Adaptive Control by Convolutional Neural Network in Plasma Arc Welding System

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Plasma arc welding (PAW) was employed in joining thick materials with groove. Due to the high-density plasma arc, keyhole welding was used in the butt welding. The gap might be taken in places due to the heat distortion during the welding. To achieve a high-quality welding, the adaptive control is required according to the gap. The authors tried to apply CMOS camera to obtain information from the top surface and achieve synchronization between the camera shutter and welding current. Thus, a clear image of the weld pool with the keyhole and the gap was taken. The brightness distribution in the front of the weld pool becomes uneven due to the plasma arc. To classify the gap and select the welding conditions, such as the welding current and the plasma gas flow rate, the authors used one of the deep learning algorithms, convolutional neural network (CNN). In the training and testing data, the performance of the CNN was found to be satisfactory. However, if the plasma torch does not trace the welding line, the pool image will be different from the training image. Hence, the CNN will not be able to estimate the correct gap. To avoid this, the authors detected the welding line from the pool image and selected the image area near the welding line as the input of the CNN, i.e., the input area is selected based on the image obtained during the welding. The validity of the proposed method was verified by the welding experiments.

KEY WORDS: keyhole plasma welding; CNN; deep learning; weld pool image; adaptive control.

1. Introduction

Welding is one of the important technologies used in joining the metal plates in the creation of machinery, shipbuilding, etc. Gas metal arc welding (GMAW) is widely used in joining thick plates. This process produces fumes.¹⁾ To get the bead of the bottom surface, the preparation of the groove and the root gap on the metal is required in conventional GMAW. Plasma arc welding (PAW) has a concentrated current density.^{2,3)} Keyhole welding has a high ability to penetrate deep in the butt welding.⁴⁾ In this case, the setup of the base metals is easier than in GMAW, since the base metals are joined without the gap. Therefore, the total efficiency of the welding becomes high. However, welding parameters, such as current, plasma gas flow rate, and traveling speed, become complicated.⁵⁾

When the thickness of the base metal is more than 9 mm, the groove and the root face are prepared without the gap. Thus, if the metal plates have no gap, the PAW quality depends on the tracking of the welding line on the base metals.⁶⁾ However, taking a clear image of the keyhole on the top surface using visual sensors, such as a charge-coupled device (CCD) camera and a complementary metal oxide semiconductor (CMOS) camera, is challenging. Visual sensors are equipment used in getting information. A CCD camera was applied in GMAW to observe the weld pool.⁷⁾ Using

the information obtained by the CCD camera, the quality control was carried out. A clear image of the weld pool was obtained using a light filter during the constant-current gas tungsten arc welding (GTAW).⁸⁾ Hence, the monitoring and controlling of the robot were proposed.⁹⁾ In GMAW, the CCD camera was used to perform a real-time detection and tracing of the welding line.¹⁰⁾ The seam gap was obtained by processing the image of the welding line.

The weld pool information was used to trace the welding line and to control the weld pool. The CCD camera was also applied in PAW.¹²⁾ The weld pool was measured using a special optical filter. However, it is difficult to take a clear image of the keyhole in conventional PAW. By synchronizing the current with the shutter opening of the CCD camera,¹³⁾ the authors tried to obtain a clear keyhole image in PAW. The quality of PAW depends on the stability of the keyhole which is based on the welding parameters.¹⁴⁾ The state of the keyhole was measured using the phototransistor. Wang and Zhao proposed the sensing of PAW quality using the welding sound.¹⁵⁾ The sound was changed according to the weld pool. In general, the sound of the welding was delayed after changing the weld pool situation. Quality control in PAW was proposed by monitoring the efflux plasma voltage signals.¹⁶⁾ Using a CCD camera from the bottom side of the workpieces, direct observation of the keyhole was proposed.¹⁷⁾ In the practical field, it was difficult to set up the visual sensor on the bottom side. The authors took the weld pool image with the keyhole using a CMOS camera from the top side.¹⁹⁾ If there is no gap in the workpieces with

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the groove, the quality of PAW will depend on the tracking of the welding line.²¹⁾ Due to heat distortion, the gap occurs in the fabrication of the thick plates. Thus, to get a high quality, it is required to adjust the welding parameters according to the gap. The weld pool with the keyhole is observed using the CMOS camera, and since the brightness distribution of the keyhole is uneven in the weld pool image without gap, it is difficult to identify the presence of the gap.

The neural network has an advantage of having high recognition ability in object classification. It was also applied in the welding field.²²⁾ The characteristic of the defect image of nondestructive testing (NDT) was identified using image processing, and the defect type was classified by the neural network.²³⁾ In submerged arc welding, the prediction of the weld metal chemistry was carried out using neural network.²⁴⁾ In the 1990s, the neural network approach was based on the sigmoidal function. If the network becomes complicated, its training becomes difficult due to the local minimum. Recently, deep learning has been developed,²⁵⁾ and the recognition rate of images has improved rapidly.²⁶⁾ A convolutional neural network (CNN) has a good recognition rate of the image. In this paper, the authors propose adaptive control using the CNN. Welding parameters, such as current and plasma gas flow rate, are determined from the CNN output. The front part of the weld pool image is selected as the CNN input. The training data and the test data were obtained from the fundamental experimental results. The CNN estimated the gap. Thus, if the plasma torch does not trace the welding line, which results in the training image becoming different from the test image, then the CNN output estimated the wrong gap. The image of the PAW is processed to improve the CNN performance. A stable image is obtained using image processing, regardless of the torch deviation of the welding line. Therefore, the CNN construction is modified. The welding current and plasma gas flow rate are adjusted according to the gap. The authors proposed a combination of the CNN and the preprocessing method based on the image processing method. The validity of the proposed method was verified by carrying out control welding experiments.

2. PAW System

The PAW system with a visual sensor is shown in **Fig. 1**. In this paper, the materials are 9-mm thick with Y groove gap, and the traveling speed of the plasma torch is 2.5 mm/s. The system is composed of two servo motors, which are for X-axis and Y-axis. A CMOS camera is fixed to the plasma torch as shown in **Fig. 2**. After the image is taken, the CMOS camera sends it to the PC using Gigabit Ethernet (GigE). The first PC controls the PAW power source by two analog signals which control the welding current and the plasma gas flow rate. This PC creates the trigger signal of the opening shutter of the CMOS camera. The welding current is synchronized with the shutter opening of the CMOS camera. The second PC receives and processes the image of the weld pool from the CMOS camera. Conventional PAW uses the constant current. Due to the strong arc light, it is difficult to observe the keyhole. If a neutral density filter is used to reduce the strong arc light, the contrast between the solid zone and weld fusion zone becomes weak. Thus, it is difficult to recognize the weld pool. When the shutter is

opened, the welding current is reduced to avoid affection of the strong arc light; thus, the authors use the pulsed current. If the shutter opens, the welding current is reduced to 30 A. The shutter trigger is synchronized with the welding current. To check the relationship between the trigger signal and welding current waveform, the trigger and the welding current are measured using a digital oscilloscope, as shown in **Fig. 3**. When the current is reduced to 30 A, the trigger sig-

Fig. 1. Plasma arc welding system with a visual sensor. (Online version in color.)

Fig. 2. Plasma arc welding (PAW).

Fig. 3. Relationship between the current and trigger signal of the shutter. (Online version in color.)

nal increases to 5 V, which is already considered as a high state. The shutter of 1 ms opens at 1.5 ms after the decrease of the welding current. The welding current increases to 240 A after closing the shutter. The welding current is reduced by almost 3.5 ms in 50 ms interval. However, 4 ms is too small to change the shape of the keyhole. Moreover, since the CMOS camera with GigE is a digital camera, the signal is stronger than the electrical noise from the welding power source. The clear images were taken as shown in **Fig. 4**. Figures 4(a), 4(c), and 4(d) show the weld pool without the gap, with a 1 mm gap, and with a 2 mm gap, respectively. Since the gap is darker than the weld pool, the gap can be found using image binarization. Otsu's method is one of the validity methods used for image binarization.²⁷⁾ This method was applied to the images in Figs. 4(a), 4(c), and 4(d). Its results are shown in Figs. 4(b), 4(d), and 4(e). Although image binarization with the use of Otsu's method easily detects the 1 mm gap in the image as shown in Fig. 4(d), the dark area is detected as the white square in the no gap image as shown in Fig. 4(b). Its square is recognized as the gap.

Moreover, the brightness in the gap which is more than 1.5 mm increases, as shown in Fig. 4(d), making it difficult to recognize the gap using binarization, as shown in Fig. 4(d).

3. CNN for Recognition of the Gap

The CNN has an advantage of having high recognition ability in object classification. The welding parameters depend on the gap when the geometry of the workpieces is not changed. It is important to perform a real-time detection of the gap in order to get a good welding quality. The gap is clearly recognized using the CNN with an input image of 160×160 pixels, as shown in **Fig. 5**. The CNN is composed of three convolutional layers and two pooling layers. The image near the keyhole is selected as the input of the CNN. The 800×400 pixels indicated by the white rectangle in **Fig. 6** is used as the input area. This area is compressed to 160×160 pixels as the input of the CNN, and the weighted mask size is 5×5 . A convolutional operation between the mask and corresponding pixels in the input

Fig. 4. Typical weld pool images and these binarizations.

Fig. 5. Convolutional neural network with three convolutional layers.

 Fig. 6. Input area of 800×400 pixels for the CNN.

Fig. 7. Categorization of the gap.

i.e., about 15 000 pieces of the weld pool images, including the gap variation, were used. The following cross entropy $E(w)$ as loss function is used to adjust weights, w , of the CNN.

$$E(w) = -\frac{1}{N} \sum_{n=1}^N \sum_{k=1}^K d_{nk} \log y_{nk} \quad \dots \quad (1)$$

where N , K , d_{nk} , and y_{nk} are the number of the training data, the number of output unit, the desired output of the output unit, and the output, respectively. In this paper, due to the number of the output unit, we set K to be 5. The weight of the CNN is adjusted using the following steepest descent method to reduce the loss function in Eq. (1):

$$w_{i+1} = w_i - l_r \left. \frac{\partial E(w)}{\partial w} \right|_{w=w_i} \quad \dots \quad (2)$$

where l_r is the learning rate and is 0.005.

The plasma arc welding is carried out under the constant welding parameters when the gap variation is from 0 to 2 mm similar to the tapered shape. The keyhole images are recorded as the testing data. The performance of the CNN is checked using the testing data with the order to be recorded. The behavior in the CNN output is shown in Fig. 8, in which the dashed line indicates the group classified by the authors. The output of the CNN is indicated by dots. The response of the CNN is faster than the classified categories. The keyhole shape during the welding is vibrated according to the variation of the gap. The variation of the keyhole is not given in the training of the CNN. The CNN estimates the group using the keyhole shape and the gap. Therefore, the output of the CNN vibrated at the boundary A, B, C and D in the group change as shown in Fig. 8. However, the welding parameters had tolerance for the gap. Even if the welding parameters for 0.5 mm gap are selected in the 1.0 mm gap, good welding quality can be obtained. Subsequently, the CNN is applied if the torch is unable to trace the welding line. The distance of the torch position from the gap is shown in Fig. 9. In this case, the shape of the keyhole becomes asymmetrical for the gap center. Thus, the behavior of the CNN output becomes unstable as shown in Fig. 10. The gap is the center of the groove in the training.

unit is carried out. The result is then forwarded to the rectified linear unit (ReLU). The representative value is selected from 3×3 values in ReLU outputs. The resultant values are the outputs in the pooling layers. Afterward, similar operations are repeated as shown in Fig. 5. The input of the fully connected layer, which is the pooling output in the second convolutional operation results, is composed of 5 000 unit. The feedforward neural network is used as a fully connected layer. The welding parameters were categorized into five groups according to the gap: group 0, group 1, group 2, group 3, and group 4 are the welding parameters for no gap, 0.5 mm gap, 1.0 mm gap, 1.5 mm and 2 mm gap, respectively, as shown in Fig. 7. The welding parameters were selected according to the group. Boundaries of each group are 0.25 mm, 0.75 mm, 1.25 mm, and 1.75 mm as shown in Fig. 7. The images between the boundaries belong to their group. Although the gap is continuous value, in the conventional welding, the discrete value of the gap, such as 0 mm, 0.5 mm, 1.0 mm, 1.5 mm and 2 mm, has been used as the threshold to change the welding parameters. Therefore, the welding parameter is determined by classifying the gap. Moreover, a large amount of the training data is required in the training of the CNN. If the continuous value is selected as the training data, the gap width shall be detected by the image processing. The detection algorithm is required, and it takes a long time to make the training data. On the other hand, if the classification of the group is used, the training data and the testing data are created by detecting each boundary in many images. Hence it is easy to make the training data than the continuous value.

3.1. Training and Evaluation

The desired output can be obtained by training CNN. In this case, the training data are composed of nine kinds of fundamental experimental results in the variation of the gap,

Moreover, the keyhole shape was symmetrical for the gap in the training data. But when the torch is unable to trace the welding line, the center of the gap becomes different from that of the groove, and the keyhole shape becomes asymmetrical for the gap in the test images.

3.2. Preprocessing of the Weld Pool

The input area of the CNN is modified to improve its performance, which depends on the difference between the images in the training data and images in the practical field.

Fig. 8. Behavior of the CNN output. (Online version in color.)

Fig. 9. Deviation from the gap center to the torch position. (Online version in color.)

Fig. 10. Behavior of the CNN output in the center deviation. (Online version in color.)

To neglect the effect of the keyhole shape, the input area is selected near the gap and reduced to 800×200 pixels from 800×400 pixels, as shown in Fig. 11. Moreover, using the binarization of Otsu's method as shown in Fig. 4(d), the center of the gap is detected. Afterward, the input area is adjusted to fit the image center to the gap center. Moreover, new training data are added to adapt to the image variation. The new data are composed of the image with the center deviation of 5 pixels and 10 pixels. The total training data catabolized by the group are listed in Table 1. The total number of data is about 20 000 images. Moreover, the structure of the CNN is modified to adapt the complex training data and is shown in Fig. 12. The unit structure is listed in Table 2. The CNN becomes more complex than that in Fig. 5. The weight of the CNN is adjusted to minimize the loss function of Eq. (1). Furthermore, the behavior of the loss function $E(w)$ in Eq. (1) is shown in Fig. 13. One set of training data corresponds to 1 epoch. Thus, the loss function $E(w)$ is decreased until 200 epoch. The behaviors of the accuracy for the training data and the testing data are shown in Fig. 13(a). The number of testing data is 1 500. The loss function for the training data and the testing data is shown in Fig. 13(b). The accuracy of the training data converged to 0.99 until 200 epoch, when the correct is 1. The accuracy of the testing data converged to 0.95.

The algorithm, including the preprocessing and the control, is shown in Fig. 14. First, the image is applied to the

Fig. 11. Input area of 800×200 pixels for the CNN.

Table 1. Group in the training data.

Gap [mm]	Group	Number of training data
0.0–0.25	0	1 690
0.25–0.75	1	5 649
0.75–1.25	2	4 815
1.25–1.75	3	4 095
more than 1.75	4	3 020
Total number		19 269

Fig. 12. Modified convolutional neural network with five convolutional layers.

Table 2. Construction of convolutional network with five convolutional layers.

Layer	Input data size	Filter size	Pooling size
Input	1×160×160		
Conv. 1	1×160×160	20×1×5×5	
Pooling 1	20×156×156		2×2
Conv. 2	20×78×78	50×20×5×5	
Pooling 2	50×74×74		2×2
Conv. 3	50×37×37	50×20×3×3	
Pooling 3	50×35×35		2×2
Conv. 4	50×18×18	50×50×3×3	
Pooling 4	50×16×16		2×2
Conv. 5	50×50×8	100×50×2×2	
Pooling 5	100×100×7		
Ip1	1 600		
Ip2	500		
Output	5

(a) Behavior of training accuracy and test accuracy.

(b) Behavior of total training loss and test loss.

Fig. 13. Training of convolutional neural network. (Online version in color.)

CNN. The existence of the gap is detected due to the output of the CNN. If more than group 1 is detected as the CNN output, the binarization method is applied to detect the gap center. Next, the input image area is adjusted according to the detected center. The adjusted input area is applied to the CNN in the next period. The modified CNN is applied to the testing data to check its performance. The behavior of the CNN output is shown in Fig. 15, in which the dashed line indicates the categorized group. The dot indicates the output of the CNN. The performance was improved compared with that in Fig. 10.

Fig. 14. An algorithm in combination of the CNN and image processing.

Fig. 15. Behavior of the modified CNN output in the center deviation. (Online version in color.)

Table 3. The welding parameters.

Group	Current [A]	Plasma gas flow rate [L/min]
0	250	3.5
1	269	3.9
2	288	4.3
3	306	4.7
4	325	5.0

4. Adaptive Control of the Welding Parameters by Identifying the Gap

4.1. Control Algorithm

The weld pool images are taken and using the robotic welding system in Fig. 1, these images are identified to online detection of the gap. In this paper, the open software openCV and caffe are used to process the image and to calculate the CNN with high-speed computing.²⁹⁾ The PC for the image processing has GPU with 768 NVIDIA CUDA cores and 4 GB memory.³⁰⁾ Using the CNN, the calculation time per the identification of one image is about 3.6 ms by. The welding parameters are selected according to the CNN output and are determined by performing preliminary

experiments without the gap and with a 2 mm gap. If the gap widens, the arc pressure flows to the gap. Thus, the penetration ability of the plasma arc becomes weak due to the arc pressure. The welding parameters for any gap are calculated using the interpolation between 0 and 2 mm. The relationship between the group and welding parameters are listed in **Table 3**.

4.2. Real-time Control of the Welding Parameters

The welding parameters are selected based on the output of the CNN. To verify the proposed method, the adaptive control experiment is performed. The traveling speed is

Fig. 16. Behavior of the CNN output during adaptive control. (Online version in color.)

(a) Surface bead appearance.

(b) Bottom bead appearance.

Fig. 17. Welding result without the adaptive control.

(a) Surface bead appearance.

(b) Bottom bead appearance.

Fig. 18. Welding result with the adaptive control.

maintained at 2.5 mm/s. The gap variation is from 0 to 2 mm similar to the tapered shape. The behavior of the CNN output is shown in **Fig. 16**. In the figure, the dot and the dashed line represent the output of the CNN and the group categorized by the authors from the weld pool images, respectively. Although the welding parameters are constant in the training data, the weld pool image during the adaptive control is under the variation of the welding parameters. The CNN output was in agreement with the categorized group. Thus, there is no variation effect on the welding parameters. When the welding current and the plasma gas flow rate are constant, the bead appearance after the welding is shown in **Fig. 17**. As shown in **Fig. 17(b)**, the width of the bead at the back side of the base metal becomes narrow. When the welding current and the plasma gas flow rate are selected according to the output of the CNN, the bead appearance after the welding is shown in **Fig. 18**. According to the traveling, the width of the bead at the back side of the base metal becomes wider than the gap. Good welding quality was obtained without the gap variation.

5. Conclusion

In the PAW, to monitor the welding quality, observing the weld pool and the keyhole is important. Since this welding uses high current density, the arc pressure related to the penetration capacity of the materials is strong. Thus, it is possible to join the metal plates using butt welding. If the gap is taken in places, the welding parameters must be adjusted to keep good quality. The authors proposed the CNN to select the welding parameters from the weld pool images.

The proposed method is based on the preprocessing method to enter the image and using the CNN to find the welding parameters. The validity of the proposed method was verified by carrying out the adaptive control of the welding parameters under the gap variation.

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