A Neural Network- Based Classification Method for Inspection of Bead Shape in High Frequency Electric Resistance Weld

Kuk Won Ko, Hyungsuck Cho, and Jong Hyung Kim

Abstract: High-frequency electric resistance welding (HERW) technique is one of the most productive manufacturing method currently available for pipe and tube production because of its high welding speed. In this process, a heat input is controlled by skilled operators observing color and shape of bead but such a manual control can not provide reliability and stability required for manufacturing pipes of high grade quality because of a variety of bead shapes and noisy environment. In this paper, in an effort to provide reliable quality inspection, we propose a neural network-based method for classification of bead shape. The proposed method utilizes the structure of Kohonen network and is designed to learn the skill of the expert operators and to provide a good solution to classify bead shapes according to their welding conditions. This proposed method is implemented on the real pipe manufacturing process, and a series of experiments are performed to show its effectiveness.

Keywords: title, abstract, keywords, introduction, heading

I. Introduction

High-frequency electric resistance welding (HERW) technique is one of the most productive manufacturing method currently available for pipe and tube production due to high welding speed. In these days, the high frequency electric resistance welded pipes have been used increasingly in various environments of industries such as boiler pipe for modern plants, automobiles, and other mechanical uses. However, the use of HERW pipe can not be applied in most severe conditions such as a chemical plant, an aerospace, an atomic plant under high pressure and temperature because of lower reliability of its weld quality compared with that of seamless pipe.

For this reason, recently various kinds of monitoring techniques have been developed to find optimal welding conditions, and many automatic welding controllers have been developed to achieve good welding condition by monitoring such reliable welding variables as the welding temperature, the magnitude of HERW current, the frequency ratio of HERW current, and the bead shape[1-12]. Upon consideration of the previous works, the bead shape is known to be an important variable to judge current welding condition among other monitoring variables[8,9]. The monitoring techniques for other welding variables were found to be useful only in the limited application due to their inability to accurately find the relationships between the welding phenomena and welding variables, and their susceptibility to external disturbances caused by cooling water, spatters, electromagnetic inference noise, variance of metal conditions, and so on.

Several researches related to visual bead shape monitoring systems in HERW pipe process have been carried out to find the correlation between the geometrical parameter of bead and welding conditions[6-12]. In these researches, the geometrical features of the bead such as the ratio of central bead height and the ratio of bottom width were used to distinguish the levels of heat input. Yutaka[8,9], et. al. tried to examine the relationship between the bead shape parameters and the weld quality by analyzing variation of normalized bead shape parameters characterized with central bead height, bottom width, and so on.

However, in using extracted geometrical parameter of bead to monitor the welding condition, two main problems arise. One is that it is difficult to acquire the stable bead shape parameter because of noises such as spatters, electromagnetic inference noise, cooling water, and so on. The other is that it is difficult to find the relation between the bead shape and the level of the heat input because the variance of geometrical features of bead is rather large. Thus, the use of the bead shape parameter does not appear to be successful for monitoring the level of heat input under various welding conditions.

These difficulties make it very difficult to obtain the relationship from a conventional analytical approach owing to the complexity of the welding process. Another problem which we are concerned with is that it takes too much time and requires a large set of experiments to investigate the relationship between the bead shape parameter and the welding condition.

In this paper, neural network approach to classify bead shape is developed to overcome the drawbacks of the previous bead shape classification methods using the geometrical feature of bead shape. Recently, artificial intelligence(AI) has been adopted to solve many problems which can not be easily handled by traditional analytic approaches. The neural network adapted here is the Kohonen network, and it is trained to classify the bead shape according to the welding conditions, as if an expert operator does it. Particularly, a robust method of laser stripe extraction is developed to improve noise reduction performance in processing of the stripe images; especially from the viewpoints of processing time, accuracy, robustness to noise. It is shown that the proposed neural network based bead shape classifier can also overcome some variation of bead shape which occurs even with the same welding conditions.

The rest of this paper addresses the followings: Section 2 describes the general outline of the weld bead shape and weld quality. Section 3 describes the visual bead shape monitoring system developed for this work and the vision processing algorithm. Section 4 provides the description of the proposed neural network based bead shape classifier. Section 5 presents experimental results, which show the performance of proposed

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bead shape classifier. Finally, some conclusions are made in the last section

II. General outline of weld bead and weld quality

In the high-frequency electric resistance pipe welding process, hot roll coils are progressively formed into cylinder shapes in several stages of forming rolls while high frequency current is applied to both edges of the formed metal to be joined with contact tips as shown in Fig. 1. Applied current flowing between the adjacent surfaces of edge on metals melts a small volume of metal along the edge by making the best use of the skin effect and proximity effects of high frequency currents. Since molten metals on both adjacent edges run together by squeeze rolls, and cools down by cold water, a weld is finally produced.

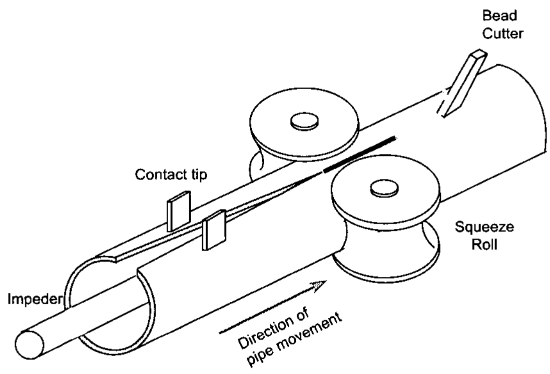
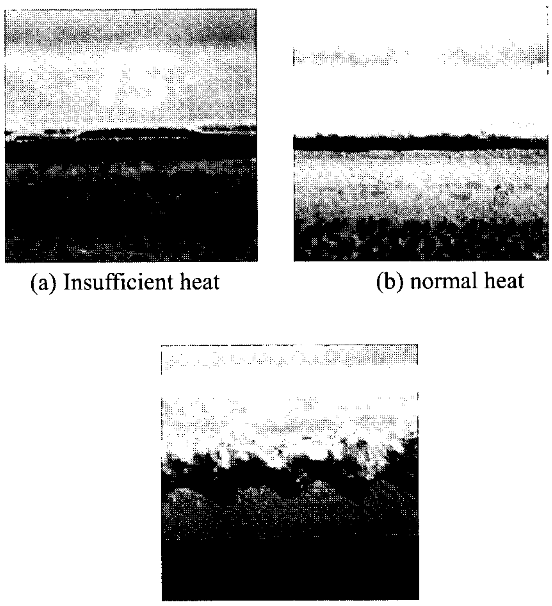


Fig. 1. High frequency electric resistance welding process.

Typical shapes of the bead in HERW are shown in Fig 2. The characteristics of the bead shape can be classified into



(a) Insufficient heat (b) normal heat

(c) Excessive heat

Fig. 2. Typical bead shape images of the HERW pipe according to welding conditions.

three stages according to welding condition, and can be described with the heat input range by their geometrical features such as central height, width, maximum height and the area of bead, which is shown in Fig 3.

Under an insufficient heat input condition, the concave shape appears on the top bead while the slope of bead is steep. The concave shape is built when the molten metals get lost between the base metal due to squeezing force. Cold weld is a main defect by the lack of heat input. Under optimum heat input condition, the concave shape disappears. In this case, the molten steel appears on the top of the bead and the smooth shape of bead can be achieved. Under excessive heat condition, the molten steel overhangs over the top of the bead, and the height of the bead becomes unstable while the bottom width of the bead increases with heat input. Penetration is one of main defects by the excessive heat input due to the inclusion of impure particles in the weld pool.

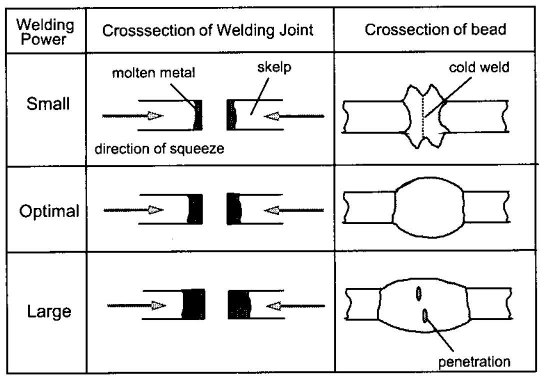


Fig. 3. Cross-sectional view of weld bead.

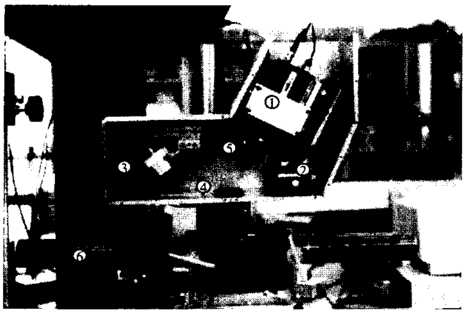
Thus, the bead shape in HERW pipe production gives a useful information on judging current welding condition. To obtain a good weld quality, the bead shape must be monitored and controlled in an on-line monitor. Therefore, the bead shape of weld zone is monitored to estimate the weld quality as does the expert operator in heat input control.

III. The monitoring system

1. System configuration

A visual bead shape monitoring system is designed to acquire stable images of the bead shape in spite of weld spatter, gas from cooling oil, and high frequency electric noise which do electric device harm. As shown in Fig 4, it consists of a CID(Charge Injection Device) camera, a laser with cylindrical lens, fine mechanical align stage sets, filters, an air spray and a cooling system.

The CID camera(C.I.D. 2710 CIDTEC Co.) is used to minimize the electro-magnetic noise(EMI) in acquiring images. It consists of a matrix of photo sensitive pixels arranged in columns and rows and is designed to improve electric noise performance. As a source of light, the 30mW laser diode emitting at 690nm is used. A band-pass filter and a polarized filter play an important role in removing the effect of spatter and in suppressing the unknown specular reflections without other image processing. An air spray system is equipped to protect the lens and filters against the smoke and fumes generated during welding. A heat reflection filter is also attached to protect vision sensor against welding heat. An image process ing module is used to analyze the image data obtained from the vision sensor.



① Camera ② Mechanical align stage sets ③ Optical filters
④ Pipe ⑤ Diode laser with cylindrical lens ⑥ Lense(f=50mm)

Fig. 4. The photograph of the visual monitoring system.

The monitoring system operates on a principle of triangulation that have been used to obtain information on the layout of bead shapes[8][9][13][14]. A plane of laser light beam generated through a cylindrical lens irradiates the welded area with an oblique angle. The resulting stripe image depicts the layout of cross-section of the weld bead. Fig 5 shows an illustrative picture of the bead shape at insufficient heat input condition and their stripe image variants.

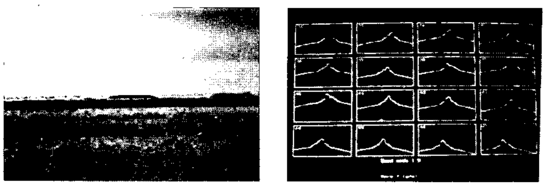


Fig. 5. The image of bead on pipe and their laser stripe.

2. Image processing algorithm

The basic idea of Image processing techniques to extract bead shape from acquired image with noise which can not be eliminated by optical filters is to convolute the pixel data with a spatial filter that only operates in the direction of the columns of the image, because the stripe is approximately parallel to the rows of the image[15][16]. The filter is designed to yield a maximum response to the center position of the stripe cross-section by using one-dimensional difference of Gaussian (DOG) filter[19]. The design parameter of the filter is related to the thickness of laser stripe in the image plane for discriminating the laser stripe from other possible brightness source.

In this research, the thickness L_w of the stripe is approximately 10 pixels and is used for dynamic design of the DOG filter. In order for the filter to run reasonably fast, however, a discrete approximation to the filter is needed. In our system,

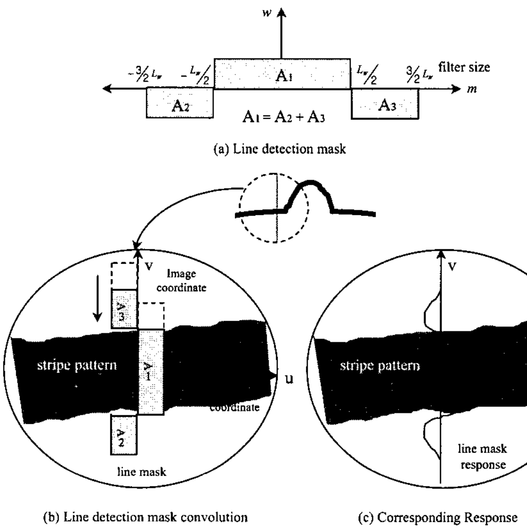


Fig. 6. Line detection mask.

the following approximation was obtained through a series of tests:

$$R(i,j) = \sum_{m=-3/2L_w}^{3/2L_w} \omega_m I(i, j+m) \quad (1)$$

where $I(i,j)$ denotes the pixel intensity at the image coordinates (i,j) and ω_m is a filter coefficient that has a distribution as depicted in Fig. 6 and subscript m denotes the horizontal pixel coordinate of the mask filter. The sum of the coefficients is equal to zero. For a given column, the filter is used to convolute the image pixel along the column and then the point of the maximum filter response is obtained. If the maximum response is larger than a given threshold value, the corresponding position is considered to be the center position of the stripe at the column. This process is performed over all the columns in the image.

After the sets of strip location data have been calculated from input image, the data are grouped into a set of connection runs. After the grouping is completed, the resulting connected runs are fitted to straight-line segments by using a line interpolation method.

IV. Neural network bead shape classifier

A Kohonen network is implemented to identify the shape of weld bead that tends to greatly vary according to welding conditions. The neural network is well known for a classifier and has been successfully applied to the fields of pattern recognition and/or classification. As pointed out previously, the information vector used as the input to the network is the laser line contour of the bead shape, not their feature value.

The system architecture of the network is shown schematically in Fig. 7. The network consists of a number of nodes arrayed in two layers: an input layer and a competitive layer. A node denotes one processing element, and a line between nodes represents the connecting link which is to compare the input vector.

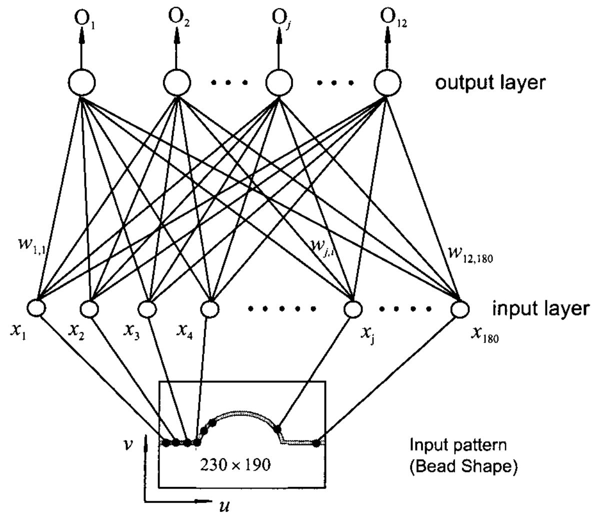


Fig. 7. NN architecture for bead shape classification.

When a bead shape information vector which consists of the array of image pixel coordinates { x_{pi} : subscript i = 1,2,.., n } is presented to the input layer, the input to the j-th node { j = 1,2,3,.. k } in the competitive layer is

$$s_j = \sum_i w_{ji} \cdot x_{pi} \tag{2}$$

where the subscript p denotes the p-th individual training data and w_{ji} denotes the weight connecting between the j-th node of the competitive layer and the i-th node of the input layer, and S_j denotes the input to the j-th node of the competitive layer. This input value to j-th output node is the correlation of the input vector and the weights and a similarity measure for clustering or classification that indicates the degree of resemblance between the input vector and the weights.

In the competitive layer, the output node competes with each other. Thus, the only one neuron with maximum input value, in other words, only one neuron of the nearest weight to the current input data is selected as winner or winning node, o_{win}, which is expressed by

$$o_{win}(s_c) = \max_{1 \le j \le k} o_j(s_j) \tag{3}$$

This wining node is to be updated towards resembling the members in its own cluster. In the training mode, the weight vector of a winning node and of some set of predefined neighbors are allowed to be updated. The detailed procedures of training the Kohonen neural network are described as follows:

First, all the NN parameters such as the number of output node, dynamic learning rate, initial number of neighborhood are defined and the initial value of vectors $w_j(0)$ are initialized randomly. And select a sample randomly, present this sample to the input layer, and then determine the winner output node o_{win} at time t by using minimum-distance Euclidean criterion.

$$o_{win} = \arg_j \min \| x(\mathbf{t}) - w_j(t) \|, \quad \mathrm{j} = 1,2,3,\ldots\ldots, \mathrm{k} \tag{4}$$

where $x(t)$ and $w_j(t)$ is the input vector and the weight vector which conntected to j-th output node, respectively, subscript j indicates the label of the output node, t is the number of iterations for learning. Then, update the weights of the winning node and those of its neighborhood as follows:

$$w_j(t+1) = w_j(t) + \eta(t)\left[x(t) - w_j(t)\right], \quad j \in \Lambda_{O_{win}}(t) \tag{5}$$

where $\eta(t)$ is the dynamic learning-rate parameter, and $\Lambda_{O_{win}}(t)$ is the neighbor-hood function centered around the winning node o_{win} ; both $\eta(t)$ and $\Lambda_{O_{win}}(t)$ are varied dynamically during for best results. And the learning rate $\eta(t)$ decreases gradually in time, as does the size of the neighborhood, in order to guarantee convergence to a unique limit. Repeat the above learning procedure until all training input samples have been assigned and the predefined learning step reaches or no noticeable changes in the weight are observed.

After the training procedure, the weight vectors of the network form a model of the input pattern space in terms of so-called prototypical feature patterns. Kohonen network can segment input bead image similar to training pattern by comparing with all trained weight vectors.

V. Classification experiments

1. System set-up and calibration

The developed vision sensor is located between squeeze rolls and a bead cutter(see Fig 1). In the given system configuration, a camera is calibrated using a known calibration object. The camera resolution is found to be 0.05 mm per one pixel after calibration. The resultant accuracy of bead height and bottom width is ± 0.1mm.

2. The classification procedure

To evaluate the performance of the proposed neural network classifier, a series of experiments for classification tasks were performed. In experiments, to get all kinds of bead shape for training data of neural network, the range of power input was selected as wide as possible in a given welding speed. Table 1 shows the welding conditions used for experiments.

Table 1. Welding conditions for the experiment.

Material		Carbon Steel
Thickness		4.7 mm
Size(outer dia.)		48.6 mm
Welding speed		48 m / min
Welding Power	Small	155.1 kW ~ 169 kW
	Optimal	169 kW ~ 194 kW
	Large	194 kW ~ 214.5 kW

From the experiments, 745 bead shapes and corresponding welding conditions were collected for training and testing the neural network. Among them, 615 samples were used for training and the remaining data of 130 were used to test the classification performance of the trained neural network. All sample images of bead shapes are grouped by an expert operator into three classes: Excessive heat input(E), optimal heat input(O) and insufficient heat input(I). Each sample image is a window sub-image automatically fitted to the location of weld bead with a size of 230 x 190 pixels. Since the classification algorithm can not overcome any shifts of the sample images in position, the location of the weld bead is automatically adjusted by calculating its relative position to the center of welding pipe from captured images.

As shown at the bottom of Fig 7, the number of input nodes which corresponds to horizontal pixel is 180, dividing at equal space the bead shape line image. Before training, each value of the weight vectors connected to the kth output node has a value lying between 0 and 100 pixel randomly. The initial value of learning rate is 0.5 and gradually decreases to 0.01 with time. The extent of the neighborhood relation is initially half the number of the output node and decreases in every 1000 iterations. The total number of iterations is 10000.

The performance of the classifier was evaluated from a classification error analysis. To do this, the appropriate neural network classifiers were designed by varying the architecture of the neural network. One of the design parameter includes the number of nodes in a competitive layer.

The classification error E used here is calculated as :

$$E = 1 - N_c / N_t (\%). \qquad (6)$$

where, N_c and N_t represent the number of correct classification samples and the total classification samples, respectively.

3. Classification results and discussion

To examine the effect of the architecture, the classification errors of various neural networks with different architectures were determined. After training different architecture of the neural network, the presence of dead output node defined as the one which contains less than 3% of total number of input patterns is checked. In this study, the number of cluster is selected as 12 because with the node number 13 the dead output node appeared as shown in Table 2. This structure is shown in Fig. 7 and the network weights connect the 180 inputs to the 12 output nodes. The weights of the trained network form a model of the input data in terms of so-called prototype images and represent their typical family of representative clusters of training data, as shown in Fig. 8.

These prototype images can also be labeled according to the class obtained with the prior knowledge of an expert. The results show that the classification error decreases with the number of output node. However, it is noted that as the number of output node increases, the computational burden increases. Therefore, the number of output nodes needs to be kept as small as possible, provided that the classification accuracy is satisfactory.

The classification results are presented for the best architectures in Table 3 and 4. Table 3 illustrates those of the training phase. For class (I), all test samples are correctly classified, resulting in a success rate of 100%. For class (E), 169 samples are correctly classified into four prototype images(first-fourth), while 2 and 3 samples are misclassified to the 6th and 7th prototype respectively, resulting in success rate of 97.13%. This misclassification is due to the unstable welding condition occurred by largely excessive heat input. At this heat input condition, the shape of bead becomes so unstable that various types of bead shape can be generated as shown in Fig 2. This irregularity gives a lower accuracy of classification. In this regard, the classification results of class (E) may be a problem for welding quality inspection of high-pressured pipe. To classify the bead shape perfectly on this condition, the other information such as the color of welding bead, current heat input, and frequency of welding current may be also examined. For class (O), 180 samples are correctly classified into four prototype(fifth-eighth) images, while 7 samples are misclassified to the 4th prototype respectively, resulting in success rate of 96.26%. The misclassification result of class (O) is not a critical problem, since , in this case, the misclassification occurs due to the very small differences of bead shape in their classificaton boundary. The total classification success rate for the whole image is 98.05%.

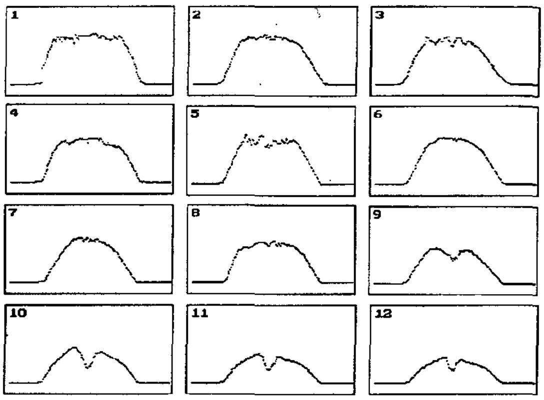


Fig. 8. Prototypical bead shapes for pattern classification.

Table 4 shows the classification results for the test which are not used for the training. For class (I), 38 samples are correctly classified and only one sample is misclassified to 8th prototype, resulting in a success rate of 97.44%. This misclassification is due to electromagnetic noise, which results in contamination in bead shape. Although the small concaveness in the image can be easily detected by the image sensor under small heat input, a few types of contamiation at the center of bead image under middle and high heat input are slightly similar to the concaveness in the bead.

For class (E), 48 samples are correctly classified into four prototype image groups(first-fourth), while 1 and 2 samples are misclassified to the 6th and 8th prototype, respectively, resulting in success rate of 94.12%. For class (O), 38 samples are correctly classified into four prototype(fifth-eighth) images, while 2 samples are misclassified to the 4th prototype respectively, which results in success rate of 95.00%. The total classification success rate of the whole image is 95.38%.

Table 2. Classification results with different number of output nodes.

Class no.	No. of output node		
	11	12	13
1	42	36	41
2	58	38	56
3	51	35	53
4	52	67	47
5	33	28	31
6	63	49	***13*
7	82	68	53
8	52	40	24
9	41	63	49
10	53	78	52
11	88	57	76
12		56	48
13			72

** : The presence of dead output node

The results obtained here reveal the relationship between heat input condition and bead shape, and the relationship has been successfully established by the neural network. If the welding condition may be changed, a similar neural bead shape classifier can be designed and trained using the experimentally obtained bead shapes. This neural network approach is more efficient to monitor weld quality and this current welding conditions for real HERW process than the geometrical feature-based method, considering accuracy, experimental cost and implementation time.

Table 3. Classification results of the training data.

Welding Power(kW)	No. of samples	Classification Result												No. of confusion
		Excess(E)				Optimal(O)				Insufficient(I)				
		1	2	3	4	5	6	7	8	9	10	11	12	
Large(194-214)	174	36	38	35	60		2	3						5
Optimal(169-194)	187				7	28	47	65	40					7
Small(155-169)	254									63	78	57	56	0
Total success rate														(1-12/615)x100=98.05%

Table 4. Classification results of the test data.

Welding Power(kW)	No. of samples	Classification Result												No. of confusion
		Excess(E)				Optimal(O)				Insufficient(I)				
		1	2	3	4	5	6	7	8	9	10	11	12	
Large(194-214)	51	5	14	17	12		1		2					3
Optimal(169-194)	40				2	15	7	10	6					2
Small(155-169)	39								1	10	9	7	12	1
Total success rate														(1-6/130)x100=95.38%

VI. Conclusions

In this paper, a neural network method has been proposed for the classification of the bead shapes in HEW pipe process. Although the images of bead shape are contaminated by noise such as welding spatters, and mutual reflection effect of laser light onto other surfaces on pipes, reliable and fast classification results have been achieved and its success rate is approximately 95%. Based upon these results, the Kohonen neural network is found to be a useful tool for bead shape classification for HERW pipe process. Compared to other feature based-classification methods[8,9], the advantage of the Kohonen network is that (1) no other image processing techniques to extract stable geometrical features from noisy image need to be required, (2) the number of experiments to find classification rules through geometrical features can be reduced, (3) this approach can be easily and quickly implemented in real HERW process even in the case when the welding condition may vary, (4) good classification results may be acquired even with noisy image. However, a disadvantage of this neural network is its probabilistic character so that classification results are not exactly reproducible.

The subjects for further research are (1) to enhance the performance of the classifier that can yield much better success rate, (2) to develop a new classification technique which can find the optimal number of cluster automatically, which guarantees the best classification performance, and (3) to apply the classification results to develop a fuzzy rule based controller to adjust heat input.

References

[1] H. Gondo, H. Haga, K. Aoki, and T. Sato, "Welding mechanisms in high-frequency electric resistance welding", *Nippon Steel technical report no. 14*, December, 1979.

[2] H. Haga and N. Mizuhashi, "High-frequency ERW phenomena and weld defect ratio under high-speed and large v-convergence angle condition", *Transaction ISIJ.*, vol. 25, 1986.

[3] H. Saito, A. Siga, T. Enami, M. Itatani, and H. Kasahara , "Relation between current voltage and power in oscillator and load circuit during HFERW", *Transactions ISIJ*, vol. 24,1984.

[4] S. Sugimura and H. Matsuda, "Welding technology in manufacture of large-diameter line pipe", *Nippon Steel Technical report no. 20*, December, 1982.

[5] H. Haga, K. Aoki, and T. Sato, "Welding phenomena and welding mechanisms in high frequency electric resistance welding - 1st Report", *Nippon steel Technical report*, 1986.

[6] N. Watanable, M. Funaki, S. Sanmiya, N. Kosuge, H. Haga, and N. Mizuhashi, "An automatic power input control system in high frequency electric resistance welding", *Nippon Steel Technical report*, 1986.

[7] N. Tanaka, T. Iwasaki, N. Watanabe, and Y. Tamura, "High frequency induction welded high-strength steel pipe", *Nippon Steel Technical report no.30*, July, 1986.

[8] Y. Mihara, "A new automatic heat input control for production of electric resistance welded pipe", *Transaction ISII*, vol, 26,1986.

[9] S. Ishiro, Y. Enomoto, Ikuo Takahashi, Isamu Komine, Yutaka Mihara, and Koji Suzuki, "Newly developed heat input control & monitoring system for ERW tube production", *Nippon Kokan Technical report*, 1987.

[10] O. Sugiyama, C. Takamadate, and T. Hikita, "Recent progress in automatic welding control system for ERW tube mill", *The Sumitomo search no.49*, April, 1992.

[11] T. Kyogoku, et. al., "Automatic welding control system for electric-resistance weld tube mill", *Sumitomo Technical report,*1983.

[12] H. S. Cho, J. H. Kim, and K. W. Ko, "Development of heat input control System for high frequency resistance welding machine", *Research Report*, Dept. of Mechanical Engineering, KAIST, Korea, 1993.

[13] K.W. Ko, H. S. Cho, and J. H. Kim, "A bead shape classification method using neural network in high frequency electric resistance weld ", pp. 1345~1349, *World Automation Congress'* 98, 1998.

[14] S. J. Gordon, "Real-time part position sensing", *IEEE Transactions on Pattern Analysis and Machine Intelligence* vol. 10. no.3, May, 1988.

[15] K. Ikeuchi and T. Kanade, "Modeling sensors : toward automatic generation of object recognition program", *Computer vision, Graphics , and Image processing*, vol. 48, P65-67, 1989.

[16] J.Paul, "Active, optical range image sensors", *Machine Vision and Application* vol. 2, pp. 127-152, 1988.

[17] R. Conzalez, and R. E. Woods, "Digital image processing", *addison wesley publishing company*, 3rd edition, 1998.

[18] H. Shapiro, "Computer and robot vision", vol. 1, *Addision Wesley Publishing Company*, 1992.

[19] D. H. Ballard, and C.M. Brown, "Computer Vision", *Prentice Hall*, 4th edition, 1999.

[20] J. Hertz, A. Krogh, and R.G. Palmer, "Introduction to the theory of neural computation", Addison-Wesley, 6th edition, 1997.

[21] Y Pao, "Adaptive pattern recognition and neural networks", *Addision-Wesley Publishing Company*, 5th edition, 1997.

[22] J. M. Zurada, "Introduction to artificial neural systems", *West Publishing Company*, 3rd edition 1998.

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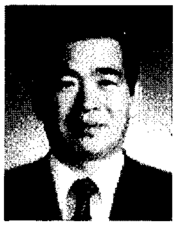

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Received his B.S. degree from Seoul National University, Korea in 1971, his M.S. degree from Northwestern University in 1973, Evanston, IL, and his Ph.D. degree from the University of California at Berkeley, CA, in 1977. From 1977 to 1978 he was a postdoctoral fellow with the Department of Mechanical Engineering, University of California at Berkeley. Since 1978 he has been a professor with Department of Production Engineering, Department of Automation and Design, Seoul Campus, and currently with Department of Mechanical Engineering, Korea Advanced Institute of Science and Technology(KAIST), Korea. From 1984 to 1985 he was a visiting scholar at the Institute für Produktionstechnik und Automatisierung (IPA), Germany where he carried out research on robot-based assembly. He has been invited as a short-term visiting scholar to several universities, Ritsumeikan University, Japan, University of Paderborn, Germany, and New Jersey Institute of Technology, USA, in 1987, 1992, 1998, respectively. From 1995 to 1996 as a visiting professor he participated in graduate school education for Advanced Manufacturing Program (AMP) of University of California, San Diego, USA.