하이브리드 지능시스템을 이용한 용접 파라메타 보상과 용접형상 평가에 관한 연구

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Estimation of Weld Bead Shape and the Compensation of Welding Parameters using a hybrid intelligent System

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요 약

현재 산업현장에서 활용하는 용접용 로봇은 대부분 오프라인(off-line)으로 작업을 수행하고 있어 생산성과 용접 품질 향상에 그 기능을 충분하게 발휘하지 못하는 실정이다. 현재에는 용접 품질 향상을 위하여 용접 매카니즘이 많이 연구되어 많은 수학적인 해석과 물리적인 해석방법을 도입하여 비선형적인 용접 메카니즘을 연구하고 있다. 이러한 여러 가지 비선형적인 문제와 해석상의 어려움에도 불구하고 용접의 결함을 보완하기 위해 보다 정확한 용접데이터를 생성하기 위하여 고감도의 센서를 도입하여 신호처리 하고 있으며, 이를 이용하여 용접시스템에 포함시키는 피드백제어시스템(feed-back control system)을 구성하여 용접선 추적 및 용접 비드(bead) 형상제어에 응용하고 있다. 또한, 최근에는 인공지능제어기술이 발달되어 인간의 학습능력과 의사결정능력을 대신하는 신경회로망(neural network)과 퍼지이론(fuzzy logic)을 도입하여 용접기술을 개발하고 발전시키고 있다. 본 연구에서는 신경회로망이론을 이용하여 실시간으로 용접시스템을 모니터링하고 퍼지제어기에 의하여 용접결함을 보정하는 지능시스템을 개발방법을 제시하고자 한다.

ABSTRACT

For efficient welding it is necessary to maintain stability of the welding process and control the shape of the welding bead. The welding quality can be controlled by monitoring important parameters, such as, the Arc Voltage, Welding Current and Welding Speed during the welding process. Welding systems use either a vision sensor or an Arc sensor, both of which are unable to control these parameters directly. Therefore, it is difficult to obtain necessary bead geometry without automatically controlling the welding parameters through the sensors. In this paper we propose a novel approach using fuzzy logic and neural networks for improving welding quality and maintaining the desired weld bead shape. Through experiments we demonstrate that the proposed system can be used for real welding processes. The results demonstrate that the system can efficiently estimate the weld bead shape and remove the welding detects

키워드

Fuzzy control, Neural network, Weld bead shape, Hybrid intelligent system

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Ⅰ. INTRODUCTION

Welding is essential for manufacturing a range of engineering components. Most manual welding methods rely heavily upon the knowledge, skill, and judgment of the welder. Methods and procedures for automatic welding should anticipate and deal with such judgmental factors. Automatic welding equipment available in the market is not necessarily intelligent, nor can it make complex judgments about welds.

The phenomena which occur during the welding processes very complex and display highly non-linear characteristics. Thus the analyses of physical phenomena arising from the welding process in horizontal fillet welding are helpful in predicting the weld quality based on certain welding conditions such as welding current, arc voltage, welding speed. It is also important to know how weld defect formations are affected by welding conditions. 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. Therefore, fuzzy system is an information processing system based on fuzzy theory which allows representation of knowledge involving multiple states instead of pure binary logic. Hence, we have employed such a system for the bead shape control.

Welding bead shape estimation is helpful in controlling the weld quality by adjusting certain welding parameters such as welding current, arc voltage, welding speed, welding gap and so on. In this paper, the weld bead shape was estimated in real time using neural networks.

Ⅱ. AUTOMATED WELDING SYSTEM

Welding process is a complex physical phenomenon and the mathematical analysis is very difficult and time consuming. Various arc welding processes, such as, gas metal arc, flux cored arc, gas tungsten arc, plasma arc, and submerged arc welding are used for automatic welding operations.

GMAW (Gas Metal Arc Welding) process is one of the most frequently used methods, because it is highly suited for a wide range of applications.

As mentioned, because of the melting and metal transfer phenomena, GMAW process is non-linear and complex to analyze. Moreover 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.

Expert welding systems are used for a variety of tasks, such as, weld quality prediction, estimation of weld joint's intensity and life, selection of appropriate welding conditions, selection of welding process and welding materials, improvement of weld defects[1][2][3]. Such expert systems represent human knowledge and furnish useful information in the form of a knowledge base.

Neural networks are a promising new generation of information processing systems that demonstrate the ability to learn, recall, and generalize from training pattern of data by assigning or adjusting the connection weights. The network is said to generalize well when it sensibly interpolates input patterns that are new to the network[4]. Our hybrid intelligent system exploits this learning ability of neural networks in order to capture the complex relationship between the welding parameters and the bead shape.

The proposed hybrid intelligent system for automatic welding is shown in Fig.1 It has three important components: initial parameter selection sub-system, monitoring sub-system and parameter controller. The initial parameter selection sub-system is composed of an inverse plant model. This sub-system and the monitoring sub-system are implemented using neural networks, while the parameter control is achieved using a fuzzy controller[5][6][7].

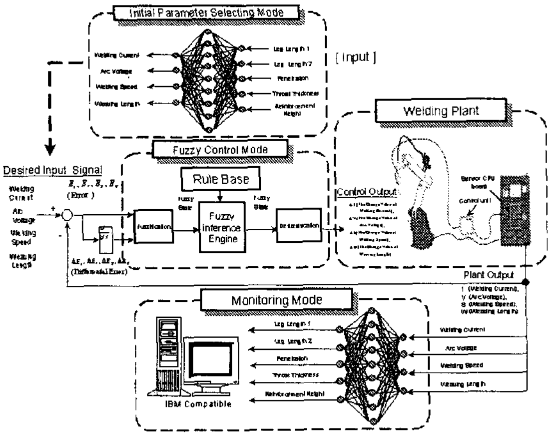


그림 1. 하이브리드 지능 시스템의 구조
Fig. 1 The structure of the hybrid intelligent system

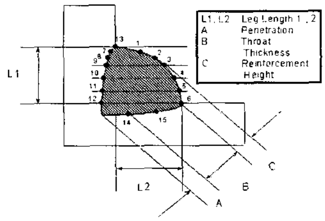


그림 2. 용접 형상 정의
Fig. 2 The parameters defining the weld bead shape

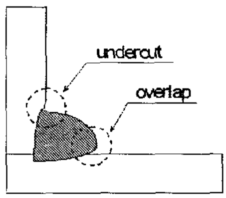


그림 3. 용접 결함 정의
Fig. 3 welding defects: undercut and overlap

Ⅲ. THE STRUCTURE OF HYBRID INTELLIGENT SYSTEM

3.1. The monitoring mode using neural network

Weld bead shape monitoring is a fundamental issue in automated welding. To predict weld bead shape, mathematical modeling in conjunction with experiments is necessary for obtaining the appropriate welding parameters. If the weld defect is detected by the sensor after welding, additional work is necessary to acquire the desired weld quality. Therefore, to avoid additional work, weld bead shape must be estimated in real time. To overcome this difficulty, weld bead shape was monitored using neural networks which can learn a mathematical relationship between weld bead shape and welding parameters. In our experiments, output parameters, that represent geometry of weld bead shape, are derived from relation with weld parameters.

Fig.2 shows and defines weld bead shape of horizontal fillet welding, there the parameters of weld bead shape are Leg length 1, Leg length 2, Penetration, Throat thickness, Reinforcement height. Fig.3 shows and defines weld defects, such as, Undercut and Overlap in fillet welding.

First the neural network is trained in an off-line process. As shown in Fig.1, during the learning stage both the neural network and the welding plant receive the same input parameter values. The welding plant is controlled by an expert human operator. The neural network generates output parameter values which define the weld bead shape. There parameters are compared with the output generated by a human controller and the error is fed back to the neural network. Back propagation algorithm was used to train the neural network.

3.2. The initial parameters selection mode using neural network

The next component of the hybrid intelligent system is the inverse plant identification model which was developed using another neural network. The user begins by defining the desired bead shape based on the welding situation. The inverse plant model is used to generate the initial welding parameters from this desired bead shape. As shown in Fig.4 the inputs to the inverse plant are parameters that define the geometry of the weld bead shape.

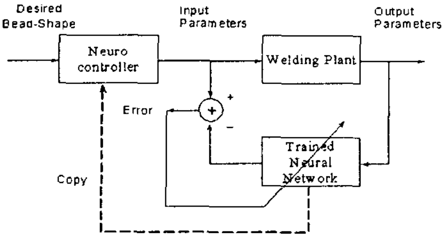


그림 4. 초기 파라메타 설정 모드
Fig. 4 The structure of initial parameter selecting mode subsystem

We used the experimental results for training and defined desirable weld bead shape using five parameters. These definitions are as follows:

Leg length 1(L1)
Leg length 2(L2)
Penetration(A)
Throat thickness(B)
Reinforcement height(C)

"Intial parameter selecting mode" in Fig.1 shows the structure of the neural network used to model the inverse of the welding plant. Based on the desired weld geometry the neural network generation the welding parameters, namely, welding current, arc voltage, welding speed and weaving length, etc.

3.3. The control mode using fuzzy controller

In this section we shall discuss the fuzzy control component of the hybrid intelligent system. The fuzzy controller sub-system receives the initial input parameter values from the inverse model neural network. It also receives a feedback, from the sensors of the welding plant, which consists of welding parameter values. The monitoring neural network sub-system supplies the welding geometry for the estimated bead shape. The environmental disturbances cause the welding plant to generate error(e) and differential of error(△e) which are also supplied to the fuzzy controller. Based on the rule-base the fuzzy controller generates the appropriate compensation for each parameter. The rule-base was developed with the help of an expert human welder.

The definitions of input and output parameters for the fuzzy controller are as follows:

▲The input parameters of Fuzzy controller

① The error and differential error of welding current: E_I, $\triangle E_I$

② The error and differential error of arc voltage: E_V , $\triangle E_V$

③ The error and differential error of welding speed: E_S, $\triangle E_S$

④ The error and differential error of weaving length: E_W, $\triangle E_W$

▲The output parameters of Fuzzy controller

① The compensation of welding current: △I

② The compensation of arc voltage: △V

③ The compensation of welding speed: △S

④ The compensation of weaving length: △W

Fig.5 shows the various components of the fuzzy controller sub-system, as well as the actual control mode for the welding plant.

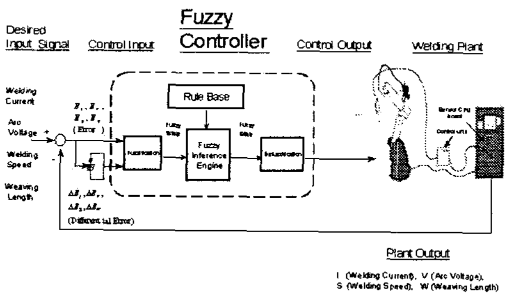


그림 5. 퍼지제어기 구성도
Fig. 5 The block-diagram of system using Fuzzy controller.

Ⅳ. PERFORMANCE EVALUATION

Training input parameters used during the learning phase of the monitoring neural network are welding current, arc voltage, welding speed. Output parameters are selected as fifteen points that represent geometry of the weld bead shape, including vertical and horizontal leg lengths, and penetration, throat thickness, reinforcement height.

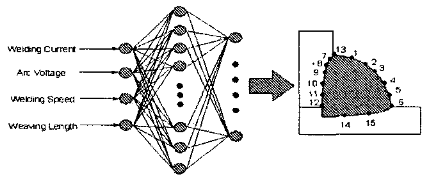


그림 6. 뉴럴네트워를 이용한 모니터링모드
Fig. 6 The monitoring mode using Neural Networks.

The structure of neural network used in the proposed monitoring system is shown Fig.6. The input parameters for the neural network were welding current, arc voltage, welding speed, weaving length and the output consisted of 15 values that precisely expressed the shape of the welding bead. Fig.2 shows the bead shape geometry defined in terms of 15 data points and the relevant parameters, L1, L2, A, B, and C.

When the length of leg length 1(L1) and leg length 2(L2) are nearly equal a good quality bead shape will develop, which will allow the weld to endure vertical load and horizontal load. Moreover as for firm welding, the penetration(A) and reinforcement height(C) are important elements. Therefore, it is necessary to output these five parameter values, which define the bead geometry, during the monitoring mode. The range of various input parameters was as follows:

Welding current : 180~370 [A]
Arc voltage : 20~32 [V]
Welding speed : 16~50 [cm/min]
Weaving length : 3~5 [cm]

The neural network architecture was a multilayer perceptron with one hidden layer consisting of 40 hidden neurons including bias (see Fig.6.). Back-propagation algorithm was used to train the neural network. During experimentation the learning rate varied from 10^{-3} to 10 progressively during the training and the momentum coefficient varied from 0 to 1. For determining convergence maximum allowable RMS error was set to 0.01(i.e. 1%).

Fig.7 shows the difference in results for convergence when momentum term is used.

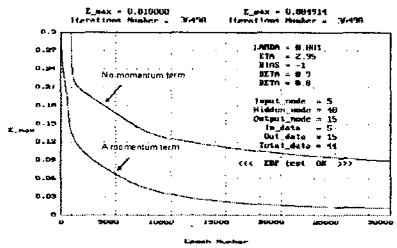
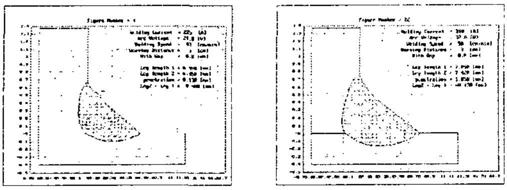


그림 7. 모맨텀 첨가에 대한 학습 속도 비교
Fig. 7 There are no momentum and momentum term

The trained neural network (Fig.7) had excellent generalization capability. It was tested for data obtained from additional welding experimentation and it was observed that there was little difference between the predicted bead shape and the actual bead shape.

For a good quality weld it is necessary to limit welding defects such as undercut, overlap, etc (see Fig.3.) and control effects such as penetration of weld. Fig.8. shows the ability of the hybrid intelligent system to control the weld penetration. Fig.8.(a) shows the result when the intelligent system was controlling the welding process. Based on the current welding parameters (welding current:225[A], arc voltage: 24[V], welding speed:43[cm/min] and weaving length:3[cm]) the monitoring system estimated the bead shape which is displayed in Fig.8(a). It can be seen that the penetration of the weld is quite poor in this case. The intelligent system updated the welding parameter values (welding current:310[A], arc voltage:32[V], welding speed:43[cm/min] and weaving length:3[cm]) and predicted the weld shape which is displayed in Fig.8.(b). It can be seen that the weld penetration is excellent in this case.



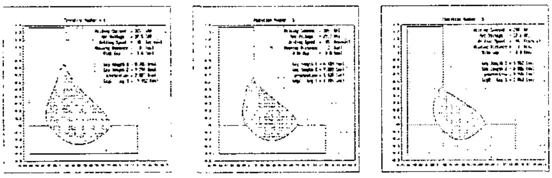
(a) (b)

Welding Current : 225	Welding Current: 310[A]
Arc Voltage : 24	Arc Voltage: 32[V]
Welding Speed : 43	Welding Speed: 43[cm/min]
Weaving Length : 3	Weaving Length: 3[cm]

그림 8. 모니터링 시스템에서의 용접형상 예측결과
Fig. 8 The results of prediction of bead shape neural network monitoring system

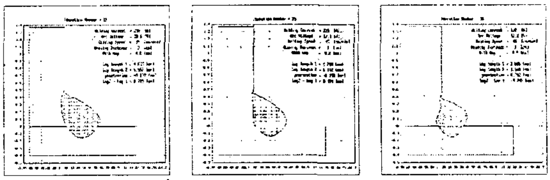
Note that, the welding parameter values used in this case were not part of the training data and the trained neural network was able to generalize and predict the bead shape with less than 1% error. Further analysis was carried out to determine the neural network's generalization capabilities with regards to welding defects, such as, overlap and undercut.

Under ideal conditions the desired bead shape will be obtained by applying these initial input welding parameters to the welding process. However, unexpected disturbances are bound to occur during in the bead shape. To produce an optimum bead shape under such disturbances, it is necessary to compensate the welding parameter value. The fuzzy system component of the hybrid intelligent system is responsible for estimating the effect of such disturbance on the welding torch and complement the effect.



(a) (b) (c)

welding current : 325[A]	305[A]	290[A]
arc voltage : 32.5[V]	29.7[V]	27.6[V]



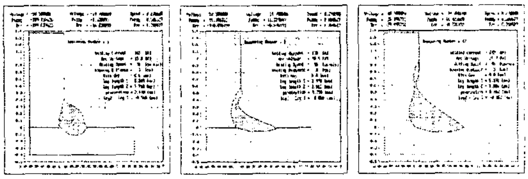
(d) (e) (f)

welding current : 248[A]	215[A]	180[A]
arc voltage : 20.6[V]	17.1[V]	12.2[V]

그림 9. 용접전류와 용접전압의 변화에 대한 용접형상 모니터링 결과
Fig. 9 The change of bead shape due to the variation of welding current and arc voltage

Fig.9 show examples if situations where disturbance occurs resulting in distortion of the weld bead shape. Fig.9(a) shows the desired bead shape provided by the user. The inverse model neural network supplied the necessary current and voltage value which are 325[A] and 32.5[V]. Fig.9(b)-(f) show the effect of disturbance in the welding voltage which drops from 32.5[V] to 12.2[V]. The bead shape prediction generated by the monitoring neural network is shown in Fig.9(b)-(f) and it closely matches the actual bead shape. Also, Fig.9(b)-(f) show the effect of both current and voltage variations which are predicted correctly by the monitoring neural network.

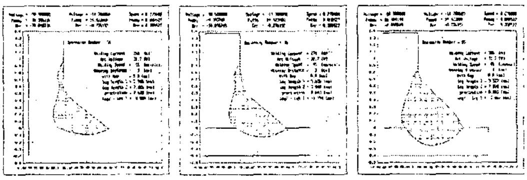
Fig.10. demonstrates the functioning of the fuzzy controller in the presence of an actual disturbance. The disturbance results in changing of welding current value to 325[A] and arc voltage to 32.5[V]. The estimated bead shape generated by the monitoring neural network is displayed in Fig.10(a). This bead geometry indicates poor quality. The fuzzy controller provides the necessary compensation for the arc voltage which results in a value of 29.5[V] Fig.10(b) shows the estimated bead shape. The resultant bead geometry shows some improvement in quality. Fig.10(c)-(f) show the sequence of compensation provided by the fuzzy controller based on the feed-back received at each sampling time. It can be seen that the bead geometry gradually improves and a good quality weld is obtained in Fig.10(f).



(a) (b) (c)

welding current : 325[A] 325[A] 325[A]

arc voltage : 32.5[V] 29.8[V] 27.5[V]



(d) (e) (f)

welding current : 325[A] 325[A] 325[A]

arc voltage : 26.5[V] 25.5[V] 24.5[V]

그림 10. 제어결과에 대한 용접형상 변화
Fig. 10 The change of bead shape during the process of compensation

V. CONCLUSION

We have proposed an intelligent system that automatizes the GMAW welding process. The system incorporates neural networks for initial parameter selection module and the monitoring module. Depending on the parts that need to be welded the user can choose the welding bead shape. The intelligent system automatically chooses the most suitable values for the relevant welding parameters. The monitoring neural network module estimates the bead shape in real time and the effect of disturbances on the weld quality is tracked. The fuzzy controller uses this information and compensates for the disturbances based on rule-set developed with the help of an expert human welder. Experiments were carried out to evaluate the performance and reliability of the proposed intelligent system. The results reported in this paper demonstrate that all the modules of the sub-system perform very well and high quality weld beads can be obtained through real time operation.

The proposed system does not need vision based sensing or image processing and it is very cost effective to implement. Hence it can provide a robust, stable and economical solution for automization in to days welding industry.

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