A Multimodal Iris Recognition Using Gabor Transform and Contourlet

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***Abstract*--Multimodal biometric systems use two or more biometric modalities in a verification process. The main reason to combine different modalities is related to improve the recognition accuracy. This paper deals with various possible scenarios in a multimodal biometric system using two iris recognitions and also the levels of fusion and the integration strategies to improve overall system accuracy. With this in mind, first, we implement the Daugman's iris system using the Gabor transform and Hamming distance. Second, we propose an iris feature extraction method having a property of size invariant through the Fuzzy-LDA with five types of Contourlet transform. Finally, we establish a multi-modal biometric system based on two iris recognition systems. To effectively aggregate two systems, we use statistical distribution models based on matching values for genuine and impostor, respectively. And then, we perform to make comparisons of performance of the fusion algorithms such as weighted summation, Support Vector Machine, Fisher discriminant analysis, and Bayesian classifier.**

***Index terms*-- multimodal biometric, iris recognition, Daugman, contourlet transform**

I. INTRODUCTION

With the evolution of information technology, our society is becoming more and more electronically connected. Daily transactions between individuals and various organizations are conducted increasingly through highly interconnected electronic devices. The capability of automatically establishing the identity of individuals is thus essential to the reliability of these transactions. Biometrics is used to identify people by their physical or behavioral characteristics and so, inherently requires that the person to be identified is physically present at the point of identification. The physical characteristics of an individual that can be used in biometric identification/verification systems are fingerprint, hand geometry, face, iris, and retina.

The iris is a thin circular diaphragm, which lies between the cornea and the lens of the human eye. The iris is perforated close to its centre by a circular aperture known as the pupil. The iris is an externally visible, yet protected organ whose unique epigenetic pattern remains stable throughout adult life. These characteristics make it very attractive for use as a biometric for identifying individuals. Although prototype systems had been proposed earlier, it was not until the early nineties that Cambridge researcher, John Daugman, implemented a working automated iris recognition system [1]. Even though the Daugman system is the commercially successful and well known, many other systems have been developed. The most notable include the systems of Wildes et al. [2] and Boles and Boashash [3].

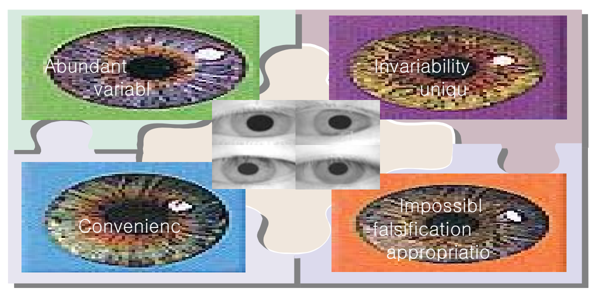

Fig. 1. Characteristic of iris recognition

On the other hand, it is noted that unimodal based biometric system is usually not acceptance because of the performance limitation of the biometric system. To overcome this, acquisition of identical biometric samples using multiple sensor or use of multiple biometric information can be considered. Moreover, in the case of using such multiple biometric information, improvement in the recognition rate can be expected. As such, a multimodal biometric system can minimize inconvenience for its user by applying multiple biometric information and show high performance with multiple targets. The following methods are used to realize multimodal biometric system; multiple sensors that recognize by measuring multiple sensors with different biometric characteristics on identical users; multiple matching that uses different algorithms during the matching process, which is the final step in the recognition process of a multiple unit that acquires and recognizes the target biometric characteristics from multiple targets; multiple impression that acquires data from the same biometric target several times, at intervals. A multimodal biometric system can be categorized into feature-level, score-level and decision-level according to the integration method of biometric information [4][5][6].

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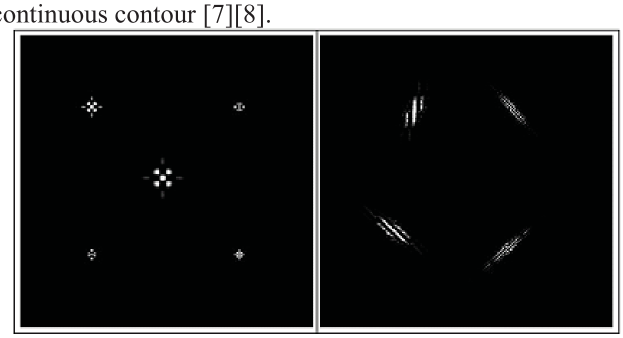
This paper deals with various scenarios that are possible in multimodal biometric system using two iris recognitions and also, the levels of fusion and the integration strategies to improve overall system accuracy. With this in mind, first, we use the Daugman's iris recognition algorithm based on Gabor transform and Hamming distance. Second, we obtain the feature vector from the iris pattern having a property of size invariant and using the Fuzzy-LDA with five types of Contourlet transform. Finally, we propose a multi-modal biometric system based on two iris recognition system. To effectively aggregate two systems, we use statistical distribution models based on matching values for genuine and impostor, respectively. We also perform comparisons of fusion algorithms with Support Vector Machine, Fisher discriminant analysis, and Bayesian classifier.

The overall structure of paper is as follows. Section 2 describes multi resolution decomposition of iris images using the Contourlet transform and feature extraction of iris pattern using the Contourlet and the Fuzzy-LDA. Section 3, describes the implementation of multimodal biometric system using Daugman's method and proposed recognition algorithm. Various experimental results for the multimodal biometric systems according to the fusion method are described in Section 4. Finally, some concluding remarks are given in Section 5.

II. Multi resolution of iris image using the Contourlet transform

A. Multi resolution using the Contourlet transform

The Contourlet transform is an extension of the wavelet transform in two dimensions using multiscale and directional filter banks. The Contourlet transform is composed of basis images oriented at various directions in multiple scales, with flexible aspect ratios. With this rich set of basis images, the Contourlet transform effectively captures smooth contours that are dominant feature in natural images. Also, 2-D wavelet transforms are only good at catching point discontinuities, but usually cannot capture the geometric smoothness of the contours. It can be seen from the Fig. 2 that the wavelet transforms are the square transforms which usually describe point wise discontinuances. But Contourlet transforms are able to creep over the linear parts of contours and therefore, require less number of coefficients for the suitably describing a continuous contour [7][8].



(a) Basis functions of 2-D Wavelet (b) Basis functions of Contourlet.

Fig. 2. Basis function of Contourlet and wavelet

The 2-D directional filter bank is often used to efficiently implement the 2-D Contourlet transform via a l -level tree-structured decomposition that leads to 2^l sub bands with wedge-shaped frequency partition (partition where $l = 3$ and there are $2^3 = 8$ real edge-shaped frequency bands) as shown in Figure 3 [9].

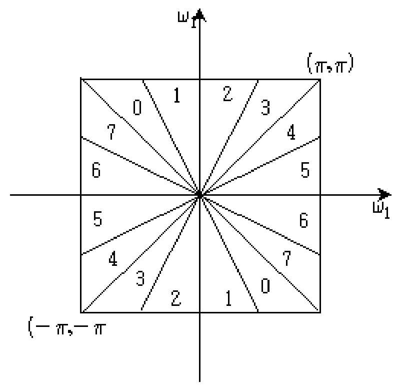


Fig. 3. Directional filter bank frequency

This property makes Contourlets a unique transform that can achieve a high level of flexibility in decomposition while being close to critically sampled. Figure 4 shows an example of the Contourlet transform on the "Peppers" image.

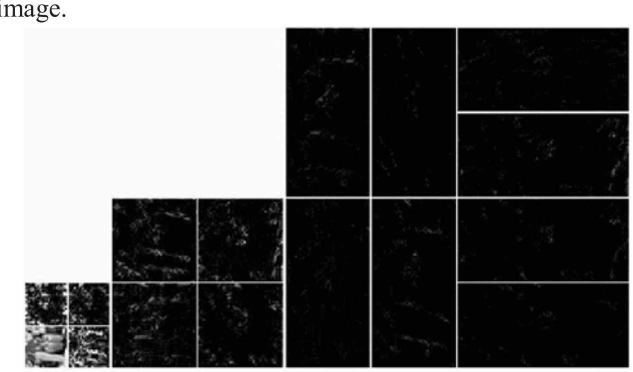
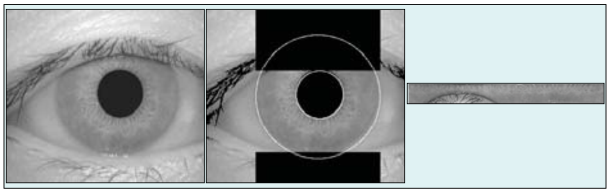


Fig. 4. An example of Contourlet transform on the "Peppers" image

B. Feature extraction of iris pattern using the Contourlet and Fuzzy-LDA

During the acquisition stage of iris images, the eyebrows hide some part of pupil and also the iris image is often bulged by make-up and lighting. These cause difficulties to find the pupil of iris and center of pupil. Therefore, the iris image was preprocessed by a median filter to remove noises causing by the eyebrows and eyelid, and so on. Here, we implemented a segmentation algorithm to extract the pupil by using the binary process based on the Daugman's method. Figure 5 (a) show an eye image from the CASIA databases and Figure 5 (b) and (c) show an eyelash region detected using threshold and denoted as black and polar mapped image with (b).



(a) eye image (b) eyelash region (c) polar mapped image

Fig. 5. Automatic segmentation using the method of Daugman method from the CISIA database.

We performed so-called polar mapping to extract the region of interest(ROI) for the detected an eyelash region shown in Figure 5 (c). After performing resize process with a linear interpolation, we got the 20*240 polar mapped images. And, as described earlier, the iris images were transformed into time-scale space by using the Contourlet to enhance the iris pattern and feature extraction is performed by fuzzy-LDA after reducing the dimensionality of original data space by PCA. Figure 6 (a) shows the gray image after polar mapping and Figure 6 (b) depicts the coefficient after Contourlet transform from the Figure 6(a). And, Figure 7 is a flowchart for the iris system expressed by Contourlet transform and Fuzzy-LDA using the three main modules.

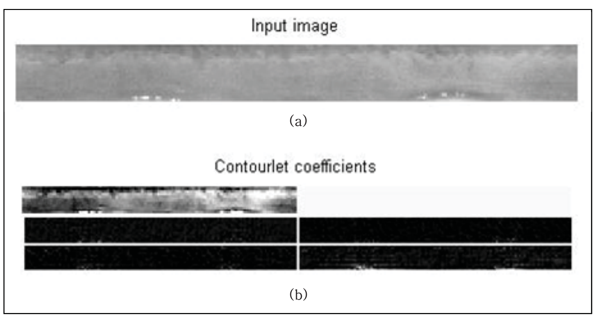


Fig. 6. Iris pattern and coefficient after Contourlet

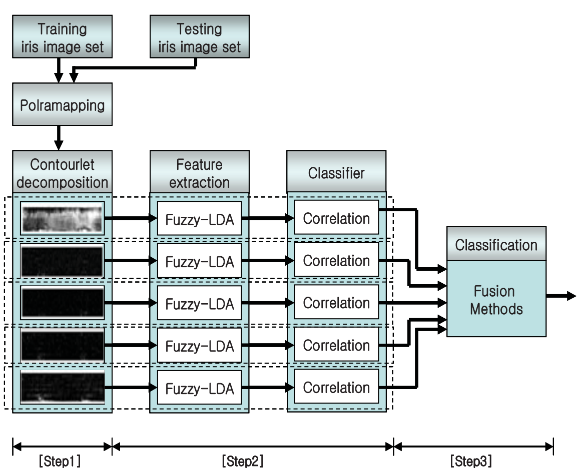


Fig. 7. Flowchart for the iris system using the Contourlet and Fuzzy-LDA

The Linear Discriminant Analysis(LDA) is used to find optimal projection from feature vectors of face. 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 of face recognition 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 procedure to assign a fuzzy membership degree to the feature vector transformed by PCA is as follows. First, obtain the Euclidean distance matrix between feature vectors of training sets. Second, set diagonal elements to infinite (large value) in the distance matrix because of zero value in $i = j$ case. Third, sort the distance matrix in ascending order. And then, select the class corresponding to from i to k 'th nearest point. Fourth, compute the membership grades for j 'th sample point using the following equation (1) [10][11].

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

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 (2). 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 $\widetilde{\mathbf{m}}_i$ is calculated by using feature vectors transformed by PCA.

$$\widetilde{\mathbf{m}}_i = \frac{\sum_{j=1}^{N} \mu_{ij} \mathbf{x}_j}{\sum_{j=1}^{N} \mu_{ij}} \quad (2)$$

where μ_{ij} be the membership in the i 'th class of the j 'th labeled sample set.

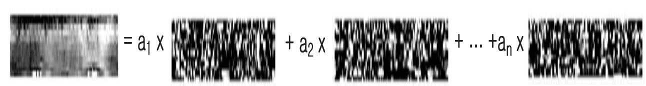


Fig. 8. An EigenIris using the Fuzzy-LDA

Figure 8 show the linearly combined iris images for the feature vector $a_1, a_2, a_3 ... a_n$ and EigenIris of the Fuzzy-LDA. Here, we extracts five dimensional feature vector $a_1, a_2, a_3 ... a_n$ by Contourlet and use them as the enrolment biometric templates.

III. A MULTIMODAL IRIS RECOGNITION USING GABOR TRANSFORM AND CONTOURLET

There have been several types to realize multimodal biometric system. The multiple matching methods uses different algorithms during the matching process, which is the final step in the recognition process. The multiple unit acquires and recognizes the target biometric characteristics from multiple targets. The multiple impression acquires data from the same biometric target several times, at intervals, and multiple biometric data that use various biometric methods simultaneously.

On the other hand, the multimodal biometric system can also be categorized into feature-level, score-level and decision-level according to the integration method of biometric information. The feature-level uses more than two other methods to extract features and then integrate characteristics. The score-level is a method to converge scores that comes after normalization. The decision-level is a method to determine whether to certify an impostor or genuine based on the reliability of conformation the result after conformity.

The purpose of this work is implementation for the multimodal biometric system using two iris recognitions. First, we use the iris system by Daugman using the Gabor transform and Hamming distance as follows. Automatic segmentation was achieved through the use of the circular Hough transform for localizing the iris and pupil regions, and the linear Hough transform for localizing occluding eyelids. And, the features of the iris were encoded by convolving the normalized iris region with 1D Log-Gabor filters and phase quantizing the output in order to produce a bit-wise biometric template[12][13]. Second, we obtain the feature vector from the iris pattern having a property of size invariant and using the Fuzzy-LDA which is further through five types of Contourlet transform described in Section 2. And eventually, this paper deals with multimodal biometric system using two iris recognition.

So far, we have looked at the composition of a multimodal biometric system. Accordingly, this study has confirmed the matching value distribution of genuine and impostor for fusion method in score-level and designed a multimodal biometric system that uses SVM, the Fisher classifier and Bayesian classifier or Weighted summation and the overall structure is as in Fig. 9. First, each iris recognition algorithms extract the feature vectors for the input iris image. The acquired feature vector is compared with the feature vector at the training process. From this, we obtain the score values from two independent iris recognition algorithms and finally fuse these values to find a merged value. Then, a classification method that classifies genuine and impostor is applied to get a final verification result.

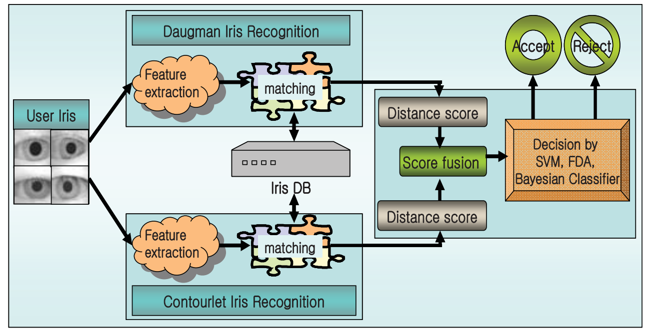


Fig. 9. Proposed multimodal iris recognition system

IV. MULTIMODAL BIOMETRIC RECOGNITION EXPERIMENTS AND RESULTS

To evaluate the performance of the proposed method, we used iris database CASIA [14]. CASIA database contains eight iris images for one hundred and eight subjects. Among them, we used six iris images for one hundred individuals and 300 images were used for training and others for testing. As described earlier, this paper deals with various scenarios that are possible in multimodal biometric system using two iris recognitions. To effectively aggregate two systems, we use statistical distribution models based on matching values for genuine and impostor, respectively. And then, we performed to make comparisons among fusion algorithms with Support Vector Machine, Fisher discriminant analysis, and Bayesian classifier. To the classifier, we used the correlation method instead of conventional Euclidean based k-NN classifier. The correlation coefficients are calculated as follows [9].

$$\rho_{x,y} = \frac{\mathrm{cov}[X,Y]}{\sigma_X \sigma_Y} = \frac{E[XY] - \mu_X \mu_Y}{\sigma_X \sigma_Y}, \left|\rho_{X,Y}\right| \le 1 \tag{3}$$

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), when $\rho_{x,y} = 0$, then X and Y are said to be uncorrelated, and if $\left|\rho_{X,Y}\right| = 1$, that is $\rho_{X,Y} = +1$ or -1, then X and Y are said to be perfectly correlated or linearly correlated. For an iris image, we calculate 5 correlation coefficients for each polar mapped image after performing Contourlet transform. And then, we compute a total matching score by adding the computed correlation coefficients. The final decision is made by taking candidate having the maximum score.

Table 1 shows a recognition performance according to the different similarity measurement method for the feature vector extracted from the first sub-band after the Contourlet transform and Fuzzy-LDA. And matching method is based on Euclidean, Mahalanobis, Hamming distances, and also correlation value between variables.

Table 1. Comparison for recognition rates according to matching method for first sub-band

	Correlation	Hamming	Mahalanobis	Euclidean
PCA	63.0	78.67	69.33	69.33
LDA	88.67	72.0	85.33	72.0
Fuzzy-LDA	90	78.0	85.33	80.67

Table 2 shows a recognition performance for each sub-band after applying Contourlet transform on the iris image for various feature extraction methods. It was noted that the first sub-band shows better recognition results than others. However, when we fuse all sub-bands, one can get better recognition rate than the case of first sub-band. On the basis of these results, a matching method is chosen as the correlation for all sub-bands after applying Contourlet transform.

Table 2. Comparison for recognition rates by the sub-band

	Band 1	Band 2	Band 3	Band 4	Band 5	Fusion
PCA	63.0	28.0	30.0	47.67	47.67	65.3
LDA	88.67	28.0	34.67	60.0	60.0	90
Fuzzy-LDA	90	28.67	37.0	60.67	60.67	93.3

We performed the iris pattern recognition under several conditions of changing the numbers of eigeniris and fisheriris and the value of α in Eq. 4 for CASIA database. The PCA method shows the recognition rates between 63% and 66%, respectively. The LDA shows recognition rates between 89% and 91%, respectively. On the other hand, the Fuzzy LDA method shows recognition rates between 89% and 94%, respectively. We can conclude that our proposed method shows better results than others at most cases as shown in Fig. 10. On the other hand, we also performed iris recognition by the method of Daugman using the Hamming distance for matching process and got the recognition rate between 96% and 97%.

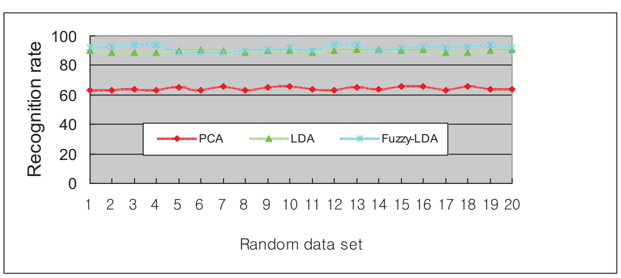


Fig. 10. Iris recognition rates for various methods

Fig. 11 shows the misclassification cases for the No. 37 and No. 39 from one hundred individuals by Daugman's iris recognition method. No. 37 of Fig. 11 show the improper acquisition case of iris pattern for the three training image and the two testing image, and correctly acquisition for only one testing image. And, the No. 39 of Fig. 11 show correctly acquisition of the iris pattern for three training image and one testing image, and improper acquisition of two testing image. From these, one can find that the recognition result goes wrong when iris pattern extracted from training image and iris pattern extracted from testing image are different. In this context, we propose a multi-modal biometric system based on two iris recognition system using the Gabor transform and Hamming distance, and using the Fuzzy-LDA which is further through five types of Contourlet transform, thus can be conducted correctly result from the improper acquisition case of second and third testing image on No.39 of Fig. 11. We applied it to an iris database consisting of 300 iris patterns extracted form 100 subjects and finally got more less than 4.66% equal error rate. Also, to effectively aggregate two systems, we use statistical distribution models based on matching values for genuine and impostor, respectively.

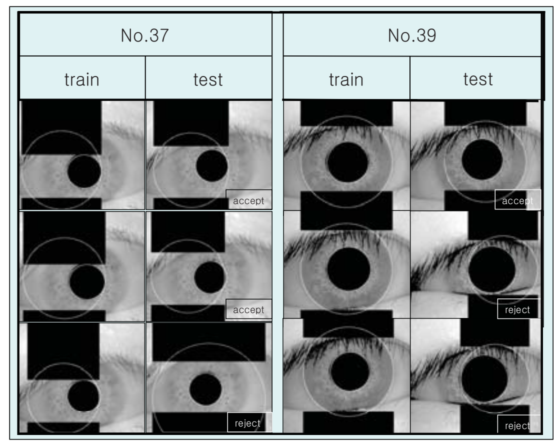


Fig. 11. Misclassification result for the iris image

As such, to fuse the recognition results, we have used the Bayesian classifier, Fisher discriminant analysis and SVM and compared the results. Figure 12 represents testing results according to the different iris recognition algorithm, and classifies genuine (o) and impostor ($*$) on original data where that the similarity values are not normalized. As shown in the Figure, when the Bayesian Classifier is used, genuine and impostor are nonlinearly classified and thus shows higher performance than the Fisher classifier and linear classifier.

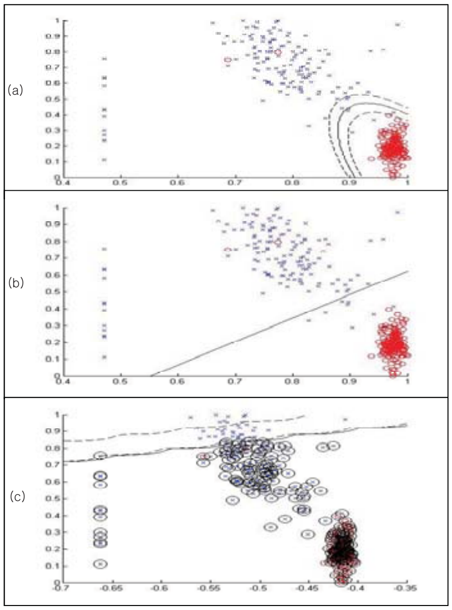


Fig. 12. Matching Scores for multimodal iris recognition

Finally, Table 3 shows a recognition performance of fusion for two iris recognition systems. Accordingly, the performance was highest at 98.67% when using the Bayesian classifier.

Table 3. Performance comparison for fusion algorithms

	Bayesian classifier	Fisher discriminant analysis	SVM
Recognition rates	98.67%	96.0%	96.0%

V. CONCLUDING REMARKS

This paper deals with various possible scenarios in a multimodal biometric system using two iris recognitions and also the levels of fusion and the integration strategies to improve overall system accuracy. At the same time, we implement the Daugman's iris system using the Gabor transform and Hamming distance. We propose an iris feature extraction method having a property of size invariant through the Fuzzy-LDA with five types of Contourlet transform.

We applied it to an iris database consisting of 300 iris patterns extracted form 100 subjects and finally got more less than 4.66% equal error rate. Also, to effectively aggregate two systems, we use statistical distribution models based on matching values for genuine and impostor, respectively.

From the experimental results, we confirm that the proposed method can be applied to the applications of authentication where high performance is required.

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