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Development and Characterization of Pattern Recognition Algorithm for Defects in Semiconductor Packages

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ABSTRACT

In this paper, the classification of artificial defects in semiconductor packages is studied by using pattern recognition technology. For this purpose, the pattern recognition algorithm includes the user made MATLAB code. And preprocess is made of the image process and self-organizing map, which is the input of the back-propagation neural network and the dimensionality reduction method. The image process steps are data acquisition, equalization, binary and edge detection. Image process and self-organizing map are compared to the preprocess method. Also the pattern recognition technology is applied to classify two kinds of defects in semiconductor packages : cracks and delaminations.

Key Words : Ultrasonic image, Defects in semiconductor package, Image process, Neural network, Pattern recognition

1. Introduction

Semiconductor components are very essential to electronic devices such as medical equipment, military weapons and so on. Therefore defects in semiconductor components may affect the mechanical or electronic performance of devices. For this reason it is very important to inspect for defects during manufacturing. Some inspection methods use a nondestructive test, which largely depends on human experience. Recent defect inspection systems, like Scanning Acoustic Tomography (SAT) for semiconductor packages, has been applied to the industrial field. By using ultrasonic nondestructive methods, some makers like Hitachi and Sonix have provided powerful test results to users based on ultrasonic images. These inspection systems help users to analyze the ultrasonic image displayed on monitor.

To accomplish this purpose, ultrasonic images are applied to image processes [1,3,5,7] and neural networks [2,3,4,10,12]. These ultrasonic images are acquired by SAT [8,9,11] equipment and the pattern recognition algorithm [2,4,6,7] is developed in order to classify defects in semiconductor packages. The defect information in semiconductor packages is fed back to the manufacturing process for process standardization. If the pattern recognition technology can be used for the inspection and evaluation process in mass production, precision products of high quality can be rapidly produced. Also, this inspection system can be helpful in setting up the best process to remove defects in actual manufacture.

In this paper, pattern recognition algorithm includes the user made software code. And preprocess was composed of image process and self-organizing map [2,4,5,6,7,8]. And then, the result of each process inputted into a back-propagation neural network [2,4,5,6,7]. Also, image process was made of data acquisition [3] and equalization [1,3,7] and binary process [1,3] and edge detection [1,3]. Consequently,

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image process and self-organizing map were compared to the preprocess method [3,4,7], which is the dimensionality reduction method [3,4,7] as input data of back-propagation neural. Also, by using neural network, the pattern recognition technology was applied to classify two kinds of defects in semiconductor packages. Defects in semiconductor packages are composed of cracks and delaminations.

2. Image Preprocess

Image processing used in this study refers to conversion for the purpose of improving image quality for ultrasonic test results of semiconductor packages obtained from the SAT, or to extract feature variables for inputting results into the neural network.

2.1 Image Acquisition

In digital images, each point on the image plane is called a pixel. And then it is saved into memory as a digital value in each section.

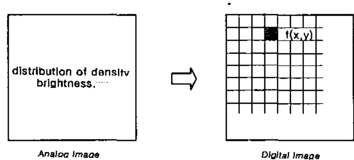


Fig. 1 Coordinates on the image plane

Light intensity means brightness of each pixel that is expressed to the function $f(x,y)$ in Fig.1. Also, light density is transformed to a digital value and the process is called digitization. Acquired image, which is taken with a gray level by SAT equipment, is expressed in digital values from 0 to 255.

2.2 Image Filtration

In order to remove noise signals included in the acquisition process, the neighborhood average method was applied.

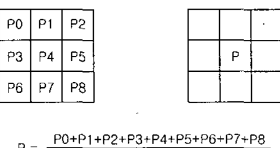


Fig. 2 Neighborhood averaging method

In the neighborhood average method the neighboring local parts of pixels are averaged with all the pixel elements in an image whose size is configured by replacing them with gray images of the pixel.

The size of image $f(x,y)$ is averaged with neighborhood parts taken with size $m \times m$, where the size of neighborhood averaging window is 3×3. And then, these averaged parts are alternated to the function $g(x,y)$ with a gray level.

$$g(x,y) = \frac{1}{M} \sum_{(m,m)\in s} f(m,m) \tag{1}$$

Where, M is the number of cells with size $m \times m$ in some part, s is expressed as the number of pixel sets.

2.3 Binary Process

The binary process converts the gray image or color images to binary images. The decision of threshold value in a simple form depends on the gray image $f(x,y)$ and the threshold value t, and can be expressed by the following equation.

$$\begin{aligned} f_t(x,y) &= 1 \qquad f_t(x,y) \geq t \\ f_t(x,y) &= 0 \qquad f_t(x,y) \leq t \end{aligned} \tag{2}$$

Where, $f_t(x,y)$ is the binary image determined by the threshold value, and $f(x,y)$ is the gray image of (x,y). By such processing, $f_t(x,y)$ is converted into the binary images of 0 and 1.

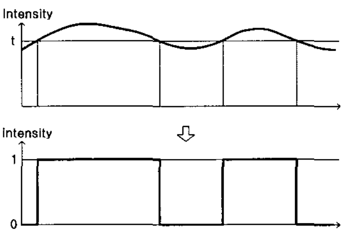


Fig. 3 Binary process

2.4 Edge Detection

An edge line indicates the boundary of an image and shows a discrete point for pixel brightness. In this study, image information used in detecting the edge line was applied as an input vector inputted into the back-propagation neural network, and the 4-connected

neighbors method was applied. The Euclidean distance between pixels p,q whose coordinates are (x,y) and (s,t), respectively is defined as follows. A pixel with a distance equal to or less than value r from a point (x,y) is a point included in a circle with a radius r at the center (x,y). The distance D_4 between p,q is defined as follows.

$$D_e(p,q) = [(x-s)^2 + (y-t)^2]^{\frac{1}{2}} \quad (3)$$

A pixel with a distance D_4 equal to or less than value r from the center (x,y) is configured in a diamond shape centered on (x,y) as shown in Fig.4.

$$D_4(p,q) = |x-s| + |y-t| \quad (4)$$

2	1	2
1	0	1
2	1	2

Fig. 4 Edge detection

2.5 Self-Organizing Map

The consequence of a self-organizing map is the input vector into a back-propagation neural network, which is applied by the dimensionality reduction method.

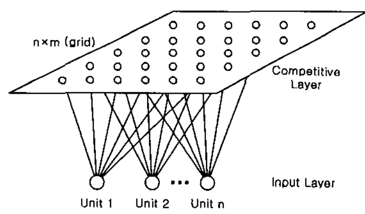


Fig. 5 Self-organizing map

As self-organizing map is a kind of neural network with two-layer. The fist layer is an input layer. And the second layer is a competitive layer. Train rule calculates the distance between input data and weight in a self-organizing map. The winner neuron is the nearest neuron from trained weight, which can only be an output neuron. Just the winner neuron and neighbor neuron of winner neuron can be adjusted through training process. The distance between input vector and weight can be expressed as follows.

$$d_j = \sum_{i=0}^{N-1} (X_i(t) - W_{ij}(t))^2 \quad (5)$$

Weight between neuron j and neighbor neuron is adjusted. At equation (5), d_j is distance between neuron j and weight. Finally, weight between neuron j and neighbor neuron can be readjusted by the following equation.

$$W_{ij}(t+1) = W_{ij}(t) + \alpha(X_i(t) - W_{ji}(t)) \quad (6)$$

3. Pattern Classifier of Defects

For the classifier for defects in a semiconductor package used in this study, the back-propagation neural network, a kind of a multi-layer perceptron with layers shown in Fig.6, was used. Here, as the nonlinear function of the hidden layer and the output layer, the sigmoid function was applied to form a decision boundary with a slow curve, not a typical straight line.

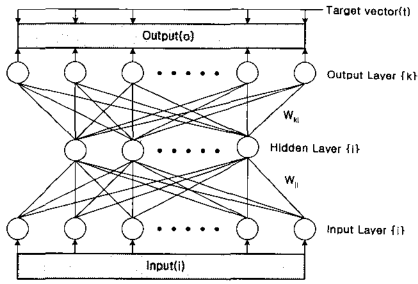


Fig. 6 Backpropagation neural network

Structure	Type of Decision Regions	Exclusive-OR Problem	Classes with Meshed Regions	Most General Region Shapes
Single-layer	Half plane bounded by hyper plane			
Two-layer	Convex open or closed regions			
Three-layer	Arbitary (Complexity limited by number of nodes)			

Fig. 7 Decision boundary in each layer structure

It was intended to improve the performance of the network by performing the back-propagation training algorithm to discover the hidden layer. With small

increases of the hidden layer, the quality of the decision boundary is better in back-propagation neural networks as Fig.7.

For the model in Fig.6, the input layer (I) , the hidden layer (H) and the output layer (O) are defined by the following equation.

$$H_j = f(\sum_i W_{ji} \cdot I_i + \theta_j) \quad (7)$$

$$O_k = f(\sum_j W_{kj} \cdot H_j + \theta_k) \quad (8)$$

In order to reduce mean square errors (E_p) between the input layer (I) and the hidden layer (H) , and between the hidden layer (H) and the output layer (O) , Weights (W_{ji}) and (W_{kj}) are readjusted by the following equation.

$$W_{ji} = -\eta_3 \cdot \frac{\delta E_p}{\delta W_{ji}} = \eta_3 \cdot \delta_j \cdot I_i \quad (9)$$

$$W_{kj} = -\alpha_2 \cdot \frac{\delta E_p}{\delta W_{kj}} = \eta_2 \cdot \delta_k \cdot H_k \quad (10)$$

Where, δ_j and η_3 indicate an output error and learning rates of the hidden layer. Also, δ_k and η_2 indicate an output error and a learning rate of the output layer. Based on the above equations, the mean square error (E_t) for all patterns (P) can be expressed as the following equation. Where, (T_{pk}) indicates a target vector, and (O_{pk}) an output vector. Through such processes, the mean square error (E_t) is wholly minimized.

$$E_t = \sum_p \sum_k \frac{(T_{pk} - O_{pk})^2}{2} = \sum_p E_p \quad (11)$$

4. SAT System and Algorithm

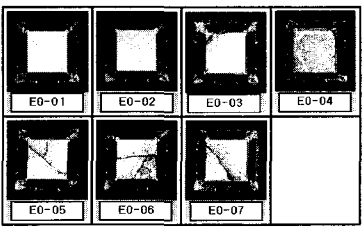
Fig. 8 SAT System

The test equipment used in this study is the SAT system made by Hitachi, which includes a 3-axis scanner and its ultrasonic transducer operating on 25MHz. The ultrasonic signal transferred from a unit for sending/receiving ultrasonic waves is converted into images by the software installed in SAT system.

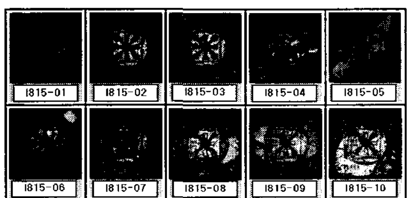
Table 1 Test specimens and inner defects

Type	Semiconductor Packages	Defects
I815 (PBGA)		Delamination & Crack
I840 (PBGA)		Delamination
E0 (SBGA)		Crack

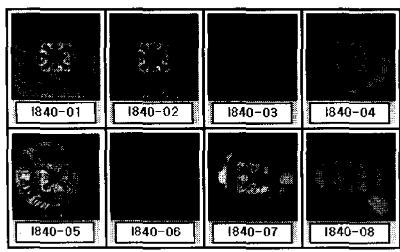
In order to evaluate the availability of the test algorithm, three types of specimens as shown in Fig.9 were examined. Defects in the three types of specimens are not natural defects but artificial defects made in a laboratory for testing purposes. In the specimen, (a) remaining cracks are shown, (c) remaining delaminations are shown, and (b) both of the remaining cracks and delaminations are shown emphasized as a type of actual defect in this study.



(a) Type of E0

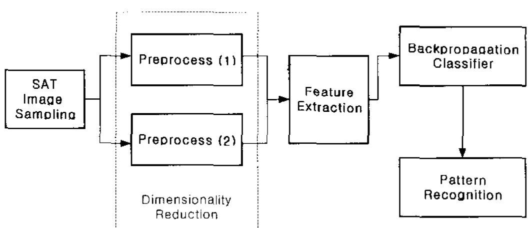


(b) Type of I815

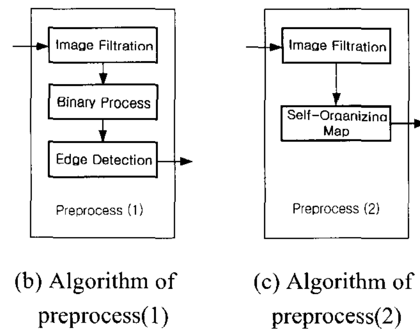


(c) Type of I840

Fig. 9 Ultrasonic images in specimens



(a) Main algorithm



(b) Algorithm of preprocess(1)

(c) Algorithm of preprocess(2)

Fig. 10 Pattern recognition algorithm

The main process of the algorithm and its sub processes verified in this study are shown in Fig.10. In order to improve pattern recognition rates of defect patterns, dimensionality reduction methods of feature images were carried out through image processing. In order to reduce the test time, the aforementioned simplified computation function was applied to the image process of the original image in the feature extraction process. This algorithm includes image process and self-organizing map as two kinds of preprocess methods. For features extracted through these processes, this classifier based on the back-propagation neural network classifies defect patterns

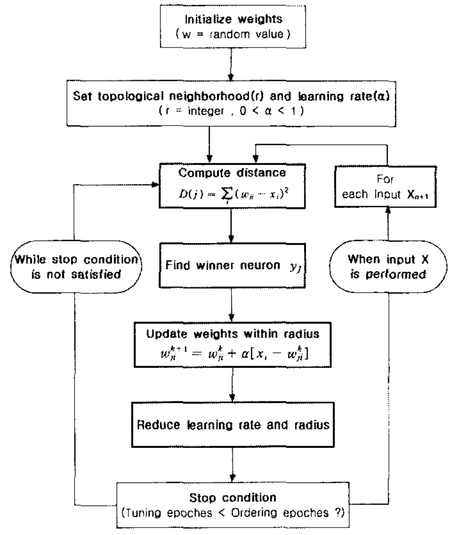


Fig. 11 Train algorithm of self-organizing map

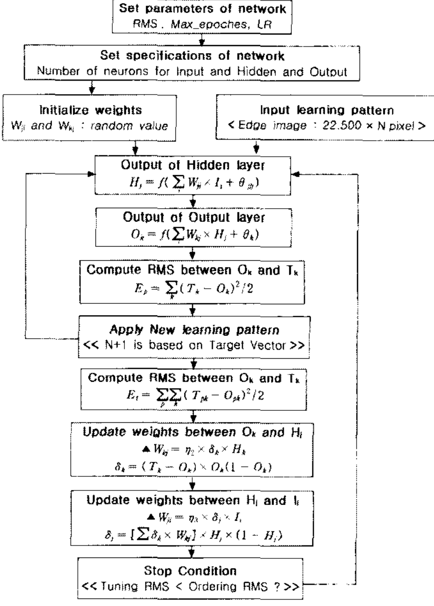


Fig. 12 Train algorithm of BPNN (**B**ack-**P**ropagation **N**eural **N**etwork)

In the case of the self-organizing map, the standard image is located in the horizontal axis, where standard image is normal image without defects. And then the test

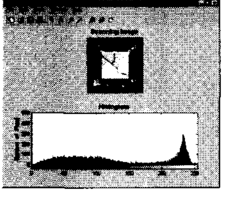
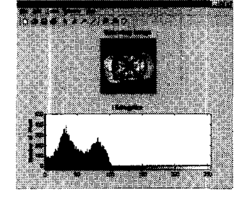
image (that is defect image) is applied to vertical axis ; the different image shape is generated by the difference between two images in 2-dimensional plane.

According to this foundation, the self-organizing map is related to the input image (that is test image) based on standard image. The train algorithm of the self-organizing map is shown in Fig.11. And the train algorithm (that is classifier algorithm in this research) of back-propagation neural network is shown in Fig. 12.

5. Experimental Results

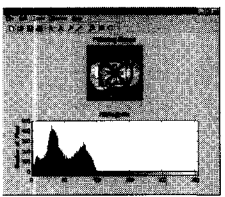
5.1 Results of image preprocess

In this research, image preprocesses mean the generation process of input vector into neural network with the back-propagation method, which is the classifier of defect pattern recognition in semiconductor packages. In case of this sequence, the main point is the feature selection on the pattern image of the defect. Its result is based on ultrasonic images obtained from the defective semiconductor package. In this viewpoint, the practical preprocess is made up two methods. One is the image process that is composed of image acquisition, image filtration, binary process and edge detection. The other is the application of neural network, that is called self-organizing map. It is a kind of competitive neural network. Such processes are shown in Fig.13 to Fig.17.

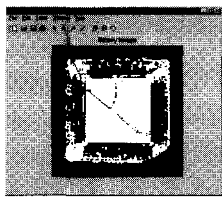
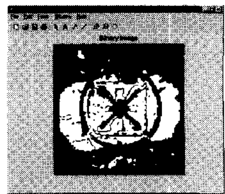
(a) Crack image (b) Delamination image

Fig. 13 Acquisition image from SAT



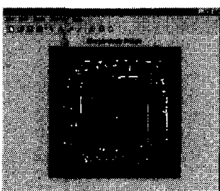
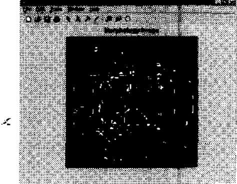
(a) Crack image (b) Delamination image

Fig. 14 Filtration image

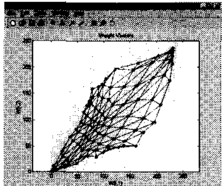
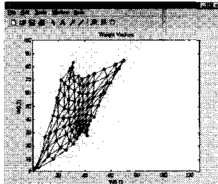
(a) Crack image (b) Delamination image

Fig. 15 Binary Image

(a) Crack image (b) Delamination image

Fig. 16 Edge Image

(a) Crack image (b) Delamination image

Fig. 17 Self-organizing map

5.2 Results of image evaluating

The error margin is reduced from initial train rate 0.01 to output error margin bellow 0.001. Which is the experimental condition by the researcher's setup. The reason for results with 100% in Fig.18 is due to applying various weights.

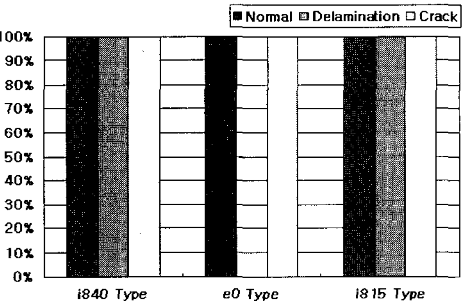


Fig. 18 Recognition result of image process

The pattern recognition algorithm of defects to verify the availability in this study sets the weights of the neural network depending on defect types. It has the advantage that it is possible to recognize all defects of a specimen with 2 or more defects, and to simplify the training process, which is the greatest disadvantage of the BPNN (that is back-propagation neural network). It also has a better application capability to the industrial field with respect to the test procedure, by integrating respective results in the algorithm.

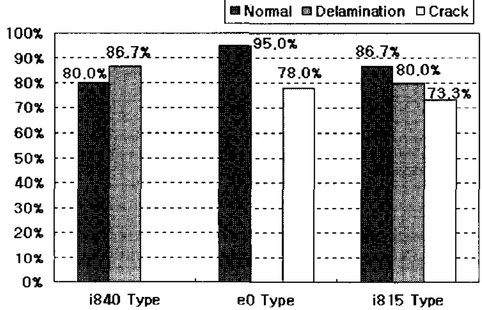


Fig. 19 Recognition result of self-organizing map

And the results of the self-organizing map are lower than in image process. It could not take on results with 100% structurally. For application to the industrial field, test time and classification rate are very important factor. And then, the application condition was chosen as optimal condition. It is shown as Table 2.

Table 2 Test performances by preprocess methods

Preprocess	Test Time	System
Image Process	≤ 02 sec.	CPU 733 MHz
Self-Organizing Map	≤ 30 sec.	RAM 256 MHz

6. Conclusions

The research results on pattern recognition algorithm for defects in semiconductor packages using image process and self-organizing and back-propagation neural network can be summarized as follows.

1) In order to improve performance of the algorithm, weights of the neural network were set and integrated in the algorithm for respective defects, and then it was possible to find high recognition rates when there were 2 or more defects in three types of specimens.

2) In this research, image process is superior to the self-organizing map as the preprocess method. Because the self-organizing map includes training time during structural tests on the other side, image process not includes training time during the test. Also, the result of the self-organizing map contains some errors as input data of the pattern recognition classifier, which makes up the back-propagation neural network.

Acknowledgement

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