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# Signal Processing using Fuzzy Logic and Neural Network for Welding Gap Detection

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## ABSTRACT

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. Especially, a domestic situation of the welding automation is still depend on the arc sensing system in comparison to the vision sensing system. Specially, the gap-detecting of workpiece using conventional arc sensor is proposed in this study. As a same principle, a welding current varies with the size of a welding gap. This study introduce 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 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.

**Key Words** : welding gap, arc sensor, fuzzy filter, ART2, neural network, pattern classification, FIR filter

## 1. Introduction

Recently, the artificial intelligence approaches, fuzzy system, neural network, have been successfully applied to various industrial system. Welding process is highly difficult to be .controlled and possesses excessive non-lincar and complex characteristics between the welding parameters and the welding quality.

The relationship between the welding conditions and the welding quality cannot represented by mathematical model and it is difficult to predict the welding quality resulting from the welding conditions.

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[1]-[6]. 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. Eq.(1) shows ARMA digital filter.

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$$y(n) = \sum_{k=0}^{\infty} h(k)x(n-k) = \sum_{k=0}^{M} a_k x(n-k) - \sum_{k=1}^{N} b_k y(n-k) \quad (1)$$

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.

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

Eq.(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 resent values of the input, $x(n)$. When FIR filters are implemented in this form, that is by direct evaluation of Eq.(2), they are always stable. Fig. 1 shows a structure of FIR filter.

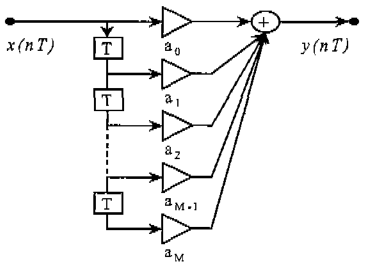


Fig. 1. Structure of FIR filter

Fig. 2 represents a concept of the fuzzy membership filter. $a_i$, $i=1, 2, \cdots, n$, are the discrete sample data of a continuous input and $\mu_j$, $j=1, 2, \cdots, m$, 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

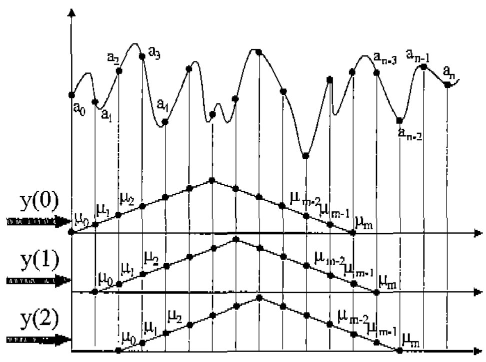


Fig. 2. Fuzzy Membership Filter

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. 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 $a_0$=0.0, $a_1$=0.25, $a_2$=0.5, $a_3$=0.75, $a_4$=1.0, $a_5$=0.75, $a_6$=0.5, $a_7$=0.25, $a_8$=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 Eq.(3) and the aggregated value is constant if a division number is once chosen.

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

where $m$ is a division number and $\mu_i$ 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 Eq.(3) makes Eq.(4) and this equation brings about the output of the fuzzy membership filter.

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

Fig. 3 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.

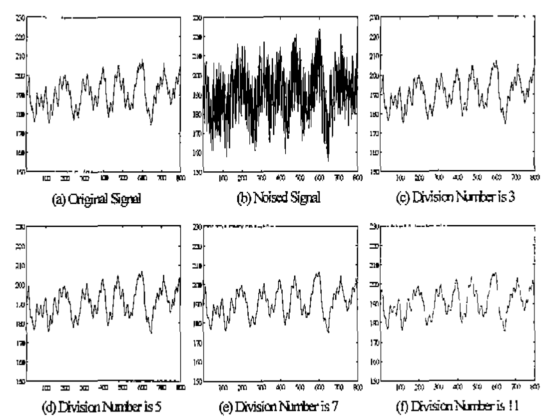


Fig. 3. Filtered Output by Fuzzy Membership Filter

## 3. ART2(Adaptive Resonance Theory2)

Architectures of ART are neural networks that self-organize stable category and pattern recognition in response to arbitrary sequences of analog and binary input patterns by Carpenter and Grossberg. The concepts of competitive learning and interactive activation are applied in the ART architecture.

ART2 is designed to perform for continuous-valued input vectors the same type of tasks as ART1 does for binary-valued input vectors. The differences between ART2 and ART1 reflect the modifications needed to accommodate patterns with continuous-valued components. The more complex F1 field of ART2 is necessary because continuous-valued input vectors may be arbitrarily close together. The F1 field in ART2 includes a combination of normalization and noise suppression, in addition to the comparison of the bottom-up and top-down signals needed for the reset mechanism[7]-[9].

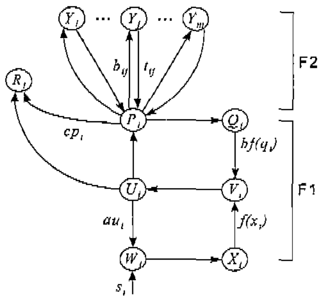


Fig. 4. Typical ART2 architecture

## 4. Simulation

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.

In this thesis, it is proposed that detecting the welding gap using a welding current is possible. This proposal covers over a disadvantage of the vision sensing system but is demanded enormous experiments to confirm a useful result.

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 differs from the usual patterns. Using this principle, it is possible to recognize a welding gap through the pattern classification for a welding current. To obtain a reliable result, the experiments must be implemented repeatedly and a proper signal processing technology is required.

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 : 18l/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. 5. 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.

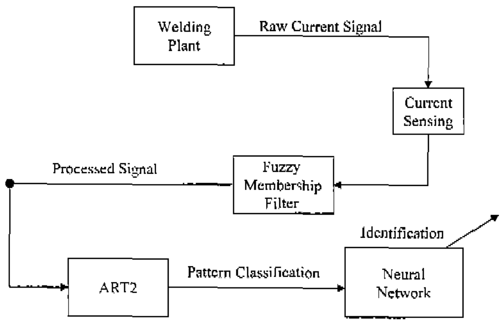


Fig. 5. Off-line Process

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. 6.

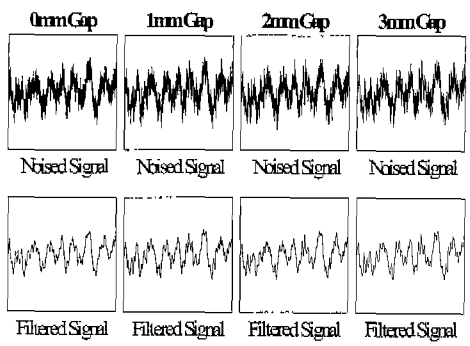


Fig. 6. Filtered Result of Welding Current

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 input patterns of 0mm welding gap are shown in Fig. 7 and they were acquired in off-line welding process to be a material for ART2. These patterns were obtained as the torch passes through a weld joint line in sequence. The classification result of 0mm welding gap

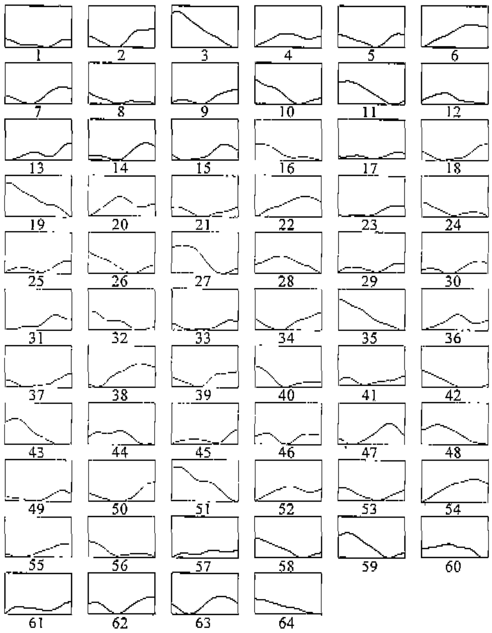


Fig. 7. All patterns in case of 0mm Welding Gap

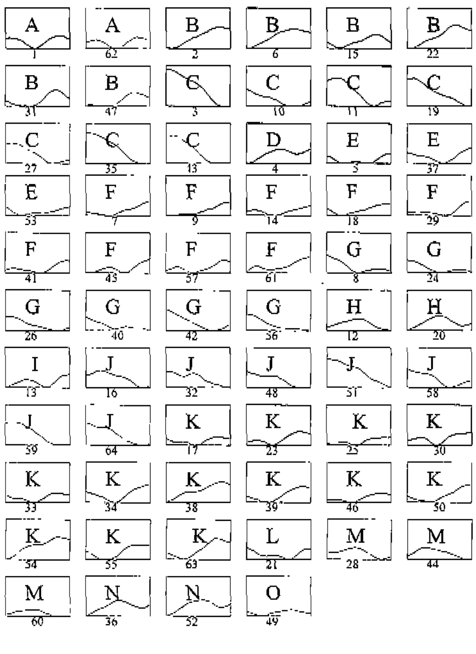


Fig. 8. Classification Result of 0mm Welding Gap

is represented in Fig. 8. The alphabetical index expresses the cluster, that is to say, the patterns that have the same alphabetical index are included in the identical cluster. As a result, 17 clusters came out in the figure. Other cases of welding gap, 1mm, 2mm, 3mm, are classified in the same manner.

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. The new distinct clusters, where the cluster of 3mm welding gap is compared to the cluster of 0mm welding gap, were marked with 'Gap' and illustrated in Fig. 9.

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 occurs or not.

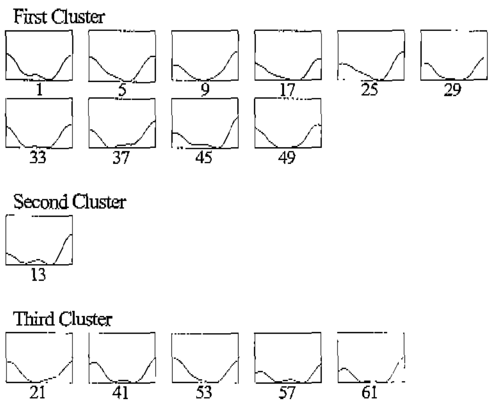


Fig. 9. Clusters of 3mm Welding Gap

In this simulation, EBPA(Error Back Propagation Algorithm) which has two hidden layer is used.

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. 5. 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.

Error transition of identification model is shown in Fig. 11. As it shows, the number of learning iteration was about 3500 till error boundary.

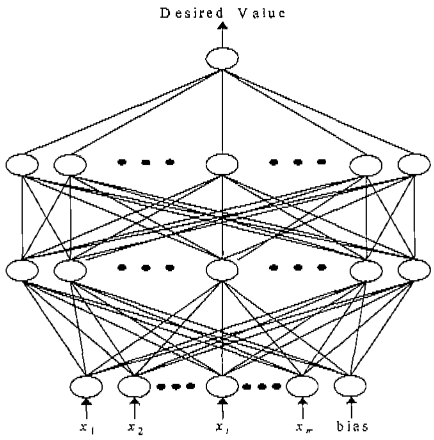


Fig. 10. Identification Model

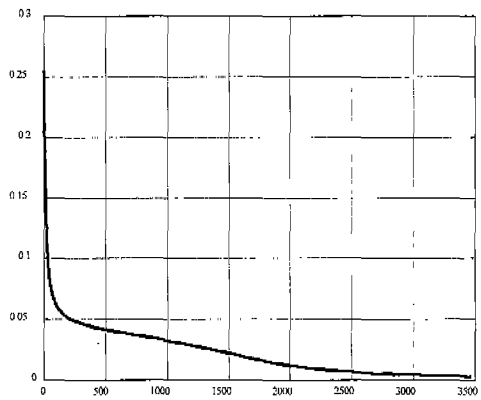


Fig. 11. Learning Iteration

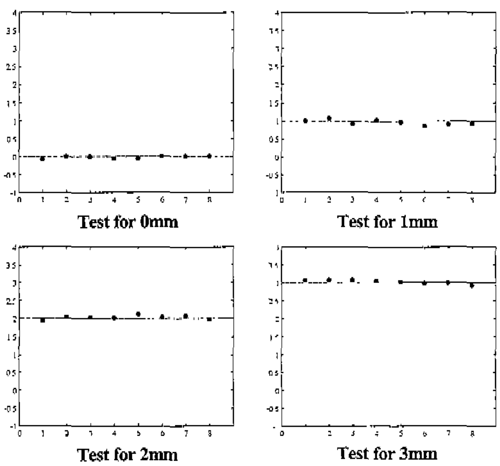


Fig. 12. Test for Identification Model

The test results of identification model are represented in Fig. 12. Respectively 8 patterns in each case, 0mm gap, 1mm gap, 2mm gap and 3mm gap were used to test the neural network. These were excepted from learning of identification and if they lie in the error limit, identification could be trusted. Where the dotted line is a desired value of neural network, each desired value is 0(0mm), 1(1mm), 2(2mm), 3(3mm), each dot is the result of feedforward calculation for the test patterns.

The results of other cases were settled to the satisfaction and the identification model was established successfully.

## 5. 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.

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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