



Adaptive Control for Laser-GMAW Hybrid All-Position Root Pass Welding

Exploring an adaptive control welding system based on PSO-BP neural network and line-structured light visual sensing

BY R. HAN, X. FANG, H. ZHANG, D. REN, L. LIU, AND G. SONG

Abstract

All-position welding is essential for pipeline installation, yet dynamic variations in butt gaps, groove mismatches, and welding positions challenge weld quality. To address these issues, this study developed an innovative adaptive control system for all-position root pass welding. The system integrated an innovative laser-GMAW hybrid all-position welding with copper liner coordinated control, offering robust process stability and a wide process window. It enables high-quality welding under dynamic fluctuations in work conditions while providing parameter adjustment margins for adaptive control. Furthermore, a particle swarm optimization-back propagation (PSO-BP) neural network was employed to establish an adaptive process database. Additionally, an improved gray centroid method was proposed for U-groove, achieving accuracies of 0.10 mm (0.00394 in.) for butt gaps and 0.07 mm (0.00276 in.) for groove mismatches. Validated on $\Phi 800 \times 12$ mm (31.5 $\times$ 0.472 in.) pipelines, the system produced welds with 3~4 mm (0.118~0.157 in.) backside reinforcement width and 0.50~0.80 mm (0.0197~0.0315 in.) height. This research provides theoretical and technical foundations for pipeline welding from double-sided to single-sided processes. Future work will focus on weld seam tracking and path planning to develop a comprehensive, all-position adaptive welding control system that integrates root, filler, and capping passes.

Keywords

- All-Position Welding
- Online Detection
- PSO-BP Neural Network
- Assembly Accuracy
- Adaptive Control
- Laser-GMAW Hybrid Welding

Introduction

All-position welding is essential for long-distance oil and gas pipeline installation due to fixed pipeline positioning (Ref. 1). This process is complicated by dynamic changes in welding positions, which alter the effects of gravity on molten pool behavior and droplet transfer. Additionally, challenges such as pipeline deformation, low groove processing, and assembly accuracy make it difficult to maintain a consistent butt gap without groove mismatches (the vertical height difference between the two workpieces). Consequently, the working conditions for all-position welding of pipelines are highly complex.

Current engineering practice predominantly employs manual gas tungsten arc welding (GTAW) and shielded metal arc welding (SMAW) for all-position root pass welding (Refs. 2, 3). GTAW offers high-quality welds with minimal spatter and slag, while SMAW requires minimal equipment investment and no gas consumption. Furthermore, these two processes can also rely on the welder's experience to adjust the welding parameters, enabling adaptation to varying working conditions. However, they show significant common drawbacks: low deposition efficiency, inconsistent quality, and high reliance on welder operation skills (Refs. 4, 5). The global manufacturing industry has faced a structural challenge recently due to a shortage of skilled welders. Therefore, SMAW and GTAW have increasingly struggled to meet welding efficiency and quality demands. Gas metal arc

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welding (GMAW) or laser-GMAW hybrid welding presents significant potential with higher deposition efficiency, cleaner welds, and automation compatibility. It demonstrates substantial application potential for improving the quality and efficiency of pipeline all-position welding. However, due to the dynamic welding conditions in pipeline all-position welding, double-sided welding is currently required to ensure quality when using these methods for the root pass. Consequently, there is an urgent need to develop an adaptive control system for pipeline all-position welding. Such a system would dynamically adjust welding parameters based on real-time welding conditions, enabling the critical transition from double-sided to single-sided welding.

Recently, welding adaptive control technology based on machine vision has significantly improved. Tang et al. (Ref. 6) developed a system using nonlinear regression, achieving weld height and width deviations of less than 0.5 mm (0.0197 in.) and 0.3 mm (0.0118 in.), respectively. However, the system did not consider the root pass weld quality, which is crucial in all-position welding. Liu et al. (Ref. 7) developed a real-time penetration monitoring system for all-position GTAW but did not include adaptive welding parameter control. Wang et al. (Ref. 8) used layered scanning for weld bead 3D point clouds, enabling automatic path planning for all-position welding. Although these studies have made significant progress in enhancing the automation of pipeline laying, the adaptive control of welding parameters has not been realized.

Despite significant advancements in online detection and adaptive control, a critical challenge in all-position pipeline welding remains the absence of a robust all-position welding technology with a wide process window and strong adaptability. This can ensure the weld quality under fluctuating working conditions and provide the interval and time for adjusting process parameters in adaptive control. To address the challenge, the authors previously proposed an innovative laser-GMAW hybrid all-position welding technology with copper liner coordinated control (Refs. 9, 10). The copper liner's high thermal conductivity accelerates solidification of the molten pool, enabling completion of the liquid-to-solid phase change before collapse occurs under gravity. This prevents the backside concave defect at the overhead welding position and improves the weld quality. Concurrently, its heat-absorption effect reduces thermal accumulation of workpieces and elevates the critical threshold of welding heat input. This broadens the process window, thus providing a margin for parameter adjustment for adaptive control. Furthermore, laser-GMAW hybrid welding exhibits superior bridging ability, enhanced welding efficiency, and remarkable stability (Ref. 11). This method addresses the limitations of low deposition efficiency and high labor costs associated with SMAW and GTAW. It is significant for reducing the construction period of pipelines, lowering costs, and decreasing the reliance on skilled welders.

This study developed an adaptive control system for all-position root pass welding based on this all-position welding technology. The system integrated a line-structured light active vision for sensing to detect the assembly accuracy. Active vision sensing is a technology that achieves high-precision detection by actively emitting structured light and analyzing reflected signals. Technology suppresses stray

light interference using a specific-wavelength laser and a narrow-band filter (Ref. 12). In addition, the adaptive control of welding parameters depends on the accurate process database. Therefore, this study used a particle swarm optimization-backpropagation (PSO-BP) neural network to construct the adaptive process database. This method offers the advantages of a fast convergence speed, fewer parameter configurations, and a strong global optimization ability (Ref. 13).

For the first time, this study developed an adaptive control system for all-position root pass welding capable of accommodating large assembly accuracy fluctuations. The system integrated three key components: (1) laser-GMAW hybrid welding with copper liner coordinated control, which ensures formation quality and process adaptability; (2) an active vision sensing system for real-time monitoring of U-groove assembly states; and (3) an adaptive process database built on a PSO-BP neural network model for welding parameter optimization and prediction. Finally, the system's accuracy and reliability were validated through comprehensive evaluations of assembly state detection precision and weld quality in pipeline welding applications.

Experimental Methods and Platform

Experimental Platform

This study developed an adaptive control system for all-position welding, incorporating a PSO-BP neural network model and a line-structured laser vision sensor. Figure 1 illustrates the hardware components: (1) laser-GMAW hybrid welding unit (Lorch S8 GMAW welder + XL-650 WF laser); (2) vision sensor module (line laser emitter, CMOS camera, narrowband filter); (3) servo-driven motion mechanism with circular track; (4) host computer; and (5) programmable logic controller (PLC). The servo system synchronizes the welding torch, laser head, and sensor movements.

The all-position welding technology demonstrated strong process robustness, with tolerances for butt gap, groove mismatch, and welding position set at 0.30 mm, 0.20 mm (0.00787 in.), and 10 deg, respectively (Refs. 9, 10). Analysis of actual groove machining and assembly accuracy revealed that the variation rates of the butt gap and groove mismatch did not exceed 5% and 3%, respectively. With a maximum welding speed of 14 mm/s, the visual sensor operated at 5 Hz. Under these conditions, the maximum variations in butt gap, groove mismatch, and welding position between consecutive samples were 0.14 mm (0.00551 in.), 0.08 mm (0.00315 in.), and 0.2 deg, respectively. These variations detected remained within 50% of the maximum tolerances, meeting the process requirements. As illustrated in Fig. 2, the system captured groove images, then transmitted them via Ethernet to the host computer for processing to obtain butt gaps and groove mismatches. The PSO-BP neural network model then determined optimal welding parameters transmitted to the PLC. The PLC system, connected to servo drives and the welding machine via Profinet, utilized the FB284 function block to control the speed of the servo driver. It also sent analog signals through the INT06-1 I/O

board to adjust the welding current. Leveraging the high process robustness of the welding method and the PSO-BP neural network’s accuracy, the PLC system dynamically adjusted welding current and speed directly based on the neural network’s predictions.

An electromagnetic proximity switch was used to calibrate the motion origin. The positioning trigger distance is 3 mm

(0.118 in.), and the response time was less than 1 ms. After calibration, the servo driver received the position command from the PLC and drove the servo motor to move the welding torch. The servo motor provided real-time position feedback to the PLC through the encoder, and the host computer subsequently integrated this data for the PSO-BP neural network to predict the process parameters.

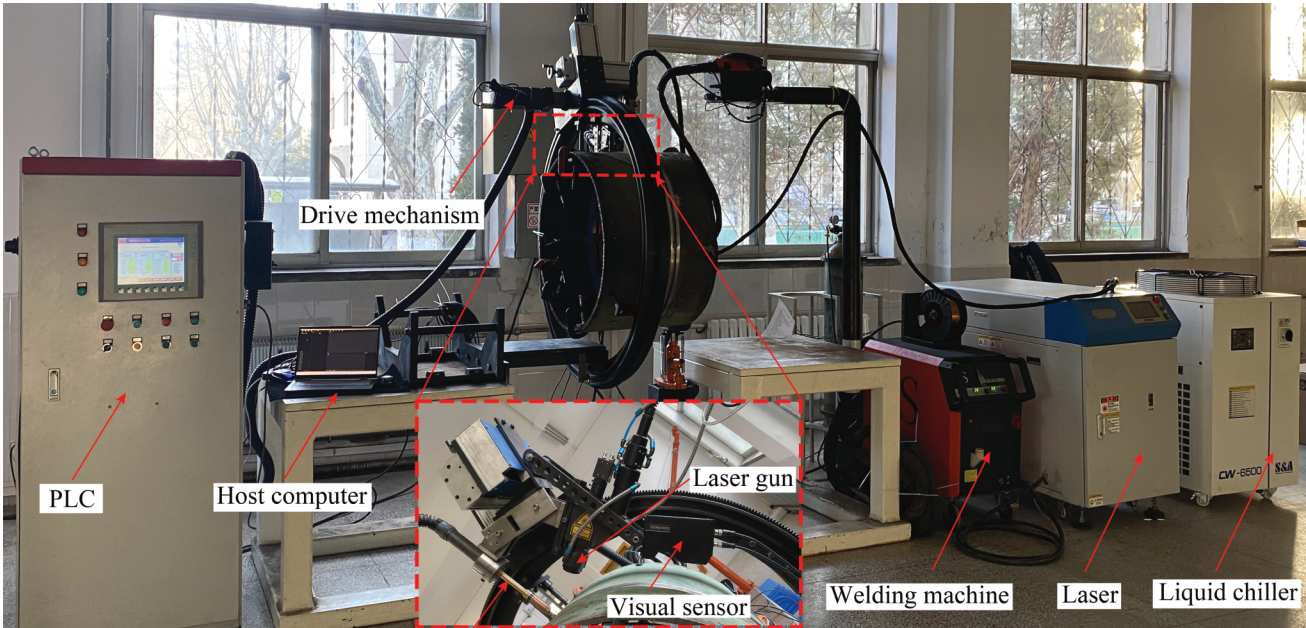


Fig. 1 – Hardware composition of the adaptive all-position welding control system.

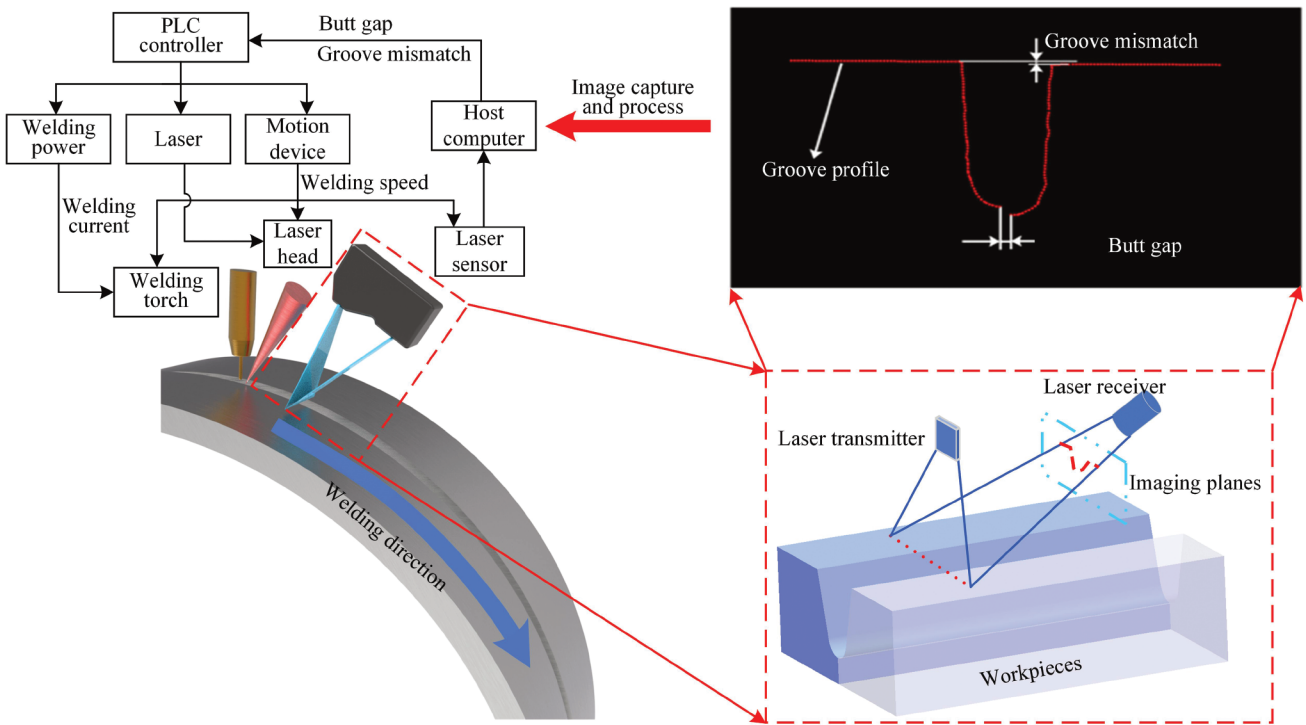


Fig. 2 – Structure and working principle of the adaptive all-position welding control system.

Online Detection and Adaptive Control Software System

The real-time monitoring and adaptive parameter control involve multi-module interactions, including device communication, image acquisition and processing, feature detection, region of interest (ROI) determination, and control signal transmission. These independent yet interconnected modules require continuous data exchange, necessitating a highly concurrent multi-threaded architecture. A Queue Message Handler (QMH) structure with parallel while loops and queue-based data exchange was implemented to enhance computational efficiency and system responsiveness.

As shown in Fig. 3, the system's software architecture was modularized into four units: (1) the main program, (2) the groove image capturing and processing module, (3) the PSO-BP neural network, and (4) the PLC control interface. The main program, image processing algorithms, and PSO-BP neural network were implemented as built-in modules within the host computer. The host computer generated control signals through these integrated programs and transmitted them to the PLC control system, subsequently adjusting welding parameters. Additionally, the main program drove the visual sensor to capture the groove image, and the image

processing algorithm (see Fig. 4) processed the extracted groove image to obtain the groove mismatch and butt gap. The PSO-BP neural network predicted optimal welding parameters based on real-time work conditions and sends the response information to the PLC. The PLC control interface dynamically adjusted welding current and speed using data from the main program.

Experimental Materials and Methods

Following system setup, comprehensive experiments were conducted to validate the accuracy and reliability of the all-position welding system. The material utilized in the experiment was a $\Phi 800 \times 12$ mm (31.5×0.472 in.) X70 pipeline, and the filler wire employed was ER50-6 with a diameter of 1.2 mm (0.0472 in.). During pre-weld preparations, assembly accuracy of the pipes to be welded was guaranteed to minimize torch deviation from the groove center, eliminating the need for torch positional adjustments to maintain torch-groove alignment during experiments. Figure 5 shows the groove geometry and dimensions. During welding, the welding current and speed were adjusted in real time, with constant parameters listed in Table 1. The vision sensor system included a 500 mW line laser emitter (420

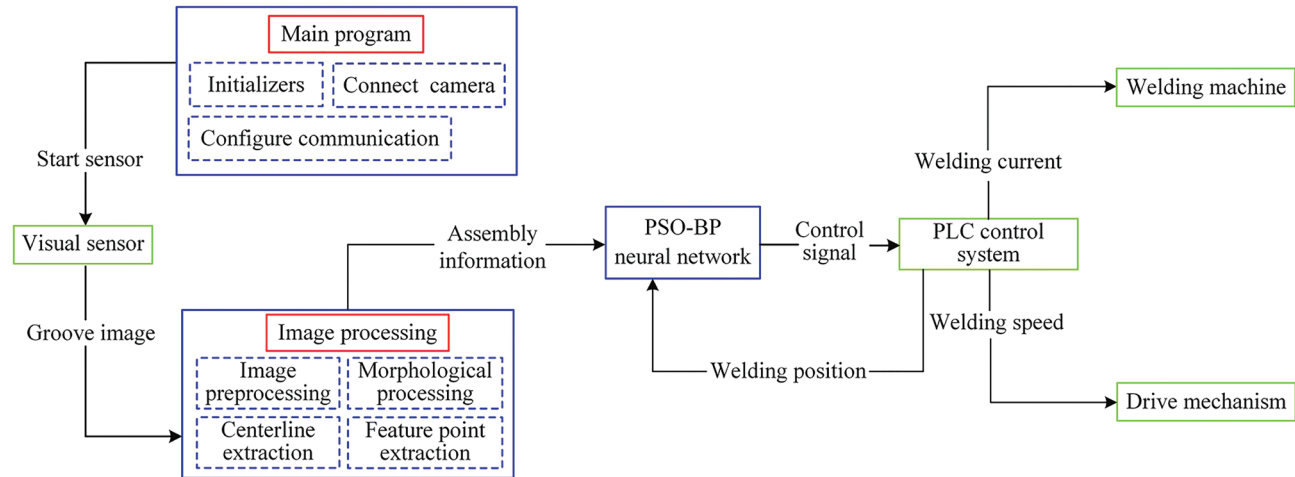


Fig. 3 – Software architecture of the adaptive all-position welding control system.

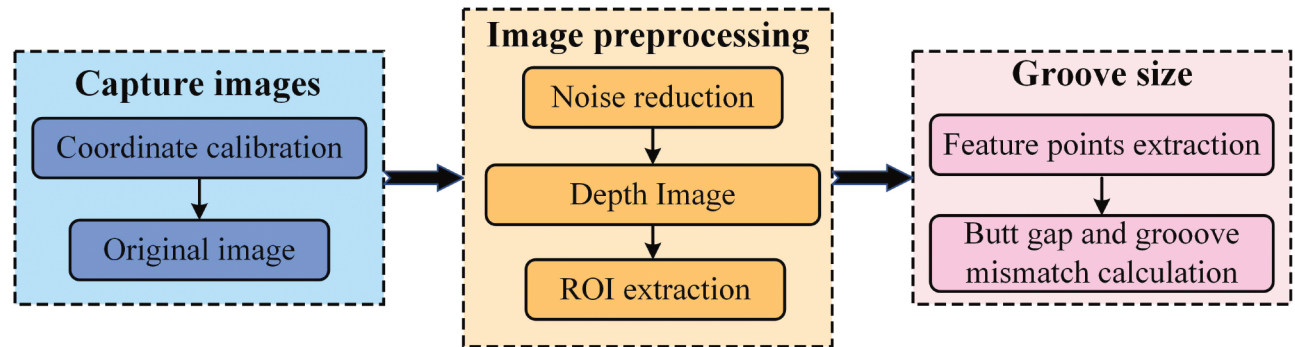


Fig. 4 – Flowchart of laser stripe image processing algorithm.

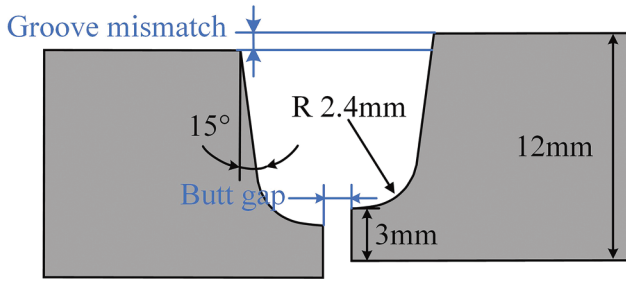


Fig. 5 – Geometry and dimensions of the weld groove.

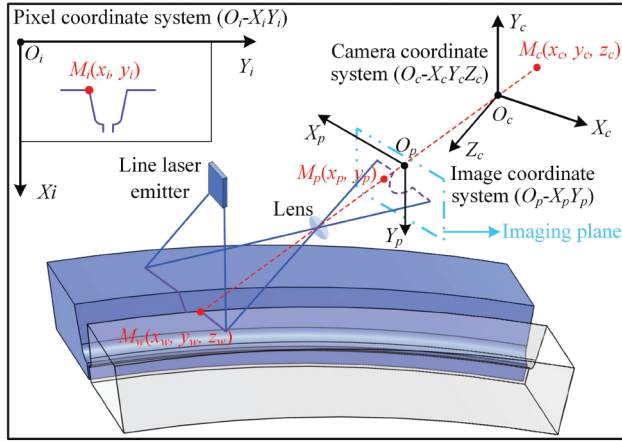


Fig. 6 – Camera imaging model and coordinate systems.

Table 1 – Constant Welding Parameters for Confirmatory Experiment

No.	Items	Value
1	Laser defocusing amount	0 mm
2	Laser-wire distance	2 mm
3	Wire extension	17 mm
4	Shielding gas	80% Ar + 20% CO ₂
5	Shield gas flow	15 L min ⁻¹
6	Laser peak power	6000 W
7	Laser pulse frequency	30 Hz
8	Laser pulse width	3 ms

nm wavelength) and a narrowband optical filter (420 ± 10 nm) to minimize ambient light interference.

To verify the detection accuracy and robustness of the sensor, manual measurements were compared with those from the visual sensor's automatic detection. Furthermore, since the visual sensor developed in this study was designed to detect the butt gap and groove mismatch of the U-shaped groove, a U-shaped groove was selected as the detection object to simulate real working conditions better. Additionally, for manual measurements, a digital wedge feeler gauge and surface difference ruler were employed to measure the actual butt gap and groove mismatch, respectively, achieving a measurement accuracy of 0.01 mm (0.000394 in.). Each position was measured three times, and the results were averaged to minimize measurement error.

Coordinate Transformation and Image Processing Algorithm

Coordinate Transformation

This study utilized a vision sensor designed to measure butt gap and groove mismatch. This imaging model focused on the transformation among three coordinate systems: the camera coordinate system ($O_c - X_c Y_c Z_c$), the image coordinate system ($O_p - X_p Y_p$), and the pixel coordinate system ($O_i - X_i Y_i$), as illustrated in Fig. 6. A point M in three-dimensional space is represented in these three coordinate systems as $M_c(x_c, y_c, z_c)$, $M_p(x_p, y_p)$, and $M_i(x_i, y_i)$, respectively.

The camera coordinate system, originating at the optical center and Z-axis aligned with the optical axis, defines the three-dimensional spatial relationship between object and camera. Both the image and pixel coordinate systems are two-dimensional and coincide with the camera's imaging plane, differing only in their origins: the image coordinate system's origin is at the intersection of the optical axis and the imaging plane, while the pixel coordinate system's origin is at the top-left corner of the imaging plane. The camera imaging model establishes a mapping relationship (Equation 1) between the pixel and camera coordinate systems.

$$(x_c, y_c, z_c) = f(x_i, y_i) \quad (1)$$

The relationship between the camera and image coordinates can be determined using the principle of similar triangles. The transformation matrix between the camera coordinates and the image coordinates is given by Equation 2.

$$\begin{bmatrix} x_i \\ y_i \\ 1 \end{bmatrix} = \frac{1}{Z_c} \begin{bmatrix} f & 0 & 0 \\ 0 & f & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_c \\ y_c \\ z_c \end{bmatrix} \quad (2)$$

where f represents the focal length of the camera.

The image and pixel coordinate systems lie in the same plane, related by a translation, as expressed in Equation 3:

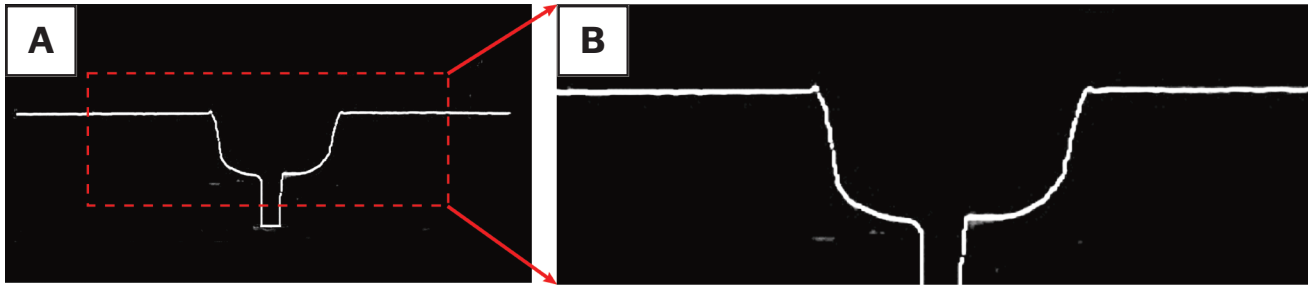


Fig. 7 – ROI definition methodology: A – Original image; B – ROI.

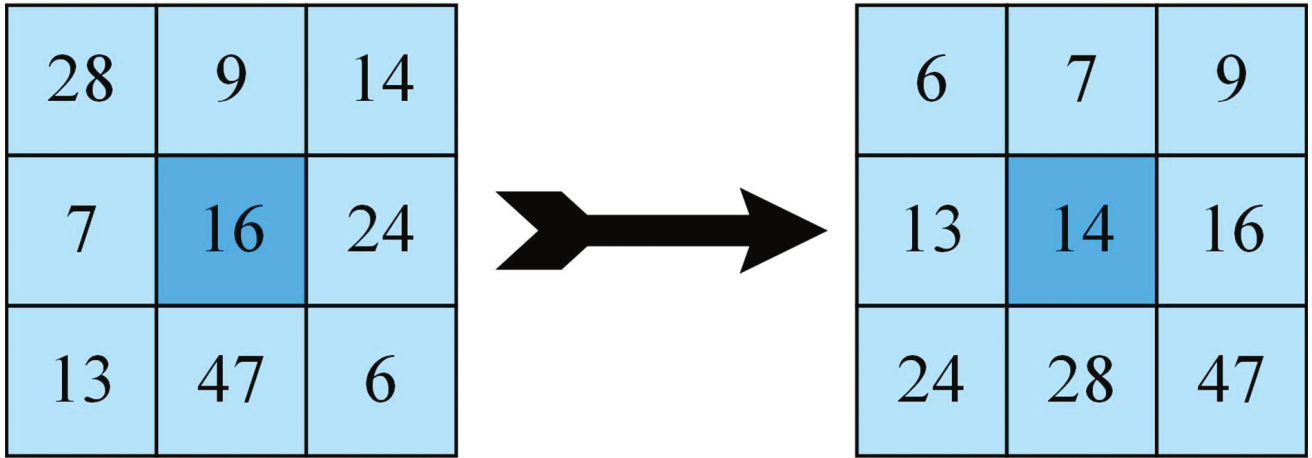


Fig. 8 – Principle of median filtering.

$$\begin{bmatrix} x_p \\ y_p \\ 1 \end{bmatrix} = \begin{bmatrix} 1/dx & 0 & x_0 \\ 0 & 1/dy & y_0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_i \\ y_i \\ 1 \end{bmatrix} \quad (3)$$

where dx and dy represent the pixel size in the image coordinate system, and (x_0, y_0) denotes the coordinates of the origin of the image coordinate system in the pixel coordinate system.

Combining Equations 2 and 3, the transformation between the pixel coordinate system and the camera coordinate system can be derived as follows:

$$\begin{bmatrix} x_p \\ y_p \\ 1 \end{bmatrix} = \frac{1}{z_c} \begin{bmatrix} f/dx & 0 & x_0 \\ 0 & f/dy & y_0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_c \\ y_c \\ z_c \end{bmatrix} = \frac{1}{z_c} H \begin{bmatrix} x_c \\ y_c \\ z_c \end{bmatrix} \quad (4)$$

where H is the camera intrinsic matrix, which depends on the structural design of the camera itself.

Since the pixel coordinate system is two-dimensional, height information cannot be determined solely from pixel coordinates. Therefore, to obtain three-dimensional coordinates, the equation of the line-structured light plane was introduced as an additional constraint. With the camera and line laser emitter positions fixed, the light plane equation was established in the camera coordinate system as Equation 5.

$$Ax_c + By_c + Cz_c + D = 0 \quad (5)$$

By integrating Equations 2, 4, and 5, the following relationship is derived:

$$\begin{bmatrix} f/dx & 0 & x_0 - x_p \\ 0 & f/dy & y_0 - y_p \\ -A & -B & -C \end{bmatrix} \begin{bmatrix} x_c \\ y_c \\ z_c \end{bmatrix} = D \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \quad (6)$$

Image Preprocessing

An ROI was defined in the captured images to optimize computational efficiency and minimize interference from non-target regions. In this study, given that the relative positions of the vision sensor and the workpieces were fixed, a fixed region can be selected as the ROI in the captured images. As shown in Fig. 7, a rectangular ROI of 1000×370 pixels was selected, covering only 32% of the original image area, significantly reducing computational load.

Images acquired by the vision sensor often contain noise due to factors like ambient lighting and surface rust, necessitating effective denoising algorithms. Currently, various denoising methods are widely used, including bilateral filtering, median filtering, and Gaussian filtering, which have been extensively applied in image denoising (Refs. 14–16). Notably, the median filter is particularly effective in removing

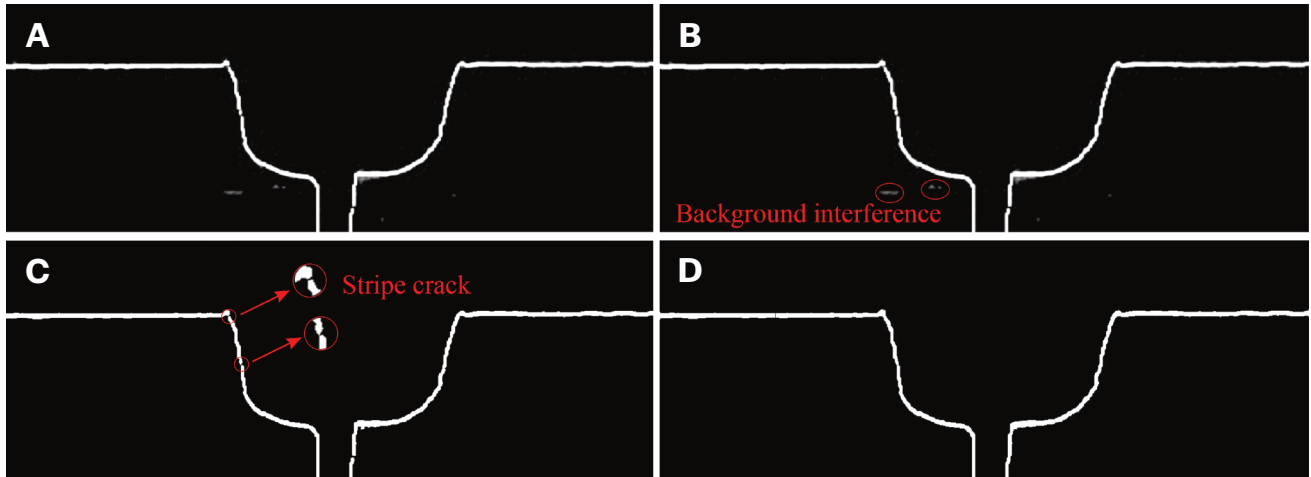


Fig. 9 – Results of image preprocessing: A – Original image; B – filtering denoising; C – threshold segmentation; D – morphological processing.

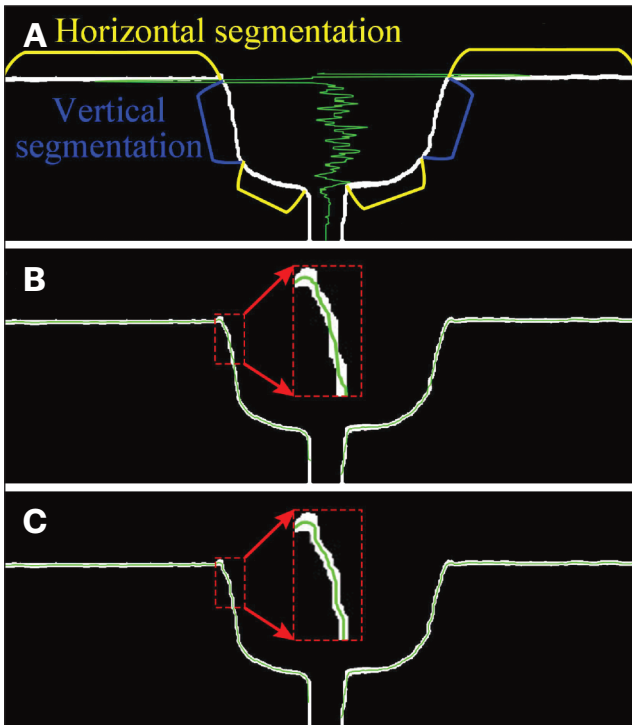


Fig. 10 – Laser stripe centerline extraction results: A – Row-wise scanning; B – column-wise scanning; C – improved gray centroid method.

“salt and pepper” noise while maintaining edge details within the image (Ref. 17). The underlying principle of the median filtering algorithm is demonstrated in Fig. 8.

However, traditional median filtering struggles in complex welding environments. To address this, a partition-based median filtering algorithm was proposed. This algorithm divides the original data into three regions: noise-affected regions, transition region, and smooth regions, utilizing a partition operator $\varphi(x)$, applying filtering only to noise-affected and smooth regions. This approach reduced computational

load while maintaining edge details. The partition operator $\varphi(x)$ is calculated as:

$$\varphi(i) = \sum_{j=1}^8 \phi(i, j) \quad (7)$$

$$\phi(i, j) = \begin{cases} 1 & |f(i) - f(j)| \leq T \\ 0 & |f(i) - f(j)| \geq T \end{cases} \quad (8)$$

where $\phi(i, j)$ evaluates pixel similarity, $f(i)$ denotes the center pixel value, $f(j)$ refers to adjacent pixel values, and the threshold T is calculated as

$$T = \sqrt{\sum_{j=1}^8 (f(i) - f(j))^2 / 8} \quad (9)$$

Points with no similarity ($\varphi(x) = 0$) were identified as noise, while points with similarity to 1–4 neighbors ($1 \leq \varphi(x) \leq 4$) were classified as transition regions. Points with similarity to 5–8 neighbors ($5 \leq \varphi(x) \leq 8$) were categorized as smooth regions and processed using median filtering.

To enhance the ROI, threshold segmentation separated laser stripes from the background, reducing environmental interference. Morphological processing, including opening and closing operations, removed cracks and burrs. Otsu’s algorithm was used for segmentation, followed by morphological processing. As shown in Fig. 9, the processed image retained fine details, with laser stripes clearly separated from the background. Discontinuities in the threshold-segmented image (Fig. 9C) were resolved through morphological processing, yielding continuous and smooth laser stripes (Fig. 9D).

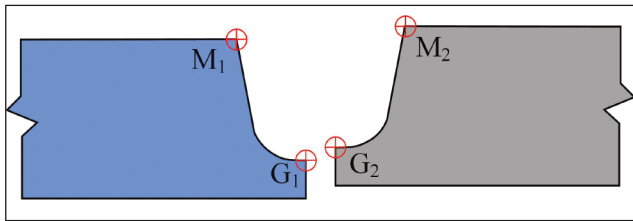


Fig. 11 – Schematic diagram of the groove feature point locations.

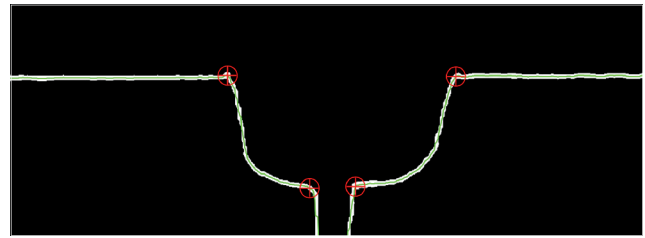


Fig. 12 – Results of groove feature point extraction.

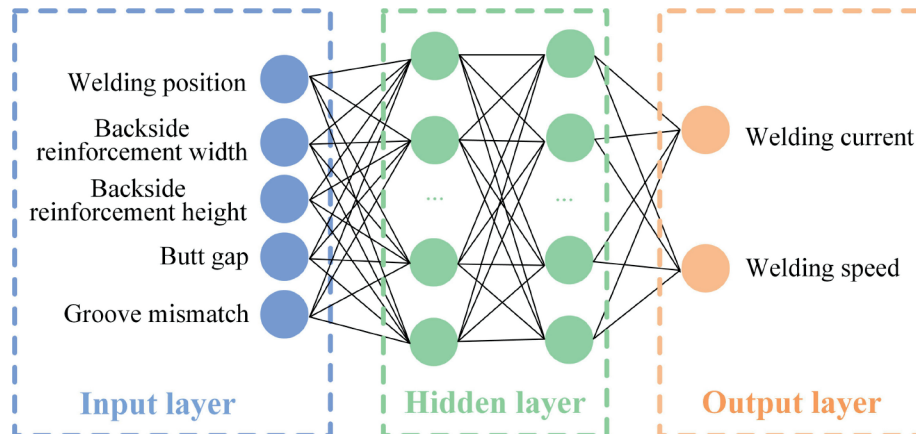


Fig. 13 – Structure of the PSO-BP neural network.

Extraction of Groove Feature Points

Following image preprocessing, most of the interference was significantly reduced. However, the laser stripe remained approximately 8 pixels wide, containing redundant pixel information that impeded the precise extraction of weld feature points. To ensure accuracy, the centerline of the laser stripe was extracted to achieve a single-pixel-width stripe. The gray centroid method is known for its high accuracy and low complexity (Ref. 18) was employed for this purpose. However, due to the U-shaped groove configuration in this study, the laser stripe consisted of nearly horizontal and vertical segments, making conventional row-wise or column-wise scanning unsuitable. Row-wise scanning failed (Fig. 10A), while column-wise scanning achieved precision in horizontal segments but deviated significantly in vertical regions (Fig. 10B). An improved gray centroid method was proposed to address this issue. First, the geometric center method was employed to preliminarily extract the centerline of the laser stripe and determine the normal direction at each point. Subsequently, the gray centroid was calculated for each point by taking k points symmetrically along the normal direction, where k was set to 8. The calculation formula for the improved gray centroid method is given in Equation 12. As demonstrated in Fig. 10C, the improved method accurately aligned the extracted centerline with the stripe's center, demonstrating excellent performance.

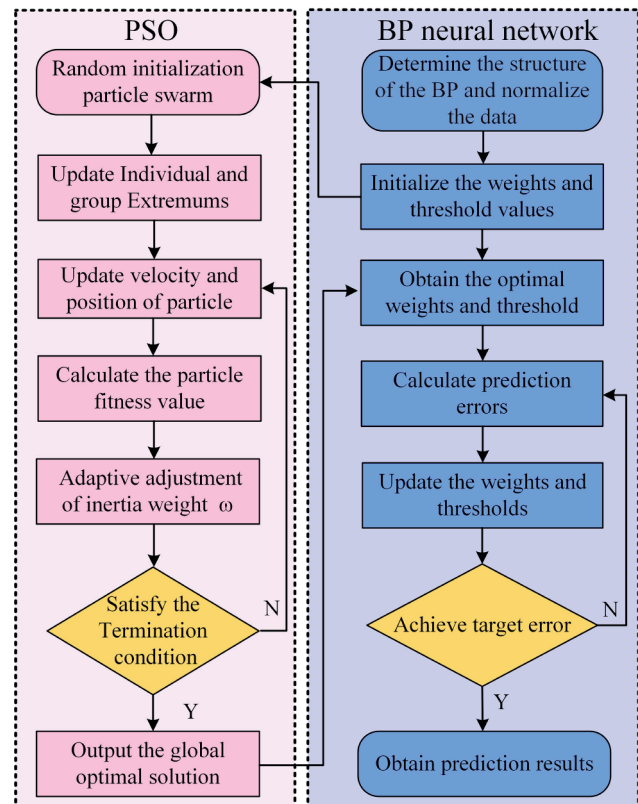


Fig. 14 – Flowchart of the PSO-BP neural network algorithm.

Table 2 – The Partial Data Set for the Developed Neural Network

No.	Welding Position (deg)	Groove Mismatch (mm)	Butt Gap (mm)	Width (mm)	Height (mm)	Welding Current (A)	Welding Speed (mm/s)
1	0	0.5	1.5	3.12	0.71	170	14
2	45	0	2	3.79	0.84	190	11
3	0	0	1.5	3.26	0.72	190	13
4	90	1.5	1.0	3.08	−0.08	240	14
5	45	0	1.5	3.74	0.63	210	10
6	135	0	2	3.86	0.86	210	11
7	180	1	1.5	2.88	0.44	200	12
8	135	0	1	2.8	0.45	210	10
9	90	0.5	0.5	2.55	−0.16	240	12
10	180	0.5	1.5	2.67	0.43	195	11

$$\begin{cases} x = \frac{\sum_{(i,j) \in S} i * P(i,j)}{\sum_{(i,j) \in S} P(i,j)} \\ y = \frac{\sum_{(i,j) \in S} j * P(i,j)}{\sum_{(i,j) \in S} P(i,j)} \end{cases} \quad (10)$$

In this study, the parameters of interest are the butt gap and groove mismatch, which require the extraction of four feature points: G_1 , G_2 , M_1 , M_2 , as shown in Fig. 11. At points G_1 and M_1 , the vertical coordinates of the pixels exhibit a significant difference, while at G_2 and M_2 , the vertical coordinates show a substantial difference. Leveraging this characteristic, this study proposed a groove feature points extraction method based on vertical coordinate differences. The specific principles are as follows:

1. A threshold Δd for the vertical coordinate difference was defined as determined by the magnitude of the vertical coordinate variation at the groove feature points.

2. The absolute difference Δy_i in the vertical coordinates between adjacent pixels was computed sequentially from left to right

$$\Delta y_i = |y_i - y_{i-n}|, i = 1, 2, 3, 4 \dots \quad (11)$$

3. Groove feature point determination:

If:

$$\Delta y_i < d < \Delta y_{i+n} \quad (12)$$

then (x_i, y_i) is identified as a feature point, and the coordinates of M_1 , G_1 are extracted using Equation 7.

If:

$$\Delta y_i > d > \Delta y_{i+n} \quad (13)$$

then (x_i, y_i) is identified as a feature point, and the coordinates of M_2 , G_2 are extracted using Equation 7.

Using this algorithm, the groove feature points were successfully extracted, as shown in Fig. 12. The result demonstrates high precision, accurately identifying the four feature points G_1 , G_2 , M_1 , M_2 .

Development of a Process Database Based on the PSO-BP Neural Network

Establishment of a PSO-BP Neural Network

In welding processes, real-time adjustment of welding parameters relies on an accurate process database. This study utilized a PSO-BP neural network to construct the database, enabling the prediction of optimal process parameters under various welding conditions.

As illustrated in Fig. 13, the neural network structure consists of 3 layers: an input layer, a hidden layer, and an output layer. Input neurons consist of the butt gap, groove mismatch, welding position, and desired height and width of backside reinforcement to achieve high-quality weld morphology. Previous studies have demonstrated that welding current and speed

significantly influence weld morphology (Ref. 19). Therefore, these two parameters were designated as output neurons. The number of hidden layer neurons, determined through repeated experiments and comparison of the minimum errors, was set to 8. However, it is important to note that the BP neural network's random initialization of weights and thresholds often leads to convergence at local optima (Ref. 20). The PSO algorithm, a form of evolutionary computation, can be employed to address this. PSO functions on the principle of optimizing solutions through individual cooperation and group information sharing (Ref. 21). The PSO algorithm was employed to iteratively search for optimal weights and thresholds, thereby replacing the initial weights in the BP neural network. The specific workflow and steps are illustrated in Fig. 14.

According to GBT 31032-2014, the maximum groove mismatch of the groove should not exceed 1.5 mm (0.0591 in.), and the butt gap should be maintained between 0.5 mm (0.0197 in.) and 2.0 mm (0.0787 in.). Based on this standard, various assembly conditions were established, and corresponding welding experiments were conducted, yielding a dataset containing 100 samples for training and testing

neural network models. Among these, 80 samples were used for training, and 20 for testing. Partial experimental data are presented in Table 2. Additionally, to reduce randomness, all data was shuffled before training. To ensure the adequacy of the neural network model, the number of training samples must be sufficient. Consequently, the literature on BP neural network modeling was reviewed, indicating that 80 training samples can achieve high prediction accuracy (Refs. 22–24).

Verification of PSO-BP Neural Network Model

After training, the model's predictive performance was evaluated using three metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), and the Coefficient of Determination (R^2). MAE quantified the absolute deviation between actual and predicted values, minimizing the impact of negative errors. MSE assessed the average squared difference between the predicted and the actual values, reflecting prediction accuracy fluctuations. R^2 indicates the goodness of

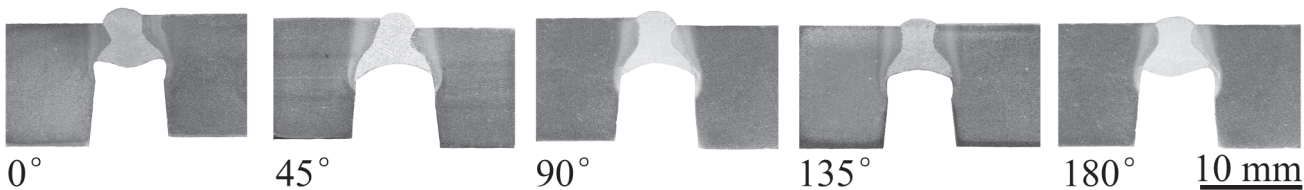


Fig. 15 — Macroscopic morphology of the weld cross section in the verification experiment.

Table 3 — Training Results of the PSO-BP Neural Network Model

	Training Set			Test Set		
	MAE	MSE	R^2	MAE	MSE	R^2
Welding Current	0.0426	0.0078	0.9827	0.0501	0.0053	0.9804
Welding Speed	0.0473	0.0083	0.9783	0.0443	0.0047	0.9811

Table 4 — Validate Experimental Parameters and Results

Welding Position (deg)	Groove Mismatch (mm)	Butt Gap (mm)	Welding Current (A)	Welding Speed (mm/s)	Width (mm)	Height (mm)
0	0.90	1.10	230	12	3.80	0.66
45	1.10	1.6	220	10	3.44	0.51
90	0.70	1.30	210	10	3.50	0.68
135	0.30	0.60	230	13	3.49	0.50
180	0.20	1.50	200	11	3.79	0.68

fit, with values closer to 1 representing better fitting performance. The formulas for these metrics are:

$$MAE = \frac{1}{N} \sum_{i=1}^N \text{abs}(y_i - \hat{y}_i) \quad (14)$$

$$MSE = \frac{1}{N} \sum_{i=1}^N (y_i - \bar{y}_i)^2 \quad (15)$$

$$R^2 = 1 - \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N (y_i - \bar{y}_i)^2} \quad (16)$$

where y_i , $\hat{y}_i$, $\bar{y}_i$ denotes the actual value, the predicted value, and the average of actual values, respectively; and N denotes the number of validating samples.

The evaluation results for the PSO-BP neural network are presented in Table 3. The model demonstrated high reliability and stability in predicting welding parameters, meeting the requirements for welding processes.

To provide intuitive validation of model accuracy, welding experiments were conducted at different positions to assess weld penetration. The assembly accuracy, experimental parameters, and results are shown in Table 4. Figure 15 presents the cross-sectional morphology of the verification weld. The results indicate that all welds are well fused, with no macroscopic defects observed. Furthermore, quantitative analysis revealed that the ranges for backside reinforcement width and height are 3.40 ~ 3.80 mm (0.134 ~ 0.15 in.) and

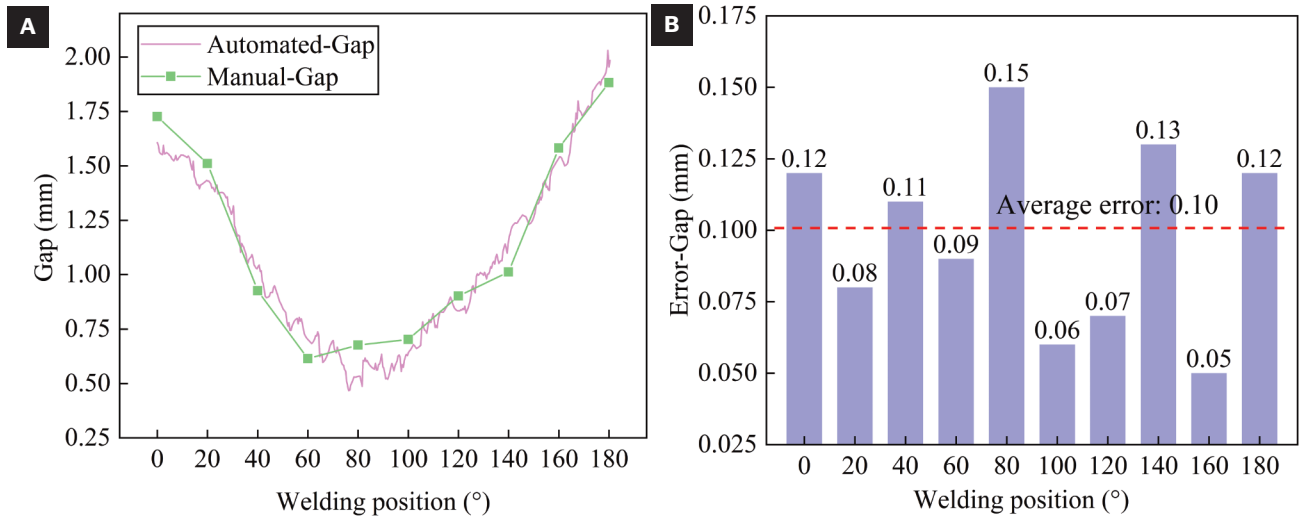


Fig. 16 – Detection results and error analysis of the butt gap: A – Measurement results; B – error analysis.

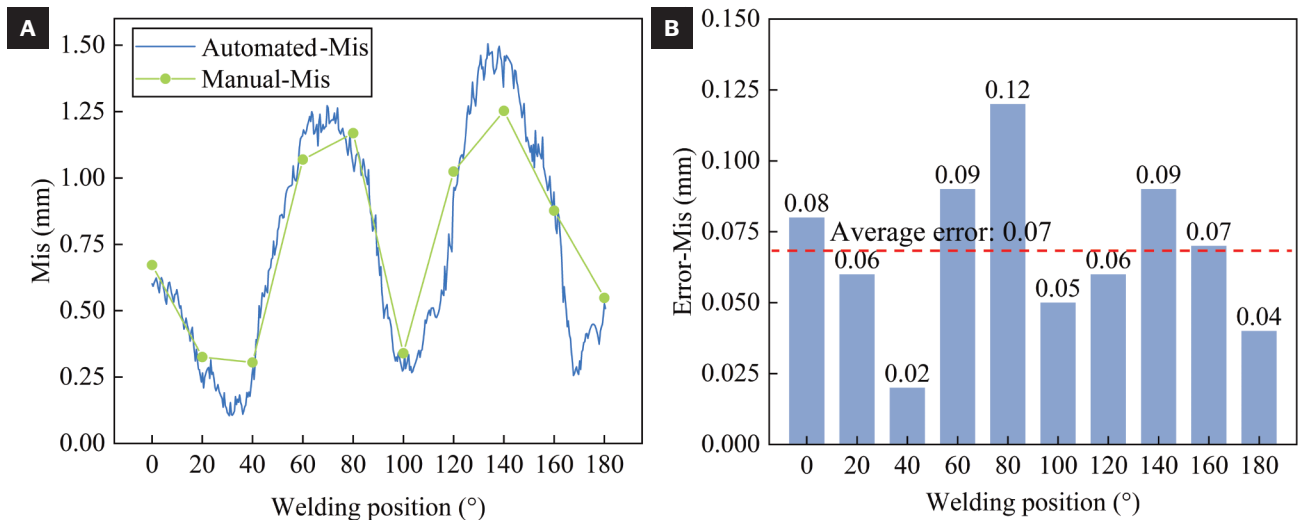


Fig. 17 – Detection results and error analysis of the groove mismatch: A – Measurement results; B – error analysis.

0.50 ~ 0.70 mm (0.0197 ~ 0.0276 in.), meeting the actual oil and gas pipeline welding specifications.

Experimental Results and System Validation

Validation of Visual Sensor Detection Accuracy

The accuracy of the vision sensor was validated by comparing manually measured data with automated detection data.

Due to the impracticality of measuring the butt gap and groove mismatch across the entire girth weld, measurements were taken at 20 deg intervals starting from the 0 deg position, yielding 10 data sets. Manual measurements were performed three times at each position, and the average value was calculated. The results, shown in Figs. 16 and 17, indicate that the butt gap ranged from 0.47 mm (0.0185 in.) to 2.03 mm (0.0799 in.), and the groove mismatch ranged from 0 to 1.52 mm (0.0598 in.). The maximum absolute errors for the butt gap and groove mismatch were 0.15 mm (0.00591 in.) and 0.12 mm (0.00472 in.), respectively, with average errors of 0.10 mm (0.00394 in.) and 0.07 mm (0.00276 in.). These results confirm the high accuracy of the vision sensor.

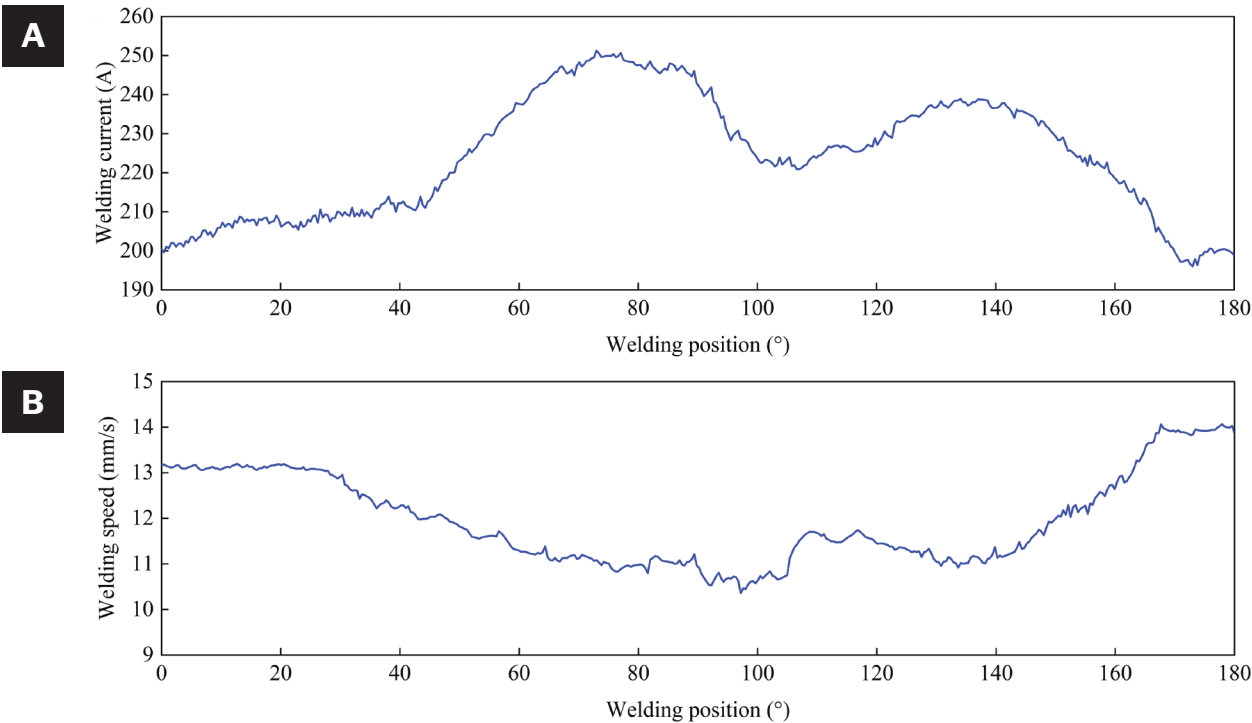


Fig. 18 — The variation sequence of welding parameters changing with welding position during welding: A — Welding current; B — welding speed.

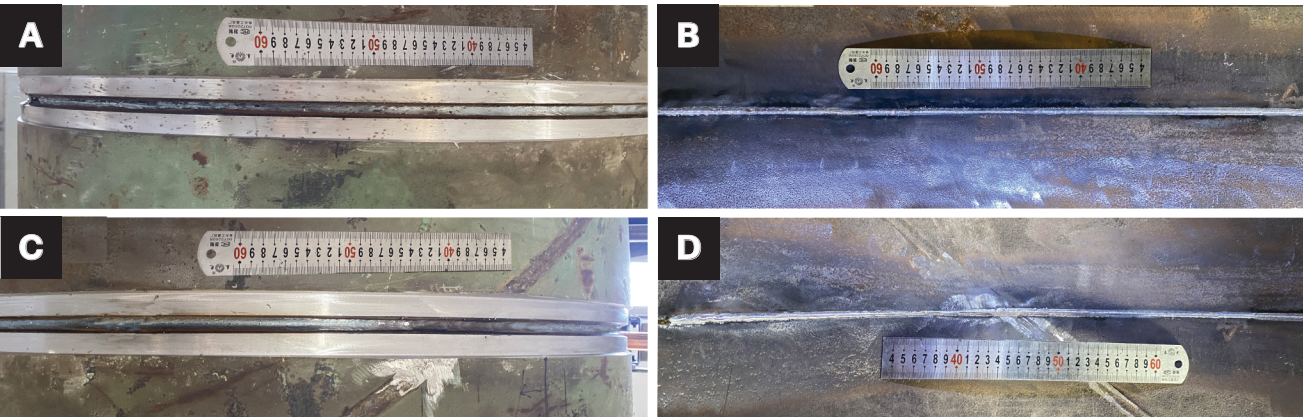


Fig. 19 — Macroscopic weld morphology: A — Front morphology at 0–0 deg; B — backside morphology at 0–90 deg; C — front morphology at 90–180 deg; D — backside morphology at 90–180 deg.

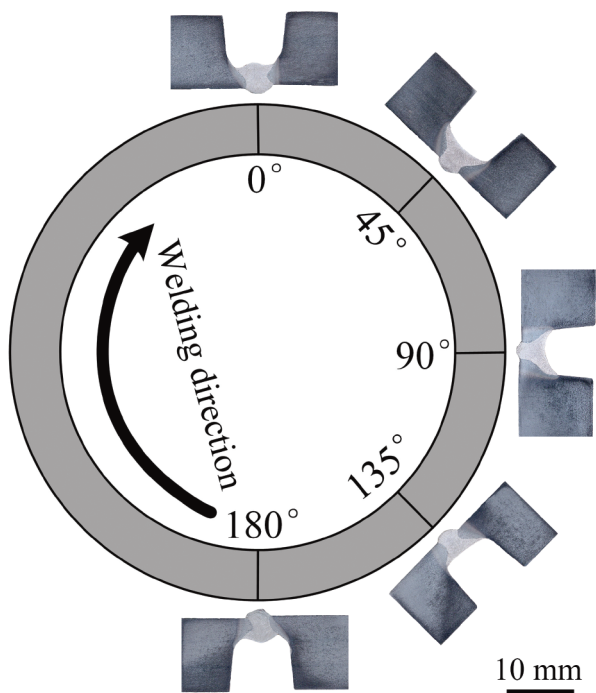


Fig. 20 — Cross-sectional weld morphology at five representative positions.

Validation of Welding Experiment

The automated all-position welding system was employed to conduct all-position root pass welding experiments on pipelines, validating its practical reliability. Figure 18 illustrates the welding current and speed across various welding positions during the welding process. Evidently, the adaptive control system dynamically adjusts the process parameters in real-time to accommodate changes in groove assembly accuracy. The welding current and welding speed range were 190 ~ 250 A and 10 ~ 14 mm/s, respectively. Further, weld quality was subsequently verified. As shown in Fig. 19, the weld exhibited smooth bead shape and size on both the front and back sides and obtained a continuous backside reinforcement. Furthermore, Fig. 20 displays the cross-sectional morphology of the weld at five representative positions (0 deg, 45 deg, 90 deg, 135 deg, and 180 deg). The results indicate good fusion and defect-free welds with distinct backside reinforcement at all positions. Additionally, measurements reveal that the width and height of the backside reinforcement range from 3 ~ 4 mm (0.118 ~ 0.157 in.) and 0.50 ~ 0.80 mm (0.0197 ~ 0.0315 in.), respectively, meeting GB/T 31032-2014 standards. The automatic welding system demonstrated superior welding efficiency, operating at an average speed of 11.6 mm (0.457 in.)/s, representing a 50 ~ 100% improvement over conventional all-position welding technologies documented in previous studies (Refs. 4, 25–27).

It should be noted that this study focused on addressing dynamic fluctuations in welding conditions during all-position root pass welding in pipelines through the development of an adaptive control system for single-side welding with

back formation. This system enables real-time detection of welding conditions and dynamic adjustment of welding parameters. Future work will involve research on automatically compensating for deviations between the welding torch and weld centerline and welding path planning. This will enable the development of a comprehensive adaptive control system and equipment for all-position pipeline welding, integrating root, filler, and cap passes, thus facilitating the application of this research in transnational pipeline construction projects.

Conclusions

Previous research proposed laser-GMAW hybrid all-position welding technology with copper liner coordinated control, demonstrating high welding quality and process robustness. Building on this foundation, the present study investigated this technology's automated implementation and advancement. An adaptive control system for all-position root pass welding was developed for the first time, achieving excellent results. The main conclusions are as follows:

1. An active vision sensor based on line-structured light was established, incorporating a laser stripe centerline extraction and feature point extraction algorithm tailored for U-shaped grooves. This vision sensor demonstrated high detection accuracy, with maximum absolute errors of 0.15 mm and 0.12 mm for the butt gap and groove mismatch, respectively, and average errors of 0.10 mm and 0.07 mm.
2. A PSO-BP neural network model was developed, providing high predictive accuracy. This model predicts optimal process parameters based on welding conditions and desired weld morphology.
3. Validation experiments confirmed that the automated all-position welding system successfully achieved high-quality root pass welding for pipelines with a diameter of 800 mm and a wall thickness of 12 mm across the 0–180 deg range. The weld exhibited excellent formation without defects, with a backside reinforcement width of 3 ~ 4 mm and a height of 0.50 ~ 0.80 mm.
4. Future work will develop a weld seam tracking system to achieve automatic alignment between the welding torch and the weld centerline. Concurrently, research will be conducted on welding path planning for filler passes and cap passes during all-position pipeline welding.

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RONGHAO HAN, XINWANG FANG, HANGE ZHANG, LIMING LIU, and GANG SONG (songgang@dlut.edu.cn) are with the School of Materials Science and Engineering, Dalian University of Technology, Dalian, China. **DAXIN REN** is with the School of Mechanical Engineering, Dalian University of Technology, Dalian, China.