Recognition of Identifiers from Shipping Container Images Using Fuzzy Binarization and Enhanced Fuzzy Neural Network

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Abstract. 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. This paper also proposes an enhanced fuzzy RBF network that adapts the enhanced fuzzy ART network for the middle layer. This network is applied to the recognition of individual codes. 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.

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]. 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 [2].

Since the identifiers are printed on the surface of the containers, shapes of identifiers are often impaired by the environmental factors during the transportation

L. Wang and Y. Jin (Eds.): FSKD 2005, LNAI 3613, pp. 761 – 771, 2005.

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, 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 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. 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 an enhanced fuzzy RBF network architecture and apply it for recognizing individual identifier codes.

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 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. 1 shows an example of extraction results by the proposed algorithm.

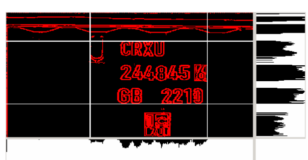


Fig. 1. Extraction results of Identifier areas

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 in a single 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, image binarization is used for extraction of recognition targets from input images since those 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 [3]. 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 membership 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:

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

$Else \quad I_{Mid}{}^{F} = I_{Mid}$

Step 3:

$If \ I_{Mid}{}^{F} \rangle I_{Max}{}^{F} \quad Then$

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

$\quad Else \ \sigma = I_{Min}{}^{F}$

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

$Else \ \sigma = I_{Max}{}^{F}$

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

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

The identifier area is binarized by applying $\alpha - cut(\alpha = 0.9)$ 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.2, scans the binarized identifier area from left to right and from top to bottom to find boundary pixels for identifier codes [4]. 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. 2) 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.

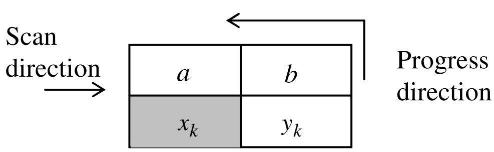


Fig. 2. 2x2 mask for 4-direction contour tracking

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

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

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 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].

3 Identifier Recognition Using an Enhanced Fuzzy RBF Network

We propose an enhanced fuzzy RBF network which constructs the middle layer using the enhanced fuzzy ART network for the recognition of extracted codes. In the traditional fuzzy ART network, the vigilance parameter determines the allowable degree of mismatch between any input pattern and stored patterns[4]. Vigilance parameter is the inverse of degree of tolerance. A large value of vigilance parameter classifies an input pattern to a new category in spite of a little mismatch between the pattern and the stored patterns. On the other hand a small value may allow the classification of the input pattern into an existing cluster in spite of a considerable mismatch. Moreover, because many applications of image recognition based on the fuzzy ART network assign an empirical value to the vigilance parameter, the success rate of recognition may deteriorate[5][6]. To correct this defect, we propose an enhanced fuzzy ART network and apply it to the middle layer in a fuzzy RBF network.

The enhanced fuzzy ART network adjusts the vigilance parameter dynamically according to the homogeneity between the patterns using Yager's intersection operator[7], which is a fuzzy connection operator. The vigilance parameter is dynamically adjusted only in the case that the homogeneity between the stored pattern and the learning pattern is greater than or equal to the vigilance parameter. Also, the proposed fuzzy ART network adjusts the weight of connection for the learning patterns with the authorized homogeneity: Let T^{p} and T^{p^*} be the target value of the learning pattern and the stored pattern respectively. If T^{p} is equal to T^{p^*}, the network decreases the vigilance parameter and adjusts the weight of connection between the input layer and the middle layer. Otherwise, the network increases the vigilance parameter and selects the next winner node.

The algorithm dynamically adjusts the vigilance parameter as follows:

$$\begin{aligned} &\mathit{if}\ \left(T^{p} \neq T^{p^*}\right) \mathit{then} \\ &\qquad \rho(t+1) = 1 - \wedge\left(1,\ \left((1-\rho(t))^{-2} + (1-\rho(t-1))^{-2}\right)^{-1/2}\right) \\ &\mathit{else}\quad \rho(t+1) = 1 - \wedge\left(1,\ \left((1-\rho(t))^{2} + (1-\rho(t-1))^{2}\right)^{1/2}\right) \end{aligned} \tag{3}$$

where ρ is the vigilance parameter.

The authorization of homogeneity for the selected winner node is executed according to Eq.(4).

$$\frac{\left\| w_{j^* i} \wedge x_i^p \right\|}{\left\| x_i^p \right\|} < \rho \tag{4}$$

If output vector of the winner node is greater than or equal to the vigilance parameter, the homogeneity is authorized and the input pattern is classified to one of the existing clusters. Moreover, in this case, the weight of connection is adjusted according to Eq.(5) to reflect the homogeneity of the input pattern to the weight.

$$w_{j^* i}(t+1) = \beta \times \left(x_i^p \wedge w_{j^* i}(t)\right) + (1-\beta) \times w_{j^* i}(t) \tag{5}$$

where β is the learning rate between 0 and 1.

When the weight is adjusted in the traditional fuzzy ART network, β is set to an empirical value. If a large value of β is chosen, the success rate of recognition goes down since an information loss is caused by the increase in the number of cluster center updates. On the other hand, if the learning is performed with a small value of β, the information of the current learning pattern is unlikely to be reflected in the stored patterns and the number of clusters increases[8]. So, in the enhanced fuzzy ART network, the value of β is dynamically adjusted based on the difference between the homogeneity of the learning pattern to the stored pattern and the vigilance parameter. The adjustment of β is as follows:

$$\beta = \frac{1}{1-\rho} \times \left(\frac{\left\| w_{j^* i} \wedge x_i^p \right\|}{\left\| x_i^p \right\|} - \rho \right) \tag{6}$$

This paper enhances the fuzzy RBF network by applying the enhanced fuzzy ART algorithm to the middle layer, as shown in Fig. 3.

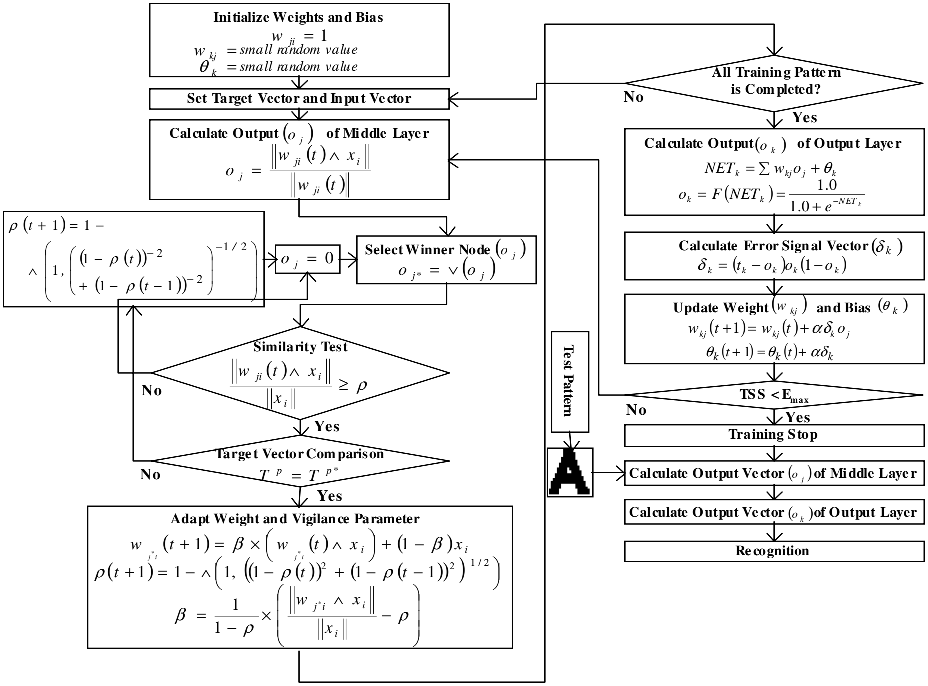


Fig. 3. Learning and recognition algorithm of the enhanced fuzzy RBF network

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 [2]. In order to evaluate the recognition performance of enhanced fuzzy RBF network, we compared the results with those obtained using the conventional fuzzy RBF network[9].

4.1 Performance of Individual Identifier Extraction

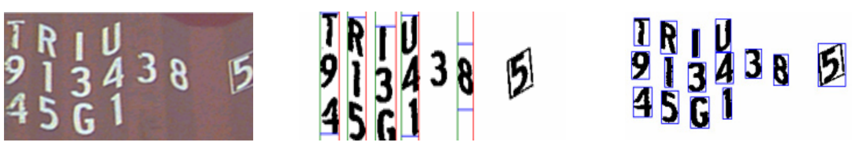
By using the proposed extraction algorithm for all 150 images the identifier areas were successfully extracted from the images. Applying identifier extraction algorithms proposed in this paper and the histogram based algorithm [2] to the extracted identifier areas, experimental results were summarized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

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.[2]	495	800	90	1385
Proposed extraction algorithm	579	878	135	1592

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.

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 [2] failed to extract identifiers. Fig.4 shows an example of the case mentioned above. Note that due to the bent surface of the container the characters in Fig. 4 (a) are not in a straight line. Fig. 4 (b) shows that the histogram based method [2] fails to identify character 3 and it tends to lump the characters in groups of three. At the same time Fig.4(c) shows that the proposed fuzzy binarization and tracking algorithm succeeds in extracting all 15 identifiers.

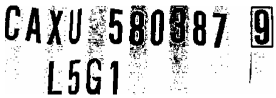


(a) Extracted identifier area (b) Histogram method in Ref.[3] (c) Proposed method in this paper

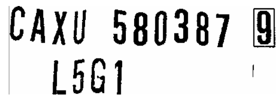
Fig. 4. Comparison of identifier extraction results

Fig.5 shows the comparison of experimental results when the mean-intensity based binarization proposed in the reference [2] and the proposed fuzzy binarization were applied to identifier area of Fig.5(a). In Fig.5, the thresholds for the mean-intensity based binarization and for the fuzzy binarization are 117 and 145 respectively. As shown in Fig.5 (c), the fuzzy binarization distinguished clearly the background and container identifiers. At the same time the mean intensity based binarization method (see Figure 5 (b)) for digits 8 and 3. It also failed to remove the background noise.

(a) Extracted identifier area



(b) Mean-intensity based image binarization



(c) Proposed fuzzy binarization

Fig. 5. Comparison of mean-intensity based binarization and proposed fuzzy binarization

4.2 Performance of Container Identifier Recognition

To evaluate the learning performance of the enhanced fuzzy ART network, this paper compared the number of clusters generated by the conventional fuzzy ART network and the enhanced fuzzy ART network in the learning experiments on individual codes. Table 3 compares learning performances in the experiment that applied the conventional fuzzy ART network and the enhanced Fuzzy ART 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.

Table 3. Comparison of the number of clusters between the fuzzy ART and the proposed fuzzy ART network

		Number of clusters /Number of patterns
Shipping Company Codes	Proposed Fuzzy ART	35 / 383
	Fuzzy ART	78 / 383
Container Serial Codes	Proposed Fuzzy ART	43 / 582
	Fuzzy ART	91 / 582
Check Digit Code	Proposed Fuzzy ART	16 / 89
	Fuzzy ART	27 / 89

As shown in Table 3, the number of clusters in the enhanced fuzzy ART network was much lower than in the traditional fuzzy ART network, so we may know that the enhanced fuzzy ART network refines the classification of the homogenous patterns properly. Table 4 shows the results of the experiment involving enhanced fuzzy RBF network for the 150 container images for recognition. In the experiment, the initial values of the vigilance parameter used for the creation and update of the nodes in the

Table 4. Result of learning and recognition by the proposed fuzzy RBF network

	The number of nodes in middle layer	The number of Epoch	The number of recognition
Shipping Company Codes	35	1204	578 /579
Container Serial Codes	43	1605	877 / 878
Check Digit Codes	16	523	132 / 135

middle layer were set to 0.9, 0.9, 0.85 for the serial code, the shipping company codes and check digit respectively. And as shown in Table 4, the proposed fuzzy RBF network was able to successfully recognize all of the extracted individual codes.

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, an enhanced fuzzy RBF network was proposed and applied in the code recognition phase. This algorithm dynamically changes the vigilance parameter in order to improve the clustering performance.

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 [2]. Moreover, an enhanced fuzzy RBF network recognized effectively the individual container code so that it showed the high success rate of recognition. And the number of clusters created at the learning process of the enhanced fuzzy ART network was much lower than the conventional fuzzy ART network, which means that it is efficient to use the enhanced fuzzy ART network in the construction of middle layer in the fuzzy RBF network. Results of the recognition experiment by applying the conventional fuzzy RBF network and the enhanced fuzzy RBF network to the 1592 extracted identifiers show that the enhanced fuzzy RBF network has a higher rate of recognition compared to the conventional fuzzy RBF network.

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