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Multimodal Biometrics Fusion at Feature Level Extraction

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ABSTRACT: Multimodal Biometric identification is an rising technology which will solve security issues in our networked society. The palmprint authentication was projected (Pattern Recognition 32(4) (1999) 691) wherever by lines and points area unit extracted from palms for private identification. Biometrics has recently attracted substantial interest for its high performance in biometric recognition system. During this paper we have a tendency to introduce multimodal biometrics for face and palm-print images exploitation fusion ways at the feature level. Gabor based mostly image processing is employed to extract discriminant options, whereas principal part analysis (PCA) and linear discriminant analysis (LDA) area unit accustomed scale back the dimension of each modality. The output options of LDA area unit serially combined and classified by a geometer distance classifier. The experimental result palm print databases proved that this fusion technique is able to increase biometric recognition rates compared to it produced by single modal biometrics.
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KEYWORDS: Face, Palmprint, Gabor Filter, Fusion, LDA, PCA

I. INTRODUCTION

Biometric technology is an automatic technique to recognize someone supported one (single modal biometrics) or combination of (multimodal biometrics) physiological or activity characteristics. This technology has become the inspiration for in depth array of extremely secure identification and private verification solutions. In recent years, multimodal bioscience has become a lot of} more necessary, notably as a result of single modal bioscience has reached its bottleneck; i.e. non-universal, uproarious sensing element knowledge, giant intra-user variations and susceptibleness to spoof attacks. Multimodal bioscience is considered to have supplementary info between completely different modalities that will increase recognition performance in term of accuracy and talent to beat the constraints of single bioscience. To use multimodal bioscience, one should apportion a combination technique that's ready to fuse this info provided by completely different modalities. To date, 3 levels of fusion techniques area unit available; particularly fusion at feature level, fusion at decision level and fusion at matching score level [1, 2]. Jain [1, 3] demonstrates a fusion technique in biometric verification system by combining 3 biometric modalities (face, fingerprint and hand geometry) at the matching score level. Ribaric [4] proposed a technique off using face and palmprint at the matching score level using unimodal results of every modality. A separate method is applied for recognition of each modality, i.e. principal lines for palmprint and Eigen face for face, whereas final judgment is formed supported a threshold value. Prabhakar [4] projected a fusion scheme for classifier combination at decision level that highlighted the importance of classifier choice throughout combination. rule [5] used a fusion technique at feature level by employing a complicated vector to represent a mixture of 2 modalities; i.e. handwriting and face images, that is then extracted by linear projection analysis ways like principal part analysis (PCA), K-L remodel and linear discriminant analysis (LDA).Computer-based personal identification, additionally called biometric computing, that tries to acknowledge an individual by his/her body or behavioral characteristics, has over thirty years of history. The primary industrial system, referred to as Identimat that measured the form of the hand and also the length of fingers, was developed within the

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Nineteen Seventies. At a similar time, fingerprint primarily based on automatic checking systems were wide utilized in enforcement. Due to the fast development of hardware, together with computation speed and capture devices, iris, retina, face, voice, palmprint, signature and DNA have joined the biometric family [6, 7, and 8]. Fingerprint identification has drawn wide attention over the last twenty five years. However, some individuals don't have clear fingerprints thanks to their physical work or problematic skin. Iris and retina recognition give terribly high accuracy however suffer from high costs of input devices or intrusion into users. Recently, several researchers have targeted on face and voice verification systems.

II. FEATURE EXTRACTION TECHNIQUE

A. Gabor Filter

Gabor filter may be a common technique to capture outstanding visual properties, multiscale, multi-direction area frequency options and to enlarge the grey selection as microscope [9]. During this analysis, the distinctive options of eyes, nose, and mouth in face image and also the made line options on palmprint are often effectively extracted by Gabor filter. Thus it's thought-about appropriate for analyzing gradual changes in knowledge of face and palmprint pictures thanks to movement, expression or ageing. Gabor remodel used to filter the image has the subsequent form:

$$G(x, y, \theta, \mu, \sigma) = \frac{1}{2\pi\sigma^2} exp \times exp[2\pi i(\mu x cos\theta + \mu y sin\theta)] \quad (1)$$

Where μ is that the frequency of sinusoidal wave, θ controls the orientation of the operator and σ is that the variance of the mathematician envelope. Gabor transform utilized in this study consists of 4 scales, σ set as and eight orientations, θ set as ×π/8

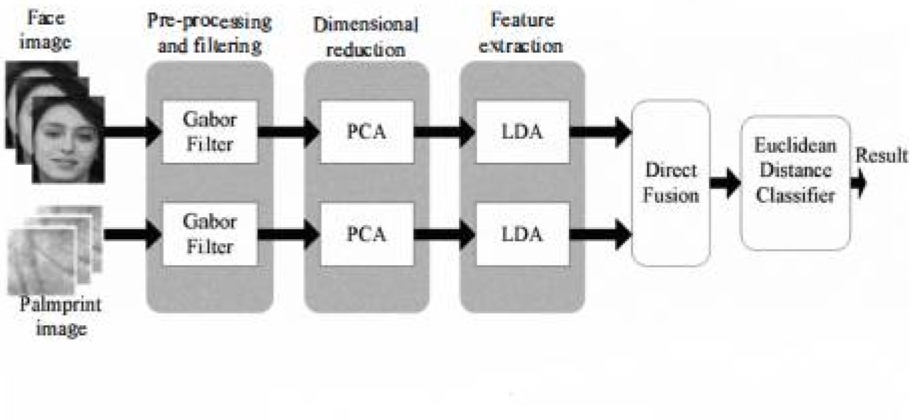

Fig.1 Overall block diagram

B. PCA

PCA is employed to calculate uncorrelated components from the variance matrix of the initial information within the orthogonal matrix rework [10]. In different words, every original eigenvectors is transformed through PCA into a replacement set of eigenvectors having similar size and linear composition with the initial vectors. during this paper, PCA is employed to extract linear options from the initial input pictures i.e. palmprint and face images because of its advantage in reworking a group of n variables (high dimensionality) to a group of k variables (low dimensionality) by maintaining as several variances of the initial information as potential. Given a group of focused input vectors $X_t(t = 1,..., l and \sum_{t=1}^{l} x_t = 0)$ every of that is of m dimension $X_t = (x_t(1), x_t(2),..., x_t(m))^T$ and usually m < I, PCA linearly transform every vector into a replacement one, by

$$S_t = U^T X_t \quad (2)$$

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Where U is m x n orthogonal matrix whose i^{th} column, μ_i is that the eigenvector of the sample variance matrix

$$C = \frac{1}{l}\sum_{t-1}^{l} X_t X_t^T \quad (3)$$

In theory [11], PCA 1st solves the chemist values,

$$\lambda_i u_i = C u_{i,} i = 1, \ldots, m \quad (4)$$

Drawback estimated u_i, S_t components are then calculated as the orthogonal transformation of X_t.

$$S_t(i) = u_i^T X_t \qquad i=1,\ldots\ldots,m \quad (5)$$

The new components are called principal components. By using only the first several eigenvectors sorted in descending order of the eigen values, the number of principal components in S_t can be reduced, thus allowing PCA to have dimensional reduction characteristics [11].

C. LDA

LDA searches for those vectors in the underlying space that best discriminate among the classes and also reduce the dimensionality of original data [12]. In comparison to PCA which describes the data, LDA has the capability of searching directions for maximum discrimination of classes. Therefore it is best for subsequent use following data projection by PCA. By given a number of independent class features, this technique creates a linear combination of these which produces the largest mean differences between the desired classes [12]. Let the between-class scatter matrix be described as,

$$S_B = \sum_{i-1}^{c} N_i (\mu_i - \mu)(\mu_i - \mu)^T \quad (6)$$

And the within-class scatter matrix is described as

$$S_w = \sum_{i-1}^{c} \sum_{x_k \varepsilon X_t} (X_k - \mu_i)(X_k - \mu_i)^T \quad (7)$$

Where μ_i is the mean image of class X_i, and N_i is the number of samples in class X_i. S_W If is nonsingular, the optimal projection W_{opt} is chosen as the matrix with orthonormal columns that maximizes the ratio of the determinant of the between-class scatter matrix of the projected samples to the determinant of the within-class scatter matrix of the projected samples $\left(\frac{\det |S_B|}{\det |S_W|}\right)$

.

$$S_W = \arg max_w \frac{|W_T S_B W|}{|W_T S_W W|} = [W_1 W_2 \ldots . W_m] \quad (8)$$

Where $\{W_i \,|i = 1, 2, \ldots..m\}$ is the set of generalized eigenvectors of S_B and S_W corresponding to the m largest generalized Eigen values $\{\lambda_i \,|i = 1, 2, \ldots..m\}$, i.e.,

$$S_B W_i = \lambda_i S_w W_i, \iota = 1,2, \ldots, m \quad (9)$$

Note that there are at most c-1nonzero generalized eigenvalues, and so an upper bound on m is c-1, where c is the number of classes. According to Belhumeur [12], at least t + c samples are required in order to guarantee that S_W does not become singular and therefore the proposed use of intermediate space. In this research, we use PCA space as the intermediate space, thus, the original t-dimensional space is projected onto an intermediate g-dimensional space using PCA and subsequently onto the m-dimensional space using LDA.

III. PROPOSED METHODOLOGY

The proposed method consists of four main stages. Details of the operation in each stage are discussed in the following way:

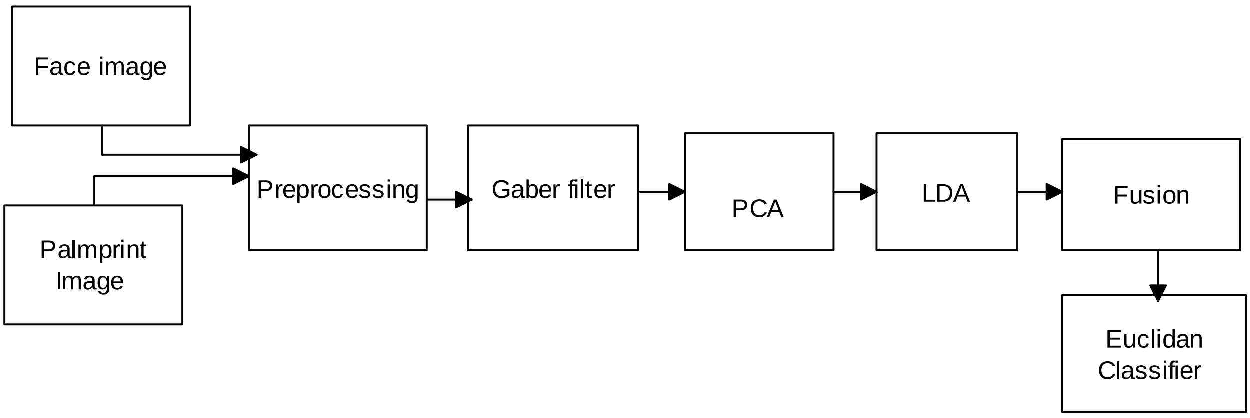

Fig.2 System block diagram

These are the steps of implementation.
i) Start is Pre-processing and filtering.
ii) Second step dimensionality reduction victimization PCA.
iii) Feature extraction for separation of sophistication victimization LDA.
iv) Fusion and classification victimization Euclidian distance classifier.
At pre-processing stage, all face and palmprint pictures were converted to grey scale and cropped to a hundredx90 for face images and 100 x 100for palmprint pictures. Following the cropping method, all images were bar chart equal so as to widen energy of all pixels. All pictures were then normalized to provide image with equal quantity of energy. Mean of those images was computed for each modality. Following that, the mean values were subtracted from the initial face and palmprint images to provide mean center. All mean center pictures were then filtered with the physicist remodel of four scales and eight orientations to provide 32(4x8) pictures every. The scale of those image are overlarge (filtered image size: four hundred x 720), therefore consuming an outsized memory and procedure value. Therefore, the filtered images were resized to a scale of zero.2 (reduced image size: eighty x 144). After that, the pre-processed and filtered pictures were rearranged during a long vector, every row representing one image. PCA has glorious capability in representing information, instead of discriminating the categories. to unravel this drawback, the output of the PCA reduced dimension (lxlOO vectors per image) was used to construct within-class scatter matrix and between-class scatter matrix. vital eigenvectors computed in equivalent 8 is accustomed separate the categories and cut back the dimensionality. It is currently clear that each one category is linearly severable. Since forty categories or people were utilized in the research; have thirty-nine eigenvectors that are ready to separate all categories. The result of recognition if LDA features were reduced to thirty, twenty and10 was also investigated. Fusion and classification are done using Euclidian distance classifier.

Algorithms for Feature Level Fusion

Let Fi = {fi,1; fi,2;…. Fi, n } and Hi = {hi,1; hi,2;…. hi, m } represent the feature vector of the face (eigencoefficients [2]) and fingerprint (geometric features) modalities of a user, respectively. The fused feature vector$X$i = {Xi,1; Xi,2;…. Xi, d } can be obtained by augmenting the normalized feature vectors F_i' and H_i' and performing feature selection on the concatenated vector. The normalized vectors F_i' and are computed by applying a transformation to the individual feature values (via normalization schemes like min-max, z-score and median absolute deviation (MAD)) in order to ensure that the feature values across the two modalities are compatible. Consider feature vectors and F_i' and H_i'obtained at two different time instances i and j. The corresponding fused feature vectors may be denoted as Xi and Xj

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, respectively. Let SF and SH be the normalized match (distance) scores generated by comparing Fi with Fj and Hi with Hj, respectively and let Sfus = (SF + SH)=2 be the fused match score obtained using the simple sum rule.

Thus, the fused vectors Xi and Xj are also used in the decision process. We observe that in the case of genuine pairs, a high match score is typically the effect of a *few* feature values constituting the vector while a similar score for an impostor pair is typically the cumulative effect of *all* feature values. Thus, two distance measures are considered to distinguish genuine and impostor pairs (Fig. 1(b)): (i) the euclidean distance, $S_{euc} = \sum_{k=1}^{d}(X_{i,k} - X_{j,k})^2$, and the feature distance, $S_{feat} = \sum_{k=1}^{d} I(|X_{i,k} - X_{j,k}|)$, where I(.) is the indicator function such that I(y) = 1, if y > t1 (and 0 otherwise). Now Sfeat and Seuc along with Sfus is used to arrive at the final decision. This technique is termed as the *feedback technique* since a feedback routine is implemented between the feature extraction and the matching modules of the biometric system.

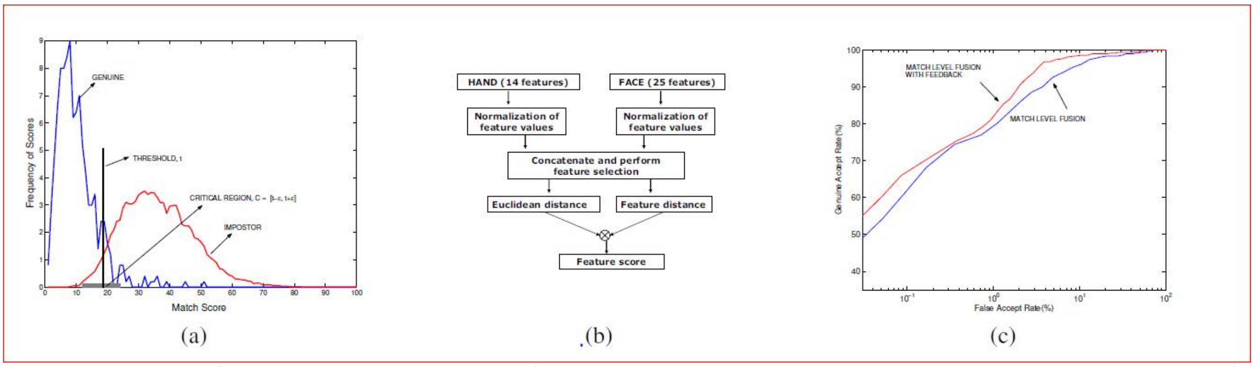

Fig 3 Distribution of genuine and impostor scores (Sfus) showing the critical region. (b) Procedure to compute the Seucand Sfeat scores. (c) Performance gain obtained using the feedback technique.

IV. EXPERIMENTAL RESULTS

A set of 5 face images and hand images were acquired from 20 users. Two different experiments were conducted to evaluate the performance of the proposed technique. In the first experiment, the efficacy of the feedback technique was studied. In the set of experiment, the evidence at the match score level was integrated with the evidence at the feature level. Fig. 4 indicates the performance gain obtained when such type of an integration is performed. The EER, in this case, is observed to be 1:58%. Also, there has been a substantial improvement in GAR at very low FAR values thus underscoring the importance of feature level fusion. For example, at a FAR close to 0:01%, the GAR is seen to improve from 50% to 65%.

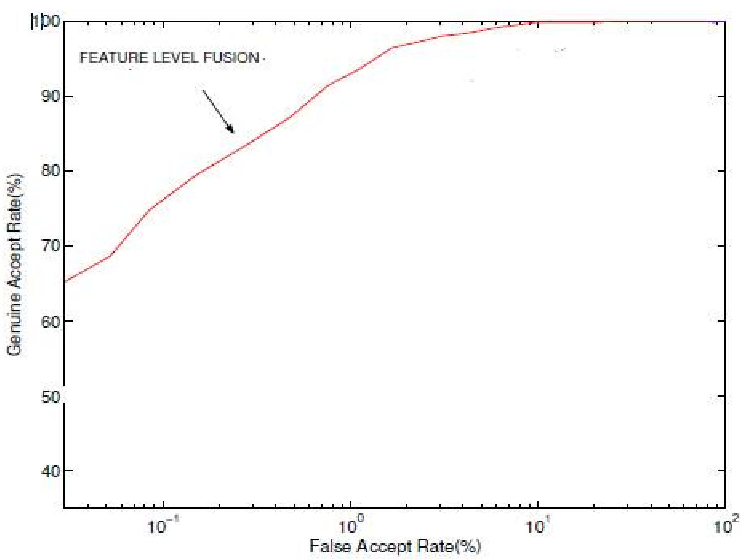

Fig 4. Performance gain observed after merging information at the feature level

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V. CONCLUSION

We can conclude that multimodal biometrics by direct fusion of face and palmprint options extracted by PCA and LDA are able to extend the popularity rates to a higher value compared to it achieved by single modal statistics. By exploiting the benefits of each feature extracting strategies, i.e. PCA representation of knowledge in class and LDA discrimination of knowledge between the categories.

VI. FUTURE WORK

A feature level fusion scheme to improve multimodal matching performance has been proposed. The scheme has been tested on two relatively weak biometric systems, face and fingerprint geometry. The performance gain observed has been substantial thereby indicating the importance of pursuing research in this direction. Future work will include studying the effect of noisy data on the performance of the technique and the adoption of other biometric traits in this work (viz., fingerprint and iris).

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