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An Intelligent System for Recognition of Identifiers from Shipping Container Images using Fuzzy Binarization and Enhanced Hybrid Network

Kwang-Baek Kim

Department of Computer Engineering, Silla University

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. In this paper we propose and evaluate a novel recognition algorithm for container identifiers that effectively overcomes these difficulties and recognizes identifiers from container images captured in various environments. The proposed algorithm, first, extracts the area containing only the 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. Then a contour tracking method is applied to the binarized area in order to extract the container identifiers which are the target for recognition. In this paper we also propose and apply a novel ART2-based hybrid network for recognition of container identifiers. The results of experiment for performance evaluation on the real container images showed that the proposed algorithm performs better for extraction and recognition of container identifiers compared to conventional algorithms.

Key words : Container Recognition, Fuzzy Binarization, Contour Tracking, ART2-based Hybrid Network

1. Introduction

Recently, the quantity of goods transported by sea has increased steadily since the cost of transportation by sea is lower than other transportation methods. Various automation methods are used for the speedy and accurate processing of transport containers in the harbor. The automation systems for transport container flow processing are classified into two types: the barcode processing system and the automatic recognition system of container identifiers based on image processing. However, these days the identifier recognition system based on images is more widely 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. Other features such as the foreground and background colors of containers, the font type, and the size of identifiers, vary from one container to another. These variations in features for container identifiers, makes the process of extraction and recognition of identifiers quite difficult [3].

Since the identifiers are printed on the surface of the containers, shapes of identifiers are often impaired by the environmental factors during the transportation by sea. The damage to the surface of the container may change shapes of identifier characters in container images. So after preprocessing the container images, an additive procedure must be applied, in order to decide whether the results are truly the edges of identifiers or just the noise from the background.

2. Container Identifier Extraction

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

In this paper, considering the specific attributes of the 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

(a) Horizontal arrangement of Identifiers

(b) Vertical arrangement of Identifiers

Fig. 1. Examples of Container Images

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are the minimum rectangles including only all identifiers, are extracted from input images. We used image binarization method to extract individual identifiers from the 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 varying intensity and various types of noise, so that the selection of threshold value for image binarization is not easy. Therefore, we propose a fuzzy binarization method to binarize the identifier areas and apply 4-directional contour tracking to the results for extracting individual identifiers. We also propose a novel ART2-based hybrid network architecture and apply it for recognizing individual identifier codes.

2.1 Extraction of Container Identifier Areas

Fig 2 shows the various steps in the algorithm for identifier area extraction. 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 disconnected in several directions and isolated individually. These edge maps are efficient for the separation of identifiers and the background in container images. Canny masking is similar to noise removal carried out using Gaussian masking and edge extraction performed by Sobel masking sequentially.

Since the container images include noise caused by the distortion of the outer surface and shape of containers on the upper and lower areas, the calculation of vertical coordinates of identifier areas ahead of horizontal coordinates can generate more accurate results. Hence, 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. 3 shows an example of extraction results by the proposed algorithm.

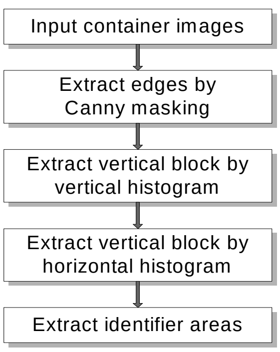


Fig. 2. Extraction algorithm of identifier areas

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 in a single row by

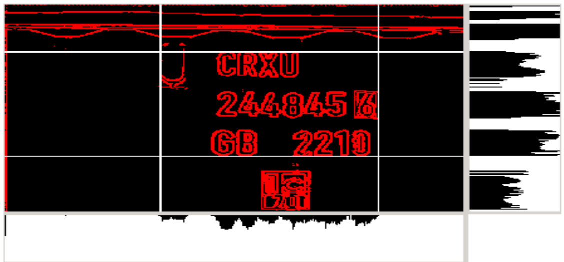


Fig. 3. Extraction results of Identifier areas

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, image binarization is used for extraction of recognition targets from input images since that results in data compression in a fashion that is usually loss less as far as relevant information is concerned. However, various features of container identifiers, such as size, position, color etc., are not normalized, and the shapes of identifiers are impaired by the environmental factors during transportation and the container breakdown. Moreover, container images include diverse colors, globally changed intensity and various types of noises, so that the selection of threshold value for image binarization is difficult using traditional methods which use distance measures [4]. Therefore, we propose a 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).

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

where I_{ij} is the intensity of pixel (i, j) of identifier area, and H and W are the pixel lengths of height and width of identifier area respectively. I_{Min} and I_{Max} define the minimum intensity value and the maximum value in the identifier area respectively. The algorithm determining the interval of member function $[I_{Min}^{New}, I_{Max}^{New}]$ 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 :

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

Step 3 :

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

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 the identifier area and the noise between identifier codes and the background is caused by shadows. We used the fuzzy binarization algorithm to remove the noise from the shadows. The membership function of the proposed fuzzy binarization is shown in Fig.4.

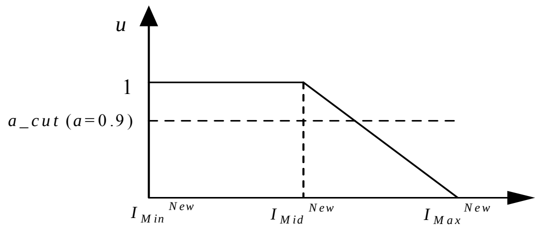


Fig. 4. Proposed fuzzy membership function

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

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

The identifier area is binarized by applying α-cut(α=0.9) to the degree of membership $u(I)$. Next, we extracted the 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 Fig.5, scans the binarized identifier area from left to right and from top to bottom to find boundary pixels for identifier codes [5,6]. If a boundary pixel is found, that pixel is selected as the start position for tracking and placed at the x_k position (see Fig. 5) of the 2x2 mask. By examining the two pixels below the ***a*** and ***b*** positions of the mask and comparing them with the conditions in Table 1, the next scanning direction of the mask is determined and the next boundary pixel is selected for tracking. The selected pixels below 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.

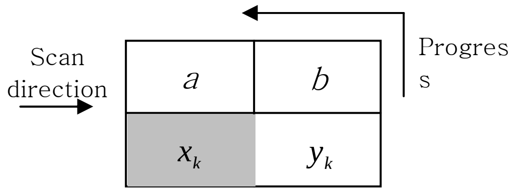
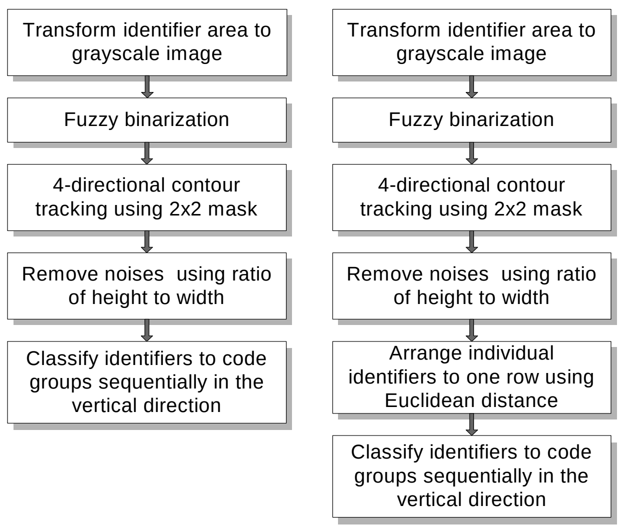


Fig. 5. 2x2 mask for 4-direction contour tracking

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 into three code groups, shipping company codes, container serial codes and check digit code for the information processing following the identifier recognition. However, extracted identifiers are not normalized in size and position and the vertical coordinates of identifiers placed on the same row are different from each other because of the application of contour tracking to images with distortion caused by the bent surface of containers. As a result, the grouping of related identifiers by using only coordinates of individual identifiers generates inconsistent results. In this paper, the extracted identifiers are arranged in a single row by using Euclidean distances between identifiers and classified into three code groups. If the row containing the identifiers was distorted, resulting in multiple rows within identifier area, initially, the first identifiers from each row were selected. Then in each row identifiers are arranged according to the Euclidean distance. The Euclidean distance is calculated by measuring the distance between the start pixel of the first identifier and the start pixel of the other identifier having a vertical offset from the first identifier. The vertical



(a) Identifier extraction in vertical identifier area

(b) Identifier extraction in horizontal identifier area

Fig. 6. Two types of identifier extraction algorithms

offset must be less than one half of the vertical size of the first identifier. Then, by combining identifier sequences in every row, one row of identifiers is created. Finally, identifiers in the row are classified sequentially to code groups according to the ISO standard [1]. Fig.6(a) shows the procedure for identifier extraction in identifier area with vertical arrangement (as shown in Fig.1(b)) and Fig.6(b) shows the extraction procedure in the area with horizontal arrangement (as shown in Fig.1(a)).

3. Identifier Recognition using ART2-based Hybrid Network

The error backpropagation algorithm uses gradient descent as the supervised learning rule to minimize the cost function defined in terms of the error value between the output value and the target one for an given input. Hence, the algorithm has the drawback that the convergence speed of learning is slower and the possibility of falling into the local minima is induced by the insufficient number of nodes in the hidden layer and the unsuitable initial connection weights [7,8,9]. During the learning process, the algorithm uses credit assignment for propagating error value of the output layer's nodes backward to the nodes in the hidden layer. As a result, paralysis can be induced in the hidden layer. Generally, the recognition algorithms using the error backpropagation are plagued by the falling-off of recognition rate caused by the empirical determination of the number of hidden layer nodes and the credit assignment procedure [10,11].

The ART 2 architecture was evolved to perform learning for binary input patterns and also accommodate continuous valued components in input patterns [12, 13]. In the ART2 algorithm, connection weights are modified according to the calculation of mean values of all input patterns (equation 6). Then the cluster center is calculated by adapting it to the new pattern using equation (7). However, the averaged mean value of the difference in input vector and connection weight is used for comparison with the vigilance factor, which leads to the possibility of an input pattern being classified to a similar cluster having different properties [14]. This could happen particularly in cases where the pattern dimensionality (N in equation 3) is large and one feature drastically differs from the cluster center but it's impact is minimized due to averaging all differences (see equation 3). When the traditional ART2 algorithm was applied to the recognition of container identifiers, it was observed that the recognition rate declined due to the classification of such different input patterns to the same cluster. Therefore, we propose a novel ART2-based hybrid network architecture where the middle layer neurons have RBF (Radial Basis Function) properties and the output layer neurons have a sigmoid function property. By adapting the ART2 algorithm for learning structure between the input layer and the middle layer and using the delta rule for training the weights to the output layer neurons, we improve the recognition rate for container identifiers.

The ART2-based hybrid network performs learning in two phases. The first phase of learning involves competitive learning between the input layer and the middle layer, and the second phase carries out supervised learning between the middle layer and the output layer. In the proposed hybrid neural network, output vector of middle layer is calculated using Eq.(3) and the node with minimum output vector (Eq.(4)) is selected as the winner node.

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

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

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

The similarity test for the selected winner node is given by Eq.(5).

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

where ρ is the vigilance parameter.

The ART network is an unsupervised vector classifier that accepts input vectors that are classified according to the stored pattern they most resemble. It also provides for a mechanism allowing adaptive expansion of the output layer of neuron until an adequate size is reached based on the number of classes, inherent in the observation. The ART network can adaptively create a new neuron corresponding to an input pattern if it is determined to be "sufficiently" different from existing clusters. This determination, called the vigilance test, is incorporated into the adaptive backward network. Thus, the ART architecture allows the user to control the degree of similarity of patterns placed in the same cluster.

If the output of the winner node is less than or equal to the vigilance parameter, the input pattern is classified into the same cluster, otherwise a new cluster is created with that pattern as the cluster center. In the former case, connection weight is modified to adapt the weight vector to reflect the impact of the new input pattern. The modification of connection weight vector is based on 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 the middle layer is normalized using Eq.(7) and used as the input vector for the output layer.

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

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

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

Then the error values and error signals between the output vector and the target vector are calculated and used to modify the connection weights, using 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 using an IBM-compatible PC with Intel Pentium-IV 2GHz CPU and 256MB RAM. Totally 150 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 those obtained by previous researchers [3]. In order to evaluate the recognition performance of ART2-based hybrid network, we compared the results with those obtained using the error backpropagation algorithm.

4.1 Performance of individual identifier extraction

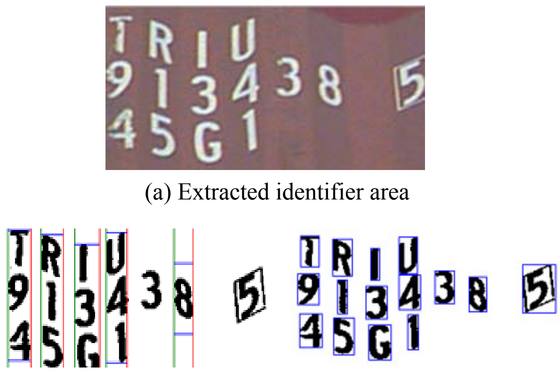
By using the proposed extraction algorithm for all 150 images the identifier areas were successfully extracted from the images. Applying identifier extraction algorithms proposed in this paper and the histogram based algorithm [3] to the extracted identifier areas, experimental results were summarized and compared in Table 2.

As shown in Table 2, the algorithm proposed in the reference [3] is inferior to our algorithm because it failed to extract identifiers in cases where the background and the container identifiers may not be distinguished from each other or the shape of identifiers and the interval between identifiers are changed by the bent surface of the containers.

Table 2. Performance comparison of identifier extraction

	The number of extracted identifiers			
	Shipping Company Codes (600)	Container Serial Codes (900)	Check Digit Code (150)	Total number of identifiers (1650)
Algorithm proposed in Ref.[3]	495	800	90	1385
Proposed extraction algorithm	579	878	135	1592

Our algorithm, first, distinguished the background and container identifiers by using the proposed fuzzy binarization, and then, extracted identifiers by using the contour tracking. As a result, our algorithm could extract successfully container identifiers in the images where the algorithm of reference [3] failed to extract identifiers. Fig.8 shows an example of the case mentioned above. Note that due to the bent surface of the container the characters in Fig. 7 (a) are not in a straight line. Fig. 7 (b) shows that the histogram based method [3] fails to identify character 3 and it tends to lump the characters in groups of three. At the same time Fig.7(c) shows that the proposed fuzzy binarization and tracking algorithm succeeds in extracting all 15 identifiers. Fig.8 shows the identifier arrangement process and the arrangement result for container identifiers extracted in Fig.7 (c).

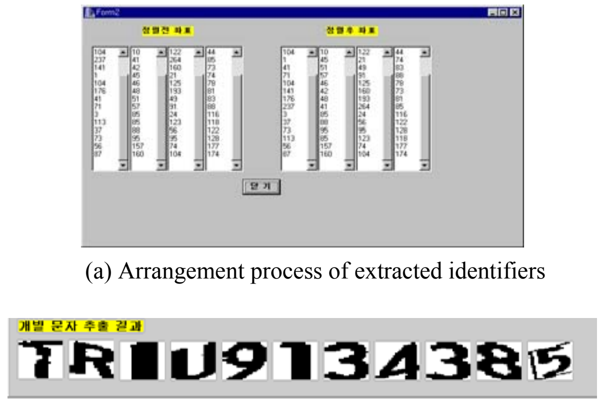


(a) Extracted identifier area

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

(c) Proposed method in this paper

Fig. 7. Comparison of identifier extraction results



(a) Arrangement process of extracted identifiers

(b) Output of identifier extraction and arrangement

Fig. 8. Example of identifier extraction and arrangement

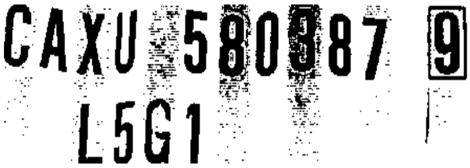
Fig.9 shows the comparison of experimental results when the mean-intensity based binarization proposed in the reference [3] and the proposed fuzzy binarization were applied to identifier area of Fig.9(a).

In Fig.9, the thresholds for the mean-intensity based binarization and for the fuzzy binarization are 117 and 145 respectively. As shown in Fig.9 (c), the fuzzy binarization distinguished clearly the background and container identifiers. At the same time the mean intensity based binarization method (see Figure 9 (b)) for digits 8 and 3. It also failed to remove the background noise.

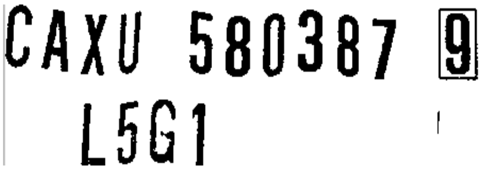
4.2 Performance of container identifier recognition

Table 3 compares learning performances in the experiment that applied the error backpropagation algorithm and the ART2-based hybrid network to container identifiers extracted by the proposed algorithm mentioned above. In the learning experiment, 1054 container identifiers were used, which consisted of 383 shipping company codes, 582 container serial codes and 89 check digit codes.

(a) Extracted identifier area



(b) Mean-intensity based image binarization



(c) Proposed fuzzy binarization

Fig. 9. Comparison of mean-intensity based binarization and proposed fuzzy binarization

The initial connection weights used for learning in each algorithm were set to values between –1 to 1. For the ART2-based hybrid network, the vigilance parameter used for the creation and update of clusters was empirically set via the priori test. Based on simulation results the optimum value for the vigilance parameters for container serial codes was set as 0.10 and for shipping company codes and check digit as 0.15. The rate of learning and the momentum were set as 0.5 and 0.6 respectively.

As shown in Table 3, The learning time required for the ART2-based hybrid network was reduced by about 20~45% compared with the error backpropagation algorithm.

Table 4 compares recognition performances of the two algorithms by the number of recognition successes in the experiment. In the recognition experiment, 1592 container identifiers were used, which consisted of 579 shipping company codes, 878 container serial codes and 135 check digit codes. As shown in Table 4, the recognition rate of the ART2-based hybrid network was higher than the error backpropagation algorithm.

Table 3. Comparison of learning performance

	Learning results of individual identifiers			
	Error backpropagation		ART2-based hybrid network	
	# 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

Table4. Comparison of recognition performance

	# of recognition successes		
	Shipping Company Codes (579)	Container Serial Codes (878)	Check Digit Codes (135)
Error backpropagation Algorithm	569	867	126
ART2-based hybrid network	575	874	130

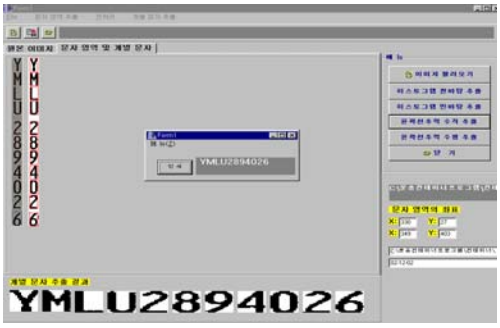


Fig. 10. Identifier extraction and recognition for vertical container image

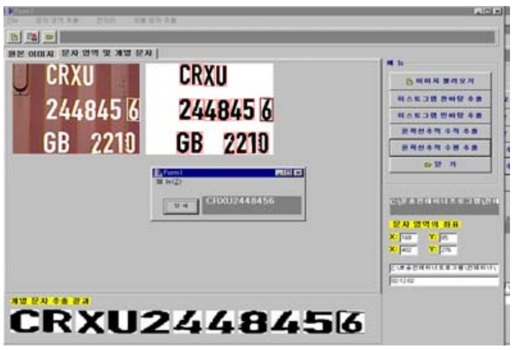


Fig. 11. Identifier extraction and recognition for horizontal container image

Fig.10 and Fig.11 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.

5. Conclusions

In this paper, we have proposed and evaluated a novel recognition algorithm of container identifiers for the automatic recognition of transport containers. Based on the structural attributes of the container image that the 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 containing only the container identifiers was extracted. The container images demonstrate certain characteristics, 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 making the identifier recognition by image processing difficult. Hence, we proposed a fuzzy binarization algorithm to separate clearly the background and identifiers and applied it along with the 4-directional contour tracking to the identifier area, extracting individual identifiers. Finally, the extracted identifiers were arranged in a single row by using the Euclidean distances between identifiers and then grouped into code groups such as shipping company code, container serial code and check digit code. For identifier recognition, we proposed and applied the ART2-based hybrid network, which adapts the ART2 algorithm for the learning structure between the input layer and the middle layer.

For performance evaluation, experiments applying the proposed identifier extraction and recognition algorithm to totally 150 real container images were performed. All 150 identifier areas were successfully extracted from container images and 1592 identifiers were extracted successfully out of a total of 1650 identifiers. This means that the proposed algorithm performed considerably better than the preprocessing algorithm used by the previous researchers [3]. Results of the recognition experiment by applying the error backpropagation algorithm and the ART2-based hybrid network to the 1592 extracted identifiers show that the ART2-based hybrid network has a higher rate of recognition compared to the error backpropagation algorithm.

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저 자 소 개

Kwang-Baek Kim

He received the M.S. and the Ph.D. degrees in Department of Computer Science from Busan National University, Busan, Korea, in 1993 and 1999, respectively. At present, he is an Associate Professor at the Department of Computer Engineering, Silla University. He is currently an Associate Editor for Korea Journal of Fuzzy Logic and Intelligent Systems. His research interests include Fuzzy Neural Networks and Application, Image Processing, Biological Signal Processing and Biomedical system, Support Vector Machines.

Phone : +82-51-309-5052
Fax : +82-51-309-5652
E-mail : gbkim@silla.ac.kr