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AUTOMATIC WELDING SPEED CONTROL BY MONITORING IMAGE OF WELD POOL USING VISION SENSOR

Ario Sunar Baskoro[1], Achmad Zaki Rahman[2] and Haikal[1]
[1]Laboratory of Manufacturing Technology and Automation, Department of Mechanical Engineering, Faculty of Engineering, Universitas Indonesia, Kampus Baru UI Depok, Indonesia
[2]Laboratory of Production Technology, Center for Machine Tools, Production & Automation, BTMEPPO - BPPT, Puspiptek Tangerang Selatan, Indonesia
E-Mail: ario@eng.ui.ac.id

ABSTRACT

This paper presents a study on automatic welding speed control by monitoring of weld pool image using vision sensor to create a welding control system that able to produce good weld bead appearance and quality. The monitoring performs on autogenous Tungsten Inert Gas (TIG) welding with constant-current. In this experiment, welding torch set to be stationary while stainless steel SS-304 as work-piece placed on moving-table driven by electric stepper motor. CCD camera captured images of weld pool that formed during the welding process to be extracted by image processing algorithm. The pool geometry values that have extracted will be applied to the real time welding speed control system using Artificial Neural Network (ANN) system. The result showed that the system developed had succeeded to produce good weld bead appearance on several current values.

Keywords: automatic TIG welding, vision sensor, artificial neural network.

INTRODUCTION

Many methods can be used to obtain a good quality welding. One of them is by observing the weld pool geometry directly from above for determining the welding quality especially in the case of sheet welding [1]. For achieving that purpose, some studies have proved that in order to build a monitoring system for the welding does not have to be expensive, it can be done quite simply by a CCD camera as vision sensor and a computer [2]. The results from image processing in computer can be used to control the welding variables to obtain the desired weld pool dimensions, for example by making it as a parameter in determining the welding speed [3,4].

Welding speed or commonly called as travel speed is one of significant variable in defining the geometry of the weld pool. The American Welding Society defines travel speed as the linear rate at which the arc is moved along the weld joint [5]. Weld pool size and travel speed are inversely related. The more highly travel speed result the weld bead is become wider and otherwise.

This experiment presents a system that using a computational neural network for predicting magnitude of the travel speed in order to obtain the desired size of weld bead. The use of neural networks on the welding process has been conducted by some researchers [6,7] has declared that the application of neural networks is a viable approach towards the weld modeling of reliable. Previous researches have built an experimental neural network model for predicting weld bead geometry in gas tungsten arc welding [8]. The same research also uses neural networks to control the automated welding system for aluminum pipe [9].

The previous researches [6-9] have demonstrated that the application of neural networks on TIG welding is effective to improvement the performance of weld process. However, using vision sensor and neural network at the automatic welding to monitoring weld bead width is still an emerging topic. Therefore, this paper studies the automatic system on TIG welding process using machine vision and artificial neural network was applied to control the width of the molten pool by modifying welding speed.

EXPERIMENTAL PROCEDURE

Device system

The welding monitoring systems that shown in Figure-1 are a real-time monitoring of weld pool dynamics to control welding speed [10]. The major functional components from the experimental system are a process control computer, a TIG welding power source, a CCD camera with filter, an electrical-motor control unit, and a moveable welding table.

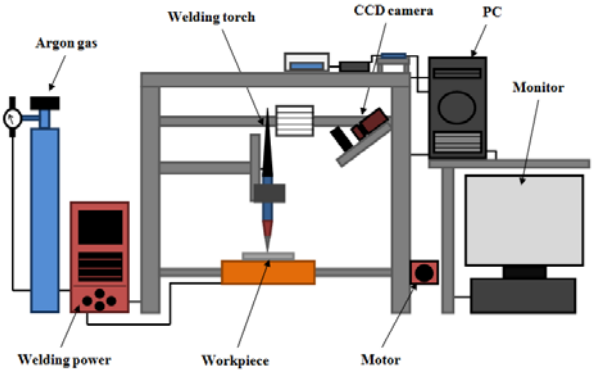


Figure-1. Schematic of experimental device.

The welding experiment had been done using TIG welding machine with DCEN mode and pure Argon shielding gas. The workpiece material was stainless steel SUS-304 with dimensions of 50 x120 mm and thickness of 3 mm. Argon was used as the shielding gas with a flow

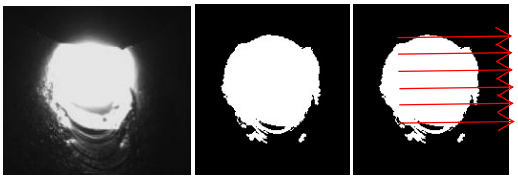
rate of 10 liter/min. The diameter of tungsten electrode was 2.4 mm with an angle of 90°. The arc length was held at 2 mm.

For this system, the CCD camera observes the weld pool at certain angle (30°). A CCD camera used for monitoring weld pool and captured the image to the process control computer where the image processing occurs.

Weld pool image processing

In order to investigate weld quality, the weld pool that occurred during welding process captured by CCD camera as an image and stored in computer (see Figure-2 (a)). Then a series of image processing would be performed to turn it into binary value pixel or black and white (BW) image (see Figure-2 (b)). It would be easier to measure the width of this binary image by counting a single type of pixel value only. After several pixel measurements as shown in Figure-2(c), the biggest result would be considered as the weld pool width.

It is necessary to get the ratio between the real length and the number of pixels, in order to find out the real width of the weld pool that had monitored. The calibration process was done by performing vision measurements on weld pool recorded images during welding process in progress, and then the results were compared with the manual measurement on the weld bead after the welding process was finished. The calibrated ratio that obtained after comparing two types measurements is 11.90 pixel/mm.



(a) (b) (c)

Figure-2. (a) Weld pool image as captured, (b) BW thresholded conversion image (c) Measuring weld pool edge process

Experiments without control

The material properties and welding conditions of this paper is shown in Table 1. Welding experiments were conducted in TIG welding to find the training data by welding autogenously on the workpiece in different amperage and welding speed.

Table-1. Material properties and welding conditions.

Work-piece / Base-metal	SUS 304
Metal thickness (*mm*)	2
Metal width (*mm*)	20
Metal length (*mm*)	100
Electrode	2% Th-W (Ø 2.4 mm)
Welding speed (*mm/s*)	1.2 ~ 2.0
Welding voltage (V)	11
Welding current (A)	55 ~ 65
Shielding gas	100% Ar

Some experiments welding are performed using the parameters listed in Table 1 by varying the amperage and welding speed. The specified amperage and speed is set to remain constant during the welding process on each experiment. Then weld-pool that created along the process had been captured and stored into computer to be compared with the finished-weld result.

The best combination amperage values and welding speeds were shown in Table-2. Those were the best combination parameters and results that have a good weld-bead and penetrations. These values in Table-2 would become references and parameters in next experiments.

Table-2. Best vision measurement results on several variations of amperage and welding speed.

Welding current (A)	Welding speed (mm/s)	Averaged weld-pool image (mm)
55	1.2	5.11
60	1.5	5.81
65	2	4.79

Welding speed control with neural network

The next experiment would be conducted by making an automatic welding speed control system using back propagation neural network as shown in Figure-3.

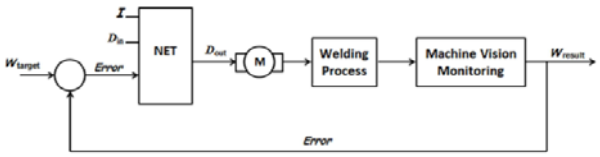


Figure-3. The schematic diagram of welding speed control system.

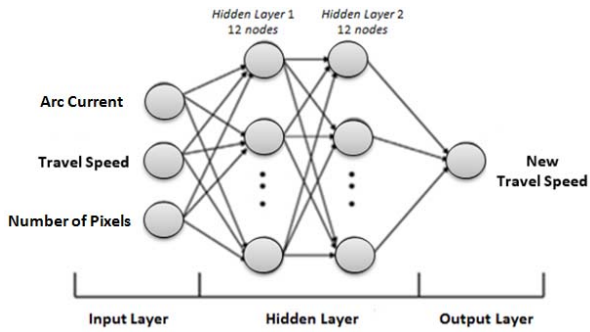


Figure-4. Neural network model.

From the picture above, it can be seen that each measurement result of weld-pool width (Wresult) will be compared with target or desired weld-pool width (Wtarget). The difference between those widths called Error, which:

$$\text{Error} = W_{target} - W_{result} \quad (1)$$

Due to the value of tolerance that we set at the beginning is 1 mm, it means that the system must ensure that the difference of width or error value is around 1 to -1. If the error value is smaller than minus one (-1), it means that the system had produced wider weld-pool ($\mathbf{W}_{result}$) than targeted ($\mathbf{W}_{target}$). It would happen if the welding speed was too slow. This is where the neural network (NET) plays a role in determining the proper value ($\mathbf{D}_{out}$) to increase the motor speed so the errors will be within the tolerance. Similarly, when the error value is greater than 1, it means the system has produced is smaller weld-pool ($\mathbf{W}_{result}$) than targeted ($\mathbf{W}_{target}$). To overcome these problems, the neural network (NET) should predict a new welding speed ($\mathbf{D}_{out}$) that can reduce rotation speed of the stepper motor in order to enlarge the weld-pool ($\mathbf{W}_{result}$).
The back propagation neural network model has built to predict proper speed for stepper motor, as shown in Figure-4. The input data from the initial experiment (without control) were used to train the process and outputted the weight of neural network. There were four layers structure consisted of one input layer that contained three nodes, those were arc current, travel speed, and number of pixels. The next three layers were composed of two hidden layers for 12 nodes each, and the output layer is new travel speed.

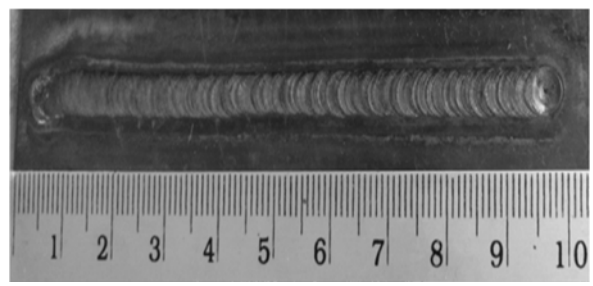
This experiment performed with the speed control system refers to the previous experiments (see Table-2). The current values that is used varies from 55 A, 60 A, and 65 A for welding 2 mm thick SUS 304 plate. And for the width of weld-pool target scenario was 5 mm, which was also based on the average width of weld bead in Table-2.

RESULT AND DISCUSSIONS

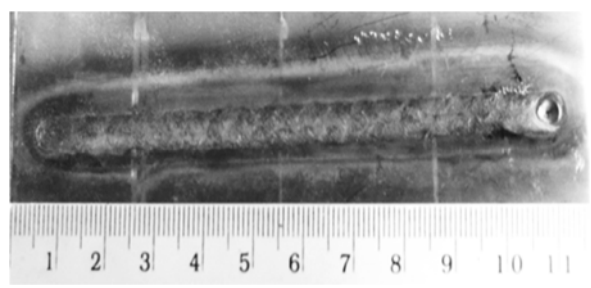
Three welding experiments were conducted by using speed control systems. The target will be achieved by those experiments is 5 mm weld bead width by using welding current variation at 55 A, 60 A, and 65 A. The initial travel speed for all experiments was set at 1.5 mm/s.

Figure-5 shows the appearance of weld bead obtained by TIG welding process using neural network with the target is 5 mm under different welding current.

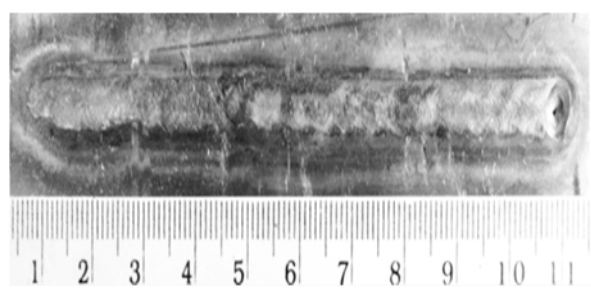
The experimental data for the weld bead width is plotted in Figure-6. It showed the changes of weld pool (blue line) and welding speed (gray line) in order to achieve the target width of 5 mm (red line). From these graphs could be seen that the system response of speed control to the weld pool had occurred.



(a)

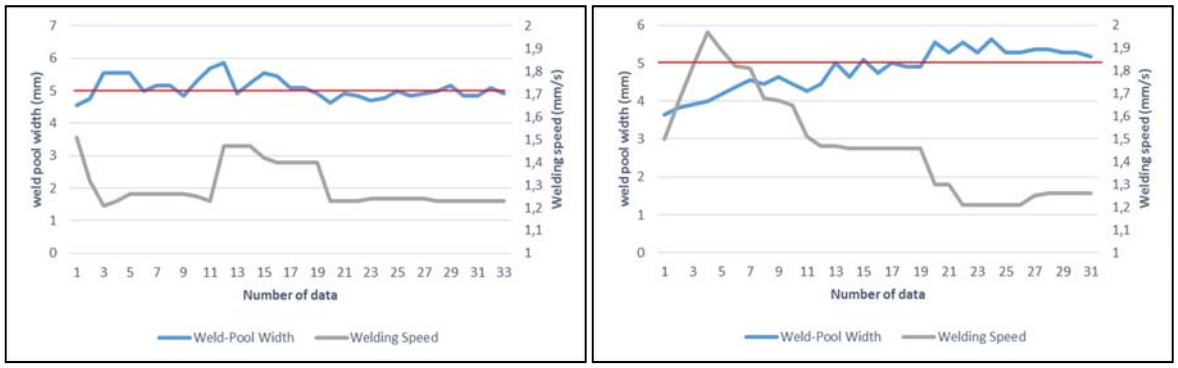


(b)

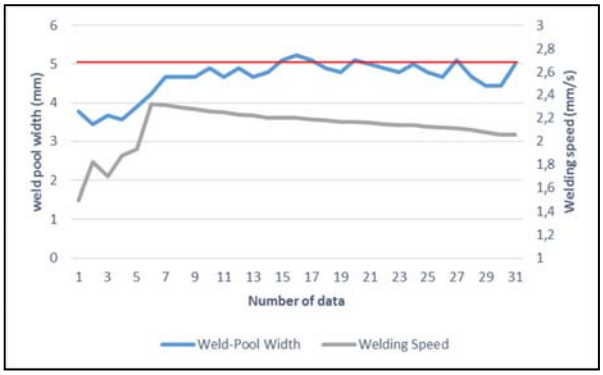


(c)

Figure-5. The appearance of weld bead with the target is 5 mm under different welding current: (a) 55 A, (b) 60 A, and (c) 65A.



(a) (b)



(c)

Figure-6. The seam tracking results of welding experiment with automatic welding speed control under different welding current: (a) 55 A, (b) 60 A, and (c) 65A.

Table-3. The result of automatic welding measurement.

Current (A)	Target (mm)	Average Results		Standard Deviation (mm)
		Actual Width (mm)	Error (mm)	
55	5	5.02	0.27	0.35
60		4.82	0.47	0.55
65		4.66	0.38	0.46

The summary of the experiment results that shown in Table-3. On the Actual Width column, the values of average result were very close to the target. The biggest error and deviation value was happened on 60 A welding. The best result was in 55 A welding configuration.

CONCLUSIONS

From the results of this paper, can be concluded as follows:

- A welding speed control system by monitoring weld-pool images using vision sensors had constructed.
- GTAW experiments at different levels of welding current were made and successfully able to perform automatic welding to obtain the desired width. In some automatic welding experiments, the average of bead width that produced is very close to the target.
- The best result from the experiments that have been done is the welding on 55 A. The average error value produced and the standard value were the lowest, each were 5.02 mm and 0.35 mm.
- This system can be used to achieve various targets weld bead by conducting further welding experiments to obtain welding parameter data that can be used to train the neural network in deciding the proper speed

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