Research of neural network for weld penetration control

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Abstract

A method has been proposed for welding penetration status prediction in the paper. First, an experimental system was set up and welding experiments were performed. Some groups of welding images could be obtained. A composite filtering system composed of a neutral light reduction filter and a narrow band filter was developed to filter the weld arc disturbance. Some operations were performed to the images, namely the median filter and gray transformation. Then a neural network was setup, containing three layers. The inner widths of pool $x_n$, the outer widths of pool $x_w$, the width difference values $e$ between the inner and outer of pool, ratios of inner pool widths $R_n$ and ratios of outer pool widths $R_w$ between two adjacent images were determined to be the input parameters. The penetration parameter $p$ was chosen to be the output. Based on the images, groups of pool parameter data have been obtained and used to train the network. In this way, the weld penetration prediction model can be deduced. Finally, verification tests have been done. It showed that weld penetration situation predicted by the model is fit to its real condition. The accuracy rate is up to 96%, which affords a new way for penetration detection.

Keywords: weld, weld pool image, weld penetration control, neural network modelling

1 Introduction

In some fields of production manufacturing, such as the automobile industry, the shipbuilding industry and so on, the metal is usually joint by welding. It is said that there are about 40% of all steel structure production is connected by welding [1]. The weld quality at the joining position is very important for the final production, which may directly affect the safety of human. Nowadays, the weld quality control is done following the correct procedures, the monitoring of the welding process and the inspection of the final quality, which can’t satisfy the need of mass production.

Actually, skilled welders watch the pool shape, adjust the welding gun posture and the welding speed to realise the welding quality control in real time. From this fact, we can infer that there is much information

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contained in the weld pool, which may imply the heat transfer situation, the stability, the welding penetration condition and so on. Therefore, information of the welding process may be indirectly inferred by the formation of weld pool, which affords a new way for weld quality control.

Therefore, the weld pool information has become very important in welding. In order to achieve this goal, much elaborate research has been done. Nowadays, there are many methods applied for weld pool detection, such as the vision sensor method, the weld arc sound sensor method, the molten weld pool oscillation method, the infrared sensor detection method, the optical sensor method and so on [2–5]. The vision method has been greatly used in weld pool detection, which has the merit of being contactless and access to a large amount of information [6]. Yongchao et al. [7] performed some analysis on the evolution process of the pool surface, which can be used for weld monitoring. A model is trained for the root-pass penetration estimation, which is the convolution neural network. Zitouni et al. [8] imported the morphology for pool image processing. The weld pool has been surveyed in order to learn the weld properties. The heat transfer condition of weld assembly can be inferred through the Tungsten Inert Gas (TIG) process. Then a mathematical model was developed and the effect of the melted liquid movement for weld pool was studied. Dukun [9] studied the weld pool centroid. A method for weld deviation prediction has been proposed. Lidong et al. [10] proposed a system composed of structured light vision sensing, in which the images, which are composed of the 3D formation of pool surface, can be captured. Then the long-short-term memory (LSTM) neural network has been researched and used for pool measurement so that the automatic weld control can be realised. Nicholas et al. [11] researched the weld pool characteristics from the high-resolution thermal imaging of the welding process. The weld pool characteristics can be investigated in this manner for welding control.

Using the pool images, a method for weld penetration control has been researched in this paper. First, the experimental platform was set up for TIG welding. Several weld experiments were performed. Then weld pool images were then acquired. Some analysis was performed on the pool images. The main factors affecting weld penetration were obtained and composed into the weld penetration status control parameters.

On this basis, a BP neural network was constructed. The widths of inner pool $x_n$, the widths of outer pool $x_w$, the difference values between the inner and outer welding pool widths $e$, ratios of the inner pool widths between two adjacent images $R_n$ and ratios of the outer pool widths between two adjacent images $R_w$, which affect welding penetration, are chosen to be the input parameters in this paper. Welding penetration situation $p$ is chosen to be the output parameter. The data, which were obtained by the welding experiments, are used for the training of the network. In this way, the model was set up, which can be used for weld penetration prediction and affords a new way for weld quality control.

2 Hardware of experimental system

First, the experimental system is setup for the TIG welding in this paper. The key components of the whole experimental system are the weld robot, the working table, the visual camera, the controller and so on, which are shown in Figure 1. The control system is used for the mechanical table motion control and image capture. A 6-axes robot is used for welding. The mechanical table is composed of two axes, namely the $x$ and $y$ axis, which are driven by stepper motors. The welding fixture on the table is used to clamp the weld assembly.

The travel switches on the axis can be used to make sure that the work table moves within a certain scope. In the experiments, one axis of the work table is determined to make a feed moving. In order to reduce the strong light produced by the weld arc, an optical filter is installed in front of visual camera. The visual camera captured images during the welding process.
The CCD system of the welding platform includes the CCD visual sensor and the camera. The visual sensor is SANYO’s VCC-6570P sensor, whose chip scale is 1/3". The total pixels of the sensor are 795 × 596. The T10Z0513CS of the Japanese company, Computar, is used as the camera lens for the visual sensor. The scale of the lens is 1/3", which is fit to the scale of the CCD sensor. The detailed parameters of lens is as follows:

| Item               | Numerical value |
|--------------------|-----------------|
| Scale              | 1/3"            |
| Focal length       | 5~50 mm         |
| Aperture           | F1.3-C          |
| Angle of view      | 51.8–56°        |
| Nearest object distance | 0.8 m     |

In the application of visual sensors, there exists distortion of the lens. However, the effect of distortion is very minimal in the setup of the penetration model. Therefore, the lens distortion is ignored in this paper. The detail demarcating process first involves placing a ruler on the welding table. The CCD sensor is then used to capture the image, which is shown in Figure 2.

The position of the demarcate line is shown in Figure 2. The distance between the adjacent lines is 4 mm, and the pixels are 29, 32, 30, 30, 29, 31, 30 and 29. The pixel equivalent can therefore be calculated as follows:

$$k = \frac{1 \times 8}{29 + 32 + 30 + 30 + 29 + 31 + 30 + 29} \approx 0.033\text{mm/pixel}$$

(1)
The motion control and image capture cards in the controller communicate using a PCI bus. An open software for the welding system can be developed using the C++ programming language. The software system can control the weld table moving along the axis. It can also capture welding images, save them onto the harddisk of a computer and perform some image processing operations at the same time. The software of the welding system is shown in Figure 3.

Clear pool images is a key factor for penetration control. There is a strong arc-light during the welding. Since the light will cover the weld pool, optical filters can be used to reduce the light disturbance. Figure 4a shows the result of the narrow band filter method. It can be found that the arc-light is still very strong. The weld pool has been covered by the strong weld arc. Some information that is very important for weld penetration control, such as the shape of pool, the width and length of pool, can’t be distinguished.

5 Obtainment of pool image

Clear pool images is a key factor for penetration control. There is a strong arc-light during the welding. Since the light will cover the weld pool, optical filters can be used to reduce the light disturbance. Figure 4a shows the result of the narrow band filter method. It can be found that the arc-light is still very strong. The weld pool has been covered by the strong weld arc. Some information that is very important for weld penetration control, such as the shape of pool, the width and length of pool, can’t be distinguished.
However, Figure 4b shows the result of the traditional neutral light reducing method. It can be found that the contrast of weld pool images has become very weak. The whole pool image has become very vague. The details of the weld pool can’t be detected. Some edge of pool image has been lost.

From Figure 4, it can be found that the two filtering methods have their own merits and demerits. In order to combine the advantages of narrow band filtering with the neutral filtering method, a composite system is used for light filtering in this paper, composed of a 650 nm narrow band filter and a 7# neutral filter. The filtering result is shown in Figure 5. It can be found that the composite filter method can reduce the arc-light disturbance more effectively allowing clearer weld pool images to be obtained.
6 Weld pool image processing

A $3 \times 3$ template median filter operation is performed to reduce the noise disturbance, which is shown in Figure 6a. Then the gray transform process is performed. The contrast between weld pool and seam has become more obvious. Clearer weld pool images could be obtained. Figure 6b showed the processing results for weld pool images.

![Result of median filter](image1)
![Result of gray enhance](image2)

Fig. 6 Procession result of median filtering and gray enhancing

7 Welding penetration status

The penetration condition of the steel plate can’t be detected directly. However, the penetration status can be speculated by means of assessing other parameters. Many researchers choose the width of weld seam at the back for the weld penetration conditions determination [12–15]. In this paper, using the width values of weld seam at the back, the penetration levels were divided into unfused, fused and over fused status, which are shown in Table 2.

| Penetration status | Unfused | Fused | Over fused |
|--------------------|---------|-------|------------|
| Width values of weld seam at the back | $<1.82$ mm | $>1.82$ mm and $<2.64$ mm | $>2.64$ mm |

8 Set up of weld penetration model

8.1 Obtainment of welding data

Using the experimental system, several welding conditions were inferred. Table 3 shows the welding conditions. Several groups of weld pool images were then acquired, which can be used to train the model for weld penetration measurement.

At the beginning of the welding process, the torch point is set to the seam. Then the feeding axis drives the working table to move. The visual camera captured the images in real time. About 400 welding images can be acquired in one instance of welding. The front side of the welding seam is shown in Figure 7, and the back side of welding seam is shown in Figure 8. The width of weld seam on the back side is shown in Figure 9.
### Table 3  Welding experiment conditions

| Material and size (mm $\times$ mm $\times$ mm) | Argon flow (L/min) | Weld current (A) | Weld speed (mm/s) | Sample time (ms) |
|---------------------------------------------|--------------------|------------------|-------------------|------------------|
| Q535(200 $\times$ 150 $\times$ 2)           | 9                  | 80               | 2.50              | 40               |

**Fig. 7** Front side of welding seam

**Fig. 8** Back side of welding seam

**Fig. 9** Widths of weld seam on the back side

### 8.2 Set up of weld penetration model

In actual application, the widths of seam at the back side are usually chosen to be the parameters for weld penetration determination. From the captured pool images, it can be easily inferred that the width of seam at the back side is greatly influenced by the width of the front weld pool. In another words, the welding penetration status can be indirectly inferred by the width of weld pool on the front side. In the welding process, the outer and inner weld pools will be formed, which is due to the uneven heating conditions under the weld arc and its surrounding areas. The outer and inner weld pool are shown in Figure 6. The widths of inner pool $x_n$ and widths of outer pool $x_{nw}$ are shown in Figure 10.
In this paper, the widths of inner pool $x_n$, the widths of outer pool $x_w$, the difference values between the inner and outer weld pool widths $e$, ratios of the inner pool widths between two adjacent images $R_n$ and ratios of the outer pool widths between two adjacent images $R_w$ are determined to be the input vectors. Weld penetration status of the weld assembly $p$ is set to be the output parameter, which is determined according to Table 2. A neural network is constructed, which can be used to build the relationship between the input vector and the output parameter.

BP network is a multilayer forward neural network [12–15]. Figure 10 shows the structure of the BP neural network setup used in this paper. It contains the input, hidden and output layers. The input contains five parameters, which are the width of inner pool $x_n$, the width of outer pool $x_w$, difference value between inner and outer welding pool width $e$, ratio of the inner pool widths between two adjacent images $R_n$ and ratio of the outer pool widths between two adjacent images $R_w$. The number of neurons in the hidden layer is 20. The output layer contains only one neuron, which is the welding penetration situation of weld assembly $p$. The train way is the elastic gradient descent method. The transfer functions for the hidden and output layer are the tansig function and the purelin function, which are shown in formula (2) and formula (3), respectively [8, 9].

$$f(x) = \frac{2}{(1 + e^{-2x}) - 1}$$  \hspace{1cm} (2)$$

$$f(x) = x$$  \hspace{1cm} (3)$$

The expression of the seam penetration model can be expressed as follows:

$$\begin{cases}
\mu^H = \omega^H \times X^T + b^H, & \nu^H = \frac{1 - e^{-\mu^H}}{1 + e^{-\mu^H}} \\
\mu^O = [\nu^H]^T \times \omega^O + b^O, & y = \mu^O
\end{cases}$$  \hspace{1cm} (4)$$

In (4) shown above, the input vector is $X$. It has five parameters, which are the width of inner pool $x_n$, the width of outer pool $x_w$, the difference value between the inner and outer welding pool width $e$, ratio of the inner pool widths between two adjacent images $R_n$ and ratio of the outer pool widths between two adjacent images $R_w$. $W^H$ and $b^H$ stand for the weight coefficients and threshold value of hidden layer. $W^O$ and $b^O$ are the weight coefficients and the threshold value of output layer. $y$ is the output value, which is 1, 2 or 3. It stands for the three welding penetration status – unfused, fused and over fused.

Groups of data were selected and input to the setup network. The training results are shown in Figure 12.
Neural network for weld penetration control

Fig. 11 Structure of the neural network for weld penetration prediction

The parameters of model can be shown as follows:

\[ \mathbf{w}^H = \begin{bmatrix} -0.1772 & 0.0636 & 0.3348 & -30.5430 & 21.0823 \\ 2.6741 & -2.2341 & -4.8141 & 10.1627 & -17.2458 \\ -0.0285 & -0.0080 & 0.1223 & 34.0417 & -20.7241 \\
\vdots & \vdots & \vdots & \vdots & \vdots \\ 1.1706 & -0.2809 & -1.3060 & -11.3749 & -29.1361 \\ 0.0383 & -0.0413 & -0.0559 & -12.9800 & 14.5041 \end{bmatrix} \]
\[ \mathbf{b}^H = \begin{bmatrix} 6.3768 \\ 13.2016 \\ -24.7479 \end{bmatrix} \]
\[ \mathbf{w}^O = \begin{bmatrix} -0.0159 \\ 0.0068 \\ -3.0137 \end{bmatrix} \]
\[ \mathbf{b}^O = 3.5833 \]
9 Testing experiments

To verify the accuracy, other groups of data were selected and input into the model. The verification result is shown in Figure 12. The average error of model can be defined as follows:

$$\text{error} = \frac{l}{L}$$  \hspace{1cm} (5)

In (5) shown above, $L$ is the total detected points. In this paper, this number is 100. $l$ are the points whose values are fit to the measured values.

In Figure 13, it can be found that there are 4 failed points. This may be due to the disturbance from weld arc. The final precision is 96%. This shows that the setup model can predict the welding penetration status well.

![Fig. 13 Verification result for the penetration prediction model](image)

10 Conclusions

A new way for weld penetration prediction has been proposed. It uses the weld pool image. Groups of weld pool images can be captured for training data by the experimental system. Several image processes have been performed to the pool image, namely the median filtering and gray transformation operations. A BP neural network has been setup, which contains three layers. Then the widths of inner pool $x_n$, the widths of outer pool $x_w$, difference values between the inner and outer welding pool width $e$, ratios of the inner pool widths between two adjacent images $R_n$ and ratios of the outer pool widths between two adjacent images $R_w$ are determined to be the input parameters. Welding penetration status $p$ is set to be output parameter. In this way, the prediction model for weld penetration detection can be set up. The final verification experiments show that the precision of the model is up to 96%. However, 4 points failed. The setup model can predict the welding penetration status well.

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