Adaptive robotic welding using vision feedback

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Abstract – The weld pool contains abundant information about the welding process. Its observation can generate data for studying the welding process. Its control could provide an entirely new method to reach the desired weld quality. A realtime sensing technique has been developed to sense the 2D shape of the weld pool. Thus, abundant data can be acquired from the weld pool and used to correlate the pool geometrical appearance with the weld penetration. The weld pool is characterized using a few parameters. The desired weld pool can be acquired by controling these parameters. A number of closed-loop control systems have been developed to control the welding process based on the vision feedback of the weld pool. *Key words*: welding, vision, neurofizzy, image.

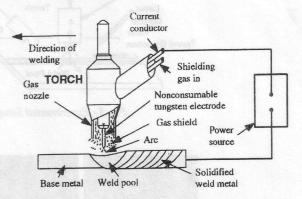
1. INTRODUCTION

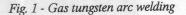
The weld pool can provide abundant information about the welding process. Human operators acquire the majority of their information about the welding process by observing the weld pool. The desired weld quality can be produced by accurately controlling the weld pool.

It is widely known that a correlation exists between weld quality and the weld pool, for example, the weld penetration is approximately proportional to the depression of the weld pool surface [1, 2]. To date, only the width of the weld pool has been reliably sensed on-line to control the weld quality [3, 4] due to the difficulty in sensing other pool parameters. However, it is known that both an increase in current and a decrease in arc length will increase the weld penetration, but the resultant changes in the weld pool width will be opposite. Thus, the weld pool width is not always a proper representation of the weld penetration [5, 6]. To acquire sufficient information about the weld quality and welding process, more weld pool parameters must be sensed in order to find the correlation between the weld quality and weld pool.

2. REAL-TIME SENSING OF WELD POOL SHAPE

Gas tungsten arc (GTA) welding is a primary welding process for producing quality welds. It is frequently used for the root pass where the joint penetration is critical. Because of its special role in welding, itd. precise control is desired. In this study, GTA welding process will be addressed. The GTA welding process is illustrated in Fig 1. A nonconsumable tungsten electrode is held by the torch. Once the arc is established, the electrical current flows from one terminal of the power supply to another terminal through the electrode, arc, and workpiece. The temperature of the arc can reach 8000 - 10500K [7], and therefore the workpiece becomes molten, forming the weld pool. The tungsten electrode remains unmolten. The shielding gas is fed through the torch to protect the electrode, molten weld pool, and solidify weld metal from being contaminated by the atmosphere.



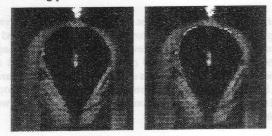


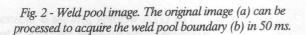
The strong arc light obscures the GTA weld pool being observed. Pool oscillation, ultrasound, infrared, and x-ray based methods have been proposed to detect the arc weld pool. However, to accurately acquire the shape of the weld pool, direct visual observations may be more appreciated. Co-axial viewing can obtain direct

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observations of the weld pool. However, the acquired images of the weld pool may not be clear enough to accurately detect the weld pool boundary in realtime [8, 9] due to the lack of contrast between the weld pool and its surrounding area.

To improve the image quality, a pulsed laser of short duration has been projected onto the weld pool in order to suppress the arc light. The resultant weld pool image is very clear (Fig. 2 (a)) from the acquired image in 50 ms, despite the variation in welding conditions and parameters. This real-time processing technology provided abundant data to study the physical processes in the weld pool and feedback for the closed-loop control of welding process.





(a)

(b)

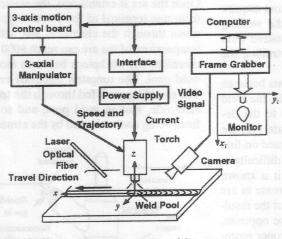


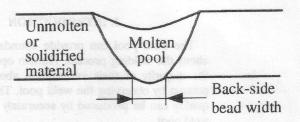
Fig. 3 - Experimental Setup

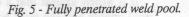
An experimental system has been developed to implement machine vision based monitoring and control of the GTA welding process at the University of Kentucky (Fig. 3). The welding current is controlled by the computer through its analog output to the power supply ranging from 10 A to 200 A. The torch and camera are attached to a 3-axial manipulator. The motion of the manipulator, i.e., the welding speed, is controlled by a 3-axis motion control board which receives the commands from the computer. The motion can be preprogrammed and on-line modified by the computer in order to achieve the required torch speed and trajectory (Fig. 3).

The camera views the weld pool from the rear at a 45° angle. The frame grabber digitizes the video signals into $512 \times 512 8$ bit digital image matrices. The extracted boundary of the weld pool is used to calculate the length and relative width, obtaining the feedback of the process.

4. DETERMINATION OF WELD PENETRATION

In order to achieve sound welds, the desired weld pool must first be determined based on the requirements of weld quality.





The weld pools shown in Fig. 4 were acquired using different welding currents. These weld pools are fully penetrated. It is known that the status of the full penetration is primarily specified by the back-side bead width W_b (Fig. 5). It is found that the weld pool tends to enlarge, sharpen, and become elongated when W_b increases. In order to quantitatively correlate the weld penetration with the weld pool geometry, the weld pool should first be characterized by a number of parameters.

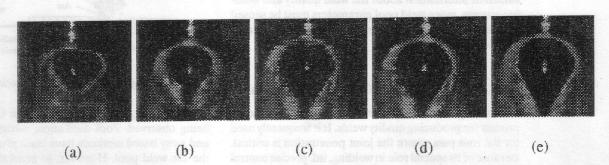


Fig. 4 - Weld pools generated using different welding currents. Arc length=3mm, torch speed=1.9 mm/s, GTA welded, SS 304. (A). 90A, $w_b = 1.8$ mm. (B). 95A, $w_b=3.0$ mm. (C). 105A, $w_b=4.0$ mm. (D). 110A, $w_b=4.5$ mm. (E). 115A, $w_b=5.0$ mm.

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4.1. Geometrical Model Of Weld Pool

The weld pool in this study refers to the two-dimensional geometry of the top-side surface view of the weld pool, and is described by the measured boundary points. However, these measured points do not directly indicate the feature of the weld pool. Also, the geometrical feature of the weld pool can not be sufficiently characterized using pool length, width, area, etc. To characterize the weld pool, a few parameters must be selected based on careful analysis. These parameters are referred to as the characteristic parameters of the weld pool.

The selection of the characteristic parameters is crucial. Three criteria must be satisfied. First, the fundamental geometrical appearance of the weld pool must be sufficiently described using the selected characteristic parameters. Secondly, the correlation between the status of the weld penetration and selected characteristic parameters must be substantial. Also, in the projected control system for weld penetration, the selected parameters must be controlled to achieve the desired weld pool and weld penetration. Although more parameters could describe the weld pool more accurately, the increase in the number of selected characteristic parameters may complicate the resultant control system. Thus, the number of selected parameters must not be too large. As a result, the following parametric model is proposed:

$$y_r = \pm a \, x_r^b \, (1 - x_r) \, (a > 0, \ 1 \ge b > 0) \tag{1}$$

where a and b are the model parameters, (x_r, y_2) , are the coordinates of the pool boundary in the normalized coordinate system $ox_r y_r$ (Fig. 6(a)). These normalized coordinates are calculated using the measured x, y coordinates:

$$\begin{cases} x_r = x/L \\ y_r = y/L \end{cases}$$
(2)

where L is the length of the weld pool.

Model (1) presents a symmetric and normalized description of the weld pool. Although actual weld pools are not perfectly symmetric, if the non-symmetry of the weld pool is not extreme, its effect on the weld penetration may be negligible. A symmetric description of the weld pool will be more suitable for correlating the weld pool to the weld penetration, in addition to reducing the number of used parameters. In Model (1), the dimensions of the weld pool along both the length and width directions are normalized relative to the length of the weld pool. This normalized description can decouple the shape from the size of the weld pool so that the shape can be characterized by the parameters a and b. This decoupling between the shape and size can clarify the role of each parameter in characterizing the weld pool and designing a perspective control system.

The location corresponding to the maximum width of the weld pool is determined by b. It can be shown that max $y_r(x_r) = y_r(b I (b + 1))$. If the weld pool is divided into the leading and trailing portions, their lengths in the

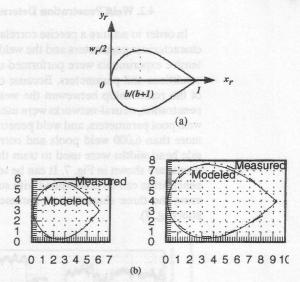


Fig. 6 - Symmetric modeling of the weld pool boundary. (a) Geometrical description (b) Modeling examples

normalized coordinate system are b l (b + 1) and l / (b + 1), respectively. Thus, b is the ratio between the leading and trailing lengths. Since the trailing length is larger, 1 b. it was found that the absolute length of the leading portion is less seriously affected by the welding parameters than the length of the trailing portion. Thus, when the current increases, b will decrease. For a stationary weld pool, the leading and trailing lengths should be equal. In addition to b, the weld pool shape is also determined by the parameter a. For a given b, the width of the weld pool in the normalized coordinate is proportional to the parameter a. This relative width characterizes the narrowness of the weld pool and can be calculated using the parameters a and b:

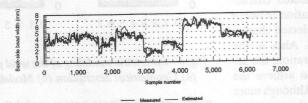
$$w_r = w/L = 2a \left[\frac{b}{1+b} \right]^b \frac{1}{1+b}$$
(3)

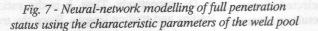
Thus, the weld pool can be characterized using three parameters: the length ratio b, the relative width w_r , and the length of the pool L. These three parameters characterize the weld pool from different points of view. It is apparent that the length L is independent of the shape parameters. The shape of the weld pool is described using two independent parameters based on the narrowness and the leading to trailing ratio. Thus, these three parameters of the weld pool and are denoted as $p_1 = L$, $p_2 = w_r$, and $p_3 = b$.

It has been shown that the proposed model can accurately characterize the weld pool shape. Two examples are illustrated in Fig. 6 (b). The small difference between the measured and modeled boundaries show the model effectiveness. Also, although the proposed model is nonlinear about the parameter b, its linear version can be acquired using a log transformation. Thus, the model parameters can be on-line identified from the weld pool boundary using the linear least squares algorithm.

4.2. Weld Penetration Determination

In order to acquire a precise correlation between the characteristic parameters and the weld penetration, extensive experiments were performed using varied weld conditions and parameters. Because of the complexity of the relationship between the weld pool and weld penetration, neural-networks were used to correlate the weld pool parameters, and weld penetration. Data from more than 6,000 weld pools and corresponding backside bead widths were used to train the networks. The results are shown in Fig. 7. It can be seen that the weld penetration can be determined with sufficient accuracy using the three characteristic parameters of the weld pool (fig. 7).





5. WELD POOL CONTROL

The low level control of the weld pool, i.e., controlling the weld penetration which is the most important determinant of the weld quality has been done in our previous work (13). It is known that the top-side bead width and back-side bead provide a description of the fusion zone geometry at the cross section. Their control can achieve the desired weld penetration and proper fusion zone which is critical in determining the heat affected zone. Hence, in this paper, the top-side bead width and backside bead width are controlled simultaneously based on the vision feedback of the welld pool. In the developed closed-loop system, the welding current and welding speed will be adjusted to achieve the desired back-side and top-side bead widths.

5.1 Neurofuzzy Modelling

When the welding current increases, both the topside and the back-side bead widths increase. However, as the welding current increases, the resultant changes in the top-side and back-side bead widths increase as the welding speed decreases. Also, as the welding speed decreases, the resultant changes in the top-side and back-side bead widths increase as the welding current increases. This implies that the correlation between an output and an input can be influenced by another input.

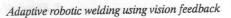
Different models and algorithms may be used to model and control non-linear processes. Recently, neural networks have been used to model and control nonlinear processes, including manufacturing processes. The non-linearity can be approximated by adding more neurons without having a detailed knowledge of the controlled process. Although the non-linearity of the process can be modeled with accuracy in most applications, the neglect of valuable process knowledge requires more neurons to be used. As a result, the training and adaptation of the networks are slowed down.

In order to increase the speed of modelling and adaptation, the model must be more efficient regarding the number of used parameters. An analytical model, derived from the physics of the controlled process, with unknown parameters, can be regarded as the most efficient and the number of parameters is usually relatively small. Its parameters can be identified very quickly and the adaptation of the resultant adaptive control system to the changed process environment can be fast. However, if the model structure is incorrect or incomplete, the resultant modelling and control performance could be poor.

A better approach is to partially assume the model structure using the knowledge of the controlled process so that the number of parameters is less than using a neural network. In order to do this, a specific model structure is required. First, the adjustment of the model structure should be connected in some way to the linguistic description of the process knowledge. Secondly, the model structure should have a mechanism to describe the addressed non-linearity through changing its parameters or increasing the model complexity.

The neurofuzzy model is a model structure which satisfies the above two requirements. First, the fuzzy partition can be done based on the linguistic knowledge about the process. This is the basic characteristic of a fuzzy system. Secondly, for a non-linear process, the dynamic model changes with the system variables. By finely partitioning the space of the system variables, the non-linear dynamics can be described using a set of local linear models with sufficient accuray. In a Segeno Fuzzy Model used in the neurofuzzy system, these local linear models correspond to the crisp functions associated with different IF-THEN implications. Hence, a neurofuzzy model has a mechanism to describe a non-linear dynamic process with satisfactory accuracy. Moreover, in a fuzzy model, the system variables are fuzzified. The outputs of the fuzzy system are generated from crisp functions with weights which are determined according to the degrees of truth of the premises. Thus, there are no sharp transitions from one local model to the other local models. As a result, the requirement on the fineness for the partition of the system variables can be greatly reduced. Hence, in addition to the ability to reach the required accuracy, neurofuzzy models can also decrease the number of needed parameters.

A neurofuzzy model has been developed to calculate the back-side bead width and top-side bead width only from the control variables (welding current and welding speed) without any use of the previous outputs. Fig. 8 shows the accuracy of the developed neurofuzzy model in predicting the back-side and top-side bead widths.



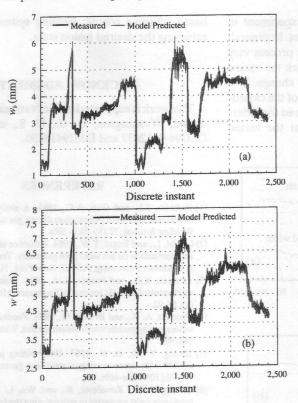


Fig. 8 - Neurofuzzy modeling results. (a) Back-side bead width (b) Top-side pool width

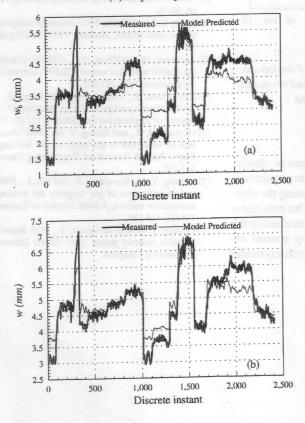


Fig. 9 - Linear modelling results. (a) Back-side bead width (b) Top-side pool width

The measured data are generated from a number of experiments. It can be seen that the errors between the measured and predicted values are always very small.' However, if a linear model is used, the errors are very large (Fig. 9). Hence, the neurofuzzy model provides an accurate description of the process being controlled.

5.2 Neurofuzzy Model Based Control

The identified neurofuzzy model can be used to predict the outputs of the system. In this work, a predictive control algorithm has been designed to control the fusion state. We notice that the non-linearity in the process being controlled is fundamental. Extensive welding experiments of closed-loop control have been conducted under different disturbances. It was found that the required fusion state was always achieved by the developed control system.

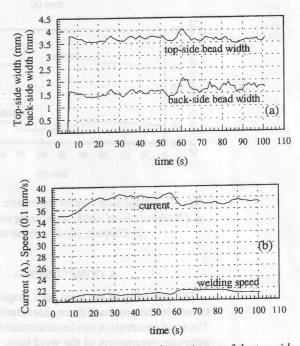


Fig. 10 - Closed-loop control experiment of the top-side and back-side bead widths under step change in the rate of the shielding gas. (a) Outputs. (b) Control actions

Fig. 10 shows a closed-loop control experiment. In this experiment, the shielding gas changes from 20 l/lim to 7 l/min at t=50 s. As a result, both the top-side and the back-side bead widths increase. By measuring the increased widths, the feedback control adjusted the welding current and welding speed so that the desired fusion state is achieved again. However, it is observed that in the case of the open-loop control where the welding current and welding speed are constant, the changes in the top-side and back-side bead widths caused by the varying rate of the shielding gas are not eliminated.