Recognition of Identifiers from Shipping Container Image by Using Fuzzy Binarization and ART2-based RBF Network

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Abstract

The automatic recognition of transport containers using image processing is very hard because of the irregular size and position of identifiers, diverse colors of background and identifiers, and the impaired shapes of identifiers caused by container damages and the bent surface of container, etc. We proposed and evaluated the novel recognition algorithm of container identifiers that overcomes effectively the hardness and recognizes identifiers from container images captured in the various environments. The proposed algorithm, first, extracts the area including only all identifiers from container images by using CANNY masking and bi-directional histogram method. The extracted identifier area is binarized by the fuzzy binarization method newly proposed in this paper and by applying contour tracking method to the binarized area, container identifiers which are targets of recognition are extracted. We proposed and applied the ART2-based RBF network for recognition of container identifiers. The results of experiment for performance evaluation on the real container images showed that the proposed algorithm has more improved performance in the extraction and recognition of container identifiers than the previous algorithms.

Keywords:

Container Recognition; Fuzzy Binarization; Contour Tracking; ART2-based RBF Network

1. Introduction

Recently, the quantity of goods transported by sea increases steadily since the cost of transportation by sea is lower in price than other transportation methods. And various automation methods are used for the speedy and accurate processing of transport container flow in the harbors. The automation systems for transport container flow processing are classified to two types, the barcode processing system and the automatic recognition system of container identifiers based on image processing. Today, the identifier recognition system is mainly used in the harbors.

The identifiers of transport containers 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[1,2]. The ISO standard prescribes only code types of container identifiers, while it doesn't define other features such as size, position and interval of identifier characters etc. And the features such as the foreground and background colors of containers, the font type, and the size of identifiers etc., are various according with containers. This variety of features of container identifiers makes the extraction and recognition of identifiers very hard[3].

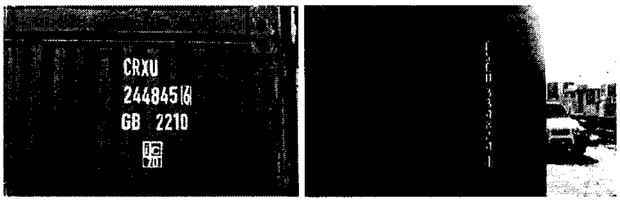
As the identifiers are printed on the outer of containers, shapes of identifiers are impaired by the environment factors of transportation by sea and the external noises so that the identifier characters may not be separated from container images. The damage of the outer of container and the bent surface of containers made for the protection of internal goods may change shapes of identifier characters on container images. So after preprocessing the container images, the additive procedure must be required, that decides whether the results are the edges of identifiers or the noises by background.

In this paper, considering features of container identifiers, we applied Canny masking to container images for generating edge maps of input images. By applying the bi-directional histogram method to edge maps, identifier areas, which are the minimum rectangles including only all identifiers, are extracted from input images. We used image binarization method to extract individual identifiers from identifier areas. In the image processing applications using binary images, the selection of threshold value decides the performance of binary image processing. The container images include diverse colors, globally changed intensity and various types of noise, so that the selection of threshold value for image binarization becomes ambiguous. Therefore, we proposed the fuzzy binarization method to binarize the identifier areas and applied 4-directional contour tracking to the results for extracting individual identifiers. And the ART2-based RBF network was proposed and applied for recognizing individual identifier codes.

This paper is organized as follows: Section II shows the extraction method of identifiers from container images, and Section III examines in detail the identifier recognition by the proposed neural network. Section IV shows the performance evaluation and Section V finishes with conclusions.

2. Container Identifier Extraction

In this paper, the procedure extracting container identifiers from input images consists of the extraction phase of identifier areas including only container identifiers in the images and the extraction phase of individual identifiers from identifier areas. Fig. 1 shows examples of container images representing two types of identifier arrangement on the surface of containers.



(a) Horizontal arrangement of Identifiers *(b) Vertical arrangement of Identifiers*

Figure 1 - Examples of Container Images

2.1 Extraction of Container Identifier Areas

For extracting identifier areas from container images, first, we used Canny masking to generate edge maps of input images. The edges extracted by Canny masking are not connected in several directions and isolated individually, and edge maps are efficient for the separation of identifiers and the background in container images. Canny masking performs the noise removal by Gaussian masking and the edge extraction by Sobel masking sequentially. As container images include many noises caused by the outward shape of containers on the upper and lower areas, the calculation of vertical coordinates of identifier areas ahead of horizontal coordinates can generate the more accurate results. So, we calculated the vertical coordinates of identifier areas by applying the vertical histogram to edge maps, and applied the horizontal histogram to the block corresponding to the vertical coordinate calculating the horizontal coordinate. Fig 2 shows the algorithm for identifier area extraction on the whole, and Fig. 3 shows an example of extraction results by the proposed algorithm.

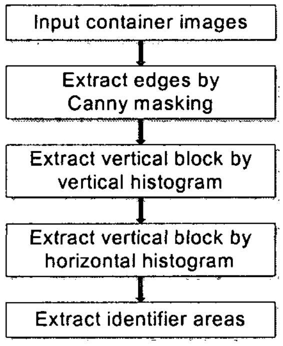


Figure 2 - Extraction algorithm of identifier areas

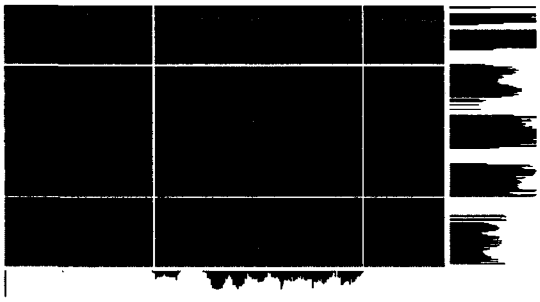


Figure 3 - Extraction results of Identifier areas

2.2 Extraction of Individual Identifiers

We extracted container identifiers from identifier areas by binarizing the areas and applying contour tracking algorithm to the binarized areas. Container identifiers are arranged to one row by calculating Euclidean distances between identifier codes and in turn classified to the three code groups such as shipping company codes, container serial codes and check digit code.

Generally the image binarization is used for extraction of recognition targets from input images because of simplicity and no information loss[4]. But various features of container identifiers, such as size, position and color etc., are not normalized, and the shapes of identifiers are impaired by the environmental factors of transportation and the container breakdown. Also, container images include diverse colors, globally changed intensity and various types of noises, so that the selection of threshold value for image binarization becomes ambiguous. Therefore, we proposed the novel fuzzy binarization algorithm to separate the background and identifiers for extraction of container identifiers.

The proposed fuzzy binarization algorithm defines I_{Mid} as the mean intensity value of the identifier area for the selection of interval of membership function. I_{Mid} is calculated like Eq.(1).

$$I_{Mid} = \frac{\sum_{i=1}^{W} \sum_{j=0}^{H} I_{ij}}{H \times W} \qquad (1)$$

where I_{ij} is the intensity of pixel (i, j) of identifier area, and H and W is the pixel lengths of height and width of identifier area respectively.

And, Defining I_{Min} and I_{Max} as the minimum intensity value and the maximum one in the identifier area respectively, the algorithm determining the interval of member function $\left[I_{Min}{}^{New}, I_{Max}{}^{New}\right]$ in the proposed fuzzy binarization is as follows:

Step 1:

$$I_{Min}{}^{F} = I_{Mid} - I_{Min}$$
$$I_{Max}{}^{F} = I_{Max} - I_{Mid}$$

Step 2:

$$If\ I_{Mid} \rangle 128\ Then\ I_{Mid}{}^{F} = 255 - I_{Mid}$$
$$Else\ I_{Mid}{}^{F} = I_{Mid}$$

Step 3:

$$If\ I_{Mid}{}^{F} \rangle I_{Max}{}^{F}\ Then$$
$$\quad If\ I_{Min}{}^{F} \rangle I_{Mid}{}^{F}\ Then\ \sigma = I_{Mid}{}^{F}$$
$$\quad Else\ \sigma = I_{Min}{}^{F}$$
$$Else$$
$$\quad If\ I_{Max}{}^{F} \rangle I_{Mid}{}^{F}\ Then\ \sigma = I_{Mid}{}^{F}$$
$$\quad Else\ \sigma = I_{Max}{}^{F}$$

Step 4:

Calculate the normalized $I_{Min}{}^{New}$ & $I_{Max}{}^{New}$

$$I_{Min}{}^{New} = I_{Mid} - \sigma$$
$$I_{Max}{}^{New} = I_{Mid} + \sigma$$

In most cases, individual identifiers are embossed in identifier area and noises between identifier codes and the background are caused by shadows. We used the fuzzy binarization to remove noises by shadows. The membership function of the proposed fuzzy binarization is like Fig.4.

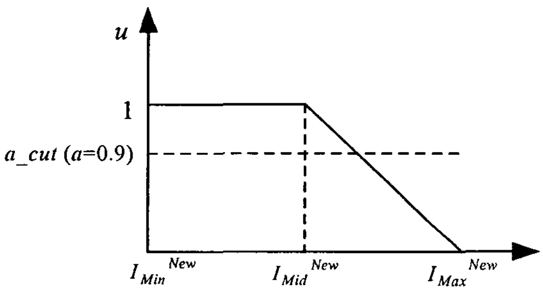


Figure 4 - Proposed fuzzy membership function

The degree of membership $u(I)$ in terms of the membership interval $\left[I_{Min}{}^{New}, I_{Max}{}^{New}\right]$ is calculated like Eq.(2)

$$\begin{aligned} &if\ \left(I_{Min}{}^{New} \le I\ \pi\ I_{Mid}{}^{New}\right) Then\ \ u(I) = 1 \\ &Else\ if\ \left(I_{Mid}{}^{New} \le I\ \pi\ I_{Max}{}^{New}\right) Then \\ &\quad u(I) = -\frac{1}{I_{Max}{}^{New} - I_{Mid}{}^{New}}\left(1 - I_{Mid}{}^{New}\right) + 1 \end{aligned} \tag{2}$$

The identifier area is binarized by applying α-cut(α=0.9) to the degree of membership $u(I)$.

Next, we extracted container identifiers from the binarized identifier area by using the contour tracking method. In this paper, the 4-directional contour tracking method using 2x2 mask was applied considering the whole preprocessing time of container images. The contour tracking, using 2x2 mask given in the Fig.5, scans the binarized identifier area from left to right and from top to bottom to find boundary pixels of identifier codes[5,6]. If a boundary pixel is found, the pixel is selected as the start position of tracking and placed at the x_k position of the 2x2 mask. By examining the two pixels coming under the ***a*** and ***b*** positions of the mask and comparing with the conditions in Table 1, the next scanning direction of the mask is determined and the next boundary pixel being tracked is selected. The selected pixels coming under the x_k position are connected into the contour of an identifier. By generating the outer rectangles including connected contours and comparing the ratio of width to height, the rectangles with the maximum ratio are extracted as individual identifiers.

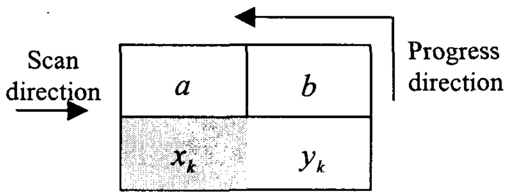


Figure 5 - 2x2 mask for 4-direction contour tracking

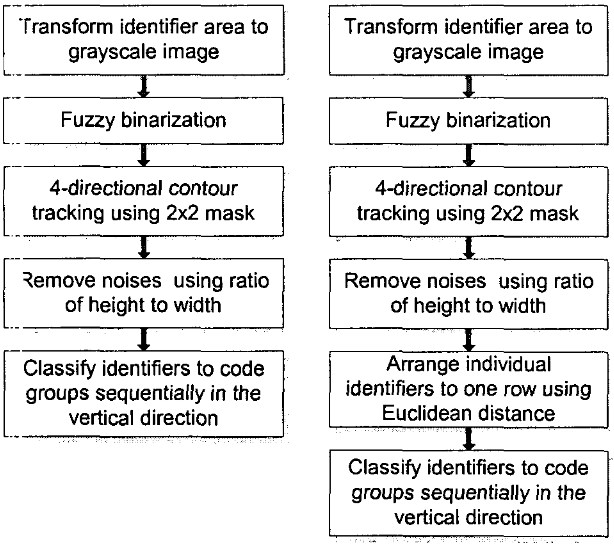
Table 1 - Progress direction of a and b by 2x2 mask

	a	***b***	x_k	y_k
Forward	1	0	a	b
Right	0	1	b	y_k
Right	1	1	a	x_k
Left	0	0	x_k	a

The extracted identifiers must be classified to three code groups, shipping company codes, container serial codes and check digit code for the information processing following the identifier recognition. But extracted identifiers are not normalized in size and position and the vertical coordinates of identifiers placed on the same row are different each other because of the application of contour tracking to images with distortion caused by the bent surface of containers. And the grouping of related identifiers by using only coordinates of individual identifiers generates inconsistent results.

In this paper, the extracted identifiers are arranged to one row by using Euclidean distances between identifiers and classified to code groups. If identifiers were placed on several rows in identifier area, first, the first identifiers at each row were selected. And in each row, by calculating the Euclidean distance between the start pixel of the first identifier and the start one of other identifiers having the vertical offset to the first identifier being less than one half of vertical size of the first identifier, identifiers are arranged according to Euclidean distance. By combining identifier sequences in every row, one row of identifiers is created. Last, identifiers in the row are classified sequentially to code groups by rule of ISO standard.

Fig.5(a) shows the procedure of identifier extraction in identifier area with vertical arrangement(like Fig.1(b)) and Fig.5(b) shows the extraction procedure in the area with horizontal arrangement(like Fig.1(a)).



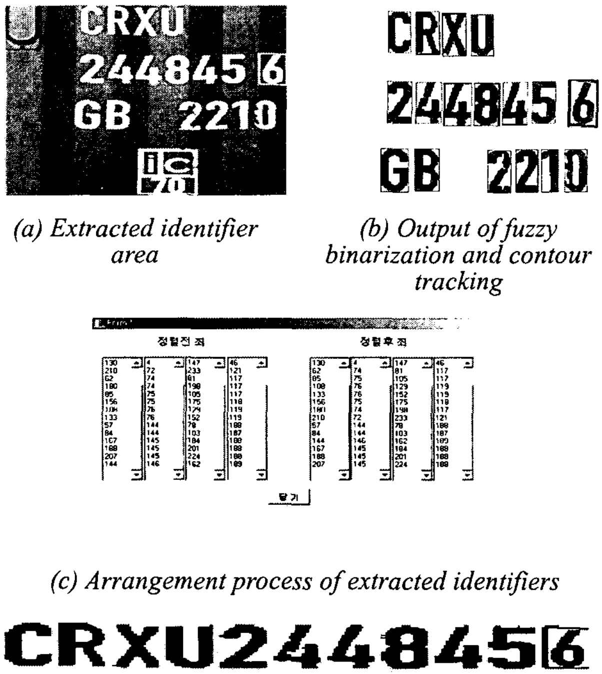
(a) Identifier extraction in vertical identifier area *(b) Identifier extraction in horizontal identifier area*

Figure 6 - Two types of identifier extraction algorithms

Fig.7 shows an example of the identifier extraction from container images with horizontal identifier arrangement. Fig.7(a) shows the identifier area extracted from input image and Fig.7(b) show the result of identifier extraction processing on the identifier area. In Fig.7(c), the identifier arrangement procedure based on Euclidean distance is showed, and last, Fig.7(d) shows the result of the identifier extraction and arrangement processing.

4. Identifier Recognition Using ART2-based RBF Network

The error backpropagation algorithm uses the gradient descent as the supervised learning rule to minimize the cost function defined in terms of error value between output value and target one for an given input. And the algorithm has the defect that the convergence speed of learning becomes slow and the possibility falling into the local minima is induced by the insufficient number of nodes in the hidden layer and the unsuitable initial connection weights[7,8]. In the learning process, the algorithm uses the credit assignment propagating error value of output layer's nodes backward to nodes of hidden layer, and the paralysis is induced in the hidden layer. Generally, the recognition algorithms using the error backpropagation are troubled with



(a) Extracted identifier area *(b) Output of fuzzy binarization and contour tracking*

(c) Arrangement process of extracted identifiers

(d) Output of extraction and arrangement of container identifiers

Figure 7 - Identifier extraction process of container image with horizontal arrangement

the falling-off of recognition rate caused by the empirical determination of the number of hidden layer's nodes and the credit assignment[9].

The ART2 algorithm may perform the learning for binary input patterns and analog input patterns[10]. In the ART2 algorithm, connection weights are modified according to the calculation of mean values of all input patterns, and the creation of clusters is done fairly. But, because mean value of input vector and connection weight vector weakens the property of connection weights, the input pattern may be classified to the similar cluster having different properties[11]. If the ART2 algorithm is applied to the recognition of container identifiers, the recognition rate is declined by the classification of different input patterns to the same cluster. Therefore, we proposed the novel ART2-based RBF network adapting the ART2 algorithm to the middle layer as the learning structure between the input layer and the middle layer and applied to the recognition of container identifiers.

The ART2-based RBF network performs the 2-phase learning: the first phase of learning is the competitive learning between the input layer and the middle layer, and the second phase is the supervised learning between the middle layer and the output layer. In the proposed neural network, output vector of middle layer is calculated by Eq.(3) and the node with minimum output vector is selected as the winner node like Eq.(4).

$$O_j = \frac{1}{N}\sum_{i=1}^{N}\left\|x_i - w_{ji}(t)\right\| \tag{3}$$

$$O_j^* = Min(O_j) \tag{4}$$

where w_{ji} is connection weight between the input layer and the middle layer.

And the similarity test for the selected winner node is like Eq.(5).

$$O_j^* \pi \rho \tag{5}$$

where ρ is the vigilance parameter.

If output vector of the winner node is less than vigilance parameter, the input pattern is classified as the same pattern; otherwise it is classified as the different pattern. In the former case, connection weight is modified to reflect the similar property of input pattern to the weight. The modification of connection weight is like Eq.(6).

$$w_{j^*i}(t+1) = \frac{w_{j^*i}(t) \times u_n + x_i}{u_n + 1} \tag{6}$$

where u_n is the number of updated patterns in the created cluster.

The output vector of middle layer is normalized as Eq.(7) and used as the input vector of output layer.

$$z_j = 1 - \frac{O_j}{N} \tag{7}$$

The output vector of output layer is calculated like Eq.(8).

$$O_k = f\left(\sum_{j=1}^{M} w_{kj} \times z_j\right)$$
$$f(x) = \frac{1}{1+e^{-x}} \tag{8}$$

The error value and error signal between the output vector and the target vector are calculated and used to modify the connection weight, like Eq.(9) and Eq.(10).

$$\delta_k = (T_k - O_k) \times O_k \times (1 - O_k) \tag{9}$$
$$w_{kj}(t+1) = w_{kj}(t) + \alpha \times \delta_k \times z_j \tag{10}$$

4. Performance Evaluation

For performance evaluation, we implemented the proposed algorithm and experimented on the IBM-compatible PC with Intel Pentium-IV 2GHz CPU and 256MB RAM. The 100's container images of 754x504 pixel size and 256 colors were used in the experiment.

In the experiment for identifier extraction, we compared the extraction algorithms proposed in this paper and the reference [3]. And to evaluate the recognition performance of ART2-based RBF network, we compared with the error backpropagation algorithm.

4.1 Performance of individual identifier extraction

By using the proposed extraction algorithm for identifier area, all 100's areas were successfully extracted from 100's images. Applying identifier extraction algorithms proposed in this paper and the reference [3] to the extracted 100's areas, experiment results were summarized and compared in Table 2.

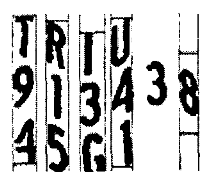
Table 2 - Performance comparison of identifier extraction

	The number of extracted identifiers			
	Shipping Company Codes (400)	Container Serial Codes (600)	Check Digit Code (100)	Total number of identifiers (1100)
Algorithm proposed in Ref.[3]	299	558	69	856
Proposed extraction algorithm	383	582	89	1054

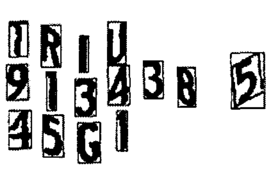
As shown in Table 2, the algorithm proposed in the reference [3] is inferior to our algorithm because it failed to extract identifiers in the cases that the background and the container identifiers may not be distinguished each other or the shape of identifiers and the interval between identifiers are changed by the bent surface of containers. Our algorithm could extract successfully container identifiers in the images where the algorithm of reference [3] failed to extract identifiers, since our algorithm, first, distinguished the background and container identifiers by using the proposed fuzzy binarization, and next, extracted identifiers by using the contour tracking.

Fig.8 shows an example of the case mentioned above. Fig.9 shows the identifier arrangement process and the arrangement result for container identifiers extracted in Fig.8.

(a) Extracted identifier area

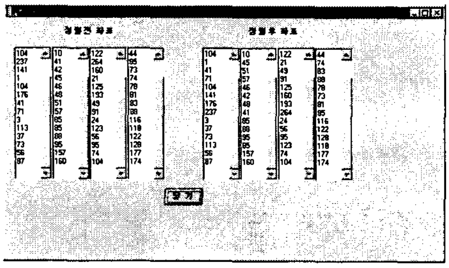


(b) Histogram method proposed in Ref.[3]

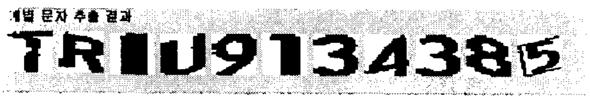


(c) Proposed method in this paper

Figure 8 - Comparison of identifier extraction results



(a) Arrangement process of extracted identifiers

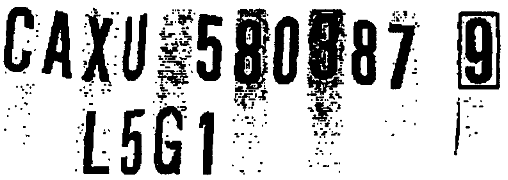


(b) Output of identifier extraction and arrangement

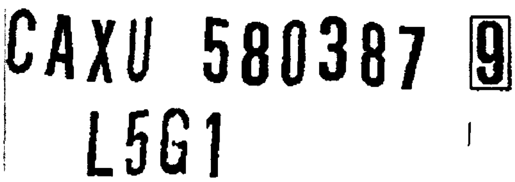
Figure 9 - Example of identifier extraction and arrangement

Fig.10 shows the comparison of experiment results when the mean-intensity based binarization proposed in the reference [3] and the proposed fuzzy binarization were applied to identifier area of Fig.10(a).

(a) Extracted identifier area



(b) Mean-intensity based image binarization



(c) Proposed fuzzy binarization

Figure 10 - Comparison of mean-intensity based binarization and proposed fuzzy binarization

In Fig.10, the thresholds for the mean-intensity based binarization and for the fuzzy binarization are 117 and 145 respectively. As shown in Fig.10, the fuzzy binarization distinguished clearly the background and container identifiers.

4.2 Performance of container identifier recognition

Table 3 compares learning performances in the experiment that applied the error backpropagation algorithm and the ART2-based RBF network to container identifiers extracted by the proposed algorithm mentioned above.

Table 3 - Comparison of learning performance

	Learning results of individual identifiers			
	Error backpropagation		**ART2-based RBF netowrk**	
	# of hidden layer' nodes	**Learning time**	**# of clustering layer's nodes**	**Learning time**
Shipping Company Codes	47	32 min 48 sec	87	25 min 12 sec
Container Serial Codes	65	41 min 25 sec	95	33 min 7 sec
Check Digit Code	25	9 min 27 sec	31	5 min 2 sec

In the learning experiment, 1054's container identifiers were used, which consisted of 283's shipping company codes, 582's container serial codes and 89's check digit codes. The initial connection weights used for learning in each algorithm were set as values between –1 to 1 and in the ART2-based RBF network, the vigilance parameter used for the creation and update of clusters was empirically set via the priori test – it was optimal that the vigilance parameters for container serial codes was set as 0.10 and for sipping company codes and check digit as 0.15. The rate of learning and the moment were set as 0.5 and 0.6 respectively. As shown in Table 3, The learning time required for the ART2-based RBF network was as shorter as about 20~45% than the error backpropagation algorithm.

Table 4 compares recognition performances of the two algorithms by the number of recognition success in the experiment. As shown in Table 4, the recognition rate of the ART2-based RBF network was higher than the error backpropagation algorithm.

Table 4 - Comparison of recognition performance

	# of recognition successes		
	Shipping Company Codes (383)	**Container Serial Codes (582)**	**Check Digit Codes (89)**
Error backpropagation algorithm	375	572	81
ART2-based RBF network	380	579	84

Fig.11 and Fig.12 show output screens of identifier extraction and recognition by the proposed algorithm in this paper for the vertical container image and the horizontal one respectively.

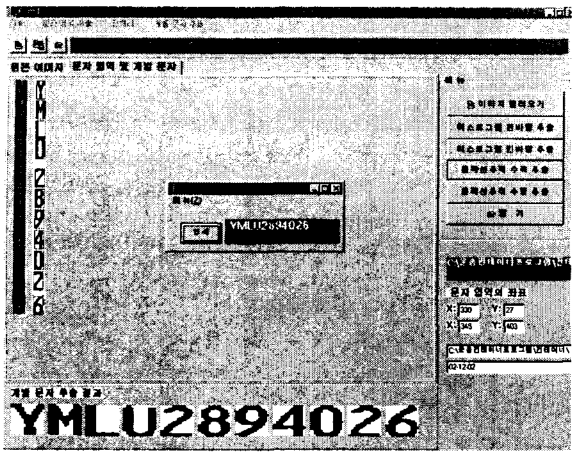


Figure 11 - Identifier extraction and recognition for vertical container image

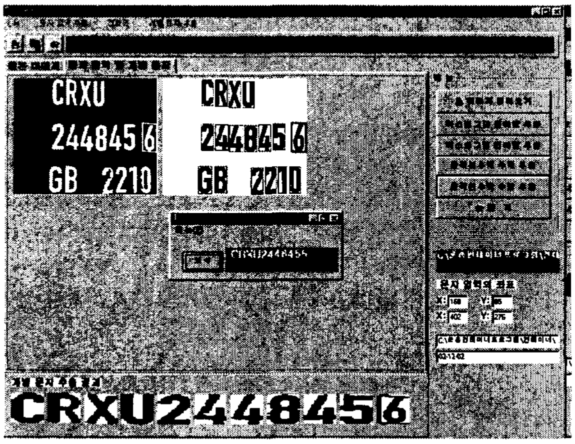


Figure 12 - Identifier extraction and recognition for horizontal container image

5. Conclusions

In this paper, we proposed and evaluated the novel recognition algorithm of container identifiers for the automatic recognition of transport containers. Using the structural feature of container image that identifier areas have more edge information than other areas, the proposed algorithm used Canny masking to generate edge maps of container images. Applying the vertical histogram method and the horizontal one sequentially to the edge map, the identifier area that is the minimum rectangle including only all container identifiers was extracted. The container images shows some features making the identifier recognition by image processing hard, such as irregular size and position of identifiers, diverse colors of background and identifiers, and the impaired shape of identifiers caused by container damages and the bent surface of containers. So, we proposed the fuzzy binarization to separate clearly the background and identifiers and applied with the 4-directional contour tracking to the identifier area, extracting individual identifiers. And the extracted identifiers were arranged to one row by using the Euclidean distances between identifiers and grouped into code groups such as shipping company codes, container serial codes and check digit code. For the identifier recognition, we proposed and applied the ART2-based RBF network, which adapts the ART2 algorithm to the middle layer as the learning structure between the input layer and the middle layer.

For performance evaluation, the experiment applying the proposed identifier extraction and recognition algorithm to 100's real container images was performed. All 100's identifier areas were successfully extracted from container images and 1054's identifiers were extracted form the areas with total 1100's identifiers, which means that the proposed algorithm has more improved performance than the preprocessing algorithm proposed in reference [3]. Results of the recognition experiment applying the error backpropagation algorithm and the ART2-based RBF network to 1054's identifiers show that the ART2-based RBF network has higher rate of recognition than the error backpropagation algorithm.

The future works is the refinement of proposed recognition algorithm to improve the performance in cases that the background and container identifiers are not distinguished well or the shapes of container identifiers are seriously impaired.

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