

신경회로망을 이용한 용접 갭 검출을 위한 모니터링 시스템에 관한 연구

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A Study on Monitoring System using Neural Networks for Welding Gap Detection

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요 약 문

일반적으로 용접 갭은 여러 가지 용접 결함들 중에 용접 품질을 저하시키는 중요한 요인중의 하나이다. Gas Metal Arc Welding (GMAW)에서 용접 갭은 용접 전류, 아크 전압, 용적률 등과 같은 여러 가지 용접 파라미터들에 영향을 미친다. 그러나 용접 공정의 비선형성 때문에 용접 갭과 많은 용접 파라미터들 사이의 관계를 분석하기가 힘들다. 그리고 아크센서를 사용하였을 경우, 감지된 신호에 대한 신호처리가 어렵지만 가격이 저렴하고 자동화하기가 쉬우므로 현재의 산업공정에서 대부분 아크센서가 사용되고 있다.

지금까지 언급된 여러 가지 어려운 문제점과 아크센서의 특징 때문에 본 논문에서는 GMAW에서 용접 갭을 검출할 수 있는 적당한 용접 파라미터들을 선정하고, 용접 갭과 선정된 파라미터들의 관계를 인식할 수 있는 신경회로망을 이용하여 용접 갭 검출 시스템을 설계하였다. 그리고 용접 공정이 매우 심한 비선형성을 갖고 있으므로 신경회로망은 고차 입력항을 사용하여 설계하였다.

또한, 용접 품질의 검사에 용접 비드 형상이 중요한 요인이다. 따라서 본 논문에서는 적당한 용접 파라미터를 선정하고 용접 비드 형상을 15개의 점으로 데이터화하여 고차 입력항을 갖는 신경회로망으로 이들의 관계를 인식하여, 용접 품질을 추정하고 여러 가지 용접 파라미터들의 효과를 분석할 수 있는 용접 비드 형상의 실시간 모니터링 시

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스텝을 제안하였다.

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 structure for the applications discussed here. Fig.1 shows multilayer 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.

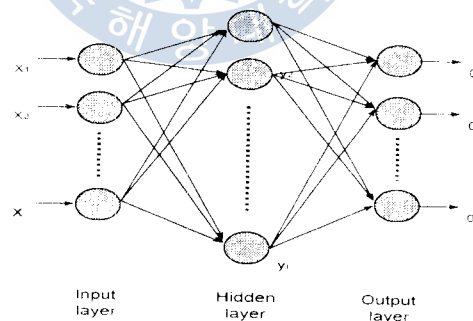


Fig. 1 Multilayer neural networks

Given are P training pairs, $\{x_1, d_1, x_2, d_2, \dots, x_p, d_p\}$, where x_i is $(i \times 1)$, d_i is $(K \times 1)$, and $i=1, 2, \dots, P$. The operator F 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

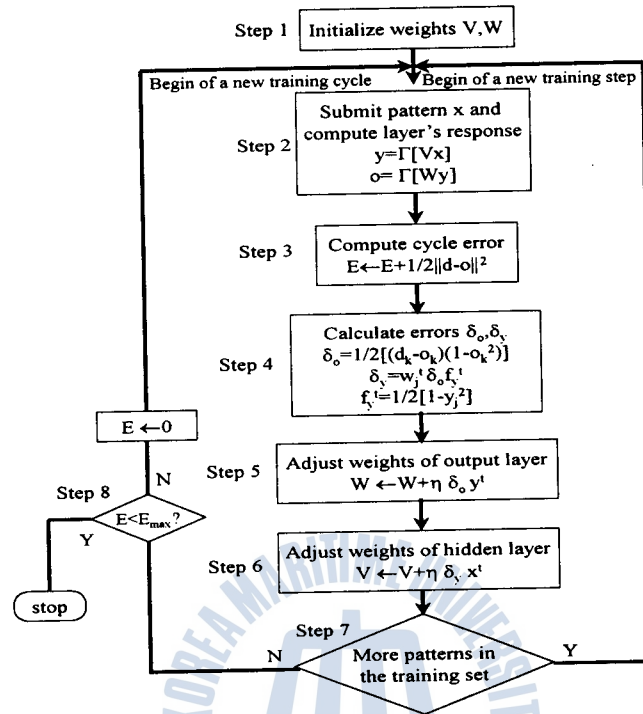


Fig. 2 Error back propagation training algorithm

determined in the output layer first, and then it is propagated toward the network input nodes. The weights are 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 $\{x_1, x_2, \dots, x_p\}$. 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

functional link networks are single-layer network. Generally, the hidden layer of neurons provides an appropriate pattern to image transformation, and the output layer yields the 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.

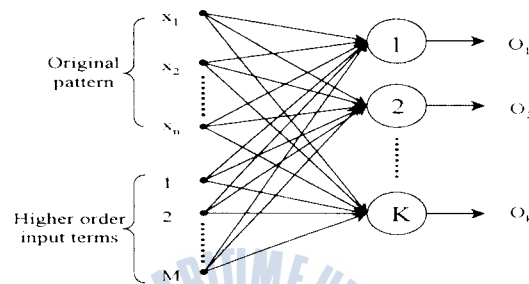


Fig. 3 Functional Link Network

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 horizontal fillet welding. But it is difficult to detect welding gap by arc sensor in welding process. Droplet rate is related to

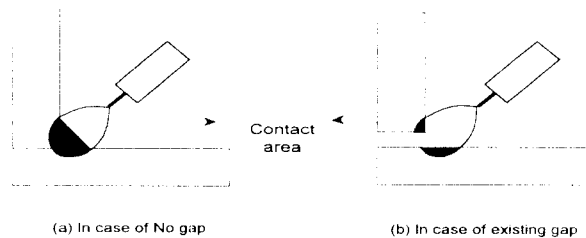


Fig. 4 The contact area between arc and workpiece

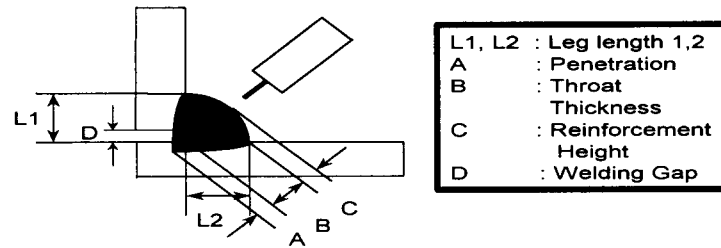


Fig. 5 Profile of weld bead shape in Horizontal Fillet Welding

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 an 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.

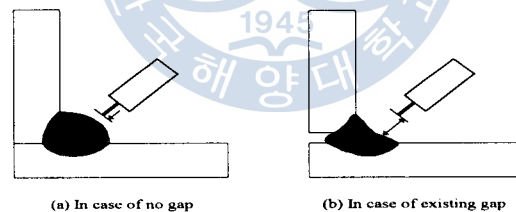


Fig. 6 The height of bead

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

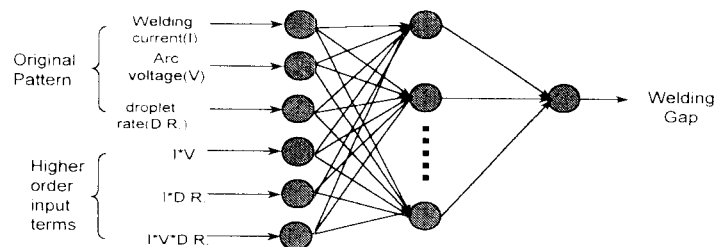


Fig. 7 Multilayer neural networks used for welding gap detecting system

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 functional link networks. 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.

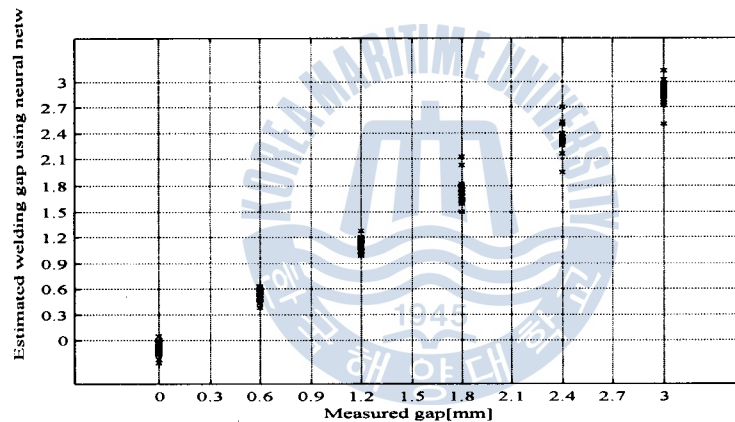


Fig. 8 Comparison between measured and estimated welding gap for training data

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.

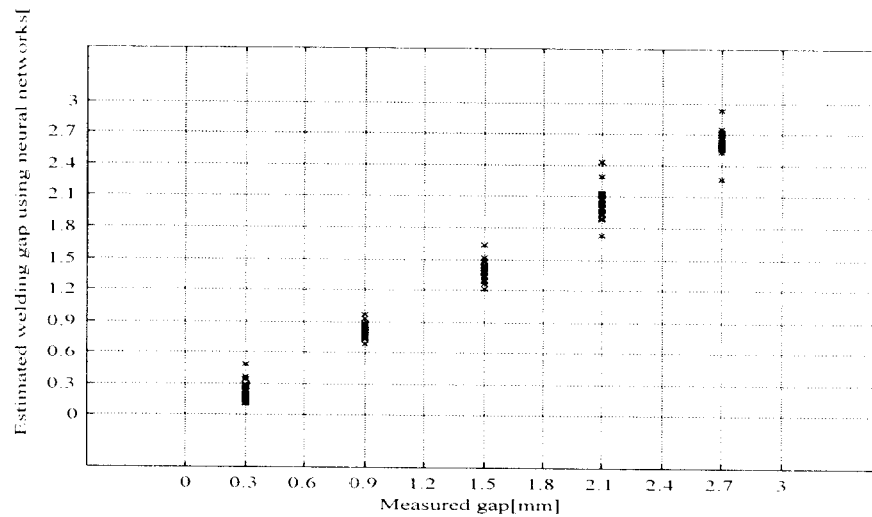


Fig. 9 Comparison between measured and estimated welding gap for optional data

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.

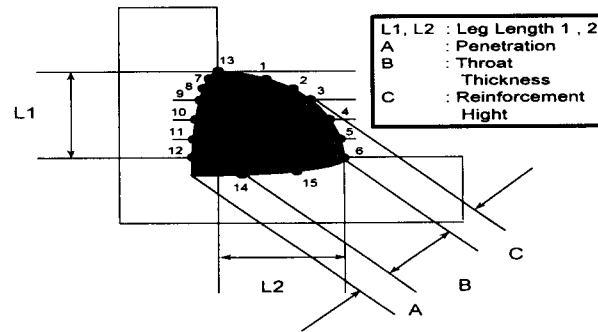


Fig. 10 Fifteen points by selected output parameters

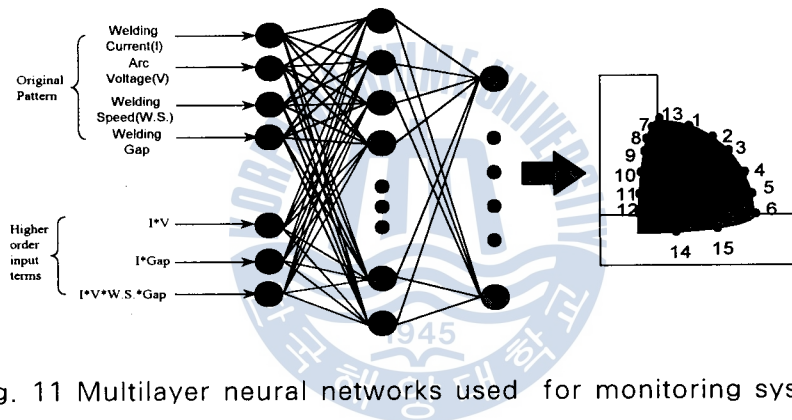


Fig. 11 Multilayer neural networks used for monitoring system

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 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.

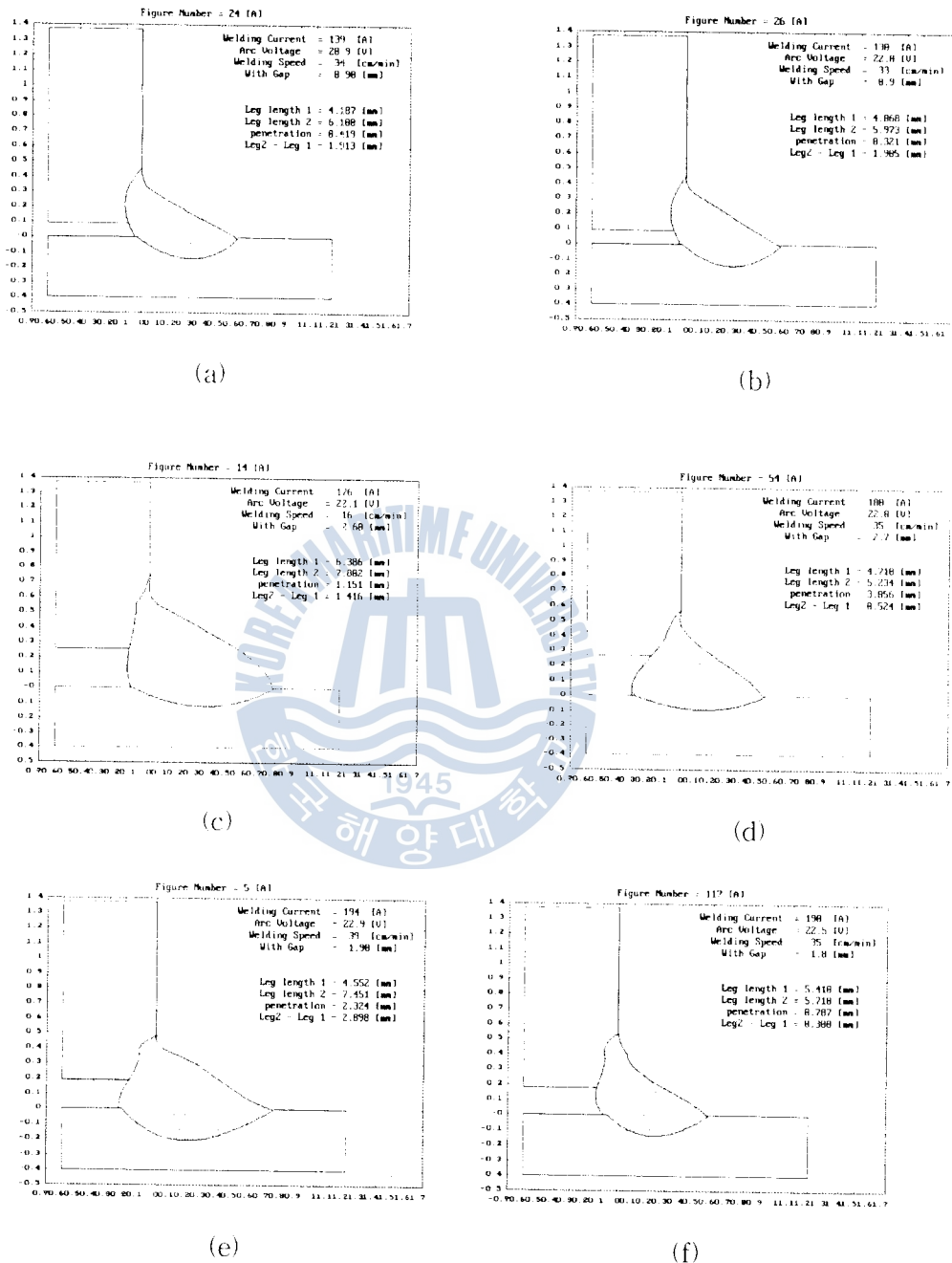


Fig. 12 Comparison between actual and estimated monitoring

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.

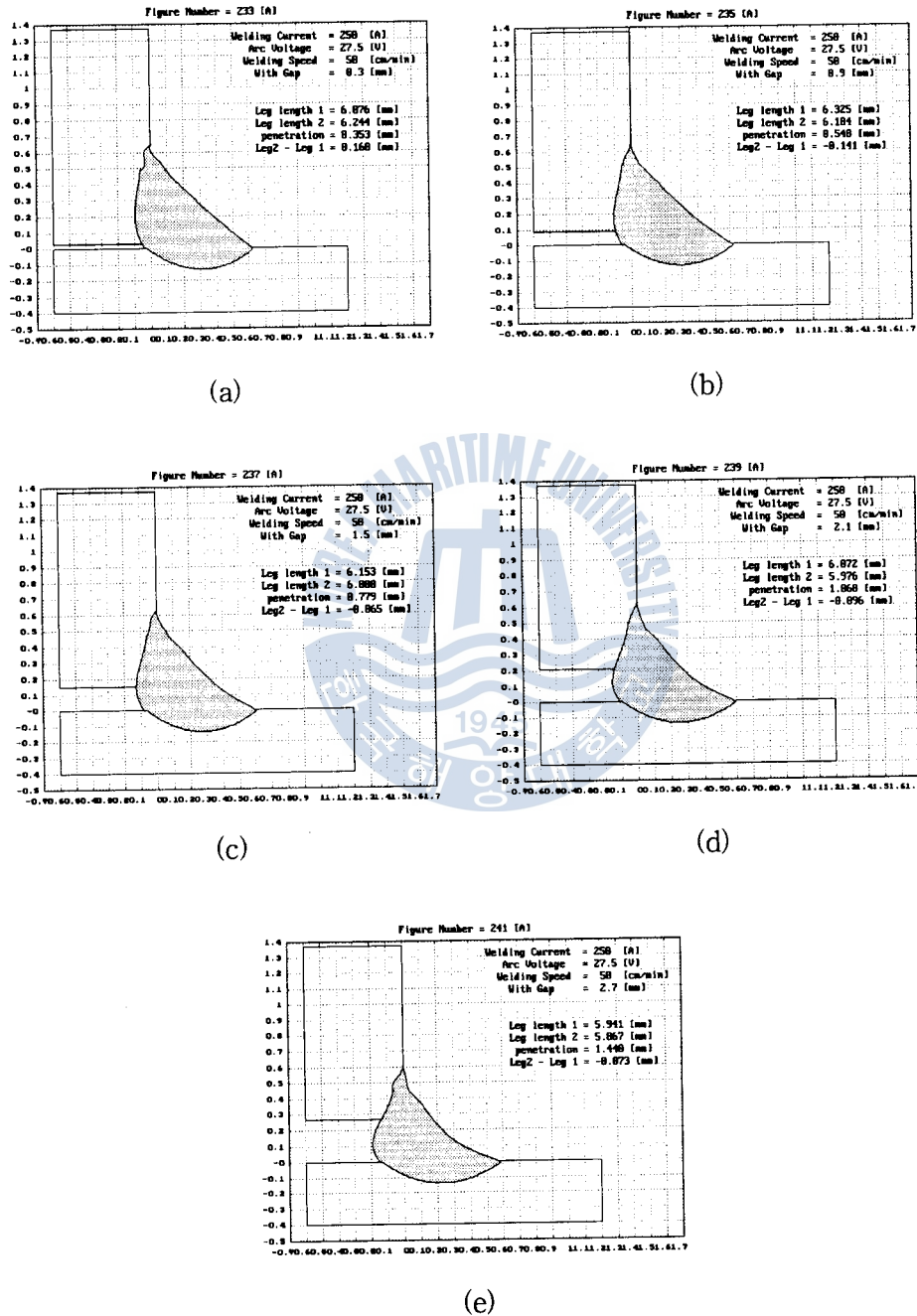


Fig. 13 The change of weld bead shape by means of welding gap

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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