MULTIMODAL BIOMETRIC RECOGNITION BASED ON FUSION OF LOW RESOLUTION FACE AND FINGER VEINS

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Abstract. Multimodal biometric systems utilize multiple biometric sources in order to increase robustness as compared to single biometric system. Most of the biometric systems in real are single or multimodal authentication system. This paper presents an efficient multimodal low resolution face and finger veins biometric recognition system based on class specific linear discriminant to client specific discriminant analysis and finger veins fusion at score level. Simulation results show that the proposed multimodal recognition system is very efficient to reduce the FAR and increase GAR, but it is more computationally complex due to processing involved in layered computation of LDA and CSLDA at runtime.

Keywords: Multimodal biometric system, Face, Finger veins, CSLDA, Fuzzy fusion

1. Introduction. Biometric is the field of pattern recognition to recognize the identity based on physical, i.e., face, finger veins, palm or behavioral, i.e., voice, signature, walking style, patterns of human. During the last decades, biometrics has been an intensive field of research and consequently the number of recognition approaches has been proposed by using either single biometric or multiple biometrics. Commonly used biometrics are face, finger veins, finger print, palm, voice, signature, iris, etc. Uni-biometric system has several limitations such as noise during sensing, non-universality, inter-class similarities, intra-class variations, spoof attach and distinctiveness, etc. [1], and thus, uni-biometric system may lead to false acceptance rate (FAR) and false rejection rate (FRR) [2]. Multimodal biometric is the combination of multi-biometrics to increase the performance and robustness against imposter attack and environment variations to overcome the limitation involved in uni-modal biometric system. However, combining the multi-biometrics is not 100% guarantee to provide the better solution.

With respect to processing methodologies biometric is classified into two classes: authentication/verification and recognition. Identification is the process to find a person by comparing the pattern with claimed identify. Where as in recognition pattern is compared with the pattern of every pattern in the database yielding either score or distance to identify probe identify. This paper presents novel recognition by performing fusion on...
finger veins and face at score level. The motivations of the proposed approach are: firstly, design recognition system instead of authentication system to avoid the overhead of user id and secondly, the use of low resolution camera for face recognition and less-intrusive from user.

Performance measurement is the most important part in biometrics four parameters used to measure the performance are FRR (False Rejection Ratio) is the ratio of genuine has been recognize as impostor, FAR (False Acceptance Ratio) the ratio of impostor has been recognize as genuine, EER (Equal Error Rate) is FAR and FRR are equal (the less EER is the better system performance) and ROC (Receiver Operating Characteristic) is the plot of FRR versus FAR [3]. Uniqueness and reliability of features are the two important factors that effect on FAR and FRR.

Beginning from late 90’s, multimodal biometrics has been developed with combination of various biometrics. Face is the most popular biometrics combined with other biometrics at different fusion level, i.e., feature, score and decision [4]. Brunelli and Falavigna presented multimodal face and voice for identification [5]. Zhou presented image reconstruction for face recognition using fast ICA [6]. Cetingul et al. presented multimodal speaker and speech recognition using lip motion, lip texture and audio and fusion is performed by reliability weighting summation [7]. Lin et al. presented face recognition system by combining the PCA with scale invariant feature transform [8]. Palm features are extracted by using four directional convolution masks from normalized palm image and for hand geometry palm, finger length and width is extracted. Fusion is performed at feature level after normalization of palm and hand geometry features. Zhou et al. presented authentication system based on face and fingerprint based on multi-route detection using SVM fusion and face image with zero turning is used as face template and other face images are used for self learning [9]. Parallel processing on face and fingerprint is used in authentication and score level matching is performed by using SVM fusion strategy. The optimum face is selected, which has minimum expression, less rotation and largest face area. Wei et al. performed feature level fusion on face and palm print for single sample and the features are extracted by using ICA over DCT and Gabor wavelet [10]. They used circular Gabor filter and feature level fusion is performed after normalizing the face and palm features and the candidate class is selected by using nearest neighbor classifier. Shahin et al. presented multimodal hand veins, hand geometry and fingerprint to provide high security [11]. The ridges and direction are calculated in frequency domain. Chin et al. presented verification system by integrating palm print and fingerprint at feature level [12]. The quality of palm and finger print is enhanced by applying series of preprocessing steps and 2D Gabor filter is used for feature extraction and fused both the feature matrixes. Poinsot et al. presented multimodal biometrics by fusing the palm and face for small sample size problems. Gabor filter is used for feature extraction on both palm and face images [13]. Chu et al. performed face and palm score level fusion for personal identification based on ordinal features [14]. The ordinal features are extracted and simple fusion rules are used to fuse the two scores. Tayal et al. presented multimodal authentication system based on iris and speech using decision theory [15]. The iris and speech biometrics are combined by using energy compaction and time frequency resolution. Chen et al. presented bilateral projection scheme using 2DPCA for effective feature extraction and face recognition [16]. 2DPCA is used to reduce the dimension whereas SCD-2DPCA compresses the image along both row and column directions. Chaudhary et al. presented multimodal biometrics system based on face, palm print and fingerprint and score level fusion is performed [17]. For face recognition prominent features, like eyes, noses, etc. they are extracted with their geometry distribution.
Veins recognition utilized the vascular patterns visible with infrared light illumination in side human body, i.e., hand, finger. Thus, finger veins identification is difficult to falsify. Lee et al. presented finger veins recognition by using minutia-based alignment and local binary pattern based feature extraction and extracted the finger veins code using LBP [18]. Kang and Park presented multimodal finger veins recognition by fusing the finger veins and finger geometry at score level based on SVM and minutiae point of finger veins and geometric features with sequential deviation are utilized for finger veins and geometry identification respectively [19]. Lui et al. presented finger veins recognition by using manifold learning and point manifold distance and ONPP is used for manifold recognition [20]. Yang et al. presented finger veins recognition by using feature combination extracted through circular Gabor filter and feature are exploited on structural topological, local moments [21]. Yang et al. presented segmentation of finger veins based on multichannel even symmetric Gabor filter in spatial domain and used eight orientation filters to exploit veins information in finger and finger veins image is segmented by using threshold.

Based on feature representation, face recognition methods can be classified into two groups: face and constituent. The face based method (appearance based technique) uses raw information face pixel, i.e., PCA, LDA, KPCA, SVM, whereas the constituent based approach uses the relationships among face features, i.e., nose, lips, and eyes. Compared with the face based method, the constituent based method is more flexible, but the performance is dependent on features. In other words, the appearance based approach works directly on images or appearance of the objects and processes the image as 2D pattern, whereas the constituent based approach is based on local level features. Among appearance based representation PCA and LDA based methods are the two most powerful methods for dimensionality reduction and successfully applied in many complex classification problems such as speech recognition, face recognition [22]. The accuracy of face recognition system is affected by small sample size problems and also by separability criteria of LDA. The separability criteria are not directly related to the classification accuracy. In order to use LDA on face recognition problem, the number of research has been done [23]. In general, LDA based methods perform better than PCA, but on the other hand, LDA based methods are facing problem with SSS. First, Belhumeur et al. involved Eigen analysis of two inverted matrix products and used class specific information for finding the projection that best discriminates among classes for face recognition [24]. Basically, it finds the projection by maximizing within the class scatters and maximizing among class scatters [25]. The aim of LDA is to find the representation of feature vector space. The accuracy of face recognition system is affected by small sample size problems and also by separability criteria of LDA. The separability criteria are not directly related to the classification accuracy. The conventional solution to misclassification for small sample size problems and large data set with similar faces is the use of PCA into LDA, i.e., fisherfaces. PCA is used for dimensionality reduction whereas LDA and radial based neural network is used for recognition [26,27]. However, the use of LDA over PCA results in loss of significant discriminatory information. To avoid this loss, direct linear discriminate analysis (D-LDA) is used [28]. It performs directly on high dimensional to avoid the loss of discriminatory information. D-LDA has several issues in large variation and its performance is degraded in this case. Fractional-step linear discriminant analysis (F-LDA) used weighting function to avoid misclassification by assigning the more weight to the relevant distance for dimensionality reduction [29]. Zhang et al. used CPCA, FLDA and maximum modal distance based HMM [30]. FLDA and CPCA are used to get better discriminant features. Penalized discriminant analyses (PDA) overcome the SSS problem and also smooth the coefficient of discriminant vector. Dia et al. presented
inverse Fisher discriminant analysis, and it modifies the procedure of PCA and derives the regular and irregular information from S. Yang et al. presented fuzzy inverse FDA based on fuzzy FDA and inverse Fisher discriminant analysis by using fuzzy K-nearest neighbor class.

The previous multimodal biometrics methods are identification system in which user identity is required and one to one matching is performed. To avoid the use of interaction with the machine, we present a novel recognition method based on low resolution face and finger veins fusion. Instead of extracting one face and finger with minimum Euclidian distance, we selected several faces based that are very close to each other using Euclidian distance. Fusion of CSLDA and finger veins is performed on each selected face and its finger veins to find the optimized results. The proposed approach is very efficient and it reduces the FAR to 0.00026. In other words, we reduce the dataset using the few face results and then one to some face and finger veins recognition is performed instead of one to one or one-to-many biometrics. The reset of the paper is organized as follows: Section 2 describes the proposed multimodal biometric; Section 3 discusses the experimental results, performance evaluation and list of benefits of proposed technique and finally the conclusion is presented in Section 4.

2. Problem Statement and Preliminaries. The problem is stated as: “Given set of N class face and finger veins biometrics, identify the probe identity by fusing finger veins and face results.”

Most of the previous system required user identity to find the one to one match and result is based on the threshold value. Unlike the previous system we proposed recognition based on score level fusion of finger veins and low resolution face images. Basically, the authentication method authenticate based on one to one matching whereas the recognition methods authenticate based on one to many match and select the biometric with minimum Euclidian distance. We proposed a novel technique, in which instead of selecting one face using recognition method, we selected few faces having minimum Euclidian distance and very close to each other and then perform authentication on few faces [31] and finger veins biometrics (one to few match) instead of one to one match. In other words, the proposed system starts from recognition and leads towards partially authentication method and finally we performed fusion on face and finger veins results.

As the face images are slightly rotated, thus we performed rotation using the eye location. Before image normalization we estimated the face orientation angle using two eye points and rotated the face along computed angle. The angle $\alpha$ is calculated from the two eye points and face is rotated by angle $\alpha$ along y-axis. The angle is calculated as

\[
\begin{align*}
    d_1 &= \sqrt{(x_1 - x_2)^2} \\
    d_2 &= \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \\
    \alpha &= \cos^{-1}(d_1/d_2)
\end{align*}
\]

The whole face is rotated pixel by pixel by using the following transformation

\[
\begin{align*}
    x' &= x \cos \alpha - y \sin \alpha \\
    y' &= y \cos \alpha - y \cos \alpha
\end{align*}
\]

Suppose there are $N$ clients and every client has six samples of face and three sample finger vein. The first step is to select $M$ client based on the face recognition using linear discriminant analysis and then these selected client are used to find most optimal client [31].
$D$ is the Euclidian distance computed using linear discriminant analysis.

$$D = \text{Euc}_d \text{dist}[d_1, d_2, \ldots, d_N]$$

$$m_j = N_j(\text{Min}[D])$$

$$\text{Min}[D] = \{ i | d_i < \theta \text{ and } |d_i - d_j| \}$$

Unlike the conventional LDA, we selected $N'$ client using Equation (12). These $N'$ clients have very less difference of Euclidian distance with each other thus they are similar to each other. To find better projection we reduced the dataset from $M$ to $N'$ clients. where

$M \subseteq N$ and $M \ll N$

$$M = \{m_1, \ldots, m_j\}$$

Now, we have small dataset selected from $M$ clients. The second step is to find the CSLDA of each selected client by using the small dataset and compute the finger veins
results by considering each client in $N'$ as identity using Step 5 of algorithm. Thus this authentication process is one to few matches instead of one to one match. Between class scatter matrix on new adaptive database is computed as

$$M' = \frac{M}{M - M_i} \sum_{j=1}^{N_i'} \nu_j \nu_j^T \quad (10)$$

Similarly within class scatter matrix is calculated as

$$\varphi_i = \phi_i' - M_i' \quad (11)$$

$$\nu = \frac{1}{M} \sum_{j=1}^{N_i'} x_j \quad (12)$$

client mean

$$\nu = \varphi_i^{-1} \nu \quad (13)$$

Thus overall client specific linear discriminant analysis if client $i$ is given as

$$ai = U_{\nu} \quad i = [1, 2, \ldots, N'] \quad (14)$$

Similarly for Finger veins identification is performed with probe finger veins and every finger veins of selected clients and we used HITACHI finger veins SDK for finger veins identification.

Algorithm: Recognition based Authentication

**Input:** A set of $M$ training classes face and finger veins, each class contain 6 face images and 3 finger veins and probe $P$ face and finger vein image.

**Output:** Identified User.

**Algorithm:**

Step 1: Calculate between class scatter matrix and within class scatter matrix on face images of $M$ classes.

Step 2: Find $N'$ minimum Euclidean distances $D_i$ of Probe $P$ by projecting face features on to the Feature Space on $M$ if

$$D_k = D_i < \theta$$

Step 3: Create new adaptive face database of size $M'$ for training where $M' << M$.

Step 4: For each Client in $M$ perform face and finger veins authentication Step 5.

Calculate new feature space on new adaptive database of size $M'$.

Step 5: Perform face and finger veins authentication on each selected face with probe.

For $i = 1 : 1 : N'$

Face and Finger Veins Verification by considering Probe as user Identity.

Face Veins Verification on new adaptive database.

End

Step 6: Fuse the finger veins and face result using R-I and R-II rules.

When scores of multimodal biometrics are consolidated to reach final recognition result, it is called score level fusion. We performed score level fusion on the face and finger veins score using rules R-I and R-II. In other words, if the client in sub dataset results both face and finger veins are true then it is accepted else it is considered as imposter. Secondly, if there is very close tie of face recognition between two clients, then finger veins contributing is more in the final decision. Although in this case, both results are not true but the final results is approximated by considering the next close results of face discussed in case-III.

R-I: $\forall N'$ such that $\exists j$ if Face AND Fingervein

Then $j$ is probe.

R-II: $\forall N' \exists j$ such that $Face_j - Face_i < \theta$
Then if \( \text{Fingervein}_j \) probe client \( j \) else \( \text{Fingervein}_i \) probe client \( i \).

3. **Experiment Results and Discussion.** For experiment purpose, we used low resolution web camera for face images and HITACHI finger veins device for finger veins images. The face and finger veins data is obtained on 35 voluntary CAIRO staff and students. For face, we have taken six images of each user and for finger veins we extracted three images of first finger. The face images may slightly rotated are taken at different time with different variation of illumination. For testing, we used C# and online testing is performed in different illumination environment. Using the eye point, face is extracted and normalized to 50×50. Before image normalization we estimated the face orientation using eye point and rotated along computed angle. We found a considerable performance in term of FAR to 0.000026 and GAR to 92.4 using the fusion of class specific to client specific of face recognition and finger veins of selected clients.

The proposed scheme find the \( N' \) classes from \( M \) classes using the minimum Euclidian distance, thus these selected faces are very close to each other. The conventional approaches, i.e., PCA, LDA, KDA, D-LDA, extract only one face with minimum Euclidian distance. These techniques performed poor, when dataset consist of similar faces or very large. Thus to avoid this issue: we extracted few faces instead of selecting one face depending upon the Euclidian distance. Then new database of selected clients is created to find the better feature vector projection. Finally, finger veins and face authentication is performed on each selected client. We presented three cases that described the performance of proposed as compared to conventional approaches.

![Figure 4](image)

**Figure 4.** Case-I: first row contain probe image, 2nd row contains the Euclidian distance computed on LDA, and row 3 contains the CSLDA results computed on adaptive new database as a result of row 2, whereas row 4 the recognized results.

The Figure 4 describes the Case-I, for probe \( P \), the Euclidian distance computed by projecting the probe on to the feature space of whole data, we selected six faces. The Figure 4 shows that for probe \( P \), the minimum Euclidian distance is .1488. The result of conventional LDA is false acceptance. To overcome this issue, we selected six faces having very less Euclidian distance and create new dataset and recomputed the feature space on to this small dataset using CSLDA. We computed the finger veins fusion and
face recognition on each client selected in new database and fused the results using AND operation. In this case, FAR is handled by finding the probe class within new dataset.

The Figure 5 describes the Case-II. For probe $P$, the 2nd row shows the minimum Euclidian distances computed by projecting the probe on to the feature space of whole dataset. In this case, the face detected by conventional approach and proposed approach is accurate (minimum Euclidian distance is 0.1266), but it is still very difficult to decide either it is imposter or claimed identity due to the small difference between other faces. Thus we applied CSLDA on each selected client by considering new dataset and also computer the finger veins result on each client finger in $N'$ data set with probe finger and Finally we fused the result of finger veins and CSLDA.

![Figure 5. Case-II](image)

The case-III describes the FAR by conventional approach and also by CSLDA based on LDA because it fails to clearly identify the exact client and the Euclidian distance computed by projecting the probe on to the feature space shown in 3rd row. It is difficult to decide from CSLDA results, so in this case, we considered both faces and let the final decision on finger veins. If the finger veins clearly spate the both client then we accept the result based on finger veins else we considered it as imposter. The Figure 6 describes the issues with Euclidian distances. The Euclidian distance of first and third client is approximately very close, i.e., 0.0012 and 0.0015. Although it represents true result from face, but to avoid the FAR and increase GAR, we selected two close faces in this case and let the final result on finger veins whereas the finger veins results on both client finger is 0.0000 and 0.6986.

Figure 7 describes the FAR and GAR. There is prominent improvement by fusing the finger veins and face recognition based on the selection of few faces from large data set based on 3 images for finger veins and 6 images for face. Figure 8 and Figure 9 present the face recognition results and FAR, GAR respectively using 2, 4 and 6 training samples. In the above experiment suggest that recognition based on authentication by fusing the finger veins and face perform better than conventional recognition technique. Moreover, it eliminates the additional requirement of identity required for authentication.
Figure 6. Case-III: first row contain probe image, 2nd row contains the Euclidian distance computed on LDA, and row 3 contains CSLDA weights on small dataset, whereas row 4 contain new results after fusion.

Figure 7. Recognition result using multimodal biometrics

4. Conclusion. We presented a novel multimodal low resolution face and finger veins recognition system at score level fusion. For face images, we used low resolution web camera. Simulation results shows that proposed multimodal recognition system is very efficient to reduce the FAR .000026 and increase GAR 97.4. Although the proposed approach is computational complex due to extra processing required in computation of CSLDA feature space at run time. The GAR and FAR can further be optimized by applying class to client approach on finger veins also. The proposed technique is very efficient in large population and small variation in luminance and expression because it does not find only one solution. It reaches to the final solution by selecting few solutions and find the optimized results from this few selections.
Figure 8. Face recognition based on authentication mechanism

Figure 9. Face FAR and GAR on 2, 4 and 6 images

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