Artificial Neural Network for GTAW Modeling and Control *

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Abstract: An artificial neural network (ANN) for gas tungsten arc welding (GTAW) process modeling and control is presented in this paper. The discussion is mainly focused on the use of ANN for the weld parameter modeling and its application for the control of the weld pool depth. The effectiveness of the proposed intelligent methods is demonstrated by the real experiments. The weld modeling method using ANN yields conspicuously improved performance.

Key words: ANN; GTAW; modeling; weld pool depth

人工神经网络 GTAW 建模及控制

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摘要: 给出一种用于钨极气体保护电弧焊(GTAW)建模及控制的人工神经网络(ANN), 重点论述利用 ANN 建立焊接参数模型的方法以及在熔深控制方面的应用. 通过实际实验证明, 所提出的智能方法具有良好的系统控制性能.

关键词: ANN; GTAW; 建模; 熔深

1 Introduction

Weld modeling is very important to the mechanics of welding process and how it can be best controlled and utilized. However, the control of the overall welding process is not easily accomplished, largely due to the inadequacy of the available process models. The arc welding process that is subject to numerous influencing factors such as arc flare, welding fumes, and spatters is substantially nonlinear. Generally, some variables affecting welding quality can not be quantified, for example, spatters, workpiece heat absorption, contamination, etc. All this perplexity results in the difficulities of designing reliable welds.

Without exception, most welding control methods are based upon the analytical welding models. Based upon these mathematical models welding controller can be designed which is associated with different optimization criteria[1~3]. Although these models are derived directly from the physical laws that govern the main features of the weld pool, a number of assumptions are made to obtain the mathematical solutions due to the complexity of the welding process. Various parameters are only approximately known, such as the arc heat distribution and efficiency, while others such as the pool circulation variations in thermal properties are ignored. In such cases control concepts based on analytical models can only provide insufficient performance and poor robustness.

2 Weld modeling neural networks

GTAW is used to exemplify modeling of a welding process using a neural network. An arc is initiatied and sustained between a pointed tungsten electrode and the surface of the welded workpiece. Argon is conducted coaxially down around the arc and thus it shields the molten weld pool from the atmosphere. GTAW is a complicated and multi-energy domain process which is essential to many types of manufacturing. Weld quality features such as final metallurgy and mechanics are not measurable on-line for control, thus some indirect ways

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of controlling the weld quality is necessary. A comprehensive method to in-process control of welding includes both geometric features of the bead such as the width, depth, and height and the thermal characteristics such as the heat-affected zone width. These features are illustrated in Fig.1. The physical geometry of the molten pool is a major factor in determining the structural adequacy of the weld. The penetration depth of the weld pool, the bead width, the transverse cross-sectional area, and the height of the reinforcement, which characterize the finished weld, are usually referred to as direct weld parameters. The direct parameters are governed by lots of factors such as welding current, welding speed, torch tip angle, and shielding gas type and flow rate which are referred to as indirect weld parameters, The objective is to select and control the indirect parameters to obtain some desired direct parameters. An approach to keep the weld pool depth constant by controlling some indirect parameters is discussed next.

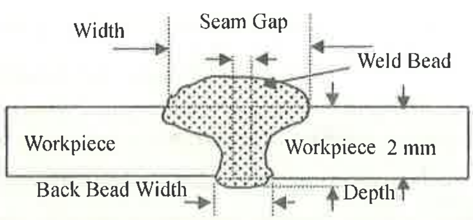

Fig. 1 Diagram of the weld pool

The weld pool depth in the joining part is one of most important factors to determine the mechanical strength. Generally, it is difficult to directly observe the weld pool depth with a CCD camera. A practical approach to estimate the pool depth is to use a reliable model of the weld pool describing the pool geometry. Here, the neural network is used to describe the weld pool depth. The depth is estimated by using the information obtained from the surface shapes of the weld pool, the state of the heat input, which corresponds to the welding current, and the state of the seam gap.

When the base metal melts to the back side, the back bead generates. The width of the back bead becomes wide when the pool depth becomes deep. The typical image of the weld pool surface is shown in Fig.2 with the CCD camera. The pool width W at 2.25mm behind the torch and the seam width G are measured by processing the image. Usually, the heat input to the metal becomes big and weld pool becomes large when the welding current increases. The weld depth becomes deep as the seam gap increases. The variation of the welding current, the seam gap, and the pool width are used to describe the dynamical system of the weld pool depth. These dominant factors of the weld pool depth are used as the input of the neural network. Fig. 3 illustrates a three-layer feedforward neural network which is used to model GTAW pool depth in terms of the welding current, the seam gap, and the pool width.

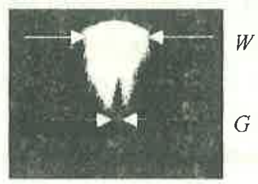

Fig. 2 Image of the weld pool

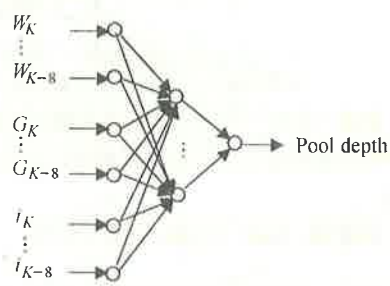

Fig. 3 A neural network used for GTAW modeling

The width of the seam gap under the torch can not be directly measured, since the molten metal fills the seam gap. The width G_{k+74} of the seam gap at 18.5mm before the torch, where k is the number of sampling, is measured. The width G_{k+74} is stored into the memory of the controller. The width G_k of the seam gap just under the torch is obtained by using the stored width of the seam gap. The width at the sensing point W corresponds to G_{k-9}. According to the results of numerous experiments, the variation of the width W in 0.5s is found to be adapted as the information of the variation of the surface shape. The values of the width W per sampling period are given to the neural network: $W_k, W_{k-1}, \cdots, W_{k-8}$, where k is sampling iteration and the sampling period is 1/18s (55.6ms). Also, the variation of the welding current and that of the seam gap are used as the input of the neural network: $i_k, i_{k-1}, \cdots, i_{k-8}, G_k, G_{k-1}, \cdots, G_{k-8}$.

The neural network is trained by using back propagation method. The learning rate (η) and the momentum term (α) are 0.5 and 0.9 respectively. The training data are constructed from the relationship among the surface shape of the weld pool, the seam gap, the welding current, and the weld pool depth in the steady state and the transient state. From the experiments, the weld pool depth of 3.6mm corresponds to the case in which the base metal is through down. Here, the thickness of the base metal is 2mm. The output of the neural network is chosen from 0mm to 3.6mm. The number of units at the hidden layer is decreased while the training error becomes below 3.3%. The resultant number of the units in the hidden layer is 7.

Compared with other modeling methods, neural networks have conspicuously better performance. If the conditions for the neural network are general enough, by spanning the entire range of GTAW process parameters, the resulting model will capture the complexions of the process including nonlinearities and parameter cross couplings. Undoubtedly, model development is much simpler than most other models. Instead of theoretical analysis and development for a new model, the neural network tailors itself to the training data and calculates its result relatively quickly, since the input data are only propagated once through the network in the application mode.

3 Experimental results of controlling the pool depth

The pool depth controller which is depicted in Fig.4 is performed on a HFGZ-XY welding equipment. The two base metals are joined by carrying out the GTAW. The CCD image sensor detects the welding pool and the seam gap. A narrow band optical interference filter centered on a definite frequency blocks most of the ambient and welding arc light. A gradient algorithm is used to process the weld image obtained by CCD and to recognize the width of the pool and seam gap. The welding conditions are shown in Table 1.

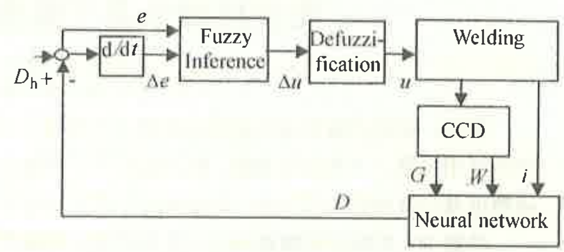

Fig. 4 Control scheme of the pool depth

Table 1 Welding exprimental conditions

Welding speed mm·s⁻¹	Plate thickness mm	Seam shape	Pool depth Ref. mm	Welding current A	Argon flow L/min	Gap width mm
4.5	2	"S"curve line	2.7	70 ~ 98	7	0 ~ 0.6

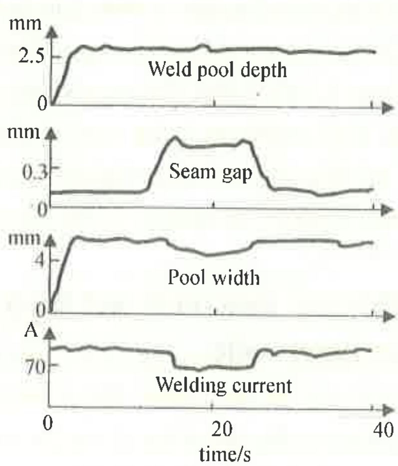

Fig. 5 Experimental results

As shown in Fig.4, the neural network procedures the weld pool depth D, D_h is the desired pool depth and e is the deviation between D and D_h. The error e is calculated from the output of the neural network. The manipulating variable Δu is inferred from the e and the error change Δe. Fig.5 shows the welding result. It can be obviously seen that the weld pool depth is about constant. The welding current changes according to the fluctuation of the width of the seam gap. When the width of the seam gap becomes narrow, the welding current is increasing. On the other hand, when the width of the seam gap becomes wide, the welding current is decreasing. The strong robustness is obtained. The base metal, whose shape of the seam is related to the "S" curve line after welding, is shown in Fig.6. The experimental results

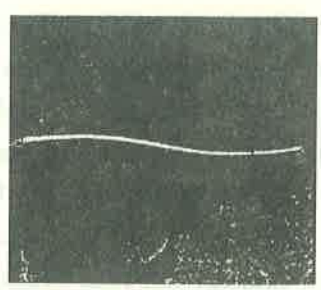

Fig. 6 The base metal after welding

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judge the existence of the flaw but also can estimate the position of the flaw approximately.

4 Conclusion

In this paper, a new multisensor data fusion based on fuzzy logic architecture for NDT is presented. The ways to decide the membership functions and the operators of fuzzy logic are given. The architecture introduced is being used now. It also can be used in other fields. This research can be improved by adopting the neural network to decide the weight automatically.

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have shown that the proposed method for controlling the weld pool depth yields superior performance.

4 Conclusion

Within this paper the neural network for modeling the GTAW and controlling the weld pool depth has been investigated. The neural network offers significant abilities in the development of welding process models and control. The weld pool depth is estimated by using the information obtained from the welding pool and the seam gap. The depth can be kept constant during the welding process. It is demonstrated that the proposed neural network can produce highly complex nonlinear multi-variable models of the GTAW process that offer accurate prediction of weld properties from control parameter values.

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