

Zongyao Chen
Zhili Feng
Jian Chen

Key Technologies of Intelligentized Welding Manufacturing

Visual Sensing of Weld Pool Dynamic
Characters and Defect Prediction
of GTAW Process



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Preface

Welding is one of the most important manufacturing technologies. Eliminating weld defects is crucial due to the detrimental effects on the component integrity and safety. Today, welds are made in a prescribed manner—welding conditions such as welding current and welding speed are predetermined based on weld qualification trials. It is very difficult, if not impossible, to proactively adjust in real time the welding conditions to compensate unexpected variations in real-world welding causing the formation of welding defects. Post-weld quality inspections such as ultrasound, X-ray, and dye-penetrant are generally mandatory per code requirement. Repair and correction of the weld defects after the weld is made is time-consuming and expensive, often much more than the cost of welding. Furthermore, undetected weld defects left in the structure are a major threat to the safety and integrity of nuclear reactor structural components.

GTAW is one of the main manufacturing representative technics and has a wide range of applications in the manufacturing industry. This book describes the typical application of vision sensing technology and machine learning algorithm on dynamic GTAW process, one of the key technologies of intelligent welding manufacturing. The development of intelligent automatic welding monitoring system with vision sensing for real-time weld defect detection and adaptive adjustment to the welding process conditions to eliminate or minimize the formation of major defects is presented.

The book is divided into eight chapters. Chapter 1 reviews the related works in the field of defect detection and control using visual sensing during welding. In Chap. 2, the approach of monitoring weld pool surface geometry based on the active vision images is discussed. Chapter 3 describes the adaptive passive vision system to measure the 3D weld pool surface geometry for bead on plate welding. A novel method based on the reversed electrode image (REI) was proposed to calculate weld pool surface height in real time based on simple 2D image. Chapter 4 presents penetration prediction with machine learning approach for bead on plate weld and butt joint weld. The implementation of a closed penetration control system is presented in Chap. 5. Penetration detection was further applied on the U-joint, and the implementation and experiment result is presented in Chap. 6.

Chapter 7 presents the lack of fusion detection in multi-pass welding U-groove joint. Chapter 8 draws the conclusions.

This book is mainly based on the research work done by Zongyao Chen during the Ph.D. study in University of Tennessee, Knoxville. The state-of-the-art technology in computer vision, image processing, and machine learning and its application to detect welding defects, including incomplete penetration and lack of fusion, are presented. These technologies offer the valuable strategies to detect the defects with the non-destructive methods to improve the welding productive. Researchers, scientists, and engineers who working in the field of advance manufacturing can benefit from this book.

Knoxville, TN, USA

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Abbreviations and Symbols

2D	Two dimensional
3D	Three dimensional
ANN	Artificial neural network
ASM	Active shape model
BW	Backside width
DERI	Distance between REI and electrode
IP	Incomplete penetration
LOF	Lack of fusion
Lt	Weld pool trailing length
MAE	Mean absolute error
MSE	Mean square error
PCA	Principal component analysis
PID	Proportional–integral–derivative
REI	Reversed electrode image
RF	Root face
RMSE	Root mean square error
SFS	Sequential feature selection
SH	Surface height
SVD	Singular value decomposition
SVM	Support vector machine
Wt	Weld pool topside width

Chapter 1

Introduction



1.1 Background

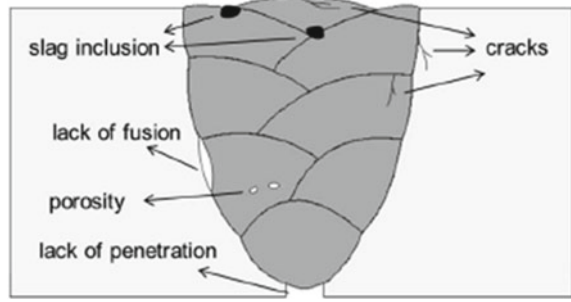
Among the hundreds of welding technics which have been applied to the assembling and joining of metal material, the gas tungsten arc welding is one of the most commonly used technologies for the welding and joining of stainless steel, carbon steel, and aluminum. GTAW (also known as TIG welding) uses a non-consumable tungsten tip with the protection of inert shielding gas to conduct the weld. Currently, this process can be conducted manually or automatically. The manual GTAW is a relatively difficult technic for human welders to master. And longtime exposure to the strong arc and dangerous gases produced during welding is harmful to human welders' health. Hence, the cost of manual welding remains high for many manufacturing industries. Automatic GTAW is performed by a robotic or automatic welding system which highly increased the efficiency of production. The welding parameters such as welding current and welding speed are usually predetermined before automatic welding. However, it is very difficult to proactively adjust the welding parameters in real time to compensate unexpected variations that will cause welding defects.

According to the industrial standards and codes, such as the ASME Boiler and Pressure Vessel Code [1], the typical welding defect can be found in the multi-pass weldment such as incomplete penetration, lack of fusion, porosity, and cracks as shown in Fig. 1.1. The incomplete penetration (IP): It happens when the weld bead does not penetrate the toe of a fillet weld but only bridges across it.

Lack of fusion (LOF): This type of defect usually occurs due to the poor adhesion of the current weld bead to the base metal or adjoining weld beads. Cracks: As the most detriment defects, the cracks can grow under tensile stress resulting in component failure. The locations of cracks can be near and under the weld surface [2].

These defects left in the welding structure are a major threat to the safety of the structural components such as pipeline or the pressure vessel [3]. The detection and repair of these defects are time-consuming and expensive.

Fig. 1.1 Typical defect in a multi-pass weldment



In manual welding, the adjustment can be made by the well-trained welder to produce a high-quality weld without defects. However, the welding quality highly relies on the experience of the human welder which may vary from person to person. Second, some operations in special hazard environments such as the nuclear industry may not be suitable for the human welder to participate in the task. For these reasons, recent years have seen growing demands for developing intelligent welding control systems which can automatically adjust the weld parameters during the welding process and produce a high-quality weld with less defect.

Although, a number of researches have been conducted to develop intelligent arc welding systems to reduce welding defects [4–6]. They are still far from practical application in industry. The major issue is how to detect welding defects during the GTAW process. Since no direct measurement of weld defects in real time is available, indirect measurement should be developed with advanced sensing technology.

1.2 Research on Visualizing Dynamic Molten Pool Characters in GTAW

Many sensing techniques have been attempted to monitor weld quality such as radiographic sensing [7], visual sensing [8, 9], ultrasonic/acoustic sensing [10], and arc voltage and current measurement [11]. In manual welding, a skilled welder determines the weld quality based on his/her observation of the weld pool top surface. Recently, the vision sensing approaches have drawn more and more attention since it can directly monitor the weld pool dynamic characters during the arc welding process. Many researchers [12–17] have been motivated to develop an advanced sensing system to monitor the weld pool, which is an important way to detect the weld defects including incomplete penetration, lack of fusion, and porosity during the welding process.

1.2.1 Weld Pool Image Segmentation

Extracting weld pool boundary from the acquired weld pool images is an important task of visual sensing. Although many image processing algorithms have been developed, the weld pool segmentation task remains challenging due to the following reasons: First, the interference from intensive arc light affects the quality of the weld pool image. Second, the variation of the weld pool boundary can be different from one welding application to another. Third, some of the objects including the electrode and the droplet may hide part of the weld pool boundary. Early researchers applied conventional edge detection methods, which work on images without the presence of strong arc light. As shown in Fig. 1.2, an edge detection procedure proposed by a previous researcher was applied to the aluminum GTAW [18].

A passive vision system was established to obtain the weld pool image without the presence of additional light sources. Edge detection procedures are as follows. First enhance the image with filters [15, 19–21]. The next step is to select the region of interest (ROI) [22, 23] to decrease the processing time and to decrease noise. ROI can be determined automatically or manually. Following is to create the binary image with thresholding [24]. The last step is boundary generation by thinning [20, 21], template matching [21, 24], curve fitting [18], and clustering [24].

In a passive vision system, the arc light that was utilized as the light source may also overwhelm important features in the image. An alternative approach is to use the auxiliary laser light to illuminate the weld pool area [25] which is known as the

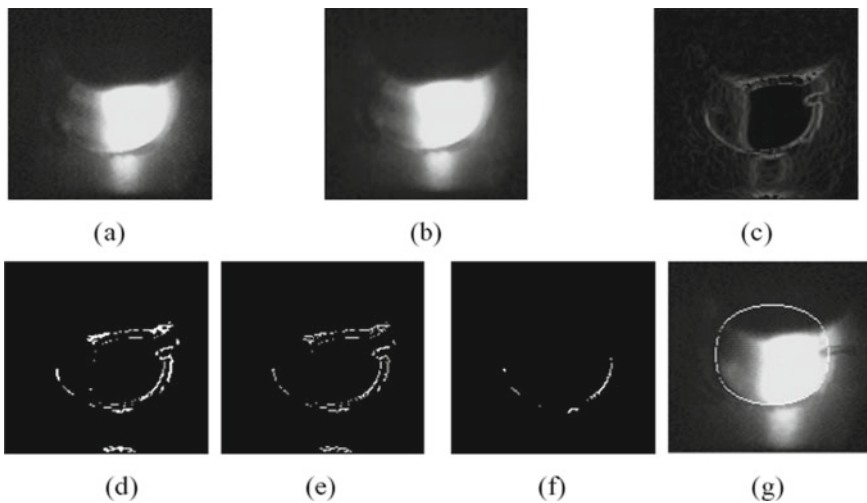


Fig. 1.2 Process flowchart of an entire pulsed image. **a** Original image; **b** median filtered image; **c** sharpened image; **d** transformed threshold image; **e** fined image; **f** image after false edge cutting; **g** image after curve fitting

active vision system. In [26], the weld pool boundary was extracted from laser light illuminated active vision image with sufficient accuracy. Useful features including weld pool width, weld pool length, and weld pool size were calculated and further applied in the adaptive control of welding penetration. However, all these methods using conventional segmentation method to extract the weld pool profile were verified on the weld within a certain range of welding and optical conditions.

In some practical welding conditions, the weld must be performed on designed joint types such as butt joint, V-groove joint, and U-shaped groove joint. The weld pool edge is more difficult to detect inside these joints due to the pool illumination condition inside the welding joint.

Conventional segmentation methods such as edge detection, thresholding, and region-based techniques may be affected by noise and artifacts due to lack of ability of handling prior knowledge. Deformable models, on the other hand, incorporate prior knowledge such that it is more robust to noise and the presence of foreign objects. Deformable models are curves or surfaces that move under certain driving forces. Deformable models can be classified into three categories: active contour models (ACM), level set methods, and active shape models (ASM).

Deformable models have been used for weld pool segmentation in various types of welding processes. Snakes were used in [27] and [28] for extracting the weld pool boundary in GMAW and [9] for laser welding. In [27], the active contour with an application-dependent prior using AdaBoost is proposed to track the weld pool during GMAW. These algorithms were implemented with sufficient accuracy to detect the weld pool contour inside the V-groove joint.

In [29], the level set method was used to detect welding defects with small shapes in images characterized by low contrast levels. The active shape model was used in [30] for weld pool segmentation in Plasma arc welding. Shi et al. [31] used a part-based model for visual detection and localization of the gas tungsten arc weld pool.

1.2.2 Monitoring 3D Weld Pool Geometry

Three-dimensional geometry of the weld pool in principle would provide more comprehensive information for penetration detection [8]. However, extracting the 3D information remains a challenging task for welding automation.

As an active vision method, structural light has been reported in a series of papers for 3D reconstruction of the weld pool [32–36]. In their works, a structured laser pattern is projected onto the weld pool at a certain angle and laser light is reflected on an image plane. A high-speed camera equipped with a bandpass filter is used to capture the reflected laser pattern. The triangulation principle is applied to reconstruct the height information of the weld pool.

An early attempt has been made by Zhang et al. [26] to observe the three-dimensional weld pool surface with a commercial camera whose shutter was synchronized with a short duration pulsed illumination laser. This camera eliminated the

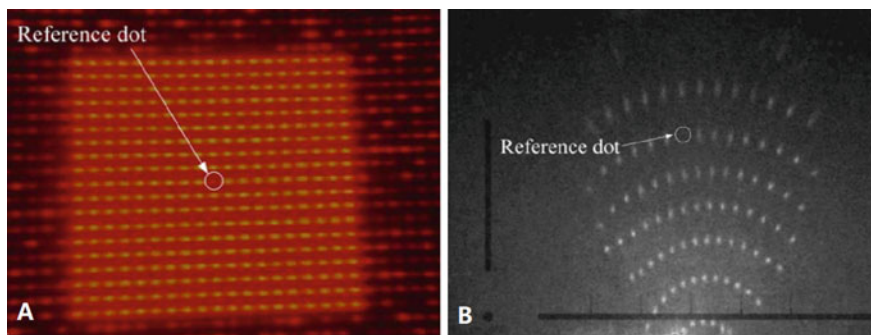


Fig. 1.3 Projection and reflection patterns. **A** Dot matrix laser pattern; **B** Reflection pattern at resolution 480×640

bright arc light from the image, and the two-dimensional boundary of the weld pool was clearly imaged. For three-dimensional weld pool surface imaging, the illumination laser is projected through a frosted glass to form multiple strips. However, due to the difficulty of precise system positioning, the system is only used for 3D observation and not 3D measurement. Moreover, the camera is expensive, and the frame rate can only reach 30 frames per second.

The same group [32–34, 37] further developed a structured light technique to reconstruct the 3D weld pool surface in GTAW. Laser light was projected onto the weld pool surface using a dot-matrix pattern as shown in Fig. 1.3, and the reflected laser light is received on an image plane. The projected points are then matched with the reflected ones to reconstruct the weld pool surface. The reconstruction results and accuracy are quantitatively discussed in [37]. The surface depth of the weld pool extracted from 3D reconstruction is used for real-time control of welding penetration.

The structural light method usually obtains clear weld pool images without interference from arc light. However, it requires an extra light source and is not cost-efficient in the real application. Shape from Shaping (SFS) is a 3D reconstruction technique that recovers the three-dimensional information from variation of shading in a 2D image. It is first introduced by Horn [38] in the 1970s. In this paper, a Lambertian model in Eq. (1.1) maps the surface orientation of each scene point (x,y) to the pixel intensity in the 2D image.

$$I = R(p, q) \quad (1.1)$$

where $R(p, q)$ is the reflectance map of the surface point (x,y) , $p = \frac{\partial z}{\partial x}$, $q = \frac{\partial z}{\partial y}$, z is the surface height, and I is the normalized pixel intensity at each pixel (x,y) .

The inverse problem of recovering surface shape from the known pixel intensity, I , is known as the shape from shading problem [39]. To find the unique solution to this problem, an additional constraint is required. Zhang et al. [40] divided the existing solutions into four groups: minimization, propagation, local, and linear. Zhao et al. [41, 42] first introduced SFS into welding research. The SFS techniques

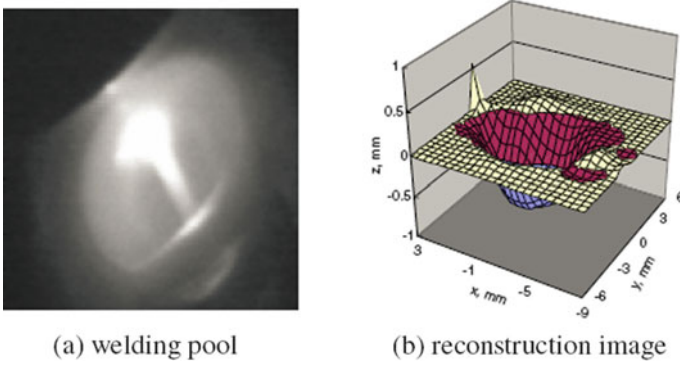


Fig. 1.4 Welding pool image and its 3D reconstruction using SFS technique

applied in welding 3D reconstruction are all based on minimization theory. In his research, the SFS technique is used in passive vision image as shown in Fig. 1.4, which does not require an additional light source. Thus, it is cost-efficient. However, it assumes that the light source is ideal, which is away from the illumination of arc light. Moreover, the weld pool image is interfered with noises, which may cause the image intensity to deviate from the reflection model. In addition, it is difficult to determine the illuminant direction. All these conditions may affect the accuracy of the SFS method.

Stereo vision is another method to extract 3D information from digital images obtained by two or more CCD cameras. Mnich and his colleagues used a stereovision method to determine the 3D shape of the weld pool [43]. By comparing information about a scene from two or more viewpoints, 3D information can be extracted by examination of the relative positions of objects in the two planes. The main error in this system comes from the correspondence process.

1.3 Research on Welding Defect Detection Using Vision Sensing Method

Penetration has been a long-standing issue that affects the safety and integrity of welded structures [4, 44, 45]. Many sensing and measurement technologies have been developed to monitor welding penetration in decades.

The geometry weld pool can is a major source of information related to welding penetration. Extended researches were conducted using the vision sensing approach to detect penetration using the infrared camera or high-speed digital camera [5, 46–50].

In the bead on plate and butt joint welding, the backside weld pool width can directly indicate the penetration. As the full penetration started, a second weld pool surface was formulated on the backside on the base metal. An experiment setup that

can monitor the backside weld pool image during GTAW was developed as shown in Fig. 1.5. The welding penetration can be directly detected from the weld pool image on the backside. However, monitoring the weld pool backside image can be a challenging task in real applications such as welding inside the pipeline.

Monitoring of the weld pool topside image requires less complex experiment setup. As shown in Fig. 1.6, the 2D geometry of the weld pool top surface can be identified from the passive vision weld pool image [41, 42, 49, 51]. Significant differences in weld pool geometry can be found between partial penetration weld

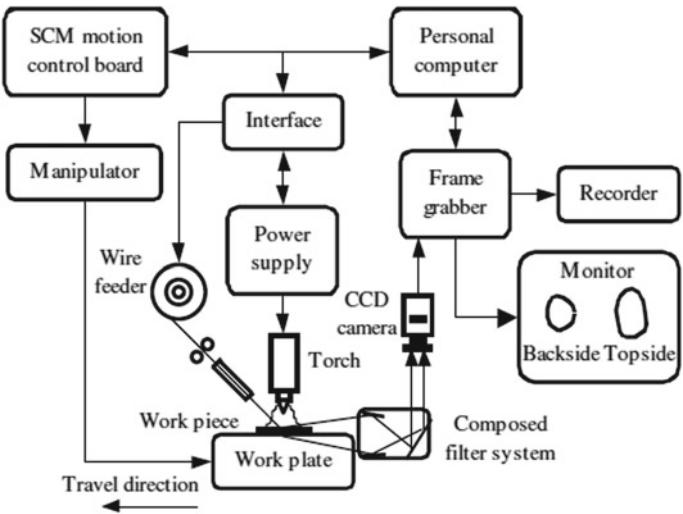


Fig. 1.5 The diagram of experimental system for weld pool monitoring during pulsed GTAW

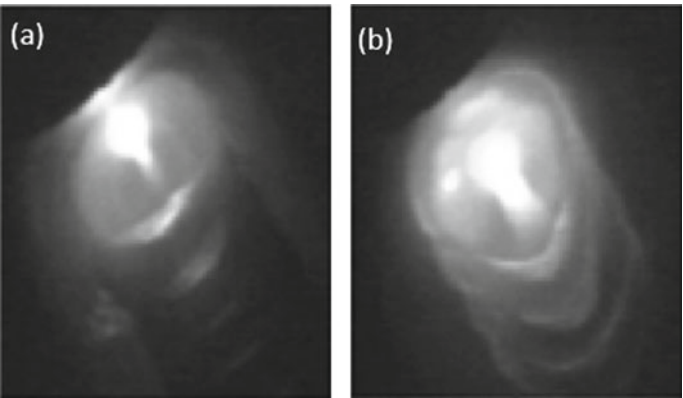


Fig. 1.6 Weld pool image of weld on aluminum alloy. **a** Partially penetrated weld; **b** completely penetrated weld

and full penetration weld [51]. Based on the features extracted from the topside weld pool, the backside weld pool geometry can be calculated using the predicted model.

In reference [26, 36], the geometry characters such as weld pool width and length were measured from active vision weld pool images. The artificial neural network model was applied to predict the backside width. The feedback control system was then established to control the weld penetration in real time. The algorithms to detect 2D weld pool geometry characters are discussed in Sect. 2.1.1.

The weld pool surface height can also be extracted based on the 3D weld pool surface reconstruction discussed in Sect. 2.1.2. In reference [52], the convexity of the weld pool top surface was calculated and used as a feature to detect penetration. In [53], the weld pool surface height was estimated using machine vision method and further related to the penetration during the pulsed gas metal arc welding (P-GMAW) process [54].

The penetration depth of the weld pool is an important variable to describe the welding penetration. However, the depth of penetration cannot be observed from the surface of the weldment. In reference [35, 55], an ultrasonic sensor was applied to detect the welding penetration depth from the received ultrasonic signal. The real-time closed-loop control system was established as reported in previous reference [56].

Recently, the researchers from Kentucky University developed an analytic model to compute the depth of the welding penetration based on the computed temperature distribution and measured 3D weld pool surface which provided a possible way to estimate the penetration depth inside the welding material [57].

Several studies found out that the weld pool oscillation was related to penetration during Pulsed GTAW. In pulsed GTAW, the weld current was changed from pulse current to base current repeatedly which triggers the oscillation. In reference [58–61], the arc voltage was used to monitor the oscillation of the weld pool during the Pulsed GTAW process. The oscillation was found in the voltage signal due to the minor fluctuation of arc length. The oscillation frequency was extracted with FFT transform of the voltage signal. The oscillation frequency was found reduced during full penetration state compared with partial penetration state. The oscillation frequency was also extracted from the reflection of laser pattern using high-speed camera. The method can be further applied to detect penetration in real time [59].

The sound of welding is a useful source of information for sensing. During manual welding, the welder could distinguish a good weld and the bad weld based on the sound. In reference [62, 63], the welding sound was studied through time domain, frequency domain, and wavelet transform. Different features were extracted and was found related to the penetration state of weld.

From the research pattern created by the University of Kentucky, the measurement of arc length can be used to monitor penetration in Pipe welding. The arc length can be measured from the arc voltage [64, 65]. The measured arc voltage increases as the arc length increases. In reference [52, 66], the detection of welding penetration was developed based on the assumption of the weld pool surface dynamic behavior. During the partial penetration stage, arc length and arc voltage were found reduced due to the elevation of the weld pool top surface. The arc voltage was then decreased

as the full penetration was created. The feedback control algorithm was further developed based on this assumption.

1.4 Contribution

This research aims at developing a novel system using multiple visual sensing techniques to monitor the GTAW process. The systematic method was established based on the theory and technology from multiple fields including computer vision, machine learning, welding technology, and control theory. Through these efforts, the huge human labor and maintenance cost can be saved which will significantly increase the quality and efficiency in the manufacturing industry. The specific contributions are listed as follows:

1. Established a new welding monitoring system to obtain the weld pool image during GTAW. The interference of arc was significantly reduced through the narrow bandpass filter and laser-based auxiliary light.
2. Observed the weld pool dynamical behaviors during GTAW process using both active and passive vision methods. Studied and compared the weld pool geometry between partial and full penetration.
3. Developed a new weld pool edge detection algorithm to measure weld pool 2D geometry in real time. The algorithm can determine the optimal camera exposure condition using the support vector machine (SVM) method. It can automatically track the weld pool boundary with sufficient accuracy and robustness.
4. Developed a new method based on a reversed electrode image (REI) to calculate the weld pool surface height (3D information) via 2D weld pool image in real time.
5. Detected welding penetration during autogenous bead on plate welding using a machine learning approach. Features related to 3D weld pool geometry were calculated using real-time software. Welding backside width (BW) was predicted using the regression model. The accuracy of prediction was further improved after feature selection.
6. Implemented a welding penetration feedback control system based on the predicted backside width. Developed the self-tuning PID controller to adjust the welding current in real time. Conducted welding experiments on the workpiece with different thicknesses.
7. Established a new data-driven model to predict the penetration for the root pass weld in U-groove joint. The essential features were extracted from reversed electrode images.
8. Studied the REI under multi-pass welding inside U-groove joint. Established a bagging tree classification model to determine the fusion condition based on the features extracted from reversed electrode images.

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Chapter 2

Monitoring Weld Pool Surface with Active Vision Image



In this chapter, a new weld pool monitoring system was established with laser light illumination, allowing us to observe the dynamic weld pool geometry during welding. The weld pool dynamic behavior under different welding currents and speed ranges was studied. Section 2.1 presents the implementation of an active vision sensing system. Section 2.2 presents the weld pool characters with active vision image; weld pool surface depression can be observed in many experiment conditions. In Sect. 2.3, a Robust algorithm was developed to extract features from images based on the image registration method. Section 2.4 presents the experiment results from the Monitoring Surface condition and welding pool depression under different currents and speeds. In Sect. 2.5, the formation of welding surface depression, welding penetration, and undercut welding defect was further discussed. The conclusion was drawn in Sect. 2.6.

2.1 Visual Sensing System Design

The intensive arc is a major issue to monitor the weld pool dynamic property during GTAW. The intensity distribution of arc radiation during GTAW with argon gas is shown in Fig. 2.1 [1]. The spectrum covers the wavelength from 200 to 1100 nm. It is worth noting that the spectrum between 650 and 950 nm contains the most intensive radiation. Bandpass filter can be used to reduce the arc radiation. Hence, the selection of bandpass filter will avoid this range.

The interference of arc light can be completely suppressed with bandpass filters. An additional method was made to eliminate the rest arc light. One method is to adjust the camera exposure time and aperture to reduce the brightness of the whole image. The arc light can be suppressed by reducing the exposure time and aperture. However, the weld pool may not be visualized if the image is underexposed. Thus, selecting the right camera exposure time and aperture are required to observe the weld pool shape. In many literature, it is called as passive vision method since no

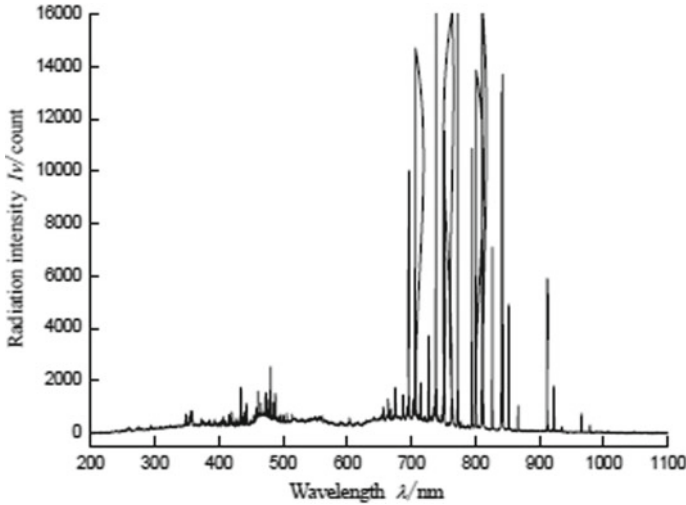


Fig. 2.1 Arc radiation from 200 to 1100 nm

auxiliary light source is used, and the arc light becomes the only light source. The other way is to use laser light as the light source while eliminating the arc light during the weld. The arc light can be almost suppressed with very short exposure time. Meanwhile, the synchronized laser light was projected on the weld pool area. The wavelength of the laser light can be selected to be able to pass the bandpass filter. Such a method was also called a active vision method since the optical system has its own light source. The photo of the experiment system is shown in Fig. 2.2. The welding torch was set perpendicular to the workpieces. Welding direction is toward left.

The laser illumination light was set at the front side of the welding direction of the incident angle of 45° . A high-speed camera was set on the opposite side. A diffuser was added in front of the camera lens to increase the illumination area. Thus, the illuminated area can be increased to cover the whole welding pool. The laser light and digital camera were fixed with the welding torch. To eliminate the effect of arc light, a bandpass filter with specific wavelength was added in the front of the camera lens and only the laser light and only limited amount of arc light could pass through the filter.

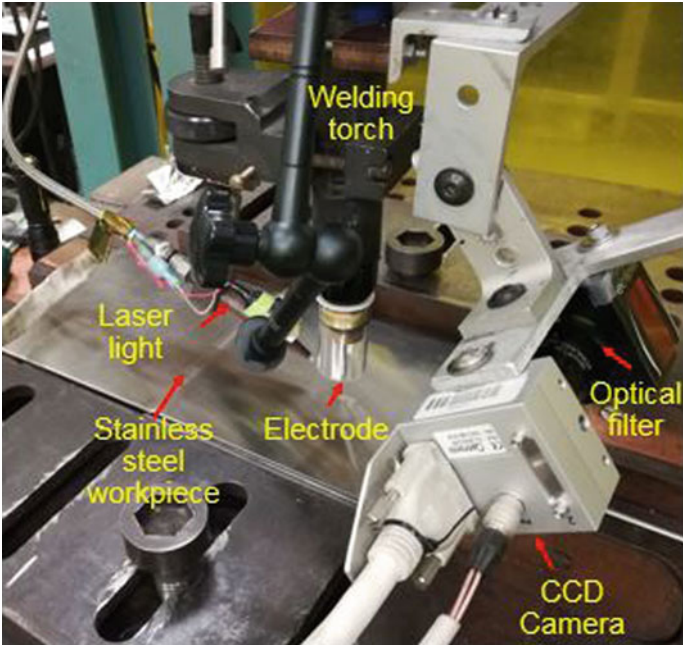


Fig. 2.2 Photo of weld pool monitoring system with laser light illumination

2.2 Weld Pool Characters in Active Vision Image

The typical weld pool image obtained with active vision method was shown in Fig. 2.3. The effect of arc light was suppressed, and the laser light became the major light source. The reflection of the laser light was received by the digital camera on the opposite side of the laser light source. As shown in the diagram of the tracing

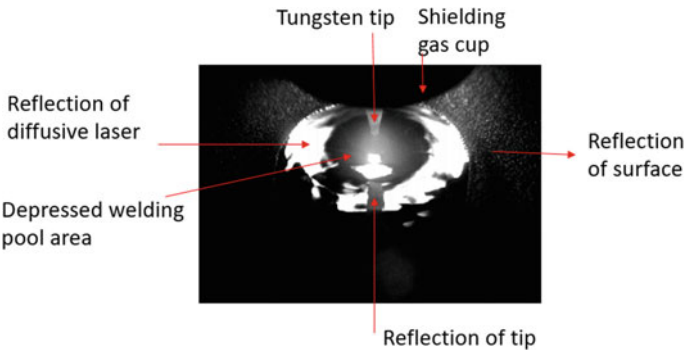


Fig. 2.3 The active vision weld pool image

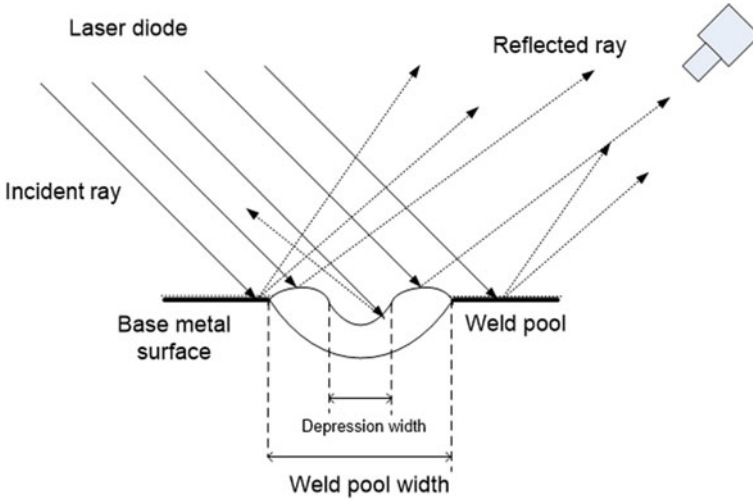


Fig. 2.4 The tracing ray of laser light on the weld pool surface

ray of light in Fig. 2.4, the surface of the metal near the weld pool area produced the diffuse reflection which can be visualized in the image.

The mirror-like weld pool surface produced the specular reflection of the laser light. Previous research indicated that if the weld current is beyond 200 A, the intensity plasma jet impinges, which may produce a depressed area in the central of the weld pool [2]. This area was defined as center depressed area (CDA) in the following description. In Fig. 2.3, the intensity of CDA was much lower than the outside area of the weld pool since the reflection of laser light cannot be captured from CCD camera due to the deep surface depression. A continuous circular shape white area was formed around CDA, which is defined as a light reflection area (LRA). The weld pool surface inside LRA is relatively close to a flat surface. Therefore, the reflection of laser light inside LRA can be captured by CCD camera.

2.3 Weld Pool Image Segmentation

The detection of the weld pool boundary is required to measure the weld pool geometry from the image. An algorithm developed to automatically extract the edge of weld pool from the laser reflection image is shown as follows:

Algorithm Active vision weld pool image segmentation

Input: Image of weld pool, reference location on electrode

Output: ellipsoid contour of the weld pool

1. Locate the center of weld pool based on the reference location
2. Extract binary image.
3. Remove the noise on the binary image using Median filter
4. Reduce the reflection on the material surface using morphological method
5. Generate the ellipsoid contour
6. Using the LRA as the reference image, align the ellipsoid contour to the edge of the LRA

The edges in the original weld pool image belong to the shielding gas cup and the tungsten tip which increases the challenge of algorithm design. The proposed method utilized the edge of the laser reflected area which is close to the weld pool's edge.

As shown in Fig. 2.5, the laser light reflected area (LRA) can be distinguished from the rest part of the image after image banalization. By taking morphological filters can reduce these small dots outside the area of the weld pool.

The weld pool shape is close to an ellipsoid. Based on the LRA, the edge of the welding pool was fitted using an ellipsoid shape contour model with optimal length and width. The LRA plays the most important role in the proposed algorithm. And the algorithm has been validated in many bead on plate experiments. However, due to the dynamic change of LRA under different speeds and currents, the accuracy may be affected. The limitations of the algorithm are listed as follows:

- (1) The algorithm can be applied to the welding condition with low traveling speed.
- (2) The rear edge cannot be detected due to insufficient illumination.

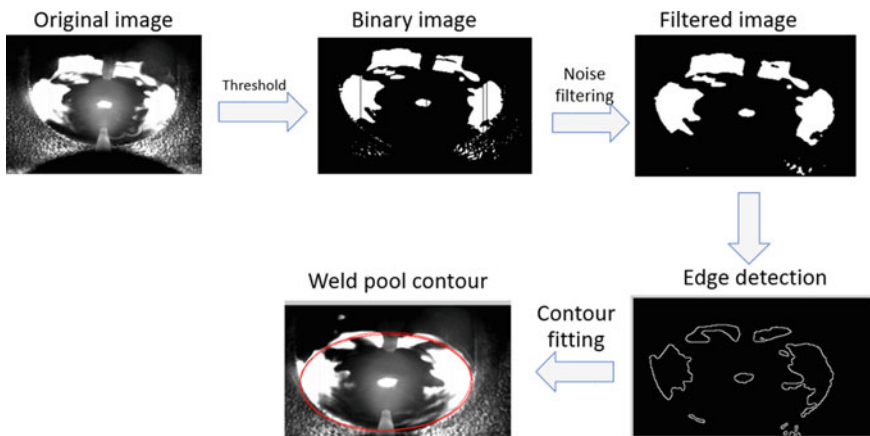


Fig. 2.5 Active vision welding pool image segmentation

- (3) The reflection on the unmelted area may affect the contour detection. Thus, the material surface condition should be consistent.

2.4 Experiment Result

Weld pool geometry was highly related to the current and travel speed. In this section, the bead on plate welding experiments with different currents and travel speeds were conducted on 6 mm SS304 workpiece. The welding voltage was controlled through AVC unit. The welding parameters are listed in Table 2.1. After each weld, the weld beads were sectioned and etched. The penetration depth can be measured after welding.

The weld pool surface depression, surface tension, and weld penetration have been found highly related to the welding current. The weld pool images with different currents at 2 mm/s welding speeding are shown in Fig. 2.6. For the case of welding current less than 200 A, the effect of arc pressure is insignificant, and the area of depression is small. The numerical study indicated that the weld pool surface can be considered as a flat surface if the current is less than 200 A [3–5].

In Fig. 2.6a, b, the LRA occupied the whole weld pool surface, and the whole weld pool area was saturated, which indicated that the flat weld pool surface was produced. In Fig. 2.6c–f, the low intensity of the weld pool center indicated that the weld pool center was depressed with the increase in welding current. The numerical study also found out that the weld pool depression will significantly increase due to the arc pressure for high-current GTAW above 200 A [2–5]. The arc pressure formulates a depression area in the center of the weld pool underneath the electrode. The arc force will also push the liquid pool toward the side of the weld pool area if

Table 2.1 Welding parameters on 6 mm SS304 plate

Parameters	Value
Shielding gas	100% Argon
Gas flow rate	30 CFH
Electrode diameter	2.4 mm
Voltage	12 V
Current	(100, 130, 160, 200, 250, 300, 350, 400) A
Welding speed	(1.5, 2, 3.3, 6.5) mm/s
Arc length	2–5.1 mm

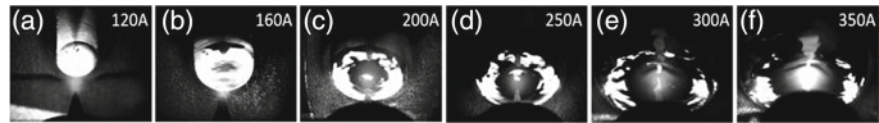


Fig. 2.6 Weld pool images under changing currents with 2 mm/s travel speed

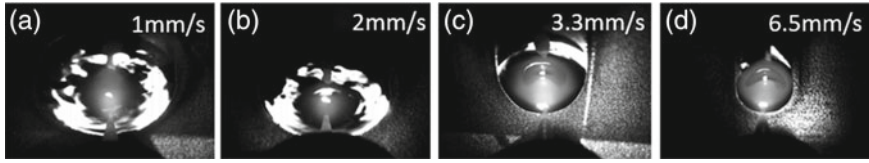


Fig. 2.7 Weld pool image under changing welding speeds with 250 A welding current

the weld is partially penetrated. The simplified relationship between welding current and arc plasma force can be described as follows:

$$F_{\text{arc}} = \mu_o I^2 / 8\pi \quad (2.1)$$

μ_o is the magnetic permeability of a vacuum. The arc force was found approximately proportional to the square of current.

In Fig. 2.7, the weld pool width and the width of the depression area were compared under four different speeds and the same welding current. The volume of the weld pool was decreased as the travel speed increased. The depression can be found in four conditions. However, the depression area at low travel speed (less than 2 mm/s) is located in the center of the pool as shown in Fig. 2.7a, b. As the travel speed goes up, the weld pool width was decreased, and the depression area only occupied the front of the pool. The liquid was pushed toward the rear part of the weld pool and the width of the depressed area is the same as the weld pool width.

2.5 Discussion

2.5.1 Weld Pool Depression

Figure 2.8 shows all the calculated depression area of the weld pool for different travel speeds and welding currents based on the active vision image. The calculation is based on the image pixels of the CDA. The real area can be calculated with calibration. The CDA was found positively related to welding current. For all the welding speeds, the CDA is quite small and can be neglected at current below 160. The flat surface model is valid for a low current condition. As the current increases above 200 A, the CDA is significantly increased due to increase in arc pressure.

For the low welding speed condition at 1.5 and 2 mm/s, the empirical Eq. (2.2) can be calculated based on the experiment data. The linear correlation can be found when the current is above 135 A.

$$A = 0.3813 * \text{current} - 50.238 \quad (2.2)$$

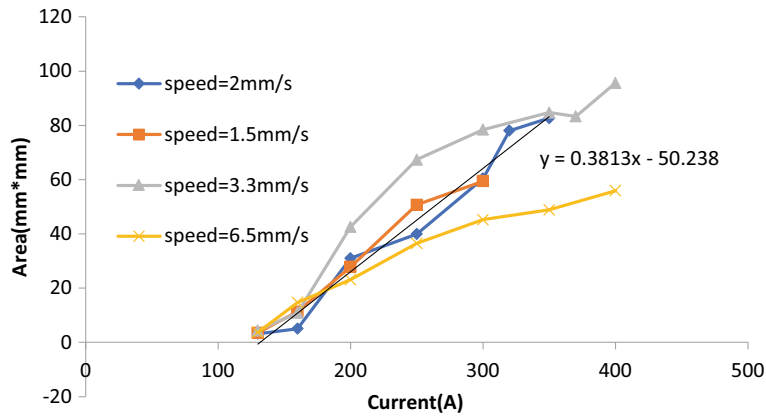


Fig. 2.8 Weld pool depression area

The increasing rate of CDA with the current is significantly between the high-speed welding condition and the low-speed condition. For high-speed welding conditions, the arc pressure may not be the domain factor of CDA. Due to the increase in welding speed, the heat input was reduced, which result in the decrease in weld pool volume.

2.5.2 Welding Penetration

The weld penetration was further analyzed based on the cross-section view of the weld bead. The weld bead width and penetration depth are the major variables to evaluate the penetration. The measured weld bead width vs. heat input is shown in Fig. 2.9.

The calculation of heat input is described as follows:

Fig. 2.9 Weld bead width versus heat input

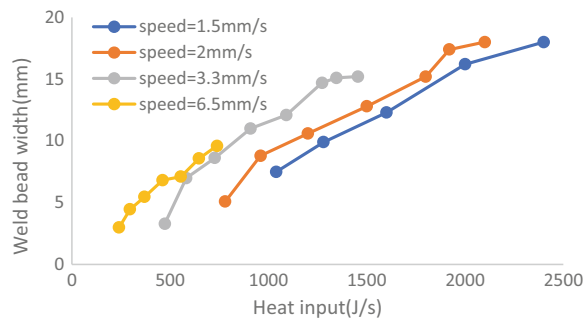
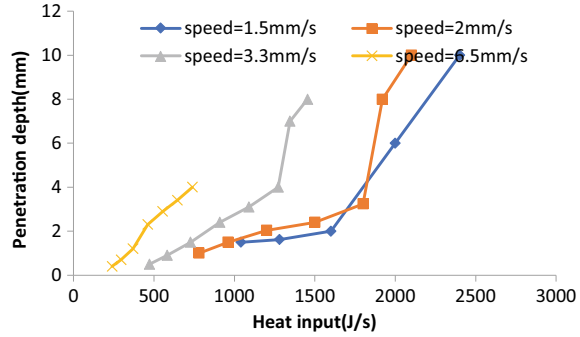


Fig. 2.10 Weld penetration depth versus heat input



$$\text{Heat input} = \frac{\text{Voltage} \times \text{Current}}{\text{Travel speed}} \quad (2.3)$$

Heat input unit (J/s), speed unit (mm/s).

The weld pool width was increased with current and decreased with increase in travel speed. For the same welding speed, the weld bead width linearly increased with heat input. The heat input to produce the same weld width with high-speed welding is less than the low-speed condition.

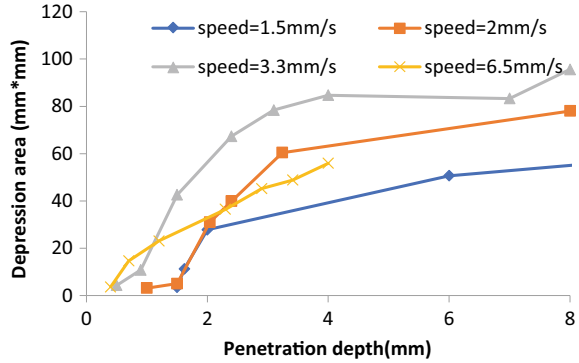
The measured weld penetration depth vs. heat input is shown in Fig. 2.10. For the same welding speed, the penetration depth linearly increased with heat input as the penetration depth is lower than 4 mm. The weld partially penetrated the 6 mm plate. A small increase in heat input changed the partially penetrated weld with 4 mm penetration depth into full penetration (above 6 mm).

In Eq. (2.4), the empirical model was established to estimate penetration depth from welding current and speed. The model was calculated with the least square fitting method based on the experiment data.

$$D = 0.0199 * I - 0.0336 * V - 0.0007 * I * V - 1.5485 \quad (2.4)$$

It is worth noting that the working condition of this model is restricted for the bead on plate weld on a 6 mm SS304 plate without filler wire, and the welding voltage is controlled under 12 V through AVC control unit. It is assumed that the weld is under partial penetration in which the penetration depth is below 4 mm. If the calculated result is above 4 mm, a complete penetration may occur. The heat input to produce the same weld penetration depth using high-speed condition is less than the low-speed condition. The high-speed welding condition also produced a high depth to width ratio compared to low-speed welding. Hence, the high-current and high-speed welding condition is more energy efficient to achieve the same penetration depth compared to welding with low current and low speed. The calculated depression area vs penetration depth is shown in Fig. 2.11. The depression area was increased with penetration depth as the penetration depth was below 4 mm. The increasing rate was decreased as the weld is close to full penetration.

Fig. 2.11 CDA versus penetration depth



2.5.3 Undercut Defect in High-Speed Welding Condition

Although high-speed welding can achieve better efficiency, the welding speed was limited due to the defect of undercut or humping [6]. These defects reduced the integrity of the welding joint. Figure 2.12 shows the cross-section view of the weld bead with an undercut.

The defect was formulated under 6.5 mm/s welding speed and 250 A welding current. The undercut created the sharp groove on the side of the weld bead unfilled by the solidified weld metal. The formation of undercutting may relate to surface tension, arc pressure, and metallostatic pressure. The arc pressure balance model proposed by Yamauchi and Taka [7] explained the formation of the undercut. The schematic of the weld pool side view during welding is shown in Fig. 2.13, there is a static balance between the arc pressure and metallostatic pressure [6]. If the metallostatic pressure is higher than the arc pressure, weld pool liquid exists underneath the arc. Conversely, if the arc pressure is much higher than metallostatic pressure, the weld pool liquid will be pushed toward the tail of the pool. An arc gouging region was formulated underneath the electrode. The undercut was produced when travel speed is too fast,

Fig. 2.12 Cross-section view of the weld bead with undercut

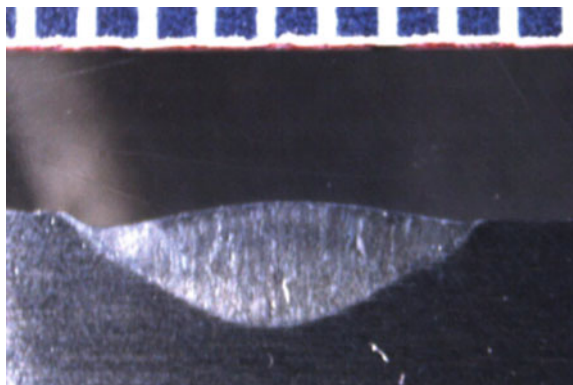
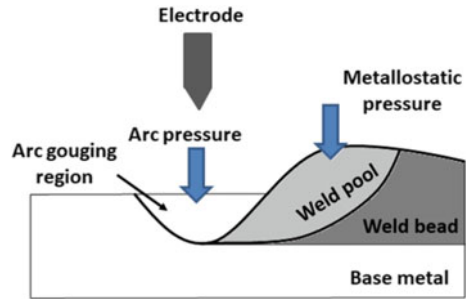


Fig. 2.13 Schematic of weld pool with undercut



and the molten pool failed to fill the arc gouging region before solidification and left a gap at the boundary of the weld bead. The weld pool image with undercutting defect is shown in Fig. 2.7d. Due to the concave shape of arc gouging region, the intensity of this area was much lower than the surrounding area. The liquid existed at the tail of the weld pool. The solidified bead width is less than the width of the weld pool. A gap can be visualized at the trail of the weld pool, which indicates the formulation of the undercut defect.

2.6 Conclusions

In this chapter, a new image acquisition system based on laser light reflection was established to observe the weld pool top surface shape during bead on plate welding. An experimental study was conducted under different welding speeds and current conditions. The following conclusion can be drawn based on the experiment result:

1. The depression on the weld pool surface can be visualized with the reflection of laser light.
2. Arc plasma force creates a depression on the weld pool top surface during the GTAW. The force is proportional to the square of the current. The depression is insignificant for the low current. And the welding pool surface can be considered as a flat surface.
3. A significant depression was produced for the high-current welding above 200 A. The weld pool cannot be considered as a flat surface. For low-speed welding condition, CDA is increased with the current.
4. It was found that the welding penetration depth for partially penetrated welds linearly increased with heat input during the same welding speed. The penetration depth was increased rapidly with the heat input when the weld was close to full penetration. The high-speed welding achieves better efficiency to produce the same penetration depth compared to the low-speed welding condition.
5. The undercut defect was found during welding with 6.5 mm/s speed. Hence, the upper limit of welding speed is required to avoid this defect.

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Chapter 3

Visual Sensing of 3D Weld Pool Geometry with Passive Vision Image



Three-dimensional weld pool surface geometry provides important information for welding defect detection during arc welding. In this chapter, new algorithms were developed to measure the weld pool 3D geometry based on the two-dimensional passive vision images. The passive vision system does not need an additional light source. Compared to the active vision images, the passive vision image does not have interference from laser light reflection and the experiment setup is simple.

However, extracting weld pool geometry from the camera with a passive vision method remains challenging due to the interference of arc light. It was found out that the interference of arc light in the weld pool image can be effectively controlled by adjusting the camera exposure time based on the decision made from the machine learning classifier. Meanwhile, a new method was established to calculate the surface height (SH) from the reverse electrode image (REI). The method presented here established the foundation for real-time penetration monitoring and control.

In this chapter, Sect. 3.1 provides the definition of the 3D welds pool geometry. Section 3.2 describes the method to acquire passive vision images. Section 3.3 described the algorithm to detect 2D weld pool edge with an adaptive passive vision method. Section 3.4 discussed the new method to calculate weld pool surface height based on the REI. In Sect. 3.5, the bead on plate experiment was conducted on a wedge-shaped plate. The weld pool width, trailing length, and surface height (SH) were calculated in real time and the result agrees well with the measurement of weld bead geometry.

3.1 Description of 3D Weld Pool Geometry for Bead on Plate Welding

An illustration of the variables related to 3D weld pool geometry in bead on plate welding is shown in Fig. 3.1. In Fig. 3.1a, the topside view contains 2D information of the weld pool top surface. A tear-drop-shaped weld pool surface is formulated

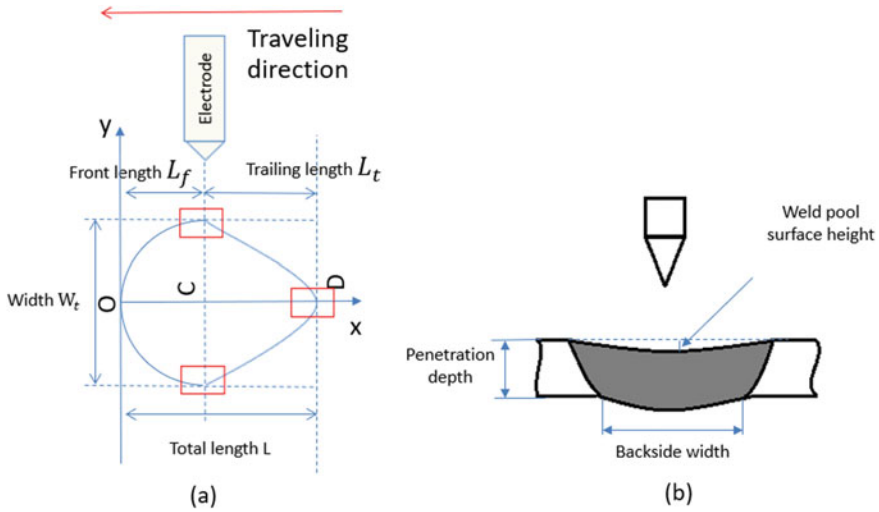


Fig. 3.1 Definition of weld pool geometry. **a** Topside view of the weld pool top surface; **b** the cross-section view of the weld pool

for bead on plate weld, where L is the total length of the weld pool and W_t is the width of the weld pool top surface. Point C is the center of the weld pool which is underneath the tungsten electrode. The distance between OC is defined as the front length L_f . The weld pool trailing length L_t is defined as the distance between points C and D . Welding penetration and travel speed can change the ratio between trailing length and the total length. The tear-drop shape will change to ellipsoid shape if the trailing length is reduced.

Figure 3.1b describes the cross-section view of the weld pool at full penetration condition. The surface height is defined as the distance between the base metal surface and the vertex of the weld pool surface. SH is less than zero as a concave surface is formulated. Weld backside width W_b and root reinforcement on the backside of the workpiece are the direct variables to describe welding penetration.

3.2 Passive Vision Image Acquisition

The configuration of the passive vision weld pool image acquisition system is shown in Fig. 3.2. The welding torch was set perpendicular to the workpiece. The hall-effect current sensor and arc voltage control unit were integrated into the welding system to measure the welding current and voltage in real time. The high-speed digital camera was mounted on the right side of the moving torch following the welding direction. A bandpass filter was placed in front of the CCD camera to reduce the interference of arc light. The camera exposure time and aperture are the important factors to change the image intensity.



Fig. 3.2 Passive vision weld pool image acquisition system

In passive vision mode, no active laser light was applied during welding. The reflection of arc light was used as the major illuminations. By changing the camera exposure time and aperture, the intensity of the passive vision image can be adjusted.

The passive vision images obtained under a different camera exposure time are shown in Fig. 3.3. The exposure time is increased from Fig. 3.3a, b. As shown in Fig. 3.3a, most of the arc light was suppressed at 10 μs exposure time. And the tungsten electrode and the reversed electrode image (REI) were visible in the image.

In Fig. 3.3b, as the weld pool image was obtained at 40 μs , the intensity of the arc was increased, and the REI was blocked by the saturated arc light. The weld pool edge was not visible due to the insufficient illumination. In Fig. 3.3c, as the camera exposure time is increased to 100 μs , the weld pool edge became clearly visible. However, the saturated arc area only blocks the weld pool front edge. The overexposed image is shown in Fig. 3.3d, and the size of the saturated area expands as the exposure time is increased to 700 μs . The intense arc overwhelms the whole weld pool and the weld pool edge is not visible. Therefore, 100 μs is the right exposure time to extract the weld pool profile for this condition. Since the weld pool size varies with different welding parameters, the range of right exposure time is also changed accordingly.

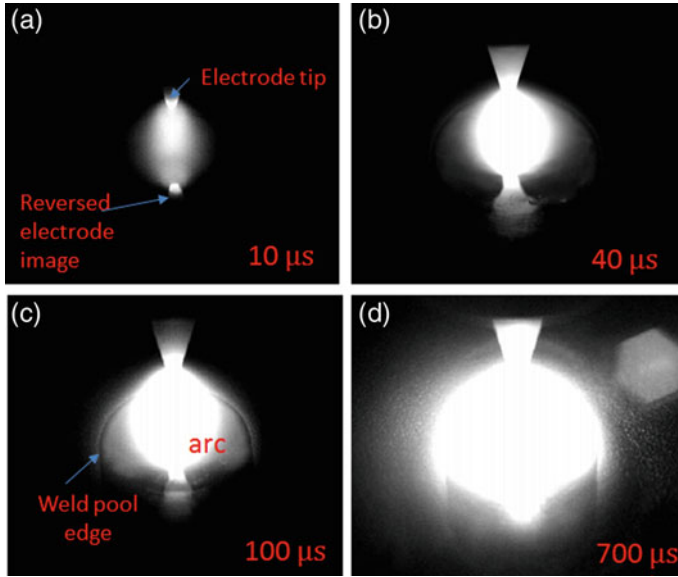


Fig. 3.3 Passive vision weld pool image. **a** Image captured with 10 μs exposure time; **b** underexposed weld pool image; **c** right exposed weld pool image; **d** overexposed weld pool image

3.3 2D Weld Pool Geometry Measurement with Adaptive Passive Vision Method

3.3.1 Conventional Image Segmentation Method

To calculate the weld pool geometry, image segmentation is required to detect the weld pool edge first. Many image segmentation methods have been developed for this task.

In Fig. 3.4, the Canny edge detection was applied on both laser reflection image (a) and passive vision image (d) in the same welding condition. The threshold of the Canny detector was changed from 0.15 to 0.45. The weld pool edge was covered by large amounts of pseudo edge. These pseudo edges belong to the features such as saturated arc area, unmelted surface, and reflection of the laser. Hence, it remains a challenge to distinguish the edge that belongs to the weld pool from other edges.

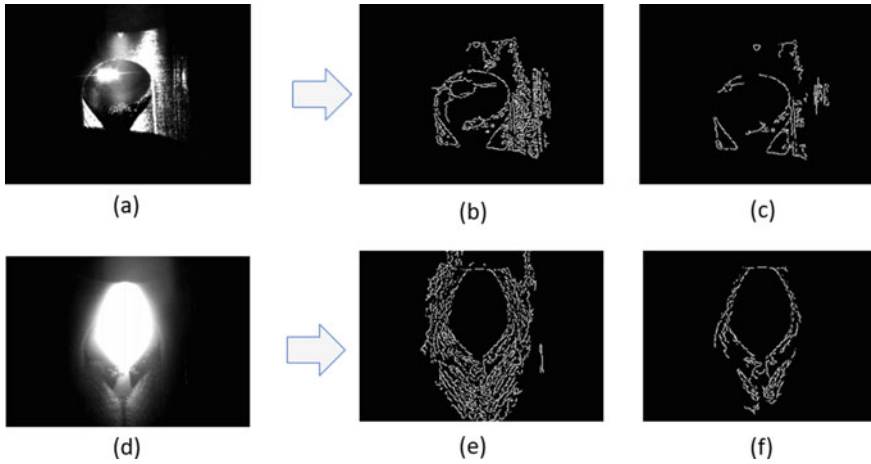


Fig. 3.4 Result of using Canny detectors on active and passive vision weld pool images. **a** The original active vision image; **b, c** result of edge detection with thresholds 0.15 and 0.45; **d** the original passive vision image; **e, f** result of edge detection with thresholds 0.15 and 0.45

3.3.2 Software Framework of Adaptive Passive Vision Method

The flowchart of the software to measure the 2D weld pool geometry is shown in Fig. 3.5. First, the weld pool image was acquired with a given exposure time. Landmark searching was conducted on the weld pool image. The features related to camera exposure conditions were generated based on the distribution of the detected landmarks. SVM classification model was trained to determine the exposure condition of the weld pool image. If the weld pool image was underexposed or overexposed, the camera exposure time will be regulated until the right exposed image was obtained. Once the weld pool image is right exposed, the landmarks can be found on the edge of the weld pool. The weld pool edge was fitted based on the detected landmarks. Then, two-dimensional weld pool geometry such as weld pool width and weld pool length can be calculated with the detected weld pool edges.

3.3.3 Landmarks Detection

The landmarks searching method was mostly used in the shape analysis of the image object. There are two major functions for the landmark detection in this algorithm. First, the useful features related to camera exposure conditions were extracted based on the distribution of landmarks. Second, these landmarks were used to determine the weld pool edge for the weld pool image obtained at the right exposure condition. As shown in Fig. 3.6, the detection of landmarks was conducted along the scanning lines in the vertical and horizontal directions. Each landmark was generated based on

Fig. 3.5 Flowchart of 2D weld pool geometry measurement with adaptive passive vision method

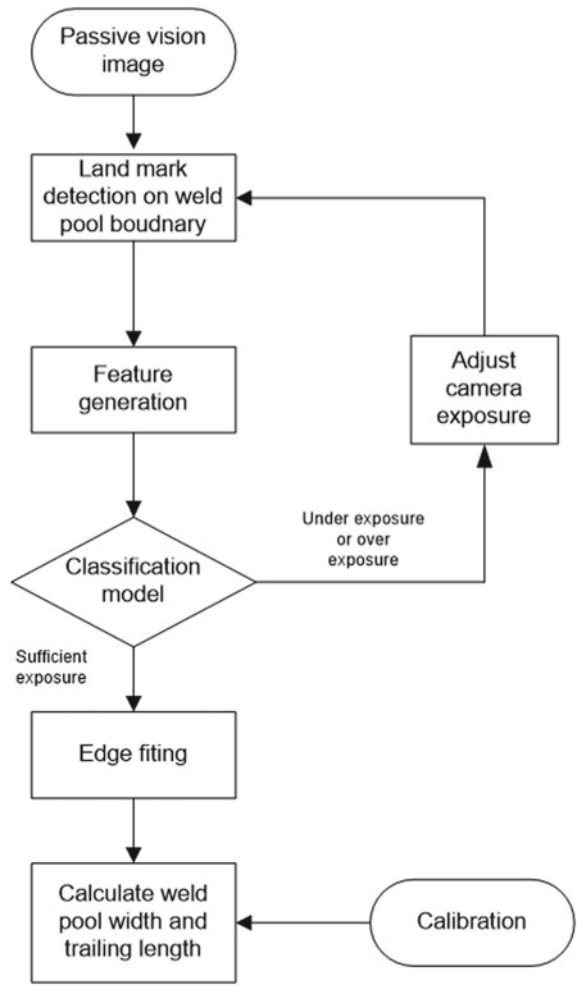
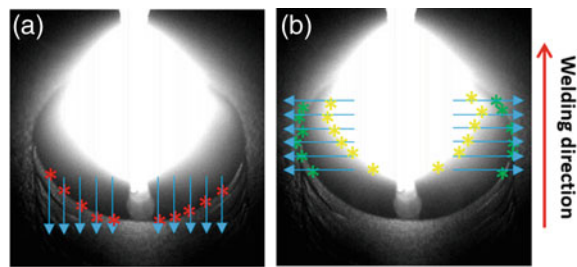


Fig. 3.6 Searching Landmarks on passive vision image



the intensity variation along one scanning line. There are three kinds of landmarks generated from the weld pool images. The red landmarks indicated the maximum intensity gradient along the vertical scanning line in Fig. 3.6a. In Fig. 3.6b, the green landmarks indicated the maximum intensity gradient along the horizontal scanning line, and the yellow landmarks indicated the edge of the saturated arc light area.

3.3.4 Camera Exposure Time Determination Based on SVM

The camera exposure time can affect the accuracy of landmarks detection. As shown in Fig. 3.7a, the green landmarks on the weld pool side edge can hardly be detected correctly due to the insufficient exposure.

In the right exposure condition shown in Fig. 3.7b, the green landmarks were detected on the weld pool side edge. For the overexposed image shown in Fig. 3.7c, the saturated arc light covered the side edge. And the green landmarks were randomly distributed outside the weld pool area. To improve the accuracy of landmarks detection, a support vector machine classification model was trained to determine the exposure conditions into underexposed, right exposed, and overexposed conditions. The camera exposure time in the following capture period will be adaptively adjusted to keep it in appropriate exposure conditions.

In the linear SVM classification problem, a hyperplane was found that separates the data with a maximal margin [1, 2]. Given training vectors $x_i \in R^n$, $i = 1, \dots, m$, where n is the number of feature and m is the number of training data. The label vector $y \in I$ such and $y_i \in [1, 3]$, SVM determines the hyperplane by solving the following optimization problem.

$$\begin{aligned} \min_{\omega, b, \xi} \quad & \frac{1}{2} \omega^T \omega + C \sum_{i=1}^l \xi_i \\ \text{s.t.} \quad & \begin{cases} y_i (\omega^T x_i + \omega_0) \geq 1 - \xi_i, \\ \xi_i \geq 0, i = 1, \dots, l, \end{cases} \end{aligned} \quad (3.1)$$

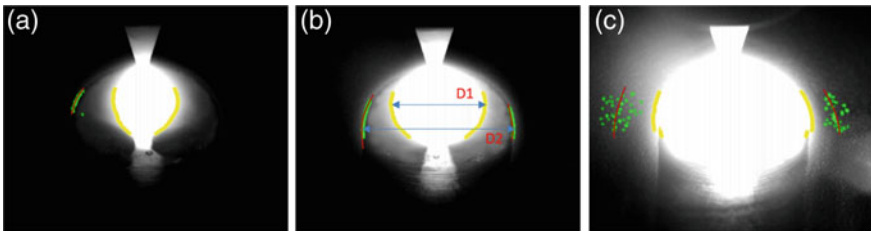


Fig. 3.7 Landmarks detection under three exposure conditions. **a** Underexposed image; **b** right exposed image; **c** overexposed image

Table 3.1 Extracted features from detected landmarks

No	Features description
1	Average intensity of the image
2	Number of green landmarks on left edge
3	Number of green landmarks on right edge
4	D1: width of the saturated area
5	D2: maximum distance between two fitted curves
6	SSR of the curve fitting on left edge
7	SSR of the curve fitting on right edge
8	STD of green landmarks on left edge in y-direction
9	STD of green landmarks on right edge in y-direction

where ω is a weight vector, ω_0 is the threshold, and $C > 0$ is a cost coefficient, which represents a balance between the model complexity and the approximation error. When the constraint conditions are infeasible, slack variables ξ_i are introduced [3, 4].

As shown in Table 3.1, nine features were extracted for the detected landmarks and the original image. Two polynomial curve fittings were applied on the green landmarks as reference. Features 6 and 7 were the sum of squared errors (SSR) of curve fitting. Features 8 and 9 are the standard deviation of the location of the green landmarks in y-direction.

The training database uses 120 weld pool images, including 30% insufficiently exposed images, 30% overexposed image, and 40% completely exposed images. The SVM provides a good generalization for this pattern classification problem. The accuracy of the classification model was 98.6% through five-folds cross-validation.

3.3.5 Experiment Validation

Two bead on plate autogenous welds were performed on the 6 mm-thick SS304 plate. The welding current changed between 100, 120, and 150 A during one weld. The welding voltage was controlled at 11 V through arc voltage control system. Welding speed was 2 mm/s. The Argon shielding gas flow rate was set at 20 CFH. As shown in Fig. 3.8a–c, the weld pool images of the first weld were obtained under constant exposure time at 750 μ s. However, the arc light overwhelmed the weld pool area when the welding current is 100 and 120 A. The weld pool boundary can be observed as the current went up to 150 A. Thus, a constant camera exposure time may not able to obtain high-quality weld pool images when the welding current is changed during the weld.

A second weld was performed with the same welding parameters as the first one. However, the adaptive exposure control algorithm was applied during the weld. The weld pool images and the detected landmarks were shown in Fig. 3.8d–f. The

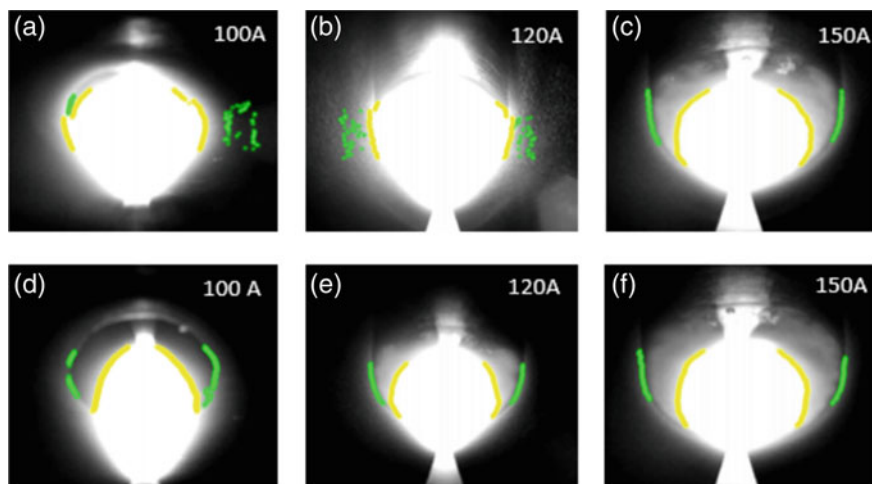


Fig. 3.8 a–c Landmarks detection on the weld pool image obtained with constant exposure time for experiments 1–3; d, e landmarks detection on the weld pool image obtained with adaptive controlled exposure time for experiments 1–3

exposure time was increased with the increase in the weld pool area because more illumination is required to extract the whole weld pool boundary. The green marks were detected on the side edge for all the three currents. Hence, the weld pool images with appropriate exposure condition were obtained using the proposed algorithm. The weld pool boundary can be further extracted based on the green landmarks.

3.4 Monitoring Weld Pool Surface from Reversed Electrode Image

The surface height (SH) of the weld pool top surface provides important information about the state of weld penetration during welding. In this section, a new method was developed to calculate weld pool surface height (SH) based on the reversed electrode image (REI) reflected on the weld pool surface. Due to the specular reflection of the weld pool top surface, REI is visible on the weld pool surface during GTAW. The position of the REI was determined with a robust image processing algorithm. Based on the principle of light reflection, the distance (DERI) between the electrode tip and the REI was related to the SH. By assuming the weld pool surface as a spherical mirror, a reflection model was established to calculate the SH based on the measurement of DERI, arc length, and weld pool geometry. This method was verified with bead on plate welding experiments. The calculated SH index was found positively related to the face reinforcement or depression of the weld bead. Section 4.5 is written based on a paper published by Zongyao Chen, Jian Chen, and Zhili Feng. Monitoring the

weld pool surface and penetration using reversed electrode images. Welding Journal 96, no. 10 (2017).

3.4.1 Acquisition of Reversed Electrode Image During GTAW

The schematic to acquire REI is shown in Fig. 3.9. Considering the weld pool top surface as a spherical surface mirror, a virtual reversed image of the tungsten tip is formulated on the other side of the weld pool due to specular reflection on the weld pool surface. Based on the pin-hole camera model, both images of the electrode and the REI are visible from the camera with an adequate camera posture as shown in Fig. 3.9.

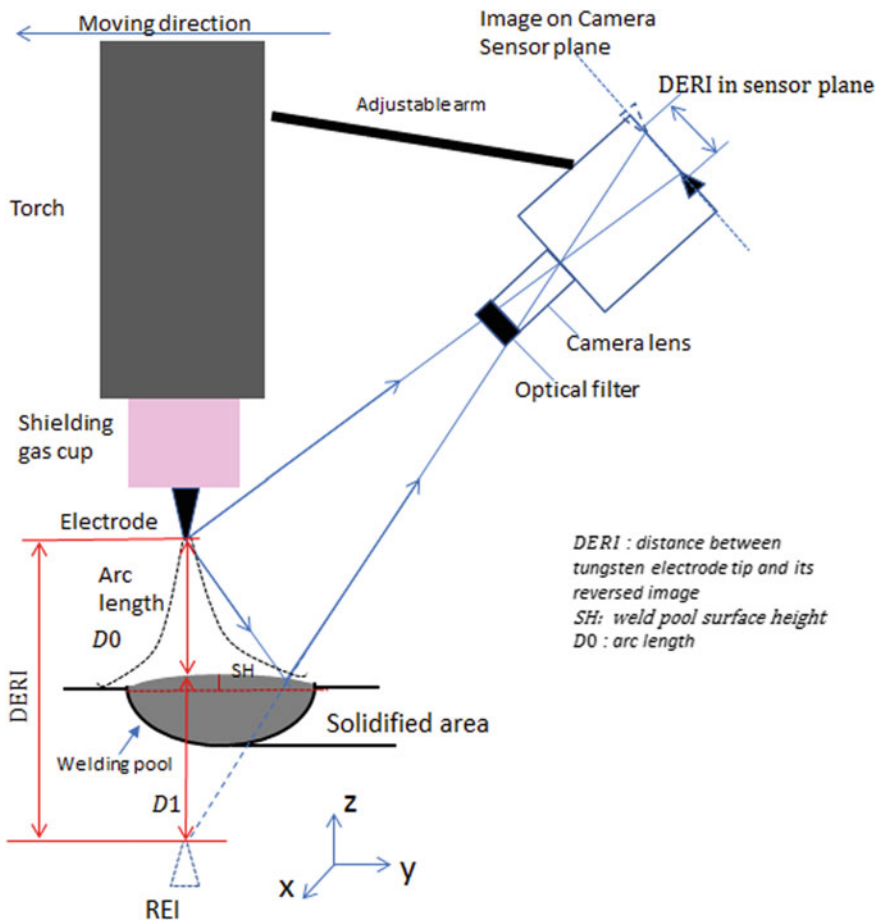


Fig. 3.9 Diagram of acquired REI from rearview camera

The weld pool surface height is defined as the vertical distance from the vertex of the weld pool surface to the workpiece. The distance (DERI) between the electrode tip and the reverse image is defined as

$$\text{DERI} = D0 + D1 \quad (3.2)$$

Object distance, $D0$, is equal to the arc length during welding. As mentioned in previous research [5, 6], the arc length is defined as the distance from the tip of the welding electrode to the adjacent surface of the weld pool. The image distance, $D1$, is the distance from REI to the weld pool surface, which is related to the shape of the weld pool surface.

3.4.2 Reflection Model of Weld Pool Surface

In this research, the sphere-shaped model was used to describe the weld pool top surface. The reflection diagram of two types of spherical weld pool surface is shown in Fig. 3.10. In Eq. 3.3, R is the radius of the sphere and d is the total length of the partial sphere which equals to the width of the weld pool. Thus, SH is calculated as follows:

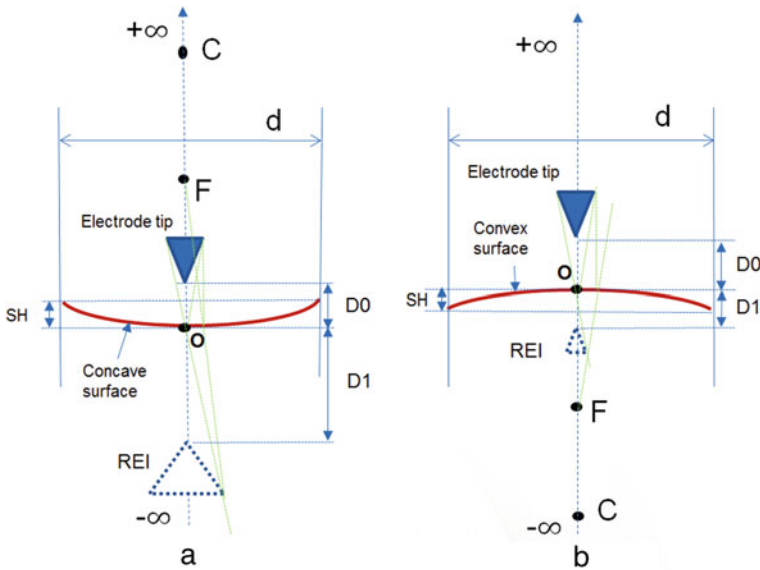


Fig. 3.10 **a** Reflection diagram of concave weld pool surface; **b** reflection diagram of convex weld pool surface

$$(R)^2 = (R + SH)^2 + (d/2)^2 \quad (3.3)$$

In Fig. 3.10, O is the vertex point on the spherical surface. Point C is the center of curvature, where $OC = R$. F is the focal point of the curved mirror. The distance between OF is the focal length, f , which is equal to $R/2$. The concave weld pool has positive SH and the convex one has negative SH.

Based on the reflection law, the virtual image is formed on the opposite side of the mirror since the object distance $D0$ is smaller than the focal length f . The mirror equation describes the relationship between the object distance, $D0$, and the image distance, $D1$, as follows:

$$\frac{1}{f} = \frac{1}{D0} + \frac{1}{D1} \quad (3.4)$$

The object distance, $D0$, is less than the absolute value of image distance $|D1|$ in the concave surface ($SH < 0$ and $F > 0$) in Fig. 3.10a. A magnified REI is formed on the other side of the weld pool surface. For the convex surface in Fig. 3.10b, a focused REI was formulated on the other side of the weld pool. The object distance $D0$ is larger than image distance $|D1|$. When the $SH = 0$, weld pool surface is a flat mirror, $D0$ equals to $|D1|$. The REI image with the same size as the electrode tip is formed.

In the proposed reflection model, the DERI is determined by the height, weld pool width, and arc length. In Fig. 3.11, the simulation curve described the relationship between DERI and SH. Figure 3.11a shows DERI is monotonically decreasing with the weld pool SH at constant arc length ($D0 = 4.5$ mm) and weld pool width ($d = 10$ mm). In Fig. 3.11b, the arc length is the only constant variable ($D0 = 4.5$ mm), and the 3D surface plot describes the relationship among DERI, weld pool SH and weld pool width. The trend of the plot shows that the increase in SH causes a decrease in DERI.

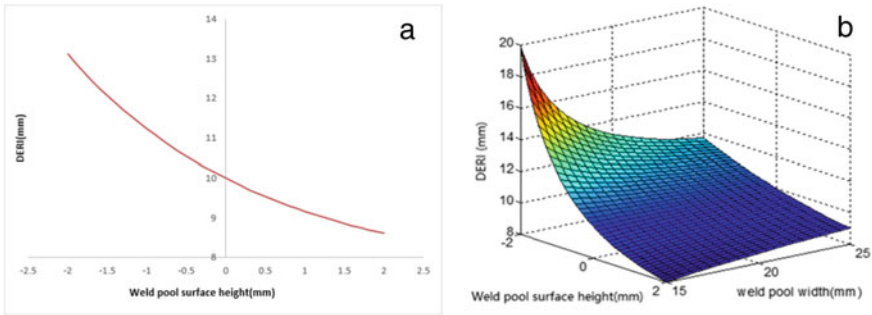


Fig. 3.11 a DERI versus SH; b 3D surface plot of DERI versus SH and weld pool width

3.4.3 Algorithm of Weld Pool Surface Height Calculation

The procedure of SH calculation is presented in Fig. 3.12. Camera calibration is performed to identify the camera parameters before welding experiments. The position of REI was automatically extracted from the image obtained using designed image processing algorithm in real time, and the DERI in real object coordinate system is further calculated. Meanwhile, the arc length was determined from the arc voltage. With the measurement of weld pool width from passive vision image, the index of SH was calculated based on the proposed reflection model. The location of electrode tip Z_A is fixed because the camera is mounted on the moving welding torch. It is challenging to track the location of REI (Z_B) in the passive vision image, due to the disturbance of droplet and arc as shown in Fig. 3.13a. The algorithm was developed to automatically extract Z_B location and compute DERIs from the image sequence based on the ROI method. The region of interest (ROI) was first identified from the binary image shown in Fig. 3.13b. Then a second search was conducted inside ROI to find the location of REI. Based on the proposed algorithm, DERIs can be calculated in real time with the error range within ± 2 pixel.

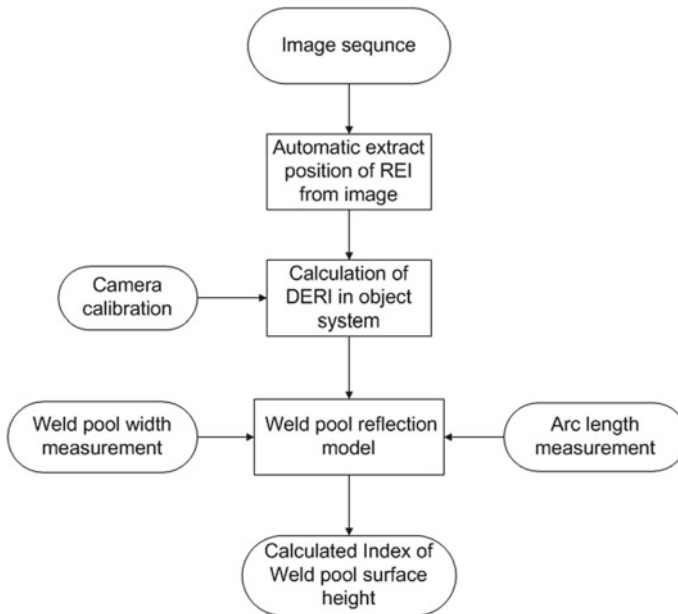
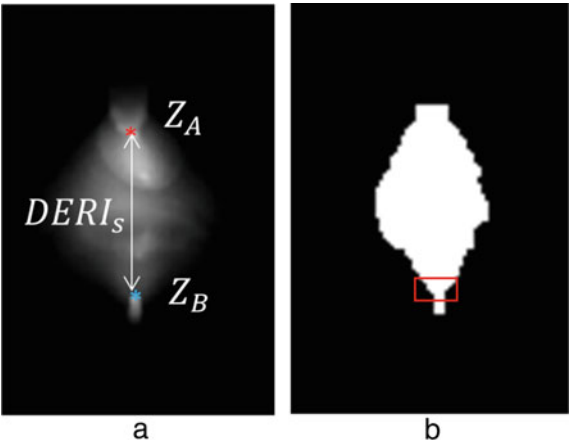


Fig. 3.12 Flowchart of SH calculation

Fig. 3.13 **a** Finding REI location in underexposed image; **b** image binarization and window search



3.4.4 Experimental Validation of SH Measurement

The experiment setup of the weld pool surface monitoring system is the same as we describe in Fig. 3.2. To validate the proposed method to calculate SH, bead on plate welding experiments were conducted on SS304 workpiece with a uniform thickness from experiment 1 to 4. The workpiece was clamped tightly before welding. The welding parameters are shown in Table 3.2. All the welds were conducted at a constant current and welding speed. Experiments 1 and 2 were conducted on a 3 mm-thick stainless-steel workpiece with the same welding current and welding voltage. Welding speed of experiment 1 is much lower than that of experiment 2. The experiments 3 and 4 were conducted on the 6 mm-thick SS304 workpiece. Experiment 3 was conducted with filler wire to increase the convexity of the weld pool surface.

The weld bead cross-section views of cases 1–4 are shown in Fig. 3.14. In case 1, a fully penetrated weld was produced on the 3 mm-thick plate. A concave-shaped weld bead was made on the workpiece. The depression of the weld bead was to -1.1 mm. In case 2, a partially penetrated weld was produced on the same plate by increasing the travel speed. In case 3, a convex weld bead was created on the 6 mm-thick workpiece with filler wire at 25 inch/mm, and the face reinforcement measured

Table 3.2 Welding parameters of surface height measurement

Number of experiment	Material	Thickness (mm)	Current (A)	Travel speed (mm/s)	Voltage (V)	Wire feed rate (mm/s)
1	SS304	3	120	2	11	/
2	SS304	3	120	3	11	/
3	SS304	6	150	2	11	10.6
4	SS304	6	150	2	11	/

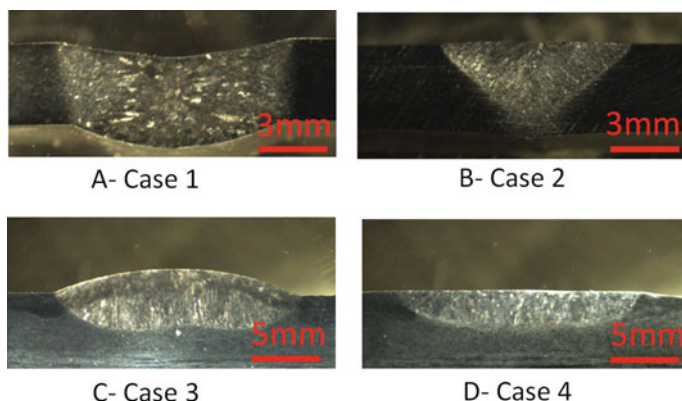


Fig. 3.14 Weld bead cross-section view of experiments 1–4

from the cross-section view was 1.2 mm. The face reinforcement of the weld bead in case 2 and 4 was close to zero.

For the cases 1–4, DERI was calculated from the REI using the developed method as shown in Fig. 3.15. Once the arc started, the weld torch was automatically raised up in 2 s to maintain the arc length. The DERI continuously increased for the first 10 s until weld pool shape became relatively stabled.

The REI images in Fig. 3.16 were obtained at 20 s when the weld pool became stabled. The REI is symmetrical since the shape of the weld pool surface is close to a symmetrical sphere. And the unsymmetrical weld pool surface will cause aberration of the REI image which may affect the measurement of DERI.

From the REI image in Fig. 3.16a, b, the measured DERI was larger in case 1 than that in case 2 due to the decreased weld pool SH. In case 2, the weld pool surface is

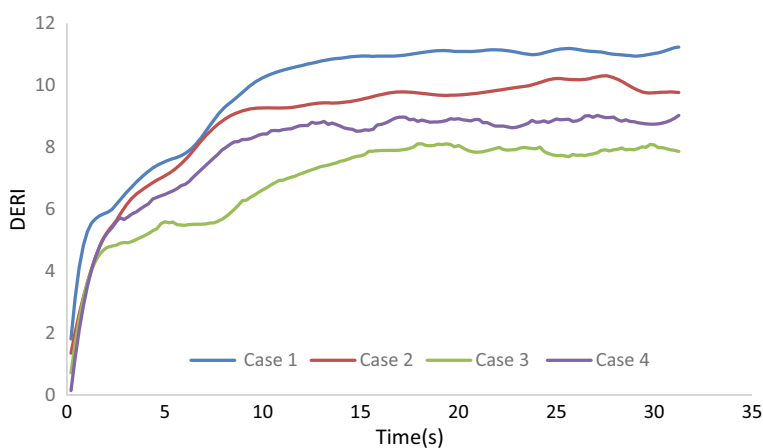


Fig. 3.15 Calculated DERI curve of welds 1–4

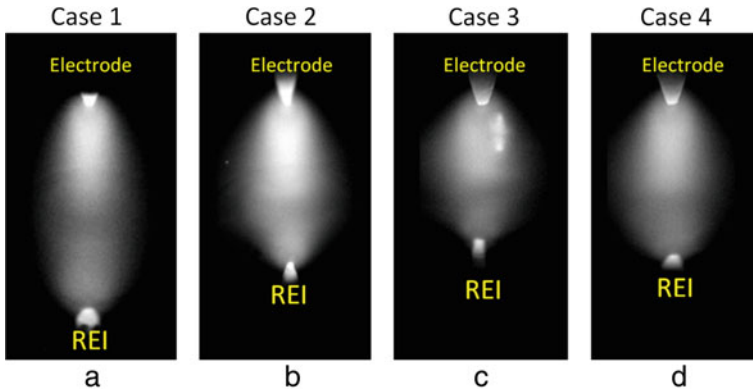


Fig. 3.16 Reversed electrode image of cases 1–4 at 20 s after welding started

close to flat when the partially penetrated weld occurred. The weld pool surface was considered as a flat mirror. The size of REI is close to the image of the electrode tip. As the penetration increased in case 1, a concave weld pool surface was formed in case 1. Compared to Fig. 3.16b, the specular weld pool surface served as a concave mirror which increased the size of REI image and DERI in Fig. 3.16a.

During case 4, the weld pool surface was considered as a flat surface mirror since the convexity of the weld pool was relatively small. In case 3, the convex weld pool with increased convexity was produced by adding filler wire. A small and focused REI image was found in Fig. 3.16c due to the specular reflection on the convex-shaped weld pool surface. Compared with case 4, the increase in weld pool SH caused a decrease in measured DERI in case 3 as shown in the measured curve in Fig. 3.15.

The changing of arc length was another factor that caused the difference in measured DERI in the four cases. The changing of welding current caused the different arc length, which was 4.5 ± 0.32 mm in cases 1 and 2 and 3.6 ± 0.32 mm in cases 3 and 4. Thus, the measured DERI in cases 1 and 2 were largely increased than cases 3 and 4.

Based on the experiment result, we can conclude that DERI decreased with the increase in weld pool SH with the same arc length, which is consistent with the simulation results.

In Fig. 3.17, the index of SH was calculated during a stable stage from 15 to 30 s based on the measured variables, including DERI, arc length, and weld pool width. Consequently, the calculated index of SH was close to the measurement of the weld bead from the cross-section view in Fig. 3.16.

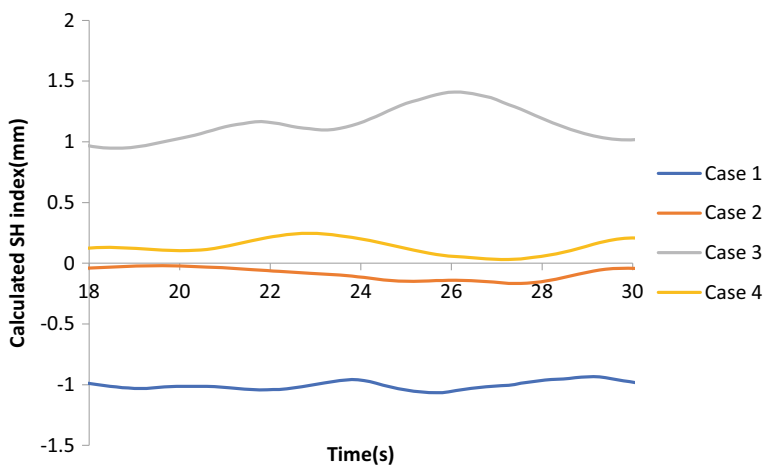


Fig. 3.17 Calculated SH index of experiment cases 1–4

3.5 Validation of 3D Weld Pool Geometry Measurement

The experiment of measuring weld pool geometry was conducted on a wedge-shaped SS304 plate as shown in Fig. 3.18. The weld current remains constant at 120 A. Welding speed was 2 mm/s. The thickness of the plate gradually reduced from 6 to 2 mm.

The topside and backside view of the weld were shown in Fig. 3.19. The blue arrow bar indicated the timeline of the welding process. The weld was started from the 6 mm side end travel to the 2 mm thick side. The topside width of weld bead was increased with the decrease of thickness. The weld pool gradually penetrated the plate as the thickness reduced, which can be seen from the backside.

In Fig. 3.20, cross-section views of the weld bead were collected at four locations (marked in Fig. 3.19) with different penetration conditions: partial, complete, and over-penetration. Figure 3.20a, b shows a partially penetrated weld where the fusion did not extend through the whole material. The face reinforcement of the weld bead in Fig. 3.20a,b is close to zero. Figure 3.20c shows a completely penetrated weld as

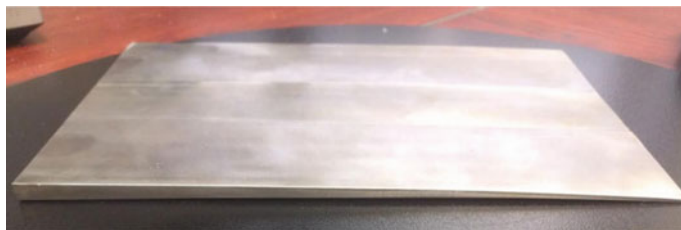


Fig. 3.18 Wedge-shaped SS304 workpiece

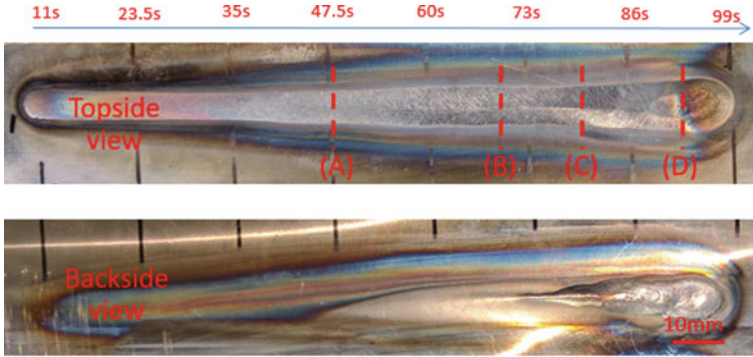


Fig. 3.19 Front view and backside view of the weld bead

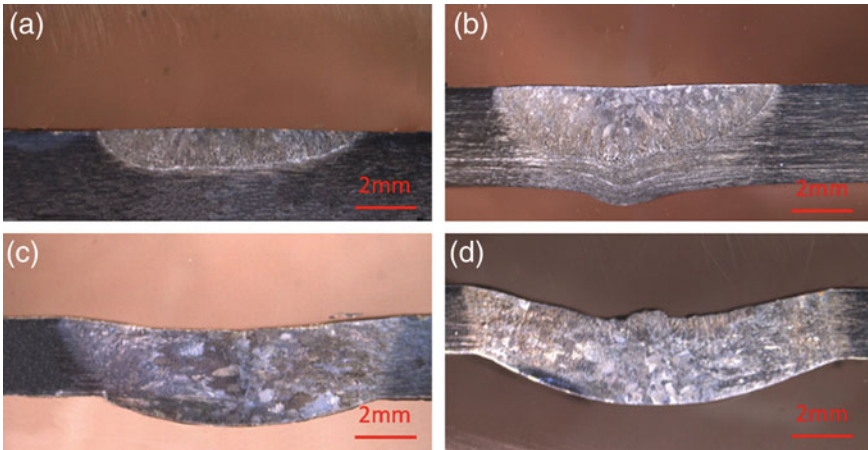


Fig. 3.20 Cross-section view of the weld bead

the fusion extends completely through the plate, and a concave weld bead surface was formulated. The concavity of the weld bead top surface was increased in Fig. 3.20d, as the penetration depth increased. This weld can be considered as over-penetration since the root reinforcement exceeded the $\frac{1}{4}$ of material thickness based on the ASME pressure vessel code [7].

The corresponded REI images obtained with $10\text{ }\mu\text{s}$ were shown in Fig. 3.21. The image was obtained at 50, 70, 80, and 90 s after the weld started. As the penetration increased, DERI was extended, and the area of REI increased, resulting from the concavity of the weld pool surface. The concave weld pool surface serves as a concave mirror to generate an amplified REI. The DERI was increased with the increase in weld pool surface concavity.

The corresponded weld pool images obtained at 50, 70, 80, and 90 s were shown in Fig. 3.22. The weld pool can be visualized with appropriate camera exposure

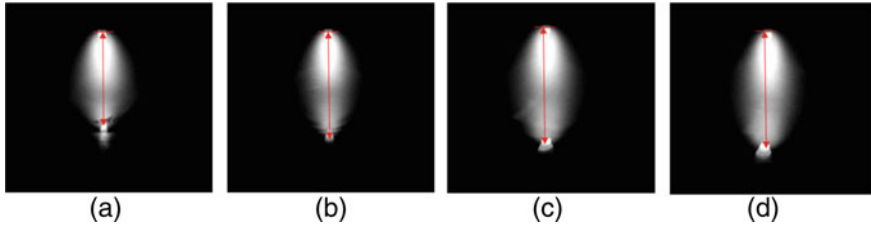


Fig. 3.21 Comparison of DERI from image type I

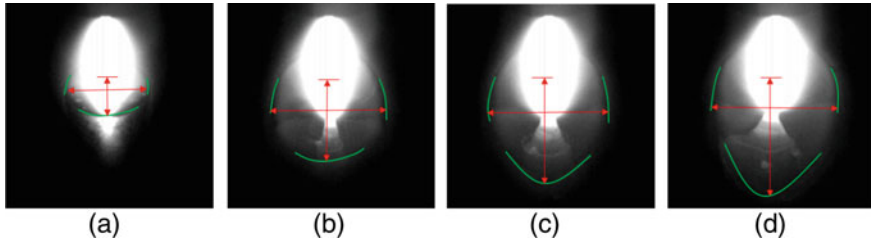


Fig. 3.22 Weld pool edge detection from image type II

time. The 2D weld pool boundary was fitted using polynomial regression with the detected landmarks. An ellipsoid-shaped weld pool can be observed from the rear camera as shown in Fig. 3.22a, b, the weld pool area was increased with the increase in weld penetration. A tear-drop-shaped weld pool was formulated at full penetration in Fig. 3.22c and d.

The distortion of the workpiece was more likely to be created at the end of the weld as the workpiece thickness is reduced. Due to the workpiece distortion, the unsymmetrical weld pool shape in Fig. 3.22d was observed. Thus, a good clamping is required to further reduce this effect.

The weld pool width can be calculated in real time with the proposed algorithm. The algorithm was implemented using MATLAB. The image processing time to extract REI took less than 10 ms per frame. And time consumption for weld pool edge detection was between 20 and 50 ms. The overall time consumption for each period of measurement was below 100 ms which can be applied in real time. Figure 3.23 shows the calculated result of weld pool width w_t and trailing length L_t based on the weld pool edge detection algorithm. The green dots indicate the bead width measured after welding.

The calculated weld pool width is coherent with the bead width on the topside of the workpiece. The mean square error (MSE) between the calculated weld pool width and weld bead width is 0.12 mm. From the curve in Fig. 3.23, the increasing rate of w_t was slow down when the weld is close to complete penetration. The weld pool trailing length continuously increased and exceeded the width of weld pool as the complete penetration occurs. Meanwhile, the weld pool area changed from an ellipsoid shape to a long tear-drop shape with a small rear angle.

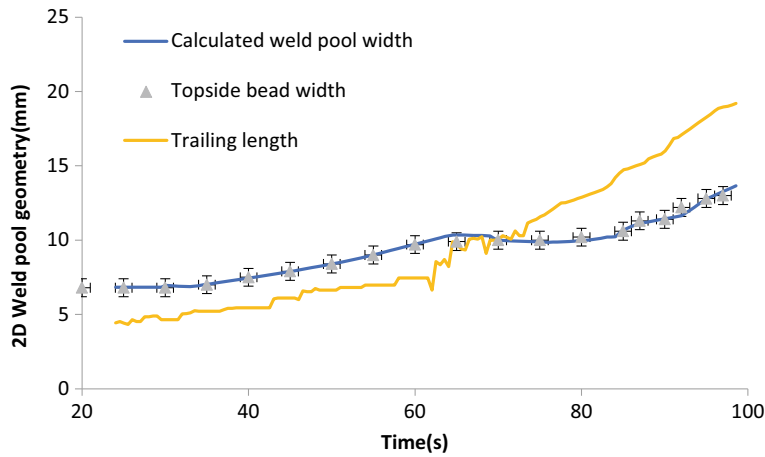


Fig. 3.23 2D geometry measurement of the topside weld pool

In Fig. 3.24, the weld pool surface height was calculated using REI method. The red dot around the curve was the face reinforcement of the weld bead. The calculated SH was close to the measurement of face reinforcement. The standard deviation between the calculated SH and weld bead face reinforcement was 0.25. The decreasing rate significantly increased as the weld became over penetrated. Surface tension becomes the major force to hold the weld pool without burning through. The concavity of the weld pool top surface increased due to gravity.

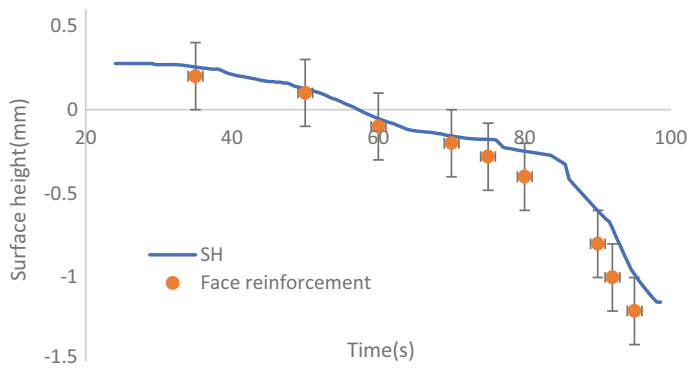


Fig. 3.24 Measurement of weld pool surface height

3.6 Conclusion

In this paper, new image processing algorithms based on adaptive passive vision image were developed to measure weld pool 2D and 3D geometry. Based on the result from the experiment, the conclusions can be drawn as follows:

The SVM classification model can determine the exposure condition of the weld pool image with sufficient accuracy. The camera exposure time was adaptively adjusted to obtain a weld pool image in the right exposure condition. This method increased the robustness and accuracy of the weld pool edge detection. The weld pool surface height can be calculated based on the measurement of DERI, arc length, and weld pool width. Three-dimensional weld pool geometry was measured in real-time welding condition. The calculated 3D weld pool surface geometry from the proposed algorithm was close to the weld bead size. The measured 3D weld pool surface geometry was closely related to the weld penetration.

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Chapter 4

Penetration Prediction with Machine Learning Models



The backside width can be used as the major variable to identify the penetration status of the weld. However, measuring the backside width of the weld usually requires a sensor on the back of the weldment which is not practical in many welding applications. In the manual welding process, the geometry of weld pool top surface geometry is a major reference for welder to determine the penetration condition. This chapter focuses on establishing an artificial intelligent model to predict penetration.

Based on the method discussed in the previous chapter, multiple features can be extracted from the weld pool images. Some important features, including weld pool width, weld pool trailing length, and the surface height, were measured during bead on plate autogenous GTAW. These features can be used as the input for the data-driven model [1].

Supervised machine learning method: linear regression, artificial neural network (ANN), and bagging trees were tested on the database. Through feature importance analysis, we found out that the weld pool width, trailing length, and surface height (SH) played a major role to predict backside width. The performance of prediction was further improved through feature selection. Finally, the trained model was validated with butt joint welding experiments with satisfactory accuracy. The proposed method can be further applied to build real-time closed-loop penetration control system.

4.1 Definition of Welding Penetration

The welding penetration can be determined by measuring the root reinforcement on the backside of the weld. For incomplete penetration condition, the weld metal does not extend through the joint thickness, and the backside width and the depth of root reinforcement are zero.

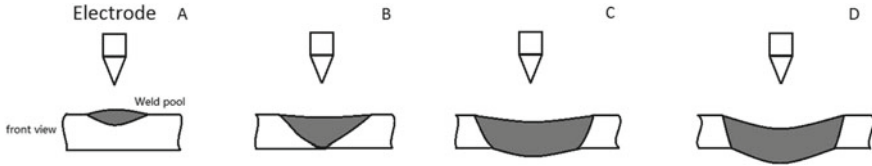


Fig. 4.1 Weld pool surface shape; weld in four penetration states during autogenous GTAW. **a** Partial penetration; **b** critical penetration; **c** full penetration; **d** over-penetration

According to the ASME Boiler and pressure vessel code [1], to conduct a full penetration weld, the backside width of the weld should be above the width of the root gap. And the root reinforcement must be lower than the maximum to avoid over-penetration.

In this research, most of the weld was conducted on the plate or butt joint with no gap. The root gap is close to zero. We classified the penetration into four categories based on the weld pool backside width W_b . Incomplete penetration, $W_b = 0$; critical penetration, $0 < W_b < 2$ mm; complete penetration, $2 \text{ mm} < W_b < 8$ mm; over-penetration, $W_b < 8$ mm.

In this section, the study focuses on the bead on plate welding under low current (<200 A) and low speed (1.5–3 mm/s) level. Under this condition, the depression due to the arc plasma force is insignificant. Previous numerical studies of weld pool behaviors indicated that weld pool surface shape is an important characteristic that is associated with welding penetration [2–4]. As shown in Fig. 4.1, the weld pool surface gradually changed from convex shape to concave shape as the penetration depth increased.

During a partial penetration state, the weld pool surface is convex due to the expansion of the liquid metal. The critical penetration is the transition state from partial penetration to full penetration, when the bottom surface of the weld pool started to form on the backside of the workpiece.

For the fully penetrated weld, the area of weld pool bottom surface is increased, and the surface tension becomes the major force to support the liquid metal.

Therefore, the gravity force forms a concave-shaped top surface of the weld pool. The depression of the weld pool surface is further increased at the over-penetration state as shown in Fig. 4.1d. For filler wire welding, the volume of liquid weld pool increases. Convexity of the weld pool surface for partially penetrated weld can be further increased. And depression of the weld pool surface in the fully penetrated weld can be reduced. The wire feed speed can be another factor that changes the surface height during welding.

Table 4.1 Welding parameters range of training database

Current	100–150 A
Welding speed	1 ~ 2 mm/s
Thickness	2 ~ 6 mm
Argon flow rate	30 CFH
Arc length	3.6 ~ 5.1 mm
Arc voltage	11 ± 0.2 V

Table 4.2 Description of Input features

Abbreviation	Description
I	Welding current
w_t	Topside weld pool width
L_t	Weld pool trailing length
DERI	Distance between electrode and the REI
$D0$	Arc length
SH	Weld pool surface height
V	Welding speed
R	Ratio between weld pool width and length

4.2 Data Collection

Welding penetration is affected by welding parameters such as welding current, welding voltage, arc length, gas flow rate, and workpiece thickness, which should be wisely selected to cover a wide range of welding conditions for building the regression model. In this paper, the welding voltage is set constantly at 11 V by arc voltage control unit during the experiments, and the argon shielding gas flow rate was set at 30 CFH. The training data includes 1423 instances obtained from 12 trails of weld with different parameters. The range of the welding parameters is shown in Table 4.1. For each dataset, eight input features, as shown in Table 4.2, were used and the predicted output is backside width W'_b .

4.3 Evaluation Criteria

The performance of the regression model is evaluated by root mean square error (RSME), mean absolute error (MAE), and R^2 .

The RSME and MAE calculate the difference between the predicted value W'_b and the real backside width W_b . The equation to calculate RSME is given by

$$\text{RSME} = \sqrt{\left(\sum_{i=1}^n (w'_b(i) - w_b(i))^2\right)/n} \quad (4.1)$$

The mean absolute error (MAE) errors are defined as follows:

$$\text{MAE} = \sum_{i=1}^n (|w_b'(i) - w_b(i)|/m) \quad (4.2)$$

The calculation of R^2 is shown as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^n (w_b(i) - \bar{w}_b)^2}{\sum_{i=1}^n (w_b'(i) - \bar{w}_b)^2} \quad (4.3)$$

$\bar{w}_b$ is the mean of the target data w_b , i is the index of the dataset, and n is the total number of instances. The RSME and MAE indicate the accuracy of the regression model. A high RSME or MAE value means the model may suffer from underfitting or the features in the regression model are insufficient to predict the backside width. R^2 indicated how well the variables in the selected features subset are correlated to the target.

4.4 Linear Regression for Penetration Prediction

4.4.1 Linear Regression Model

The linear regression is one of the commonly used supervised learning models. In previous research, the 3D weld pool geometry characters were used to predict weld penetration by applying the least square fitting on a linear model.

The linear model to estimate the backside width $\hat{w}_b(i)$ takes the form as follows:

$$\hat{w}_b(i) = \theta_0 + \sum_{j=1}^p \theta_j x_j(i) \quad (4.4)$$

where p is the total number of the input features, i is the index of the dataset, and θ is the coefficient of the linear model. The coefficient of the model is determined by minimizing the cost function given as follows:

$$J(\theta) = \frac{1}{2} \sum_{i=1}^m \left[\sum_{j=0}^n \theta_j x_j(i) - w_b(i) \right]^2 \quad (4.5)$$

where m is the total number of the datasets, and $x_0 = 1$.

The value of the θ which minimizes the cost function can be calculated by the normal equation:

$$\theta = (X^T X)^{-1} X^T W_b \quad (4.6)$$

where $X = \begin{bmatrix} 1 & x_{11} & \cdots & x_{1p} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & x_{n1} & \cdots & x_{np} \end{bmatrix}$.

The performance of the linear regression model can be evaluated by RSME, MAE, and R-square which are described in Sect. 4.3.

4.4.2 Feature Selection

All the eight features can be used to build the prediction model. However, some of the variables may not correlate with penetration. Sequential forward feature selection (SFS) helps to identify the useful variables in the model. The procedure of SFS is described in algorithm 3.

Algorithm 3 Sequential forward feature selection

Input: Database with eight features

Output: Selected feature subset

1. Conduct five-folds cross-validation using one feature. Find the feature $\{x\}$ which produces the best prediction accuracy using feature $\{x\}$ as the initial subset.
2. K is the number of features in the current subset. Sequentially add the other feature into the subset and conduct five-folds cross-validation test on the dataset.
3. Find the optimal feature subset with $k + 1$ features which provide the best accuracy for the feature subset.
4. If the accuracy of using feature subset with $k + 1$ features is better than all feature subset with k features, then $k = k+1$, go back to step 2; If not, the k th feature subset becomes the final output.

33 features subset were tested based on the SFS method. The performance of 33 feature subsets is shown in Table 4.3. The bold values indicated the feature subset which has the best performance among the feature subsets with the same number of features. For example, the first eight subsets shown in the top four rows of the table contain only one feature. The subset with L_t has the highest R-square value and the lowest RMSE and MAE errors. Thus, it was selected as a permanent feature. The

Table 4.3 Result of the sequential forward feature selection

Feature subset	I	w_t	L_t	DERI	$D0$	SH	v	R
RMSE	4.29	2.87	2.04	3.79	4.3	2.64	3.91	4.07
R^2	0.08	0.59	0.79	0.28	0.08	0.65	0.24	0.17
MAE	3.64	2.33	1.639	3.3	3.65	2.17	3.52	3.3
Feature subset	I, L_t	w_t, L_t		DERI, L_t	$D0, L_t$	SH, L_t	V, L_t	R, L_t
RMSE	2.87	1.75	/	1.995	2.006	1.91	1.86	1.85
R^2	0.59	0.85	/	0.8	0.8	0.82	0.83	0.83
MAE	2.3	1.38	/	1.65	1.63	1.56	1.51	1.43
Feature subset	I, w_t, L_t			DERI, w_t, L_t	$D0, w_t, L_t$	SH, w_t, L_t	v, w_t, L_t	R, w_t, L_t
RMSE	1.75	/	/	1.73	1.755	1.754	1.71	1.759
R^2	0.85	/	/	0.85	0.85	0.85	0.85	0.85
MAE	1.38	/	/	1.37	1.3804	1.38	1.34	1.38
Feature subset	I, v, w_t, L_t			DERI, v, L_t, w_t	$D0, v, w_t, L_t$	SH, v, w_t, L_t		R, v, w_t, L_t
RMSE	1.71	/	/	1.69	1.71	1.7	/	1.71
R^2	0.85	/	/	0.86	0.85	0.85	/	0.85
MAE	1.35	/	/	1.347	1.35	1.34	/	1.35
Feature subset	DERI, v, w_t, L_t, I				DERI, $v, w_t, L_t, D0$	DERI, v, w_t, L_t, SH		DERI, v, w_t, L_t, R
RMSE	1.695	/	/	/	1.695	1.66	/	1.698
R^2	0.86	/	/	/	0.86	0.86	/	0.86
MAE	1.35	/	/	/	1.35	1.33	/	1.35
Feature subset	DERI, v, w_t, L_t, SH, I				DERI, $v, w_t, L_t, SH, D0$			DERI, v, w_t, L_t, SH, R
RMSE	1.67	/	/	/	1.669	/	/	1.677
R^2	0.86	/	/	/	0.86	/	/	0.86
MAE	1.336	/	/	/	1.337	/	/	1.33

seven features leftover were sequentially combined with L_t to create a new subset with two features shown in row 5. And the feature subset with w_t and L_t has the best performance among all the feature subsets with two features.

SFS determined the optimal feature subset of five features including weld pool width, training length, DERI, SH, and travel speed. And the performance of the feature subsets with six features did not improve the prediction. The remaining features such as current, arc length, and ratio are less important variables. The expression of the final linear regression model is calculated as follows:

$$w'_b(i) = -0.329 + 0.255 * w_t + 0.659 * L_t - 0.3 * DERI - 1.71 * SH - 1.764 * v \quad (4.7)$$

The RSME of the final linear regression model is 1.669, and 1.33 for MAE. The highest R-square value was 0.86 which is the best result with the linear regression model.

4.5 Penetration Prediction Using Artificial Neural Network

The linear regression provides an approximate prediction of BW. However, the welding process is a nonlinear dynamic process. The linear model has the limitation to predict the penetration with certain accuracy. In this section, the ANN model was applied to establish the nonlinear relationship between features and predictors.

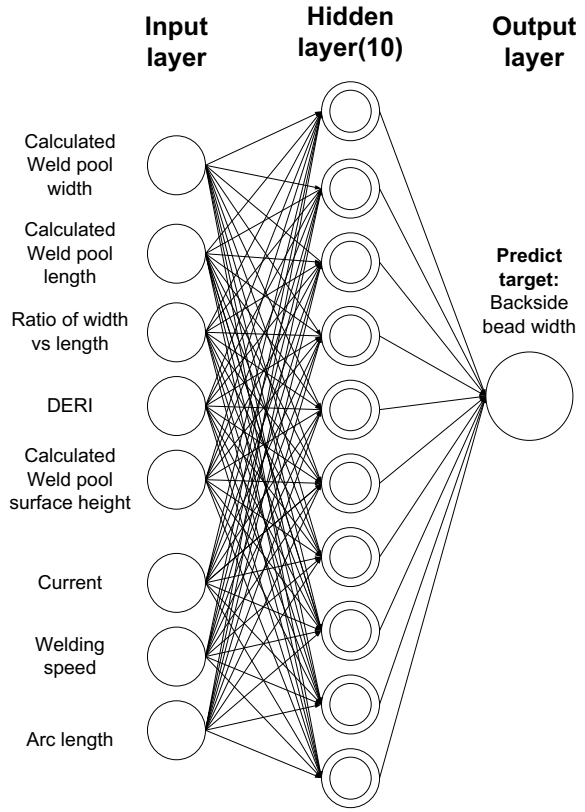
The relationship between the measured variable (front side weld pool geometry and welding parameters) and the backside width was established by artificial neural network (ANN) regression model. The structure of ANN is shown in Fig. 4.2. All the eight variables in the input layer include the topside weld pool geometry extracted from the passive vision images and the welding parameters collected from the welding machine.

A standard three-layer feed-forward neural network is established as shown in Fig. 4.2. The input layer contains eight features. The first six input features were measured from the weld pool image and current sensor. The weld pool voltage is constant during all the experiments we did. The weld speed and the thickness of the material were predetermined before the experiment and were constant for each weld. The number of elements n_2 in the hidden layer can be determined based on Eq. (4.8), where n_1 is the number of the input feature, N is the number of samples, and n_3 is the number of the output layer [5].

$$\frac{N}{10(n_1 + n_3)} < n_2 < \frac{N}{5(n_1 + n_3)} \quad (4.8)$$

Feature selection is an important procedure to reduce the complexity of the prediction model and running time. Principle component analysis is one of the widely used methods to reduce the dimension of prediction model. Principal component analysis (PCA) can transform the existing features matrix into new sets of orthogonal components through single value decomposition (SVD). In (4.3), U and V are the orthogonal matrices. The value of the diagonal entries $\sqrt{\lambda_i}$ of Σ indicates the variance of the related component. The first principal component describes the highest variance of the input feature. The importance of succeeding components was reduced. By conducting PCA analysis on the database, the first three components explained the 99.6% variance of all input features.

Fig. 4.2 The structure of feed-forward neural network for penetration prediction



$$M = U \Sigma V^H = [u_0, u_1, \dots, u_{r-1}] \begin{bmatrix} \sqrt{\lambda_0} & & \\ & \ddots & \\ & & \sqrt{\lambda_{r-1}} \end{bmatrix} \begin{bmatrix} v_0^H \\ v_1^H \\ \vdots \\ v_{r-1}^H \end{bmatrix} \quad (4.9)$$

One issue of applying PCA is that its output is not corresponding to the original features. Thus, we may not know the importance of each feature with PCA. An alternative is to apply sequential forward feature selection (SFS) to the existing features.

The performance of the regression model after feature selection is shown in Table 4.3. The performance of regression was evaluated using five-folds cross-validation. All the datasets were randomly distributed into five folds. For each round of test, one fold was selected for testing and the rest for training. The accuracy was calculated by taking the average of the five testing results. The result in Table 4.4 shows that the feature subset includes weld pool width, weld pool length, and surface height, and DERI achieved the best accuracy than other combinations. And the performance was quite close to that of PCA. This result reflects the fact that the variables related to the topside weld pool geometry are more important than others.

Table 4.4 Performance evaluation of ANN regression model

Feature selection	Root mean square error (RMSE)
PCA	0.533
$w_f + w_L$	1.235
$w_f + w_L + \text{SH}$	0.737
$w_f + w_L + \text{SH} + \text{DERI}$	0.545
$w_f + w_L + \text{SH} + \text{DERI} + \text{current}$	0.557

4.6 Bagging Tree Model Prediction

The bagging trees, also called bootstrap aggregation, is a supervised learning method that can be used in regression and classification. The algorithm is developed based on the decision tree, which suffers from high variance also known as overfitting. The bagging trees are built over n_{tree} bootstrap samples $D_n^1, \dots, D_n^{n_{\text{tree}}}$ on the training dataset $D_n = \{(x_1, w_{b1}), \dots, (x_n, w_{bn})\}$. Each tree is fully grown and provides a prediction. The final prediction is calculated based on the average of all predictions. By splitting the training data into several parts with bagging, the variance can be reduced [6].

Bagging tree method can be used to determine the importance of each variable. The importance of each variable x_j can be calculated as follows:

$$I(x_j) = \frac{1}{n_{\text{tree}}} \sum_{t=1}^{n_{\text{tree}}} \left[\frac{1}{|D_n^{tj}|} \sum_{(x_i, w_{bi}) \in D_n^{tj}} (w_{bi} - w'_{bi})^2 - \frac{1}{|D_n^t|} \sum_{(x_i, w_{bi}) \in D_n^t} (w_{bi} - w'_{bi})^2 \right] \quad (4.10)$$

The D_n^t is defined as a collection of out-of-bag samples without permutation of the observed variables. The D_n^{tj} indicates the out-of-bag samples with the permutation of observed j -th variables [7].

The permutation importance of the eight input features is shown in Fig. 4.3. The three most important variables are weld pool width, trailing length, and SH.

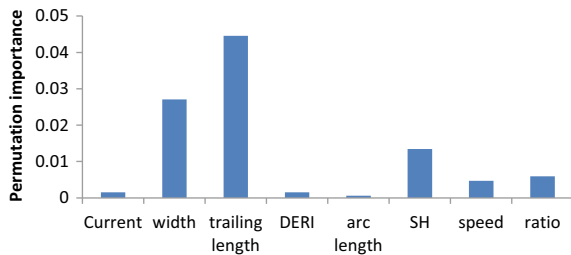
Fig. 4.3 Feature importance analysis

Table 4.5 Performance of predication with bagging tree

Feature subsets	Root mean square error (RMSE)	R-square	MAE
L_t	1.72	0.85	1.08
$w_t + L_t$	0.91	0.96	0.505
$w_t + L_t + SH$	0.81	0.97	0.454
$w_t + L_t + SH + \text{ratio}$	0.751	0.97	0.378
$w_t + L_t + SH + \text{ratio} + \text{speed}$	0.696	0.98	0.334
$w_t + L_t + SH + \text{ratio} + \text{speed} + \text{current}$	0.659	0.98	0.311
$w_t + L_t + SH + \text{ratio} + \text{speed} + \text{DERI} + \text{current}$	0.635	0.98	0.286
All eight features	0.645	0.98	0.29

According to the importance analysis, the key welding parameters such as welding current and welding speed are less important variables in the prediction model. The training database applied here covers a wide range of welding conditions. The thickness of the material changed from 2 to 6 mm. Thus, the variance of welding current was increased accordingly. If the thickness of the material does not change in the experiment database, the weld penetration will be linearly correlated with the current.

The result shown in Fig. 4.3 indicated the heat input was increased with the increase in welding current under the same welding speed. And the welding penetration was increased linearly with the heat input. However, for the large database with a large variation of material thickness and welding speed, the correlation between current and penetration was reduced and even can be neglected. The variables indicate weld pool 3D geometry became the major reference to predict penetration. Further feature selection can be performed based on the importance calculation.

As shown in Table 4.5, the eight feature subsets were tested on the training dataset. Based on the importance from high to low, each feature was sequentially added into the feature subset, and a new model was trained. The computational expense is less than using SFS method. The training and testing were conducted with five-folds cross-validation. The model includes 100 trees. The performance of prediction significantly increased as the number of variables increased from one to five. The performance improvement is less significant when the current and DERI were added into the model.

This result reflects that the variables related to the topside weld pool geometry are more important than others. The best performance model contains seven features. The minimum RSME was reduced to 0.659. And R^2 was increased to 0.98, which means the response has been well explained by the input variables.

4.7 Penetration Prediction on Butt Joint Welding

To verify the performance of the prediction model in real welding condition, a new welding experiment was conducted on the butt joint weldment with zero gap. The weld was conducted on a 3 mm thick SS304 plate with 2 mm/s travel speed. The welding current changes from 100 to 125 A. The topside and backside views of the weld are shown in Fig. 4.4. A partially penetrated weld was formulated in the first 65 mm of the weld with 100 A current. Then, the weld changed to full penetration as the current increases to 125 A.

The weld images were obtained and processed in real time. It took less than 200 ms in MATLAB to calculate weld pool surface geometry from a passive vision image and less than 100 ms to predict backside width. The passive vision images of partially penetrated weld under 100 A welding current are shown in Fig. 4.5a, b. The images of a fully penetrated weld under 125 A welding current are shown in Fig. 4.5c, d. It was found that the weld pool geometry was significantly increased with the increase in welding current. The length of DERI observed from a short exposed image in Fig. 4.5c was extended compared to Fig. 4.5a due to the formulation of complete penetration.

In Fig. 4.6, the calculated w_t shown in the blue curve is consistent with the topside weld bead width measured after welding. w_t was increased during the complete penetration period. The SH calculated with REI method is shown in Fig. 4.7. The data in the first 20 mm will not be counted due to the unstable arc at the beginning of welding. The SH is close to zero during partial penetration period from 20 to 65 mm.

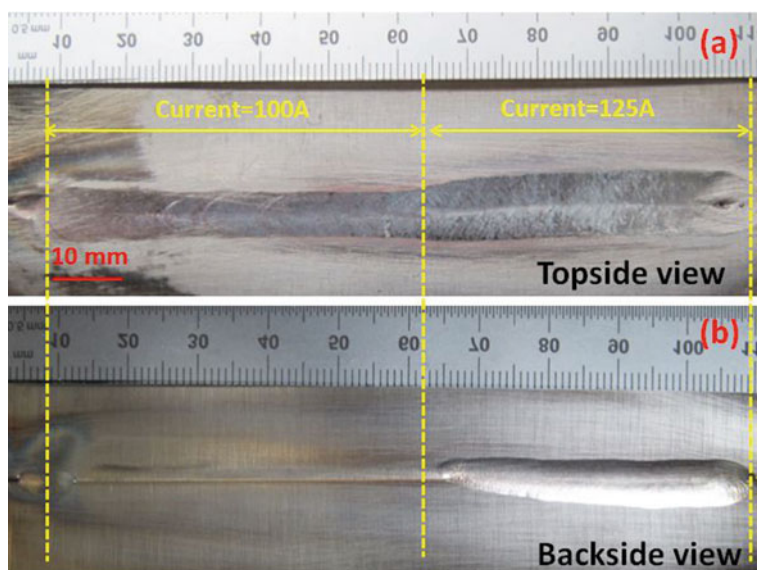


Fig. 4.4 a Topside view of weld bead; b backside view of weld bead

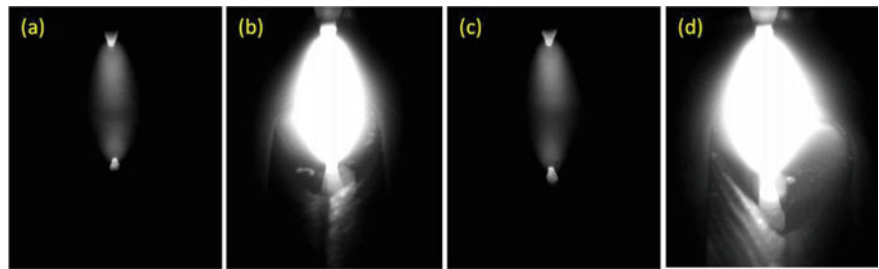


Fig. 4.5 **a** REI of partially penetrated weld; **b** weld pool image of partially penetrated weld; **c** REI of completely penetrated weld; **d** weld pool image of the completely penetrated weld

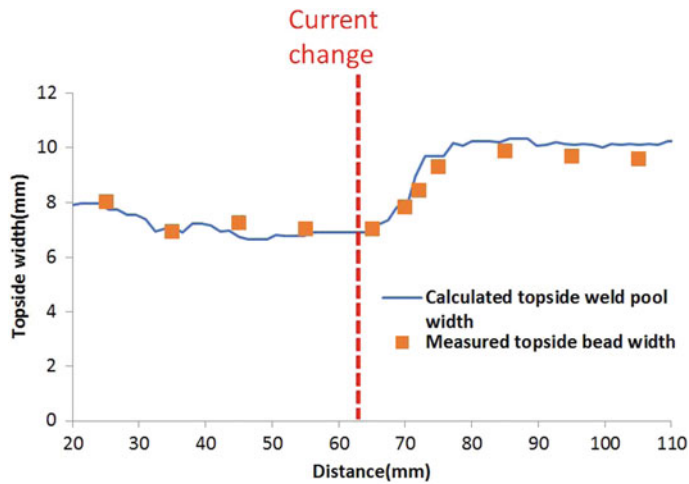


Fig. 4.6 Calculation of weld pool topside width

A significant decrease in SH can be found as the complete penetration started after 65 mm.

The weld pool backside width was predicted with the proposed machine learning models. The prediction results of linear regression and bagging trees model were shown in Fig. 4.8. The prediction result using the linear regression model has large bias from the real measurement of the weld bead. The prediction error using the bag tree model is less than linear regression. The standard deviation between the w'_b and w_b is 0.394 mm. The maximum error is 0.86 mm.

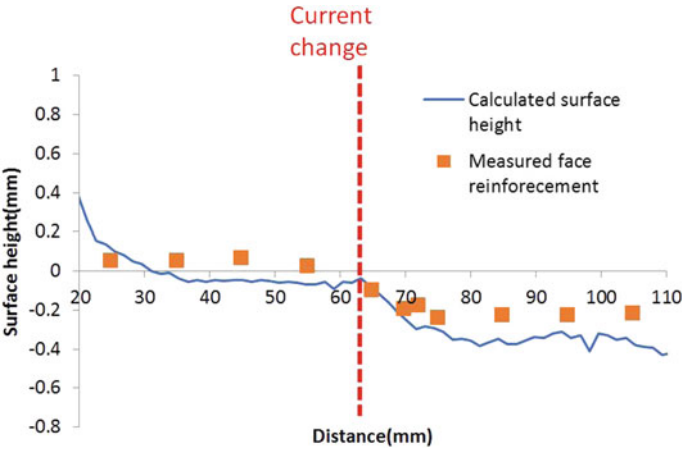


Fig. 4.7 Weld pool surface height calculation

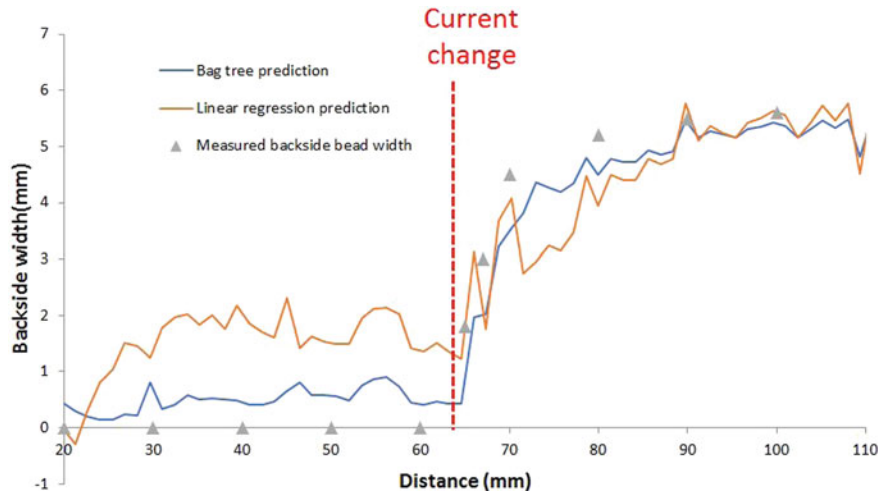


Fig. 4.8 Prediction of weld pool backside width

4.8 Conclusion

In this section, the supervised machine learning method was applied to monitor welding penetration based on the new features calculated from passive vision images. A training database with a large variance of welding conditions was established. The weld pool backside width was predicted with linear regression, artificial neural network, and bagging tree method. The conclusion was drawn as follows:

1. The importance analysis and feature selection were conducted for both linear regression and bagging tree. The result shows that the variables related to topside weld pool geometry including weld pool width, weld pool length, and surface height play the most important role to predict penetration.
2. The sequential feature selection was used to find out a better feature subset to improve the performance of the linear regression model. However, the computation expense is relatively high.
3. The performance of the bagging tree method is better than linear regression for the tests on the training database and new experiment data.
4. The time consumption of image processing and prediction is less than 300 ms which can be applied in real-time welding penetration monitoring and control.

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Chapter 5

Penetration Control of Bead on Plate Welding



5.1 Framework

The closed-loop control algorithm plays an important role to ensure full penetration during welding. The schematic of the penetration control system is shown in Fig. 5.1. PID control method was applied to adjust the welding current. As a direct indicator of welding penetration, the weld pool backside width was used as the feedback of the welding process. However, the backside width $W_b(t)$ cannot be measured directly from the sensors. In the previous section, the data-driven penetration prediction model was established to calculate the estimated backside width $W'_b(t)$ based on the features obtained from the weld pool topside images. The welding current $I(t)$ can be regulated through the PID controller.

The target backside width $W_r(t)$ is the reference of the feedback control system. The error $e(t)$ is the difference between the current backside width $W_b(t)$ and the reference.

The proportional–integral–derivative (PID) control mechanism was applied in the control system. The function can be described as follows:

$$u(t) = K_p e(t) + K_i \int_0^t e(t') dt' + K_d \frac{de(t)}{dt} \quad (5.1)$$

The $e(t)$ is the error between the reference and the feedback value. The K_p , K_i , and K_d are the coefficient of proportional–integral–derivative terms. Adjustment of the coefficient highly affected the result of control. The large K_p results in a quick response of the controller but will make the system unstable. The K_i will increase the movement of the process toward reference and reduce the residual error. However, it may cause an overshoot issue at the beginning of the movement. The K_d can reduce the overshoot error and improve the stability of the system during a steady state. The determination of the three parameters can highly affect the performance

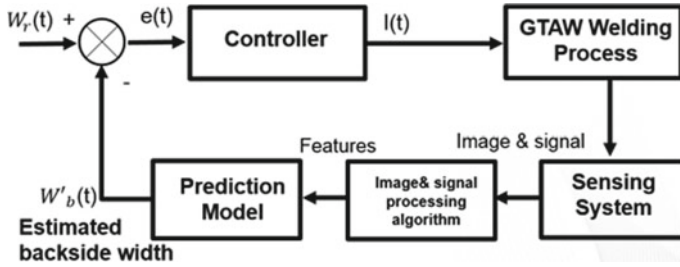


Fig. 5.1 The schematic diagram of PID closed-loop control system

of penetration control. The procedure for adjusting the three parameters is shown as follows:

1. Identifying the dynamic model of the welding process.
2. Adjusting the parameter with PID tuner.
3. Simulation and experiment.

5.2 Modeling Welding Dynamic Behavior

5.2.1 Dynamic Modeling Identification

The dynamic model is the foundation of developing control algorithm. In this section, a linear single input and single output (SISO) model was established to describe the welding process.

To obtain the discrete model for the dynamic welding process, an ARX (Auto-Regressive with exogenous input) model was identified through the least square method. The equation of ARX model is expressed as follows:

$$W_b(k) = \sum_{i=1}^n W_b(k-i) + \sum_{i=0}^m b_i I(k-j-d) + e(k) \quad (5.2)$$

where n and m are the order of the model, and d is the delay of the model.

The z transform of Eq. (5.2) can be written as follows:

$$\begin{aligned} A(z)y(z) &= B(z)u(z) + e(z) \\ \begin{cases} A(z) = 1 + a_1 z^{-1} + a_2 z^{-2} + \dots + a_n z^{-n} \\ B(z) = b_0 + b_1 z^{-1} + b_2 z^{-2} + \dots + b_n z^{-m} \end{cases} \end{aligned} \quad (5.3)$$

where $y(z)$ is the output backside width and $u(z)$ is the input current.

The transfer function $H(z)$ was given as

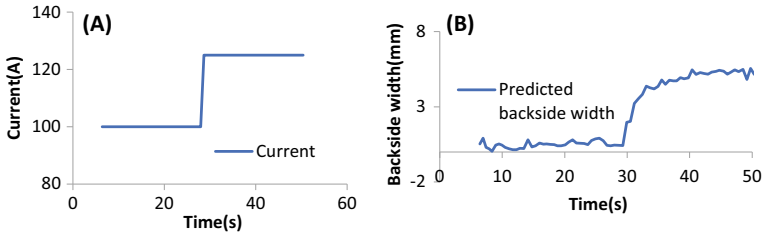


Fig. 5.2 **a** Input signal of step test; **b** output signal of step test

$$H(z) = \frac{y(z)}{u(z)} = \frac{B(z)}{A(z)} \quad (5.4)$$

The dynamic model of the welding process was identified based on the input and output data of the step response. As shown in Fig. 5.2, the input current changed from 100 to 125 A. And the output backside width was obtained from the result of prediction.

The least squares method was applied to identify the parameters of ARX model as shown in Eq. (5.6). MSE was the criteria to evaluate the preformation of estimation. The best MSE was 0.23 with $n = 3$, and $m = 2$, $d = 0$.

$$W_b(k) = 1.3778W_b(k-1) - 0.3003W_b(k-2) + 0.1521W_b(k-3) + 0.05I(k-1) - 0.03I(k-2) \quad (5.5)$$

5.2.2 Simulation

The simulation of closed-loop control system using MATLAB Simulink was established as shown in Fig. 5.3. The ARX model was used as the plant to simulate the welding process. The gains of the PID controller were adjusted through MATLAB PID tuner. The controller with proportional gain at 6.8, integral gain at 4.7, and

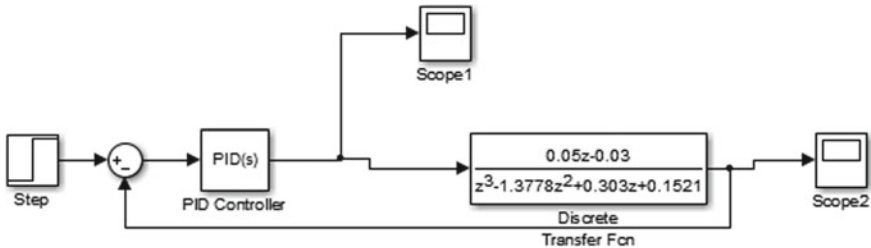


Fig. 5.3 PID control system blocks using Simulink

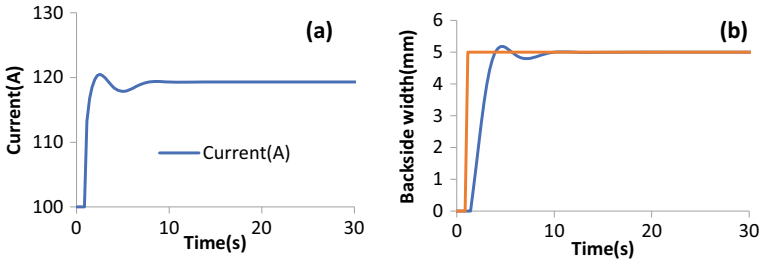


Fig. 5.4 **a** Observation of input current; **b** observation of system output

derivative gain at 0.28 can meet the requirement of control. The performance of the controller was analyzed through simulation as shown in Fig. 5.4. 5 mm weld pool backside was used as the reference. The initial current was 100 A. The output W_b increased from 0 to 5 mm in a few seconds. The overshooting is less than 3%. The error band is less than 1% after the output was stabilized. The setting time is 5.3 s and the rising time is 1.12 s.

5.3 Penetration Control on Uniform Thickness Plate

To evaluate the performance of PID controller, two experiments were conducted on 3 mm SS304 plate with 2 mm/s travel speed. Both experiments were started with the same welding condition. The initial welding current is 100 A which is insufficient to penetrate the plate. The value of PID gain was different.

The weld bead of the welding experiment with non-optimized gains is shown in Fig. 5.5. The controller of the experiment has the proportional gain at 8.25, integral gain at 3.3, and derivative gain at 0.1. The large proportional gain can reduce the

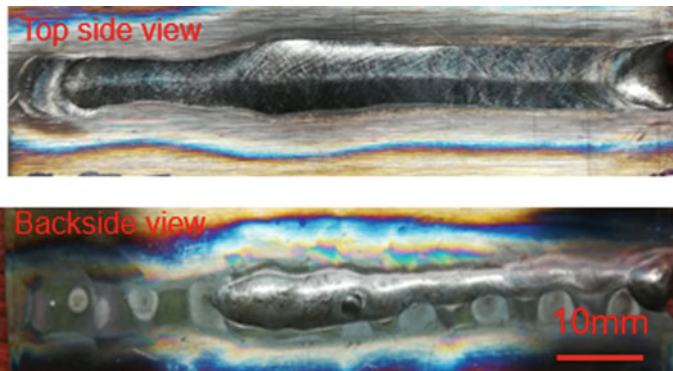


Fig. 5.5 Topside view and backside view of weld bead with non-optimized PID gains

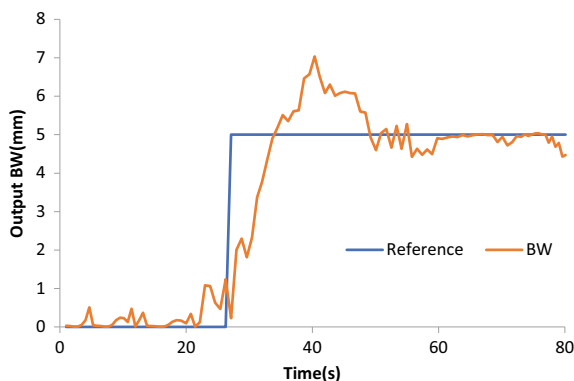


Fig. 5.6 Output signal of non-optimized PID gains

setting time. However, the stability of the system was highly affected. The system output curve was shown in Fig. 5.6, and the target increased to 5 mm at 26 s. Overshoot was observed at the beginning of control. The over-penetration was produced. The control system took more time to get stabled. The performance of the controller cannot meet the requirement due to the large overshooting and long setting time.

The weld bead of the welding experiment with optimized gains is shown in Fig. 5.7. The backside width control started at 30 s. The proportional gain was 6.8, the integral gain was 4.7, and the derivative gain was 0.28. The output curve was shown in Fig. 5.8. The overshooting was less than 5%. The setting time was 14 s. And the error band was less than 3% of the reference. The performance of the PID controller satisfied the requirement.

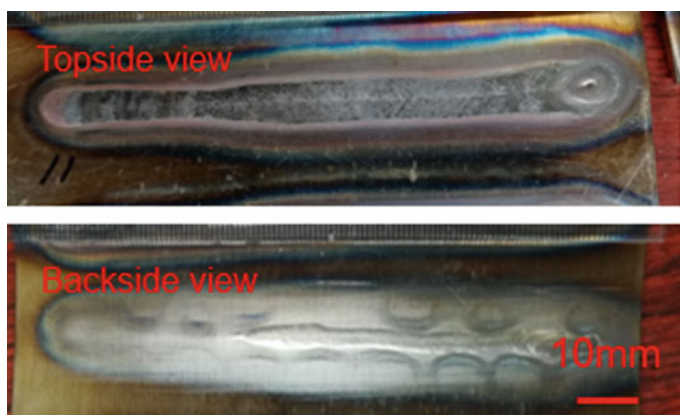
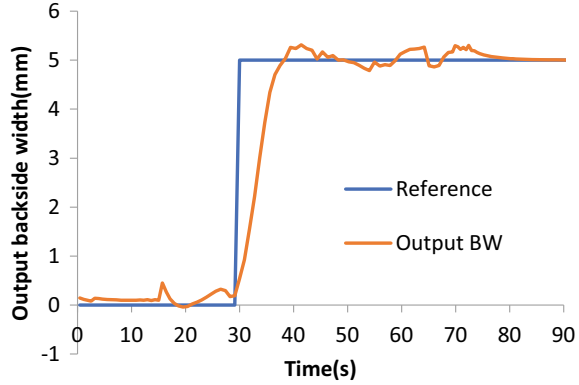


Fig. 5.7 Topside view and backside view of weld bead with optimized PID gains

Fig. 5.8 System output with optimized PID gains



5.4 Penetration Control on Different Thickness Plate

5.4.1 System Modeling

The material thickness is a major factor that affects the penetration condition. In many manufacturing conditions, the welding parameters and the PID gains should be adjusted due to the thickness change of the weldment. In this section, a new control algorithm was developed to control penetration on the workpiece with thickness changed from 2 to 3 mm.

In the previous chapter, several bead on plate experiments conducted on 2 and 3 mm plates were included in the database. Based on the experiment result with the same welding speed (2 mm/s), the static correlation between welding current and backside width was plotted in Fig. 5.9. For a 2 mm thick plate, full penetration was produced as the current was above 65 A. It was observed that the current and backside

Fig. 5.9 Static correlations between the welding current and backside width on different thickness plate

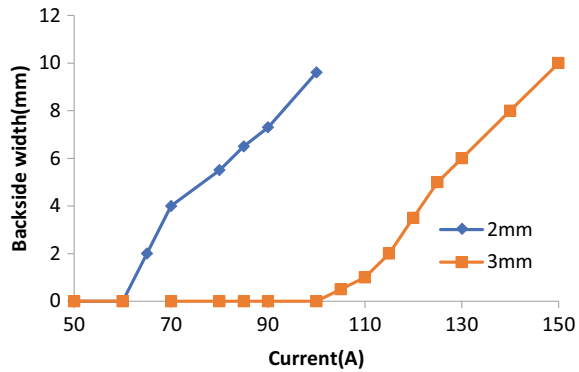


Table 5.1 Identified coefficient for the experiment on 2 mm workpiece

	k	T	τ
Test 1	0.4028	5.789	0
Test 2	0.3804	6.606	0
Test 3	0.36	7.034	0
Mean	0.36	6.4	0

Table 5.2 Identified coefficient for the experiment on 3 mm workpiece

	k	T	τ
Test 1	0.202	6.772	0.25
Test 2	0.24	5.387	0.39
Test 3	0.242	5.996	0.97
Mean	0.23	6.03	0.536

width are linearly related for the same thickness weld. However, a large change of current is required to produce the same backside width weld on different thickness plate.

As an example, if the reference backside width is 5 mm. Since the heat dissipation of the workpiece is different, 75 A current is required to produce full penetration on 2 mm, while 125 A is required for 3 mm. However, the conventional PID controller developed in the previous section takes a long time to adjust the current from 70 to 125 A if the material changed from 2 to 3 mm. Hence, it is important to establish a separate dynamic model for the weld on different thickness plate. And the optimal PID parameter will be changed accordingly. The first-order system transfer function is shown in Eq. (5.6). The time coefficient T , gain coefficient K , and delay constant τ were identified using MATLAB identification toolbox. Three experiments with a step change of welding current were conducted for each thickness of the workpiece. The coefficients of each experiment were shown in Table 5.1 and Table 5.2. The final coefficient was the average of the three experiments. The system gain coefficient K of the test under 2 mm is higher than the test on 3 mm. And time delay was found in 3 mm. The result indicated that the $W_b'(t)$ is more sensitive to current change for the test on a thin plate.

$$G(s) = e^{-Ts} \cdot \frac{K}{1 + Ts} \quad (5.6)$$

Due to the significant change of plant model, the PID parameters need to be adjusted adaptively. A modified control system framework with self-tuning PID controller was proposed in Fig. 5.10. A logistical classifier was established to determine the thickness of the workpiece from $W_b'(t - 1)$ and $I(t - 1)$. The accuracy of thickness determination is 99.1%. The PID gains will be adjusted to an optimal value based on the determined thickness. The optimized PID parameters are shown in Table 5.3.

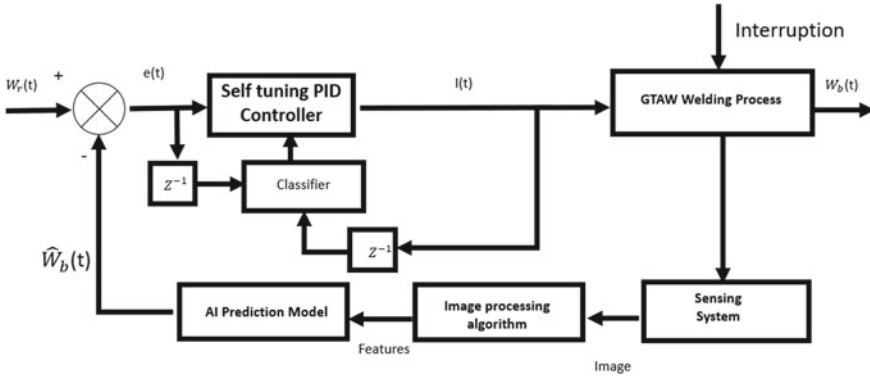


Fig. 5.10 The schematic diagram of self-tuning PID closed-loop control system

Table 5.3 Optimized PID parameter

	K_p	K_i	K_d	Over shoot (%)	Setting time	Rising time
2 mm	3.96	2.38	0.168	4.32	6.82	2.49
3 mm	6.8	4.7	0.28	4.36	14	2.68

5.4.2 Experiment

A bead on plate experiment was conducted on the 2 and 3 mm thickness plates with 2 mm/s welding speed. As shown in Fig. 5.11, the weld started from 2 mm plate and traveled toward 3 mm plate. The first part of the weld was uncontrolled with a constant current. The closed-loop control was then started, and the reference backside width was 5 mm. The PID gain was optimized, which was able to meet the requirement to weld on a 2 mm thin plate. Once the welding touch was traveled to the 3 mm thick plate, the partial penetration occurred due to the step change of material thickness. The reduction of backside width was detected with the AI prediction model.

Once the thickness change was detected from the classifier, the gains of PID were automatically adjusted, which is suitable for welding on a 3 mm plate. The control system needed 10 s to adjust the penetration back to the target. The input current signal and output prediction result was shown in Fig. 5.12.

5.5 Conclusion

In this section, a closed-loop control system was implemented to control uniform backside width during bead on plate weld. The conclusion can be drawn as follows:

- The overshooting problem can be solved with optimized PID gains.

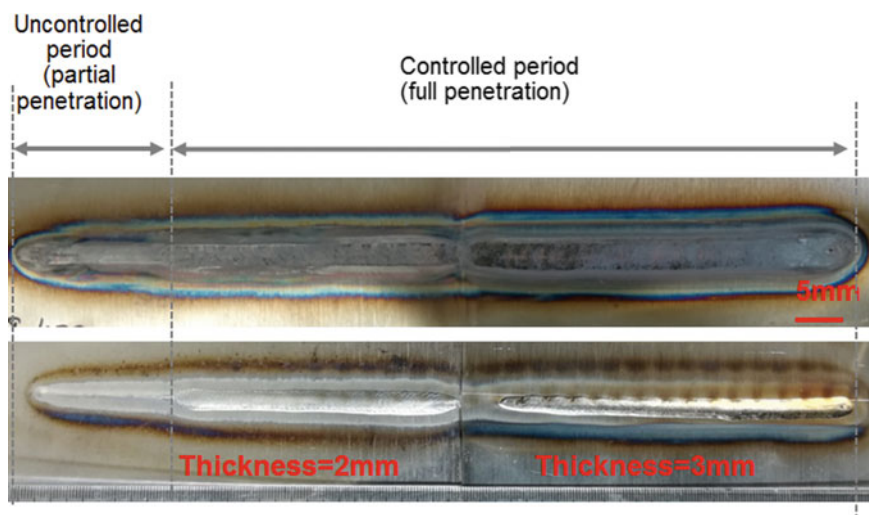
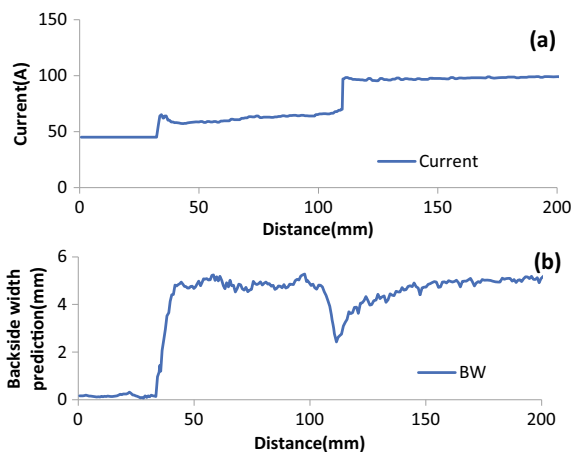


Fig. 5.11 Topside view and backside view of weld bead on non-uniform thickness plate

Fig. 5.12 a Input current during welding on non-uniform thickness plate; **b** Output backside width during welding on different thickness plate



- The setting time was reduced to 10 s to reach the reference backside width.
- The PID gains were optimized for the weld on different thickness plate.
- The experiment on the uniform thickness plate verified with the self-tuning PID controller. The gains of PID were adaptively adjusted to reach the control reference while the thickness of the workpiece was suddenly increased.

Chapter 6

Penetration Detection of Narrow U-Groove Welding



The multi-pass groove weld is more commonly used in welding manufacturing. For thick material welding, large heat input is required to get full penetration for the butt joint weld. By filling a groove design joint makes it possible to weld the workpieces with less heat input. The root pass weld is the first weld performed on the root of the groove joint. To perform a high-quality weld, the first pass of the weld should fully penetrate the root face. In this chapter, we focus on predicting the welding penetration of the root pass welding for the U-shaped groove weld based on the weld pool images.

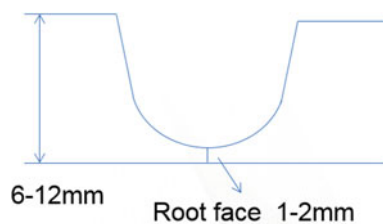
6.1 Welding Parameters

6.1.1 Welding Joint Design

There are many typical groove designs including U-type groove, V-type, and J-type. The V-type groove has been used in many manual welding conditions. The U-type groove is applied during automatic welding. Most of the welding inside the groove requires filler wire. In this section, we focus on developing a new method using computer vision and machine learning techniques to detect defects of multi-pass groove welding in the U-type joint. The design of the weld joint is shown in Fig. 6.1. The U-groove was milled on the side of the square butt joint. The thickness of the plate was 6 and 12 mm. The radius of the groove bottom was 5 mm. The root face ranges from 1 to 2 mm.

Since the zero-gap configuration was applied for the welding joint, no filler wire is required for the root pass weld. To eliminate the potential defects such as incomplete penetration, it is crucial to produce a full penetration for the root pass weld. In this section, a machine learning approach was applied to detect penetration for the root path of weld inside U-groove joint.

Fig. 6.1 Design of narrow U-groove welding joint



6.1.2 Establishment of Database

There are 15 trails of the first path weld that was conducted on the U-groove joint as listed in Table 6.1. The welding current changed from 90 to 150 A. The welding speed changed from 1 to 2 mm. The root face thickness changed from 1 to 2 mm. Among all the 15 welds, 8 welds were incompletely penetrated, 5 welds were fully penetrated, and two welds were over penetrated.

The three penetration conditions were determined based on the backside width. The backside width of the incomplete penetration weld was less than 2 mm. The complete penetration was between 2 and 8 mm. And the over-penetration was above 8 mm. A negative reinforcement of the bottom bead was formulated as the weld becomes over penetrated. The surface tension is a major force, which changes the shape of the bead.

Table 6.1 Welding parameters of root pass welding

No.	Root face thickness (mm)	Thickness of workpiece (mm)	Current (A)	Speed (mm/s)	Penetration condition
1	1	6	100	1	Complete
2	1.5	6	100	1	Incomplete
3	2	6	100	1	Incomplete
4	1	6	120	1	Complete
5	1.5	12	120	1.5	Incomplete
6	2	6	120	1	Incomplete
7	1.5	6	90	1	Incomplete
8	1.5	6	100	1.5	Incomplete
9	1.5	6	120	1	Incomplete
10	1.5	6	130	1	Complete
11	1.5	6	140	1	Complete
12	1.5	6	150	1	Over
13	1	6	150	1	Over
14	1.5	12	150	2	Complete
15	1.5	12	150	3	Incomplete

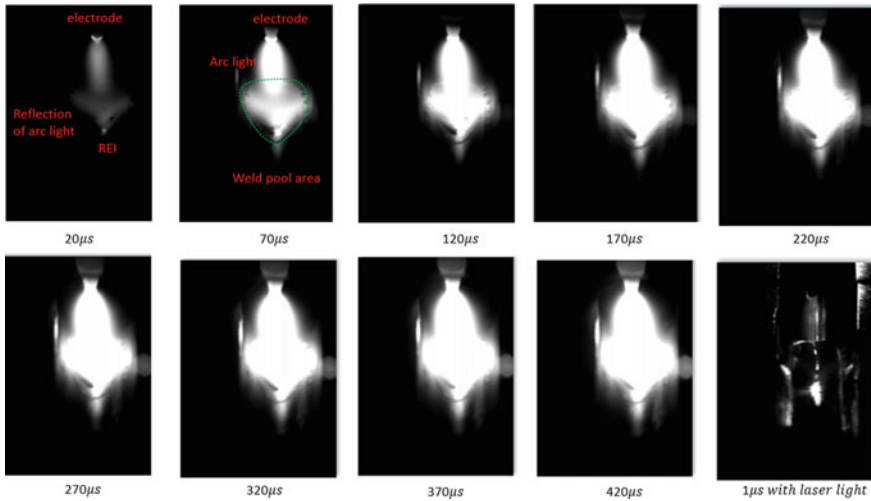


Fig. 6.2 Images acquired during U-groove welding with changing exposure time

6.2 Image Characters of Root Pass Welding

6.2.1 Images Character of Multi-optical Sensing Condition

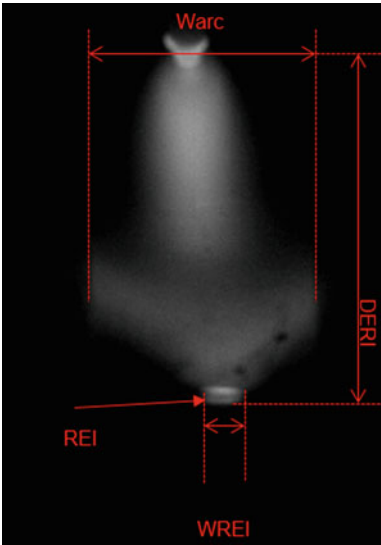
The images obtained with different optical conditions were shown in Fig. 6.2. The exposure time increased from 20 to 470 μs with an increment of 50 μs . All ten images were obtained within 10 ms during one weld. In Fig. 6.2, the electrode and the REI can be visualized in a short exposure time image under 20 μs .

The arc reflection area was distorted due to the curvature weld pool surface. The weld pool can be visualized with 70 and 120 μs exposure time. By increasing the camera exposure time, reflection of the arc area became saturated. And the weld pool was overwhelmed due to overexposure. The active vision image was obtained in the last frame. However, it is difficult to visualize the weld pool boundary due to the shadow of the groove sidewall. In this paper, the images obtained between 20 and 120 μs exposure time were used for penetration detection.

6.2.2 Acquire Images with Different Welding Conditions

The images obtained under different optical conditions are the important information source that can be used to predict welding penetration. In this section, the images obtained with 20 and 120 μs exposure time were studied in different welding conditions. To quantitatively compare the difference between experiments, four features were extracted as shown in Fig. 6.3. WREI is the width of the REI. WARC is the

Fig. 6.3 Features extracted from passive vision image



width of the arc reflection area. IREI is the intensity of the REI. DERI is the distance between electrode location and REI.

To further understand the effect of input current on the penetration. The experiments with different welding currents on the same welding joint were compared in Fig. 6.4. The root face of the five welds was 1.5 mm.

The partially penetrated welds were produced under 100 and 110 A. A small weld pool was produced in the middle of the groove as shown in Fig. 6.4b1, b2. In the

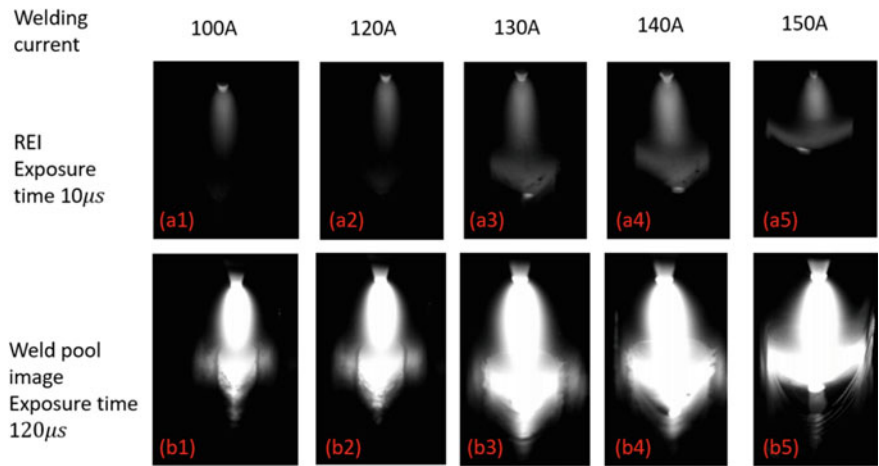


Fig. 6.4 Passive vision images of five welds with different welding currents

image obtained under $10\ \mu\text{s}$ shown in Fig. 6.4a1, a2. The REI and reflection of the arc area were not found in the image because the weld pool area is too small.

The fully penetrated welds were produced under 130 and 140 A. The weld pool area was increased and changed into a triangle shape. REI and reflection of the arc can be visualized in Fig. 6.4a3, a4. WARC area is close to the width of the weld pool.

A over-penetrated weld was produced with 150 A. As shown in Fig. 6.4a5, the WARC area was expanded to the whole groove. Besides that, the WREI was increased due to the concave weld pool surface.

Another important factor that affects the penetration was the root face(RF) thickness. In many manufacturing processes, the root face of the U-groove may vary due to the machining error. The image of three welds produced by the same welding current, $I = 120\ \text{A}$ but different RF was compared in Fig. 6.5. For the $\text{RF} = 1\ \text{mm}$ case, the weld was fully penetrated. For the case of $\text{RF} = 1.5\ \text{mm}$, the weld was just penetrated with small backside width. The weld is not penetrated for the third case with a $2\ \text{mm}$ root face. From the passive vision image shown in Fig. 6.5, the weld pool area was decreased with the increase in the root face. The reflection arc area and REI were also reduced with the increase in root face. This also indicated that the features extracted from REI are related to welding penetration instead of current change.

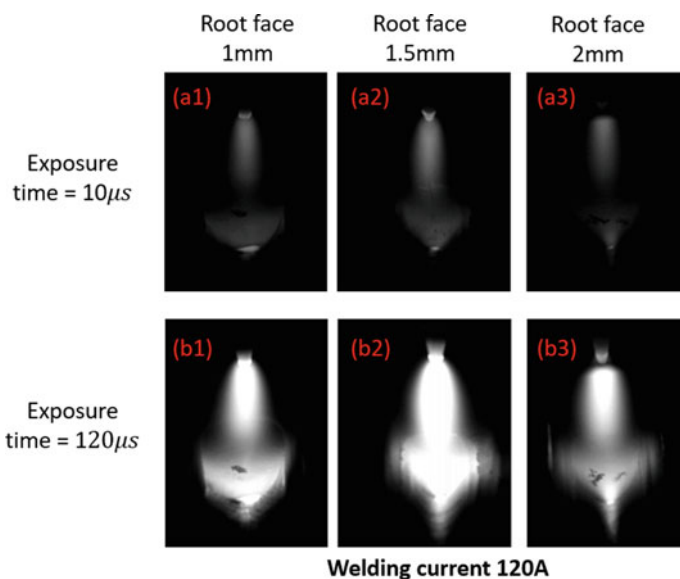


Fig. 6.5 Passive vision images of three welds with different root faces

6.3 Training of Prediction Model

6.3.1 Classification Based on the Extracted Features

Many features related to penetration can be found from the passive vision images. In this section, a bag tree model was trained to classify the penetration based on the features extracted from the image, which include WREI, WARC, DERI, and IREI. The database includes 620 instances obtained from 15 trails of weld shown in Table 6.1. Statistical analysis was conducted based on the training database. Each instance of data was labeled based on the backside bead width. The three penetration conditions were included in the database. In Fig. 6.6, the mean value and standard deviation of all the four variables under three penetration states were compared. The significant change of WARC can be found as the penetration changed from partial penetration to over-penetration. This feature is related to the weld pool geometry. The weld pool area increased with the increase in heat input. The width of the arc reflection was also increased.

The feature of DERI is shown in Fig. 6.6b, the DERI is related to arc length and the weld pool surface shape. The arc length is reduced with the increase in welding current. The mean value of DERI does not change significantly between the three different penetration conditions. However, based on the reflection model in our previous research, the surface height of the weld pool can be further calculated based on DERI and arc length.

The REI width is related to the weld pool surface shape. The width of the REI was increased from partial penetration to over-penetration. In the partial penetration stage, the WREI is close to zero. This feature may due to the two reasons: first, the REI cannot be detected since the weld pool area is small. If the REI cannot be

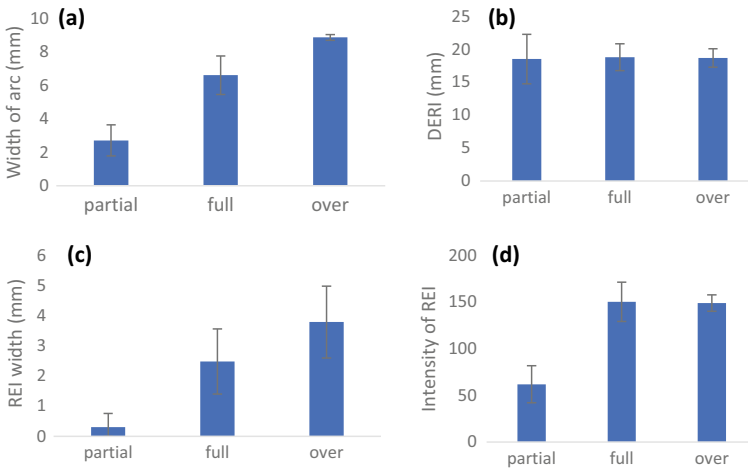
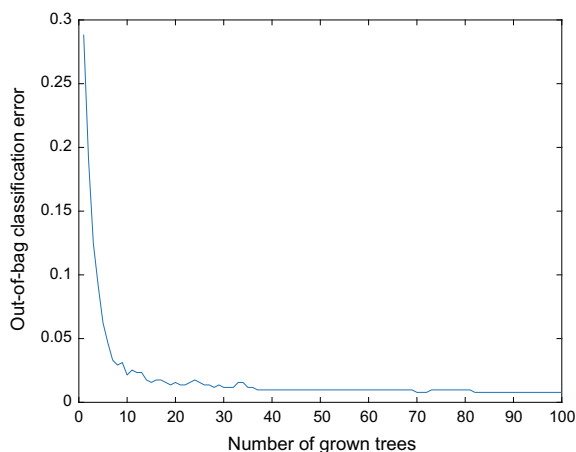


Fig. 6.6 Comparison of the four features under three penetration conditions

Fig. 6.7 Out-of-bag error versus the number of grown trees



detected on the surface, the IREI value will be much lower than the fully penetrated condition. Second, once a convex weld pool surface is formulated in completely penetrated weld, the area of REI can be reduced due to mirror reflection.

Finally, six features were used as the input for the bag tree model which include welding current, arc length, WARC, DERI, WREI, and IREI. Figure 6.7 shows the out-of-bag error's change during the training procedure. The out-of-bag error estimates the weighted ensemble error for out-of-bag observations. In the classification problem, the weighted ensemble error means the weighted misclassification rate.

The out-of-bag error was significantly reduced over the number of grown classification trees. The upper limit of the grown tree is 100. The error was reduced less than 0.02 after 20 trees, which means 20 trees were enough to provide a good classification on the training database. The importance of the six features was also given in Fig. 6.8. The third feature WARC and the IREI are the important features for classification. The final accuracy for classification is 98.5%, which was evaluated with five-folds cross-validation.

6.3.2 Backside Width Prediction with Bag Tree Model

Backside width of the weld pool is the important variable for closed-loop penetration control. The Wb can be predicted using regression tree. First, similar as we did before in Chap. 5, all the datasets in the database were labeled with the backside width which is measured after welding.

The distribution of the error of training and testing dataset was shown in Fig. 6.9. 70% of the database was used for training, and 30% was used for testing. The RSME of the training is 0.28. And the RSME of the testing datasets was 0.56.

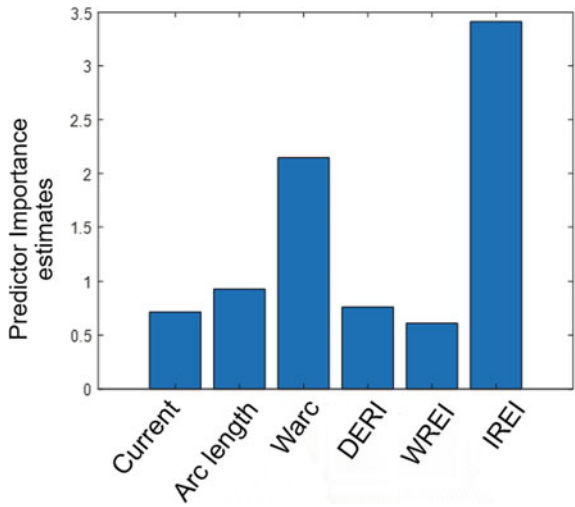


Fig. 6.8 Predictor importance estimates

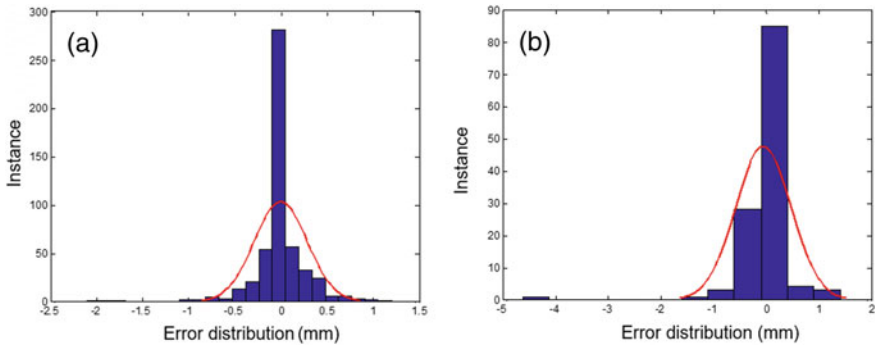


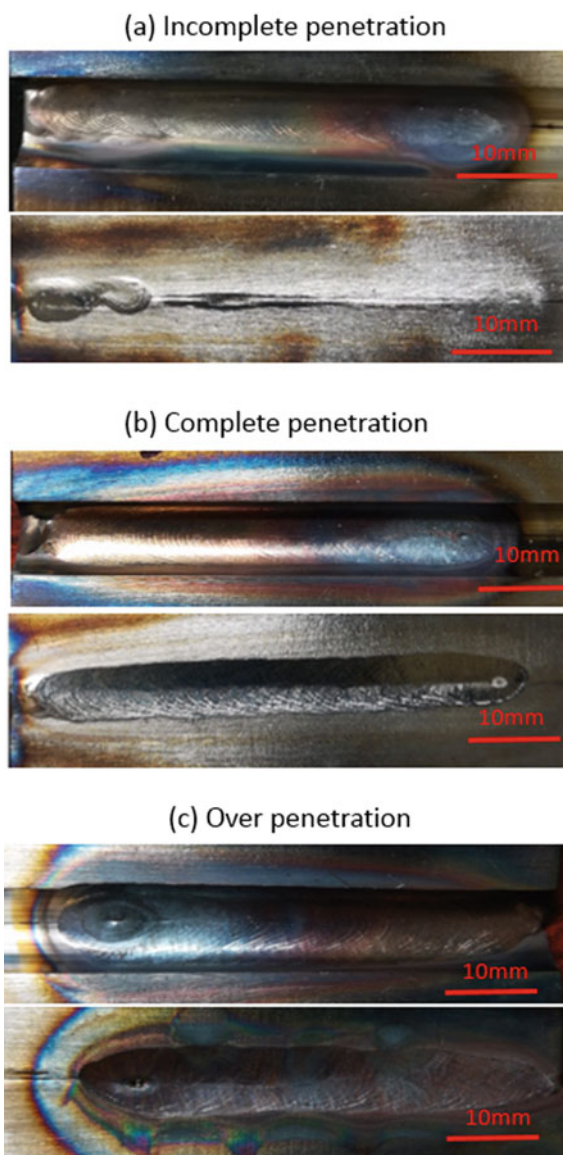
Fig. 6.9 Error distribution for training and testing. **a** Error of the training dataset; **b** error of the testing dataset

6.4 Experiment Validation

The performance of the trained bagging tree model was further tested on the new experiments which were not included in the database. In Fig. 6.10, three new welds were produced with 100, 130, and 150 A current, which represents the three different penetration conditions. The welding speed is 1 mm/s. And the root face length is 1.5 mm.

First, the bagging tree classification model achieved 87.5% accuracy to determine the three different penetration stages. This model may suffer from overfitting during the training process. The predicted result using the bagging tree regression model

Fig. 6.10 Three penetration conditions inside U-groove weld. **a** Incompletely penetrated weld performed at 100 A current and 1 mm/s welding speed; **b** completely penetrated weld performed at 130 A current and 1 mm/s speed; **c** over-penetrated weld performed at 150 A current



was shown in Fig. 6.11. The predicted backside width is close to the measurement after welding. The RSME of regression is 1.01 and the MAE of the error is 0.71. Thus, the predicted result can be further used as feedback in the closed-loop control systems.

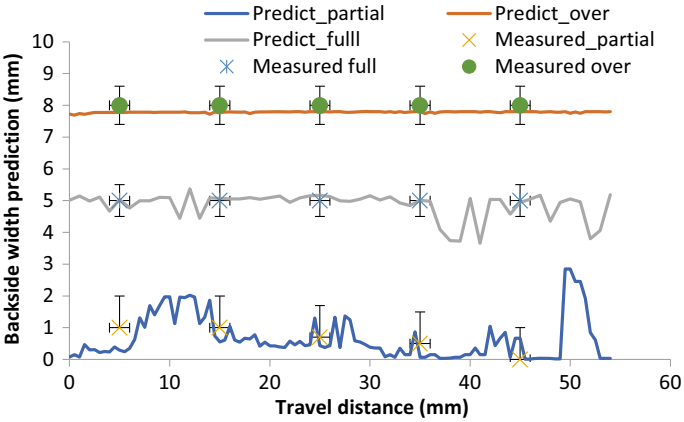


Fig. 6.11 Real-time backside width prediction of root pass weld

6.5 Conclusions

In this section, the welding penetration was studied for the root pass inside U-groove. The images from the passive vision system were used as the major information source to predict penetration. Welding current and root face thickness are the major parameters that affect joint penetration. New features extracted from reversed electrode image (REI) and weld pool images were found closely related to the penetration. The classification and regression model were also trained based on the established database.

Chapter 7

Lack of Fusion Detection Inside Narrow U-Groove



The lack of fusion (LOF) defect has been a crucial issue for multi-pass groove welding. It is very challenging to detect this defect with a non-destructive method. In some circumstances, the LOF can be detected with radiography or ultrasonic sensors if the defect includes voids or inclusions [1]. In reference [2], the ultrasonic device was used to detect a lack of fusion on the groove sidewall. The reflection of ultrasonic waves indicated the presence of a lack of fusion in a certain depth. However, the equipment to conduct these tests increased the cost of production. And, currently, there is no effective method, which can directly detect the LOF due to discontinuity of welds.

In this section, we proposed a new real-time method to predict LOF defect formulated on the groove sidewall. The prediction model was established based on the features extracted from passive vision images.

7.1 Design of Multi-pass Welding Experiments

The design of U-groove is the same as we described in Chap. 7. The schematic of the layer planning is shown in Fig. 7.1. The first path was conducted with filler wire and melted through the root face. Additional 5–10 paths of weld with filler wire were performed to fill the groove. The final weld path was on the top of the groove which covers the entire joint. The electrode travels along the center of the groove without swing. In this configuration, the sidewall fusion is the major issue that needs to be taken care of.

Since the width of the groove is increasing from the bottom layer to the top layer, the welding parameters, including current, traveling speed, and wire feeding speed to conduct different layers, should be adjusted to prevent lack of fusion on the sidewall.

The welding parameters to fill the U-groove were shown in Table 7.1. Twelve trails with filter wire were performed on the two types of workpieces. Both two types have a similar design at the bottom of the U-groove. The radius of the groove bottom

Fig. 7.1 Schematic of layer plan in U-groove joint

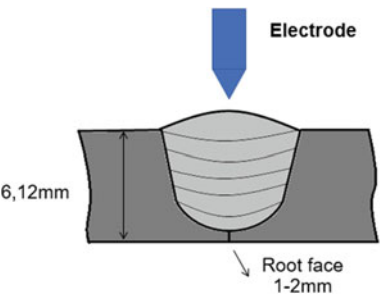


Table 7.1 Welding parameters of multi-pass narrow gap weld

No.	Layer number	Current (A)	Travel speed (mm/s)	Wire feeding speed (inch/min)	workpiece Thickness	Lack of fusion
Dataset I	I	150	1->2	25	6	Y
	II	150	1->2	30	6	Y
	III	150	1->2	30	6	Y
	IV	150	2	25	6	Y
	V	150	2	20	6	Y
Dataset II	I	150	1->2	25	12	Y
	II	200	1->2	40	12	Y
	III	200	1.8->2	40	12	Y
	IV	200	1->2	40	12	Y
	V	220	1	40	12	N
	VI	220	1->2	40	12	Y
	VII	220	1	50	12	N

was 5 mm. And the root face is 1.5 mm. However, the total thickness of type II is 12 mm and type I is only 6 mm. The first five trails shown in Table 7.1 were conducted on the workpiece type I with 6 mm thickness. And the rest of them were performed on workpiece type II. Since the first layer of the weld was conducted with no filler wire, they are not included in this table.

The welding speed for some of the experiments shown in the table was manually increased during the middle of the welding. Then the lack of fusion defect may be produced due to a decrease in heat input. The wire feeding speed is also changed for different weld layers.

7.2 Experimental Observations

7.2.1 Weld Bead Geometry

In this research, the welding seam is kept in the center of the weld seam without any swing. The weld bead shape for different fusion conditions is shown in Fig. 7.2. In good fusion condition, the concave weld pool surface was formulated due to the surface tension and electromagnetic force. A lack of fusion welds may be produced with insufficient heat input. As shown in Fig. 7.2b, the volume of the weld pool was reduced by the decrease in heat input. And the edge of the weld pool was detached from the groove sidewall. A convex weld pool surface may be formulated under this condition.

The topside views of experiments 1–5 were shown in Fig. 7.3. The travel speed was increased during the middle of the welding. The lack of fusion defect on the sidewall was formulated in most of the welds due to insufficient heat input. The significant defect can be found in the cross-section view of the finished welding joint as shown in Fig. 7.4.

The topside views of experiments 6–12 that were conducted on workpiece II were shown in Fig. 7.5. The significant lack of fusion was formulated at the fourth and fifth layers due to the increase in travel speed during the middle of welding. Completed fusion welds may have a concave bead surface, while the incomplete ones have a convex shape. An insignificant welding defect can be visualized from the cross-section view of the finished welding joint shown in Fig. 7.6. The weld on the upper layers can reduce the lack of fusion formulated on the bottom layers. Thus, the lack of fusion in workpiece II was less significant than the defect in workpiece I.

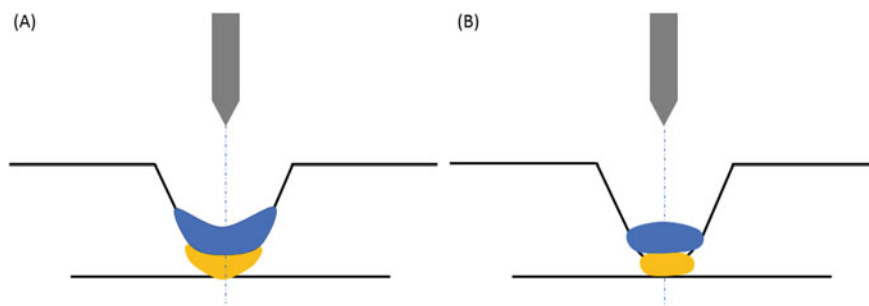


Fig. 7.2 Description of weld pool surface inside U-groove

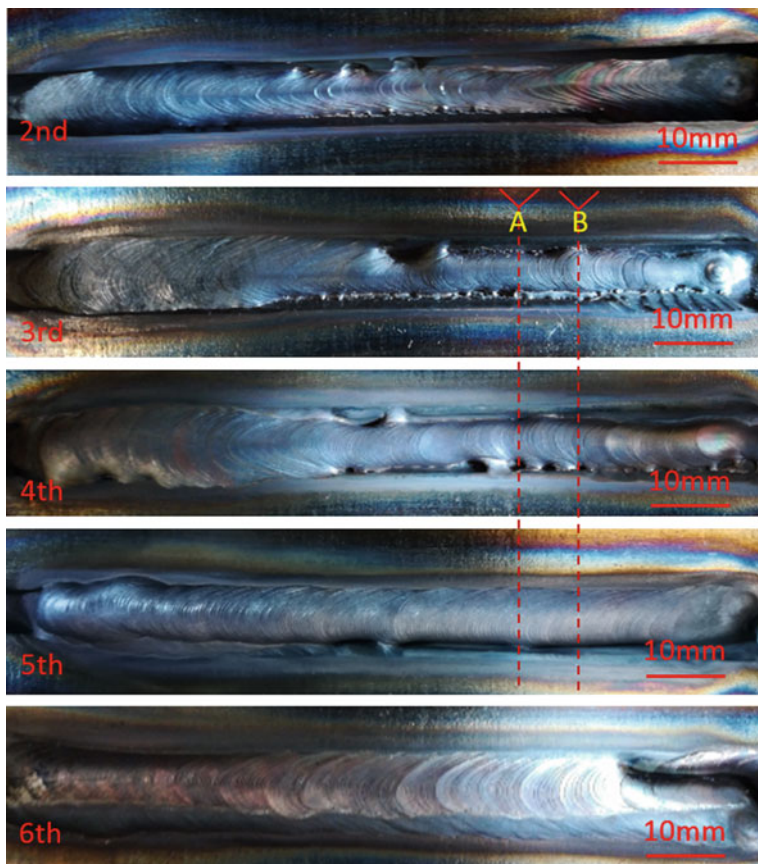


Fig. 7.3 Topside view of the multi-pass weld on workpiece I

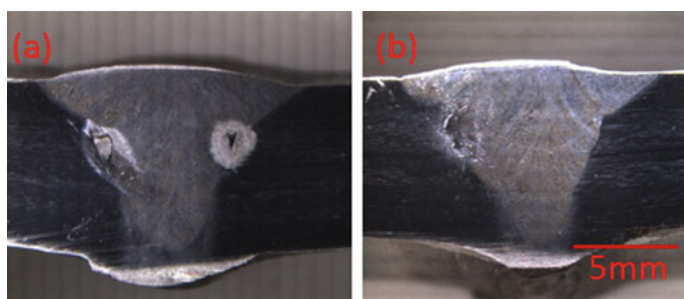


Fig. 7.4 Cross-section views of the finished weld joint on workpiece I

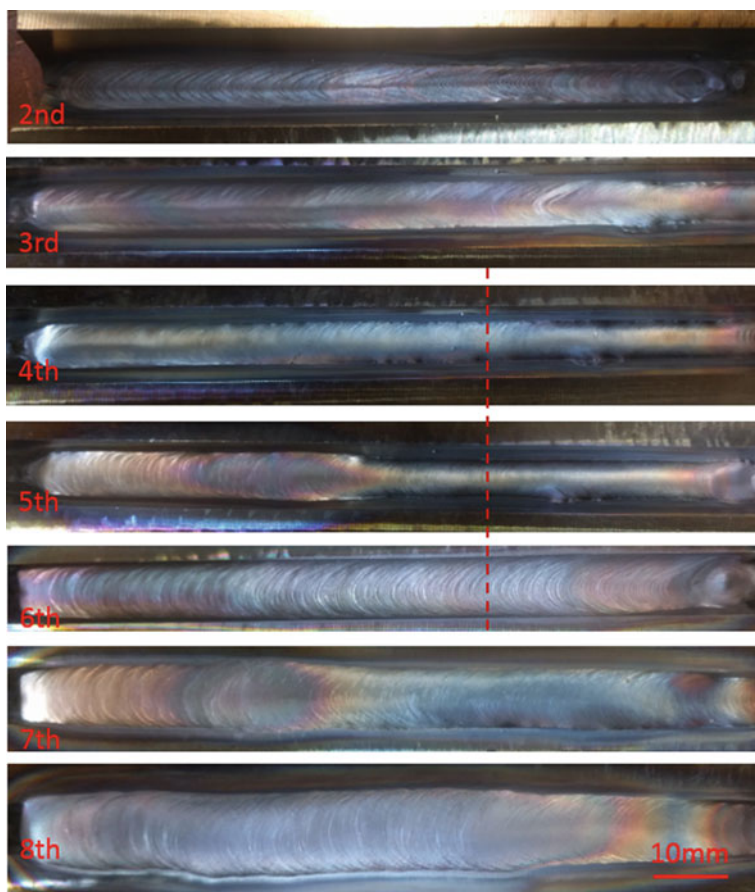


Fig. 7.5 Topside view of the multi-pass weld on workpiece II

7.2.2 Characters of Passive Vision Images

The passive vision images in Fig. 7.7 are related with the cross-section A in the workpiece I. The REI and weld pool images of the five passes were obtained. In this experiment, the second path was fully penetrated the root and no LOF defect was produced. The LOF defects were created in the middle of the joint when we produced the 3rd, 4th and 5th weld. The discontinuous weld was created as we increased the travel speed. Since the weld pool did not fully attach to the sidewall. The weld pool area was shrinking into a ball. Convex weld pool surface was formulated due to surface tension. The REI size in III to IV was reduced, which can be explained by the law of reflection on the convex surface [3]. The significant lack of fusion was also produced on the weld V, the weld pool was only attached to one sidewall of the U-groove which formulated an unsymmetrical weld pool. The REI was not able

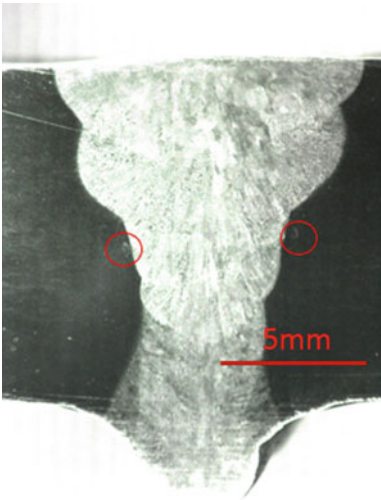


Fig. 7.6 Cross-section views of the finished weld joint on workpiece II

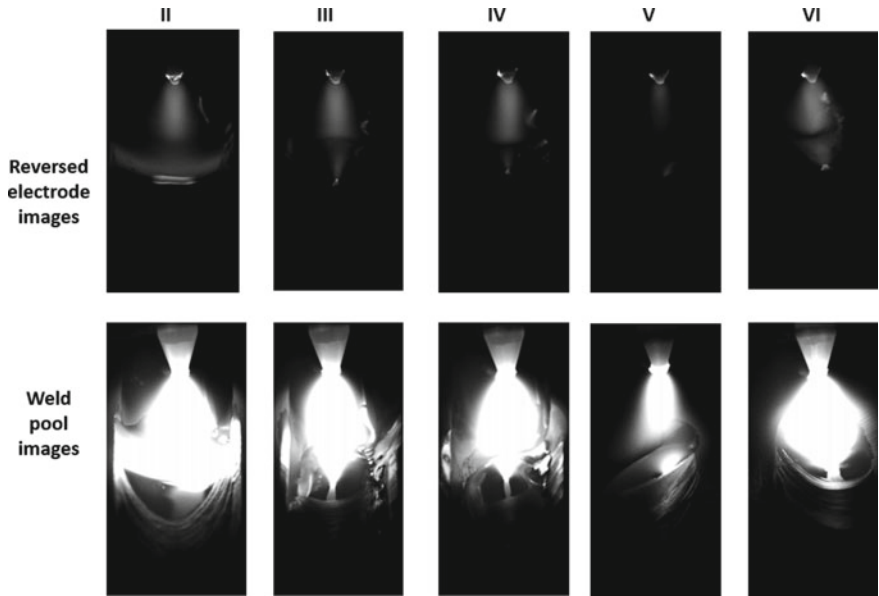


Fig. 7.7 Passive vision images under lack of fusion condition

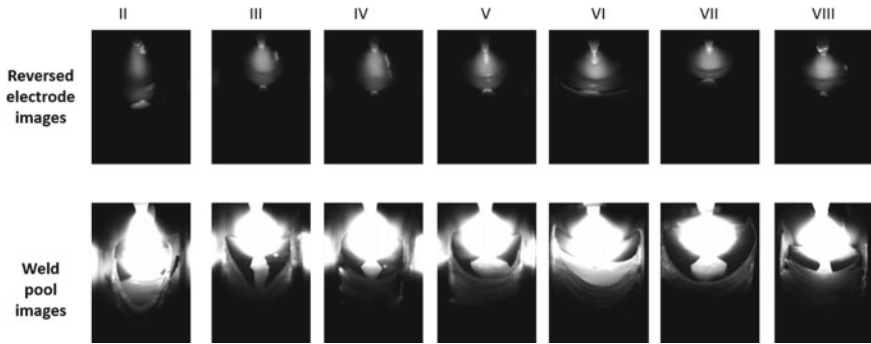


Fig. 7.8 Passive vision images under complete fusion condition

to be visualized under a low exposure image. The VI layer was the final layer that covered the top of the joint. A convex weld pool surface was produced to increase the face reinforcement of the joint.

The passive vision images in Fig. 7.8 are related with the cross-section C in the workpiece II. And in this time moment, the welds from the second layer to the seventh layer were under completely fusion condition. The weld pool geometry shown in Fig. 7.8 are symmetrical. The REI can be observed from the image with short exposure time. The size of REI was increased compared with the lack of fusion condition shown in Fig. 7.8.

In complete fusion condition, a concave weld pool surface was formulated during welding. The geometry REI was affected by the concavity of the weld pool. As an example, the REI area of the fifth layer was significantly increased with the concavity of the weld pool surface, which can be explained by the law of mirror reflection.

7.2.3 Features Extraction from Passive Vision Image

Based on the observation of passive vision images, many important characters were found related to LOF. Four major features were extracted from the REI as shown in Fig. 7.9. The four features were automatically calculated using the ROI algorithm we developed in Chap. 4.

The extracted features of the welding on the third layer of workpiece I were shown in Fig. 7.10. The lack of fusion was produced on the third path of the weld. At the beginning of welding, the weld was fully fused with the sidewall. The weld pool surface was concaved. The welding speed was increased after complete 10 mm of weld. The volume of the weld pool was decreased. The weld pool detached from the sidewall and formulates a lack of fusion defect.

The width of REI (W_{REI}) and the intensity of the REI were reduced as the lack of fusion started. The convex weld pool surface works as a curve mirror which changed the reflection path of light. The feature of DERI was found increased as the lack of

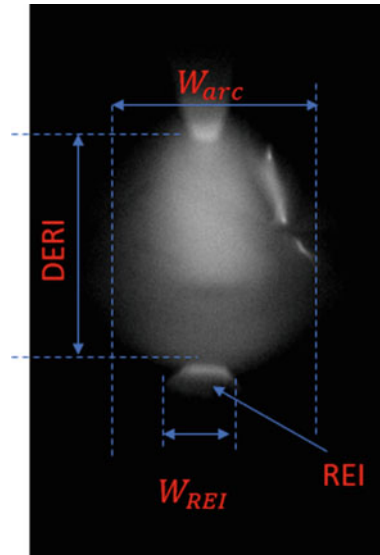


Fig. 7.9 Features extraction from weld images

fusion started. The weld pool area moves upward as the lack of fusion started. The difference can be found in these three features. Since the standard deviation of the measurement is large, it is hard to determine the threshold which distinguishes the lack of fusion condition based on one feature.

7.3 Predict Lack of Fusion with Data-Driven Model

The data-driven model was established to predict LOF defect using machine learning method. The database to predict lack of fusion was established based on the experiment result. The dataset I contained 190 instances of data, which was obtained from the experiments on workpiece 1; the dataset II includes 1244 instances of data obtained from experiments on workpiece 2. All the datasets were labeled based on the final weldment. The lack of fusion detection was considered as a binary classification problem. The lack of fusion condition was considered as the positive case (P), and the complete fusion was considered as the negative case (N). The correct detection of lack of fusion is defined as true positive cases (TP), the correct detection of complete fusion is defined as true negative (TN), the incorrect detection of LOF is defined as FP, and the incorrect detection of complete fusion is defined as FN.

Each instance of the database contains four features extracted from reversed electrode images. The average value of the selected features in complete fusion and lack of fusion condition is compared in Fig. 7.11. A significant difference can be found

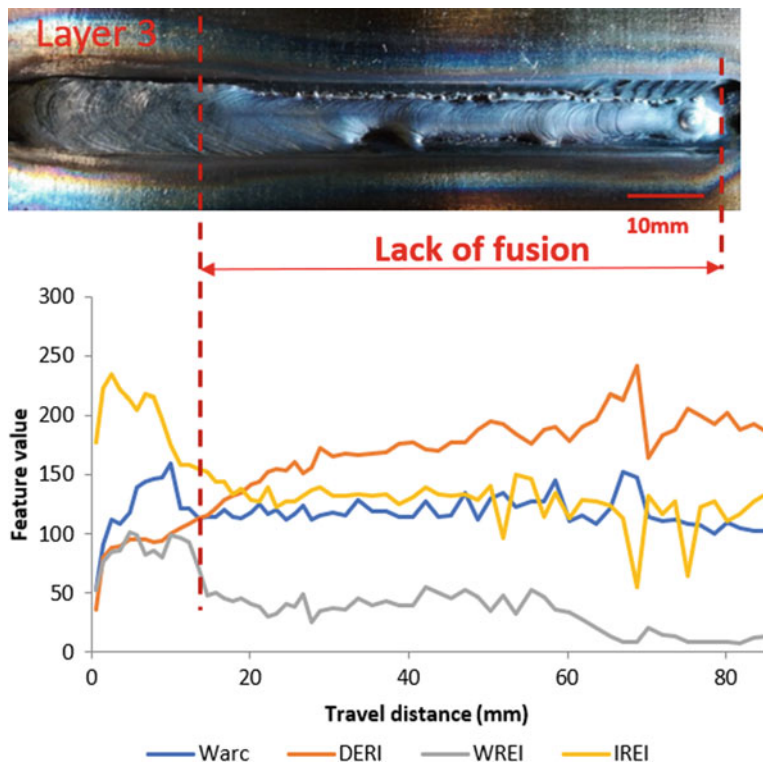
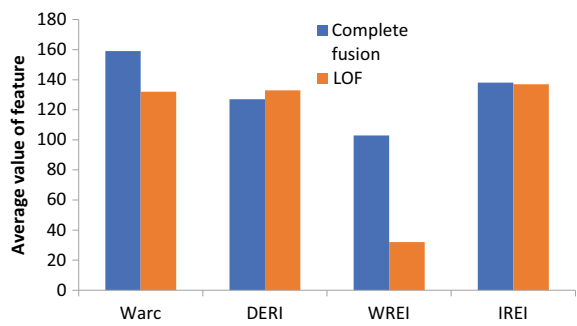


Fig. 7.10 Extracted features of the third weld with lack of fusion defect

Fig. 7.11 Comparison of feature in fusion and lack of fusion condition



in the feature of Warc and WREI, which indicated that these two features are more important for classification.

The bagging tree model was trained to detect a lack of fusion. All the four features were used for prediction. The performance of the model with different training datasets was shown in Table 7.2. The following metrics were used to evaluate the performance of LOF detection:

Table 7.2 Performance of bagging tree model with different training datasets

Number of model	Training data	Testing data	Accuracy (%)	Sensitivity (%)	Specificity (%)
I	70% dataset I	30% dataset I	97.58	90.14	99.44
II	100% dataset I	100% dataset II	95.79	95.45	99.1
III	70% dataset I and II	30% dataset I and II	95.49	94.39	96.13

- Accuracy indicates the ability to correctly determine fusion condition, $\text{accuracy} = (\text{TP} + \text{TN})/(\text{TP} + \text{FP} + \text{TN} + \text{FN})$;
- Sensitivity indicates the ability to correctly detect the defect with LOF, $\text{sensitivity} = \text{TP}/(\text{TP} + \text{FN})$;
- Specificity indicates the ability to correctly determine the weld does not have LOF defect, $\text{specificity} = \text{TN}/(\text{TN} + \text{FP})$.

The model 1 was trained with 70% of dataset I and tested with 30% of dataset I. Since all the data were obtained under similar welding condition, the accuracy is much higher. The model II was trained with dataset I and tested on dataset II which were conducted on a different workpiece. Since the welding parameter is slightly different from the training dataset, the accuracy is lower than the first model due to the variance of data. To reduce overfitting on one dataset, both data in datasets I and II were used for training model 3. The final accuracy is 95.49%.

7.4 Software Integration

A real-time multi-functional software was developed for LOF and LOP detection using MATLAB. The software interface was shown in Fig. 7.12. All the images with different exposure conditions can be obtained and processed in real time. The trained machine learning models were integrated into the software. For the root pass weld in U-groove and bead on plate weld, the software can be used for LOP detection. The weld pool backside width can be estimated and used for closed-loop control. The LOF detection function can be used for the welds with filler wire in U-groove.

7.5 Conclusions

In this chapter, a new method was developed to detect a lack of fusion defect in multi-pass groove welding. The lack of fusion was formulated due to inappropriate welding speed and current. The weld pool surface geometry was also an important source of information related to LOF. Major features extracted from reversed electrode images may reflect the weld pool surface condition. The bagging tree model was trained to

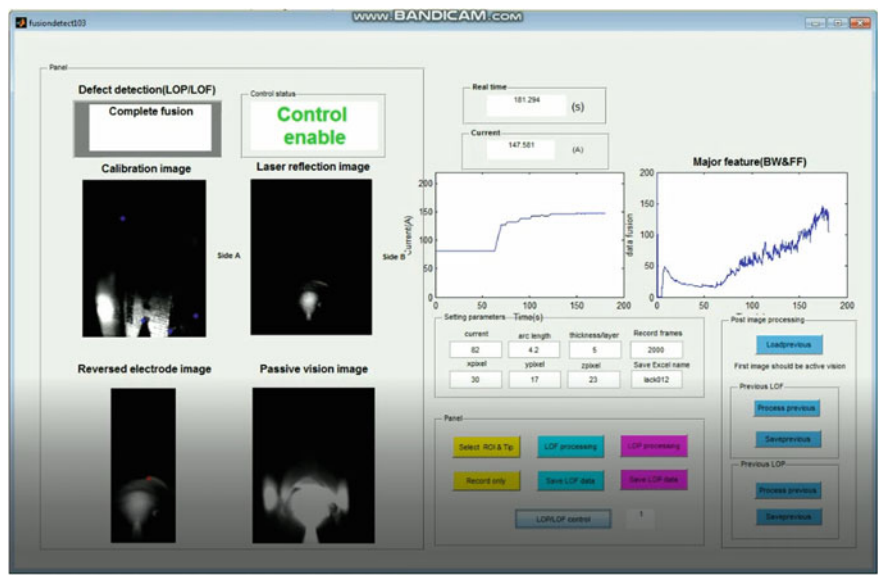


Fig. 7.12 Software interface for LOP and LOF detection

predict LOF defect based on these features. The test accuracy of LOF detection is 95%.

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Chapter 8

Conclusions and Recommendations



8.1 Conclusions

The welding defects such as incomplete penetration and lack of fusion are critical issues that affect the integration of welding component. The weld pool geometry is the major source of information related to the formation of these defects. In this dissertation, a new visual sensing and control system was developed to eliminate the welding defects during GTAW.

The development of the weld pool surface visual sensing approach is the foundation of all the works in this book. The unique visual sensing system can visualize the weld pool area to overcome the interference from arc light. Both active vision image and passive vision image were obtained during the welding process.

In active vision images, the weld pool can be visualized with a clear boundary. The random distributed reflection from laser light increases the challenge of boundary extraction. An algorithm with conventional image processing operation was developed to extract weld pool boundary under special optical conditions. Meanwhile, the depression of the arc plasma force can also be observed with the presence of laser light reflection. An experimental study was conducted under different welding speeds and current conditions on 6 mm SS304. It was found that the high-speed welding achieves better efficiency to produce the same penetration depth compared with the low-speed welding condition. The depression area was found to increase with the increase in welding current. The large arc pressure may cause undercut defect for high-speed welding.

The passive visual system requires a simple experiment setup which is more practical in the manufacturing environment. New algorithms were developed to automatically calculate the 3D weld pool surface geometry. The landmarks detection algorithm was developed to calculate the weld pool boundary from 2D passive vision images. It was found that the camera exposure time significantly affected the accuracy of edge detection on weld pool images. To solve this issue, the adaptive exposure control method was developed to adjust the camera exposure time under appropriate

exposure conditions. The bead on plate experiment shows that the accuracy of weld pool edge detection was improved with the adaptive exposure control method.

A new concept of using a reversed electrode image (REI) to monitor weld pool surface height was first proposed in this work. It was found that the measured distance between REI and electrode (DERI) is relevant to the weld pool surface shape. The increase in surface height will cause a decrease in DERI. A reflection model was developed to calculate the SH based on the measurement of DERI, arc length, and weld pool width. The method was verified with bead on plate experiments. The calculated SH is closely related to the face reinforcement of the weld bead. Thus, the convex and concave weld pool surface shape can be determined based on the calculation result.

The new software framework which integrated all the image processing algorithms was established to obtain three key features of 3D weld pool surface geometry such as weld pool width, trailing length, and surface height in real time. The calculated weld pool width and surface height were close to the actual weld bead size measured after welding.

Another major contribution of this book is applying machine learning methods to predict defects based on the features extracted from weld pool images. The supervised machine learning methods such as linear regression and bagging trees were applied to monitor welding penetration for bead on plate and butt joint welding. The new features extracted from the weld pool image and reversed electrode images played an important role to predict weld pool backside width during welding.

The developed algorithms have been further applied in the U-groove welding joint. The obtained images have unique features compared to the bead on plate welding. It was found that the new features extracted from the reversed electrode image were correlated with the penetration and lack of fusion. A new database was established for penetration prediction in root pass welding. And the bagging tree regression model was trained to predict the backside width. Meanwhile, another database was also established for LOF detection. The classification model was trained to determine the fusion condition of the weld. The proposed method was applied to real-time experiments. The limitation of the method is the root pass welding must be conducted without filler wire. And for all the multi-pass welds I did before, the welding torch must align with the centerline of the U-groove. Thus, the method works better for a narrow groove. For the U-groove with wide width, an additional experiment with swing touch should be conducted.

The closed-loop control algorithms were further implemented to control the uniform backside width during bead on plate welding. The predicted backside width was used as the feedback for prediction. The PID gains were adjusted to reduce the overshooting and setting time. Optimized PID gains were identified through MATLAB simulations. The optimal PID gains should be changed for different thickness workpiece. Thus, a self-tuning PID controller was developed to perform backside width penetration control for the workpiece with changing thickness.

8.2 Future Work

The improvement of the work in this book can be done in many aspects which include the following:

For current research of penetration prediction in bead on plate and butt joint welding, the range of welding current is between 50 and 150 A, and travel speed is between 1 and 2 mm/s. To improve the efficiency of welding, the high-current and high-speed cases can be further studied. The weld pool surface geometry can be affected by increasing arc pressure. The REI method can be further improved to be applied under these conditions. Besides that, machine learning algorithms such as convolution neural network and reinforce learning can be further applied to improve the accuracy of defect detection.