Circumferential TIG Welding of Aluminum Pipe Using Neural Network

Ario Sunar Baskoro[1], Yasuo Suga[2]
[1] Department of Mechanical Engineering, University of Indonesia During the Study at Graduate School of Science and Technology, Keio University, Japan
E-mail: ario@suga.mech.keio.ac.jp
[2] Faculty of Science and Technology, Keio University
Hiyoshi3-14-1, Kohoku-ku, Yokohama, Japan

Abstract

This paper presents the circumferential Tungsten Inert Gas (TIG) welding of fixed aluminum pipe. The research is conducted for welding of aluminum alloy Al6063S-T5 with square-wave AC welding polarity and CCD camera to monitor backside molten pool. Image processing algorithm is developed to recognize image parameters of molten pool. Neural network model is utilized to control the welding penetration by modifying speed as welding parameter. The utilized neural network model is 6 units of input layer, 7 units of hidden layer, and 1 unit of output layer. The output of neural network is the difference of welding speed to obtain uniform weld bead over the entire circumference of the pipe. By controlling welding speed the back bead width of aluminum pipe are in the permitted range.

Keyword: TIG welding, aluminum pipe, neural network

1. Introduction

Tungsten Inert Gas (TIG) arc welding process is widely used in the industries for circumferentially butt-welded pipes and welding aluminum alloys. However, arc welding process are nonlinear and multivariable-coupled because it involves many uncertainties, such as, influences of metallurgy, heat transfer, chemical reaction, arc physics, and magnetization. So that, the weld seam accuracy is difficult to be controlled due to the non-linearity and uncertainties of the process. Moreover, it is difficult to weld thin aluminum alloy pipe in fixed position while the welding torch moves circumferentially along the pipe. If the constant welding conditions are maintained over the full joint length, the bead width becomes wider as the circumferential welding of small diameter pipes progresses. As a result, it is important to control welding process in real time.

In the previous researches, welding processes have been conducted by rotating aluminum pipe and welding torch was kept static [1-4]. The theoretical and experimental study of heat flow during welding of pipes with seam and girth welding method was carried out [1], which confirmed that under a constant heat input and welding speed, the size of the fusion zone remains unchanged in seam welding but continues to increase in girth welding of pipes with small diameters. The other researches are the study on parameter optimization in the circumferential GTA welding of aluminum pipes with numerical heat conduction model [2], and semi-analytical finite-element method [3]. Another mathematical method for the determination of the optimum heat input condition to control the temperature field was also conducted [4], which the algorithm was also applied to a circumferential aluminum pipe welding with GTA. The experiment using the image sensing to control the TIG weld width for aluminum alloy plate was conducted with the algorithm of image processing and pattern recognition of molten pool's edge [5]. The visual sensing system is analyzed from the point of the view of light intensity and recovers the shape and height of the weld pool by SFS (shape from shading) algorithm from the welding pool image [6].

The excessive arc current yields melt down of metals; in contrary, insufficient arc current produces imperfect welding. In order to avoid these errors and to obtain the uniform weld bead over the entire circumference of the pipe, the welding conditions should be controlled as the welding process proceeds. The purpose of the study is to investigate circumferential welding process of fixed aluminum alloy pipe A6063S-T5 using vision sensing to control welding penetration by neural network by modifying speed as welding parameter.

2. Experimental Device and Method of Study

The experimental device, which is used in this experiment, is shown in Fig.1. The overall system uses the circumferential welding system, CCD camera and the image digitizer to acquire of molten pool image, the personal computer which processes image and controls, two stepping motors which are used for the revolution and longitudinal movement of the welding torch, the small-sized stepping motor which is used for arc length control, arc current measurement equipment, the gearbox, and the TIG welding machine of AC square-wave current.

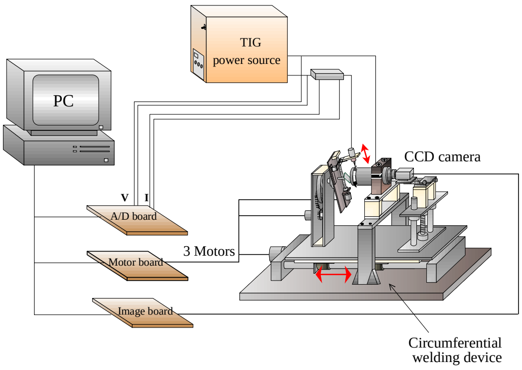

Fig.1 Experimental device

Table 1 Material properties and welding conditions

Base metal	Al-6063S-T5
Diameter of pipe (mm)	37.8
Thickness of pipe (mm)	2.0
Density (g/cm^3)	2.69
Melting point (^{o}C)	615-655
Thermal conductivity (W/m.K at 25^{o}C)	209
Welding machine	AC
Electrode	2% Th-W (∅ 2.4 mm)
Nominal arc length (mm)	1.5
Welding current, I (A)	50 ~ 90
Welding speed, v (cm/min)	7 ~ 20
Shielding gas, q (l/min)	8 ~ 15

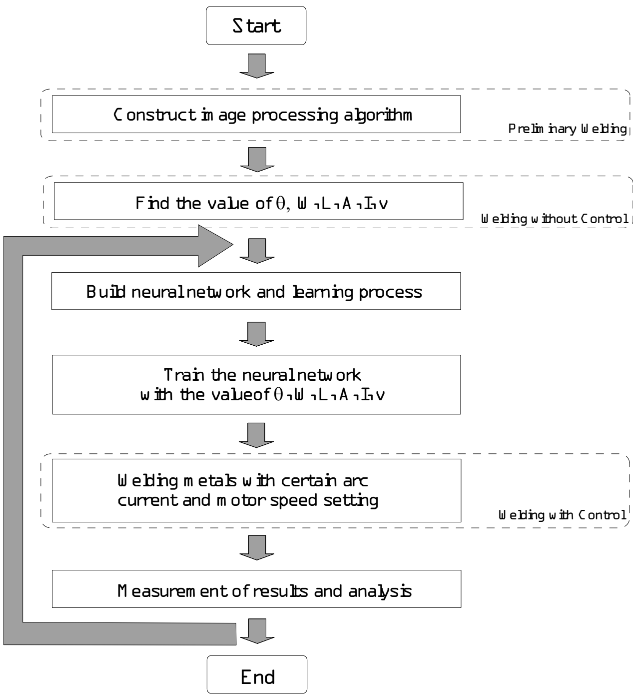

Fig.2. Method of study

The material properties and welding conditions of this study are shown in Table 1. Method of study is shown in Fig.2. First, the image processing algorithm is designed by considering the image characteristics of molten pool. After several test from the sample image, then the next step is welding the pipe without controlling the welding parameter. The purpose of this step is to collect the data of image parameters, which are: image width (W), image length (L), and image area (A), with the complement of angle (θ), arc current (I) and welding speed (v). With several combination of welding speed, the data are composed and ready to be processed into neural network training. The learning data will be trained into two parts, which are: training data and test data with the percentage of 90% and 10%, respectively. Finally, after several times iteration, and to find the better error value, then the weight of neural network can be obtained. This weight values will be used to control welding process. Finally, the result of control welding will be measured and analyzed.

3. Experimental Without Control

The experiment without control is conducted to obtain the data that used as input of neural network training process. The combination of several welding speed ranges from 9 – 17 cm/min has been conducted to obtain the parameters of welding torch rotation angle (θ), welding speed (v), arc current (I), image width (W), image length (L), and image area (A), back bead width (b).

In this experiment, the current pattern is symmetrical square-wave AC current. The first step of welding process is the welding torch is kept steady at the 0^o for several time. In this case, the waiting time to make sure the penetration of aluminum pipe occurs is 25 s. Then the torch rotates along the pipe until reaching 360^o. Fig.3 – Fig.5 shows the results of experiment without control conducted at I = 70 A, frequency of 50 Hz, with different welding speed, Fig.3 with v = 9 cm/min, Fig.4 with v = 12 cm/min, and Fig.5 with v = 15 cm/min. From that results, the lower welding speed the higher top and back bead width. Moreover, the lower welding speed yields the unstable bead width. In this experiment, the tolerance of back bead width to be used for input data of control system ranges from 4 – 6 mm, with the target of 5 mm.

Fig.6 shows the relation between back bead width and width of molten pool, W. Although the distribution of back bead width and W are not fit each other, but the tendency of the graph seems to be same.

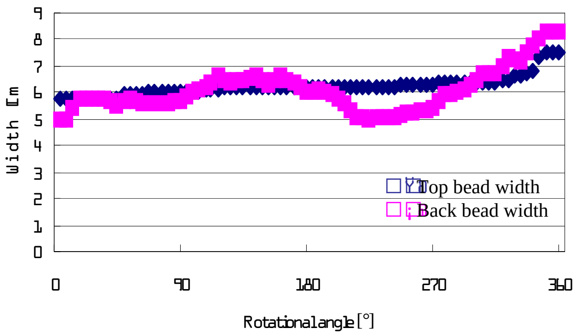

Fig.3 v = 9 cm/min, I = 70A

Fig.4 v = 12 cm/min, I = 70A

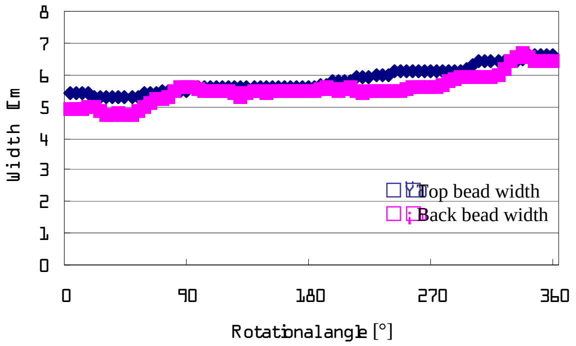

Fig.5 v = 15 cm/min, I = 70A

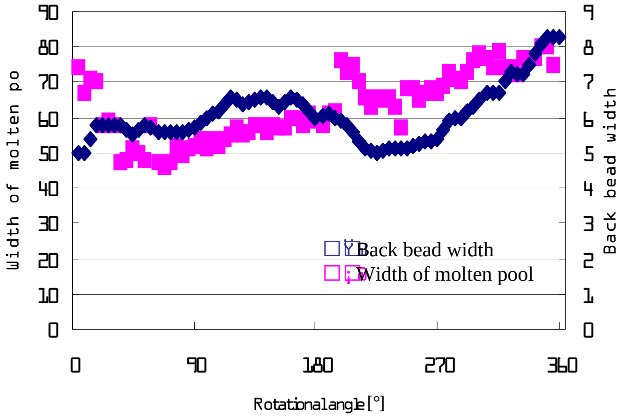

Fig.6 Relation between back bead bead with and width of molten pool (v = 9 cm/min, I = 70A)

4. Training of Neural Network

A multilayer feedforward network is an important class of neural networks that typically consists of a set of sensory units of source nodes that constitute the input layer, one or more hidden layers of computation nodes, and an output layer of computation nodes. The input signal propagates through the network in a forward direction, on a layer by-layer basis. These neural networks are commonly referred to as multilayer perceptrons (MLPs), which represent a generalization of the single-layer perceptrons. Multilayer perceptrons have been applied successfully to solve some difficult and diverse problems by training them in a supervised manner with a highly popular algorithm known as the errors *back-propagation algorithm.* This algorithm is based on *the error-correction learning rule*.

The error back-propagation process consists of two passes through the different layers of the network: a forward pass and backward pass. In the forward pass, an activity pattern of input vector is applied to the sensory nodes of the network, and its effect propagates through the network, layer by layer. Then, a set of outputs is produced as the actual response of the network. During the forward pass the synaptic weights of the network are all fixed. During the backward pass, the synaptic weights are all adjusted in accordance with the error-correction rule. The actual response of the network is subtracted from a target response to produce an *error signal.* This error signal is the propagated backward through the network, against the direction of synaptic connections. This process then named as "error back-propagation." The synaptic weights are adjusted so as to make the actual response of the network move closer to the desired response. The error back-propagation algorithm is also referred to in the literature as the *back-propagation algorithm* (*back-prop*). The learning process performed with the algorithm is called *back-propagation learning.*[7]

Fig.7 presents the neural network model used in this research. The model uses back-propagation algorithm with three layers structure consists of six units in the input layer, seven units in the hidden layer, and one unit in the output layer.

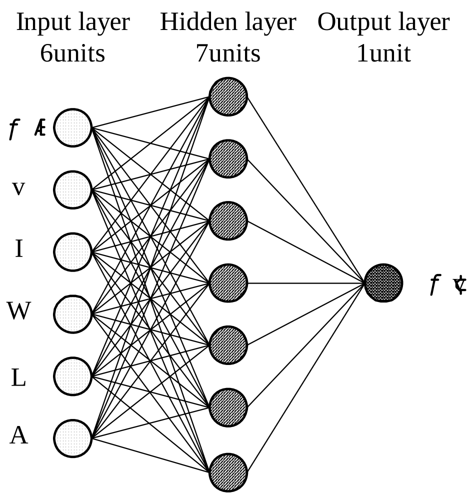

Fig.7 Neural network model

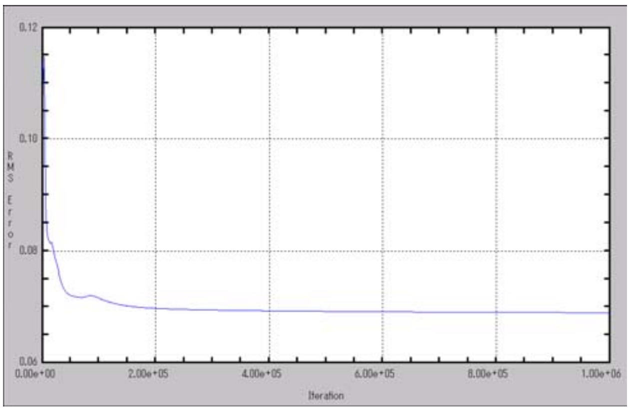

Fig.8 Training error of neural network configuration: 6 input units – 7 hidden units – 1 output unit

In this process, the good structure of neural network will be examined with the given training data. The preliminary training process was conducted for different hidden layer. The combination of 6 units input layer, 5 – 8 units hidden layer, and 1 unit output layer were examined. The value of momentum is 0.75, the learning rate is 0.05, iteration is 10^5, the training data is 294, and the testing data is 34 as 10% from the training data are selected randomly. The resume of training and test error is shown in Table 2. Because the training and test error of 6 input – 7 hidden – 1 output are lowest than the other configuration, so this structure is selected as the neural network model. Finally, by applying the configuration with 10^6 iteration and the same training condition, the weight of neural network can be obtained. The results of training error are shown in Fig.8.

Table 2. Training results of neural network

Input layer (unit)	Hidden layer (unit)	Output layer (unit)	Iteration	Training data	Test data	Training error	Test error
6	5	1	100,000	294	34	0.094312	0.146186
6	6	1	100,000	294	34	0.102220	0.120318
6	7	1	100,000	294	34	0.090779	0.109966
6	8	1	100,000	294	34	0.092342	0.131322

5. Results and Discussion

To produce stable arc condition, the welding speed at 0^o – 45^o is made constant. In this case, the given welding speed is 12 cm/min. For controlled welding process, appearance of top and back welding bead are shown in Fig. 9 and 10, respectively. The top and back bead width is shown in Fig. 11. The top bead width is constant along the rotation progresses. The back bead width tends to stable from 0^o – 180^o. Then, it decreases to about 270^o and rises to the width of about 6 mm due to the change of welding speed. From the welding results, back bead width tends to stable condition from 0^o – 180^o. Then, it decreases to about 270^o and rises to the width of about 6 mm. From this experiment, the target back bead width of 5 mm is in the permitted range of 5±1 mm with the standard deviation of 0.53 mm.

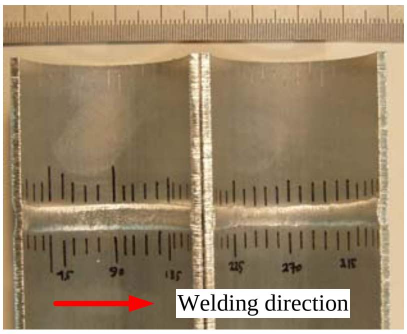

Fig.9 Back bead appearance

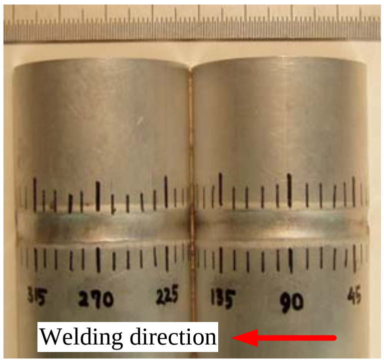

Fig.10 Top bead appearance

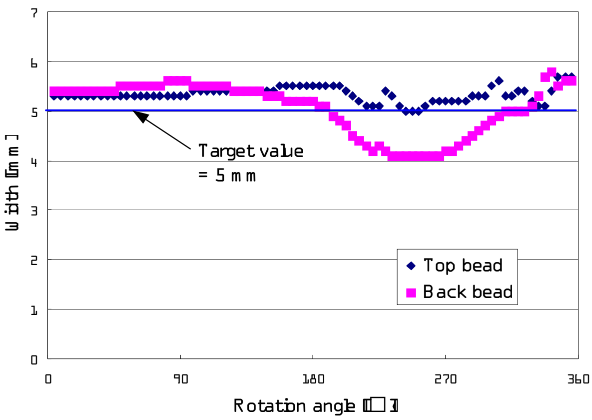

Fig.11 Top and back back width

Fig.12 Top bead appearance

The welding speed tends to increase from 45^o until the range of 180^o – 270^o as shown in Fig. 12. Then it decreases to about 270^o and finally rises until the end of rotation angle. At the end of 360^o, the welding speed values are saturated at 20 cm/min. This condition probably caused by insufficient training data, error of image processing, error of motor control, and time delay problems.

6. Conclusions

1. The circumferential TIG welding using vision sensing to control welding penetratrion is constructed. The workpiece material is aluminum alloy pipe A6063S-T5, and welded in fixed position and moving welding torch.
2. The neural network as control model was developed. Six parameters of image parameters of molten pool: width (W), length (L) and area (A), rotation angle (θ), welding speed (v) and welding current (I), are the input for training process which outputs the modified welding speed, Δv.
3. The utilized neural network model is back-propagation algorithm with 6 units of input layer, 7 units of hidden layer, and 1 unit of output layer.
4. The result of experiment with control shows that the back bead width is in the range of 5±1 mm with the standard deviation of 0.53 mm.

7. References

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