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# Noise Rejection for Joint Configuration Detection of Arc Welding by Using Neural Network<sup>†</sup>

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## Abstract

*On using the signal processing ability of Backpropagation Model of Neural Network, the noise rejection is performed on the image of a joint part of arc welding. The object image, which is obtained by the slit light slice method, is often used for the detection of joint configuration on the purpose of welding automation. The noise caused by the welding arc is superimposed on the image and disturbs the detection. Such noise is rejected through the learning process of Neural Network which is carried out for the noise imposed input images and the noiseless teacher images. The structure of the network, the image input method, the selection of the teacher image and the method to recover the resolution of the processed result are investigated experimentally. It is shown that the noise rejection is successfully done as the results.*

**KEY WORDS:** (Arc welding)(Automation)(Sensor)(Joint configuration)(Weld line detection)  
(Light slice method) (Noise rejection)(Neural network)(Backpropagation)

## 1. Introduction

The perfect automation of welding, especially, arc welding is an important problem for the application of high temperature engineering. The detections of the weld line and the shape of the weld joint configuration are part of this problem<sup>1)</sup>. Many discussions have been made and various kinds of method have also been proposed for this detection problem over these last twenty or thirty years, however, it is not yet settled conclusively. The application of the light slice method was proposed as one of the effective methods for this detection and many instances of its practical use have been presented<sup>2)</sup>. This method is a type of image measurement. The disadvantage of this method is that the noise caused by the welding arc is superimposed on the image and disturbs the detection. Signal processing of any kind is required to reject such noise effectively.

On the other hand, the neural network, and especially, the learning ability of "Perceptron"<sup>3)</sup>, had

attracted the attention of many researchers. It received further attention after the publication of the backpropagation algorithm<sup>4)</sup> because of its robustness and has enjoyed a certain boom as a consequence. This boom is now settling down, but, it seems that fundamental and application researches on neural networks advance steadily. Though there are many instances of pattern recognition as an application of the backpropagation algorithm, the applications for signal processings such as enhancement, data compression, and noise rejection have also been proposed.<sup>5)</sup>

Here, the author remarked on its noise rejection ability and examined the rejection of noises which would be imposed on the images of the light slice method during arc welding. The method is described in the following sections.

## 2. Pickup of Object Image and Processing

### 2.1 Pickup of image data preprocessing

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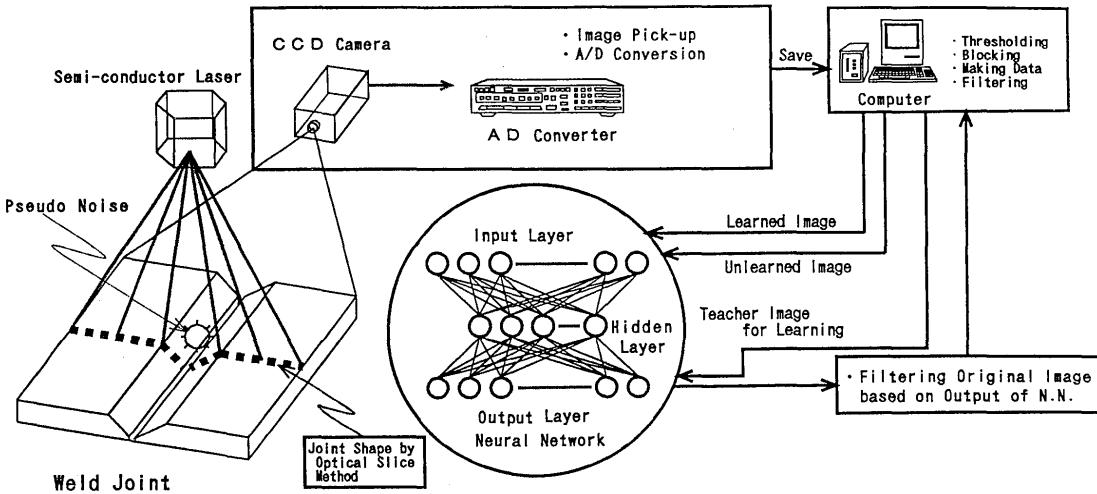


Fig. 1 Schematic illustration of processing system.

First, the hardware system used in this work is shown in **Fig.1**. The light of a semiconductor laser (780nm, 30mW) is used to irradiate on the joint part of the work piece by rectilinear shaping through a cylindrical lens. The light slice figure of the joint configuration obtained is as shown in the left part of Fig.1. The pseudo noise which simulates the influence of the welding arc light is superimposed on the figure by projecting other spot lights simultaneously here and there near the weld joint part. This figure is converted into a digital image of 512x480 pixels, and 8 bits, with an image data input device and saved in the external memory of a PC(Personal Computer, NEC PC98). The image signal is recorded as analogue data with the video floppy device at the same time so as to be able to replay and perform reprocessing as occasion calls. These image data become the input of the specially designed neural network device (MiTech Co., NEURO\_TURBO\_MAX\_SYSTEM) after compressing them into 30x30 pixels of data and thresholding with the PC. The dynamic algorithm, which can determine automatically the threshold level based on the profile of the gray level histogram of the image data, is adopted at the thresholding. All processing algorithms, which include those shown in the following text, are described in C language(TURBO C(v.2.0)).

## 2.2 Outline of learning and noise rejection

The neural network which performs the learning and the noise rejection is constructed as a version of the

back propagation method with one hidden( middle ) layer. A network of this type, in which each element in a certain layer is connected to all elements in other nearby layer(s) as shown in Fig.1, performs the learning on the basis of the generalized delta rule. The equation according to its algorithm is shown as **Eq.1**.

$$\Delta w(n) = -\alpha E + \beta \Delta w(n-1) \quad (1)$$

In Eq.1,  $\Delta w(n)$  is the value to modify the weight on connecting two elements in different layers at the  $n$ -th learning,  $E$  is the value derived from the error( the difference between the output data and the teacher data). Therefore, Eq.1 indicates that the weight is to be modified by the first term, which is proportional to the value of error and the learning coefficient  $\alpha$  and the second term which is proportional to  $\Delta w(n-1)$ , the modifying value of the previous time, and the momentum coefficient  $\beta$ . The proper setting of the learning and the momentum coefficients allows the balancing of learning speed and stability of performance. Here, let the former be 0.2, the latter 0.9.

The number of elements of the hidden layer is variable, that of the output layer is equal to 30x30, the same value of the input layer. The sigmoid function as expressed by **Eq.(2)** is used as the neuron function for each element of the hidden and the output layers. ( Normalization only is done in the input layer. )

$$f(x) = 1/[1 - \exp(-\mu x)] \quad (2)$$

As is seen in Eq.(2), the function  $f(x)$  is of the saturation type, the change of slope near the origin becomes steep

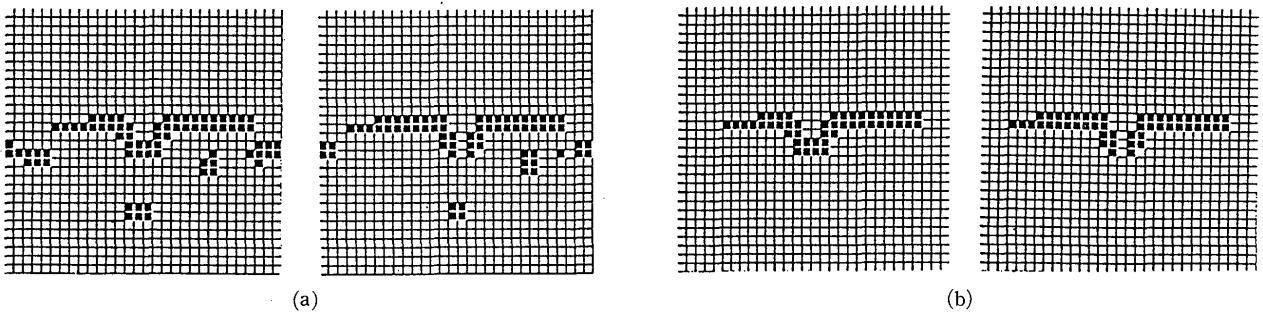


Fig. 2 Examples of input images for learning and teaching. (a) Learning images. (b) Teacher images.

or gentle according to the value of the parameter  $\mu$ . Here, let  $\mu$  be 1<sup>9</sup>.

The teacher data in the learning process are given in the manner to be described in Sect.3. The learning process is evaluated by the difference between the output data and the teacher data, the learning process finishes at the time when the evaluation value converges to a small enough value. The result of learning is saved in the external memory of the PC as the weight on connection joining each element in the input, the hidden and the output layers. The virgin data( inexperienced in learning process ) are processed with the network which is created using these weight data and the noise rejection result is obtained as the output of the processing.

### 2.3 Evaluation for noise rejection result

The noise rejection result is evaluated as the degree of coincidence of joint shape and the noise rejection ratio, which are calculated using Eqs.(3) and (4), shown in the following, from the input, the output and the teacher data. Averaging of these data is done for the evaluation of many image figures.

$$C = 100(2s - t)/s \quad (3)$$

$$R = 100(n - t + s)/n \quad (4)$$

where

$C$  : coincidence degree of joint shape (%)

$R$  : noise rejection ratio (%)

$t$  : total output values of all elements in output layer

$s$  : total normalized output of teacher image

$n$  : total output of elements in output layer which correspond to pixels of noise in the input image for the learning process

In the above equations, in the case that  $t=s$  the

output data fully coincide with the teacher image data ), both values of  $C$  and  $R$  become 100(%), but in the case  $t>s$ , where the noise is not completely rejected in the output image, both values become less than 100. Therefore, they are the indices by which the former represents the coincidence with the teacher image and the latter represents the degree of noise rejection. Specifying the noise pixel is done by eye measurement for obtaining the  $n$  value in the above processing. The center position of the weld joint( position of weld line ) and the output state of the joint configuration, etc. are also measured and judged by eye in the necessary case.

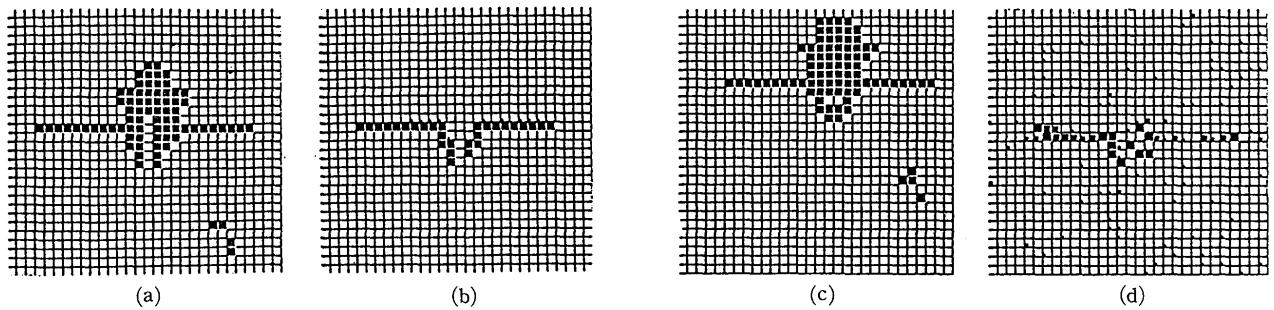
## 3. Examination for Learning Method

### 3.1 Position of object and learning method

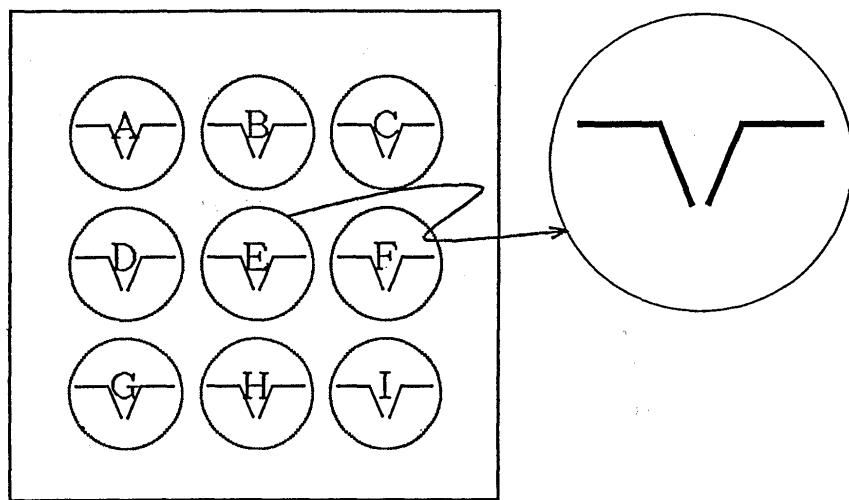
An example of the noise imposed weld joint image which has been used in the learning process is shown in Fig.2(a), the teacher image corresponding to the example image is shown in (b) of the same figure. The teacher image is obtained by rejecting the noise artificially( by eye measurement ) from the image for learning. The 40 teacher images in which the center of the joint exists, near the center of the figure, have been obtained by this method, the learning processes are done according to the algorithm described in Sect.2.

The examination for the processing is performed by using these results.

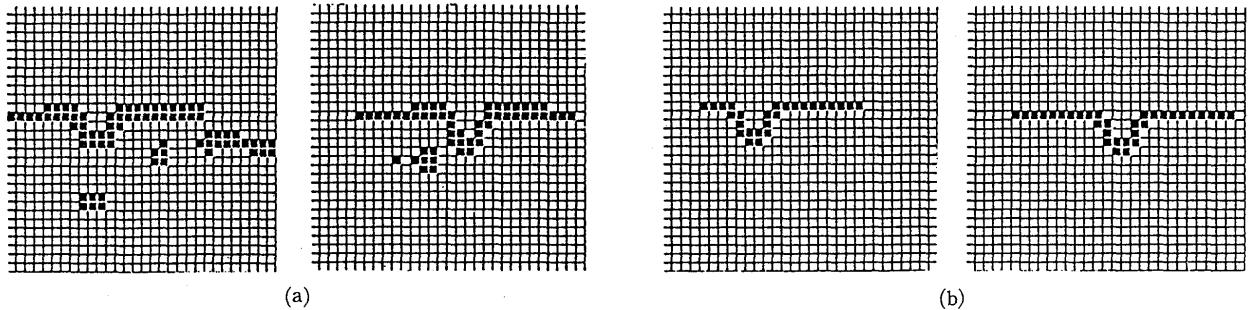
The result of the examination is shown in Fig.3. An example of the input image for the examination is shown in (a) of this figure. In case that the center of the joint exists at almost the same position as in the teacher images, even if severe noise is superimposed, as is seen in this example, a noise-fully-rejected image is put out



**Fig. 3** Examples of input and output images for processing test.(a) Input image 1. (b) Output image 1. (c) Input image 2. (d) Output image 2.



**Fig. 4** Position index of object in learning image.



**Fig. 5** Examples of learning image and teacher image for learning method ②.(a) Learning image.(b) Teacher image.

from the network as shown in (b). The figure(c) is another example of the input image in which the center of joint exists in the upper part of the frame. In this case, the improper image as shown in the figure(d) is put out due to the difference of the object position between the input image and the teacher image. It is understood that variation of the object position must be considered in the learning process.

Therefore, the images for learning are selected so that the center position of the weld joint can be located equally on the 9 segments( A-I ) of the figure, which are

shown in Fig.4. An adequate response is then obtained concerning the variation of the object position in the input image in the results, as described later.

### 3.2 Examination of teacher image

A comparative examination is done of the next items ① and ② for the teacher image at the learning stage.

- ① The image is obtained by rejecting the noise artificially( by eye measurement ) from the input image

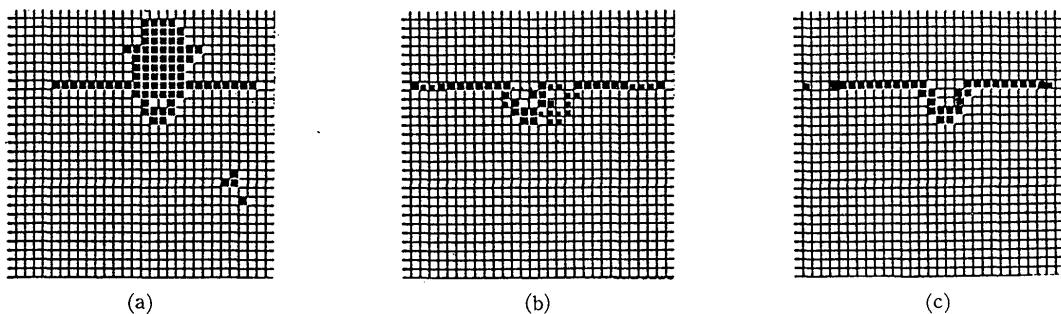


Fig. 6 Example showing difference between learning method ① and ②. (a) Input. (b) Output image by learning method ①. (c) Output image by learning method ②.

- Average Coincidence Ratio for Learned Images
- Average Coincidence Ratio for Unlearned Images
- Average Noise Elimination Ratio for L. Images
- Average Noise Elimination Ratio for U. Images

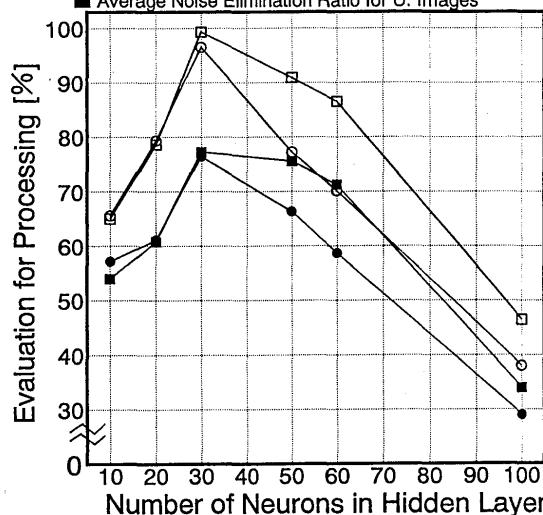


Fig. 7 Effect of number of neurons in hidden layer on coincidence ratio.

as described in the previous section.

② The image has a standard preset configuration regardless of the joint shape of the original input image. Only the center position of the joint coincides with that of the input image as is seen in Fig.5 (a) and (b). Hereafter, it is called as the standard teacher image.

The learning is conducted by using the teacher image ① or ② on 40 images which have the joint center position in any of the segments A - I described above and which have various degree of noise in themselves. Hereafter, these images are called as the standard images at the learning stage. The noise rejection ability is tested by using the learning result on 90 inexperienced images. Judging from the joint shape of the output image of the test results, 79 and 80 images are successful in the case that the teacher image is of type ① or ② respectively.

The example which shows the difference of the

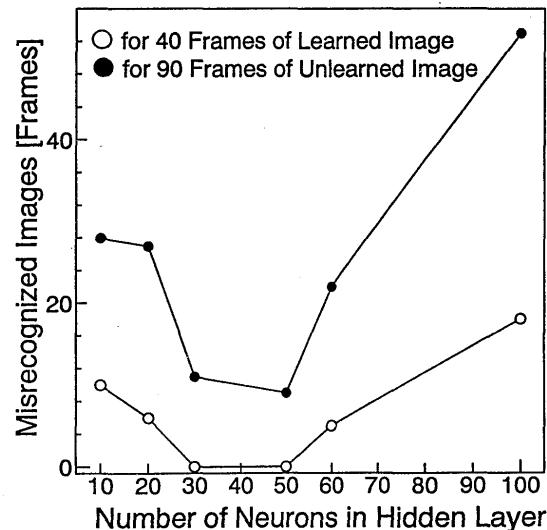


Fig. 8 Effect of number of neurons in hidden layer on mis-recognition.

processed results by ① and ② is given in Fig.6. An unsatisfactory result is obtained, as shown in this example, when the image is very noisy. The mean noise rejection ratio, defined by Eq.(2), for the 90 tested images is 88.0% by ① and 92.1% by ②. It may be concluded that a slightly better result is obtainable for the learning stage when a teacher image of ② type is used.

However, it is better that the teacher image ① or ② should be selected on the basis of whether the joint shape changes greatly or not during the detection process.

#### 4. Construction of Neural Network

The number of elements( neurons ) of the input and the output layers in the neural network must be limited as 30x30( =900 ), as described in the previous section,

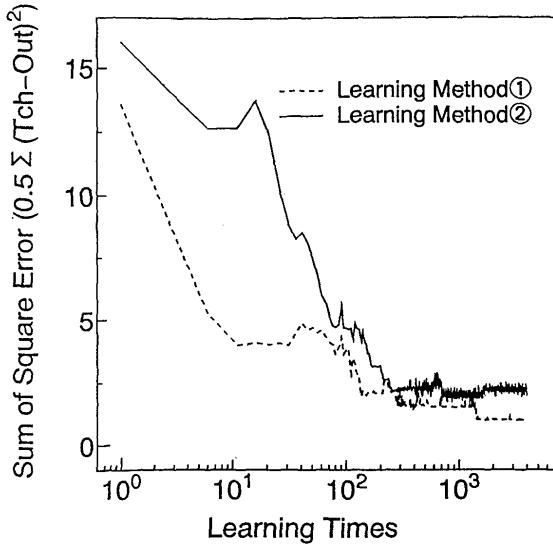


Fig.9 Example of learning curves.

owing to the restriction of the hardware.

The number of the elements in the hidden layer is examined in this section. It is confirmed that a linear relationship exists between the time and the number of the elements in the hidden layer when the learning is made using the standard images with 10 - 100 elements in the hidden layer. The mean coincidence degree of joint shape and the mean noise rejection ratio( the mean values of  $C$  in Eq.(1) and  $R$  in Eq.(2).) are obtained by using the learning result from the 90 images, the standard image for the test. Figure 7 shows the result. This figure also shows the result for the standard image at the learning stage. The relation between the number of the elements in the hidden layer and the number of the mis-recognised images is shown in Fig.8. It is concluded that there is an optimum value, which is 30 under the condition of this study, for the number of the elements in the hidden layer.

The structure of the neural network composed of this optimum value resembles a sand glass form whose middle part is constricted. The noise rejection method in this study can be regarded as an associative memory model, because it recovers the noiseless image from the noise disturbed image. As it is well known that the form of the network becomes of this type in such a model,<sup>7)</sup> it is in good agreement with the experiments in this study.

## 5. Learning and Its Results

### 5.1 Learning process

The learning curves for the standard images of the learning process( mentioned in Sect.3.2 ) are shown in Fig.9 (a) and (b). They correspond to the teacher images ① and ② respectively. The total error is plotted as the ordinate in this figure. The total error is defined as the total sum of the square of difference between the output of all elements in the output layer for all standard learning images, and the output of the corresponding pixels of the teacher image. The convergence is better and the total error at the convergence is somewhat smaller in the case of the teacher image ①.

It takes about 30 minutes for 1000 learning cycles under the learning condition shown above. This time is estimated to be of the order of 1 hour at the most for larger volumes of learning data.

### 5.2 Noise rejection ability

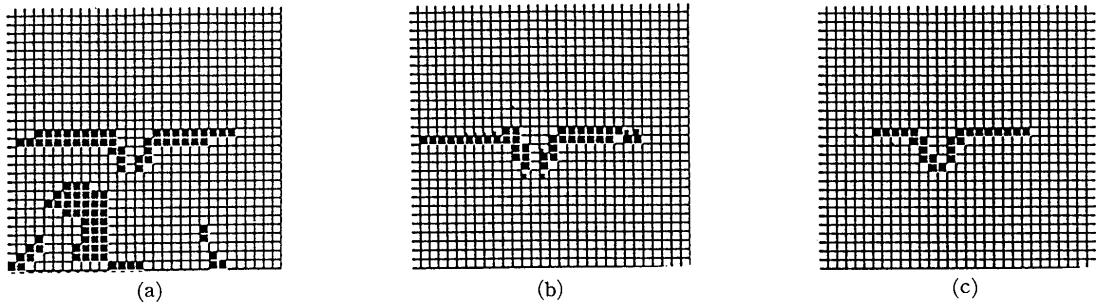
Similar results for noise rejection, as shown above, are obtained for various kinds of images using the same method as is described. Both good and bad examples for noise rejection states are shown in the following figures. In Figs.10-12, the input images are shown in (a) and the learning results with the teacher image ① and ② are shown in (b) and (c) respectively.

Figure 10 shows an example where gross noise is superimposed on the image, but it is applied at a position away from the joint line, so proper results are obtained in both the cases of (b) and (c).

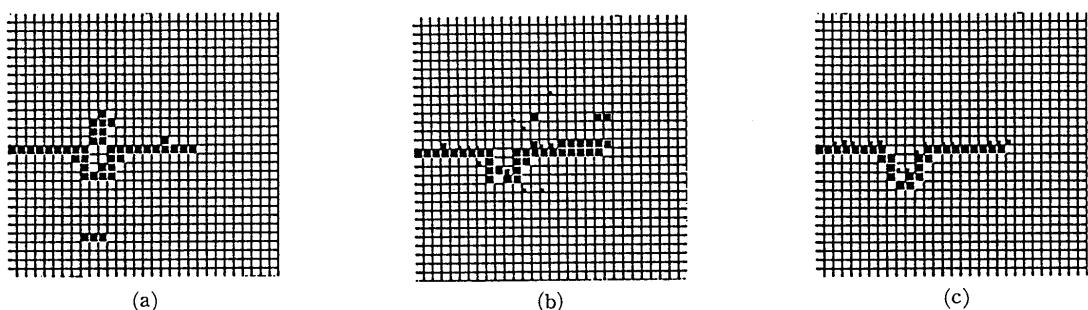
In Fig.11, the noise is smaller than that in the former example, but it is applied near the joint line, so the rejection state is poor in (b), while it is good in (c).

The noise rejection is incomplete and the joint shape itself also generates inaccurate information in the case where the gross noise, which touches the joint image directly and fully, is applied as is seen in the example of Fig.12 (a). An improvement of image pickup using optical filters and further investigation for the learning method is necessary to solve this problem. The processing time( from the input of image data into the neural networks to the output of the processed result ) is about 50(ms) for all the examples cited here.

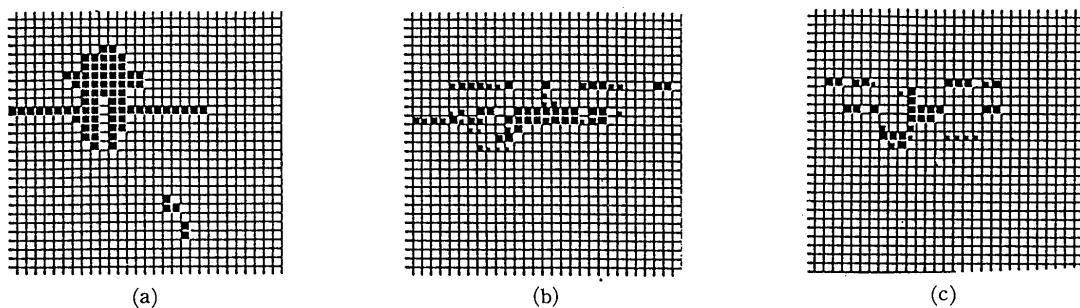
### 5.3 Processing for improving resolution of detection



**Fig. 10** Example of noise rejection — ordinary(good) case.(a) Input image. (b) Output image by learning method ①. (c) Output image by learning method ②.



**Fig. 11** Example of noise rejection — not good case.(a) Input image. (b) Output image by learning method ①. (c) Output image by learning method ②.



**Fig. 12** Example of noise rejection — worst case.(a) Input image. (b) Output image by learning method ①.(c) Output image by learning method ②.

An image is entered into the processing system as 512x480 pixels, 8 bits of data at first, and these are compressed into 30x30 pixels at the preprocessing stage. This process reduces the resolution of the image, and therefore the output of the neural network, to about 3.5(mm/pixel). This value is too low from a practical view. Therefore, further processing is necessary to improve the resolution.

At first, the output image is thresholded to 1 or 0 with the half value of its dynamic range. Then, the image, whose resolution is equal to that of the original image ( 0.2mm/pixel ), can be obtained from the logical product of this binary image and the original. Although operation( OP ① ) is sufficient in most cases, a better

result can be obtained by a series of operations( OP ② ), which are matching operation of this binary image with the standard teacher image, shift of the center position of the teacher image to the maximum point of matching ratio, and product operation of the shifted teacher image and the original image.

The result of this processing to improve the resolution of detection is shown in **Fig.13**. The original image, the input and the output images are shown in (a), (b) and (c) in this figure. The image which has a discontinuous part, as is seen in (d), is obtained only by the processing of OP ①, because the original image of the joint shape has a discontinuous part in this example. However, the perfect joint shape

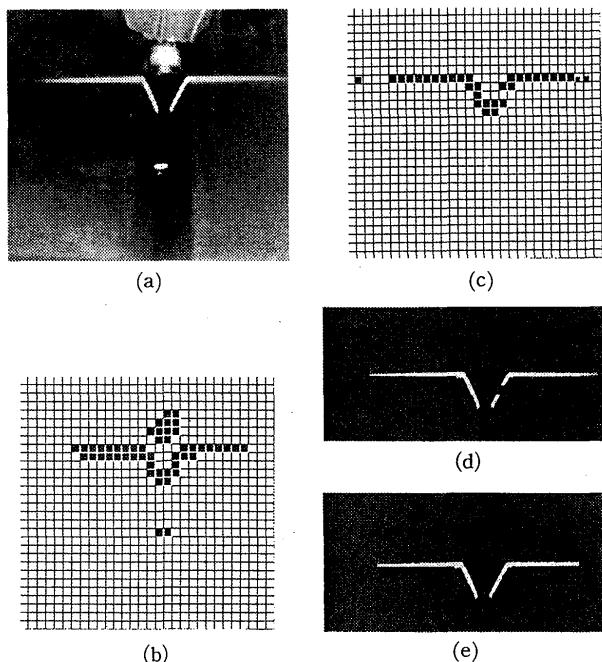


Fig. 13 Resolution improving process for output image.(a) Original image. (b) Input image. (c) Output image. (d) Result of resolution improving process.(e) Result of more sophisticated processing.

as shown in (e) can be obtained by adding OP ②. The throughput( time required from the input of the original image data to the output of the processed result ) is about 300(ms) in the latter case. It appears possible to shorten this time to as little as 100(ms) by improvement of the algorithm and the development of exclusive hardware for part of the pre- and post- processing.

## 6. Detection Ability of Weld Joint Position

From another view point, the learning via the teacher image ② and the noise rejection process may be regarded as the detection of the joint position. The neural network recognizes the center position of the weld joint in the input image as a result of learning. It then transmits the standard teacher image so that the center positions of both images coincide. Accordingly, if a marker of appropriate shape at the position corresponding to the center of the weld joint, instead of the standard teacher image, is used in the learning stage, the detection of the center position of the weld joint becomes possible at a resolution of 0.2 mm through the

processing described in Sect.5.3. This is high enough accuracy for the automatic tracking of weld lines.

## 7. Conclusion

The rejection of noise imposed on the weld joint image by the light slice method during arc welding is examined as an application of signal processing by neural networks of the backpropagation type. The results are summarized as follows.

- (1) Excellent noise rejection is achieved as long as the imposed noise is not too severe. The time required for the noise rejection processing is short enough from the practical view point.
- (2) The resolution of the joint shape detection can be maintained at the same level as in the original image by the filtering process.
- (3) The selection of the learning method ① or ② is decided depending on the joint shape to be detected.
- (4) The noise rejection method reported here can be interpreted as a kind of the associative memory model judging from the optimum number of the elements in the hidden layer of the network.
- (5) This method can also be regarded as a weld joint position detection method of satisfactory accuracy.

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