Adaptive Control of an Arc Welding Process

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A pseudogradient adaptive algorithm is successfully applied to self-tune a proportional-integral (PI) puddle width controller for consumable-electrode gas metal arc welding. The gradient of the output with respect to the controller parameters is approximated here and used to form a steepest descent algorithm to minimize the squared output error. Experimental data is presented confirming the algorithm performance.

**Consumable-Electrode Gas Metal Arc Welding**

Consumable-electrode gas metal arc welding (GMAW) is one of the most frequently employed and important welding processes. The reliability of the weld is strongly correlated to the microstructure and overall geometry of the joint [11]. These properties are determined by the thermal and mechanical history of the weld puddle and the rate at which it cools. The thermomechanical dynamics are driven by the flow of heat and mass from the torch as it travels along the weld joint.

Several researchers have developed methods for measuring and regulating puddle geometry. Vroman and Brandt [2] measured puddle width using a line scan camera. They regulated it via a torch velocity PI controller. Richardson [3,4] and Corby [5] designed an integrated through-torch vision system for coaxial puddle viewing. Baheti [6] developed an algorithm for estimating weld puddle area and width and designed a proportional-integral-derivative (PID) controller using arc current as the controlled variable.

Self-tuning promises to extend the capabilities of such a simple and reliable controller to a wide range of operating conditions. Thus, Suzuki and Hardt [7] used a model reference adaptive controller to regulate puddle width by adjusting arc current. In most cases, a simple PI or PID controller was sufficient for satisfactory regulation provided it was tuned properly for a particular operating range and material. This article reports on the successful application of a pseudogradient adaptive algorithm for self-tuning of a PI puddle width controller using torch travel rate (TR) as the control input. The design of this adaptive control is based on the pseudogradient properties established by Rhode and Kokotovic [8].

The pseudogradient approach relies upon the properties of slow adaptation because, under slow adaptation, the response of the underlying linear system remains close to its steady state response. The slow manifold technique of Riedle and Kokotovic [9] is then employed to separate the slow parameter dynamics from the fast linear state dynamics. Using sensitivity techniques from the 1960s, the gradient of the output with respect to the controller parameters is approximated. With this "pseudogradient" information, a steepest descent algorithm approximately minimizes the squared output error. In contrast to other adaptive methods, the sensitivity-based pseudogradient algorithm does not tie the number of parameters or controller structure to the order of the plant transfer function. This is ideally suited for self-tuning reduced-complexity controllers such as the PI puddle width controller for GMAW. Another advantage to this approach is that it is applicable to extremely noisy processes as is the case with this application.

After a brief review of sensitivity functions and the stability conditions for pseudogradient algorithms, experimental data confirming the performance of the pseudogradient adaptive algorithm are presented.

**Sensitivity Functions**

Sensitivity functions — the partial derivatives of the output with respect to parameters — are generated by the "variable component" method [10,11] which is applicable to all linear systems which can be placed into the form of Fig. 1. The transfer function $H_a(s,8)$ is the closed loop sensitivity function as shown in Fig. 2. This filter is often referred to as a sensitivity filter. It is important to note that $H_a(s,8)$ depends on the plant and adjustable control parameters.

For identification, the transfer function $H_{a}(s,8)$ is part of a known adjustable model, hence the exact sensitivity function can be used for steepest descent adaptive algorithms. A difficulty arises in adaptive control. Although $w(t,8)$ is usually available because it is part of the...
controller, \( H_{c}(s,\theta) \) depends upon the plant transfer function which is assumed unknown. For online adaptive systems, the exact gradient cannot be generated without knowledge of the plant. Hence pseudo-gradient adaptive schemes use only an approximation to the true sensitivity function \( \frac{\partial l}{\partial \theta} \).

Many controller structures have two or more gains feeding a common junction as in Fig. 2, if \( \theta \) represents \( \theta_1 \) and \( \theta_2 \). In this case, the sensitivity filters are identical for each parameter. The PI controller used to regulate puddle width possesses this property, therefore; the sensitivity filters for all parameters will be identical. For an adaptive scheme, this means that all the regressor filters are identical.

When in an adaptive system the reference model is represented by a fixed copy of the adjustable system and a primed error \( e^*(t) \), Fig. 3 results. Manipulating the adjustable system, the parameter error, \( \theta - \theta_0 \), can be separated from the system, and an auxiliary input formed. Defining the error as \( e(t) = v(t) - y_0(t) \), we obtain Fig. 4. For an \( N \) parameter system, superposition gives

\[
et(t,\theta) = \sum_{j=1}^{N} H_{c_j}(s,\theta)\theta_j + e^*(t) \tag{1}\]

**Stability Properties**

The class of slowly adapting systems, which includes the pseudo-gradient scheme, can be described by the system of nonlinear equations

\[
\dot{X}(t) = A(\theta)X(t) + B(\theta)v(t), \tag{2}
\]

\[
\dot{\theta}(t) = \eta f(r, \theta, X) \tag{3}
\]

To assure that the dynamics of the underlying linear system (2) are faster than the parameter update dynamics in (3) for \( \epsilon \) sufficiently small, we make the following assumptions.

**Assumption 1**: The parameter \( \theta \) is assumed to remain in a "stable set" \( \Theta \) such that \( \text{Re}\lambda_{i}(A(\theta)) \leq 0 \; \forall \theta \in \Theta \).

**Assumption 2**: The input \( r(t) \) is uniformly bounded. The update law function bounded and Lipschitzian in \( \theta, X \) uniformly with respect to \( t \in \mathbb{R}, \theta \in \Theta, X \in X \), where \( X \) is the desired operating range of values of \( X \). The first assumption, that a region of the parameter space is known for which the linear system is stable, is not restrictive for our application.

The bounds imposed by the second assumption insure the applicability of the slow manifold method [9] which separates the slow and fast dynamics. Using this method, the uniform asymptotic stability of (2)-(3) can be determined from the analysis of the slow parameter dynamics by considering the parameters, \( \theta \), in (3) constrained to the so-called "Frozen Parameter Manifold". On this manifold, the state of the plant, \( X(t) \), is given by the expression for its "steady state" constant parameter response

\[
v(t, \theta) = \int_{-\infty}^{t} \exp(A(\theta)(t - \tau)) B(\theta)v(\tau) \, d\tau \tag{4}\]

For small \( \epsilon \), the expression \( X(t) = v(t, \theta) \) is approximate because \( \theta \) varies slowly. With \( R(s) \) and \( V(s, \theta) \) as the Laplace transform of \( r(t) \) and the \( l^0 \) element of \( v(t, \theta) \) and we have

\[
V(s, \theta) = H_{c}(s, \theta)R(s) \tag{5}\]

The averaging theorem of Bogoliubov allows the analysis to be further simplified by averaging the parameter update equation (3). Assuming for simplicity that \( r(t) \) is periodic, \( r(t + T) = r(t) \), and given by a finite sum:

\[
r(t) = \sum_{k=1}^{K} \rho_k \sin(\omega_k t + \phi_k^\circ). \tag{6}\]

Thus the averaged update law is

\[
\dot{\theta}_m = \eta f_{av}(\theta_m). \tag{7}\]

where \( X \) contains the states of the plant, controller and all filters, and \( \theta \) is the vector of adjustable parameters.
This averaging is now applied to the update law of the form shown, where \( \Psi(t) = [\psi_1(t), ..., \psi_N(t)] \) is the regressor vector and \( e(t) \) is the output error \( e(t) = y(t) - y_{\text{ad}}(t) \).

\[
\dot{\theta}(t) = -\epsilon \Gamma \Psi(t, \theta)e(t, \theta)
\]  

(8)

If \( \Psi(t, \theta) = \partial \ln \Theta \), then (8) is a steepest descent algorithm for \( e^2(t) \). Recall that in our case the regressor is only an approximation of the gradient.

From (7) the average equilibrium \( \Theta^* \) is defined by \( f_{\text{av}}(\Theta^*) = 0 \), that is

\[
0 = -(\epsilon \Gamma \Psi(t, \Theta^*)e(t, \Theta^*))dt.
\]  

(9)

In the frequency domain approach [8], the uniform asymptotic stability of the average equilibrium \( \Theta^* \) is shown to depend upon the spectral measure \( S_\Psi \) of the regressor \( \Psi \). Denoting by \( \Psi(t) \) the autocovariance of \( \Psi \), we have

\[
R_{\Psi}(\tau) = \frac{1}{T} \int_0^T \Psi(t + \tau)^T \Psi(t) dt = \int \exp^{i\omega \tau} S_{\Psi}(d\omega).
\]  

(10)

Returning to the output error expression (1), we assume that the tuned error is zero, \( e^*(t) = 0 \). Then, a fundamental condition for the uniform asymptotic stability of the average system requires the matrix \( P(\theta) \) be positive definite, \( P(\theta) > 0, \Theta \in \Theta \). Where,

\[
P(\theta) = \sum_{k=1}^{N} (-\epsilon_{\text{av}}(j\omega \theta)^T S_\Psi(j\omega \theta) + H_\epsilon(j\omega \theta)^T S_\epsilon(j\omega \theta)).
\]  

(11)

\[
H_\epsilon(j\omega \theta) \triangleq H_{\epsilon,1}(j\omega \theta)H_{\epsilon,2}(j\omega \theta^*).
\]  

(12)

It can be shown that a sufficient condition for \( P(\theta) \) to be positive definite is that the following inequalities hold

\[
|H_{\epsilon,1}(j\omega \theta)|^2 \text{Re} H_\epsilon(j\omega \theta^*) > 0, k = 1, ..., N,
\]  

(13)

\[
\sum_{k=1}^{N} \text{Re} S_\epsilon(j\omega \theta) > 0,
\]  

(14)

For (13) to be satisfied, the phase of the regressor filter must be within \( \pm 90^\circ \) of the tuned sensitivity filter \( H_{\epsilon,1}(j\omega \theta)^* \) at all frequencies present in the input. Thus (13) is similar to the SPR condition, while (14) is a PE condition [12]. However, the above sufficient condition is too conservative because not all the terms in the sum need to be positive definite for \( P(\theta) \) to be positive definite. This can be interpreted to mean that the phase condition does not have to be met for all the spectral components in the regressor, but only the dominant components. It is important to point out that for a single frequency input, the sufficient conditions (13) and (14) are also necessary.

When \( e^*(t) \neq 0 \) a bound must be placed upon the tuned error \( e^*(t) \). From assumption 1,

\[
\| \Psi(t, \theta) - \Psi(t, \theta^*) \| \leq \alpha \| \theta \|.
\]  

(15)

If (13) and (14) are satisfied, the norm of the matrix \( P(\theta) \) is bounded from below

\[
\| P(\theta) \| \geq \beta > 0.
\]  

(16)

Then, if the tuned error \( e^*(t) \) satisfies

\[
|e^*(t)| < \frac{\beta}{2\alpha^*}
\]  

(17)

the averaged equilibrium is uniformly asymptotically stable.

Because the stability conditions (13), (14), (17) are not particularly restrictive, we were encouraged to use them to guide the selection of regressor filters in the design of the adaptive PI puddle width controller for our GMAW process. Through a simulation study, it was determined that the pseudogradient satisfied the above stability conditions with fixed sensitivity filters based on a simplified nominal model of the welding process. These sensitivity filters were used as regressor filters for all experiments described in this paper. As shown in [13], the above theory for continuous time processes is verbatim applicable to sampled-data models described in the next section.

**Adaptive Puddle Width Controller**

The facility at which these GMAW control system experiments were performed was developed at the US Army Construction Engineering Research Laboratory in collaboration with the University of Illinois Decision and Control Laboratory. Fig. 5 is a photograph of the system, which was also used for the experimental work described in [14].

A dc power supply is connected between the workpiece and electrode contact tube. Consumable-electrode wire is fed to the workpiece through a set of pinch rollers. The wire feed rate determines both the arc current and the rate of metal deposition. As the torch is moved along the workpiece, the joint is filled with a solution of electrode wire and workpiece material. The region surrounding the weld puddle is purged.
with a shield gas to prevent oxidation and contamination of the weld joint. The control input for the experiments reported here is the torch travel velocity, \( TR \). Arc current, which is the other control variable, was regulated to a constant value.

The range of operation of this GMAW system covers travel rate from 8 to 18 in/min and arc current from 310 A (Amperes) to 410 A. Three small signal models for the transfer function from the travel rate \( TR \) to the puddle width \( W \) were identified using a 1 in thick plate preheated to a temperature of 250°F.

**Nominal-Current (360 A) Model:**

\[
\frac{W(z)}{TR(z)} = -0.0006z^2 - 0.0032z - 0.0006 + \frac{1}{z^4 - 1.0658z^3 + 0.01z^2 + 0.0383z + 0.134} \tag{18}
\]

**High-Current (410 A) Model:**

\[
\frac{W(z)}{TR(z)} = 0.0004z^2 - 0.0016z - 0.0023 + \frac{1}{z^4 - 0.9716z^3 - 0.0427z^2 - 0.0543z + 0.1693} \tag{19}
\]

**Low-Current (310 A) Model:**

\[
\frac{W(z)}{TR(z)} = -0.0013z^2 + 0.009z - 0.0039 + \frac{1}{z^4 - 1.0377z^3 + 0.0641z^2 + 0.0682z + 0.037} \tag{20}
\]

All three models were employed for simulation tests of the adaptive scheme before its implementation on the actual welding process. The nominal-current model is used for the sensitivity filter design.

Preliminary experiments showed a 10% overshoot in the open-loop puddle width response to a travel rate step input. Uniformity and smoothness of the weld were adversely affected by this overshoot. Hence the following overdamped second-order reference model was selected

\[
\begin{align*}
   \frac{W_{ef}(z)}{R(z)} &= 0.0165z^2 + 0.0143 \\
   &= \frac{1}{z^2 - 1.62 + 0.6589} \tag{21}
\end{align*}
\]

The block diagram of the adaptive puddle width PI controller is shown in Fig. 6(a). The adjustable parameters of the PI controller, \( K_p \) and \( K_i \), are indicated in Fig. 6(a) by two multipliers. In the sensitivity filter in Fig. 6(b), the control parameters are fixed at their nominal values and the sensitivity filter incorporates the nominal-current plant model given by (18). To apply the rule in Fig. 2, our desire is to use the actual system to implement the transfer function \( H_{r, \text{eff}} \). Therefore this transfer function is implemented as

\[
H_{r, \text{eff}}(z) = H_{r, \text{nom}}(z) \frac{1}{C(z)} \tag{22}
\]

where \( H_{r, \text{nom}}(z) \) is implemented by the actual plant and \( C(z) \) is the controller transfer function

\[
C(z) = K_p + \frac{T}{z - 1} \tag{23}
\]

evaluated at the nominal values \( K_p = K_p^{\text{nom}}, k_i = k_i^{\text{nom}} \). These nominal values and the nominal plant model are also used in the sensitivity filter in Fig. 6. The discrete time update law is then given by:

\[
K_p(k + 1) = K_p(k) - \epsilon T e(k) \psi_1(k) \tag{24}
\]

**Welding Experiments**

Six experiments were conducted over the arc current operating range of the welding system with arc currents of 330A, 360A and 390A. In each experiment, a single bead was deposited on a 48 in x 16 in steel plate. The first three experiments were done on a 1 in thick plate, the last three on a 1/2 in thick plate. The change in plate thickness is a major challenge. The actual welding process in the case of thin plates is drastically different from that of a thicker plate. A thicker plate acts as a heat sink, which is not the case for a 1/2 in plate. Several other control algorithms failed to be robust with respect to changes in plate thickness, and some even went unstable. The major and somewhat surprising success of the designed adaptive controller is that it not only rapidly converged, but also achieved good performance for thick and thin plates.

Figs. 7 and 8 show the results from these experiments. Part (a) of the figures gives the input, reference model response, and puddle width response. Part (b) of the figures gives the parameter convergence history. Fig. 7 shows the result from a typical experiment run on a 1 in thick plate. In this experiment, even though the adaptation was initiated with a poorly oscillatory response close to instability, the parameters converged in less than one minute. Fig. 8 shows the result from a more challenging experiment performed on a 1/2 in thick plate. Because of the plate thickness difference, the plant model used in the sensitivity filter for this adaptive system does not match the plant at any of the thin plate operating points. In spite of this large mismatch, the puddle width responses in this figure shows that the adaptive system performs well.
In such experiments, the parameters converged in about the same amount of time as in the thick plate experiments.

References


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