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Steganography based Multi-modal Biometrics System

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Abstract

This paper deals with implementing a steganography based multi-modal biometric system. For this purpose, we construct a multi-biometrics system based on the face and iris recognition. Here, the feature vector of iris pattern is hidden in the face image. The recognition system is designed by the fuzzy-based Linear Discriminant Analysis(LDA), which is an expanded approach of the LDA method combined by the theory of fuzzy sets. Furthermore, we present a watermarking method that can embed iris information into face images. Finally, we show the advantages of the proposed watermarking scheme by computing the ROC curves and make some comparisons recognition rates of watermarked face images with those of original ones. From various experiments, we found that our proposed scheme could be used for establishing efficient and secure multi-modal biometric systems.

Key words : steganography, information hiding, biometrics, iris recognition, face recognition

1. Introduction

Biometrics is using physiological or behavioral characteristics for personal identity, ensure much greater security than password and number systems. Face recognition among biometrics is a natural intuitively appealing and straightforward method. Furthermore, face recognition is one of the most interesting and challenging areas in computer vision and pattern recognition. The popular approaches for face recognition are eigenface and fisherface method. Eigenface method or Principal Component Analysis (PCA) is most well-known method for face recognition[1]. Each of them comes with some advantages but is not free from limitations and drawbacks. The PCA approach exhibits optimality when it comes to dimensionality reduction. However, it is not ideal for classification purposes as it retains unwanted variations occurring due to lighting and facial expression [2]. To overcome this problem, proposed was an enhancement known as a fisherface method or Fisher's Linear Discriminant (FLD). This statistically motivated method maximizes the ratio of the determinant of between-class scatter matrix and within-class scatter matrix. Several studies have been made on various enhancements to the generic form of the FLD technique [3].

On the other hand, iris recognition is an emergent approach to personal identification since iris pattern is known as one of the most reliable biometrics. The human iris, an annular part between the pupil appearing black in an image and the white sclera, has an extraordinary structure and provides many interlacing minute characteristics such as freckles, coronas, stripes, etc. These visible characteristics, which are generally called the texture of the iris, are unique to each subject. There is an iris pattern in front of eyeball that exists between cornea and crystalline lens. Obverse of iris has irregular rudiments and circular pattern that is near pupil margin. Daugman has studied an iris pattern recognition method using 2-D Gabor filter and Boles has used the wavelet transform[4][5] to extract feature vectors. However, in case of Daugman's method, the iris code is 256 bytes which is rather large template size. Also, since the feature vector of Boles's method is not rich, it may not be applied for large population.

In this paper, we propose a steganography based multi-modal biometrics system using the face and iris recognition for efficient transmission of multimodal biometric data and biometric information security on the network. For this purpose, we combine face with iris recognition to perform multi-modal biometrics. First, we use face recognition using a fuzzy-based Linear Discriminant Analysis(LDA) method, which is an expanded approach of the LDA method combined by the theory of fuzzy sets. Fuzzy sets were introduced by Zadeh in 1965 [6]. Many researchers have found numerous ways to utilize this theory to generalize existing techniques and to develop new algorithms in pattern recognition. Here, an assignment of fuzzy membership value is performed by Fuzzy k-Nearest Neighbor(FKNN) initialization [7]. On the other hand, we obtain a feature vector from the LDA after performing 2D Gabor wavelet transform for iris recognition. After that, we

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compute the similarity measure based on the correlation. Here, since we use four matching values obtained from four different directional Gabor wavelets and select the maximum value among them, it is possible to reduce the recognition error.

On the other hand, encryption and watermarking are the possible techniques to achieve the security of biometric data. Encryption does not provide security if the data is decrypted. However, watermarking involves embedding information into the host data itself so that it can be preserved the security even after decryption. Thus, we use watermark technique in the wavelet transform domain for the information security on the networks. We also use the two-dimensional (2-D) wavelet analysis to efficiently decompose an image for watermarking. Finally, we perform user authentication based on a normalized score value for each feature of face image and iris image. The experimental results reveal that the proposed multimodal biometrics shows a good performance in comparison with single-modal biometric recognition technique. Furthermore, it is noted that the watermarking techniques in the multi-modal biometrics show a similar performance for information security on the networks.

The organization of this paper is as follows. In Section II, we propose face and iris recognition system based fuzzy LDA approach. Section III is concerned with the steganography with watermarking method for biometric information security on the networks. The experimental results are covered in Section IV. Finally, some concluding remarks are given in Section V.

2. Face Recognition and Iris Recognition

2.1 Face Recognition

Generally, the LDA is used to find optimal projection from feature vectors of face images. Rather than finding a projection that maximizes the projected variance, LDA determines a projection, $V = W_{FLD}^T X$ (W_{FLD}^T is the optimal projection matrix), that maximizes the ratio between the between-class scatter and the within-class scatter matrix. However, this method uses crisp class information for the given face images. On the other hand, the fuzzy-based LDA method assigns feature vectors to fuzzy membership degree based on the quality of training data. The procedures to assign a fuzzy membership degree to the feature vector transformed by PCA is as follows[8].

[Step 1] Obtain the Euclidean distance matrix between feature vectors of training sets.

[Step 2] Set diagonal elements to infinite (large value) in the distance matrix because of zero value in i=j case.

[Step 3] Sort the distance matrix in ascending order. And then, select the class corresponding to from i to k'th nearest point.

[Step 4] compute the membership grades for j'th sample point using the following equation.

$$\mu_{ij}(x) = \begin{cases} \alpha + (1-\alpha(n_{ij}/k)), & if \;\; i = the\ same\ as\ the\ label \\ (1-\alpha(n_{ij}/k)), & if \;\; i \neq the\ same\ as\ the\ label \end{cases} \tag{1}$$

The value n_{ij} is the number of the neighbors belonging to the i 'th class in j 'th data. And then, we can calculate new feature vectors by using LDA based on fuzzy membership as shown in equation (1). The optimal k value in computing FKNN(Fuzzy K-Nearest Neighbor)initialization is determined by value representing the best recognition rate through each experiment.

The mean value of each class $\tilde{m}_i$ is calculated by using feature vectors transformed by PCA and the fuzzy membership degree expressed in equation (1) as the following equation

$$\tilde{m}_i = \frac{\sum_{j=1}^{N} \mu_{ij} x_j}{\sum_{j=1}^{N} \mu_{ij}} \tag{2}$$

where μ_{ij} be the membership in the i 'th class of the j 'th labeled sample set. The between-class fuzzy scatter matrix S_{FB} and within-class fuzzy scatter matrix S_{FW} are defined as follows, respectively.

$$S_{FB} = \sum_{i=1}^{c} N_i (\tilde{m}_i - \bar{m})(\tilde{m}_i - \bar{m})^T \tag{3}$$

$$S_{FW} = \sum_{i=1}^{c} \sum_{x_k \in C_i} (x_k - \tilde{m}_i)(x_k - \tilde{m}_i)^T = \sum_{i=1}^{c} S_{FW_i} \tag{4}$$

The optimal fuzzy projection W_{F-FLD} and the feature vector transformed by the fuzzy-based fisherface method can be calculated as follows.

$$W_{F-FLD} = \arg\max_{W} \frac{|W^T S_{FB} W|}{|W^T S_{FW} W|} \tag{5}$$

$$\tilde{v}_i = W_{F-FLD}^T x_i = W_{F-FLD}^T E^T (z_i - \bar{z}) \tag{6}$$

2.2 Iris Recognition

The Gabor wavelets, which capture the properties of spatial localization, orientation selectivity, spatial frequency selectivity, and quadrature phase relationship are considered as good approximation to the filter response profiles encountered experimentally in cortical neurons. The Gabor wavelets have been found to be particularly suitable for image decomposition and representation when the goal is the derivation of local and discriminating features. The Gabor wavelets can be defined as follows:

$$W(x, y, \theta, \lambda, \varphi, \sigma, \gamma) = e^{\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}} \cos(2\pi \frac{x'}{\lambda} + \varphi) \tag{7}$$

$$x' = x\cos\theta + y\sin\theta \qquad (8)$$

$$y' = -x\sin\theta + y\cos\theta \qquad (9)$$

where θ specifies the orientation of the wavelet and it rotates the wavelet about its center. The orientation of the wavelets dictates the angle of the edges or bars for which the wavelet will respond. In most cases, θ is a set of values from 0 to π. The λ is the wavelength of the cosine wave or inversely the frequency of the wavelet. Wavelets with a large wavelength will respond to gradual changes in intensity in the image. The φ is the phase of the sinusoid. Typically Gabor wavelets are based on a sine or cosine wave. In the case of this algorithm, cosine wavelets are considered to be the real part of the wavelet and the sine wavelets are considered to be the imaginary part of the wavelet. The s specifies the radius of the Gaussian. The size of the Gaussian is sometimes referred to as the wavelet's basis of support. The Gaussian size determines the amount of the image that effects convolution. The g specifies the aspect ratio of the Gaussian. This parameter was included such that the wavelets could also approximate some biological models.

After applying the Gabor filter, we performed so-called polar mapping to extract the Region of Interest (ROI) for the filtered iris image. Since we perform the process for four types of Gabor filter($\theta = 0^\circ, 45^\circ, 90^\circ, 135^\circ$), we could get four types of polar mapped images. At the first step, we extracted a part of iris pattern from a predefined inner radius to an outer radius, which looks like doughnut. Here, we should consider the variation of the radius of a pupil for lighting condition. If we get the iris image under bright condition, then the size of pupil becomes smaller. On the contrary, if we get the iris image under dark condition, then the size of pupil becomes larger. These mean the variation of the size of ROI. So, the recognition algorithm should be robust to endure this variation. This is our motivation to adopt the fuzzy concept in our recognition algorithm. After performing resize process with a linear interpolation, we got the 40*500 polar mapped images [9].

As described earlier, the iris images were transformed into space-scale space by using the Gabor wavelet to enhance the iris pattern. And then, feature extraction is performed by fuzzy-LDA after reducing the dimensionality of original data space by PCA. Here we use the correlation value to establish the classifier instead of conventional Euclidean based k-NN classifier. The correlation coefficients are calculated as follows.

$$\rho_{x,y} = \frac{\mathrm{cov}[X,Y]}{\sigma_X \sigma_Y} = \frac{E[XY] - \mu_X \mu_Y}{\sigma_X \sigma_Y}, |\rho_{X,Y}| \le 1 \qquad (10)$$

where the correlation coefficient $\rho_{x,y}$ is a measure of the correlation between the feature vectors X and Y (actually these are LDA coefficients). For an iris image, we calculate four correlation coefficients for each polar mapped image after performing the Garbor wavelet transform. Finally we compute a total matching score by adding the computed correlation coefficients. The final decision is made by taking one having the maximum score.

3. Biometric Information Security based on Digital Watermarking

3.1 Watermarking Process

Digital watermarking has been used to protect illegal reproduction and monitor illegal multimedia data. The watermarking is a technique for inserting additional information to protect the intellectual property rights. Fig.1 shows the general process of image watermarking. As shown in Fig.1, watermarking technique includes encoding and decoding process. In encoding process, original image is modified by using the watermark image to create watermarked image. More specifically, original image is transformed to frequency domain by wavelet or wavelet packet. To use watermarked image for the legal users, watermarked image should be extracted in decoding step. Here, inverse transformation is performed on the modification transform domain coefficient to produce the watermark image.

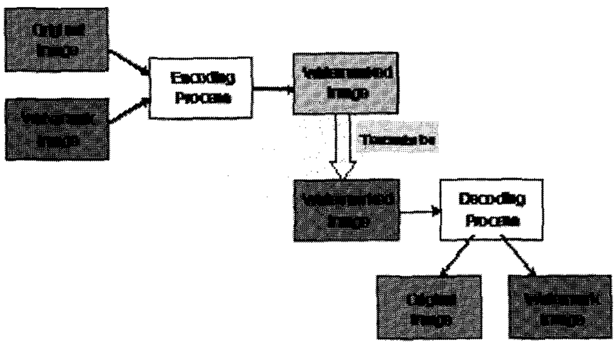

Fig. 1 General process of image watermarking

3.2 Steganography with Digital Watermarking for Multi-modal Biometrics

In this paper, we use a digital watermarking technique to implement a steganography. Steganography is a technique of hiding information in seemingly innocuous carriers in an effort to conceal the existence of the embedded information. In our case, the innocuous carrier is face image and the embedded information becomes the feature vector of iris pattern.

First, we perform a single level wavelet decomposition of the resulting image. This decomposition generates coefficient matrices of the one-level approximation and horizontal, vertical, and diagonal details, respectively. From the obtained coefficients, we construct the approximation and three detailed images via the high-pass and low-pass filtering realized with respect to the column vectors and the row vectors of array pixels. In this manner, we can repeatedly perform a multilevel wavelet decomposition, such as two-level, three-level, and so forth.

In this work, we use the well-known Daubechies (db6), along with wavelet D4 (db2, db4, db6, and db8) [10]. Fig. 2 shows the architecture of the 2-D wavelet decomposition realized at level 1. Here, H and L represent the high-pass and low-pass filter, respectively. The symbol $\downarrow 2$ denotes the down sampling by 2. As shown in Fig. 2, in this way we can obtain four sub images $(Z_{HH}, Z_{HL}, Z_{LH}, Z_{LL})$ [11].

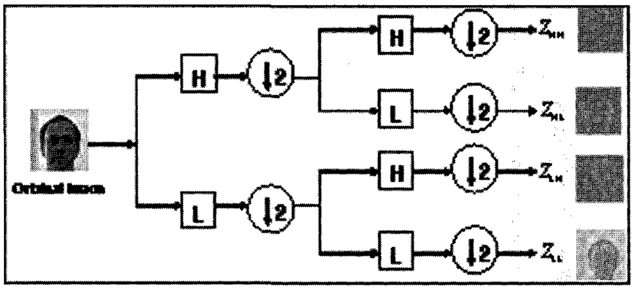

Fig. 2 Architecture of 2-D wavelet decomposition at level 1

Here, we adopts the watermarking technique of biometrics data through wavelet transform. Then, we compare the recognition rates obtained from original biometrics data and watermarked biometrics data, respectively. Biometrics data grafting of watermarking prevents damage of biometrics data at data transmission, and displays good performance in user authentication [12]. Fig. 3 and Fig. 4 show our proposed a secure multi-modal biometric system with encoding of watermark and decoding of watermark. For further details on these decomposition processes, see[11].

4. Experiments and Analysis

In this work, we use two biometric databases for face and iris images. First, we use Chinese Academy of Science (CASIA) and Chungbuk National University (CBNU) iris database. The CASIA database contains eight iris images for one hundred and eight subjects. Among these images, we use six iris images for fifty individuals. On the other hand, the CBNU database contains six iris images for fifty individuals. Thus, the total number of iris images becomes three hundreds for each database and the image size of an iris images is 280*360 having gray levels ranged between 0 and 255. Here 150 iris images were used for training and others were used for testing. Second, we use 150 face images from 50 individuals in the FERET face database. The total number of images for each person is 3. These images vary in position, rotation, scale, and facial expression. As described earlier, the iris images were transformed into space-scale space by using the Gabor wavelet to enhance the iris pattern. And then, feature extraction is performed by fuzzy-LDA after reducing the dimensionality of original data space by PCA.

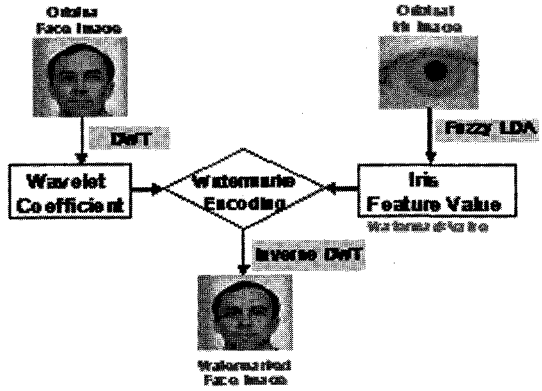

Fig. 3 Encoding of Watermark

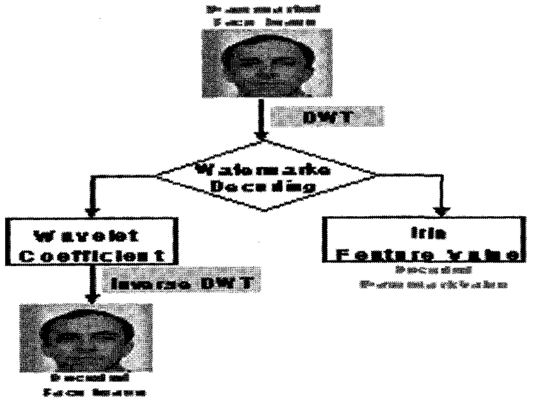

Fig. 4 Decoding of Watermark

The experimental results obtained from PCA method for CASIA iris database yield the recognition rates between 83% and 86%. The results obtained from LDA method show the recognition rates between 89% and 90%. On the other hand, the fuzzy LDA method shows recognition rates between 91% and 92%. We found from these results that the proposed method shows better performance in comparison with the previous approaches. In the same manner, the experiments are carried out for the CBNU iris database. Among them, the proposed method has the highest recognition rate ranges from 92% to 93%. On the other hand, we obtained 81% recognition rates for face recognition based on PCA. This could be attributed to the fact that PCA retains unwanted variations due to lighting and facial expression. On the other hand, in the case of LDA method, we noticed substantial improvement and the recognition rate of 86%, whereas the experimental result through fuzzy LDA method is close to 90%.

To evaluate the proposed multi-modal biometric system, we use both the face recognition and iris recognition. Here we compute the FAR, FRR, and GAR as the performance indices. Fig. 5 and 6 show the experimental results for face and iris recognition, respectively. Fig. 7 shows the results obtained from the proposed multi-modal biometrics system.

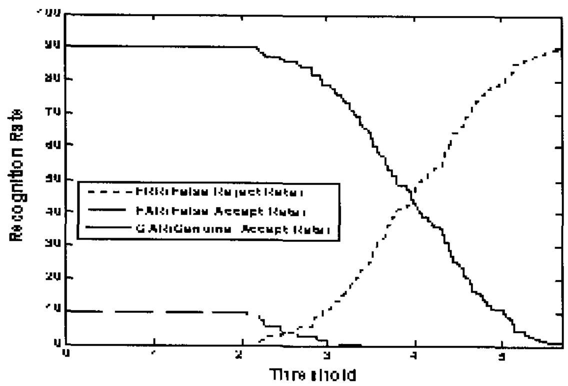

Fig. 5 Recognition result for face recognition

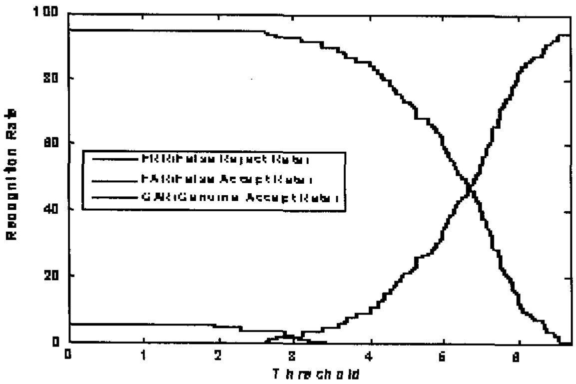

Fig. 6 Recognition result for iris recognition

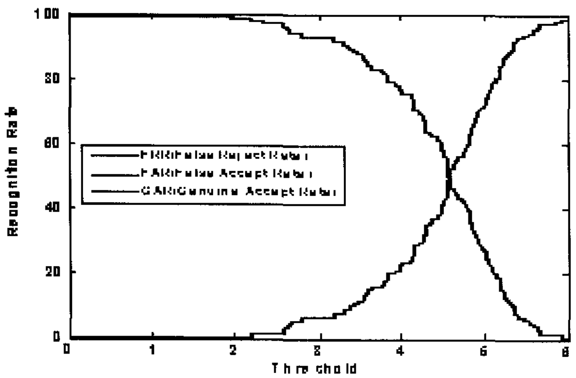

Fig. 7 Recognition result for the proposed multi-modal biometrics system

Fig. 8 shows ROC Curve to evaluate performance. The proposed method has the highest recognition rate ranges from 93% to 95%. As shown in Fig. 8, the fusion scheme showed a better performance than face or iris recognition. Table 1 lists the recognition results obtained with the max-min normalization method. This shows that the multi-modal scheme can improve overall recognition rate.

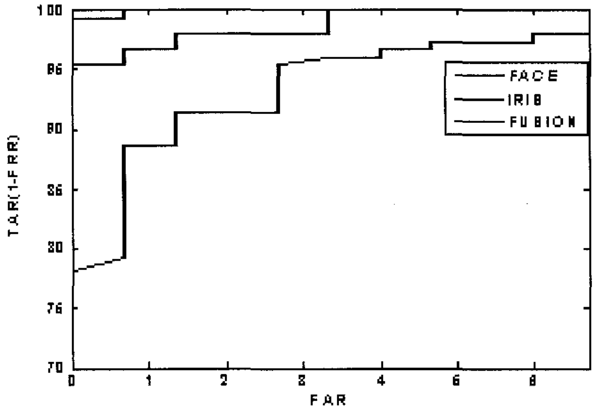

Fig. 8 ROC curve for recognition results

Table 1. Recognition results by the normalization methods

Iris Recognition	Face Recognition	Fusion
92.66%	90%	94.66%

Here, we used watermarking technique for FERET face data and CBNU Iris data. First, we performed the feature extraction for original face and iris image based on Fuzzy-LDA algorithm. We also obtained decoded data through the encoding and decoding process of watermark as shown in Fig. 3 and Fig. 4. The experimental results showed that the recognition rate of original date is equal to that of decoded data. Table 2 lists the recognition rate of original data and decoded data as well as that of original face data and watermarked face data. As you can see, the recognition rate is almost not affected by the embedded iris feature vector. From various experiments, we found that the recognition performance based on watermarked images is not usually inferior in comparison with that based on non-watermarked images. So, if someone wants to operate our proposed scheme for face recognition, it can be easily established without additional efforts by simply using the watermarked face image.

Table 2. Recognition rates for original and watermarked image

Recognition rate for original face image	Recognition rate for Decoded face image	Recognition rate for watermarked face data
90%	90%	90%

5. Concluding Remarks

We have developed a steganography based multi-modal biometrics system for security and efficient transmission of biometric data. Since the fuzzy LDA method assigns the fuzzy membership value to the feature vector of a face image, it can reduce the sensitivity to similar variation between the face images due to illumination and pose. From several experiments, we found that the proposed approach shows a better performance in comparison with other methods. Furthermore, the recognition accuracy based on decoded watermarked face images is quite similar to that of original face images. So, this scheme can be applied to conventional face recognition system without major modification.

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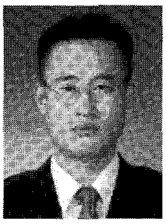

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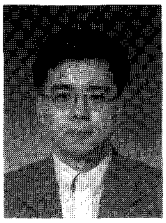

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