

퍼지로직과 신경회로망을 이용한 용접 갭 검출을 위한 신호처리

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

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요 약 문

아크용접시 모재간의 갭을 검출하고 제어하는 것은 용접자동화에 있어 용접품질의 향상이란 측면에서 대단히 중요한 문제이다. 특히, 대다수의 국내 용접환경에서는 아직도 아크센서에 의한 용접자동화가 비전시스템보다는 의존도가 높다. 비전시스템에서는 카메라를 이용한 손쉬운 갭의 인식이 가능하지만 높은 가격과 공간에 따른 제약 때문에 조선소와 같은 환경에서는 부담이 되는 방법이다. 따라서 본 논문에서는 기존의 아크센서를 이용한 갭의 검출을 제안하고자 한다. 용접선의 추적원리는 모재와 토치간의 거리에 따른 전류변화를 이용한다. 동일한 원리로 모재간의 갭의 크기에 따라 정상적인 경우에 비해 전류의 변화가 일어난다.

본 논문에서는 우선 용접전류신호의 고주파 잡음을 없애기 위한 신호처리 방법으로 퍼지멤버십 필터를 제안하고 필터링된 전류신호를 토대로 인공 신경회로망중 경쟁식 학습을 하는 ART2를 통해 신호의 패턴을 분류한다. 갭의 유무나 크기에 따라 전류신호는 특정한 형태를 가지게 되고 이런 특정한 형태들은 갭이 없을때와 비교했을 때 다른 분류 결과를 나타낸다. 갭이 1mm, 2mm, 3mm인 경우의 전류신호 패턴분류결과와 갭이 없을 때의 패턴분류 결과를 비교했을 때 나타나는 특정한 패턴들은 신경회로망의 학습을 통해서 식별시킨다. 오프라인상에서 이러한 과정들이 진행이 되고, 온라인상에서는 식별된 신경회로망 모델을 용접플랜트의 이전에 설치하고 순방향으로 통과시키게 되면 모재간의 갭의 발생유무와 갭의 크기정도를 알수 있다.

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1. Introduction

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]-[5]. 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.

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

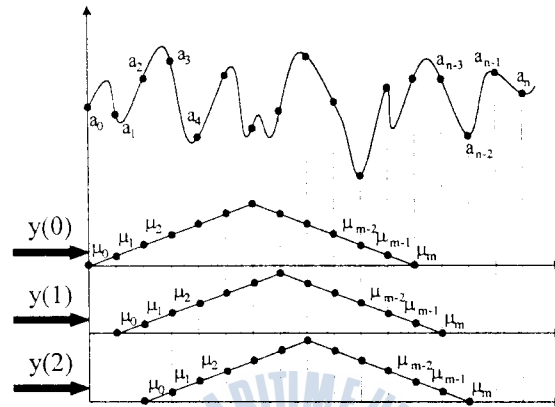


Fig. 1 Fuzzy Membership Filter

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 $a_0=0.0$, $a_1=0.25$, $a_2=0.5$, $a_3=0.75$, $a_4=1.0$, $a_5=0.75$, $a_6=0.5$, $a_7=0.25$, $a_8=0.0$ 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 Equation (1) and the aggregated value is constant if a division number is once chosen.

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

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 (1) makes Equation (2) and this equation brings about the output of the fuzzy membership filter.

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

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.

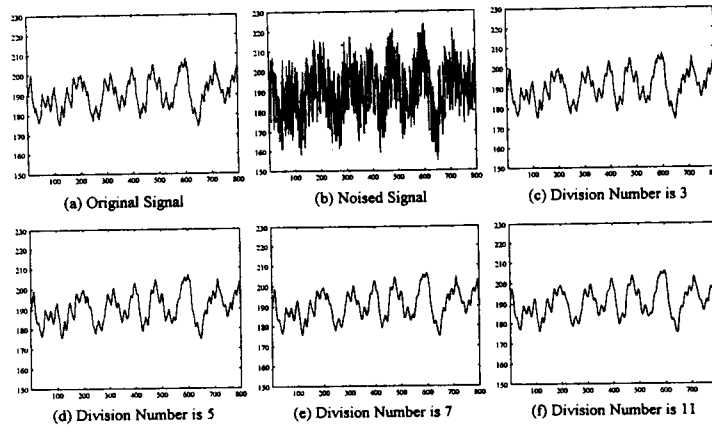


Fig. 2 Filtered Output by Fuzzy Membership Filter

3. Result

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.

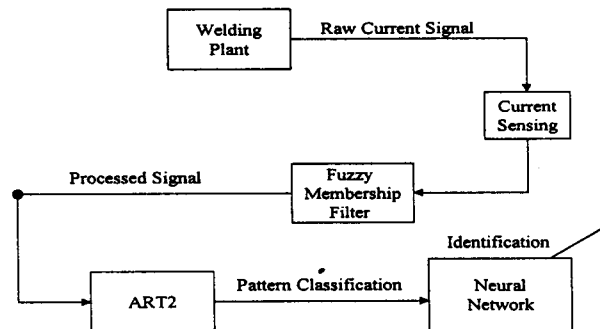


Fig. 3 Off-line Process

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.

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[6]-[9].

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.

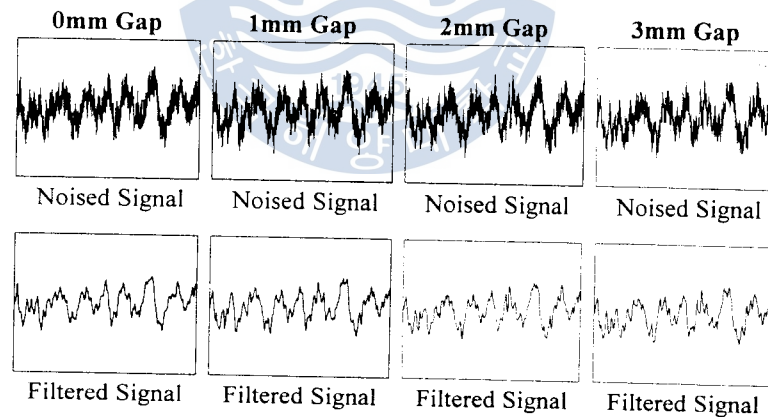


Fig. 4 Filtered Result of Welding Current

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. 4.

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.

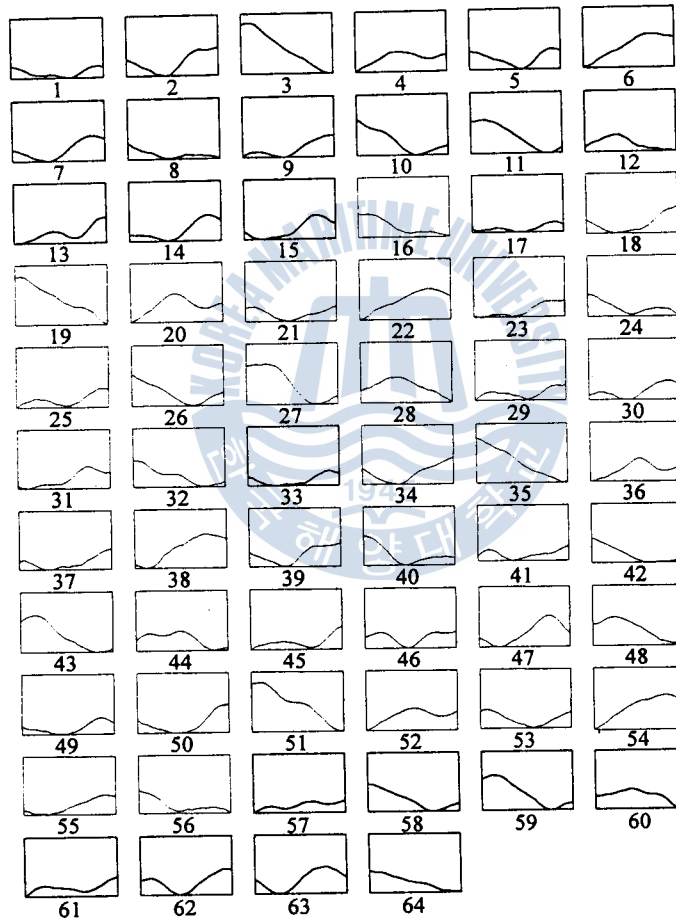


Fig. 5 All patterns in case of 0mm Welding Gap

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. 5. 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.

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.

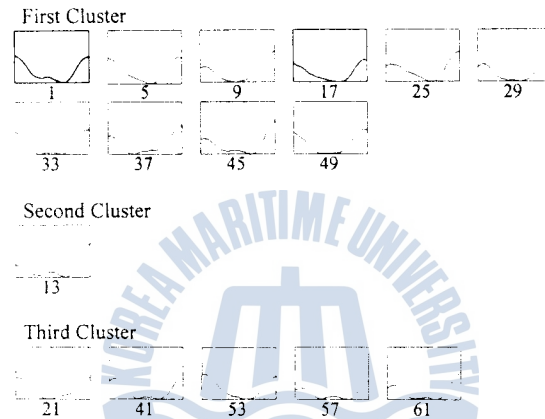


Fig. 6 Clusters of 3mm Welding Gap

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. The same procedure is applied to detecting 2mm and 1mm welding gap.

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

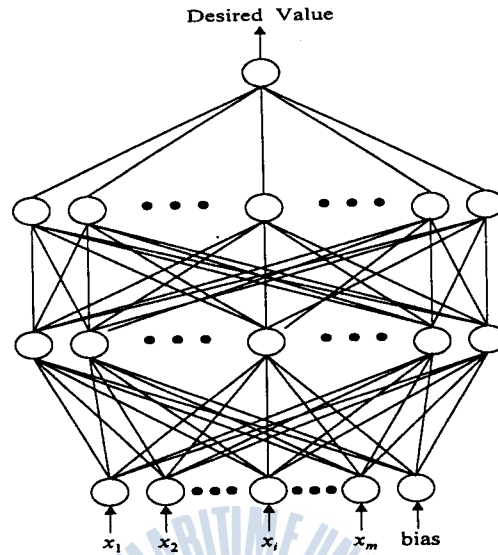


Fig. 7 Identification Model

Error transition of identification model is shown in Fig. 5-13. As it shows, the number of learning iteration was about 3500 till error boundary.

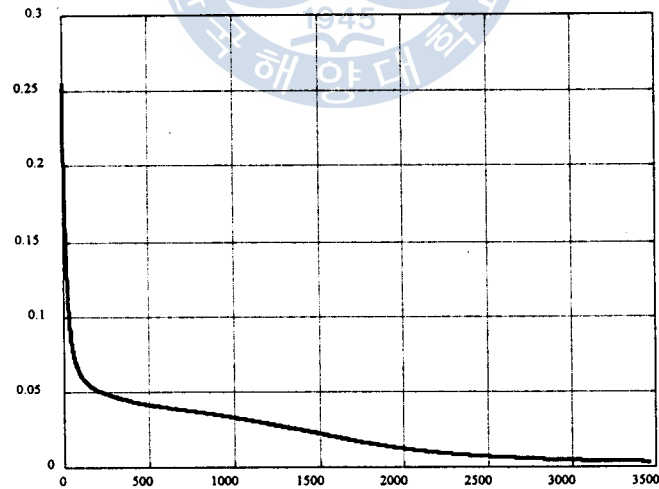


Fig. 8 Learning Iteration

Test results of identification model are represented in Fig. 9. 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.

For instance, in case of test for 0mm welding gap, all dots are located in the desired value closely. Due to this result, it is a matter of course that learning of a neural network was well done. The results of other cases were settled to the satisfaction and the identification model was established successfully.

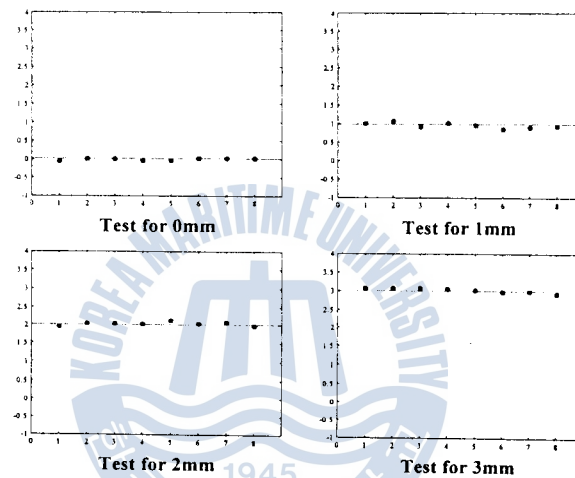


Fig. 9 Test for Identification Model

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.

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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