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Passport Recognition using Fuzzy Binarization and Enhanced Fuzzy RBF Network

Kwang-Baek Kim

Department of Computer Engineering, Silla University

Abstract

Today, an automatic and accurate processing using computer is essential because of the rapid increase of travelers. The determination of forged passports plays an important role in the immigration control system. Hence, as the preprocessing phase for the determination of forged passports, this paper proposes a novel method for the recognition of passports based on the fuzzy binarization and the fuzzy RBF network. First, for the extraction of individual codes for recognizing, this paper targets code sequence blocks including individual codes by applying Sobel masking, horizontal smearing and a contour tracking algorithm on the passport image. Then the proposed method binarizes the extracted blocks using fuzzy binarization based on the trapezoid type membership function. Then, as the last step, individual codes are recovered and extracted from the binarized areas by applying CDM masking and vertical smearing. 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 the experiments for performance evaluation on the real passport images showed that the proposed method has the better performance compared with other approaches.

Key words : Passport, Fuzzy Binarization, CDM Masking, Fuzzy RBF Network, Fuzzy ART Network

1. Introduction

The immigration control system authorizes the immigration of travelers by means of passport inspections which includes the determination of forged passports, the search for a wanted criminal or a person disqualified for immigration, etc. The determination of forged passports plays an important role in the immigration control system, for which automatic and accurate processing is required because of the rapid increase of travelers. We propose a fuzzy image binarization method and a fuzzy RBF network, and by employing these methods, implement a novel system for the preprocessing phase for the determination of forged passports.

For extracting the individual codes from the passport image for recognizing, we extract the code sequence blocks including individual codes using Sobel masking [1], horizontal smearing[2] and 4-directional contour tracking[3]. Then we extract the individual codes from the code sequence blocks using a novel fuzzy binarization algorithm, CDM masking[4] and vertical smearing. Moreover, in this paper a novel fuzzy RBF network is proposed and applied for the recognition of extracted codes. The network constructs the middle layer using the enhanced fuzzy ART network for the adjustment of the weight of connections between the input layer and the middle layer. It supports the dynamical change of vigilance parameter, which makes it more efficient. The experiments for performance evaluation of the proposed fuzzy RBF network showed considerable improvement in learning performance and recognition rate.

This paper is organized as follows. Section II and III examine in detail the individual code extraction and the code recognition respectively. Section IV shows the performance evaluation, and Section V finishes with conclusions.

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2. Individual Code Extraction

The passport image consists of the three areas, the picture area in the top-left part, the user information area in the top-right part, and the user code area in the bottom part. For the recognition of passports, we extract the user codes from the passport image and digitalize the extracted codes. The proposed algorithm for passport recognition consists of two phases, the individual code extraction phase from the original image, and the code recognition phase for identifying the extracted codes. This section examines the individual code extraction phase.

A. Code Sequence Block Extraction

Fig. 1 shows an example of passport image used for experiments in the paper. First, we extract the user code area, and next, extract the picture area to obtain the raw information from passport images.

The user code area in the bottom part of passport image has a white background and two code rows containing 44 codes.

For extracting the individual codes from the passport image, first, we extract the code sequence blocks including the individual codes by using the feature that the user codes are arranged sequentially in the horizontal direction. The extraction procedure for code sequence blocks is as follows: First, Sobel masking is applied to the original image to generate an edge image[1]. By applying the horizontal smearing to the edge image, the adjacent edge blocks are combined into a large connected block. By successively applying contour tracking to the result of smearing process, a number of connected edge blocks are generated, and the ratio of width to height for all the blocks are calculated. Finally, the edge blocks with the maximum ratio are selected as code sequence blocks.

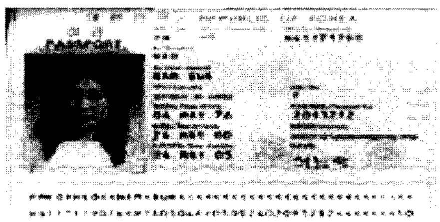


Fig. 1. An example of a passport image

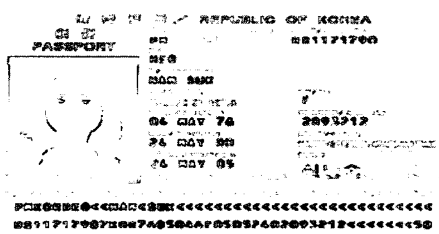


Fig. 2. Result of Sobel masking

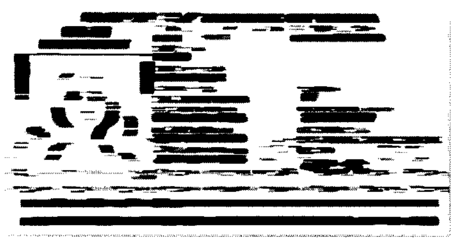


Fig. 3. Result of horizontal smearing

Fig. 2 shows an edge image generated by applying Sobel masking to the image in Fig. 1. Fig. 3 shows the results generated by applying horizontal smearing to the edge image. We use 4-directional contour tracking to extract code sequence blocks from the results in Fig. 3.

The contour tracking extracts outlines of connected edge blocks by scanning and connecting the boundary pixels. The paper uses a 2x2 mask shown in Fig. 4 for the 4-directional contour tracking[3]. Contour tracking scans the smeared image from left to right and from top to bottom to find the boundary pixels of edge blocks. If a boundary pixel is found, the pixel is selected as the start position of tracking. The selected pixel is placed at the x_k position of the 2x2 mask, and by examining the two pixels coming under the *a* and *b* positions 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 the edge block. By generating the outer rectangles including contours of edge blocks, and comparing the ratio of width to height of the rectangles, the code sequence blocks with the maximum ratio are extracted.

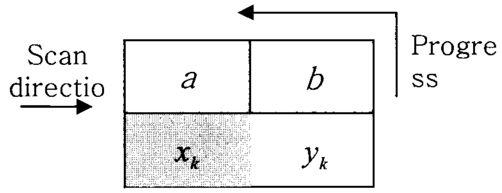


Fig. 4. 2x2 mask for 4-direction contour tracking

Table 1. Progress direction of *a* and *b* for 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*

B. Individual Code Extraction

The individual codes are extracted by applying the proposed fuzzy binarization method and the CDM (Conditional Dilation Morphology) masking to the areas corresponding to code sequence blocks in the original passport image.

We propose a novel fuzzy binarization method based on the membership function of trapezoidal shape, which supports adaptive binarization for images with diversely shaped objects and various changes of intensity. Let *T* be the mean value between the maximum value (I_{Max}) and the minimum value (I_{Min}) of intensity in the original grayscale image. Eq.1 shows the relationship between the mean value T, I_s and I_e. In the interval $[I_s, I_e]$ the degree of membership function of trapezoidal shape becomes 1.

$$I_s = \frac{T}{3}, \quad I_e = I_s \times 2 \tag{1}$$

Hence, the membership function for the interval $[I_{Min}, I_{Max}]$ is formulated using Eq. 2 and it is used to calculate the degree of membership.

$$\text{if } (I_{Min} < I \le I_s) \text{ then } \mu(I) = \frac{1}{(I_s - I_{Min})} \times (I - I_s) + 1 \quad (2)$$
$$\text{if } (I_s < I \le I_e) \text{ then } \mu(I) = 1.0$$
$$\text{if } (I_e < I \le I_{Max}) \text{ then } \mu(I) = \frac{1}{(I_{Max} - I_e)} \times (I - I_e) + 1$$

For each pixel in the passport image, the degree of membership is calculated using Eq. 2 and the binarization is executed by applying $\alpha - cut$ to the degree of membership. Here, the α value used in the $\alpha - cut$ processing is given using Eq. 3 for the adaptive binarization of passport image.

$$\alpha = (T \times 2.02 - 75)/100 \quad (3)$$

That is, if the degree of membership of a pixel is greater than or equal to the a value, the intensity value of the pixel is set to 255. Otherwise, the intensity value is set to 0. Fig. 5 shows the proposed membership function of trapezoidal shape.

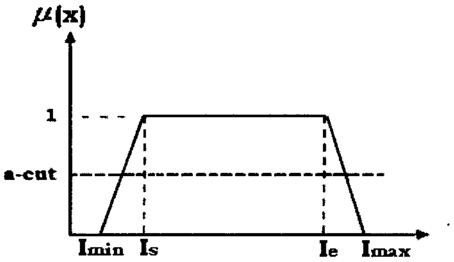


Fig. 5. Fuzzy membership function of trapezoidal shape with *a-cut*

We apply CDM(Conditional Dilation Morphology) masking to the result of binarization to recover the information loss caused by the low resolution of input. The CDM masking recovers outer pixels of individual codes by executing only the dilation process without erosion and it is efficient in the images with low resolution[4]. Finally, we use the vertical smearing and the horizontal projection to extract individual codes form the result of CDM masking. By projecting the vertical smeared areas in the horizontal direction, the horizontal coordinates of individual codes are calculated.

C. Picture Area Extraction

After individual codes are extracted, we extract the picture area containing the face using the start position of code sequence blocks and the characteristic that the vertical edge of picture area is greater than the horizontal edge, and the ratio of horizontal edge to vertical edge becomes approximately 3:4. As seen in Fig. 1 the picture area containing the face occupies 1/3 of the entire width of the passport page image, starting from its left edge, which matches with, left edge of the code sequence blocks. Hence, we select the start position for horizontal phase to matches with the code sequence block, and the end position is determined by scan which covers up to 1/3 of the width of the image.

Since, the Sobel masking makes the contour of picture more vivid by generating the thick edges, it is applied to the candidate area to extract edges. By generating the horizontal and vertical histograms in terms of the result of Sobel masking, the position of the picture area is calculated based on the feature information. The proposed method using only the Sobel masking and the histogram reduces the time required for face area extraction.

Fig. 7(b) shows the passport page image along with the result of extraction of picture area containing the face. This data can now be sent to a face recognition system, which recognizes the face by matching with the passport database. The face recognition system can identify the person and provide name and other information from the passport database for validation of given passport.

3. Recognition of Passports 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[5,6]. 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[7,8]. 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, which is a fuzzy connection operator. The vigilance parameter is dynamically adjusted only in the case that the homogeneity between the saved 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 saved 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:

$$\begin{aligned} &if\ \left(T^p \neq T^{p^*}\right)\ then \\ &\quad \rho(t+1) = 1 - \wedge\left(1, \left((1-\rho(t))^{-2} + (1-\rho(t-1))^{-2}\right)^{-1/2}\right) \\ &else\ \ \rho(t+1) = 1 - \wedge\left(1, \left((1-\rho(t))^{2} + (1-\rho(t-1))^{2}\right)^{1/2}\right) \end{aligned} \tag{4}$$

where ρ is the vigilance parameter.

The authorization of homogeneity for the selected winner node is executed according to Eq. 5.

$$\frac{\left\| w_{ij^*} \wedge x_i^p \right\|}{\left\| x_i^p \right\|} < \rho \tag{5}$$

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. 6 to reflect the homogeneity of the input pattern to the weight.

$$w_{ij^*}(t+1) = \beta \times \left(x_i^p \wedge w_{ij^*}(t)\right) + (1-\beta) \times w_{ij^*}(t) \tag{6}$$

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[9]. 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:

$$\beta = \frac{\dfrac{\left\| w_{ij^*} \wedge x_i^p \right\|}{\left\| x_i^p \right\|} - \rho}{(1-\rho)} \tag{7}$$

This paper enhances the fuzzy RBF network by applying the enhanced fuzzy ART algorithm to the middle layer, as shown in Fig. 6.

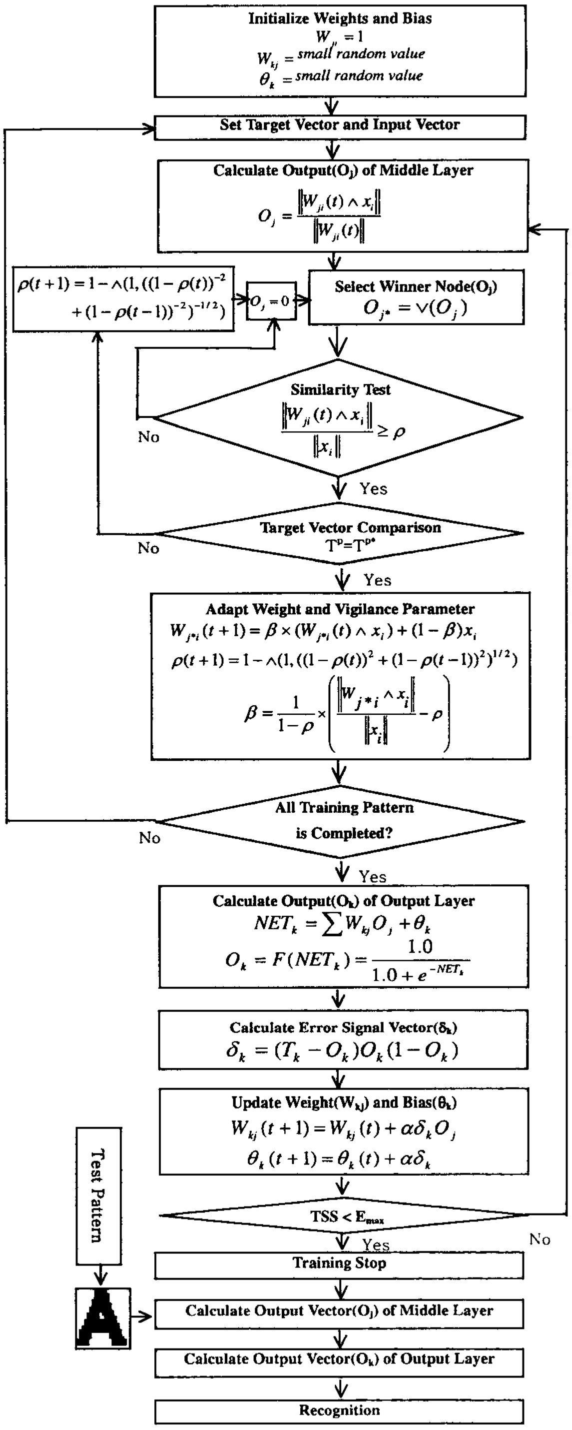


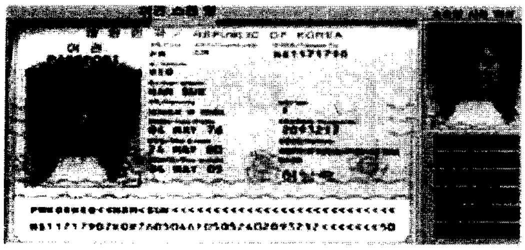
Fig. 6. Learning and recognition algorithm of the enhanced fuzzy RBF network

4. Performance Evaluation

For performance evaluation, we implemented the proposed algorithm and experimented on an IBM-compatible PC with Intel Pentium-IV 2GHz CPU and 256MB RAM. And the 20's passport images of 600x437 pixel size were used in the experiments.

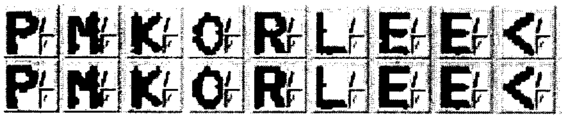
Fig. 7 (a) shows the result of individual code extraction from the passport image in Fig. 1, and Fig. 7 (b) shows the result of picture area extraction. Fig. 8 shows the individual codes finally extracted by using fuzzy binarization and CDM masking

(a) Example of individual code extraction

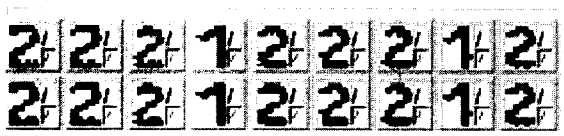


(b) Example of picture extraction

Fig. 7. Example of individual code and picture extraction



(Alphabetic Code)



(Numeric Code)

Fig. 8. Example of codes extracted by fuzzy binarization and CDM masking

Table 2 shows the number of code sequence blocks and individual codes extracted from the 20 passport images. The extracted individual codes contained 1140 alphabetic codes and 620 numeric codes. In the paper alphabetic codes and numeric ones were used separately in the learning and recognition experiments.

Table 2. Number of extracted for code sequence blocks and individual codes

	Code Sequence Blocks	Individual Codes
The number of extraction (success/target)	40 / 40	1760 / 1760

To evaluate the learning performance of the enhanced fuzzy ART network, this paper compared the number of clusters generated by the traditional fuzzy ART network and the enhanced fuzzy ART network in the learning experiments on individual codes.

Table 3 shows the result of the learning experiments. In the experiments, the vigilance parameters for the traditional fuzzy ART network were set to 0.9 and 0.85 for the alphabetic and the numeric codes respectively, and for the enhanced fuzzy ART network, the initial values of the vigilance parameter were set to 0.9 and 0.85 respectively.

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

		Number of clusters / Number of patterns
Alphabetic Codes	Proposed Fuzzy ART	48 / 1140
	Fuzzy ART	303 / 1140
Numeric Codes	Proposed Fuzzy ART	14 / 620
	Fuzzy ART	142 / 620

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 20 passport images for recognition. In the experiment, the initial values of the vigilance parameter used for the creation and update of the nodes in the middle layer were set to 0.9 and 0.85 for the alphabetic and the numeric codes respectively. As shown in Table 4, the proposed fuzzy RBF network was able to successfully recognize all of the extracted individual codes.

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
Alphabetic Codes	48 / 1140	4068	1140 /1140
Numeric Codes	14 /620	1527	620 / 620

Fig. 9 shows the dynamical change of the vigilance parameter in terms of the update progress of the parameter in the clustering of the middle layer.

In conclusion, the experiment for performance evaluation shows that the proposed fuzzy RBF network improves the learning performance and the success rate of recognition by supporting the dynamical change of the vigilance parameter and the adjustment of the weight of connection between the input layer and the middle layer.

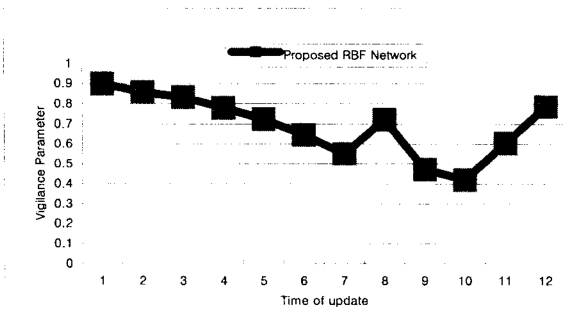


Fig. 9. Dynamical change of vigilance parameter

5. Conclusions

Due to rapid increase of travelers globally, automatic and accurate processing of passports has become a necessity in order to avoid fraud and long waiting time for passengers. In this paper, we discuss an automated system for detection of forgeries in passports.

First, we proposed a novel method for the recognition of passports based on the fuzzy image binarization and the fuzzy RBF neural network. In the individual code extraction phase, we extracted the code sequence blocks including individual codes by using Sobel masking, horizontal smearing and the 4-directional contour tracking based on the 2x2 mask. Then we extracted the individual codes form the code sequence blocks by using the proposed fuzzy binarization, the CDM masking, and the vertical smearing. In this paper, 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. In the experiments for performance evaluation using 20 passport images, it was found that the enhanced fuzzy RBF network outperforms traditional approach.

In the future studies, we plan to implement a face authorization module, which can search many databases including driver licenses in order to detect the identity of the perpetrator.

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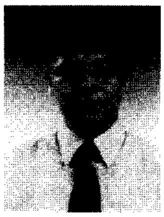

Kwang-Baek Kim

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.

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