A Model-free Adaptive Control of Welding Pool Dynamics during Arc Welding

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Abstract—**Arc welding process is characterized as nonlinear, time varying, and uncertain. So it is very difficult to design an effective control scheme by conventional modeling and control methods. Quality control of arc welding process is the key component in robotic welding system. This paper addresses model-free adaptive control with functional reinforce of Al alloy weld pool dynamics during pulsed gas tungsten arc welding (GTAW). This control method only needs the observed input output data and also has functional reinforce to improve the performance of the controller. The shape and size parameters for the weld pool are used to describe the weld pool geometry. The welding current is selected as the control variable, and the backside width of weld pool is selected as the controlled variable. To achieve the goal of full penetration and fine weld seam formation, a model-free adaptive controller with functional reinforce is designed for control of the maximum backside width. This controller of weld pool is independent on mathematic model. Numerical simulations confirmed that the developed control system is effective in achieving the desired fusion state.**

Keywords—**GTAW, model-free adaptive control, welding pool**

I. INTRODUCTION

The dynamic identification and control of arc welding processes has been explored through a number of studies. Up to the present, to find advisable control strategy for arc weld pool dynamics still is a perplexed problem whether in welding or automation domains. Advanced control techniques such as adaptive control were used to generate sound welds [1,2]. Artificial intelligence methodology has been developed for modeling and controlling the welding process. George E. Cook [3] studied the application for the variable polarity plasma arc welding. A self-learning fuzzy neural network control system of topside width enabled adaptive altering of welding parameters to compensate for changing environments in Chen S.B.'s study [4]. Yu M. Zhang [5] used a neurofuzzy model to model the welding process. Based on the dynamic fuzzy model, a predictive control system has been developed to control the welding process. Zhang G.J. [6] investigated feasible intelligent control schemes. A double-variable controller was designed. In fact, it just is a supervisory control, not considering the couple relationship of variables. Apparently people were trying to find a feasible method to control the welding processes, but all above methods had limitations more or less in practical applications.

Classical PID controllers are designed on the assumption that the plant is linear or varying slowly. Traditional adaptive control methods, either model reference or self-tuning, usually require some kind of identification for the process dynamics. In addition, traditional adaptive control methods assume the knowledge of the process structure. They have major difficulties in dealing with nonlinear, structure variant, or large time delayed process. The learning processes of neuro network controllers are converging slowly. Obviously, they are inconvenient to use in practical applications. Fuzzy controllers disregard the time-variation of controlled system.

Because arc welding is characterized as inherently multivariable, nonlinear, time varying and having a strong coupling among welding parameters, it is very difficult to find a reliable mathematical model and to design an effective control scheme for arc welding by conventional modeling and control methods. However, extensive control methods which to be used depend upon effectiveness of modeling. So, how to design control system only based on information from the I/O data of the GTAW process will be of great significance. Recently, a model-free adaptive control scheme has been explored, which based on information from the I/O data of the controlled plant [7,8]. The model free control method has excellent performance in oil refining, chemical industry, power, light industry [9,10]. In fact, model-free adaptive control is the approach of unity of modeling and control [11]. The modeling and real time feedback control are united in the identification approach, and the pattern of parameter adaptive is broken up. Simulation comparisons among neural networks control, model-free adaptive control and PID control [12] indicate that the model-free control method is superior to the other two methods because it can deal well with the control problem of the discrete time nonlinear plant whose structure, parameters and order are time-varying. So the attempt to apply model-free adaptive control for the shape of the weld pool is significant and novel.

The main objective of this research is to develop the mode-free adaptive control algorithm with functional reinforce in arc welding control to overcome shortcomings of other controller methods, and is a development from the work in Ref.13.

II. GTAW PROCESS MODELING

GTAW process is controlled by a number of parameters, including the welding current, arc length, and welding speed. In general, the welding pool increases as the current increases and the welding speed decreases. When the arc length increases, the arc voltage increases so that the arc power increases, but the distribution of the arc energy is decentralized so that the efficiency of the arc decreases. As a result, the correlation between the weld pool and arc length may not be straightforward.

Compared with the arc length, the roles of the welding current and welding speed in determining the weld pool and weld fusion geometry are much more significant and definite. For the case of full penetration, the state of the weld penetration is specified by the backside bead width(w_b). In this study, we selected the welding peak current (I_p) as the control variable. The controlled process can therefore be defined as a GTAW process in which the welding current adjusted on-line to achieve the desired backside width of the weld pool.

A polynomial AutoRegressive with exogenous input or ARX model representation [14] is selected as the model representation. Consider the ARX model below:

$$A(q^{-1})y(k) = B(q^{-1})u(k) + e(k) \qquad (1)$$

The model belongs to linear-in-the-parameter model, therefore, the parameter estimation can be performed using least square method. The model in equation (1) can be represented

$$y(k) = \mathbf{\Phi}^{\mathrm{T}}(k)\boldsymbol{\theta} + e(k) \qquad (2)$$

Where

$$\boldsymbol{\theta}^{\mathrm{T}}(k) = \begin{bmatrix} a_1 & \cdots & a_n & b_1 & \cdots & b_n \end{bmatrix}$$

$$\mathbf{\Phi}^{\mathrm{T}}(k) = \begin{bmatrix} y(k-1) & \cdots & y(k-n) & u(k-d-1) & \cdots & u(k-d-n) \end{bmatrix}$$

The identification is thus simplified by estimation the model parameters. There are n+n parameters to be identified, and u is welding current, y is backside width of the weld pool. Based on the input output data $\{u(k), y(k)\}, k = 1, 2, \ldots, N$, and the variation of square sum of residuals, we can determine approximately that the evaluation of n is 5 and the time delay constan d=2.

Also through experiment data, ARX model of backside weld width (w_b) with welding parameters (I_p) is derived using the least square method developed with the Matlab program. The model can be derived using statistic hypothesis testing method as follows:

$$y(k) = a_1 y(k-1) + a_2 y(k-2) + a_3 y(k-3) + a_4 y(k-4) + a_5 y(k-5)$$

$$+ b_1 u(k-1) + b_2 u(k-2) + b_3 u(k-3) + b_4 u(k-4) + b_5 u(k-5) \qquad (3)$$

Where

$$A = \begin{bmatrix} a_1 & a_2 & a_3 & a_4 & a_5 \end{bmatrix} = \begin{bmatrix} 1.2245 & -0.7935 & 0.45269 & -0.23124 & 0.11518 \end{bmatrix}$$

$$B = \begin{bmatrix} b_1 & b_2 & b_3 & b_4 & b_5 \end{bmatrix} = \begin{bmatrix} 0.0085696 & -0.3748 & 0.0039714 & -0.16826 & 0.0023674 \end{bmatrix}$$

The feasibility of this model is verified by comparing the simulation results with the Matlab program and actual outputs. The square sum of residuals is 0.0303437.

III. MODEL-FREE ADAPTIVE CONTROL WITH FUNCTIONAL REINFORCE

A. *universal process model*

The following general discrete SISO nonlinear systems is considered

$$y(k+1) = f\left(Y_k^{k-n}, u(k), U_{k-1}^{k-m}, k+1\right) \qquad (4)$$

Where

- $k = 0, 1, \cdots,$ stands for discrete time
- $y(k+1)$ represents a one-dimensional state output
- $u(k)$ is an input variable
- $Y_k^{k-n} = \{y(k), \cdots, y(k-n)\}$ are the sets of system outputs
- $U_k^{k-m} = \{u(k), \cdots, u(k-m)\}$ are the sets of system inputs
- n and m are the orders of output $y(k)$ and input $u(k)$
- $f(\cdots)$ is a general nonlinear function

Following assumptions are made about the controlled plant:

When the system is in the steady state, it satisfies the condition that if $u(k) = u(k-1)$, then $y(k+1) = y(k)$.

The nonlinear function $f(\cdots)$ has a continuous gradient with respect to control input $u(k)$.

From the assumptions above and using the mean value theorem in the Calculus, we have

$$f\left(Y_k^{k-n}, u(k), U_{k-1}^{k-m}, k+1\right) - f\left(Y_k^{k-n}, u(k-1), U_{k-2}^{k-m}, k+1\right)$$

$$= \nabla f\left(Y_k^{k-n}, \overline{u(k-1)}, U_{k-1}^{k-m}, k+1\right)^{\mathrm{T}} \left[u(k) - u(k-1)\right] \qquad (5)$$

Where $\overline{u(k-1)} = u(k-1) + \theta\left(u(k) - u(k-1)\right)$, θ satisfies $0 \le \theta \le 1$. Therefore, we have

$$y(k+1) - y(k) = \nabla_{u(k-1)} f\left(\overline{u(k-1)}, k+1\right)\left[u(k) - u(k-1)\right] + \xi(k+1) \qquad (6)$$

If $\left\|u(k) - u(k-1)\right\| \neq 0$, let

$$\varphi(k) = \nabla_{u(k-1)} f\left(\overline{u(k-1)}, k+1\right) + \left[\left(u(k) - u(k-1)\right) / \left\|u(k) - u(k-1)\right\|^2\right] \cdot \xi(k+1)$$

Then equation (4) can be written as

$$y(k+1) - y(k) = \varphi(k)\left[u(k) - u(k-1)\right] \qquad (7)$$

where $\varphi(k)$ can be considered a pseudo gradient of model (7). Note that when the system is in a steady state, because of $\|u(k)-u(k-1)\|=0$, we have $y(k+1)=y(k)$, so in this case, (7) is a valid expression. Equation (7) is called universal model.

B. model-free adaptive control algorithm

1) estimation of the pseudo gradient $\varphi(k)$

It is clear that the necessary condition that the universal model (5) can be used in practice is that the estimation of $\varphi(k)$, denoted as $\hat{\varphi}(k)$, is available in real-time, and is sufficiently accurate. Considering the control action is known, define the cost function

$$J(\varphi(k))=\left[y^*(k+1)-y(k)-\varphi(k)^{\mathrm{T}}\Delta u(k-1)\right]^2$$
$$+\mu\|\varphi(k)-\varphi(k-1)\|^2 \quad (8)$$

where $\Delta u(k\text{-}1)=u(k\text{-}1)\text{-}u(k\text{-}2)$, because at the moment $\Delta u(k)$ is unaccessible we substitute $\Delta u(k-1)$ for it, $y^*(k+1)$ is the desired output of the controlled plant, μ is positive weighting constant which constrains the change of the pseudo gradient $\varphi(k)-\varphi(k-1)$.

By using (7), the minimization of the cost function (8) gives estimation

$$\hat{\varphi}(k)=\hat{\varphi}(k-1)+\left(\eta\Delta u(k-1)/\mu+\Delta u^2(k-1)\right)$$
$$\cdot\left(\Delta y(k)-\hat{\varphi}(k-1)\cdot\Delta u(k-1)\right) \quad (9)$$

where η is a suitable small positive number.

2) design of model-free adaptive control

At k+1, the controller needs to determine the control action ($u(k)$) based on the feedback ($y(k)$) to drive the welding process to reach the desired output ($y^*(k+1)$). The model-free adaptive control is then described as follows: Assume that the observed data $\{u(k-1),y(k)\}$ $(k=1,\ldots)$ are known, and the expected output $y^*(k+1)$ at (k+1)th time is given. Find a controller $u(k)$, such that the output of the system $y(k+1)$ matches $y^*(k+1)$. In order to achieve a robust control, it is required that the following cost function is minimized:

$$J(u(k))=\left|y^*(k+1)-y(k+1)\right|^2 \quad (10)$$

It is known that fluctuations in welding parameters will generate nonsmooth weld appearance, which is not acceptable. Also, the large changes of the control actions could make the closed-loop system unstable. Hence, the following modified cost function is used:

$$J(u(k))=\left|y^*(k+1)-y(k+1)\right|^2+\lambda\|u(k)-u(k-1)\|^2 \quad (11)$$

where λ is the weight. The analytic solution is

$$u(k)=u(k-1)+\left(\rho\varphi(k)/\left(\lambda+\varphi^2(k)\right)\right)\cdot\left(y^*(k+1)-y(k)\right) \quad (12)$$

where ρ is called a control parameter, which selection is closely related to the convergence of the control law. Equation (12) is called the basic form of the model-free adaptive control law.

C. model-free adaptive control with functional reinforce algorithm

In our scheme, the model-free adaptive control with functional reinforce is described as following.

$$u(k)=u(k-1)+\left(\rho\varphi(k)/\left(\lambda+\varphi^2(k)\right)\right)\cdot\left\{\left[y^*(k+1)-y(k)\right]+G\right\} \quad (13)$$

where G is a feasible function and represents the part of functions combination of controller. The necessary condition that the model-free adaptive control with functional reinforce algorithm can be sued is that this algorithm is convergent.

Let

$$\eta(k)=\begin{cases}1, & y^*(k+1)-y(k)=0\\ 1+G/\left(y^*(k+1)-y(k)\right), & y^*(k+1)-y(k)\neq 0\end{cases} \qquad k=2,3,\cdots$$

Then if $y^*(k+1)-y(k)\neq 0$ we have

$$y^*(k+1)-y(k)+G=\left[1+G/(y^*(k+1)-y(k))\right]\cdot\left[y^*(k+1)-y(k)\right]$$
$$=\eta(k)\cdot\left[y^*(k+1)-y(k)\right]$$

If $y^*(k+1)-y(k)=0$ we have

$$y^*(k+1)-y(k)+G=0$$
$$=\eta(k)\cdot\left[y^*(k+1)-y(k)\right]$$

So the model-free adaptive control with functional reinforce (13) can be transformed to the basic form (12), which has been proved convergence [7,8].

IV. Simulation of GTAW process

Having analyzed the GTAW process and developed the GTAW model (3), we will demonstrate the effectiveness of the model-free adaptive control with functional reinforce algorithm developed in GTAW process. Following are several steps that describe how the model-free adaptive algorithm works.

1. For the observed input output data $\{u(k-1), y(k)\}$, we can obtain $\hat{\boldsymbol{\varphi}}(k)$ which is the estimation of pseudo partial derivative $\boldsymbol{\varphi}(k)$, using least squares algorithm.

2. For the desired output $y^*(k+1)$, we have

$$u(k) = u(k-1) + \left(\rho\varphi(k)/\left(\lambda + \varphi^2(k)\right)\right)\cdot\left\{\left[y^*(k+1) - y(k)\right] + G\right\}$$

where

$G = \begin{cases} a, & e\cdot\dot{e} > 0 \\ b, & e\cdot\dot{e} < 0 \\ c, & e\cdot\dot{e} = 0 \end{cases}$, and a, b, c are constants, $a > 1 > b > c = 0$ .Then a new set of data $\{u(k-1), y(k)\}$ can be achieved, applying the control action $u(k)$ to the GTAW process (here we use the model (3)).

3. Repeat steps 1 and 2 above to generate a serial of data $\{u(k-1), y(k)\}$.

The desired backside weld width was chosen as $y^* = 6$ mm. On selection the initial estimation of pseudo partial derivative as $\varphi(0) = -1.5$. Fig.1and Fig.2 show the response of the system under the model-free adaptive control and the model-free adaptive control with functional reinforce with $\eta = 1.2$, $\mu = 1$, $\rho = 3.3$ and $\lambda = 25$. Results show the maximum overshoot of the model-free adaptive control with functional reinforce is smaller than the usual model-free adaptive control, also the regulating time and steady-state error is little smaller.

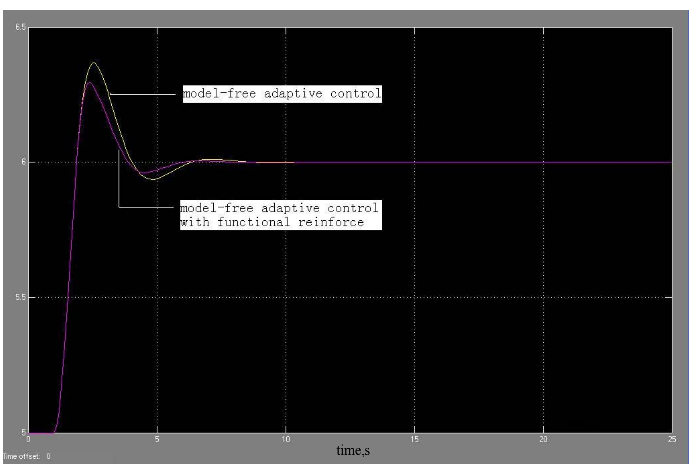

Figure 1. Backside weld width

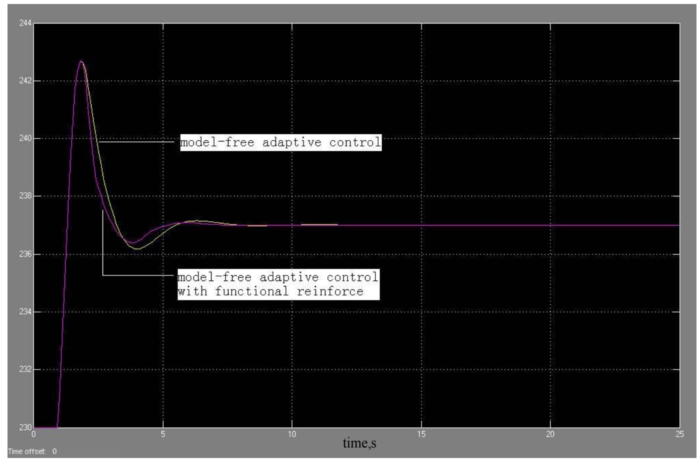

Figure 2. Control inputs

V. CONCLUSIONS

Because arc welding is characterized as inherently multivariable, nonlinear, time varying and having a coupling among parameters. Also the variations in the welding conditions cause uncertainties in the dynamics. So it is very difficult to design an effective control scheme by conventional modeling and control methods. The dynamic characteristics of arc welding are investigated. Furthermore, usual model-adaptive control and its functional reinforce algorithm are investigated. By the comparison of the two controls, it is found that the model-free adaptive control with functional reinforce can achieve better, rapid control performance. Meanwhile this control method only needs the observed input output data. Thus, the developed model-free adaptive control with functional reinforce provides a promising technology for GTAW quality control.

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