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Data-driven process characterization and adaptive control in robotic arc welding

Peng Wang [a, b], Joseph Kershaw [b], Matthew Russell [a], Jianjing Zhang [c], Yuming Zhang [a], Robert X. Gao (1) [c]

[a] *Department of Electrical and Computer Engineering and Department of Mechanical Engineering, University of Kentucky, Lexington, KY, USA*
[b] *Department of Mechanical Engineering, University of Kentucky, Lexington, KY, USA*
[c] *Department of Mechanical and Aerospace Engineering, Case Western Reserve University, Cleveland, OH, USA*

Robotic arc welding (RAW) has been an essential process in various assembly systems, such as automotive manufacturing. However, its implementations lack adaptivity to compensate for process variations. This paper presents a data-driven process characterization and online adaptive control framework for RAW to automatically and efficiently achieve desired weld pool condition, given any initial conditions. Based on optical imaging, pool width is characterized through a pixel-level image segmentation network and then used for determining the parameter adjustment for robotic execution through a gradient-based controller. Experiments demonstrate quick process convergence within 7 adjustment periods and an error band within 10.9%.

Robot, welding, adaptive control

1. Introduction

Welding robots have significantly advanced the state of automotive welding by improving operational efficiency and precision. However, robotic welding is not fully autonomous yet. Still relying heavily on preprogramed welding parameters, current welding robots cannot adaptively adjust parameters to compensate for task variability, material heterogeneity, and process uncertainty as skilled human welders do. The transition from preprogramed to adaptive robotic welding requires the seamless integration of in-situ perception and process characterization, process-quality relationship quantification, closed-loop control, and robotic execution (see Fig. 1). Prior efforts in this regard include optimizing welding sequences to reduce project cycle time [1], leveraging kinematic redundancy for efficient robot motion planning [2], determining optimal welding parameters using offline process simulation [3], etc. A fully functional adaptive process control solution is still lacking.

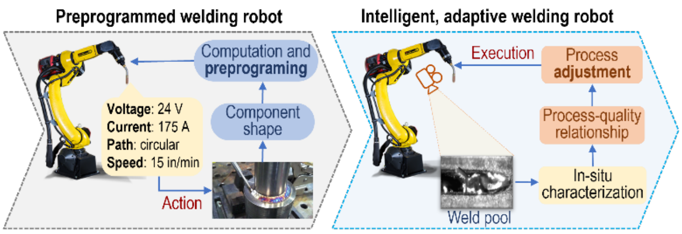

Fig. 1 Transitioning from welding robots that require preprograming of parameters to intelligent robots that adaptively adjust parameters

Early work on robotic arc welding control has used two cameras to capture the arc, weld pool, and solidified bead [4]. Subsequent to a few steps of image preprocessing and filtering, features such as pool area and pixel profiles were defined, from which defects could be detected for emergency stop of robots. Although no closed-loop process adjustment was made online to compensate for process instability, this work has established a foundation for feature engineering-based process monitoring and characterization. In the years that followed, sensing and modelling techniques have seen continuous improvement. In [3], laser welding was monitored through measuring temperature, visible light, and back-reflection by a photodiode sensor, and extracted features were then used to estimate the joint quality. Further work include a machine learning (ML)-based stochastic model that correlates process parameters with weld quality considering task variations [5]. The model was iteratively updated by in-process data, and used offline for selecting parameters that fit dynamic welding tasks.

Despite progress, challenges remain to realize online adaptive robotic welding process control, including: 1) efficient sensing data processing for in-situ weld quality inference, and 2) relatively long stabilization period for process adjustment to take effect. Recent advancement in ML and reinforcement learning (RL) offers potential solutions to these challenges. Neural networks (NNs) were investigated on correlating in-situ sensing with arc welding quality (e.g., bead width), based on which a gradient-based controller was developed for online adjustment of welding speed and/or current [6-7]. An RL-based control framework was developed for laser welding [8], where an NN-based encoder was applied to mapping the radiation data to process adjustment, followed by another NN that detects the weld quality after the adjustment. The quality feedback was then used to generate either a reward or penalty to update the encoder. However, these solutions were either completely data-driven that lacks physics-based causal reasoning, or were limited due to slow convergence (more than 10 adjustment periods) or large error band (approximately 20%) for online control.

This paper presents an online adaptive control approach to robotic arc welding, where weld pool width is controlled in a closed-loop. From in-situ optical imaging, an efficient pixel-level image segmentation network is first developed to outline the pool area and estimate the pool width. Then based on a perceptron that describes the dependence of pool width on parameters (i.e., welding speed, current, torch angle), an advanced gradient descent algorithm is investigated to backpropagate the needed pool geometry changes to parameter adjustments based on individual parameters' contributions to pool status change, while minimizing the settling time and steady-state error band. The main contribution of this work lies in the following two areas:

- **Efficiency**: in-situ images can be processed within milliseconds, thus enabling sub-second periodical process adjustment. Also, the control algorithm greatly reduces the settling time of process adjustment.
- **Physical interpretation**: no black-box mapping from pool state to action determination is involved, as compared to the RL approach. The outputs from the networks and controller can be readily interpreted and evaluated by humans.

2. Online adaptive robotic welding control

Online adaptive robotic welding control requires effective and efficient integration of perception, process characterization, process-quality modelling, adjustment, and robotic execution.

Robotic perception, enabled by in-situ sensing, can have better observability of process dynamics than human welders do. One criterion for selecting proper sensing techniques is whether they support meaningful inference of variable(s) to be controlled. For example, weld pool imaging cannot directly characterize penetration and back-side bead width. Although pool area is generally proportional to penetration and bead width, their relationships vary with welding tasks and then become nonlinear [9]. Hence, in the case of controlling bead width upon weld pool imaging, data-driven indirect inference is needed, and it may introduce additional characterization errors [7]. In this paper, weld pool is set as the control target while its evolution is directly captured by the optical pool camera, without indirect inference.

Process-quality modelling provides the causal reasoning basis for adaptive process adjustment. Since the welding processes are highly complex to model analytically, empirical knowledge is often relied on to provide a qualitative description of the process-quality relationships [10]. For example, if a split pool is detected during the welding process, it indicates that energy flux is less than needed and can be improved by slowing down the welding speed and/or increasing the current. However, such qualitative analysis guides only the directions not the magnitudes of the parameter adjustments. This issue gets more complicated when parameters have similar effects on the control target. Then if parameters are adjusted at the same pace (i.e., same percentage of delta changes), overcorrection and oscillation may occur. Data-driven modelling can complement the solution by providing a quantitative evaluation of individual parameters' effects on quality, which are represented by the weights connecting parameters and quality in NNs. Then adjustments of parameters can be designed at different paces based on their respective effects, with the objective of minimizing oscillation, settling time, and error band.

Attention also needs to be paid to the limits of robotic handling load, motion speed and precision, rotating angle, etc. For example, while welding speed changes can be readily realized by changing the robotic tip motion speed, torch angle changes involve robotic joint rotation and large angle change may take a few seconds to realize. It is then necessary to set a tight boundary for the angel change per adjustment period, to ensure that any periodic change is sufficiently implemented within that period, without interfering with subsequent adjustment periods.

3. Machine learning-based adaptive control

In the developed online, closed-loop adaptive robotic control system (shown in Fig. 2), in-situ optical images are processed for estimation of the current pool width. The result is compared to the desired width to determine parameter adjustments, which are sent to the robot for execution, and then the next adjustment period starts. Three ML elements are included in the system.

3.1 Pixel-level segmentation for weld pool characterization

Accurate outlining of weld pool from optical images is challenging, as the images contain not only the pool but also the arc, bead, and background objects. The pool is also obscured by the bright arc, leading to a blurry pool boundary. Standard image processing techniques (e.g., edge detection) cannot precisely outline the pool contour. Recent development in convolutional NN has advanced image processing [11-12] by enabling hierarchical extraction of abstract image representations.

As shown in Fig. 2, a pixel-level image segmentation network, consisting of a convolutional encoder and a de-convolutional decoder, is developed to outline the weld pool. Under supervised learning, the convolutional and pooling operations in the encoder are trained to focus on weld pool-related abstract features. The features are then transformed through trainable deconvolutional and unpooling layers to a mask map (of the same size as the input image), which indicates the probability of each pixel being part of a weld pool. Pool height is then calculated based on the outlined pool contour. Since split weld pool needs specific control actions, its occurrence needs to be detected. Towards this, a classifier consisting of one convolutional and pooling layer and two fully connected layers is attached to further classify extracted features against single or split pools. Binary cross-entropy is used as the loss function for training the network and classifier.

3.2 Perceptron for process-quality correlation

Adjustment of welding parameters to minimize the difference between current and ideal pool width is based on the correlation between parameters and pool width, so that the width difference

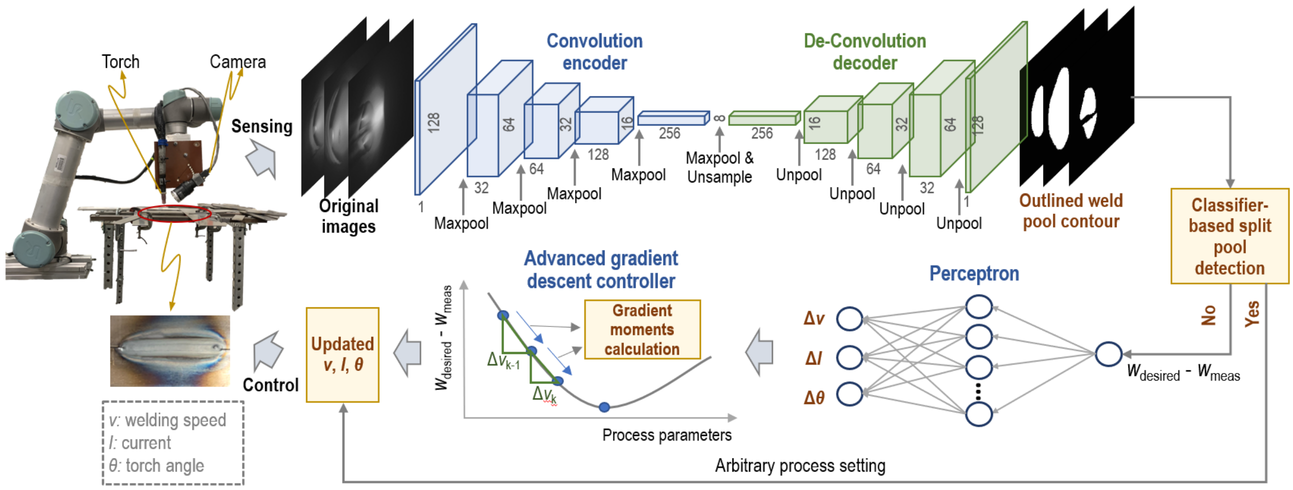

Fig. 2 Overall flowchart of the developed process characterization and adaptive control system

can be reversely mapped through the correlation to deltas of parameters. Three critical parameters, welding speed (v), current (I), and torch angle (θ) are considered. Correlation among these variables is modelled by a three-layer perceptron:

$$W = \sigma\left(\sigma\left(\left[v, I, \theta\right]^T * \Phi_1\right) * \Phi_2\right) \tag{1}$$

where W is the predicted pool width, Φ_1 and Φ_2 are the weights connecting perceptron layers, * denotes the matrix multiplication, and σ is the Sigmoid function. The training data here does not include data associated with a split weld pool. When a split pool is detected, an arbitrary set of parameters would be implemented to generate a single weld pool, from which the developed control method as detailed below can be applied.

3.3. Advanced gradient descent-based adaptive control

Based on the established correlation shown in Eq. (1) and the estimated pool width at moment k-1, parameter adjustments can be obtained as the gradients of the difference between desired and estimated pool width regarding current parameters:

$$\left[\Delta v, \Delta I, \Delta\theta\right]_k^T = \partial \frac{1}{2}\left(W_{desired} - W_{meas,k}\right)^2 \Big/ \partial\left[v, I, \theta\right]_k^T |_{\Phi_1,\Phi_2} \tag{2}$$

Since the gradients are calculated given the trained perceptron weights Φ_1 and Φ_2, gradients are evaluated in terms of individual parameters' importance to pool width change. For example, if the connection from one parameter to pool width consists of more excitatory weights, it plays a more important role in changing the pool and hence a larger gradient would be generated through (2). The new set of parameters can be adjusted as $[v, I, \theta]_k = [v, I, \theta]_{k-1} - \eta[\Delta v, \Delta I, \Delta\theta]$ under gradient descent, where η is the learning rate that controls the process adjustment speed.

Standard gradient descent directly uses the instantaneous gradients to generate the parameter adjustments. It is hence sensitive to process variation and measurement noise, leading to unnecessary correction and large steady-state error band [11]. Adaptive moment adjustment, as an advanced gradient descent algorithm, normalizes the instantaneous gradients with respect to the mean and variance of the historical gradients. Then parameters are adjusted considering both instantaneous gradients and historical gradient variation, reducing unnecessary changes. Using welding speed as an example, it is periodically updated as:

$$v_k = v_{k-1} - \eta\frac{m_k}{\sqrt{s_k}}\Delta v_k = v_{k-1} - \eta\frac{\beta_1 m_{k-1} - (1-\beta_1)\Delta v_k}{\sqrt{\beta_2 s_{k-1} - (1-\beta_2)\Delta v_k^2}}\Delta v_k \tag{3}$$

where m and s are the mean and variance of historical gradients, calculated in a moving average. Parameters β_1 and β_2 control the temporal decay rate of moving average. Once the process is stabilized with the new parameters, measurements are taken and processed towards a new round of parameter adjustment.

4. Experimental evaluation

To experimentally evaluate the performance of the developed online adaptive control system, tests were conducted on a robotic Gas Tungsten Arc Welding (GTAW) process testbed. In the setup, a welding torch and an optical camera (with 60Hz sampling rate) were installed on a UR5 robot. The robot has a maximum payload of 5kg and positional accuracy of 0.1 mm. Its speed and angle adjustment were handled through the inverse dynamics in URScript. Linear welding was performed to weld low-carbon steel plates (3.18 mm thickness) together, and no shielding gas was applied. Different welding speeds (2, 3, 4, 5 mm/s), currents (130, 140, 150, 160 A), and torch angles (0, +10, -10 degrees) were tested, where the 0-degree angle is perpendicular to the workpiece and positive degree pushes the weld pool. This results in 4 x 4 x 3 = 48 combinations of parameters, and each was run for 15 seconds.

A total of 10 steady-state images from individual trials were used for training the segmentation network and classifier, creating a training data pool of 480 images. Weld pool(s) were outlined manually to generate binary masks as labels. These 480 images, after random cropping, random brightness adjustment, and resizing, were split into 432 training and validation images and 48 testing images. Testing images were selected to ensure a representative number of split pools. To evaluate network performance variation due to the small training data size, five-fold cross-validation was conducted. Results from the testing data indicated a mean error of 5.06 ± 0.36 pixels (equivalent to 0.5 ± 0.04 mm) in generating the pool masks, and a 100 ± 0% accuracy in identifying split pools. Fig. 3 shows samples of the generated pool masks. The network were coded in PyTorch, which took 75 ± 6 ms to process and generate masks for ten images on an Intel Core i9 @ 2.80 GHz. The efficiency was further improved to 25 ± 3 ms by compiling the network into the ONNX format (an open format for ML models) The computational efficiency is shown to be higher than needed for sub-second online process control.

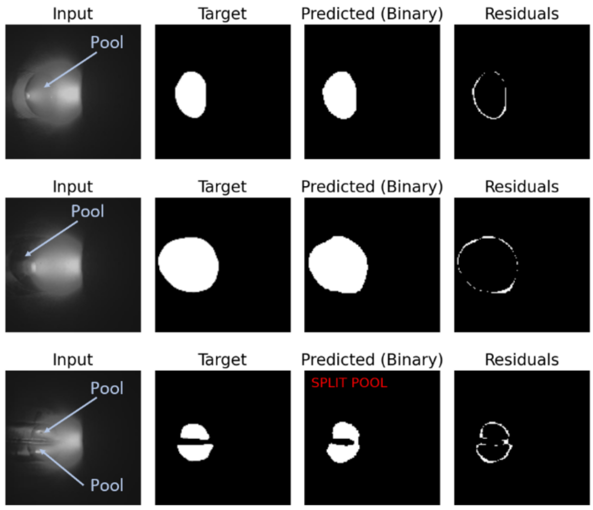

Fig. 3 Samples of generated pool masks (3rd column) by the network

The pool widths estimated from the labelled images were also used for training the three-layer perceptron. A number of 12 hidden neurons and a learning rate of 0.0085 were chosen from a grid testing of perceptron hyperparameters. The trained perceptron achieved a coefficient of determination over 0.93 within 400 epochs. The trained perceptron was able to strongly correlate process parameters to pool width, as shown in Fig. 4.

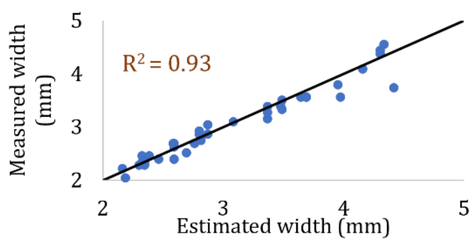

Fig.4 Performance of perceptron in predicting weld pool width

The trained networks were then applied to online adaptive robotic welding control. The adjustment period was set as 0.75 seconds. The first 0.3 seconds were used to stabilize the process under new parameters. 18 images were then collected from the next 0.3 seconds and transmitted to the computer for processing. Correspondingly, 18 pool width values were obtained and averaged to represent the current process status. The final 0.15 seconds were reserved for calculating and sending new parameters to the robot for a new round of process adjustment.

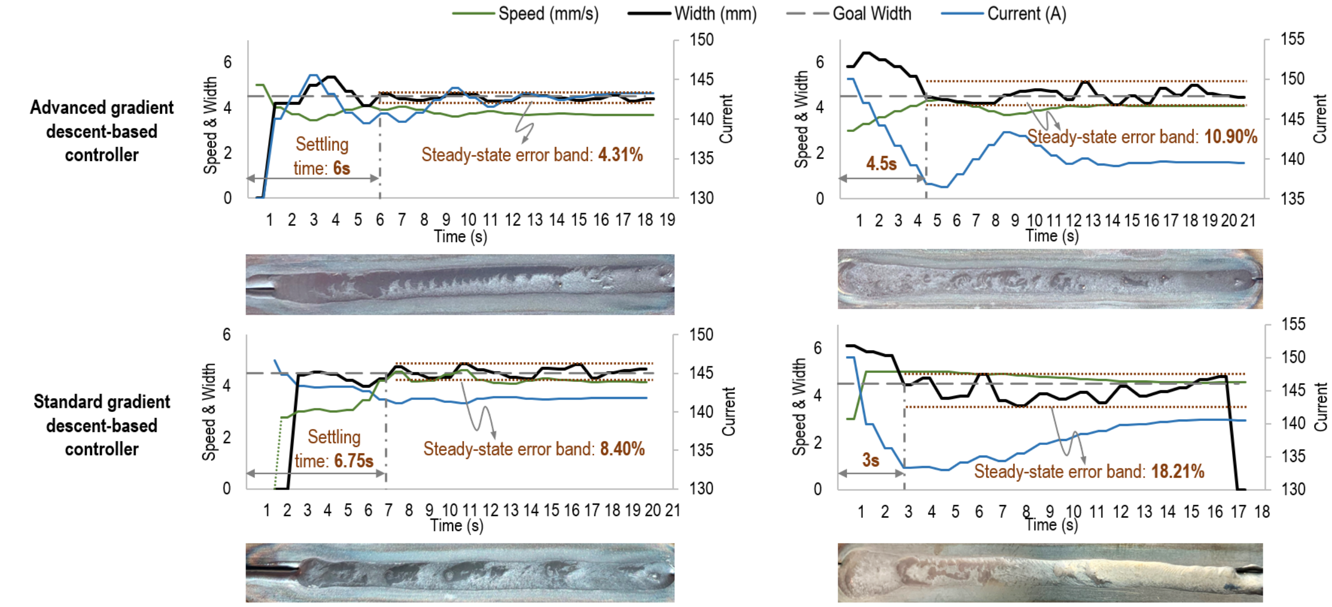

Fig. 5 Performance of standard and advanced gradient descent-based controller for two initial conditions: split pool (left) and large pool (right)

If a split pool was detected, an arbitrary control policy would be invoked to enable sufficient heat flux to generate a single weld pool. In the first adjustment period, welding current and speed were set as 140 A and 4 mm/s. If a split pool was still detected in the next period, the current would be increased by 5 A and the speed decreased by 0.5 mm/s, until a single pool was detected. Then the process adjustment could be performed by the gradient descent-based controller. Since the robot was unable to realize a large angle change in 0.3 seconds (process stabilization time), angle adjustment was capped to ±5 degrees per period.

Two types of tests were conducted: one with an initial larger than desired pool (4.5 mm); the other with initial split pools. Both the standard and advanced gradient descent controllers were evaluated on these two testing scenarios. In the advanced controller, the two temporal decay rates were set as 0.1, and the learning rate was set as 0.1 with a 0.005 decay per adjustment period, to avoid large oscillation when the process entered a relatively stable stage. In the standard controller, the learning rate was set as 5 with a 0.25 decay per adjustment period.

The experimental results (see Fig. 5) indicate that both controllers could quickly transit the pool from initial conditions to the desired range. The settling time by the advanced controller is below 6 seconds (i.e., 7 adjustment periods). It is seen that both controllers could decrease speed and increase current when pool width was below desired, and vice versa. Also, the percentage of speed change was larger than current, especially in the early stage of adjustment. This suggests that welding speed played a more important role in tuning the pool. Parameter adjustments in the advanced controller were more linked to pool variation (in terms of oscillation) than in the standard controller, as the former considered historical gradients for adjusting parameters. This also resulted in lower error bands by the advanced controller, with 48.7% and 40.1% improvements in the two testing scenarios, respectively. The reason why error bands in the initial large pool tests were larger than in split pool tests is that initial excessive heat flux preheated workpiece, which were unable to be completely compensated. The results confirmed the effectiveness and efficiency of the online adaptive robotic welding control system.

5. Conclusions

A data-driven adaptive robotic welding control system has been developed for online process parameters adjustment to achieve and maintain the desired weld pool width, irrespective of the initial process conditions. Experimental results indicate that the process can be adjusted within 7 adjustment periods to a less than 11% error band, enabled by efficient image processing and advanced gradient descent-based control algorithm. Since weld pool status is a critical and measurable metric in all types of welding processes, choosing it as the control target enables direct physical interpretability and generalizability of the developed system. The system can be readily transferred to other application scenarios, such as different welding processes or workpieces, with minimum modifications (e.g., process adjustment frequency, desired pool width).

Acknowledgment

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