Recognition of Container Identifiers Using 8-directional Contour Tracking Method and Refined RBF Network

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Abstract— Generally, it is difficult to find constant patterns on identifiers in a container image, since the identifiers are not normalized in color, size, and position, etc. and their shapes are damaged by external environmental factors. This paper distinguishes identifier areas from background noises and removes noises by using an ART2-based quantization method and general morphological information on the identifiers such as color, size, ratio of height to width, and a distance from other identifiers. Individual identifier is extracted by applying the 8-directional contour tracking method to each identifier area. This paper proposes a refined ART2-based RBF network and applies it to the recognition of identifiers. Through experiments with 300 container images, the proposed algorithm showed more improved accuracy of recognizing container identifiers than the others proposed previously, in spite of using shorter training time.

Index Terms— Container Image, Identifier Areas, ART2-based Quantization, 8-directional Contour Tracking, Refined ART2-based RBF Network.

I. INTRODUCTION

Identifiers of a shipping container are given in accordance with the terms of ISO standard, which consist of 4 code groups such as shipping company codes, container serial codes, check digit codes, and container type codes. Only the first 11 identifier characters are prescribed in the ISO standard and shipping containers can be discriminated by automatically recognizing them [1]. However the ISO standard prescribes only the code type on container identifiers, so other features such as the foreground and background colors, the font type, the size and the position of container identifiers, etc., vary from one container to another. Sometimes shapes of identifiers can be also impaired by the environmental factors during the transportation by sea, since the identifiers are just printed on the surface of a container. Furthermore, the damage to a container surface or image noises may lead to distortion of shapes of identifier characters in a container image. Such variations and distortions make it quite difficult to extract and recognize the identifiers using simple morphological information like shape, size, and position [2].

In the preprocessing of a container image for the extraction of container identifiers, it is necessarily required to distinguish whether extraction results are contours of identifiers or background noises. In this paper, at first, color information of a container image is clustered by using the ART2 algorithm [3] and is quantized based on the predefined bin vectors, then the 8-directional contour tracking method [4] is applied to the quantized image. By using feature information of container identifiers, background noises are removed and identifiers are extracted from the areas labeled by the contour tracking method.

This paper proposed a refined ART2-based RBF network and applied it to the identifier recognition. In the proposed ART2-based RBF network, the refined ART2 algorithm is applied to the middle layer of RBF network, which dynamically adjusts the vigilance parameter by using the fuzzy logic connection operator, and the learning ratio is dynamically adjusted by applying the delta-bar-delta method to the learning between the middle and the output layers of RBF network.

II. EXTRACTION OF IDENTIFIER AREAS AND INDIVIDUAL IDENTIFIERS

In this paper, the extraction process of container identifiers quantizes a container image, extracts identifier areas from the quantized image, binarizes the extracted areas and last, extracts individual identifiers from the binarized areas.

A. ART2-based quantization of a container image

Color information of a container image is able to be classified by using an image quantization method. Generally, it may occur in the image quantization the problem that two pixels having similar color information at the neighborhood of quantization boundary are classified to different bins, incurring the loss of effective information. This paper, to refine the problem, clusters color information of a container image by using ART2 algorithm and quantizes the container image based on the similarity between the predefined n color bins and the centers of clusters. For the quantization of a container image, at first, this paper classifies similar color vectors to a cluster by apply ART2 algorithm to a container image. The input

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patterns of ART2 algorithm are three-dimensional vectors indicating color coordinates in RGB space, and the center vector of a cluster is the mean vector of color vectors included in the cluster. Fig. 2 shows the result of ART2-based clustering of an original container image, Fig. 1.

For the optimal quantization of a container image in RGB color space, a standard bin group with n elements defined as (R,G,B) vectors is given in advance. After calculating the similarity between the center vector of a cluster and each bin vector like Eq. (1), the bin vector with the highest similarity is selected as a quantization code, and color vectors included in the cluster are quantized by using the selected bin vector.

$$S(x,y)=\alpha\cdot\left(1-\sum_{i=1}^{n}(x_i-y_i)^2\right)+\beta\cdot\left(1-\frac{|x\cdot y|}{\sqrt{|x||y|}}\right) \quad (1)$$

Where x and y are three-dimensional vectors in RGB space and α and β are parameters adjusting the ratio between the Euclidean distance and color values. Fig. 3 shows the quantized image of Fig. 1.

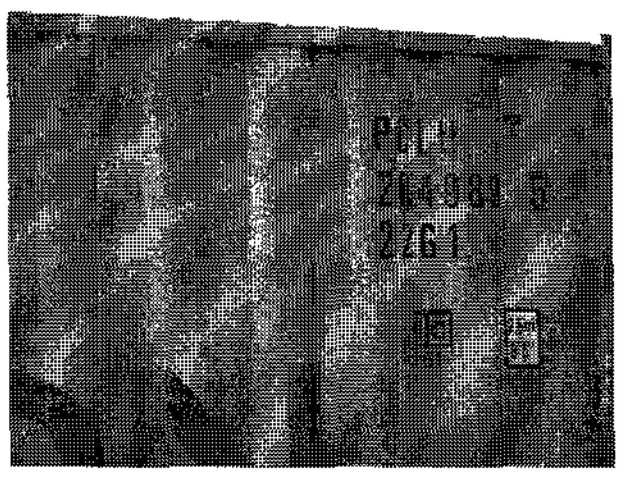


Fig. 1 An original container image

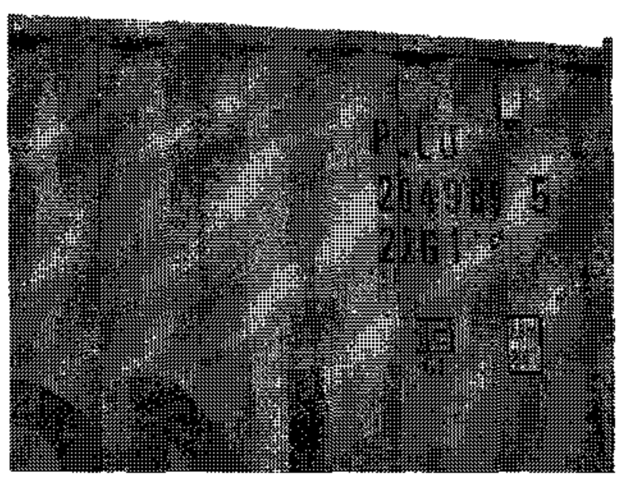


Fig. 2 Result of ART2-based clustering

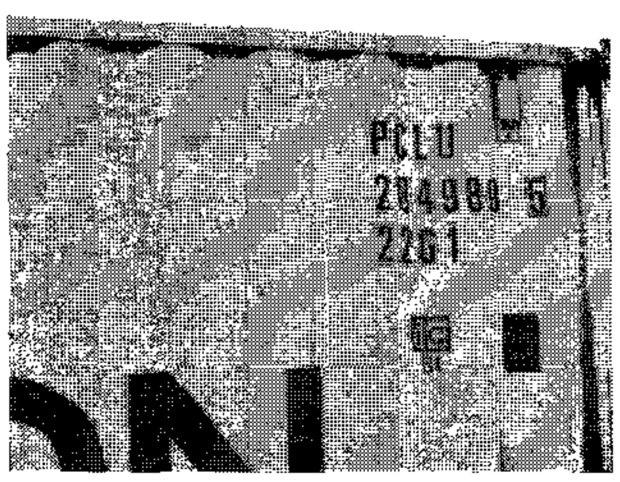


Fig. 3 Quantized container image

B. Extraction of identifier areas

An Identifier area means the rectangle area including only container identifiers in a container image. This paper, at first, extracts candidate areas for identifier areas by applying the 8-directional contour tracking method to the quantized image, and next, selects target areas among candidate ones by using two types of noise-removal method which remove areas corresponding to background noises.

Although the size of a container identifier is not constantly prescribed, the ratio of height to width is kept to be constant. So, the first type of noise-removal method removes noise areas by using the ratio of height to width. Fig. 4 shows candidates for identifier areas extracted from Fig. 3 and Fig. 5 shows the result image obtained by applying the first-type noise-removal method to Fig.4.

Fig. 4 Extraction of candidate areas from Fig. 3

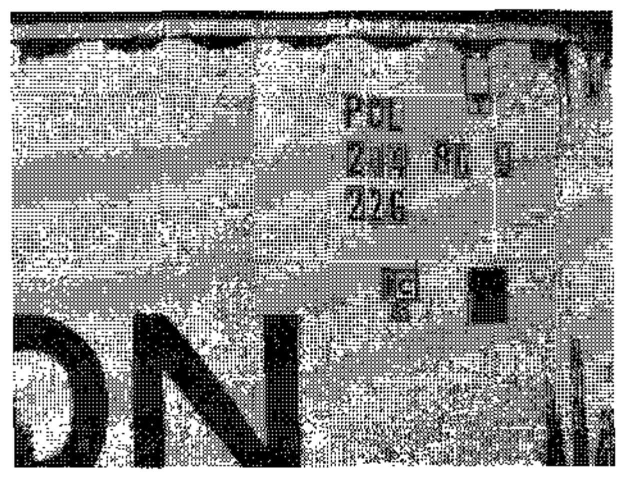


Fig. 5 Noise removal using the ratio of height to width from Fig. 4

Container identifiers have similar colors and arranges in the vertical or horizontal direction on the container surface, keeping a constant interval from other ones. In the second type of noise-removal method, after measuring the distance between candidate areas, areas being apart over the given interval from other ones may be removed as noises, and identifier areas are selected from remaining candidates by using color information.

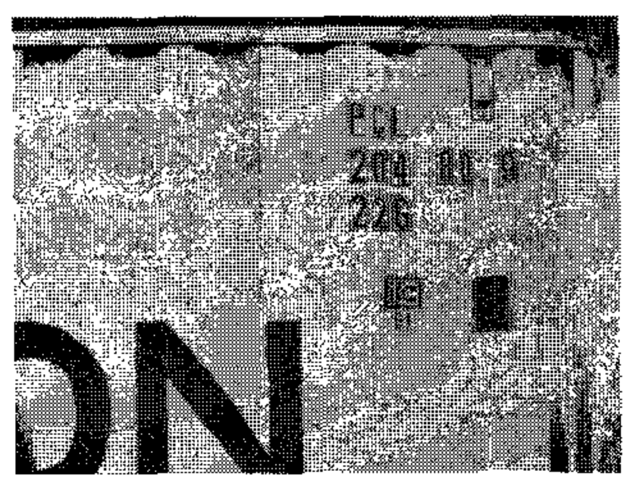


Fig. 6 Noise removal using information on color and interval from Fig. 5

Fig 6 shows the noised-removed quantized image obtained to applying the second-type noise-removal method to Fig. 5 in succession.

C. Binarization of identifier areas and extraction of individual identifiers

After converting identifier areas to grayscale areas, the iterative binarization method is applied to converted areas for image binarization. In a container image, bends exit in the horizontal direction, and the distortion of color information occurs in areas shaded by the bends. Since container identifiers arrange in the vertical or horizontal direction, identifier areas including horizontally-arranged identifiers may contain noises caused by shadows of bends. So, considering the arrangement direction of identifiers, the binarization method has to be applied by the different schemes.

This paper determines the arrangement direction of identifiers by measuring the ratio of the number of horizontally-arranged areas to vertically-arranged ones. Vertically-arranged identifier areas are binarized by applying the iterative binarization method once in the vertical direction. For horizontally-arranged areas, to remove noises caused by bends, the iterative method is applied twice in the vertical and the horizontal directions separately and two outputs are combined by using AND image operation to one binarized area. Fig. 7 shows the binarization result of vertically-arranged identifier areas. Fig. 8(a) shows the binarization result obtained by applying the iterative method in the vertical direction to horizontally-arranged areas, indicating that the simple binarization scheme for horizontally-arranged areas may be failed due to noises by bends. On the other hand, Fig. 8(b) shows that the proposed scheme for horizontally-arranged areas is successful in the binarization.

Individual identifiers are extracted by applying 8-directional contour tracking method to identifier areas, generating pixel areas corresponding to 11 prescribed identifier codes. Fig. 9 and Fig. 10 show the extraction results of individual identifiers in vertically-arranged areas and horizontally-arranged ones, respectively

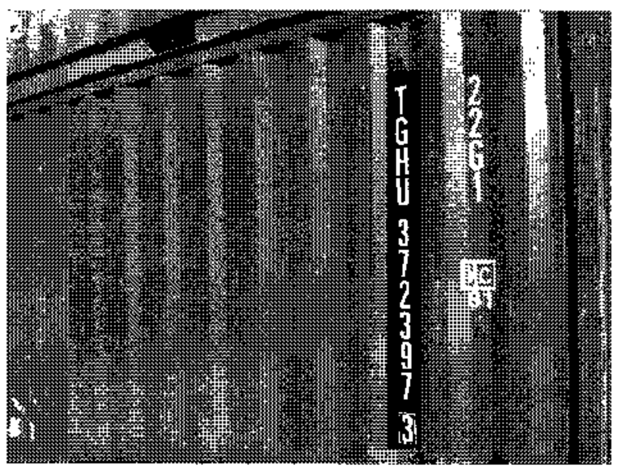
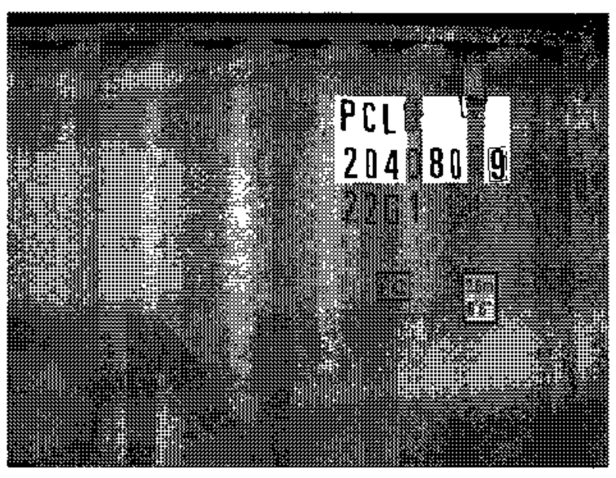
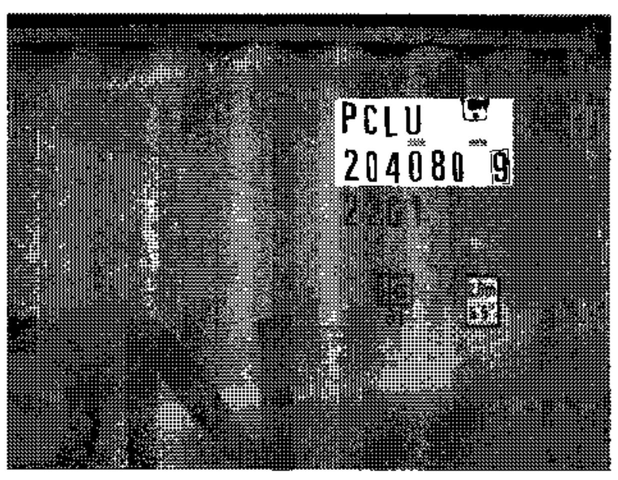


Fig. 7 Binarization result of vertically-arranged identifier areas

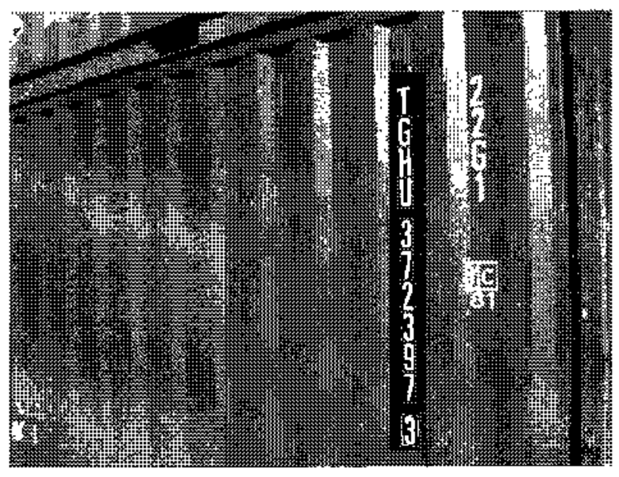


(a) Binarization result in the single vertical direction



(b) Binarization result by the proposed scheme

Fig. 8 Binarization result of horizontally-arranged identifier areas

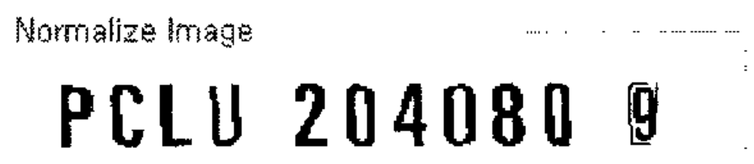


(a) Extraction process of vertically-arranged identifiers

(b) Extraction result of individual identifiers

Fig. 9 Extraction of individual identifiers in vertically-arranged areas

(a) Extraction process of horizontally-arranged identifiers



(b) Extraction result of individual identifiers

Fig. 10 Extraction of individual identifiers in horizontally-arranged areas

III. IDENTIFIER RECOGNITION USING REFINED ART2-BASED RBF NETWORK

This paper proposed a refined ART2-based RBF network for the recognition of container identifiers. In the conventional ART2 algorithm, vigilance parameters are heuristically fixed, causing the problem that similar patterns are classified to different clusters or different patterns are classified to the same cluster [5].

This paper, first, proposed the refined ART2 algorithm having the learning structure that dynamically adjusts vigilance parameters by using fuzzy logic intersection operator, selects a node with minimum output value as a winner node and transmits the winner node to the output layer. And the refined ART2 algorithm was applied to the learning between the input and the middle layers in RBF network. Also, in the proposed RBF network, the generalized delta learning method was applied to the learning between the middle and the output layers and delta-bar-delta algorithm was used to improve the performance of learning [6]. The learning algorithm of the refined ART2-based RBF network is summarized as follows:

1. The competitive learning adjusting dynamically the learning rate is performed between the input and the middle layers by applying the refined ART2 algorithm.

2. Nodes of the middle layer mean individual classes. Therefore, while the proposed RBF network has a fully-connected structure on the whole, it takes the winner node method that compares target vectors and output vectors and backpropagates only the connection weight to the representative class.

3. The proposed RBF network performs the supervised learning by applying the generalized delta learning to the learning structure between the middle and the output layers.

4. The proposed RBF network improves the performance of learning by applying delta-bar-delta algorithm to the generalized Delta learning for the dynamical adjustment of a learning rate. When defining the case that the difference between the target vector and the output vector is less than 0.1 as an accuracy and the opposite case as an inaccuracy, Delta-bar-Delta algorithm is applied restrictively in the case that the number of accuracies is greater than or equal to inaccuracies with respect to total patterns. This prevents no progress or an oscillation of learning keeping almost constant level of error by early premature situation incurred by competition in the learning process.

The detailed description of the refined ART2-based RBF network is like Fig. 11.

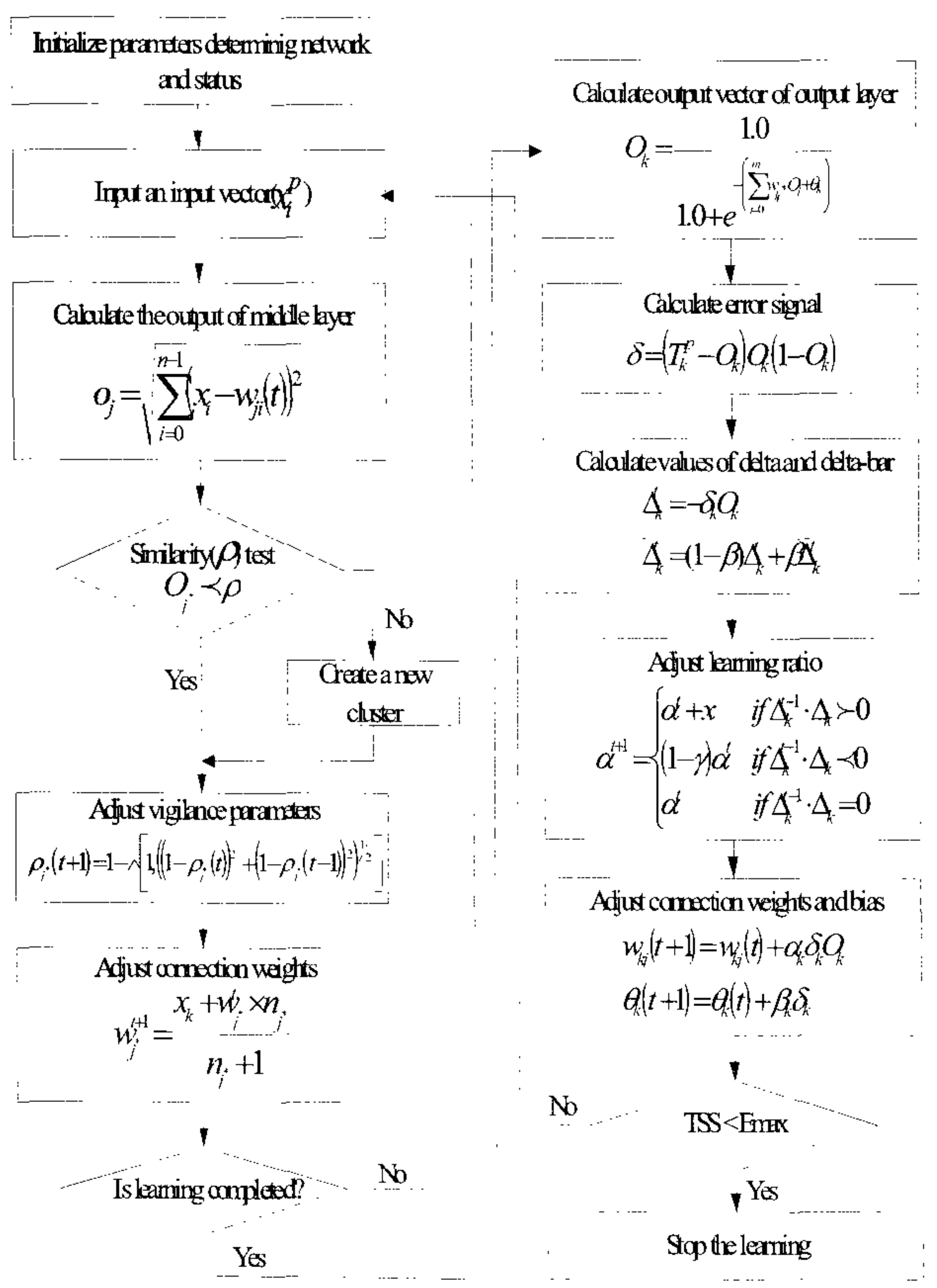


Fig. 11 Refined ART2-based RBF network

IV. EXPERIMENTAL RESULTS

The proposed algorithm was implemented by using Microsoft Visual C++ 6.0 on the IBM-compatible Pentium-IV PC for performance evaluation. 300 container images with size of 640x480 were used in the experiments for extraction and recognition of container identifiers. The implemented output screen of identifier extraction and recognition is like Fig. 12.

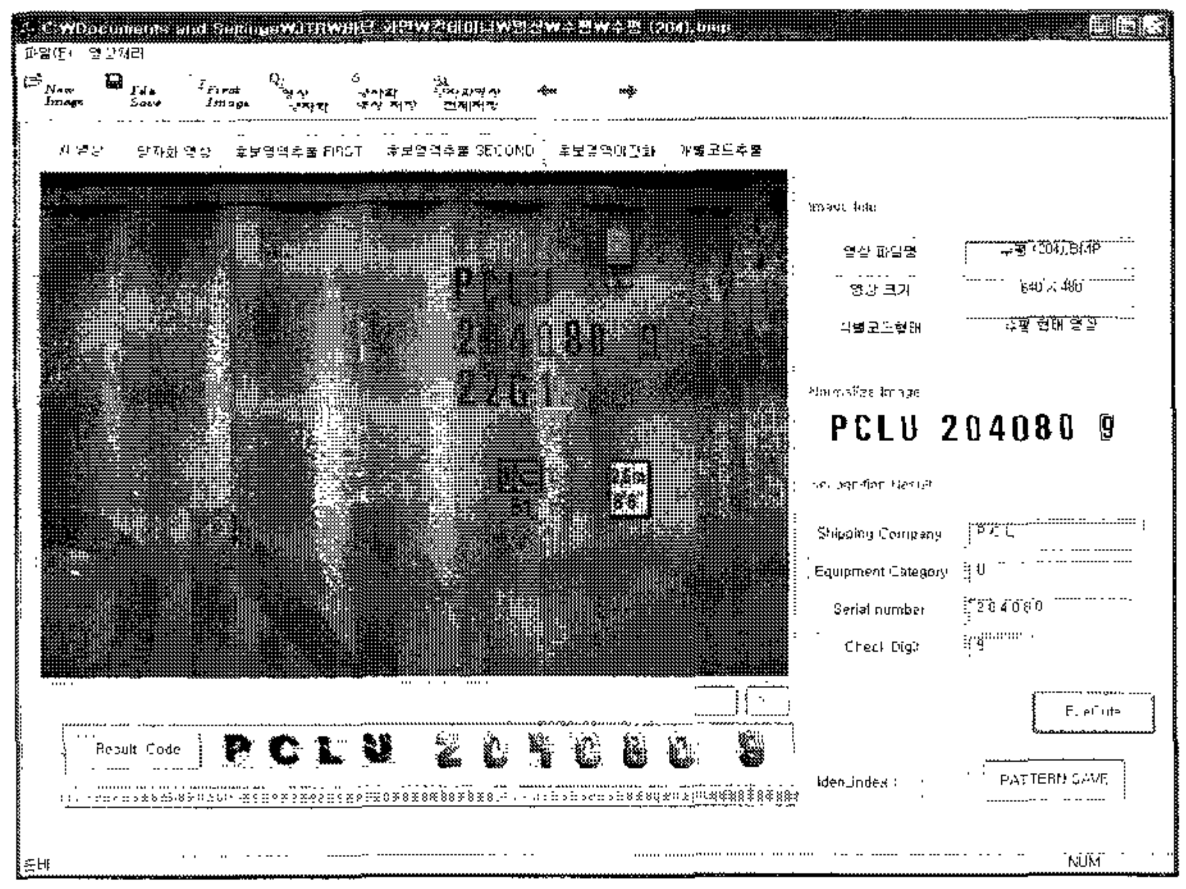


Fig. 12 Experiment screen of extraction and recognition of container identifiers

In the extraction of identifier areas, the previously proposed method in Ref. [7] fails to extract target areas due to noises caused by an external light and the rugged surface shape of containers. On the other hand, the proposed extraction method detects and removes noises by using ART2-based image quantization method and feature information of container identifiers, improving the success rate of extraction compared with the previously proposed. The comparison of the success rate of identifier area extraction between the proposed in this paper and the previously proposed in Ref. [7] is like Table 1.

Table 1 Comparison of the success rate of identifier area extraction

	Previously-proposed method in Ref. [7]	Proposed method in this paper
Success rate	209/300 (69.6%)	282/300 (94%)

For the experiment of identifier recognition, by applying 8-directional contour tracking method to 282 identifier areas extracted by the proposed extraction algorithm, a total of 3102 identifier codes were extracted. The extracted codes consisted of 1128 shipping company codes, 1692 container serial codes and 282 check digit codes. This paper performed the learning in the proposed RBF network using 200 container serial codes and 480 shipping company codes and 100 check digit codes as learning data, and the experiment for identifier recognition was performed using all extracted identifier codes. Table 2 shows the performance of learning and recognition of the proposed RBF network.

Table 2 Performance of learning and recognition in the proposed RBF network

	Refined ART2-based RBF network	
	# of Epoch	# of success of recognition
Shipping Company Codes (1128)	1170	1126
Container Serial Codes (1692)	669	1681
Check Digit Codes (282)	319	282

Fig. 13 shows the change process of TSS according to the number of Epochs with respect to each type of container identifiers in the refined ART2-based RBF network. As shown in Fig. 13, the proposed RBF network is fast in the initial convergence and performs the stable learning. In the experiment for performance evaluation, parameter setup for the proposed RBF network was like Table 3. In Table 3, ρ, α and μ mean the vigilance parameter, the learning rate and the momentum coefficient, respectively, and κ, γ and β are delta-bar-delta constants.

The refined ART2-based RBF network failed to recognize container identifiers in the cases that individual identifiers are largely damaged in an original container image or the loss of information on identifiers occurs in the binarization phase of identifier areas.

Table 3 Parameter setup for the refined ART2-based RBF network

Parameters	ρ	α	μ	κ	γ	β
Refined ART2 -based RBF network	0.05	0.8	0.6	0.03	0.2	0.7

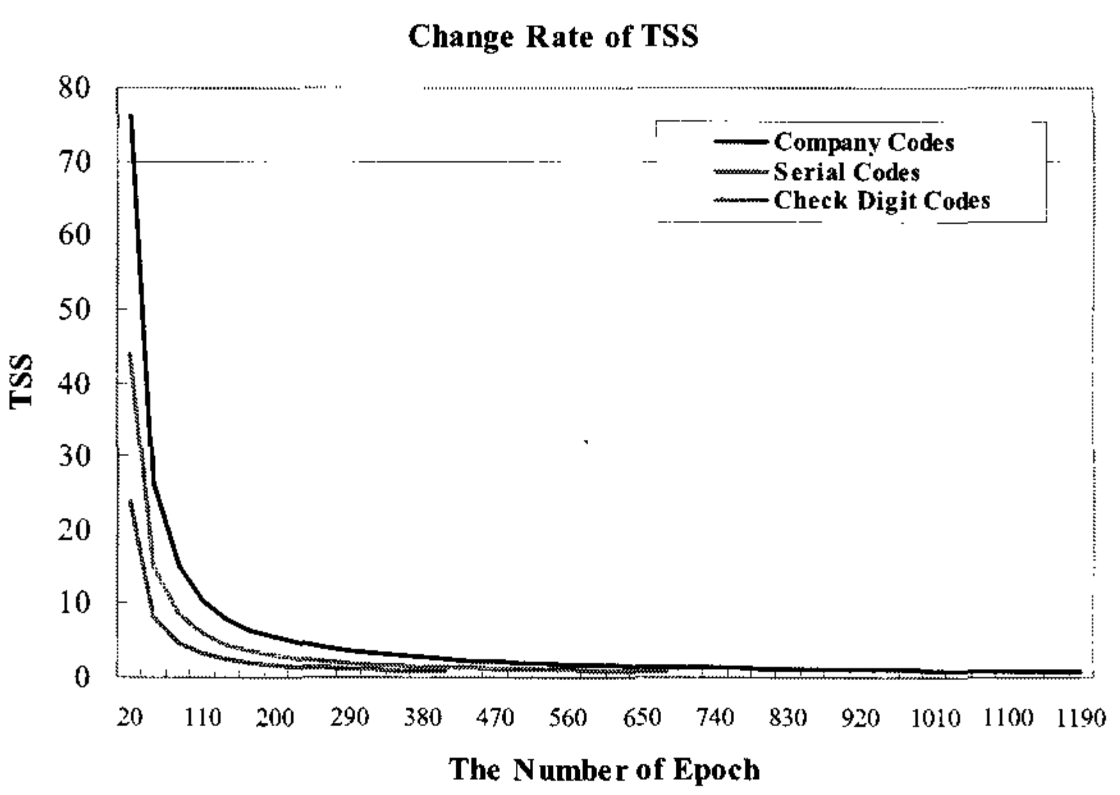


Fig. 13 Change process of TSS according to the number of Epochs

V. CONCLUSIONS

This paper, at first, distinguished identifier areas from background noises and removed noises by using ART2-based quantization method and morphological information on container identifiers such as color, size, ratio of height to width and an interval between identifiers, etc. And, using 8-directional contour tracking method, individual identifiers were extracted from identifier areas. This paper proposed a refined ART2-based RBF network and applied to the recognition of individual identifiers.

Experiments using 300 container images showed that 282 areas of identifiers and 3102 individual identifiers were extracted successfully. The proposed RBF network recognized 3089 identifiers. Failures of recognition were caused by the damage of shapes of individual identifiers in original images and the information loss on identifiers shaded by bends in the binarzation process.

A Future work is the development of fuzzy association algorithm that may recover damaged identifiers to improve the performance of extraction and recognition of individual identifiers.

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