Intelligent Control for the Shape of the Weld Pool in Pulsed GTAW with Filler Metal

The technical characteristics of pulsed GTAW with wire filler metal were investigated and intelligent control was developed to control the shape of the weld

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ABSTRACT. This paper addresses a practical, intelligent technique for controlling the top and bottom shape of the weld pool during pulsed gas tungsten arc welding (GTAW) with wire filler metal. For full penetration, the weld surface was concave in GTAW without filler metal, while a satisfactory convex shape on a bead could be achieved in GTAW with wire filler metal.

Technical characteristics, such as the parameters of feeding wire and weld joint penetration, were investigated first. Then, a root surface width and face reinforcement dynamic neural network model (DNNM) for relating the welding parameters and the weld face shape parameters to the root surface width and face reinforcement was established. The root surface width and face reinforcement were accurately predicted with DNNM and input to the controller as feedback. A single-variable controller was not capable of ensuring a simultaneously stable root surface width and face reinforcement.

Finally, a double-variable, self-adaptive fuzzy controller was designed for controlling the shape of the weld. The results indicated the root surface width and face reinforcement were stabilized perfectly by regulating the pulse-duty ratio and wire-feed speed at the same time.

Introduction

Recently, extensive and thorough research has been carried out concerning GTAW control. The shape of the weld pool was found to be crucial for weld quality and was determined by welding parameters such as welding current, arc voltage, travel speed, etc. The image of the weld pool was captured clearly by the active principle of intense-pulsed laser illumination on the weld pool (Refs. 1-4), by the passive principle of self-radiation of the weld pool, or by the electric arc (Refs. 5-9).

Based on image sensing and processing of the weld pool, geometric parameters for describing the shape of the weld pool could be extracted, such as pool length, width, etc. For control of GTAW, the process model describing the correlation between welding and shape parameters of the weld pool should be established first.

With numerical analysis of the heat and fluid flow during GTAW and some hypothesis, static and dynamic models were built to relate the welding parameters to the temperature field of the weld pool. The temperature field reflected the shape of the weld pool directly, then the shape parameters were determined (Refs. 10-11).

Another modeling technique, pool oscillation, has been extensively studied. The width of a stationary weld pool could be determined by the resonance frequency found by Cheever, Howden, and Kotecki (Ref. 12). Weld pool oscillation sensing was first proposed by Hardt, et al. (Ref. 13), as a method of sensing pool geometry, and hence penetration, for closed-loop feedback control of the depth of penetration. An interesting discovery was the distinction of the weld pool oscillation frequency between partial and full joint penetration. A drop in oscillation frequency occurred as partial

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Due to its computational complexity, and a simple analytical method was not accurate enough for characterizing the complex welding process, intelligent techniques such as fuzzy logic and neural network tended to model the correlation of the GTAW process. During GTAW, the relation between welding current, arc voltage, travel speed, wire-feed speed, and bead geometry such as width, depth, reinforcement, and cross area was established from an ANN model and trained by experiment data (Ref. 16). Based on the weld pool geometrical appearance, Zhang developed a control system to simultaneously control the weld face and root surface pool widths using a neurofuzzy model (Ref. 17). In our previous studies, two dynamic neural network models were established; one related the welding parameters to the weld face shape parameters (the weld face length, width, and nine rear widths), while the other related the welding parameters and weld face shape parameters to the root surface width (Refs. 18-19).

Other intelligent controls with good performance have been achieved with other arc welding processes, such as resistance welding by R. W. J. Messler (Ref. 20), the GMAW process by Y. Kaneko (Ref. 21), and laser welding by J. F. Tu (Ref. 22). For the GTAW process, an intelligent monitoring and control system was presented that regulated the total heat input in order to maintain constant fusion zone geometry under varying thermal regions (Ref. 23).

A self-learning, fuzzy neural network control system of the weld face width enabled adaptive altering of the welding parameters to compensate for changing environments (Ref. 24). Aiming at the variation of heat-sink conditions, a single variable, self-learning neural network controller was proposed for guaranteeing the root surface width during bead-on-plate GTAW process (Ref. 18), and a self-learning, fuzzy neural network controller incorporated with an expert system was proposed for pulsed GTAW with a butt joint (Ref. 19).

Although many achievements on the control of GTAW have been proposed, studies on GTAW with wire filler metal were seldom carried out and published. For full penetration, the weld surface was depressed in GTAW without wire filler metal, while a satisfactory convex shape on a bead could be achieved in GTAW with wire filler metal.

In this paper, the basic technical characteristic of pulsed GTAW with wire filler metal was analyzed first. Then, a neural network model for relating the welding parameters and the weld face shape pa-
parameters to the root surface width and the face reinforcement was established. With the designed double-variable, self-adaptive fuzzy controller, the root surface width and face reinforcement were sufficiently stabilized to maintain constant penetration by regulating pulse-duty ratio and wire-feed speed.

Technical Experiments

Experiment Setup

Based on the developed experimental system for pulsed GTAW (Ref. 18), a wire feeder AWGW-3001 and its driving circuit were applied for feeding wire into the weld pool during pulsed GTAW. The wire-feed speed was initially manipulated manually or by the welding power source, then later by a computer for improved control. The welding wire was H08Mn2Si with a 0.8-mm diameter, and the workpiece was mild steel plate with a 2-mm thickness.

The setup is shown in Fig. 1. The welding torch was held stationary and the workpiece moved during the welding process. Using the experimental system, a clear image of the weld pool was captured. The shape parameters for describing weld pool shape were proposed, and an algorithm of surface shape reconstructed from a single weld-pool image was developed in Ref. 23. A flowchart of the image processing is shown in Fig. 2. So the shape parameters, such as the weld face length $L$, width $W$, half-length ratio $R_m$, and height $H$ (the maximum height of the weld pool along the rear center of the welding direction), and the root surface width $W_h$ and length $L_u$, could be calculated.

Wire-Feed Parameters

The time sequence was to feed wire into the weld pool during pulse peak current, so it could be melted sufficiently and prevented from becoming oxidized.

The wire-feed parameters consisted of time, speed, amount, and mode. Experiment results showed the wire feed amount was the most important parameter of the wire-feed parameters for bead shape. Because the wire had to be fed during pulse peak time, the wire-feed mode could be divided into two classifications. One was to set the wire-feed time in direct proportion to the pulse peak time. The other was to set the wire-feed time constant, as shown in Fig. 3. Experiments showed little difference in bead shape with a different wire-feed mode, so the second mode was adopted in the following experiments due to constant feed time and the simple correlation between the wire-feed speed and amount.

Weld Penetration with Wire Filler

During pulsed GTAW without wire filler metal, weld penetration formed the root surface width of the weld pool. In pulsed GTAW with wire filler metal, however, the definition of weld penetration was different.

A butt joint welding experiment was conducted on mild steel with a variation of pulse duty ratio $\eta$ (the ratio of pulse peak time to pulse duration). The welding parameters were as follows: pulse peak current $I_p = 145$ A, travel speed $V_w = 2.5$ mm/s, wire-feed speed $V_f = 5.0$ mm/s, and others were tabulated in Table 1. The variations of shape parameters of the weld pool are shown in Fig. 4, which was extracted with the developed algorithm of image processing (Ref. 25). With the increase of the pulse-duty ratio, the weld face length $L$ increased significantly, the top and bottom widths $W$ and $W_u$ and the weld face half-length ratio $R_m$ increased while the face reinforcement $H$ decreased from positive to negative.

The variation of shape parameters of the weld pool could be clearly seen in the weld pool images shown in Fig. 5. The corresponding macrophotographs of bead cross section are shown in Fig. 6. So, in the experiment, different weld penetration modes were excited and explained as follows:

Partial Penetration: This was similar to that of pulsed GTAW. The root surface bead was not formed or discontinuous, corresponding to the root surface width from zero to 2 mm (referred to as $V_w = 2.5$ mm/s). In the meantime, the face reinforcement was positive (reinforcement)}
Neural Network Modeling

The welding parameters and technical parameters of using a wire filler metal were key factors to bead shape, such as the root surface width, the weld face width, and reinforcement, etc. Neural network modeling was an appropriate method for establishing the complex relationship. Then, using the model, the root surface width and face reinforcement of the weld pool were predicted in real time and could be input to controllers in the next part.

The face reinforcement could not be extracted in real time (Ref. 25), and, in most cases, the root surface width could not be measured. The root surface width and face reinforcement dynamic neural network model (DNNM) was established for predicting these parameters in real time and for further control.

To establish a valid process model, all kinds of welding conditions should be considered during the experiment design. The major welding parameters, such as $I_p$, $\delta$, $V_w$, and $V_f$, were taken as input signals of the model. The input signals were designed as random distribution for stimulating all kinds of modes of the welding process. The varying scope and step of the random signals were as follows: $I_p = (120-170 \text{ A}, 5 \text{ A})$, $\delta = (35-65\%, 5\%)$, $V_w = (1.5-3.5 \text{ mm/s, } 0.33 \text{ mm/s})$, $V_f = (2-8 \text{ mm/s, } 1 \text{ mm/s})$. A total of 1900 welding parameter numbers were generated using a pseudo-random sequence method. Other welding conditions were also tabulated in Table 1. Welding experiments with 1900 pulses were conducted on butt joints of mild steel plate, then 1900 images of the weld pool were captured during pulse base time and shape parameters extracted. The first 1700 of the entire 1900 pieces of data were taken as the training data of DNNM, the following 100 pieces of data were taken as validation data, and the
final 100 data taken as testing data. The DNNM structure is shown in Fig. 7. Both the welding parameters and the weld face, two-dimensional shape parameters and the last two history values were inputs of DNNM. The current root surface width and face reinforcement were outputs of DNNM. The number in the hidden layer was five. The training and simulation of DNNM were carried out with the neural network toolbox (Nnet 3.0) of Matlab 5.3. The training algorithm was “Trainlm.”

With the trained DNNM and inputs of the model, the root surface width and face reinforcement could be predicted, as shown in Fig. 8. Statistical results showed mean errors between the predicted and the measured were 0.004 mm and 0.042 mm, respectively, and the relative mean square errors were 5.54% and 7.83%, respectively. The statistical results verified the feasibility of DNNM.

Double-Variable Intelligent Control

Under the variation of heat-sinking conditions, the root surface width and face reinforcement varied irregularly. The root surface width and face reinforcement were predicted accurately with the developed DNNM, and the prediction was input to the controller for feedback control. A single-variable neuron, self-learning PID controller was designed. With the controller, either the root surface width or face reinforcement was controlled singly by regulating the pulse-duty ratio or wire-feed speed. Both shape parameters could not be simultaneously controlled, making the double-variable controller with the pulse-duty ratio and the wire-feed speed as output necessary.

Open-Loop Experiment

To verify the validity of the double-variable controller, an open-loop experiment was conducted for comparison. The specimen was mild steel plate of 2-mm thickness with a dumbbell shape to imitate sudden changes in heat-sink conditions during pulsed GTAW with wire filler metal. The wire was H08Mn2Si with a diameter of 0.8 mm. Other welding parameters were the same as in Table 1. The shape parameters changed with the heat-sink conditions. The open-loop experiment results were shown with the weld pool images (Fig. 9), curves (Fig. 10), and photographs of the workpiece (Fig. 11). The photographs show the root surface width changed from discontinuous to large and the heat-sink condition changed to poor.

A Double-Variable, Self-Adaptive Fuzzy Control

The fuzzy controller was capable of human-like deduction. During design of the fuzzy controller, the decision to have a membership function and fuzzy rules was a hindrance. An improved, double-variable, self-adaptive fuzzy controller based on a single-layer neural network for learning fuzzy rules was designed. The system’s schematic diagram is shown in Fig. 12. MS was the measuring system for detecting the weld face shape parameters TSP (L, Wf, and Rp), and the welding parameters WP, such as welding current, travel speed, etc. The predicted root surface width (Wfp) and face reinforcement (Hfp) were generated with DNNM. The given root surface width (Wfg) and face reinforcement (Hfg) were input to a signal converter for calculating the errors e, (i = 1, 2), and change in errors ce, (i = 1, 2).

Fuzzy Rules and Inference

Takagi-Sugeno rules were adopted as the fuzzy rules (Ref. 26).

Rule 1: If e, is E11 and ce, is CE11 and e2 is E21 and ce2 is CE21, then \( A8 = U_{11} \) and \( AV_f = U_{21} \)

Rule 2: If e, is E12 and ce, is CE12 and e2 is E22 and ce2 is CE22, then \( A8 = U_{12} \) and \( AV_f = U_{22} \)

\( \ldots \)

Rule n: If e, is E1n and ce, is CE1n and e2 is E2n and ce2 is CE2n, then \( A8 = U_{1n} \) and \( AV_f = U_{2n} \)

Case: e, is E10 and ce, is CE10 and e2 is E20 and ce2 is CE20

Conclusion: \( A8 = U_{10} \) and \( AV_f = U_{20} \)

Where \( E_{ij} \) and \( CE_{ij} \) were the fuzzy set of e, and ce, \( U_{ij} \) was the control variable, \( e_{10} \) and \( ce_{10} \) were the actual sampling values, \( i = 1, 2 \), \( j = 1, 2, \ldots, n \).

The matching degree of the fact in the rules was

\[
A_i = \left[ \mu_{e_i}(e_{10}) \mu_{e_{10}}(e_{10}) \mu_{e_{10}}(e_{10}) \mu_{e_{10}}(e_{10}) \right] \Rightarrow \left[ A_{i1}, A_{i2}, \ldots, A_{in} \right] = [1, 2, \ldots, n] \quad (1)
\]

Where \( \mu_{e_i}(e_{10}) \) and \( \mu_{e_{10}}(e_{10}) \) were the membership of e, ce, to fuzzy sets \( E_{ij} \), \( CE_{ij} \), and “A” denoted the minimum calculation.

Fig. 10 — Shape parameters of the weld pool of the dumbbell-shaped workpiece in an open-looped experiment with constant welding parameters.

Fig. 11 — Photographs of the dumbbell-shaped workpiece in an open-looped experiment with constant welding parameters. A — Weld face; B — root surface.
The conclusion \( u_n \) was derived as follows:

\[
\sum_{j=1}^{n} h_j u_j = \sum_{j=1}^{n} h_j' u_j = \sum_{j=1}^{n} h_j' u_j = \sum_{j=1}^{n} u_j = u_{i, \text{max}}, i = 1, 2
\]  

Where \( h_j' \) represented the normalized value of the membership \( h_j \).

In the fuzzy control rules, the premise variables were described as fuzzy set and kept constant. The conclusion variable was described as constant, adapted according to control performance, and derived without de-fuzzier calculation.

Single-Layer Neural Network

The memberships of the premise variable in the rules were set as an isosceles triangle, shown in Fig. 13. The sets of \( e_i \) were \([-1, 1]\) and 11 fuzzy sets were defined. The sets of \( c_i \), \( c_i \), were \([-0.5, 0.5]\), and 5 fuzzy sets were defined. The set of error and change in error were \([-2, 2]\) and \([-1, 1]\) for the root surface width, and \([-1, 1]\) and \([-0.5, 0.5]\) for the face reinforcement. Overlap of the neighboring fuzzy sets was 50%, so a known value of any premise variable could activate two fuzzy sets. There were four variables in the premise, so a known fact could activate 16 (2^4 = 16) fuzzy rules. That is, there was a maximum of 16 nonzero values in the \( n \) normalized matching degrees, and they were numbered renewably as \( h_m, m = 1, 2, \ldots, 16 \).

The above inference process could be realized with a single-layer neural network, shown in Fig. 14. The single-layer neural network had 16 inputs, corresponding to the 16 normalized matching degree \( h_m \). The network had two outputs corresponding to the two control outputs of the fuzzy controller. The transferring function of the neuron was a sigmoid function.

\[
u_i = \frac{1 - e^{-\alpha_i}}{1 + e^{-\alpha_i}}
\]

\[
\alpha_i = \sum_{m=1}^{16} h_m' u_{ij}, \quad i = 1, 2
\]

Where \( u_{ij} \) was the largest scope of output variable, \( u_{ij, \text{max}} = \Delta y = 10\% \), \( u_{ij, \text{max}} = \Delta V = 5 \text{mm/s} \). \( u_{ij} \) denoted the weight \( m \) connecting to neuron \( i \), as well as the conclusion constant to be regulated in the control rules.

Learning Algorithm

The performance cost of the neural network learning was the output errors of the welding process.

\[
E(t) = \frac{1}{2} \sum_{i=1}^{2} [r_i(t) - y_i(t)]^2
\]

Where \( r_i(t) \) represented the given root surface width and face reinforcement \( W_{hr} \) and \( H_{hr} \), and \( y_i(t) \) represented the predicted \( W_{hr} \) and \( H_{hr} \). Then the weights of the neural network were corrected as follows:

\[
u_i(t+1) = \nu_i(t) + D\nu_i(t)
\]

\[
\frac{\partial E(t)}{\partial \nu_i(t)} = \frac{\partial E(t)}{\partial y_i(t)} \cdot \frac{\partial y_i(t)}{\partial u_i(t)} = \frac{\partial E(t)}{\partial y_i(t)} \cdot \frac{\partial y_i(t)}{\partial u_i(t)} \cdot \frac{\partial u_i(t)}{\partial \nu_i(t)}
\]

Where \( \beta \) was learning coefficient, \( \beta = 1.0 \). \( \partial y_i(t)/\partial u_i(t) \) was the partial differential of the output \( I \) in the input \( i \) at time \( t \).

\[
\frac{\partial y_i(t)}{\partial u_i(t)} = \frac{\partial y_i(t)}{\partial u_i(t)} \cdot \frac{\partial u_i(t)}{\partial u_i(t)} = \frac{\partial y_i(t)}{\partial u_i(t)} = \frac{\partial u_i(t)}{\partial u_i(t)} = \frac{\partial u_i(t)}{\partial u_i(t)}
\]

and,
then the final formula of weight correction was derived.

\[
\frac{\partial u(t)}{\partial \theta(t)} = \frac{1}{2} u_{t,\text{max}} \left( 1 - \left( \frac{u(t)}{u_{t,\text{max}}} \right)^2 \right) (8)
\]

\[
\frac{\partial u(t)}{\partial \theta(t)} = h_m(t) (9)
\]

Control Experiments

To verify the performance of the fuzzy controller, butt joint welding experiments were conducted on dumbbell-shaped specimens. The minimum regulating unit was 1% for pulse-duty ratio, and 0.1 mm/s for \(V_s\). The root surface width and face reinforcement were given as 4.0 and 0.2 mm. Errors and changes in errors were calculated with the given and predicted value by DNNM and were looked up in the fuzzy control rules. If matched, the change of the control variable could be directly derived. If not, self-learning was carried out.

The control started from pulse 7. The weld pool images were shown in Fig. 15, and it was concluded the shape of the weld pool was reliably controlled.

The variation of shape parameters are shown in Fig. 16. This indicated the root surface width and face reinforcement accessed to the given value quickly when control affected. The controlled parameters were maintained around the given values even in hard heat-sink conditions.

Statistic results showed the maximum errors of the root surface width and face reinforcement were -0.44 and 0.06 mm, the mean errors were -0.09 mm and 0.006 mm. The results were evidence of the feasibility and accuracy of the double-variable, self-adaptive fuzzy controller. Photographs in Fig. 17 also showed the root surface width and face reinforcement of the bead were stable.
Conclusions

Using the pulsed GTAW process with wire filler metal, the dynamic control of the weld pool shape was investigated with the following conclusions:

1) Based on technical experiments, partial- and full-penetration and excessive reinforcement modes were presented. Full penetration with a convex shape on the bead was the weld to be achieved.

2) A dynamic neural network model was established for relating welding parameters and weld face shape parameters to the root surface width and face reinforcement, using the neural network toolbox Nnet3.0 of Matlab 5.3.

3) A double-variable, self-adaptive fuzzy controller was designed, and its outputs were varied constants that could be regulated on-line according to different welding conditions. Control experiments conducted on 2-mm-thick mild steel plate with butt joints indicated the root surface width and face reinforcement were reliably stabilized by regulating pulse-duty ratio and wire-feed speed at the same time.

Glossary

Lw = weld face length
Ww = weld face width
Hw = weld face height
Khw = weld face half-length ratio
Lw = root surface length
Ww = root surface width
Iw = pulse peak current
Ib = pulse base current
q = pulse-duty ratio
Vw = travel speed
Vf = wire-feed speed

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