A Neural Network Closed-loop Control of CO_2 Welding Spatter by means of Arc Sound†

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Abstract

This paper deals with the problems of decreasing CO_2 welding spatter by utilizing neural networks to achieve intelligent control. The arc sound energy produced at the beginning and end of short circuit transfer was used to sense the spatter ratio. One multi-layered neural network was utilized to identify the relation of the arc sound energy to the frequency of short circuit transfer. Both the arc sound energy and the frequency of short circuit transfer were taken as the input of the neural network controller and the output parameters were welding voltage and current (wire feed rate). The result of simulation and experiment showed that this system could control CO_2 welding process and decrease the welding spatter remarkably through some times self-learning. The technique explored here could be applied to a wide variety of nonlinear control problems in welding.

KEY WORDS: (Neural network) (Intelligent control) (Arc sound energy) (On-line) (CO2 arc welding)

1. Introduction

CO_2 gas shielded arc welding is of high efficiency, low cost and widely used in industrial production for advanced manufacture such as in robotic welding systems. However, it suffers from welding spatter, which causes an increase in man-hours and instability of the welding process. To decrease the CO_2 arc welding spatter is still one of the research topics in the welding field. Because the welding arc system is highly nonlinear and the main method adopted in the past is PID control, the control effects are limited.

An artificial neural network is a multiple dimension nonlinear dynamic system and can identify any nonlinear system. A control system based on a neural network can

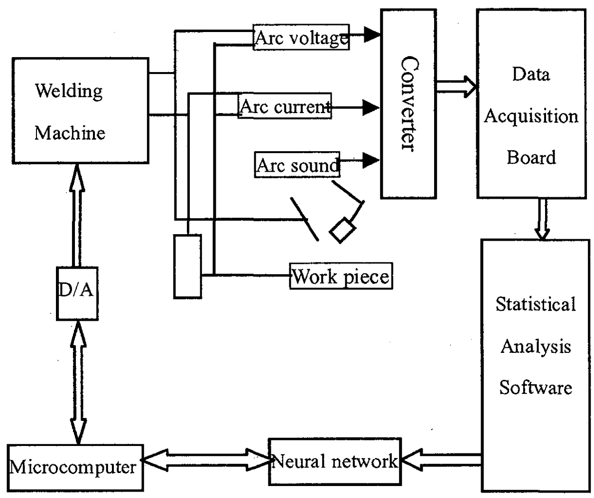

Fig. 1 The construction of experiment

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be taken as a kind of self-learning adaptive controller [1]. A self-learning control system can improve the systems future quality through a closed-loop exchanging function with the equipment and environment. In this paper, a self-learning control technique that was realized by a neural network was used to resolve the CO_2 welding spatter problem, and an intelligent CO_2 welding system has been primarily developed. This system could automatically optimize the welding condition through self-learning abilities so as to decrease the welding spatter ratio.

2. Experimental System

The whole system is shown in **Fig. 1**. During the CO_2 welding process, the arc sound signal was received by two microphones and then amplified and filtered. The arc voltage, current and arc sound signals were collected in a personal computer through a data acquisition board after transformation by a converter. A specially developed statistical analyzing software was used to process the stored data. Thus the frequency of short circuit transfer and the characteristics of arc voltage, arc current and arc sound signals could be obtained. The statistical results could be used to on-line train a neural network controller. The output of the neural network controller was sent to a microcomputer to control the CO_2 welding machine [2].

3. The Relation of Arc Sound with Welding Spatter

The relationship between CO_2 welding arc sound and welding spatter has been studied in a previous paper [2]. The typical result is shown in **Fig. 2**. From Fig.2 it can be found that the average arc sound energy of short circuit transfer is proportional to the welding spatter ratio in CO_2 arc welding.

The arc sound energy (*Es*) was defined as [2]:

$$Es = \int_{t_0}^{t_0+\Delta t} s^2 dt \qquad (1)$$

S was the voltage signal transformed from the arc sound signal by microphone. The arc sound energy at the beginning of a short circuit transfer was the integral arc sound energy from the time at the beginning of the short circuit transfer to 1.44 microseconds after that. The arc

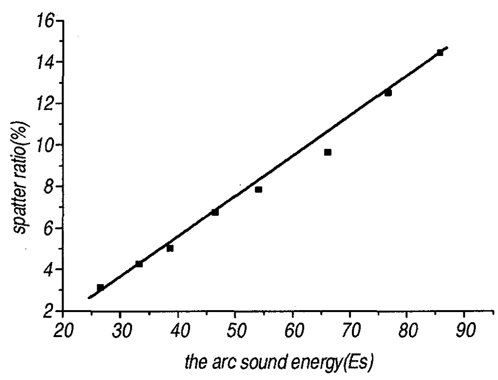

Fig. 2 The relation of Es and spatter ratio

sound energy at the end of a short circuit transfer was the integral of arc sound energy from the time at the end of short circuit transfer to 1.44 microseconds after that. t_0 was the time at the beginning or end of the short circuit transfer. Δt was the time delay and the value was 1.44 microsecond. So far, there is no effective method to quantitatively represent the welding spatter on-line. In this work, the average arc sound energy was firstly proposed to sense the welding spatter.

Another parameter is the frequency of short circuit transfer. It was found that there was a relation between the frequency of short circuit transfer and the spatter ratio. A higher frequency of short circuit transfer was associated to a lower spatter ratio. However, the relation was nonlinear.

4. Control Model

Fig. 3 shows a method of training the neural network on-line. The desired value (*d*) that included the arc sound energy and the frequency of short circuit transfer were used as the input of the neural network controller. The output of the NN controller was the welding voltage and current (wire feed rate). The NN controller learnt to find the optimum welding parameters used to control welding machine by means of the BP algorithm by utilizing the error between the desired and actual response of the welding arc system [3, 4]. The neural network controller must be preliminarily trained before it is trained on-line, so that the system's response can be faster. The weakness of the architecture for this control model was that modifying the weights based on the total error must involve the equipment mathematical model, which normally was approximately known. Thus the following algorithm was used in this paper [1].

$$\varepsilon = \| d - y \|^2 \quad (2)$$

$$y = g(T,t) \quad (3)$$

Where ε was the error of the desired value (d) and the actual output (y) of arc system. (y) was a function of the output vector of the NN controller $T = (T_1, T_2 \ldots, T_\lambda)$ and time. The output vector of the NN controller was a function of ω_{ij} and v_{jk}. So

$$\Delta\omega_{ij} = -\rho \frac{\partial \varepsilon}{\partial \omega_{ij}} \quad (4)$$

$$\Delta v_{jk} = -\rho \frac{\partial \varepsilon}{\partial v_{jk}} \quad (5)$$

Then

$$\frac{\partial \varepsilon}{\partial \omega_{ij}} = \frac{\partial \varepsilon}{\partial y} \bullet \frac{\partial g(T,t)}{\partial T_i} \bullet \frac{dT_i}{d\omega_{ij}} \quad (6)$$

When the NN controller was trained on-line, $\partial\varepsilon/\partial y$ was known and $dT_i/d\omega_{ij}$ could be obtained from the NN controller. Although the function of the arc system ($g(T,t)$) was unknown, we could use following method:

$$\frac{\partial g(T,t)}{\partial T_i} \approx \frac{g(T + \Delta T_i, t) - g(T,t)}{\Delta T_i} \quad (7)$$

The difference function in the right hand of eq.7 could be obtained from adjacent input and output of the equipment. Because the relation between the arc sound energy and the welding spatter was linear while the relation between the frequencies of short circuit transfer and welding spatter was nonlinear, the relation between the arc sound energy and the frequency of short circuit transfer was nonlinear. In order to qualify the desired value that was satisfied by the output of the arc system, the control model was modified as follows (see Fig. 3).

In Fig. 3, NN1 was used to identify the relation between the arc sound energy (Es) and the frequency of short circuit transfer (F). With the decrease of the desired value (E_{ds}), the actual arc sound energy of the welding process would decrease step by step. Because of training the neural network controller and acquiring the data need some time, the weights of the neural network did not revise at every short circuit transfer. With weights revised, the neural network controller could approach the contrary model of the arc system. In order to avoid the local minimum, a promising technique, which greatly improved the performance of the neural networks, was adding noise to the input training set [1, 3].

The "Even Design Method" was adopted to optimize the neural network's parameters. By using "Even Design Method", the training times for adjusting the BP neural network's parameters could be decreased effectively, the training error could also be much reduced, and good results have been obtained [5].

5. Results of Simulation and Experiment

In the whole simulation system, a simulator was used to identify the dynamic characteristics of the arc system. In the theory, three layers of neural network could identify any nonlinear system. So both the neural network controller and simulator had three layers, two input neurons, two output neurons and six hidden neurons.

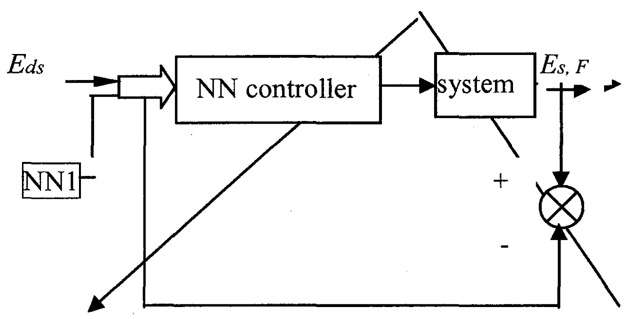

Fig. 3 The modified control model

Table 1 Training samples

Sample	1	2	3	4	5	6
Es	49.58	26.69	33.33	54.13	38.64	76.72
F	115	100	95	55	62	51
I(A)	123	172	175	114	159	145
U(v)	16.1	16.1	17	18.1	18.1	19

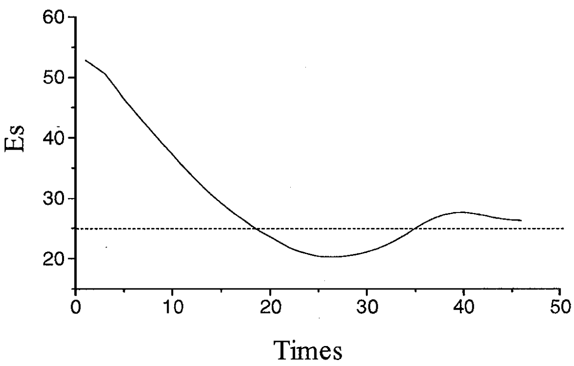

Fig. 4 The simulated dynamic response of typical *Es*

Table.2 Result of simulation and experiment

E_s	67.80	48.90	25	78.70	86.20
Learning times	16	41	45	16	18
Result of E_s	66.40	49.03	26.17	78.47	84.31
Spatter ratio(%)	9.16	5.81	2.82	12.42	14.18

Before simulation, the weights of NN controller were set randomly. The simulator was trained by the following samples. The simulation was carried out in a personal computer. All the samples were obtained from experiments.

After simulation, the actual convergent times of very desired arc sound energy is shown in **Table 2**.

When the desired arc sound energy is 25, the typical convergent process simulated is shown in **Fig. 4**. The result of simulation shows that the whole system has a good dynamic quality.

In order to render the neural network controller to have a fine general ability, the neural network controller was trained by the samples in Table 1 before the actual experiments. When the diameter of welding wire was 1.2 mm, the gas flow rate was 20 *l/min,* the experimental results showed that through self-learning it took 23 *min* to decrease the arc sound energy (*Es*) from 55.73 to 26.17 and the corresponding spatter ratio decreased from 6.94% to 2.82%. Because in practice the voltage of the power source frequently fluctuates, the gas flow rate and the wire composition always change, the CO_2 welding parameters can not keep in the best condition all the time, so as to cause large welding spatter. Therefore, the self-learning control system is very useful to on-line revise the welding parameters and keep the system in a relative optimum condition.

6. Conclusion

In this paper, a self-learning control system using neural networks is investigated for controlling CO_2 welding process. The arc sound energy during short circuit transfer is used to identify quantitatively the welding spatter. The simulation and experimental results showed that this intelligent control system could find an optimum match of welding parameters and decrease the welding spatter for CO_2 arc welding. The technique explored here can be applied to a wide variety of nonlinear control problems in welding.

Acknowledgement

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