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A Visual-inspection System Using Self-organizing Map

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Abstract

The visual inspection task is generally difficult for a machine, and is carried out by examiners usually. The task is desired to be mechanized and automated because it often causes bottleneck of production processes.

In order to satisfy the requirement, we study an image recognition using the self-organizing map (SOM) for visual inspection equipments. The SOM maps high-dimensional input data onto a low-dimensional (typically two-dimensional) space. And the data are clustered based on their similarity. On the map, input data is thus classi ed based on its position of the mapped data. The reason we use the SOM for inspections is that it can visualize the results of clustering. With the visualized results, the user can understand data classi cation intuitively.

We have implemented a visual-inspection system based on the SOM and tested it using actual product images. In the implementation, we preprocess the images to decrease data size before input them into the SOM because large input data size causes poor clustering. The image data is preprocessed in three steps, that is, binarization, 2D-FFT and converting to one-dimensional data.

We rst considered only one inspection point, and obtained high recognition accuracy of 98%. We second considered two inspection points, and also obtained high recognition accuracy of 96%.

Keywords: Image Recognition, Self-Organizing Map, Visual Inspection, FFT

1 Introduction

Many visual inspection tasks are carried out by examiners, because the task is generally difficult for a machine. As the examiners check products by hand, the task often causes bottleneck of production processes. And the task has serious problems that training of examiners and securing of manpower of the task are indispensable. It also causes another problem that the results of inspection di er from person to person. Therefore, the visual inspection is desired to be mechanized and automated.

In order to satisfy the requirement, we study image recognition using the SOM (Self-Organizing Map) for visual inspection. The SOM is one of neural networks, and is used as a clustering method by unsupervised learning and a data visualization method by dimensional reduction. We use the SOM to cluster the image data of test object products. The reason we use the SOM is that it can visualize the results of clustering. With the visualized results, the user can understand data classi cation intuitively.

2 Self-Organizing Map

The Self-Organizing Map (SOM) is proposed by Kohonen [1]. Its feature is mapping high-dimensional input data onto a low-dimensional (typically two-dimensional map) space, where the map consists of grid nodes usually. Each node has n-dimensional data vector called the weight vector, $m_{i,j}$. The input data x is also n-dimensional vector data. The values of all weight vectors are randomly initialized. The learning of the map is performed by repeating the following steps.

1. One input data is fed into the map, and its Euclidean distances to all weight vectors are computed.
2. The node with the smallest distance to the input data vector gets selected as the winner node.
3. The neighbor nodes of the winner node are updated as follows:

$$m_{i,j} := m_{i,j} + \quad (i,j)\{x \quad m_{i,j}\}$$

where hc(x) is called neighborhood function. As the result of the updating, the distance between weight vectors of updated nodes and input vector is smaller.

Repeating the above steps for di erent input data makes the data clusters on the map. On the map, input data is classi ed based on the position of the mapped data. In other words, similar data are put close to each other on the map, and di erent data are put far separately.

After learning of the map, test object data are input into the map, and each datum's cluster is judged. The SOM also decides the winner node for the test object data. On the map the cluster which this winner node belong to is the one which the test object data belong to. The boundary of each cluster is shown on the map, but the SOM doesn't de ne the boundary clearly. The boundary is able to be de ned arbitrarily by the user.

3 Test Object Products

Fig.1 shows the product we use as the target for our visual-inspection system. It is a dental injection needle made from plastic and is currently examined by examiners. The sample products are provided from the BETHEL Inc. in Japan. In the actually examination, some inspection points are considered, but in this paper, we focus on two inspection points, that is, burr and foreign object. Fig.2 shows the closeup of the acceptable product (a) and the disquali ed ones (b), (c). Fig.2 (b) shows the disquali ed product with a burr, and (c) shows the one with foreign object.

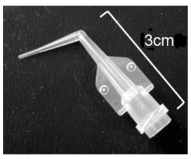

Figure 1: Objective Product (Dental Injection Needle)

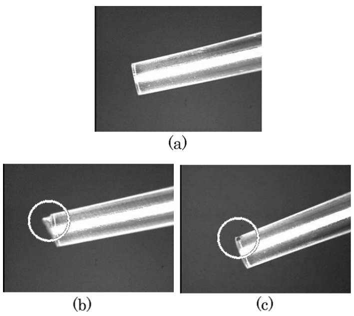

Figure 2: The Acceptable Product and Disquali ed Products

4 Preprocessing

We basically use the image data as the input into the SOM. But the size of the original image is too large. Large input data size causes huge amounts of calculation time and poor clustering in the SOM. We thus decrease the images data size. (Fig.3)

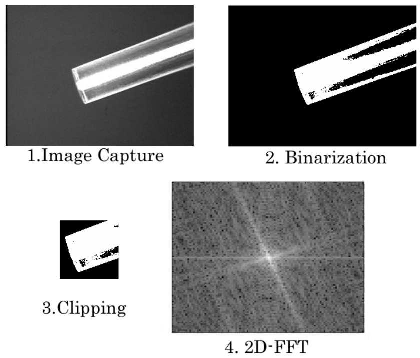

Figure 3: Preprocessing

First, we binarize the closeup image of the product. Second, the image of the point of the product is clipped to 100x100 pixels. Third, the image is transformed into one in the frequency space by 2D-FFT. It is expected that the transformation extracts the feature more e ectively. Finally, the data is converted to one-dimensional data in frequency space. The frequency data are concentrically averaged as shown in Fig.4 [2]. As a result, the image data are converted 70 dimension data.

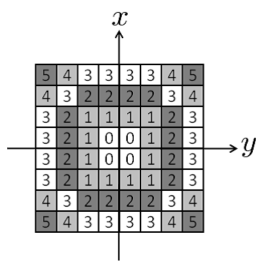

Figure 4: Concentrically Average

5 Experiments And Results

5.1 Experimentation Environment

We have implemented the SOM using the C-language. The map consists of 100x100 nodes. The map has the torus structure to eliminate the edge effect of the map [3]. The sample products that have been previously examined by examiners are provided for the test. We have used cross validation method to evaluate recognition rate. The map rst trained by the learning data, and after training, the test object data is examined by inputting it into the learned map. In one learning cycle of the SOM, all learning data are input to the map, and the learning is repeated 100 times.

5.1.1 One Inspection Point Experiment

We rst consider only one inspection point that is burr at the needle point. 100 sample data has used, where 50 data are acceptable products data and 50 data are disquali ed ones with burr. We have evaluated the recognition accuracy 5 times using cross validation method as shown Table 1, and averaged the results.

Table 1: The Cross Validation Method

# of Test	Learning Data Sets	Test Data Sets
1	ABCD A'B'C'D'	E E'
2	ABCE A'B'C'E'	D D'
3	ABDE A'B'E'E'	C C'
4	ACDE A'C'D'E'	B B'
5	BCDE B'C'D'E'	A A'

50 acceptable data and 50 disquali ed data are divided into 5 sets of A,B,C,D,E and A',B',C',D',E' , respectively.

The result of the examination is shown in Table 2, and resultant maps are shown in Figs 5 and 6. In Figs 5 and 6, the acceptable nodes, whose weight vector is similar to the acceptable data, are shaded. When a test object is input into the learned map, the good judgment is that its winner node is selected from the group of right nodes [4]. On the map, acceptable data nodes and burr data nodes are clustered each other.

As shown Table 2, we have obtained high recognition accuracy of 98 % for the disquali ed data.

Table 2: The Recognition accuracy (One Inspection Point)

Acceptable Data	100%
Disquali ed Data (Burr)	98%

5.2 Two Inspection Points Experiments

We consider two inspection points that are burr at the needle point and foreign object in the needle. 40 disquali ed products data with foreign object are added to the sample data. These data are generated from the acceptable images arti cially. We have tested the map using the same method as the one inspection point experiment above.

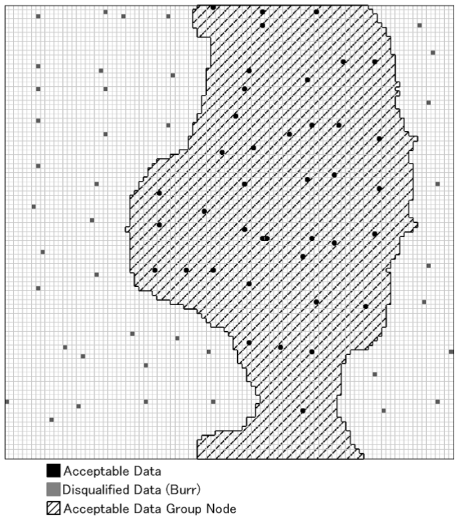

Figure 5: The Learned Map (One Inspection Point)

The result is shown in Table 3, and resultant maps are shown in Figs 7 and 8. In Figs 7 and 8, nodes to the disquali ed data with foreign object are dotted. On the map, burr and foreign object data nodes are clustered each other as well as acceptable data nodes.

As shown Table 3, we have also obtained high recognition accuracy of 96% for the disquali ed data.

Table 3: The Recognition accuracy (Two Inspection Points)

Acceptable Data	100%
Disquali ed Data (Burr)	96%
Disquali ed Data (foreign object)	100%

5.3 Discussion

One of the goals of the visual inspection is to screen the disquali ed products completely. To achieve the goal, we newly propose the method in which the user can arbitrarily move the boundary of acceptable data and disquali ed data.

On the map, the boundary of cluster is not shown, and it can be de ned arbitrarily and interactively. Thus the user can de ne the boundary that picks out only acceptable data, and check the data easily as expert examiners.

6 Conclusion and Further Work

In this paper, we proposed the visual inspection system using the Self-Organizing Map. We have implemented the map by the C-language and tested it using actual products. As the result, we have visualized the

Figure 6: The Result of Inputting Test Object Data (One Inspection Point)

clustering results, and obtained high recognition accuracy.

In the further work, we are planning to test using more sample data. The recognition accuracy using more data must be measured for the practical use. And we are going to implement the function that the user can arbitrarily de ne the boundary on the map.

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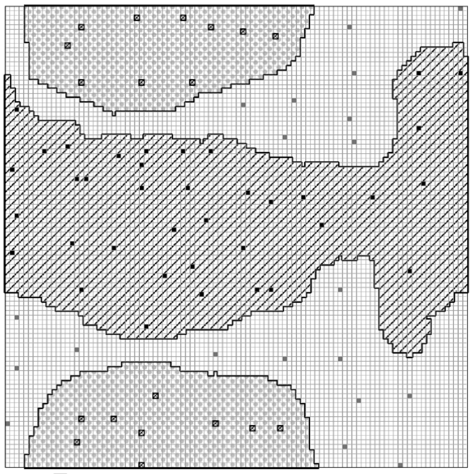

Figure 7: The Learned Map (Two Inspection Points)

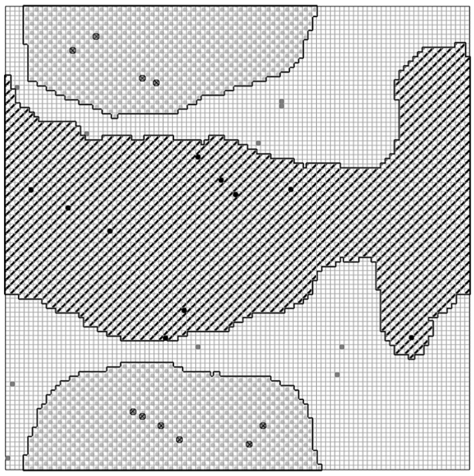

Figure 8: The Result of Inputting Test Object Data (Two Inspection Points)