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Three Dimensional Surface Reconstruction Method for the Welding Pool Using the Fuzzy Neural Network

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In order to automatically control the quality of the welding process, this paper concentrates on the problem of three dimensional surface reconstructions for the welding pool. As the relationships between size and shape of the welding pool are very complex and nonlinear, we utilize the fuzzy neural network to solve the proposed problem. In the fuzzy neural network, the input vector with 48 dimensions is made up of three parts: 1) welding parameters, 2) welding pool size parameters, and 3) shape parameters. In particular, the size of the welding pool negative side is regarded as the output. In the experiment, the welding process is implemented using direct current electrode negative GTAW, and then we suppose that the weld pool rotates when torch orientation, imaging plane, laser projector, and camera are fixed. Experimental results demonstrate that 1) the speed of the fuzzy neural network training process is fairly quick, and 2) the proposed three dimensional surface reconstruction method is robust under current disturbances.

1. Introduction

The welding process is a complex process that is constrained by multiple parameters. To automatically control the quality of the welding process, the welding quality should be detected with high accuracy, because welding pool contains information which can both directly and indirectly affect the quality of welding process (Jin et al, 2016). With the rapid development of welding automation, efficient welding method has been an important research topic. Among them, three dimensional surface reconstruction methods for welding pool have attracted more and more attentions (Wu et al, 2016).

By observing the shape of the pool, and the flow of liquid metal arc shape, we can provide accurate information for the quality control. However, welding process pool is a dynamic process flow, it is necessary to improve the general sensing system, and then to get clear and stable pool image (Li et al, 2016). With the development of computer vision and image processing technology, we are able to obtain a two-dimensional or three-dimensional shape of the weld pool, and then it is possible to solve the problem of welding automation with high efficiency (Jian et al, 2015).

Currently, welding pool images are mostly extracted from pool image sensor using visual methods. Furthermore, it is of great importance to construct the relationships between welding parameters and welding quality (Tong et al, 2015). In this paper, will discuss how to implement welding pool three dimensional surface reconstructions with the fuzzy neural network. Particularly, in recent years, surface reconstruction has been applied in many fields, such as Helium Ion Microscopy (Hlawacek et al, 2016), anterior segment optical reconstruction (Williams et al, 2016), Transport of Epitaxial PtLuSb (001) thin Films (Patel et al, 2016), Helimagnetic Thin Films (El et al, 2016), Au(110)-(1x3) Surface Reconstruction (Smith et al, 2016), Robust Tooth Reconstruction (Jiang et al, 2016), FePt3 Film (Kim and Kim, 2016).

The rest of the paper is organized as follows. Section 2 illustrates the literature review of fuzzy neural network. In section 3, the fuzzy neural network based welding pool 3D surface reconstruction algorithm is proposed. Section 4 provides experimental results and related analysis. In the end, the conclusions are drawn in section 5.

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2. Literature review

The main innovations of this paper are to introduce the fuzzy neural network to solve the welding pool three dimensional surface reconstruction problems. Fuzzy neural network is belonged to a type of machine learning technology which is able to accurately estimate the parameters of the fuzzy system using approximation techniques from neural networks. On the other hand, fuzzy neural network is designed by integrating neural networks and fuzzy systems, and it can be widely used in intelligent computing, such as pattern recognition, regression and density estimation. The following section provides the literature review for fuzzy neural network.
Shinde et al. proposed an improved fuzzy min-max neural network (MFMMN) classification model to implement the supervised classification. The basic fuzzy min-max neural network is used to the continuous attribute values and cannot solve the discrete values. In the proposed model, each hyper box holds min-max values defined according to continuous attributes (Shinde and Kulkarni, 2016).
Loussifi et al. proposed a novel computational intelligent method by integrating kernel methods with wavelet Multi-resolution Analysis, and then they constructed a fuzzy wavelet network construction and initialization. Particularly, in this work, a set of kernel parameters is chosen to design a Wavelet Kernel based Fuzzy Neural Network through wavelet kernels in Support Vector Machine for Regression (Loussifi et al, 2016).
Anastassiou et al. proposed a Recurrent Fuzzy Neural Network with the Particle Swarm Optimization. Each particle includes the parameters of the membership function and the weights of the recurrent neural fuzzy network. The RFNN is not similar to the others variants of RFNN models (Anastassiou, 2016).
Xu et al. studied on the fuzzy cellular neural network with distributed delays, via Gaines and Mawhin's continuation theorem of coincidence degree theory. Several sufficient conditions for the existence and global exponential stability of periodic solution of such fuzzy cellular neural networks with distributed delays are provided.
Zheng et al. demonstrated on the stochastic stability of fuzzy Markovian jumping neural networks with time-varying delay and continuously distributed delay in mean square. Particularly, in this paper, the authors proposed several novel mode and delay-dependent sufficient conditions to let the stochastic stability in mean square.
Apart from the above works, fuzzy neural works can also be used in other fields, such as the First Order Partial Derivative Approximation of Nonlinear Functions, Mittag-Leffler Stability and Asymptotical Omega-Periodicity, Hybrid Maglev Transportation System, Dissipativity Analysis.
By analysing the above works, we find that neural networks and fuzzy systems should be integrated together to achieve higher performance. Neural networks can only come into play if the problem is expressed by a sufficient amount of observed examples, meanwhile, a fuzzy system should contain linguistic rules instead of learning examples as prior knowledge.

3. Fuzzy neural network based welding pool 3D surface reconstruction

Particularly, in this paper, we concentrate on the Gas tungsten arc welding (GTAW), which is also named as tungsten inert gas (TIG) welding, which refers to an arc welding process. In GTAW, a non-consumable tungsten electrode is utilized to generate the weld, and the weld area is protected from atmospheric contamination through an inert shielding gas, and then a filler metal is exploited as well. Conventional fuzzy control rules usually depends on the experience of the specific welding process, and welder should rely on their own experience without any operations of the authority rules for the controller design. Therefore, in this paper, we utilize C-means dynamic clustering algorithm to extract fuzzy control rules in the pulsed GTAW docking process.
For the pulsed GTAW flat, we establish a multi-parameter pulsed GTAW neural network model which integrates both the weld pool size and the shape parameters. Due to the complex nonlinear relationships between size and shape of the welding pool, the fuzzy neural network can provide an ideal computing model. For the fuzzy neural network, the input vector is made up of the welding parameters (such as pulse peak current, duty cycle, welding speed, arc voltage), welding pool size parameters (such as the area after half bath, half of the maximum length, and maximum width), shape parameters (such as the width of each scan line). There are total 48 dimensions in the input vector, and the number of the hidden layer nodes is set to be 30. Particularly, the size of the welding pool negative side is exploited as the output of the fuzzy neural network.
In this section, we will discuss how to conduct the welding pool 3D surface reconstruction by fuzzy neural network. The main ideas of this paper are to implement the intelligent control of the pulsed GTAW pool dynamic process by fuzzy logic inference and fuzzy neural networks. Structure of the proposed fuzzy neural network is illustrated in Figure 1.

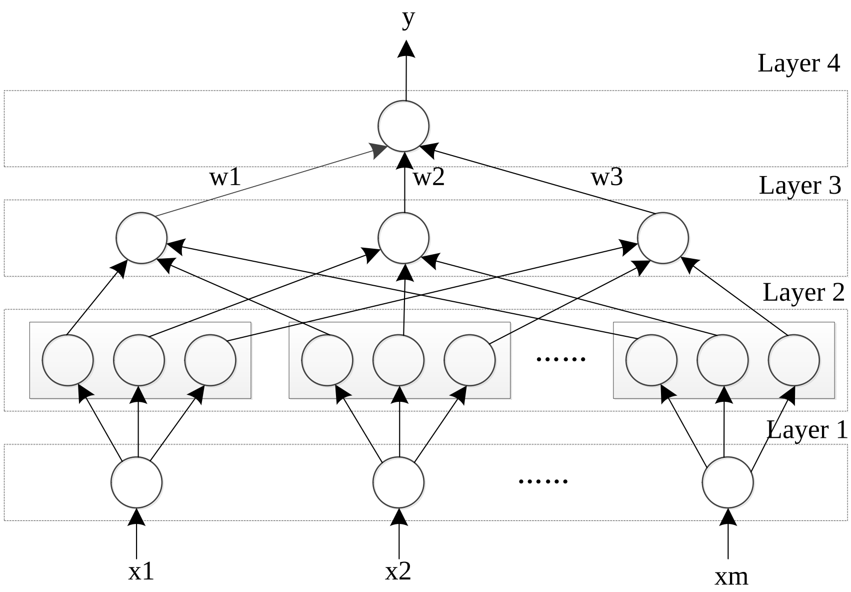

Figure 1: Structure of the proposed fuzzy neural network

As in illustrated in Fig.1, the fuzzy neural network contains four layers: 1) Input nodes, 2) Membership function nodes, 3) Rules nodes and 4) Output nodes. Fuzzy neural network is designed based on a series of IF-THEN rules, which is used to describe the input/output mapping relationship:

$$Rule(k): if\ x_1\ is\ A_{1k}\ and\ x_2\ is\ A_{2k}\ \cdots\ and\ x_n\ is\ A_{nk} \tag{1}$$

$$then\ y = w_k,\ k \in \{1, 2, \cdots, N\} \tag{2}$$

Where x_i and y refer to the input variable and output variable, and the symbol A_{ik} refers to the precondition part. Furthermore, W_k means the output action strength that is corresponding to Rule (k). Moreover, N refers to the number fuzzy rules, and n denotes the number of input variables. Based on the above definitions, the details of the fuzzy neural network model are explained as follows

(1) Input nodes layer

In this layer, each node is regarded as an input variable, and the node only can transmit input values to its neighbour and upper layer.

$$v_i^1 = x_i,\ i \in \{1, 2, \cdots, n\} \tag{3}$$

In the second layer, nodes should be divided to N clusters, and then each cluster should follow a fuzzy rule. In particular, each node of this layer is able to calculate the value of membership function. Assume that an external input is representedasV_i^1, and then the Gaussian membership function is described as followed.

$$v_{ij}^2 = \exp\left(-\frac{(v_i^1 - m_{ij})^2}{\delta_{ij}^2}\right),\ i \in \{1, 2, \cdots, n\},\ j \in \{1, 2, \cdots, N\} \tag{4}$$

Where m_{ij} and δ_{ij} refer to the centroid and the width of the Gaussian membership function respectively.

(3) Rules nodes layer

Different from the above layers, in this layer, the number of nodes means the number of fuzzy rules, and node in this layer is used to calculate the rule activation strength. Output values of this layer are listed in the following equation.

$$v_{ij}^3 = \prod_i v_{ij}^2,\ j \in \{1, 2, \cdots, N\} \tag{5}$$

(4) Output nodes layer
Based on the above four layers, output values of this layer are computed as follows.

$$v^4 = \frac{\sum_j v_j^3 \cdot w_j}{\sum_j v_j^3} \tag{6}$$

4. Experiment

To test the performance of the proposed algorithm, experiment settings are given in Table1. The welding process is implemented utilizing direct current electrode negative GTAW, and then the weld pool rotates when torch orientation, imaging plane, laser projector, and camera are fixed.

Table 1: Parameters of this experiment

Type	Parameter description	Value
Welding process	Welding current	40-70 A
	Welding speed	2 mm/s
	Electrode extension	4 mm
	Arc length	4-6 mm
	Electrode diameter	2.6 mm
	Argon Shielding gas	100%
	Flow rate of shielding gas	12.3 L/min
Monitoring process	Pattern projection angle	35
	Imaging plane to electrode (IPE) distance	60-100 mm
	Laser to electrode distance	21-26 mm
Camera	Frame rate	24
	Shutter speed	4-7ms

In order to test the training speed of the proposed approach, we construct an experiment to demonstrate the convergence speed of the fuzzy neural network training process (shown in Figure 2).

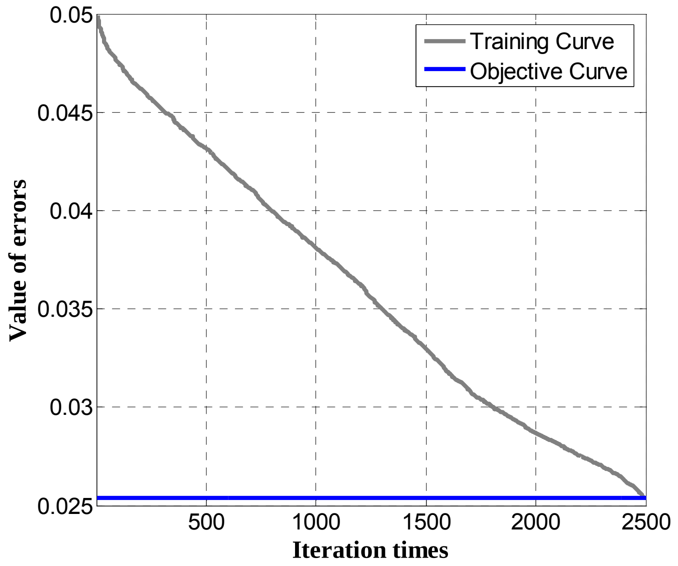

Figure 2: Error rate varying under different iteration times

It can be observed from Figure 2, training process can be converted to the objective value after 2500 iterations.

Afterwards, we will test the robustness of the control algorithm under current disturbances. The set points are set to 5mm, 0.4mm, and 0.2mm for the width of weld pool, length, and convexity. Furthermore, the initial current is set to 54A and the initial welding speed is equal to 1.1mm/s. Moreover, the weld pool width, the length, and the convexity are set to 5mm, 4mm and 0.2mm respectively. Next, input parameters with time changing are illustrated in Figure 3.
Next, we let the weld pool width, length and convexity to be 3.5mm, 4mm and 0.19mm, and weld pool parameters with time changing is given in Figure 4.

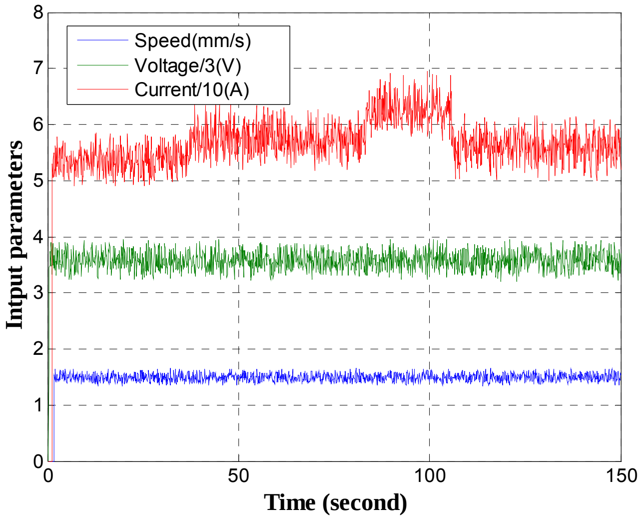

Figure 3: Input parameters with time changing

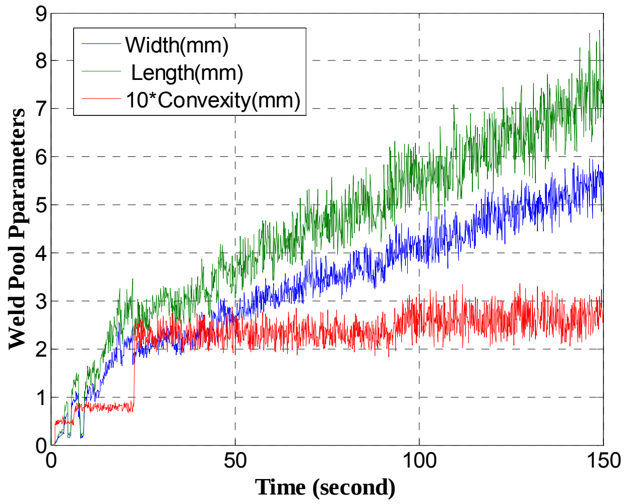

Figure 4: Weld pool parameters with time changing

From the above experimental results, we can see that the proposed fuzzy neural network model is able to enhance the 3D reconstruction quality for welding pool, and can effectively reduce the negative influence of various disturbances.

5. Conclusions

In this paper, we aim to implement three dimensional surface reconstruction for the welding pool with high accuracy. The main innovations of this paper are to implement the intelligent control of the pulsed GTAW pool dynamic process through fuzzy logic inference and fuzzy neural networks. The fuzzy neural network is made up four layers, that is, Input nodes layer, Membership function nodes layer, Rules nodes layer, and Output nodes layer. In our method, a 48-dimension vector is input to the fuzzy neural network, and then the size of the welding pool negative side is output. Finally, experimental results verify the effectiveness of our proposed algorithm.

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