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Biometric Security with a Robust Multimodal Features Level Fusion Using Modify Incremental Principal Component Analysis

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Abstract

Biometric Authentication (BA) has been recently identified as a significant paradigm on maintaining the security level to improve individual person's authenticity. With more and more advanced technology, the BA has to be enhanced to cope up with the increased insecure environment. Several schemes employing multimodal biometric system fuses the face image with certain other traditional biometric modalities to ensure security. However, changes in the facial expression significantly updates the facial geometry, thereby reduces the ranking score level. Some of the multimodal biometric research group has designed different algorithms on personal biometric feature based authentication. But, fusion multimodal biometric system did not provide robustness compromising the security level. To develop high robust multimodal biometric system, person multimodal biometric using Covariance Matrix Incremental Principal Component Analysis (CMI-PCA) method is proposed in this paper. The main goal of CMI-PCA method is to work with three principle steps and attain rank level fusion integration on the faces, ears and hand dorsal vein. First, the person's multimodal biometric features are sensed and feature extraction is performed using Gabor Filter based Incremental PCA to improve robustness level. Second step is to match the extracted features with stored test image from the database using Score Matching based on Covariance Matrix Incremental PCA. The score matching based on Covariance Matrix Incremental PCA maintain the scale of extracted features and compute the mean score value to match with test images without any Covariance Matrix range. Finally, the CMI-PCA method involves combining different biometric identification ranks for making final decision. The extended Borda Count Multimodal Ranking system is used in CMI-PCA to determine the integrated biometric outcome and ensures higher security level for individual information. Experiment is conducted on factors such as robustness level, multimodal matching score rate, rank level fusion efficiency rate.

Keywords - Covariance Matrix,Extended Borda Count, Incremental Principal Component Analysis, Multimodal Biometric System, Rank Level Fusion

I. INTRODUCTION

Traditional form of identity card and password authentication systems are increasingly obtained through theft or forgery. The recognition and authentication of biometric using human physiological or behavioral characteristics is comparatively considered to be more robust than the traditional form of detecting such attacks. To improve the confidentiality for verification of person identity, bothgovernment and commercial establishments are designing and implementingmore secure and robust form of personal identification (ID) systems using Multimodal Biometric fusion.

Islam et al have developed Automaticextractionof Local 3D Features(L3DF) to improve the identification and verification mechanisms with the aid of weighted sum rule. However, changes in the facial expression updates the facial geometry reducing the ranking score level [1]. Zengxi et al has introduced SR-based classification (SRC) techniques to improve the ranking level through novel index method called Sparse Coding Error Ratio (SCER) which was proved to be robust, but at the cost of security[2]. Kebbeb et al. has applied Topological watermarking to improve the robustness but the optimization of database protection was not ensured [3].Norman et al. have developed Multimodal biometric system which results in increased match score level using fusion algorithms but the quality of biometric features obtained using various devices was compromised [4]. A quality-based multimodal biometric fusion was designed in [5] to reduce the false acceptance rate and false rejection rates using Naïve Bayes principal. Score level fusion algorithm for multimodal biometric was designed in [6] with the objective of reducing the false rejection rate. But, fusion was not obtained for device specific nature. Multimodal biometric fusion strategy in [7] using score normalization procedure was designed with the objective of improving the prediction rate.

The occurrence of facial expressions is due to the individual's emotional state, intentions or due to the social behavior. Sima et al. has designed a dictionary based component separation algorithm to improve the facial recognition rate but the multimodal features were not included [8].

Sumit et al has designed a multimodal sparse representation method with the objective of cumulative recognition rate[9]. Though overall recognition accuracy was improved but the aspects of security was not covered which is addressed in this proposed work through Borda Count Multimodal Ranking system. Multimodal biometrics included face and ear was used in Snehlata et al. model to increase the identification rate using PCA is included in this work[10]. Feature level fusion used in Ujwalla et al. model is referred here for increasing the rejection rate and reducing the false rejection rate using Haar Wavelet based technique[11].

In this work, a robust multimodal rank level fusion using incremental principal component analysis for biometric security is designed, called Covariance Matrix Incremental Principal Component Analysis (CMI-PCA) method. The remainder of this paper is organized as follows. Section 2 describes the design of high robust multimodal biometric system using incremental principal component analysis, architecture and algorithm. Section 3 presents results of experimentation.Section 4 summarizes the performance of the existing multimodal biometric methods with the proposed algorithms. Finally, Section 5 concludes the research work.

II. PROPOSED SYSTEM

In this section, arobust multimodal biometric system with effective rank level fusion technique using Covariance Matrix Incremental principal component analysis is described. In CMI-PCA method a multimodal group of face, ear and hand dorsal vein are combined together to improve the overall performance of the biometric system even in the presence of different quality data.

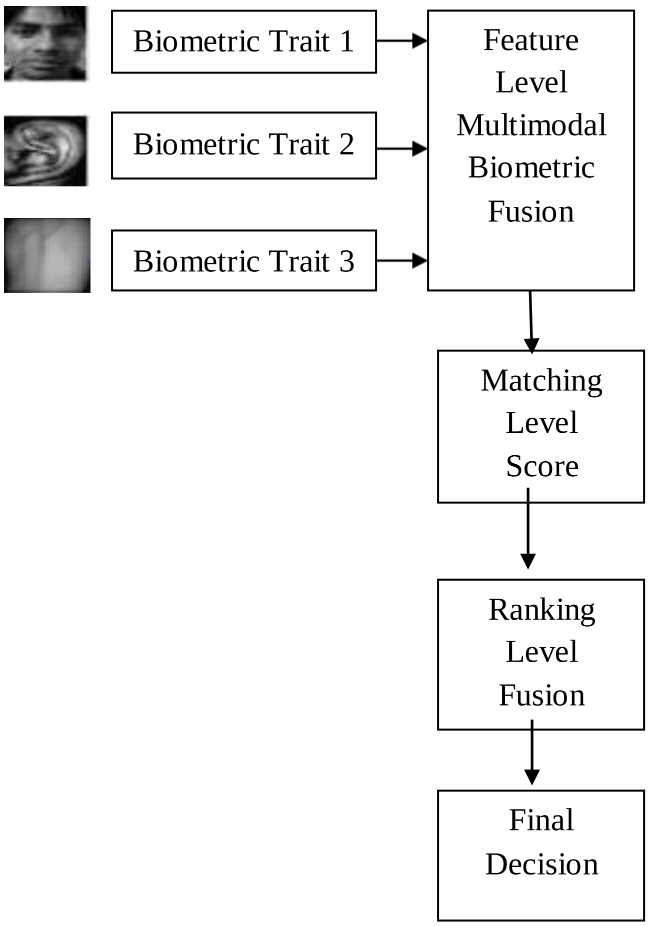

Fig.1 Multimodal BiometricSystem based on Incremental PCA

Figure 1 show the multimodal biometric based on Incremental PCA. The multimodal biometric system in the proposed paper works with face, ear and hand dorsal vein using the incremental principal component analysis. Initially, the face images are scanned and each person’s facial expression responses in accordance with the persons internal emotional conditions are obtained. Second, the ear images are scanned through sensor, which is then taken as the biometric feature. The ear biometric model is unique and eternal over the course of a humanlife and also easily captured without any assistance. Finally, the Hand Dorsal Vein chosen in this proposed work provides the security for the individual's information, where hand dorsal contains straight lines with one or more branches toward fingers. Thus, hand dorsal vein pattern works to combine the score value with face and ear.

Feature Level Multimodal Biometric Fusion

The first step involved in the design ofCMI-PCA method is to capture the multimodal images (i.e., face, ear and hand dorsal vein) through the sensors. Once the multimodal images are captured, feature extraction work is carried out using Gabor Filter. The Gabor filtering of the face, ear and hand dorsal vein features are extracted using the subsequent equation set as,

$$T_{Face}(x, y, \theta) = \frac{1}{2\pi S_x S_y} e^{-\frac{1}{2}\left(\frac{x^2}{S_x + S_y} + \frac{y^2}{S_x + S_y}\right)} e^{2\pi}$$
(1)

$$T_{Ear}(x, y, \theta) = \frac{1}{2\pi S_x S_y} e^{-\frac{1}{2}\left(\frac{x^2}{S_x + S_y} + \frac{y^2}{S_x + S_y}\right)} e^{2\pi}$$
(2)

$$T_{Hand\ Dorsal\ Vein}(x, y, \theta) = \frac{1}{2\pi S_x S_y} e^{-\frac{1}{2}\left(\frac{x^2}{S_x + S_y} + \frac{y^2}{S_x + S_y}\right)} e^{2\pi}$$
(3)

Where $T_{Face}(x,\ y,\ \theta)$, $T_{Ear}(x,\ y,\ \theta)$, and $T_{Hand\ Dorsal\ Vein}(x,\ y,\ \theta)$ denotes the Gabor filtering on the scanned biometric images, where $(x,\ y)$ are positions of scanned biometric image pixel, and 'θ' is the angle of Gabor filtering carried out in the CMI-PCA method. The standard deviation points plotted to extract the biometric features are denoted as S_x and S_y. The extracted features using Gabor filter removes all the edge (i.e.,) unwanted pixels. As a result, the storage space on the database gets minimized. Effective features extracted from all the multimodal images improve the robustness level of CMI-PCA method. After the filtering of scanned biometric images, the results of extraction process are provided to the next stage for performing. The feature extracted through filtering operation defines the result as,

$$GF_{(FaceS,angle)} = Intensity_{face}(x, y) * T_{Face}(x, y)$$
(4)

$$GF_{(EarS,angle)} = Intensity_{Ear}(x, y) * T_{Ear}(x, y)$$
(5)

$$GF_{(Hand\ Dorsal\ VeinS,angle)} = Intensity_{Hand\ Dorsal\ Vein}(x, y) * T_{Hand\ Dorsal\ Vein}(x, y)$$
(6)

From (4), (5) and (6), 'GF' is the result of Gabor filter that denotes the extracted features from a specific angle where $faceS$, $EarS$ and $Hand\ dorsalsS$ denotes the size of each biometric feature on the $angle$ 'θ'.

Matching Multimodal Score Level based on Incremental PCA

The second step involved in the design ofCMI-PCA method is to match the multimodal score level based on Incremental PCA. The extracted features obtained through Gabor filter are then matched. The test samples of biometric images are

matched with the training samples in the database to fetch the accurate matching result. The accuracy is attained using Score Matching based on Covariance Matrix Incremental PCA concept.

Covariance matrix is not estimated for matching the multimodal biometric in CMI-PCA method which reduces the matching time rate of the face, ear and hand dorsal vein test image with the training images. The matching in the CMI-PCA method is carried out by computing the mean score value. The mean score value is formularized as,

$$Mean\ Score\ Value = \frac{1}{M}\sum_{n=1}^{M} \mathbb{\Gamma}_n \qquad (7)$$

Where,

$$M = GF_{(FaceS,angle)} + GF_{(EarS,angle)} + GF_{(Hand\ DorsalVeinS,angle)}$$

$$\mathbb{\Gamma} = \frac{\theta_{Face+Ear+Hand\ dorsal\ Vein}}{T_{Face}(x,y,\theta) + T_{Ear}(x,y,\theta) + T_{Hand\ Dorsal\ Vein}(x,y,\theta)}$$

The mean score value computed on different iteration set improve the biometric security on each individuals. The ranking percentage is increased in CMI-PCA method with desired level of security as illustrated in section 2.3.

Ranking level fusion of Face, Ear and Hand Dorsal Vein

The ranking level fusion of face, ear and hand dorsal vein is the final step in CMI-PCA method, where the multimodal matches score value is ranked through the Extended Borda Count method.The value of the less rank in this proposed method determines the more accurate result on multimodal fusion. The lesser value denotes the higher-ranking score value in CMI-PCA method. The design and implementation of Extended Borda Count is briefed in section 2.3.1.

Extended Borda Count Multimodal Ranking System

Extended Borda Count Multimodal ranking method uses the sum of match score value to calculatethe final rank. The Extended Borda count ranking operation takes the match score value computed based on the mean score value as the input.

$$Ranking\ Level\ Fusion = \frac{Overall\ Matched\ Score\ Value}{3} \qquad (8)$$

The Extended Borda Count attain the output value by dividing the overall matched score value from the number of multimodal biometric features. The extended Borda count reduces the false rejection rate which in turn also improves the rank level fusion efficiency rate on authenticating the personal information. In multimodal biometric system, rank level fusion is the method of securing the system with different modalities such as face, ear and hand dorsal vein.

Overall Architecture of Proposed System

In multimodal biometric system, rank level fusion is the method of securing the system with different modalities such as face, ear and hand dorsal vein. The overall architecture diagram of CMI-PCA method is shown in Figure 2

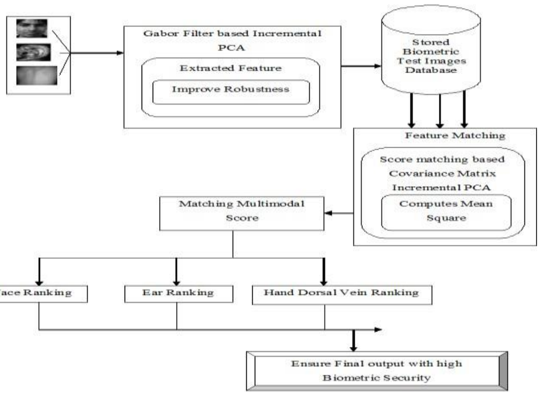

Fig.2. Architecture Diagram of CMI-PCA Method

As illustrated in Figure 2, multimodal biometric features are used to ensure the desired level of security. The multimodal biometric features such as face, ear and hand dorsal vein are extracted from the sensed images. The extraction of features is carried out using the Gabor filter based Incremental PCA. Gabor filter based Incremental PCA improves the robustness level by removing the unwanted pixels from scanned biometric images. Second, the matches are carried out with test and training images using Score Matching based Covariance Matrix Incremental PCA. The matches uses the mean score value instead of the covariance matrix range. Finally, the multimodal match score is used for ranking the system using Extended Borda Count Multimodal ranking method.

III.EXPERIMENTAL EVALUATION

This work is implemented in MATLAB for combined face, ear and hand dorsal vein. The CMI-PCA method takes the face, ear and hand dorsal vein geometric biometric images for experimental work. The research in this study was done using three different dataset test images. The first dataset provided for research work is from the ORL dataset which is composed of 15 individuals with 11 face images per individual. The University of Science and Technology of Beijing (USTB) supplies four simple ear datasets in which the database-I is chosen for experimental work. Dataset I contain 60 test images, where all images are from the right ear. Finally, hand dorsal vein images are taken from NCUT data sets. Pattern of NIR images comprises of 10 images of right hand veins and 10 images of left hand obtained from 102 persons. These 2040dorsal hand vein images have been attained from industrial university in north of china

Experiment is conducted on factors such as feature extraction efficiency, multimodal matching score rate and rank level fusion efficiency rate. Feature extraction using CMI-PCA method measures the features extracted for multimodal images using face, ear and hand dorsal vein. It is measured in terms of percentage (%). The feature extraction is the ratio of angle value of face, ear and hand dorsal vein through global filter to the total number of images given as input.

$$FE = \frac{(GF_{(FaceS,angle)}) + (GF_{(EarS,angle)}) + (GF_{(Hand\,Dorsal\,VeinS,angle)})}{n} \quad (9)$$

The multimodal matching score is obtained from the ratio of mean score value of the multimodal features for n values. It is measured in terms of percentage.

$$MMS = {Mean\,Score\,Value}/{n} \quad (10)$$

The rank level fusion efficiency rate using CMI-PCA method is the rate at which the fusion value is obtained for the multimodal features, face, ear and hand dorsal vein using (8). It is measured in terms of percentage (%).

IV. DISCUSSION

The result analysis of CPI-PCA method uses three datasets, one for face, the other dataset for ear and the third dataset used for hand dorsal vein. The CPI-PCA method is compared with the existing Automatic extraction of local 3D Features(L3DF) [1] and SR-based classification (SRC) [2] method.

TABLE I.Tabulation for Feature Extraction Efficiency Rate

No. of test images	Feature extraction efficiency rate (%)		
	CPI-PCA	L3DF	SRC
2	55.48	50.45	44.45
4	62.55	55.52	48.52
6	65.84	60.81	54.81
8	65.45	60.42	55.42
10	68.33	63.3	61.30
12	71.49	66.46	62.46
14	75.85	70.82	68.82

TABLE II.Tabulation for Matching Score Rate

No. of test images	Multimodal matching score rate (%)

	CPI-PCA	L3DF	SRC
2	68.50	57.44	52.41
4	75.57	62.51	56.48
6	78.86	67.80	62.77
8	73.47	62.41	63.38
10	81.35	70.29	71.26
12	84.51	73.45	74.42
14	88.87	77.81	78.78

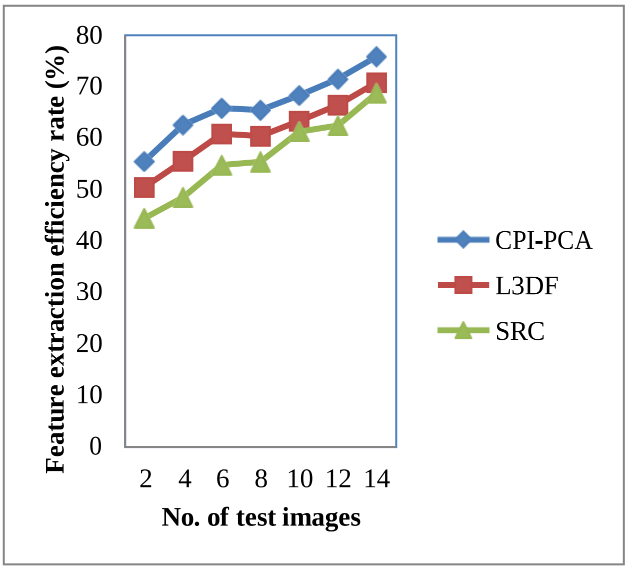

Fig.3 Measure of Feature Extraction Efficiency

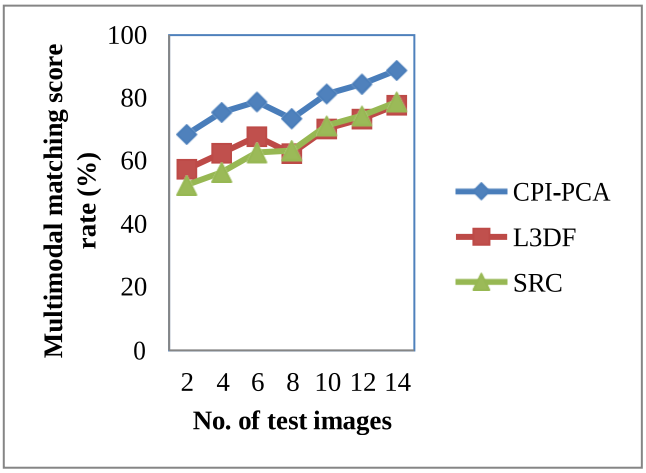

Fig.4 Measure of Multimodal Matching Score Rate

Table I and II and Figure 3 and 4shows the impact of feature extraction efficiency rate and multimodal matching score rate obtained from fourteen individuals (ORL dataset), fourteen test images of ear obtained from fourteen individuals (dataset-I from USTB) and seven images of right hand veins and seven images of left veins (NCUT) using MATLAB simulator and comparison are made with two other methods, namely L3DF [1] and SRC [3].

The proposed CPI-PCA method provides higher feature extraction efficiency rate when compared to L3DF [1] method and SRC [2] method is shown in table I. The feature extraction efficiency is increased with the application of Gabor filter which removes all the unwanted pixels and resulting in the increase in the feature extraction efficiency by 6 – 11 %. In addition, the feature extracted through filtering operation using Gabor filter extracts the features from all multimodal images in accordance with the person's internal emotional conditions in CPI-PCA method resulting in the efficiency of features being extracted by 9 – 22 % compared to SRC.

From Table II it is observed that with increase in the number of images, the Multimodal matching score rate also gets increased though not linear due to the varying size of individuals that invariably varies according to different individuals and accordingly the Multimodal matching score rate also varies.

From the figure 4 it is illustrated that the Multimodal matching score rate is higher or increased using the proposed CPI-PCA method when compared to the two other existing methods. The computation of the mean score value instead of covariance score computation increases the multimodal matching score rate by 12 – 16 % compared to L3DF and 11 – 25 % compared to SRC respectively.

TABLE III.Tabulation for Rank Level Fusion Efficiency Rate

No. of test images	Rank level fusion efficiency rate (%)		
	CPI-PCA	L3DF	SRC
2	78.45	67.44	62.41
4	85.52	72.51	66.48
6	88.81	77.80	72.77
8	83.42	72.41	73.38
10	88.30	80.29	81.26
12	89.47	83.45	84.42
14	90.82	87.81	88.78

The Rank level fusion efficiency rate for CPI-PCA method is also found to be increased is mentioned in the Table III.

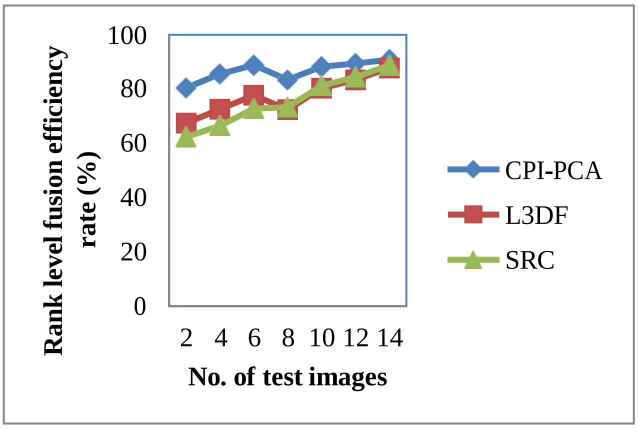

Fig.5 Measure of Rank Level Fusion Efficiency

Rate

In figure 5, the ranking level fusion efficiency rate attained using the test images of size 2 to 14 for experimental purposes are depicted. It is observed from the figure that the ranking level fusion efficiency rate is improved through the application of Extended Borda Count method. By obtaining the match score value computed based on the mean score value as the input using Extended Borda Count method, the rank level fusion efficiency rate gets increased in CPI-PCA method by 3 – 16 % compared to L3DF. Moreover, the overall match score value obtained for multimodal features using the sum of match score value for the features ear, face and hand dorsal vein increases the rank level fusion efficiency by 2 – 22 % compared to SRD.

V.CONCLUSION

Biometric authentication and developing robust multimodal biometric system has become the key for this system. It was developed with the objective of improving the level of robustness by increasing the multimodal matching score rate. In this work, the performance effects of multimodal biometric system are investigated through Covariance Matrix Incremental Principal Component Analysis (CMI-PCA) method. The CMI-PCA method efficiently obtained the features of multimodal images and produced the good results. The experiment conducted using three datasets each for face, ear and hand dorsal vein shows that the CMI-PCA method outperforms in terms of multimodal matching score rate, ranking level fusion efficiency rate and multimodal matching score rate when compared to the state-of-the-art methods.

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