A Study on the Welding Gap Detecting Using Pattern Classification by ART2 and Fuzzy Membership Filter

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〈목 차〉

Abstract

This study introduces to the fuzzy membership filter to cancel a high frequency noise of welding current. And ART2 which has the competitive learning network classifies the signal patterns for the filtered welding signal. A welding current possesses a specific pattern according to the existence or the size of a welding gap. These specific patterns result in different classification in comparison with an occasion for no welding gap. The patterns in each case of 1mm, 2mm, 3mm and no welding gap are identified by the artificial neural network.

These procedure is an off-line execution. In on-line execution, the identification model of neural network for the classified pattern is located on ahead of the welding plant. And when the welding current patterns pass through the neural network in the direction of feedforward, it is possible to recognize the existence or the size of a welding gap.

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1. Introduction

Welding is essential for the manufacture of a range of engineering components which may vary from very large structures such as ships and bridges to very complex structures such as aircraft engines, or miniature components for microelectronic applications. Among the types of welding, GMAW(gas metal arc welding) is one of the most frequently used, because it is highly suited to a wide range of applications, and to automation. Because of coarse welding environments resulting from the fumes, heats, spatters, arc sound and arc light, manual welding by human operator is considered as a harsh and difficult work.

This paper proposes to detect a welding gap under the arc sensing system. Among the position-sensing methods available, the arc sensor that utilizes the electrical signal obtained from the welding arc is one of the most prevalently used methods. Its advantages are that no particular sensing device is necessary and a real-time sensing of the groove position directly under the arc is possible.[1]~[6]

In this study, fuzzy membership filter(or moving average method) is used to cancel a high frequency noise and to smooth a raw current signal. This scheme was contrived from the principle of FIR filter which armed with a moving average method. This algorithm contain very simple mathematical process to obtain a value of average signal so that it takes very short time to calculate the result. ART2(Adaptive Resonance Theory2), a kind of neural network, which has the competitive learning network classifies the signal patterns for the filtered welding signal. A signal processing method based on the artificial neural network(ART2) was proposed for discriminating the current signal patterns when a welding gap occurs from the current signal patterns when a welding gap doesn't occur[7]. A welding current possesses a specific pattern according to the existence or the size of a welding gap. The patterns in each case of 1mm, 2mm, 3mm and no welding gap was acquired in off-line process. A neural network which has two hidden layer learned to identify the classified current patterns in off-line process. Finally, TDNN(Time Delayed Neural Network) has to be selected as an on-line type of identification neural network, seeing that a real welding signal get to the input node of neural network continuously.

2. Fuzzy Membership Filter

Now that the raw welding signal includes high frequency noise, an effective signal processing algorithm is necessary. Generally, a low pass filter composed of hardware is necessarily used but an additional signal processing should be appended to make use of it for the welding process.

In this study, fuzzy membership filter(fuzzy membership moving average) contrived from the principle of FIR filter which armed with a moving average method. This algorithm contains very simple mathematical process to obtain a value of average signal so that it takes very short time to calculate the result.

First, a brief principle of FIR filter is presented to explain fuzzy membership filter. Equation (1) shows ARMA digital filter.

$$\begin{aligned} y(n) &= \sum_{k=0}^{\infty} h(k)x(n-k) \\ &= \sum_{k=0}^{M} a_k x(n-k) - \sum_{k=1}^{N} b_k y(n-k) \end{aligned} \tag{1}$$

The common name for filters of this type is FIR(Finite Impulse Response) filters when b_k equal to 0 for all k, since their response to an impulse dies away in a finite number of samples. These filters are also called MA(Moving Average) filters, since the output is simply a weighted average of the input values.

$$y(n) = \sum_{k=0}^{M} a_k x(n-k) \tag{2}$$

Equation (2) is the FIR difference equation. It is a time domain equation and describes the FIR filter in its nonrecursive form: the current output sample, y(n), is a function only of past and present values of the input, x(n). When FIR filters are implemented in this form, that is by direct evaluation of Equation (2), they are always stable

Fig. 1 represents a concept of the fuzzy membership filter. a_i, i=1, 2, ⋯, n, are the discrete sample data of a continuous input and μ_j, j=1, 2, ⋯, m, are the membership grade of each input data, a_i, which is assigned to a fuzzy membership. Width of a fuzzy membership can be varied and as width grow wider, the filtered output become more smooth. As long as new input data occur, fuzzy membership has to be shifted to the next m-tuple data and the calculation to acquire a output should repeated in the same manner. Fuzzy membership is divided into odd numbers for the convenience of calculating, accordingly, Fuzzy grade of a central location of the divided points is always 1.0.

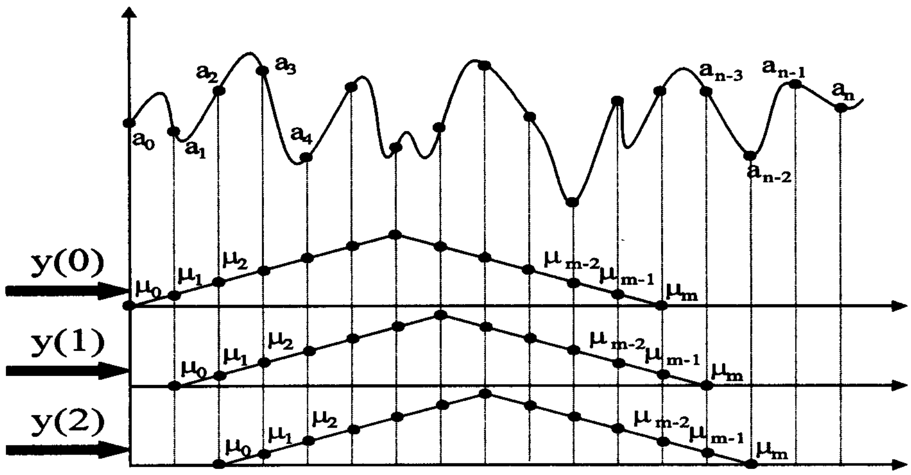

Fig. 1 Fuzzy membership filter

Seeing that the left side and right side of fuzzy membership is located on the symmetrical area, their grades have the equal value.

For instance, when a triangular fuzzy membership is divided into 9 points, each grade of all points is a0=0.0, a1=0.25, a2=0.5, a3=0.75, a4=1.0, a5=0.75, a6=0.5, a7=0.25, a8=0.0 from the extreme left side to the extreme right side.

From now on, the simple procedure of this method is represented. Above of all, a division number for fuzzy membership has to be chosen, it could be varied as the case may be, then all of grade divided into division number are aggregated. This is represented Equation (3) and the aggregated value is constant if a division number is once chosen.

$$\sum_{i=0}^{m} \mu_i = \mu_0 + \mu_1 + \mu_2 + \cdots + \mu_{m-1} + \mu_m \tag{3}$$

where m is a division number and μ_i is a fuzzy grade.

Next, it is necessary to obtain each production between the sample input, as many division number, corresponding with the grade and the assigned grade.

Then all of each production is aggregated. This procedure divided by Equation (3) makes Equation (4) and this equation brings about the output of the fuzzy membership filter.

$$y(k) = \frac{\sum_{j=0}^{m} \mu_j \cdot a[(k - \frac{m-1}{2}) + j]}{\sum_{i=0}^{m} \mu_i} \tag{4}$$

Fig. 2 shows that fuzzy membership filter well processed the random noised signal. (a) is a original signal, (b) is a random noised signal and (c)~(f) are the signal when the division number was increased step by step.

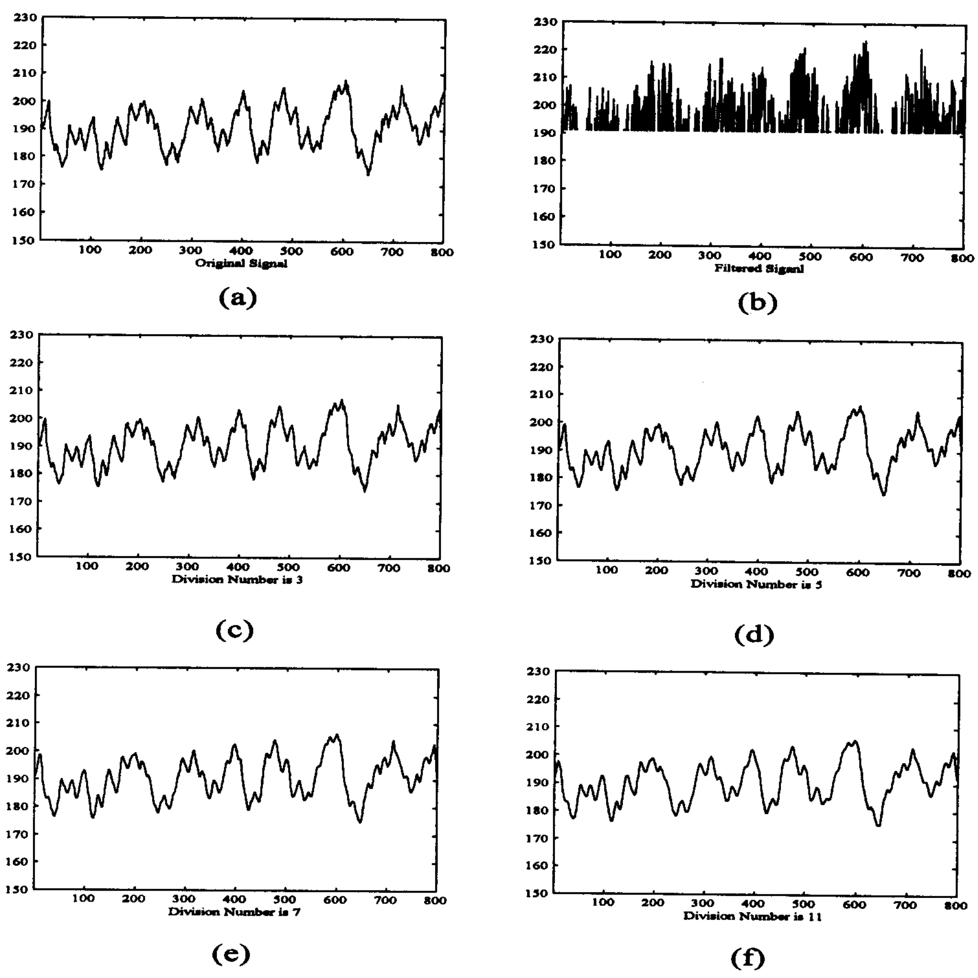

Fig. 2 Filtered signal by fuzzy membership filter

3. Simulation

3.1 Selecting Welding Current

Among various welding parameters, the welding current which is inversely proportional to the tip-to-workpiece distance in arc welding is an essential parameter needed to monitor the GMAW process of horizontal fillet joints and to implement automatic seam tracking. The measured electrical signals, such as welding current signal, play a dominant role in precise seam tracking. As the same principle, detecting a welding gap takes advantage of this method. When there is a welding gap in workpiece, distance between torch and workpiece is increased thus the welding current signal is fluctuated somewhat. It means that the current signal patterns for the existence of a welding gap is differ from the usual patterns.

The specification of selected welding signal to be simulated as follows:

- welding speed : 3~5 mm/sec
- weaving width : 10 mm
- welding voltage : 25 V
- wire feed speed : 118.5 mm/sec
- flow rate of CO2 : 18 l/min
- thickness of workpiece : 10mm

To obtain the reliable result, a set of experiments must be implemented. The off-line process is represented in Fig.3. A raw welding current signal brought about the welding plant is filtered with a low pass filter and fuzzy membership filter and then ART2 classifies the filtered welding signal.

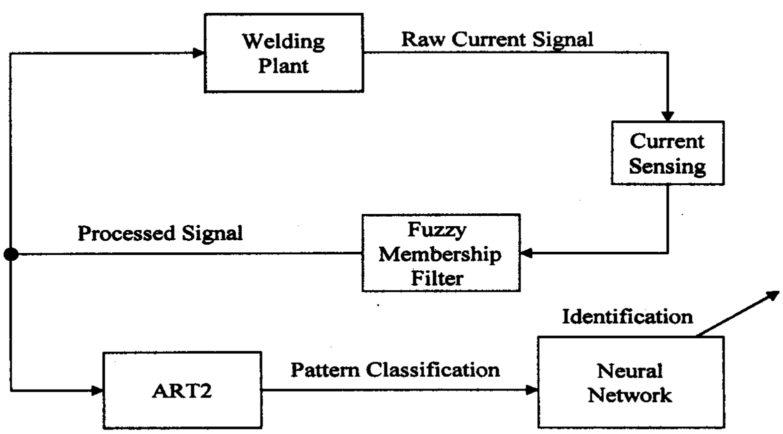

Fig. 3 Off-line Process

3.2 Filtering of the welding current

The material for a simulation is shown Fig.4. In the figure, welding current signal which has 3200 sample data when the torch weaves eight times is represented for convenience sake.

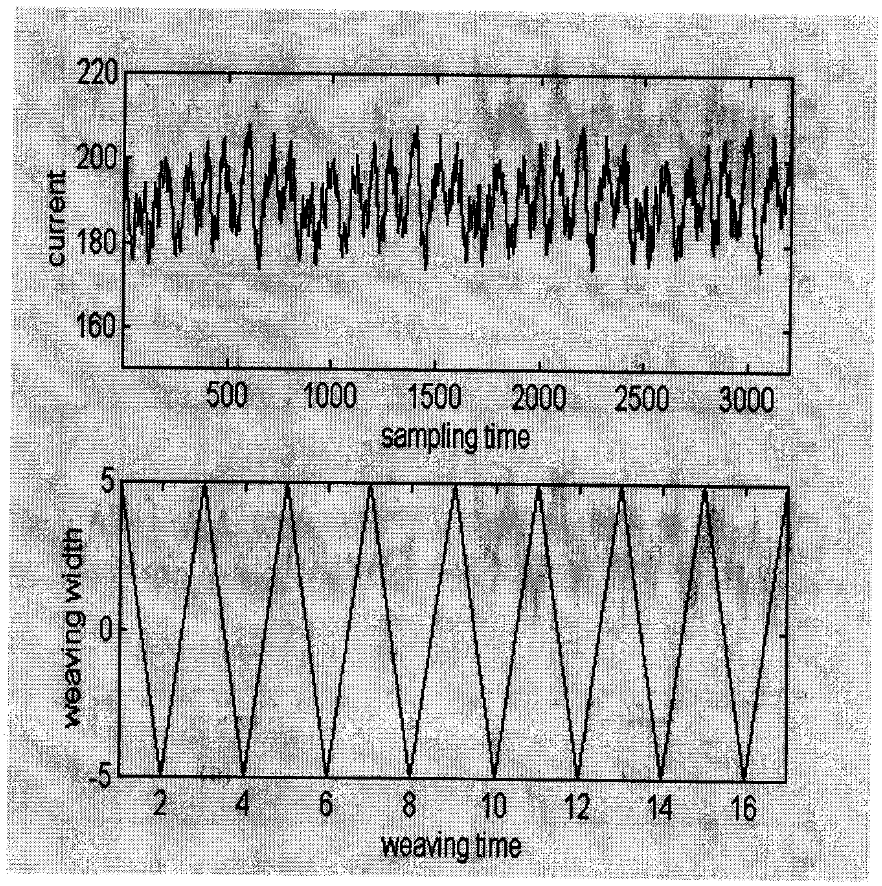

Fig. 4 Welding current and weaving motion

The random noised signal of welding current is filtered by fuzzy membership filter which has nine division numbers. A reason for choosing nine division numbers of fuzzy membership is that it shows the best output than other division number. The fidelity of filtered output depends upon division number and its choice can be altered in accordance with purpose. For example, to get a average signal of weaving motion or torch height, division number should be increased so that a average signal for the wider area is acquired. This method can be used as a simple software filter or as a kind of moving average scheme.

For the welding gap in case of 1mm, 2mm and 3mm, raw signal is generated individually and each signal is filtered by fuzzy membership filter with nine division number. The results is represented from Fig. 5.

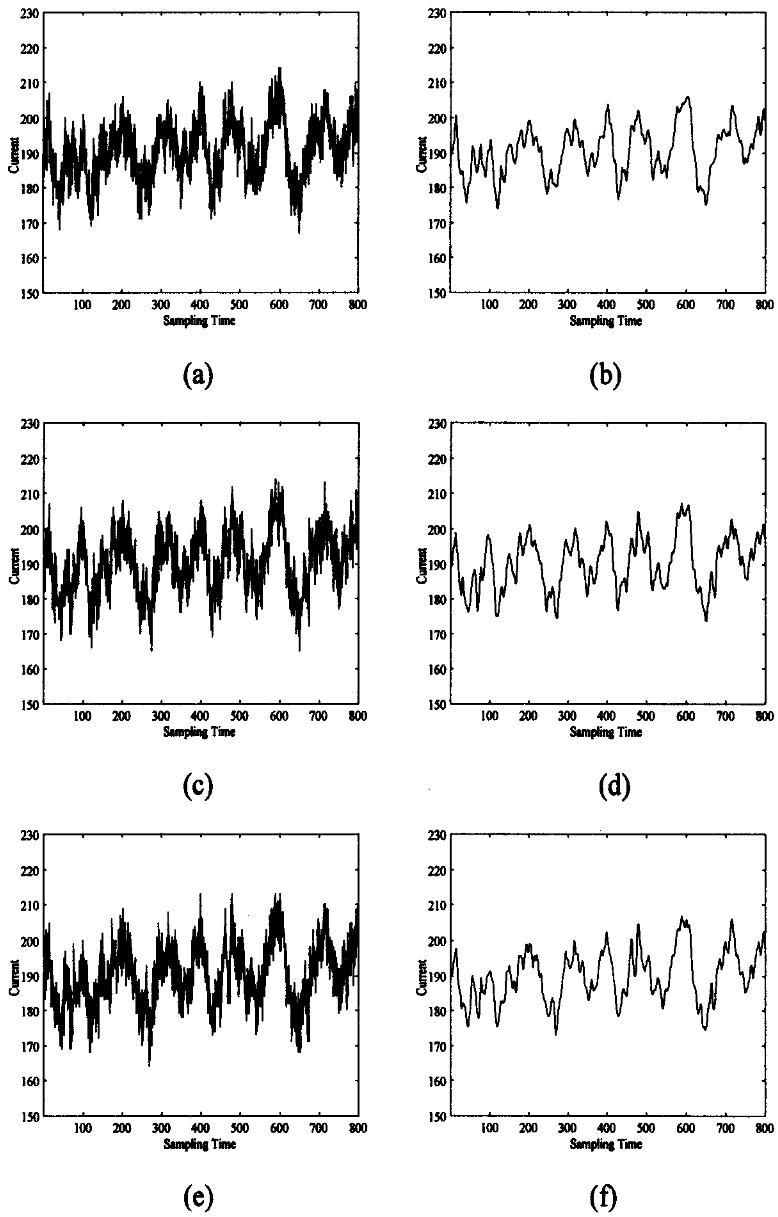

Fig. 5 Filtered signal by fuzzy membership filter

3.3 Pattern Classification Using ART2

ART2 differs from ART1 only in the nature of the input patterns: ART2 accepts analog(or gray-scale) vector components as well as binary components. This capability represents a significant enhancement to the system.

Beyond the surface difference between ART1 and ART2 lies architectural differences that give ART2 its ability to deal with analog patterns. These differences are sometimes more complex, and sometimes less complex, that the corresponding ART1 structures. For example, ART2 must be able to recognize the underlying similarity levels. Compared in an absolute sense, two such patterns may appear entirely different when, in fact, they should be classified as the same pattern.

The parameters of ART2 was settled following runs as follows.

- A	10
- B	10
- C	0.1
- D	0.9
- N	20 ; dimension of input
- θ	$\frac{1}{\sqrt{(N)}}$
- α	0.6 ; learning rate
- ρ	0.98 ; vigilance parameter
- e	0.000001

Filtered welding signal by fuzzy membership filter or another algorithm must be classified to detect a welding gap. Before anything else, to recognize the difference between 0mm welding gap and 3mm welding gap, ART2 was implemented for 64 patterns of each case.

The classification result of 0mm welding gap is represented in Fig.6.

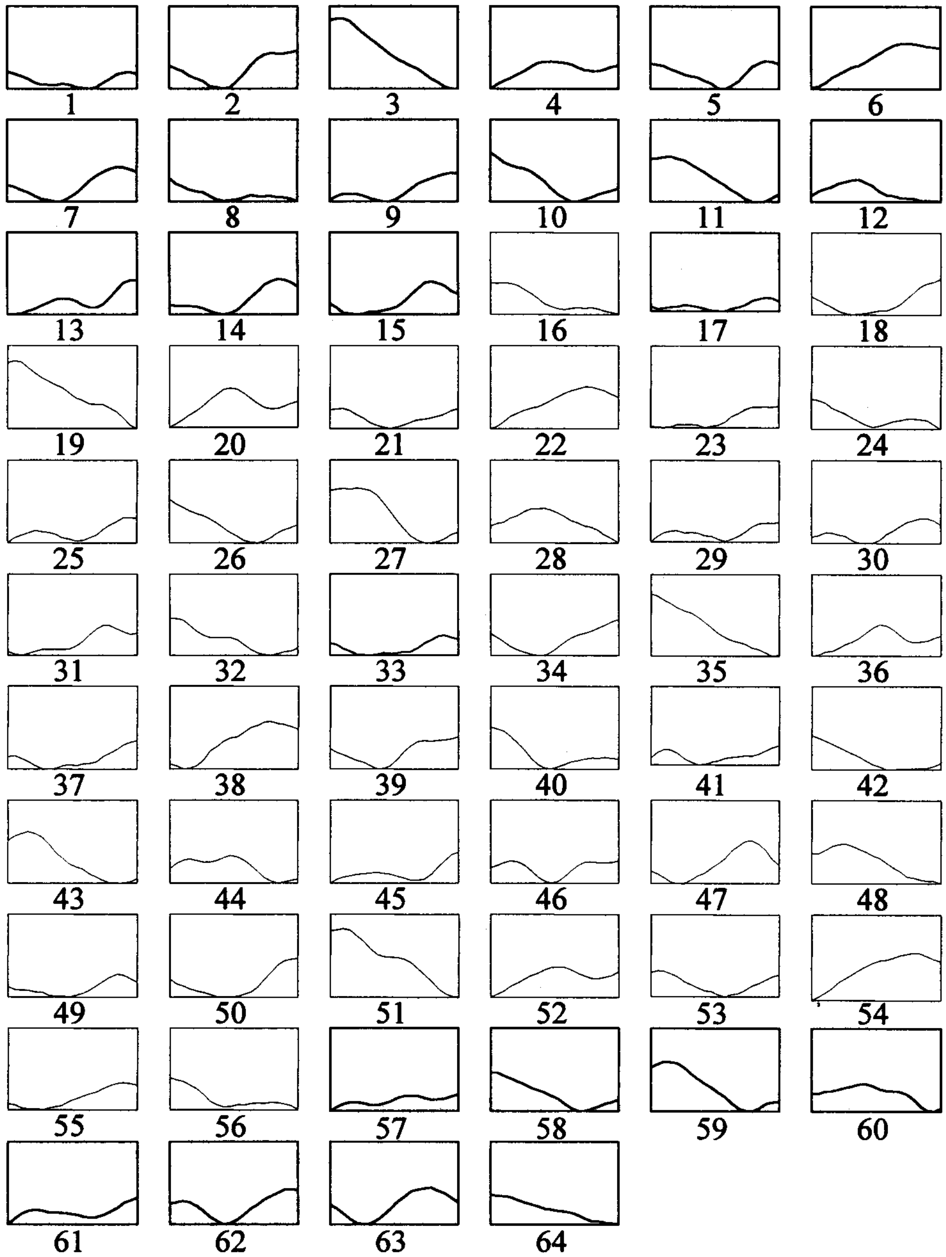

Fig. 6 All patterns in case of 0mm gap

As the same approach, the classification result of 3mm welding gap is shown Fig.7. We can assume that when the cluster of 3mm welding gap is compared to the cluster of 0mm welding gap, if there is a new cluster in 3mm welding gap, it must express that there is some variation in case of 3mm welding gap.

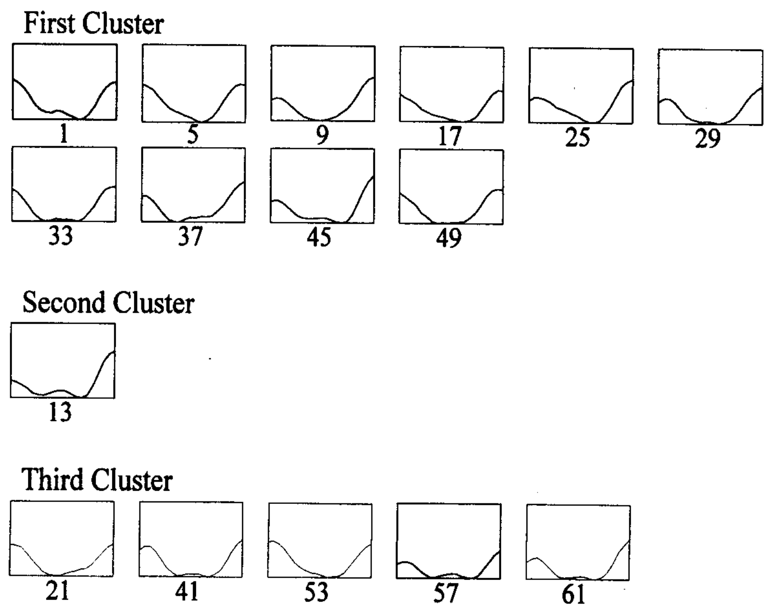

Fig. 7 Clusters of 3mm gap

By the way, all the welding parameters, material of workpiece, welding voltage, weaving width etc., is equivalent in this experiment. Furthermore, the variation of welding current signifies that some abnormal state, the welding gap, lies in the workpiece. Namely, The presence of the welding gap was revealed apparently.

We can tell the difference between the clusters of 0mm and 3mm welding gap partly because some clusters of both are identical, and partly because some clusters of both are substantially the same. The reason why some clusters of both are not identical is that several patterns are separated from due to the presence of welding gap. For example, when we consider the second cluster of 3mm welding gap in comparison to the second cluster of 0mm welding gap, 9th and 49th pattern were excluded due to welding gap.

The same procedure is applied to detecting 2mm and 1mm welding gap. The classification results are represented in Fig. 8 and Fig. 9.

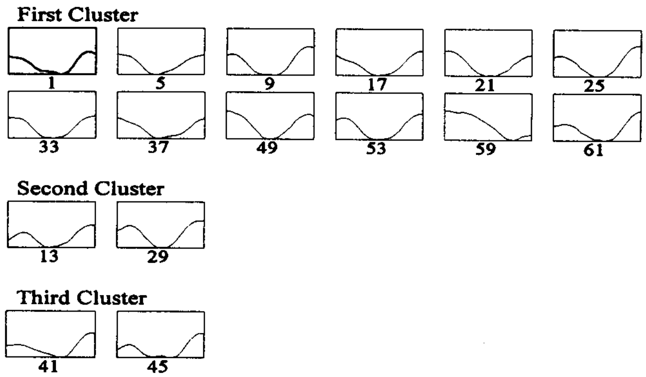

Fig. 8 Clusters of 2mm gap

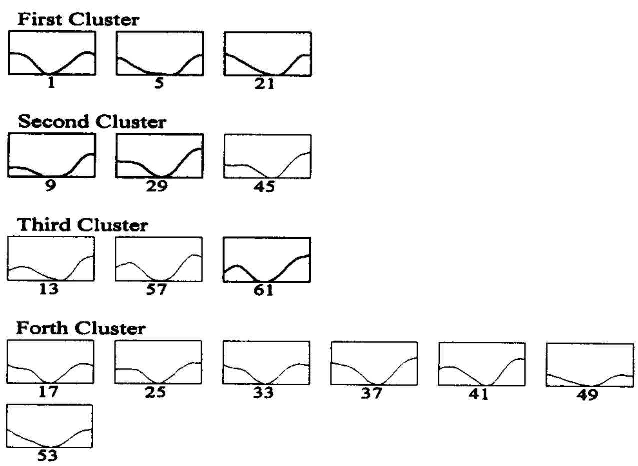

Fig. 9 Clusters of 1mm gap

3.4 Identification of classified patterns

It is indispensable to identify the welding gap because it is too insufficient to recognize the welding gap with only patterns in previous section. Numerous patterns for welding gap have to be acquired through the extensive experiments, it could make us convince whether the welding gap occur or not.

In this simulation, EBPA(Error Back Propagation Algorithm) which has two hidden layer is used. Architecture of this neural network is that it has 20 input nodes, 40 first hidden nodes, 40 second hidden nodes and one output nodes. The classified patterns for respective welding gap are used as the input patterns and each case of welding gap has its own desired value.

The specification of this neural network is following:

- Input nodes : 20
- First Hidden nodes : 50
- Second Hidden nodes : 40
- Output node : 1
- Learning rate : 0.03
- Steepness of activation function : 0.1

Fig. 10 present the multi-layer neural network which has two hidden layer in off-line process as shown in Fig. 3.

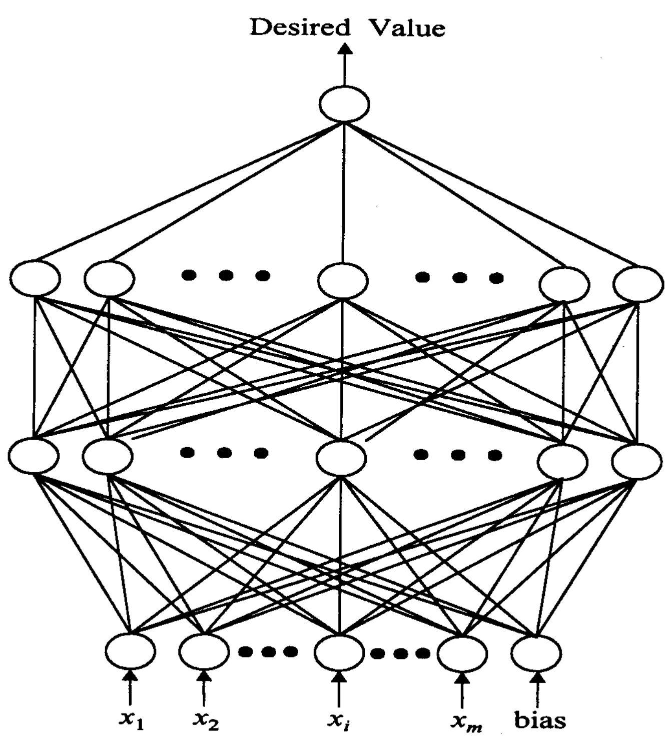

Fig. 10 2 hidden layer network

The identified neural network is used in on-line process. The current signal is processed by a low pass filter and fuzzy membership filter and the filtered signal comes into the identified neural network in real-time. In practice, this type of neural network must be a TDNN(Time Delay Neural Network) as the sampled signal turn in the TDNN piece by piece in temporal series.

4. Conclusion

In this paper, it is proposed to detect the welding gap using welding current signal and neural network.

The proposed method has an advantage in being realizing at a low cost and is not restricted by space. First and foremost, since the majority of welding automation at present employs the arc sensor system, we will not be able to add a vision system to existing facilities. Thus we have no other way but to choose this method to detect the welding gap. Using the welding current signal in detecting the welding gap is decidedly superior to the vision sensing system in many aspects. But it has a limitation in precision, This limitation will be improved all the more when a signal processing technique is developed.

To catch a very small welding gap was a hard task in this study because of high frequency noise, metal transfer and unstable arc. Accordingly, it goes without saying that the excellent signal processing algorithm is required urgently.

When the welding gap is detected, an adequate remedy is needed to fill up it, that is, there is nothing for it but to control the bead shape with the view of obtaining a fine welding quality. This study did not organize a welding gap controller. In future research, a adaptive controller using fuzzy-neuro approach will be completed. It is high time that a welding gap controller should be developed.

Finally, this paper proposed that a simple filtering algorithm based on fuzzy and classification of welding current signal is capable of detecting the welding gap. If high productivity and efficiency are intended in welding automation, the research and investment are destined to be increased still more. And fuzzy and neural network are excellent enough that they can be utilized in complex welding system.

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