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# Welding Gap Detecting and Monitoring using Neural Networks

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## Abstract

Generally, welding gap is a serious factor of a falling-off in weld quality among various kind of weld defect. Welding gap is created between two workpiece in GMAW(Gas Metal Arc Welding) of horizontal fillet weld because surface of workpiece is not flat by cutting process.

In these days, there were many attempts to detect welding gap. Though we prevalently use the vision sensor or arc sensor in welding process, it is difficult to detect welding gap for improvement of welding quality. But we have a trouble to find relationship between welding gap and many welding parameters due to non-linearity of welding process. As mentioned about the various difficult problem, we can detect welding gap precisely using neural networks which are able to model non-linear function.

Also, this paper was proposed real-time monitoring of weld bead shape to find effect of welding gap and to estimate weld quality. Monitoring of weld bead shape examined the correlation of welding parameters with bead geometry using learning ability of neural networks.

Finally, The developed system, welding gap detecting system and bead shape monitoring system, is expected to the successful capability of automation of welding process by result of simulation.

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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, bridges and heavy construction machinery to very complex structures such as aircraft engines, cars or miniature components for microelectronic applications.

In welding process. If the final weld qualities after welding using the sensor are not desirable, additional work is necessary to acquire the desired weld quality. Therefore the most important thing in implementation of welding automation is the weld quality.

The analyses of physical phenomena arising from the welding process in horizontal fillet welding are helpful to predict the weld quality according to certain welding conditions such as welding current, arc voltage, welding speed. Therefore, it is important to know how weld defect formations are affected welding conditions.

Among the various welding conditions, welding gap can be induced due to cutting process which makes workpiece to be not flat. Because welding gap is changed in process, the poor bead shape is created, which weld quality is lowered. Though welding gap is a serious factor of a falling-off weld quality in various kind of weld defect, it is difficult to detect welding gap by sensor due to welding environment.

Therefore, in this study, neural networks based on a back-propagation algorithm and the optimum design based on the feasible direction method were implemented to estimate welding gap precisely.

As mentioned, the phenomena which occur during the welding process are very complex and have highly non-linear characteristics. Therefore, it is difficult to select welding conditions, that the weld bead shape is affect by. To achieve a satisfactory weld bead shape without weld defects, it is necessary to study the effects of welding conditions on the weld bead shape.

Accordingly, neural networks, can model non-linear function, are used monitoring of weld bead shape to overcome complex and non-linear characteristics in welding process. Neural networks learn non-linear phenomena in welding process when the various welding conditions are selected. Learning capability of neural networks can be estimated the weld bead shapes in real-time.

## 2. Neural Networks

Artificial neural networks(ANN) have gained prominence recently among researchers of non linear systems. As the name implies, these networks are computer models of the process and mechanisms that constitute biological nerve systems, to the extent that they are understood by researchers.

### 2.1 Multilayer Neural Networks

Multilayer neural networks was used as basic srtucture for the applications discussed here. Fig.1 shows multilayer neural networks.

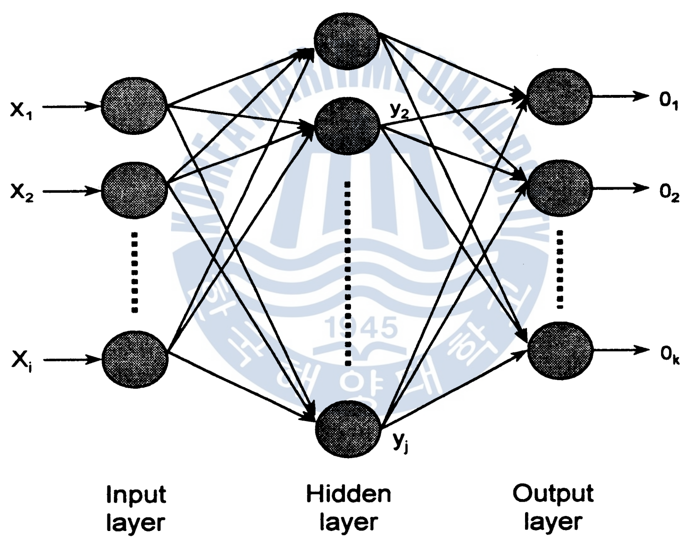



**Fig. 1 Multi layer neural networks**

The back propagation training algorithm allows experiential acquisition of input/output mapping knowledge within multilayer neural networks. Fig. 2 illustrates the flowchart of the error back propagation training algorithm for a basic two layer network as in Fig. 1.

Given are P training pairs, $\{x_1, d_1, x_2, d_2, \cdots, x_p, d_p\}$, where $x_i$ is $(i \times 1)$, $d_i$ is $(K \times 1)$, and $i = 1, 2, \cdots, P$. The operator $I$ is a nonlinear diagonal operator with diagonal elements being identical activation functions. The learning begins with the feedforward recall phase(step 2). After a single pattern vector x is submitted at the input, the layers' responses y and o are computed in this phase. Then, the error signal computation phase(step 4) follows. Note that the error signal vector must be determined in the output layer first, and then it is propagated toward the network input nodes. The weights are

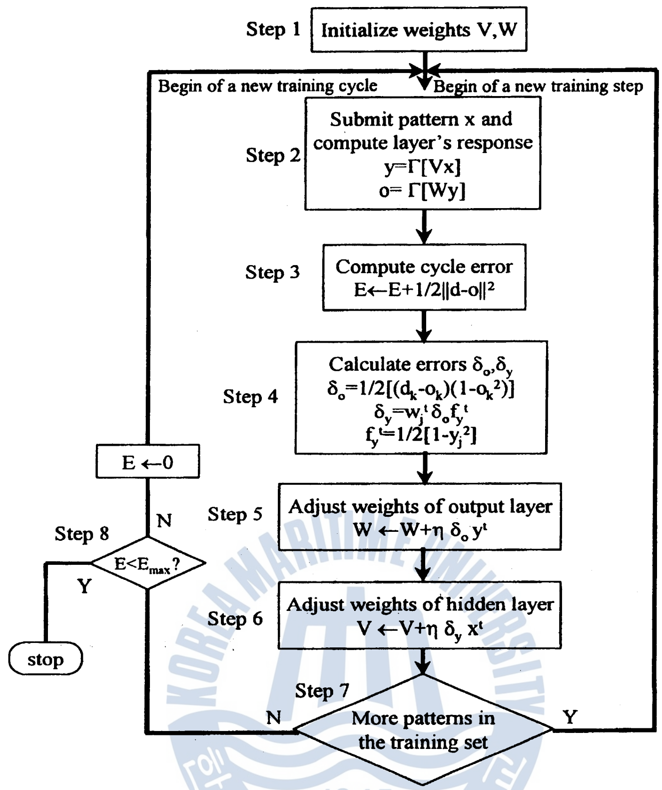



Fig. 2 Error back propagation training algorithm

subsequently adjusted within the matrix W,V in step 5, 6. Note that the cumulative cycle error of input to output mapping is computed in step 3 as a sum over all continuous output errors in the entire training set. The final error value for the entire training cycle is calculated after each completed pass through the training set $\{x_1, x_2, \cdots, x_p\}$. The learning procedure stops when the final error value below the upper bound, $E_{max}$ is obtained as shown in step 8.

### 2.2 Functional Link Networks

Function link networks are single-layer network. Generally, the hidden layer of neurons provides an appropriate pattern to image transformation, and the output layer yields th final mapping in multi-layer networks. Instead of carrying out a two-stage transformation, input/output mapping can also be achieved through an artificially augmented single-layer network. The separating hyperplanes generated by such a network are defined in the extended input space.

The key idea of the method is to find a suitably enhanced representation of the input data. Additional input data that are used in the scheme incorporate higher order effects and artificially increase the dimension of the input space. Fig. 3 shows the structure of functional link networks.

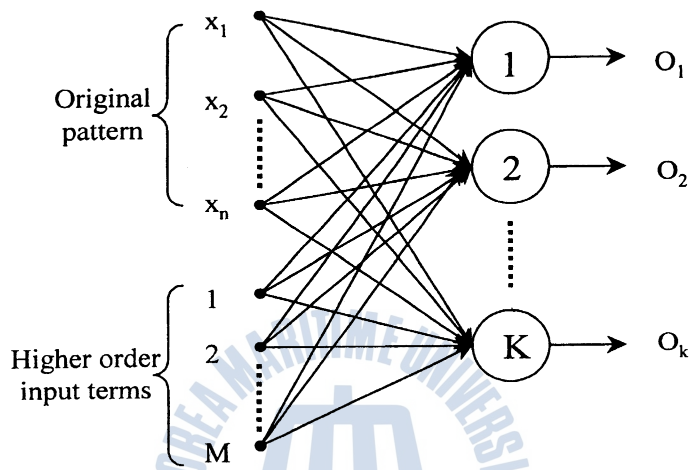



**Fig. 3 Functional Link Network**

## 3. Welding Theory

GMAW(Gas Metal Arc Welding) process are non-linear and very complex to analyze because of physical phenomena. Physical phenomena of welding process is described by various welding parameters such as welding current, arc voltage, welding speed and so on.

Among the various welding parameters, welding gap is a important fact of a falling-off weld quality in various kind of weld defect. Fig.4 shows and defines Welding gap of

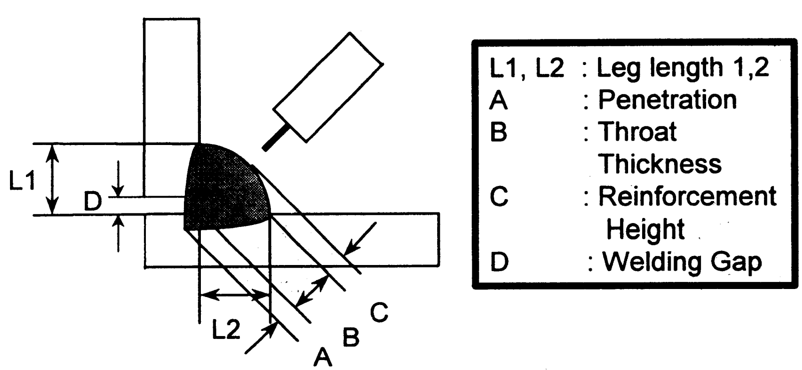



**Fig. 4 Profile of weld bead shape in Horizontal Fillet Welding**

horizontal fillet welding.

But it is difficult to detect welding gap by arc sensor in welding process. Droplet-rate is related to welding gap other than various welding parameters measured by arc sensor.

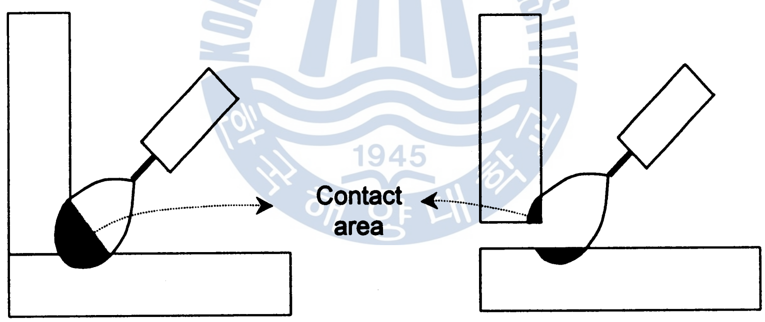
When filler metal is deposited from the electrode to the workpiece, generally droplet rate is the number of the transferred droplet per second.

As mentioned, droplet rate is a important fact in various welding parameters that estimate welding gap.

The more expanded welding gap is, the more decreased average of droplet rate is.

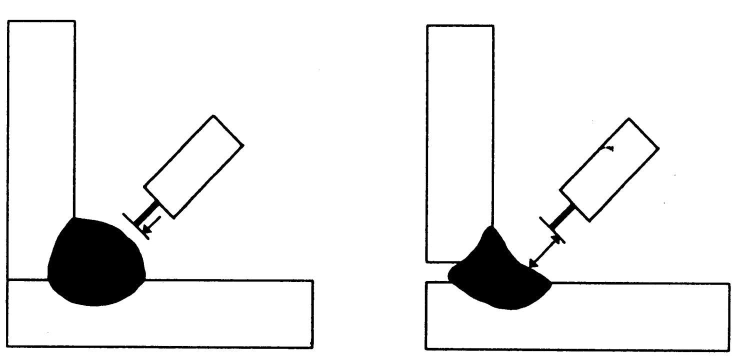
The reason by which phenomena between welding gap and droplet rate are occurred is as follows; In case that welding gap exist on workpiece such as Fig. 5, The contact area between arc and workpiece is decreased by welding gap, and then droplet rate is decreased by increased resistance.

Also, Fig. 6 shows the other reason that droplet rate is decreased as welding gap exist.




(a) In case of No gap (b) In case of existing gap

**Fig. 5 The contact area between arc and workpiece**



(a) In case of no gap (b) In case of existing gap

**Fig. 6 The hight of bead**

In contrast to no gap workpiece, the height of bead in Fig.6-(b) becomes lower, because of welding gap.

As mentioned, because of the melting and metal transfer phenomena, GMAW process are non-linear and complex to analyze. And it is important to know how weld defect formations are affected by the weld bead shape and welding parameters. Welding parameters such as welding current, arc voltage, welding speed, gas flow rate are highly coupled, and thus it is essentially difficult to derive a mathematical relationship between them. Thus there are many drawbacks to estimate weld bead shape for monitoring system.

Generally, parameters that represent bead shape is shown Fig. 4 such as vertical and horizontal leg length(L1, L2), penetration, throat thickness, reinforcement height.

## 4. Simulation results and discussion

In automation of welding processes, many attempts were implemented to improve weld quality ; weld joint test, estimate of optimal welding condition, proper welding process, selection of welding materials, examination of welding defect and trouble and so on. Among these many attempts, welding gap is a important factor of a falling-off weld quality. Also we can appreciate weld quality by means of analyzing weld bead shape.

However, it is difficult to detect welding gap, to estimate weld bead shape in real-time using current welding processes equipment. Therefore, in this chapter, it is suggested that welding gap detecting system and monitoring system using neural networks.

### 4.1 Modeling of Welding Gap Detecting System

There are many Welding parameters which influence welding gap such as the welding current, arc voltage, droplet-rate and so on. Generally, many welding parameters are coupled with each other but not directly connected with welding gap individually.

Neural networks are used in welding gap detecting to overcome non-linearity of welding process. Welding gap detecting system using neural networks is shown Fig 7. Welding parameters such as welding current, arc current, droplet-rate is used in input parameters of neural networks and output parameters is welding gap.

A good performance could not be obtained using general multi layer neural networks due to highly non-linear characteristic in welding process. Therefore, to solve these problems, The proposed neural networks as shown Fig. 7 has higher order input terms that used function link networks.

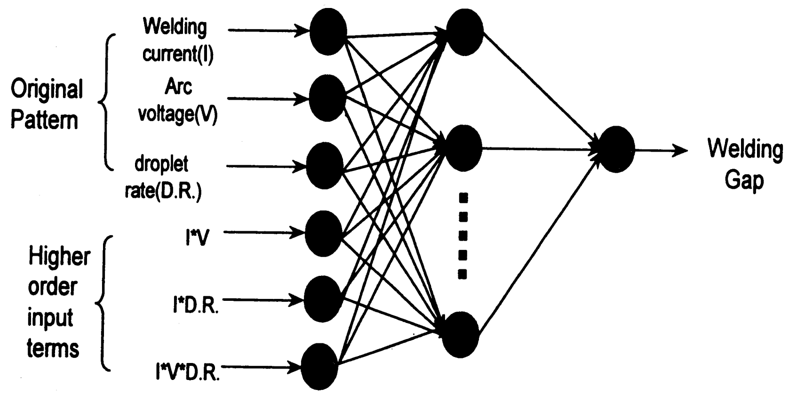



**Fig. 7 Multilayer neural networks used for welding gap detecting system**

Although no new information is explicitly inserted into the process, Additional input data that are used in higher order input terms artificially increase the dimension of the input space. Thus the proposed neural networks can represent the non-linear relationship between the input and output parameters by means of the extended input space.

The training data used learning was selected 174 patterns, and the test data was used in 145 patterns. The train and test data was derived by experiment which get droplet rate, when welding gap was artificially created in workpiece. The test results from this algorithm are shown Fig. 8, Fig. 9. Each of artificially created gap was estimated by the proposed welding gap detecting system.

According to these results, the proposed welding gap detecting system was demonstrated to be adaptive in other welding parameters except for the training data used learning.

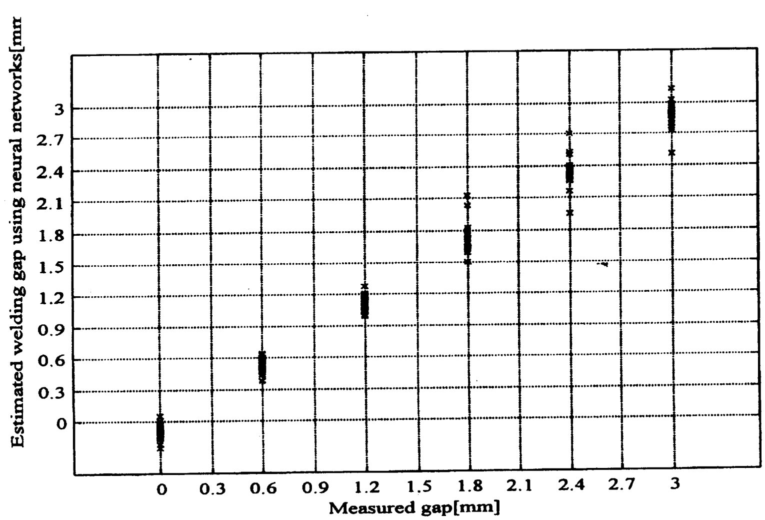



**Fig. 8 Comparison between measured and estimated welding gap for training data**

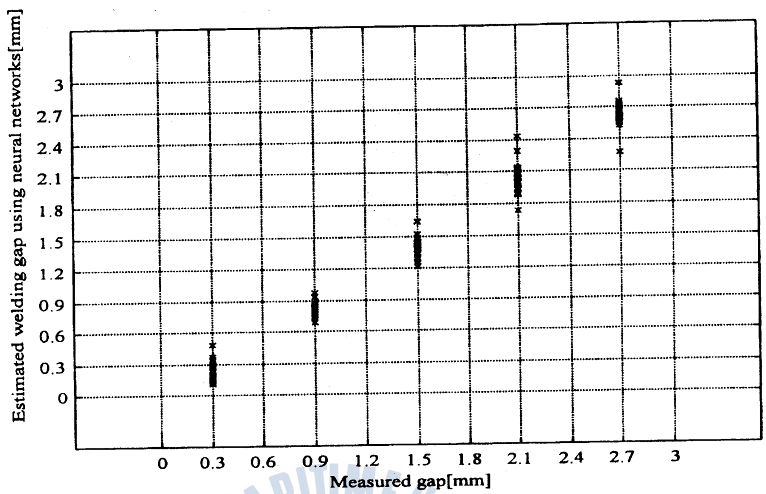



**Fig. 9 Comparison between measured and estimated welding gap for optional data**

### 4.2 Modeling of Monitoring System

Weld bead shape is helpful to predict the weld quality according to certain welding parameters such as welding current, arc voltage, welding speed, welding gap and so on. In order to estimate weld bead shape, it is necessary to derive a mathematical relationship between weld bead shape and welding parameters. but the approach to the mathematical modeling is to deepen the understanding of the basic phenomena involved in the process. Therefore, weld bead shape be monitored using neural networks which can learn a mathematical relationship between weld bead shape and welding parameters.

Training input parameters used learning of neural networks are welding current, arc voltage, welding speed, welding gap. Output parameters is selected by fifteen points that represent geometry of weld bead shape, including vertical and horizontal leg lengths, penetration, throat thickness, reinforcement height. Fig. 10 shows fifteen points that represent geometry selected output parameters.

As shown Fig 10, the manual welder easily understands welding process in terms of visual effects and weld defect is detected in real time due to the proposed monitoring system.

Structure of neural networks used the proposed monitoring system is shown Fig 11.

The proposed neural networks has higher order input terms like welding gap detecting system. The number of the training data used neural networks is 198.

The simulation result was shown Fig. 12. The actual surveyed weld bead shape was

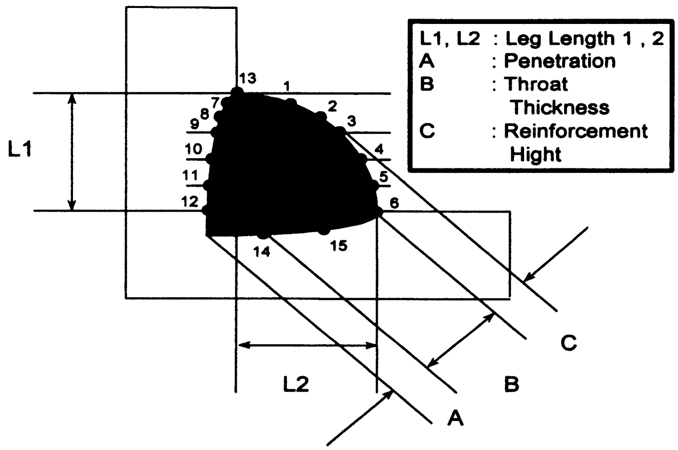



**Fig. 10 Fifteen points by selected output parameters**

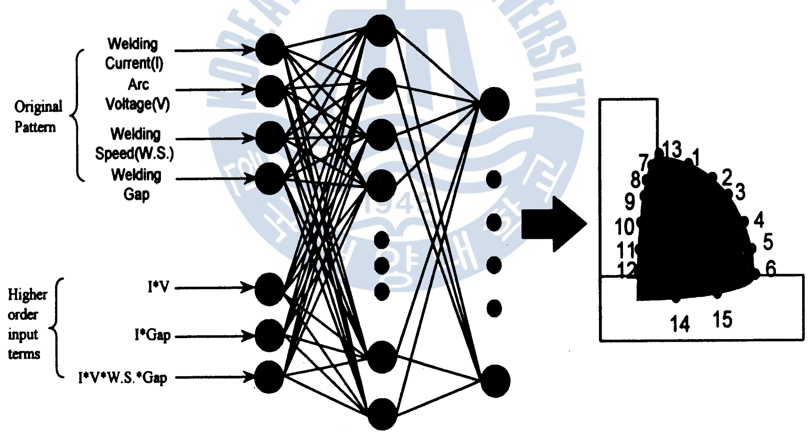
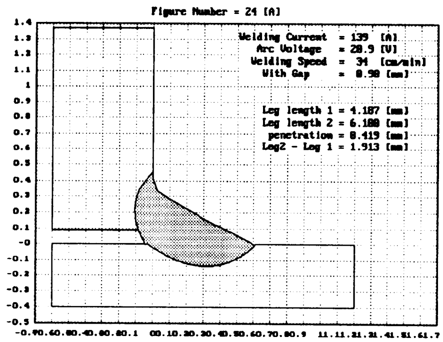


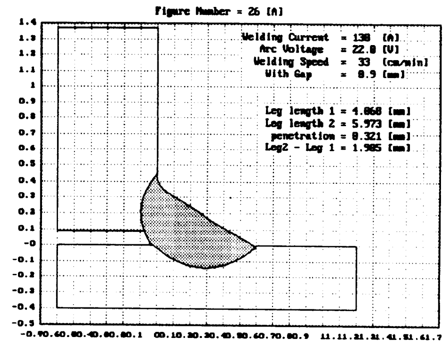

**Fig. 11 Multilayer neural networks used for monitoring system**

monitored as shown Fig. 12-(a),(c),(e) and the estimated weld bead shape was monitored as shown Fig. 12-(b)(d)(e). As compared with measured weld bead shape, the test results using the optional input parameters could be acquired the satisfied and adaptive output due to generalization capability of neural networks.

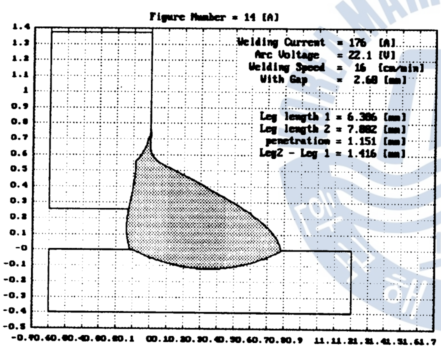
Fig. 13 shows each of weld bead shapes when welding gap is changed. In analysis of Fig. 13, we were able to analogy effect of welding gap. Therefore, the proposed monitoring system could predict weld quality precisely, and the cause of various defect could be induced in welding process.



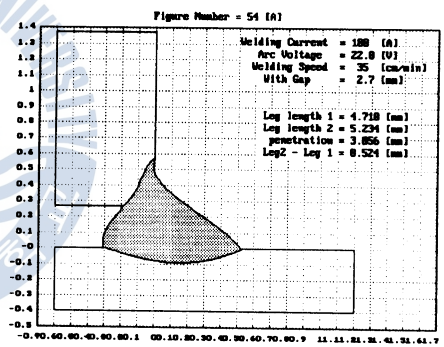

(a)



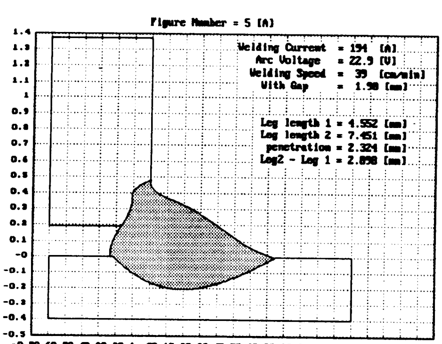

(b)



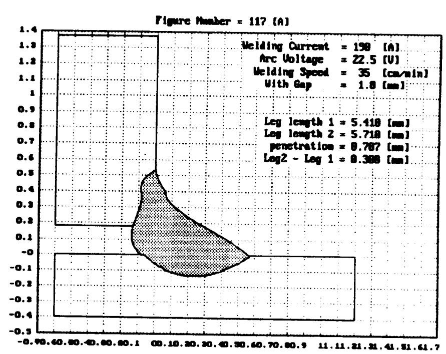

(c)




(d)




(e)




(f)

Fig. 12 Comparison between actual and estimated monitoring

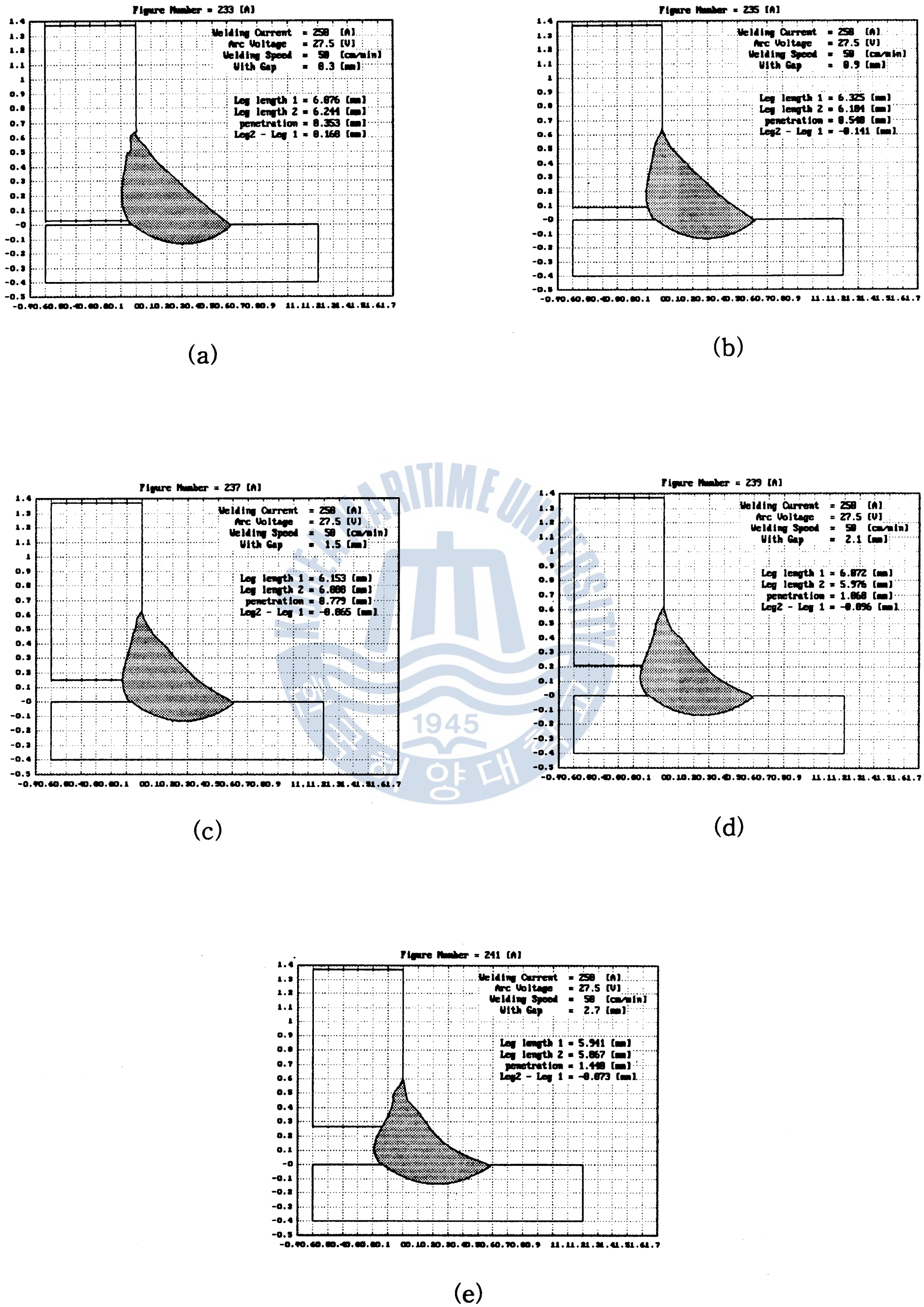



**Fig. 13 The change of weld bead shape by means of welding gap**

## 5. Conclusion

In this paper, welding gap detecting and monitoring system were introduced to estimate weld defect in real time using neural networks.

The poor bead shape which evaluate weld quality must be excessively caused by welding gap in various factors. The above results showed that the proposed welding gap detecting system was demonstrated to be adaptive in the optional welding parameters except for the training data used learning. Accordingly, welding gap was satisfactorily estimated by proposed system, that overcame non-linear characteristics and complexities of welding process.

Also, the proposed monitoring system could predict weld quality precisely, and the cause of various defect could be induced in welding process. Suppose that vision sensor is used, in order to measure weld bead shape, we must be faced with a number of problems; complexity of image processing by camera, much time and cost, improper environment and so on. But the proposed monitoring system, using neural networks, could overcome these problem, and weld bead shape can be precisely monitored in all welding conditions.

Namely, compared with other techniques, system was stable and robust in disturbance, convenient to solve problem, and benefited in economical points. Therefore, we expect that the above proposed system can effectively improve welding quality, and reduce time-consuming work in welding process due to decrease weld defect.

Finally, to improve welding automation technique, the proposed system is expected to control welding process by means of connection of other AI(Artificial Intelligence) techniques.

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