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Technical Paper

A tutorial on learning human welder's behavior: Sensing, modeling, and control

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ABSTRACT

Human welder's experiences and skills are critical for producing quality welds in manual GTAW process. Learning human welder's behavior can help develop next generation intelligent welding machines and train welders faster. In this tutorial paper, various aspects of mechanizing the welder's intelligence are surveyed, including sensing of the weld pool, modeling of the welder's adjustments and this model-based control approach. Specifically, different sensing methods of the weld pool are reviewed and a novel 3D vision-based sensing system developed at University of Kentucky is introduced. Characterization of the weld pool is performed and human intelligent model is constructed, including an extensive survey on modeling human dynamics and neuro-fuzzy techniques. Closed-loop control experiment results are presented to illustrate the robustness of the model-based intelligent controller despite welding speed disturbance. A foundation is thus established to explore the mechanism and transformation of human welder's intelligence into robotic welding system. Finally future research directions in this field are presented.

1. Introduction

In manual gas tungsten arc welding (GTAW) process skilled welders can appraise the state of weld joint penetration through their observation on the weld pool and intelligently adjust the welding parameters (e.g., current, welding speed, arc length and torch orientation) accordingly to control the welding process. Because of their versatile sensing capability and experience-based behavior in response to the information they sense, they may be preferred over mechanized welding control systems in certain applications.

Although welders' experience and skills are crucial in producing quality welds, human welders have limitations. Critical welding operations require welders concentrate consistently in order to react rapidly and accurately. Inconsistent concentration, fatigue and stress do build up such that welders' capabilities degrade during daily operations. Moreover, experience and skills needed for critical operations typically require years to develop while manufacturing industry is experiencing insufficient number of skilled welders for a long time [1]. The mechanism of welder's experience-based behavior thus should be fully explored and utilized to develop intelligent robotic welding systems that combine human welder's intelligence and physical capabilities of the mechanized welding machines, which paves the foundation for next generation manufacturing processes. Modeling human welders' responses, i.e., how they respond to the information they sense, thus plays a fundamental role in facilitating such a development. In addition, the resultant welder response models may also be utilized to understand why less skilled welders are not performing as well as skilled welders and help train welders faster in order to help resolve the skilled welder shortage issue the manufacturing industry is currently facing [2].

In the following subsections, fundamentals of GTAW process and analysis of human welder behavior are presented.

1.1. GTAW process

GTAW is the primary process used by human welders for critical applications [3]. In this process as shown in Fig. 1, an arc is established between the non-consumable tungsten electrode and base metal. The base metal is melted by the arc forming a liquid weld pool that joins the two pieces of base metal together after solidification. An optional filler metal (not shown in figure) can be added if necessary but it is melted by the arc column, rather than directly by an arc spot as in gas metal arc welding (GMAW) where the anode can much more efficiently melt a continuously fed wire than the arc column to increase the melting productivity. However, the detachment and impact of the associated droplets on the weld pool compromise the controllability of the process and limit its use in precision applications.

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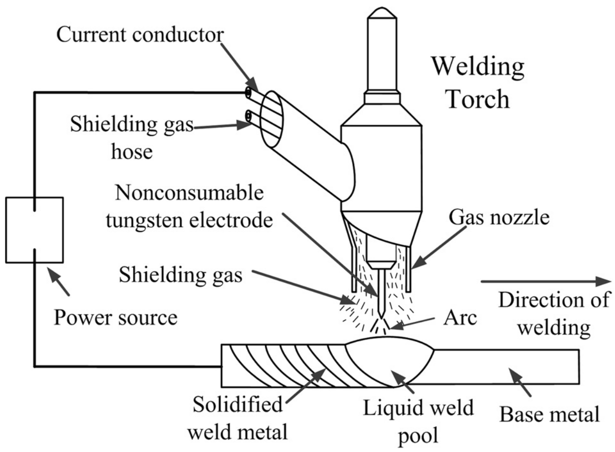

Fig. 1. Illustration of GTAW.

Because GTAW is primarily used in applications where appropriate degree of full penetration is required, the process should be mechanized/automated. However, the assurance of the weld quality is generally not guaranteed in automated GTAW using conventional sensing method. In manual welding, welders observe the weld pool and assure the desired full penetration is produced. However, in mechanized welding, welders are not required or allowed to observe the welding process with the similar level of concentration as in manual operation. Mechanized/automated systems rely on precision control of joint fit-up and welding conditions and tedious programming of welding parameters to produce repeatable results. However, precision control of joints and welding conditions is very costly and not always guaranteed. Up to date, there are no satisfactory sensors that can conveniently/automatically monitor the penetration depth or the degree of the full penetration like a skilled welder. It is thus of great interest to develop the intelligent welding machines that can sense the welding process like the human welder yet do not suffer from the limitations of the human welder. In the following section the human welder's behavior is analyzed.

1.2. Human welder's behavior

The diagram of the human welder's behavior is shown in Fig. 2 [4]. Given a certain welding task, a human welder starts with some initial estimation input I which may include the current, arc length, welding speed, etc. After the input of the initial control, the welder perceives necessary direct information Ω' from the weld pool. Ω is the information that should be sensed from the welding process which is controlled by the welding parameters:

$$\Omega = \gamma(I) \tag{1}$$

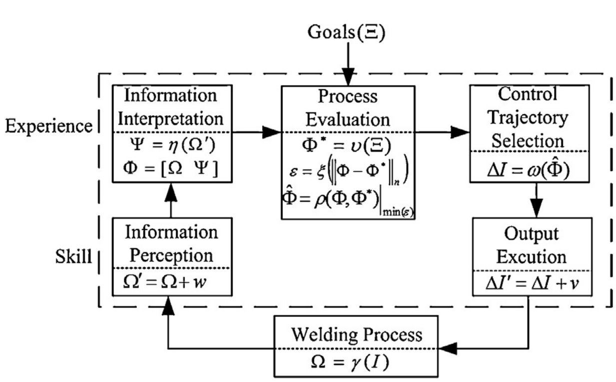

Fig. 2. Illustration of an interpretation of human welder's behavior [4].

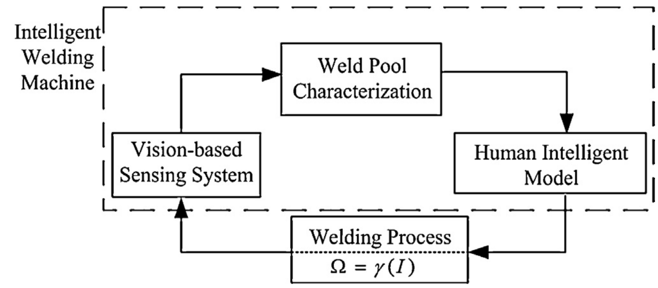

Fig. 3. Illustration of intelligent welding machine that mimics human welder's behavior.

The welder may derive indirect information Ψ from the direct information:

$$\Psi = \eta(\Omega') \tag{2}$$

The instant state of welding process Φ may contain both the direct and indirect information of welding process.

The process evaluation involves the decision-making process. Given the inconsistent nature of human welder action, there may be certain inconsistency of welding performance even for a well-trained welder. The welder first maps the goals of the welding process Ξ into the desired state of welding process Φ^*:

$$\Phi^* = \upsilon(\Xi) \tag{3}$$

Then the welder evaluates the desired and the instant state similarly like with some norm-based cost function, shown in (4):

$$\varepsilon = \xi(\left\|\Phi - \Phi^*\right\|_n) \tag{4}$$

And the optimal state for the next instant $\hat{\Phi}$ can be considered to minimize the cost function:

$$\hat{\Phi} = \rho(\Phi, \Phi^*)\big|_{\min(\varepsilon)} \tag{5}$$

Eventually, the welder performs a mathematic equivalence to mapping from the optimal state to the control:

$$\Delta I = \omega(\hat{\Phi}) \tag{6}$$

The output execution may be considered to be perturbed by a white Gaussian noise ν, which reflects the maneuver skill of the human welder. There exists a common pattern from the direct information Ω to the welder's output I which is defined as the following equation:

$$\Delta I = F(\Omega) \tag{7}$$

The model of human welder's behavior (7) can be considered as the combination of the five elements from "Information perception" to "Output execution" in Fig. 2. It is possibly nonlinear and time-varying.

As has been discussed above, human welder has limitations such as inconsistent concentration, fatigue and stress. For the intelligent welding machine that mimics the human welder's intelligence, these limitations can be overcome. The illustration of intelligent welding machine can be observed in Fig. 3. In this figure, the information perception block in Fig. 2 is substituted with a vision-based sensing system. The output of the sensing system is the 3D coordinates of the weld pool surface. Like the human welder's ability to interpret the complex weld pool shape, intelligent welding machine will characterize the weld pool, and output certain characteristic parameters to the human intelligent model. The outputs of the human intelligent model are the welding inputs, and will be inputted into the welding process.

This survey paper addresses the implementation of the intelligent welding machine, including vision-based sensing system,