation, and then using the Sobel algorithm to find the seam in the original image. After finding the desired points in the segmented image, closing and morphological operations were applied to the resulting image. Finally, the main skeleton of the desired seam was detected, and the seam was identified by passing a smoothing polynomial through these points. The steps involved in identifying the seam points and assigning the desired polynomial to the points were shown in Fig. 11.

Nevertheless, this research encountered certain limitations. The primary issue was the capacity of the existing GMAW system relative to the size of the parts being welded. Since the dimensions of the bogie frame components were substantially larger than the GMAW system's capabilities, only sections of these components could be used for the welding trials. Additionally, it was crucial for the vision system to be positioned in front of the torch at all times to accurately detect the welding path and gap width.

This method can also be used to achieve the desired accuracy for robotic welding. It is obvious that by increasing the quality of the camera and ambient light, a much higher accuracy will be achieved. On the other hand, the use of images with a much higher number of pixels will result in heavier processing and consequently reduce the processing speed. Therefore, an appropriate compromise between these two can lead to satisfactory results for welding.

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