Application of Neural Network to Visual Inspection of Weld Bead†

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Abstract

An example of application of neural network is introduced. The back propagation (BP) model is applied to the weld bead visual inspection. The bead shape data are divided into three categories. The network weight data are formed through the learning process for each category. It is shown that the discrimination between the sound bead and the defect bead can be done properly if the selection of the network parameters and the learning process are made suitably.

KEY WORDS :(visual Inspection), (Image Processing), (Neural Network),(Weld Bead)

1. Introduction

The neural network came to be paid attention again before several years and the concern of many researchers for it has presented the aspect of the boom of an overheat nature at certain time. This boom settles down a little and the breakthrough by the appearance of a more novel technique is expected. But, its practical applications to many fields are thought to be going to advance steadily in the other hand [1].

In this report, an example of application to welding engineering of the neural network in such current states is introduced. In welding engineering, the automation of the inspection process is thought to be one of the important problems to be solved. The weld bead visual inspection is focussed on here and the possibility of the neural network application is examined. A lot of models have been proposed to the neural network, and here, the application of the backpropagation(BP) model [2], which is considered to have the highest practicality, is shown. As for the BP model, the application examples have been reported in a lot of fields such as language processing, signal processing, image processing, character recognition, servo control, inspection, and economic modelling, etc. is reported. Generally, the region of each category in the characteristic space is not so clear in the product inspection such as the visual inspection compared with typical pattern classification such as character recognition etc. and the boundary is so vague. Therefore, the learning process for the neural network becomes important in application to the inspection. That is, what influence the selection of the training data on the learning result becomes a problem.

In the following, the result of examining the above-mentioned application is described from such view points.

2. Data Collection and Processing Methods

The weld bead test piece used to the visual inspection examination was made from a flat plate of mild steel by the on-plate MAG welding. The light of semiconductor laser through the optical system was irradiated from the vertical upper side to this test piece in the diagonal direction as shown in **Fig.1** and the contour shape of weld bead cross section was obtained. This contour shape was picked up with the TV camera and its image data were saved in the external memory of the personal-computer after converting in digital(512x480 pixels and 8 bits). Several examples of the contour shape of the weld bead cross sections are shown in **Fig.2**. Such image data are converted into one dimensional data which are defined in **Fig.3(a)**, show the bead shape after processings such as the thresholding, the noise rejection by expansion and reduction and thinning. The data of the edge part of the bead cross section are selectively extracted as a part where the normal bead, the undercut, and the overlap bead are characterized from such one dimensional data as shown in **Fig.3(b)**. The cross correlation coefficient of the matching pattern of **Eq.(1)** and the bead shape data is calculated as **Eq.(2)** and the point where this coefficient becomes maximum is decided in this extraction processing and 140 data sets centering on this point are obtained.

$$y_j = \begin{cases} -\overline{y} & 1 \leq j < 20, \\ -\overline{y} + \sin[(j-20)\pi/180] & 20 \leq j \leq 70 \end{cases} \qquad (1)$$

$$\overline{y} = 18/7\pi \int_0^{5\pi/18} \sin\theta \, d\theta$$

$$Ri = 1/70 \sum_{j=1}^{70} x_{i+j} \cdot y_j \qquad (2)$$

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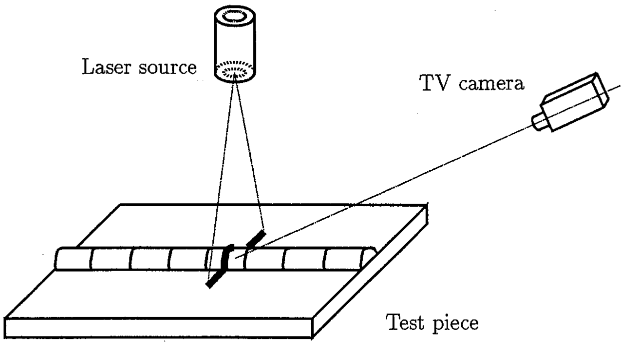


Fig.1 Slit light projection method to detect weld bead cross section.

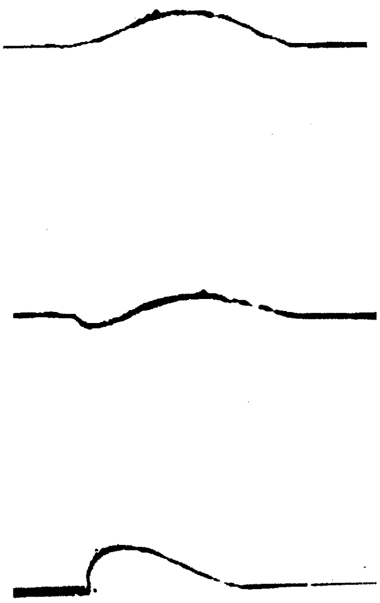
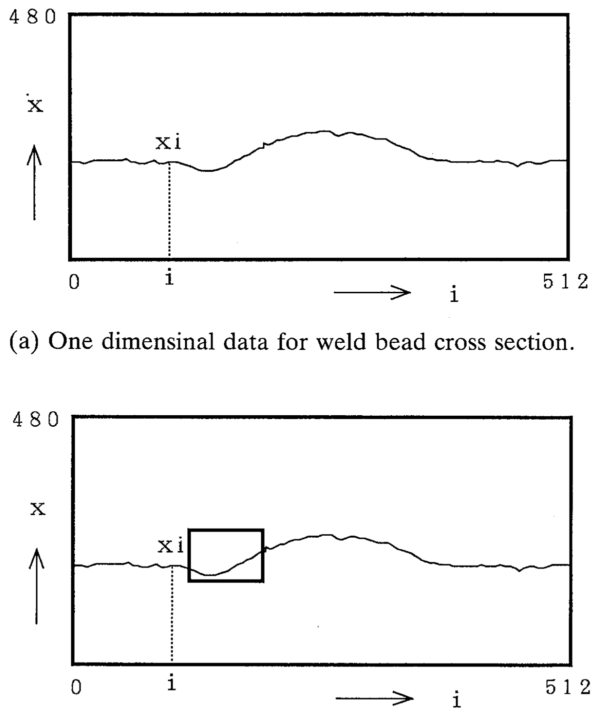


Fig.2 Three examples of detected configuration of weld bead cross section.

The matching pattern in Eq.(1) consists of the straight line part and the sine wave part as is seen in **Fig.4**. After the maximum and the minimum values are searched on these 140 data sets and they are normalized by 2^{16}-1(65,535) and 0 respectively, they become an input signal of the neural network. The bead edge data extraction processings are performed in both sides.

3. Composition of Neural Network

The composition of the BP model neural network used to the discrimination test is shown in **Fig. 5**. The network consists of three layer composition whose middle(hidden) layer is of one layer. The number of the unit in the input layer is set at 140 according to the input



(a) One dimensinal data for weld bead cross section.

(b) Extraction of edge part of weld bead cross section.

Fig.3 Data for weld bead cross section.

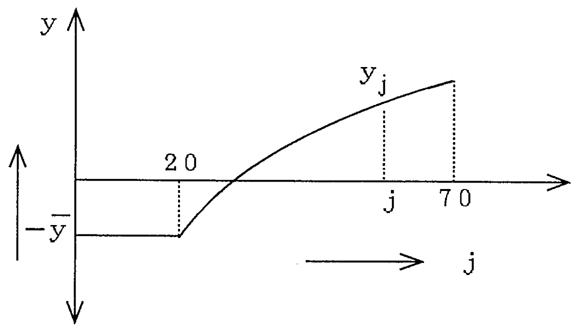


Fig.4 Matching pattern for bead edge data extraction.

signal. The number of the unit in the output layer is set at 3, corresponding to the bead shape category as the sound, the undercut and the overlap beads. The preliminary investigation was made by changing the number of the unit in the middle layer and the influence on the learning process and the discrimination result was examined. The following facts turned out as the result.

They are, the time in which the learning process converges increases with the number of the unit in the middle layer linearly, and the discrimination ability decreases with this number less than 15, but it is kept constant for the number more than 15. Therefore, the

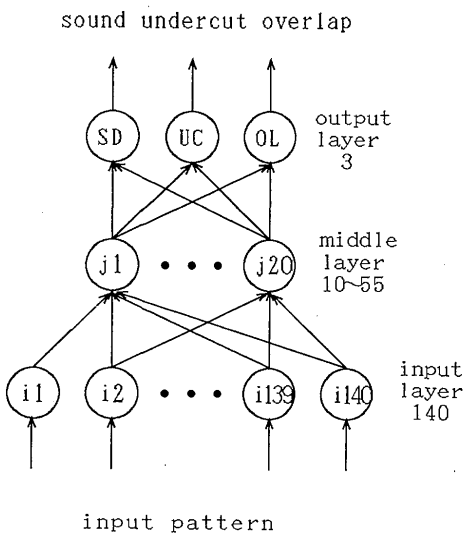


Fig.5 Composition of three layer BP neural network.

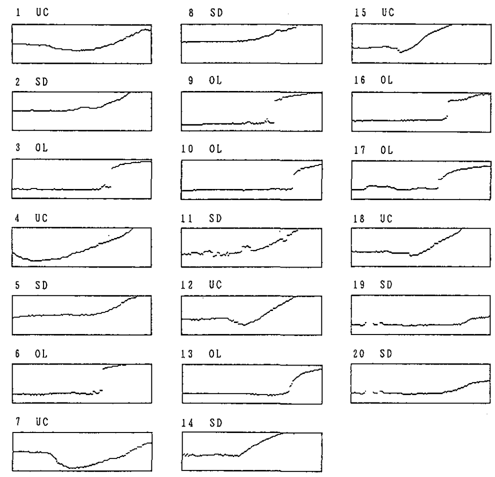


Fig.7 Input data for Learning Process(1).

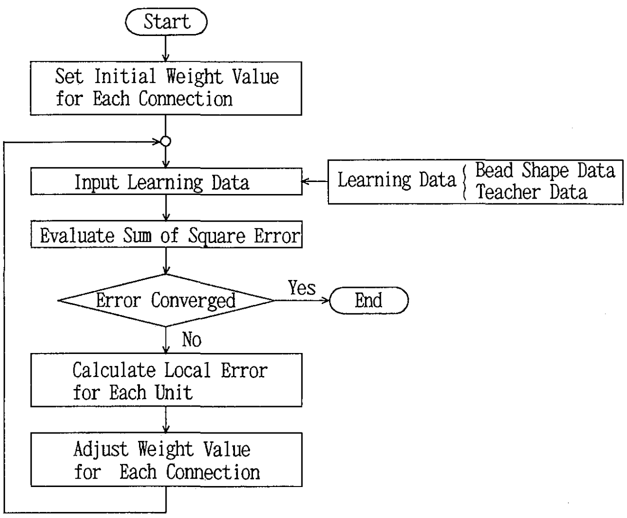


Fig.6 Algorithm for learning process.

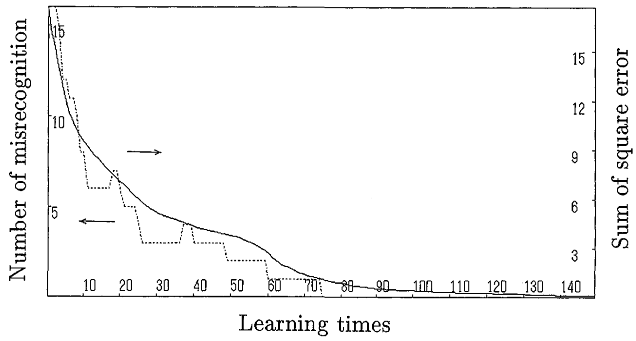


Fig.8 Characteristic curve of Learning Process(1).

number of the unit in the middle layer is set at 20 in the following test.

4. The Input Data and the Learning Process

The learning is done according to the backpropagation algorithm shown in **Fig.6**. The correction for the each weight on the connection which joints between the units in the different layers is repeated according to this algorithm by using **Eq.(3)** until the sum of the square of the difference between the actual and the desired output becomes small.

$$\left.\begin{aligned} \Delta w_{ij}^{[p]} &= -\alpha \cdot (\partial E/\partial w_{ij}^{[p]}) \\ E &= 0.5 \cdot \sum_{i=1}^{n_0} (d_i - o_i)^2 \end{aligned}\right\} \qquad (3)$$

where $\Delta w_{ij}^{[p]}$; correction value for the weight on the connection which joints between the jth unit in the p-1th layer and the ith unit in the pth layer ,E; sum of square of error , o_i; actual output of the ith unit in the output layer ,d_i; desired output of the ith unit in the output layer ,;αconnection weight correction coefficient.
First, the learning characteristic was examined on 20 different bead shape data shown in **Fig.7**. One of three kinds of the marks, SD, UC and OL is attached to each

data respectively, by which the distinction among sound, undercut and overlap bead is made in this figure. The desired data is given to the output layer unit corresponding to the category of the input data every times when one of 20 bead shape data is given to the input layer and the learning is executed. The learning characteristic curve for the connection weight correction coefficient 0.1 is shown in **Fig.8**. The ordinate expresses the deference between the desired output and the actual output(the number of mis-discrimination(left), the sum of the square error(right)), the abscissa expresses the learning times in this figure. As for the error, it is seen to settle to 0 with input data like Fig.7 in the learning of about 140 times. It turns out that the convergency of the error becomes worse as the the connection weight correction coefficient α becomes higher than 0.1 and no converging in <0.4 for the same shape data. The learning curve becomes **Fig.10** in case two data shown in **Fig.9** are appended to the shape data of Fig.7. The error converges after the converging pattern and the vibration pattern are repeated alternately in this learning curve. The learning times increases by about 30%. Such repetition of settling and the vibration is characteristic phenomenon in the learning process for the data not only in this example, but the data whoes features are not so remarkable. (It is necessary to add the data of Fig.9-1 so that the undercut bead of Fig.7-18 type may be distinguished from sound bead, and to add the data of Fig.9-2 to prevent the decrease in the discrimination ability for the sound bead of Fig.7-19,-20 type, which may be caused by adding the data of Fig.9-1.) The effect of appending these 2 data on the discrimination ability is described in the next chapter.

5. Discrimination Test

The test to discriminate three kinds of bead was performed for the unlearned data by using the connection weight obtained as the result of the learning process.

First, the 20 data shown in **Fig. 11** are selected for the test as the comparatively easily distinguishable data between sound bead and defect bead. **Table 1(a)** and **(b)** are the results of the tests which were made after the learning processes graphically shown in Figs.6 and 8. In this table, the figures in the most left column(column 1) are no. of the input data, the marks of the category corresponding to the input data are entered in the next column(column 2), for example, sd; sound bead, uc; undercut bead, ol; overlap bead, the largest data and the

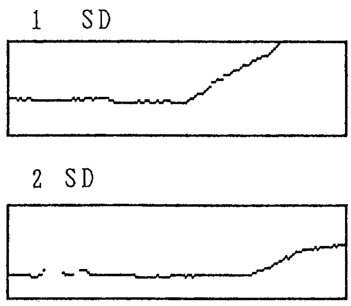


Fig.9 Input data for Learning Process(2).

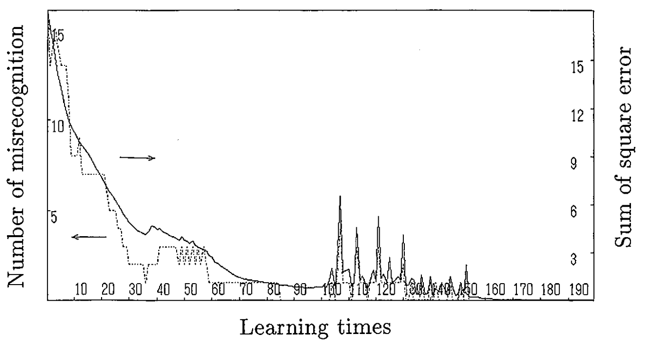


Fig.10 Characteristic curve of Learning Process(2).

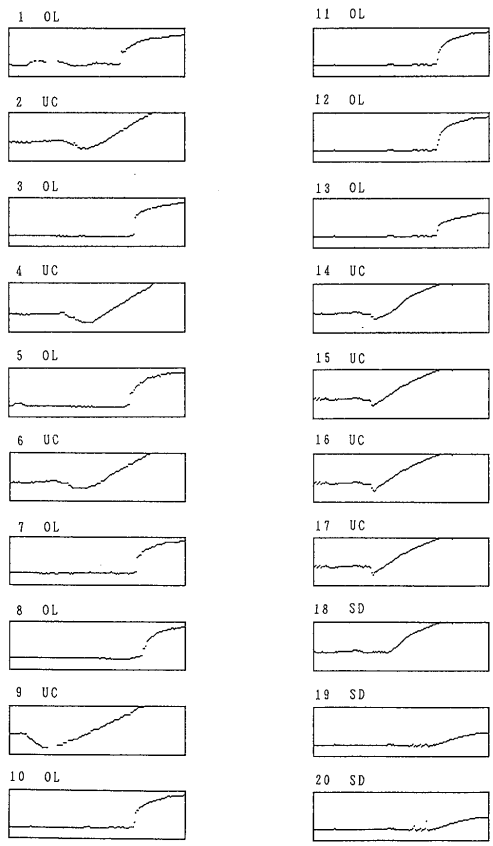


Fig.11 Input data for Recognition Test(1).

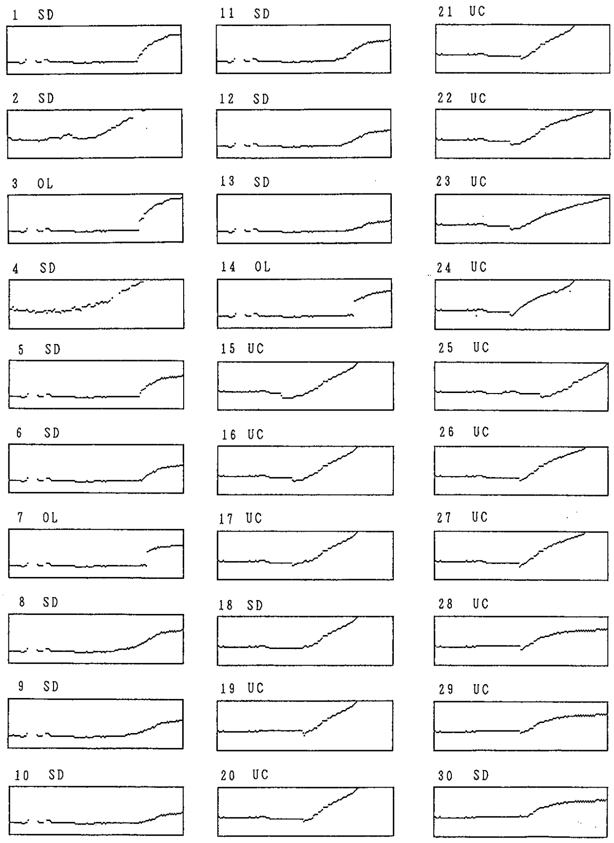


Fig.12 Input data for Recognition Test(2).

next largest data in the output values together with their category names are shown in the third and the forth columns(column 3 and 4) respectively (these values are normalized the maximum as 0.999 and the minimum as 0.000), and logarithm of the ratio of the values in both columns is put in the most right column(column 5). Therefore, it can be judged that the discrimination is correct in case the mark in the column 2 coincides with the mark in the column 3. The value in the column 5 will be named as DRI(Discrimination Reliability Index) in this report because the reliability in discrimination goes up as this value becomes large. The reliability is regarded as high in case DRI exceeds 1.0, while it should be as low for the value of about 0.3 or less. It can be seen in Table 1 that all the data of (a) and (b) in the table are discriminated correctly, but DRI values for the sound bead data such as 18,19,20 are improved, on the other hand, DRI for the most of the defect bead data decreases a little bit although it does not become a problem.

Next, the similar test was done by using the result of the same learning process on 30 data which have not so remakeable features of defect bead as shown in**Fig.12.** The test result is shown in**Table 2(2)**and**(b)**.The sound beads such as 1 and 18 are mis-discriminated as defect bead in (a) of this table, however, in (b), this mis-discrimination is not only canceled, but DRIes for some sound beads as 2, 4, 5, 8, 11, 30 are greatly improved. On the contrary, DRIes for the defect beads become lower as are seen on the data of 3, 7, 14, 17, 20, 21, 26, and 29, etc in (b). It can be said from such results that the learning method which improves the discrimination reliability for sound bead may occasionally cause the mis-discrimination for the defect bead whose feature is near the distinguishable limit as sound bead. This fact has also been confirmed by other experiments than the example

Table 1 Rsults of Discrimination Test(1).

data no.	*input*	*output 1(level)*	*output 2(level)*	*DRI*
1	ol	ol(0.949)	sd(0.043)	1.34
2	uc	uc(0.997)	sd(0.004)	2.40
3	ol	ol(0.993)	sd(0.010)	2.00
4	uc	uc(0.998)	sd(0.003)	2.52
5	ol	ol(0.998)	sd(0.004)	2.40
6	uc	uc(0.986)	sd(0.016)	1.79
7	ol	ol(0.997)	sd(0.012)	1.92
8	ol	ol(0.992)	sd(0.026)	1.58
9	uc	uc(0.995)	sd(0.007)	2.15
10	ol	ol(0.995)	sd(0.019)	1.72
11	ol	ol(0.995)	sd(0.018)	1.74
12	ol	ol(0.995)	sd(0.018)	1.74
13	ol	ol(0.993)	sd(0.023)	1.64
14	uc	uc(0.989)	sd(0.036)	1.44
15	uc	uc(0.995)	sd(0.013)	1.88
16	uc	uc(0.997)	sd(0.008)	2.10
17	uc	uc(0.997)	sd(0.007)	2.15
18	sd	sd(0.747)	uc(0.396)	0.28
19	sd	sd(0.160)	ol(0.120)	0.12
20	sd	sd(0.328)	uc(0.030)	1.04

sd ; sound bead
uc ; undercut bead
ol ; overlap bead

(a) By result of Learning Process(1).

data no.	*input*	*output 1(level)*	*output 2(level)*	*DRI*
1	ol	ol(0.965)	sd(0.030)	1.51
2	uc	uc(0.997)	sd(0.008)	2.10
3	ol	ol(0.993)	sd(0.014)	1.85
4	uc	uc(0.998)	sd(0.006)	2.22
5	ol	ol(0.998)	sd(0.006)	2.22
6	uc	uc(0.986)	sd(0.038)	1.41
7	ol	ol(0.997)	sd(0.015)	1.82
8	ol	ol(0.989)	sd(0.033)	1.48
9	uc	uc(0.995)	sd(0.007)	2.15
10	ol	ol(0.995)	sd(0.024)	1.62
11	ol	ol(0.995)	sd(0.023)	1.64
12	ol	ol(0.995)	sd(0.023)	1.64
13	ol	ol(0.994)	sd(0.026)	1.58
14	uc	uc(0.989)	sd(0.034)	1.46
15	uc	uc(0.995)	sd(0.012)	1.92
16	uc	uc(0.997)	sd(0.008)	2.10
17	uc	uc(0.997)	sd(0.008)	2.10
18	sd	sd(0.854)	uc(0.371)	0.36
19	sd	sd(0.410)	ol(0.044)	0.97
20	sd	sd(0.758)	uc(0.031)	1.37

(b) By result of Learning Process(2).

Table 2 Rsults of Discrimination Test (2).

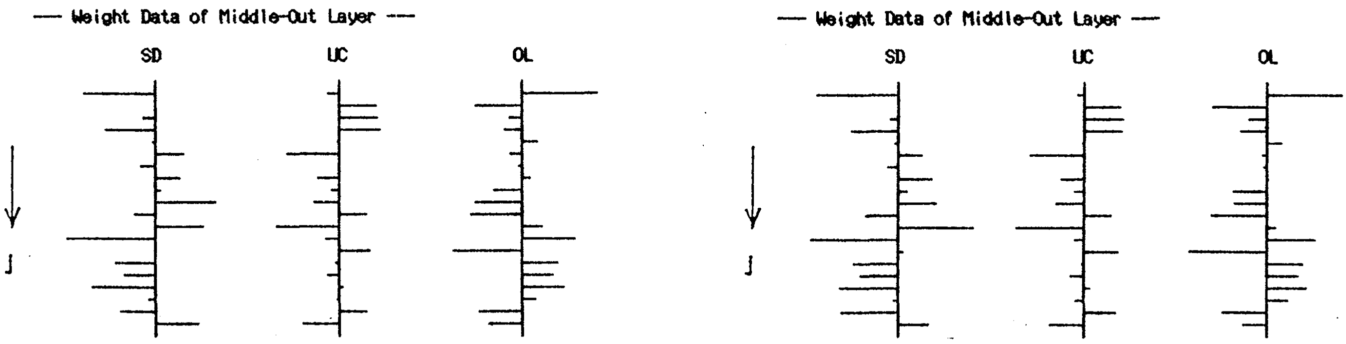
data no.	input	output 1(level)	output 2(level)	DRI
1	sd	ol(0.750)	sd(0.419)	X
2	sd	sd(0.378)	ol(0.185)	0.31
3	ol	ol(0.939)	sd(0.148)	0.80
4	sd	sd(0.368)	uc(0.335)	0.04
5	sd	sd(0.643)	ol(0.448)	0.16
6	sd	sd(0.938)	ol(0.033)	1.45
7	ol	ol(0.979)	sd(0.036)	1.43
8	sd	sd(0.832)	ol(0.227)	0.56
9	sd	sd(0.951)	ol(0.021)	1.66
10	sd	sd(0.988)	uc(0.006)	2.22
11	sd	sd(0.578)	ol(0.533)	0.04
12	sd	sd(0.953)	ol(0.022)	1.64
13	sd	sd(0.988)	uc(0.006)	2.22
14	ol	ol(0.951)	sd(0.084)	1.05
15	uc	uc(0.992)	sd(0.009)	2.04
16	uc	uc(0.978)	sd(0.013)	1.88
17	uc	uc(0.756)	sd(0.066)	1.06
18	sd	ol(0.597)	sd(0.314)	X
19	uc	uc(0.897)	sd(0.019)	1.67
20	uc	uc(0.800)	sd(0.038)	1.32
21	uc	uc(0.801)	sd(0.038)	1.32
22	uc	uc(0.974)	sd(0.028)	1.54
23	uc	uc(0.987)	sd(0.020)	1.69
24	uc	uc(0.979)	sd(0.032)	1.49
25	uc	uc(0.315)	sd(0.133)	0.37
26	uc	uc(0.747)	sd(0.093)	0.90
27	uc	uc(0.968)	sd(0.022)	1.64
28	uc	uc(0.986)	sd(0.010)	1.99
29	uc	uc(0.739)	sd(0.104)	0.85
30	sd	sd(0.727)	ol(0.121)	0.78

(a) By result of Learning Process(1).

data no.	input	output 1(level)	output 2(level)	DRI
1	sd	sd(0.784)	ol(0.312)	0.40
2	sd	sd(0.918)	uc(0.037)	1.39
3	ol	ol(0.804)	sd(0.347)	0.36
4	sd	sd(0.566)	uc(0.339)	0.22
5	sd	sd(0.945)	ol(0.060)	1.20
6	sd	sd(0.992)	ol(0.003)	2.52
7	ol	ol(0.856)	sd(0.145)	0.77
8	sd	sd(0.976)	ol(0.027)	1.56
9	sd	sd(0.993)	ol(0.003)	2.52
10	sd	sd(0.997)	uc(0.006)	2.22
11	sd	sd(0.914)	ol(0.102)	0.95
12	sd	sd(0.994)	ol(0.002)	2.70
13	sd	sd(0.997)	uc(0.005)	2.30
14	ol	ol(0.780)	sd(0.221)	0.55
15	uc	uc(0.992)	sd(0.019)	1.72
16	uc	uc(0.979)	sd(0.041)	1.38
17	uc	uc(0.723)	sd(0.358)	0.31
18	sd	sd(0.975)	ol(0.027)	1.56
19	uc	uc(0.907)	sd(0.068)	1.13
20	uc	uc(0.794)	sd(0.258)	0.49
21	uc	uc(0.798)	sd(0.256)	0.49
22	uc	uc(0.971)	sd(0.065)	1.17
23	uc	uc(0.986)	sd(0.034)	1.46
24	uc	uc(0.975)	sd(0.065)	1.18
25	uc	uc(0.475)	sd(0.068)	0.84
26	uc	uc(0.705)	sd(0.417)	0.23
27	uc	uc(0.969)	sd(0.058)	1.22
28	uc	uc(0.988)	sd(0.019)	1.72
29	uc	uc(0.718)	sd(0.330)	0.34
30	sd	sd(0.984)	uc(0.011)	1.95

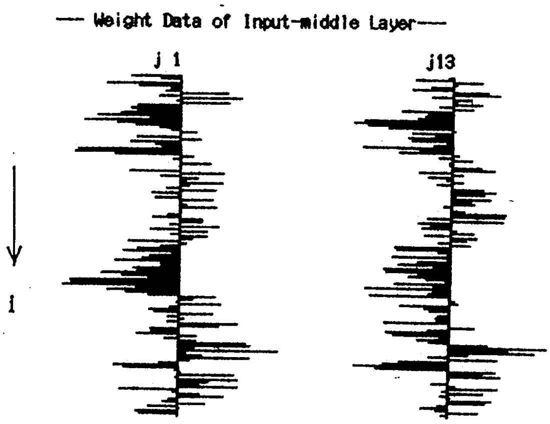
(b) By result of Learning Process(2).

sd ; sound bead
uc ; undercut bead
ol ; overlap bead

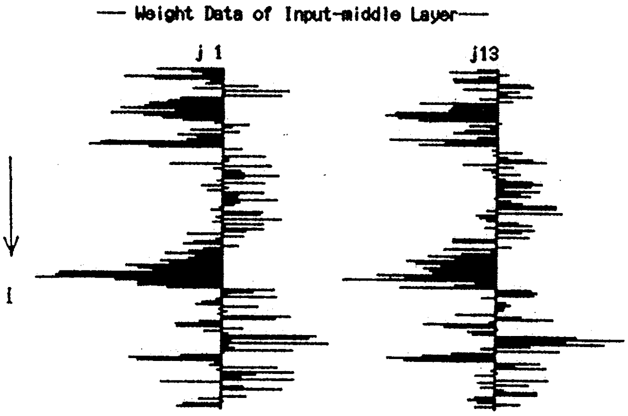


(a) Result of Learning Process(1). (b) Result of Learning Process(2).

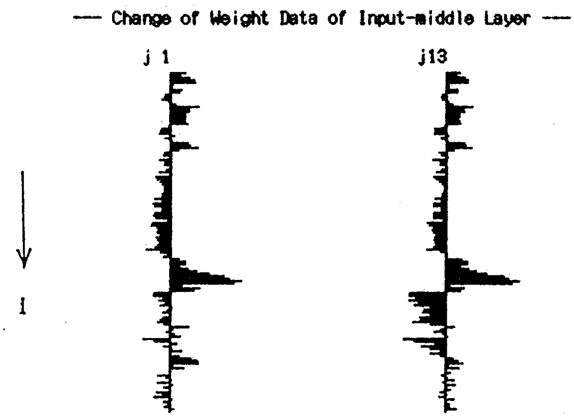
Fig.13 Diagram of weight data on connecting between middle layer and output layer.



(a) Result of Learning Process(1).



(b) Result of Learning Process(2).



(c) Difference between Learning Process(1) and (2).

Fig.14 Diagram of weight data on connecting between input layer and middle layer.

given here. The learning method which emphasizes the defect bead relatively may be preferable, because the mis-discrimination of defect bead as sound bead is at the more dangerous side than the mis-direction of sound bead as defect bead juding from the above described test result.

It is important to select the desired data suitably at the learning process according as the purpose of the inspection.

6. Examination of weight on connection

The weight on the connection jointing between the units in the middle layer and the output layer is graphically displayed as in **Fig.13(a)** and **(b)**. The formation of the weights through the learning processes in Figs.6 and 8 is visualized by these graphes. In Fig.13, (a) and (b) corresepond to the learning processes of Figs.6 and 8, each vertical line corresponds to one of 3 units in the output layer, each horizontal segment line at the position j on this vertical line expresses the size of the weight on the connection jointing between the unit itself in the output layer and the j-th unit in the middle layer by its segment length(in an arbitrary unit, right direction ; positive, left direction ; negative). It is seen in Fig.13 that the 1st, 12th 13th and 14th units of the middle layer have relatively strong influence on the output layer units as a whole, but there is no remarkable difference between (a) and (b).

Then, the weights on the connections which joint between the 1st and 13th units of them and the 140 units of the input layer are shown in **Fig.14** by similar graphic display. The graphes **(a)** and **(b)** are drawn in the same manner as the previous figure and the difference of the weight values of (a) and (b) ((a)-(b)) is calculated and displayed in the graph **(c)**. So, the graph (c) shows the effect of addition of the 2 data in the learning process straightforwardly. It is seen from this graph that the somewhat suppressing reaction to input appears in about 10 data before and behind the approximate 80th data in the 140 data sets of the input layer. Such part of data often characterizes defect bead as are seen from Fig.5 etc. Then, it is concluded that the reaction to the feature of defect bead is suppressed a little by having added two data of sound bead.

Such result gives a lot of suggestions to the learning process for the defect inspection by the BP network.

7. Conclusion

The description in this paper is summarized as follows.

1. The cross-sectional shape of the weld bead is converted into one dimensional data and the bead edge shape data

which charaterizes the quality of the weld result can be extracted by the cross correlation operation of these data with the previously set matching pattern as 100 and tens of bytes data.

2. The weld bead is classified into three categories as sound bead and two types of defect beads by the pattern of the above-mentioned weld bead edge shape. The discrimination, which works up to the level with a rather high difficulty degree, between sound and defect beads is possible by using the result of the learning process in which these weld bead edge shape data are used as the training data in the BP model neural network.

3. The set condition of appropriate neural network work parameters and the learning method were examined to improve above mentioned discrimination. As the result, it is proved that the precise control of the discrimination will become possible if the adopted training data are carefully selected according as the purpose of the visual inspection.

The discrimination and the detection technique for the defect bead described here can be applied to the defect beads of other types and categories with a little correction. Therefore, it can be added to say that the generality of the technique described here is not lost by the type of the defect beads having been limited.

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