MultiModal Identification System in Monozygotic Twins

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Abstract

With the increase in the number of twin births in recent decades, there is a need to develop alternate approaches that can secure the biometric system. In this paper an effective fusion scheme is presented that combines information presented by multiple domain experts based on the rank-level fusion integration method. The developed multimodal biometric system possesses a number of unique qualities, starting from utilizing Fisher's Linear Discriminant methods for face matching, Principal Component Analysis for fingerprint matching and Local binary pattern features for iris matching and fused the information for effective recognition and authentication The importance of considering these boundary conditions, such as twins, where the possibility of errors is maximum will lead us to design a more reliable and robust security system.The proposed approach is tested on a real database consisting of 50 pair of identical twin images and shows promising results compared to other techniques. The Receiver Operating Characteristics also shows that the proposed method is superior compared to other techniques under study

Keywords: Fisher Faces, Principal Component Analysis, Local Binary Pattern Receiver Operating Characteristics Curve.

1. INTRODUCTION

A biometric identification (matching) system is an automatic pattern recognition system that recognizes a person by determining the authenticity of a specific physiological and/or behavioral characteristic (biometric) possessed by that person. Fertility treatments have resulted in an increase in the identical twin birth rate [1].The identical twin birth rate is about twice as high for women who use fertility drugs. Identical twins are more precisely described by the term monozygotic, indicating that they come from the split of a single fertilized embryo thus, they have the same DNA. Fraternal, or dizygotic, twins are the result of two different fertilized embryos and have different DNA[2]. Identical twins has been considered to be a problem of only academic interest but due to consistent increase in twin births in recent decades. The extent of variation in a physical trait due to random development process differs from trait to trait.

Typically, most of the physical characteristics such as body type, voice, and face are very similar for identical twins and automatic identification based on face and hand geometry will fail to distinguish them [3],[4],[5].However, a recent experiment demonstrates that iris biometric template aging can be detected after as little as two years. A significant number of twin pairs (206) have been studied for handwriting. These samples were processed with features extracted and conclusions drawn by comparing verification performances with twins and non-twins. In that study, the conclusion was that twins are discriminable but less so than an arbitrary pair of individuals [5],[7].Turk and Pentland popularized the use of PCA for face recognition [8]. They used PCA to compute a set of subspace basis vectors (which they called “eigenfaces”) for a database of face images, and projected the images in the database into the compressed subspace. New test images were then matched to images in the database by projecting them onto the basis vectors and finding the nearest compressed image in the subspace (eigenspace). Kong *et al*. [9] observed that palmprints from identical twins have correlated features.

The same observation was made by Jain *et al*. [10],[14] for fingerprints also. Srihari *et al*.[4] analyzed the similarity between twins fingerprints in a study using fingerprint images from 298 pairs of twins. The authors analyzed this similarity based on the pattern of the ridge flow, and minutiae. They concluded that the similarity between twin fingers is higher than between two arbitrary fingers, but twins can still be distinguished using fingerprints .Kocaman *et al*.[11] proposed a study on PCA,FLDA,DCVA,and evaluate error and hit rates of four algorithms which were calculated by random subsampling and k-fold cross validation. . Chang *et al*.[12] compared PCA technique for both face and ear images and showed similar performance as biometrics . Gaurav *et al*.[16] proposed a method for distinguishing identical twins and the ROC shows the various comparisons for various set of facial marks in identical twins. Kodate *et al*. [17] experimented with 10 sets of identical twins using a 2D face recognition system. Recently, Sun *et al*. [6] presented a study of distinctiveness of biometric characteristics in identical twins using fingerprint, face and iris biometrics. They observed that though iris and fingerprints show little to no degradation in performance when dealing with identical twins, face matchers find it hard to distinguish between identical twins. It is believed that the texture of every iris is determined entirely at random. This implies that the iris textures of two identical twins are no more similar to each other than the iris textures of unrelated persons. The researchers compared the distribution of difference values between iris codes from the eyes of identical twins to that between iris codes of unrelated persons and found that the iris textures of identical twins are no more similar than those of unrelated persons. Among all biometric traits, the textural structure of the human iris has been observed to be robust and reliable. However, the performance of iris recognition systems is adversely affected by the quality of the acquired images.

Today technologies are well-studied, but research shows they have many drawbacks which decrease the success of the methods applied. The frequently used and most common biological traits in the field of biometrics are face, finger, and iris. Identifying identical twins is crucial for all biometric systems. The systems that cannot handle identical twins have a serious security hole.

The rest of this paper is organized as follows. Section 2 describes the Fisher linear Discriminant analysis, Principal component analysis and Local binary pattern and the results are reported to evaluate the performance of our proposed approach in Section 3. Finally, conclusions are given in Section 4.

2. BIMODAL BIOMETRIC SYSTEM DESIGN

In this section deals the development procedures of the proposed multimodal biometric system. Fisher face features are extracted from the face images and the PCA features from the fingerprints and the Local Binary pattern based texture pattern from the iris pattern are used for the enrollment and recognition of biometric traits. This system integrate multiple modalities in user verification and identification which will lead to higher performance A more detailed representation of the proposed system is shown in Fig. 1.

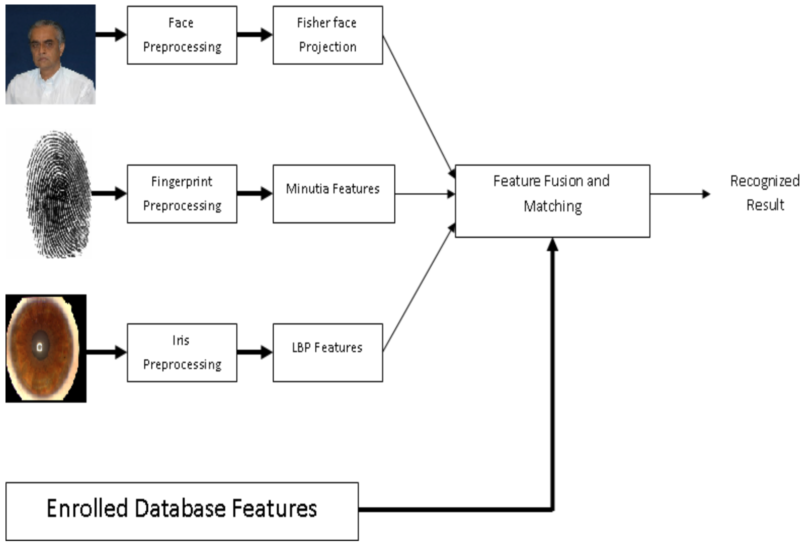

FIGURE 1: Block Diagram of the Proposed Bimodal Biometric Identification System.

2.1. Fisher linear discriminant analysis

Fisher linear discriminant analysis (LDA), a widely-used technique for pattern classification, finds a linear discriminant that yields optimal discrimination between two classes which can be identified with two random variables, say X and Y in R^n. PCA in the form of eigen space representation is very sensitive to image conditions such as background noise, image shift, occlusion of objects, scaling of the image, and illumination change. When substantial changes in illumination and expression are present in any image, much of the variation in data is due to these changes [13], and the eigenimage technique, in this case, cannot give highly reliable results. Due to certain illumination changes in the face images of the database used in this work, a fisherface based face recognition method [23] is developed to compare with the eigenface technique. The fisherface method uses both PCA and LDA to produce a subspace projection matrix, similar to that used in the eigenface method .The terms Fisher's linear discriminant and LDA are often used interchangeably, although Fisher's original article actually describes a slightly different discriminant, which does not make some of the assumptions of LDA such as normally distributed classes or equal class covariances. Suppose two classes of observations have means,

$$\vec{\mu}_y = 0, \vec{\mu}_y = 1$$

and covariance

$$\sum_y = 0, \sum_y = 1$$

Then the linear combination of features $\bar{\omega}.\bar{x}$ will have means

$$\vec{\omega} . \overrightarrow{\mu_y} = i$$

and variances

$$\vec{\omega}^T \sum_y = i . \vec{\omega}$$, for i = 0,1.

Fisher defined the separation between these two distributions to be the ratio of the variance between the classes to the variance within the classes as in eq(1)

$$S = \frac{\sigma^2_{between}}{\sigma^2_{within}} = \frac{(\overrightarrow{\omega} . \overrightarrow{\mu_{y=1}} - \overrightarrow{\omega} . \overrightarrow{\mu_{y=0}})^2}{\overrightarrow{\omega}^T \sum_{y=1} \overrightarrow{\omega} + \overrightarrow{\omega}^T \sum_{y=0} \overrightarrow{\omega}}$$

$$= \frac{(\overrightarrow{\omega} . (\overrightarrow{\mu_{y=1}} - \overrightarrow{\mu_{y=0}}))^2}{(\overrightarrow{\omega}^T \sum_{y=0} + \sum_{y=1}) \overrightarrow{\omega}} \tag{1}$$

This measure is, in some sense, a measure of the signal-to-noise ratio for the class labeling. It can be shown that the maximum separation occurs when

$$\overrightarrow{\omega} = (\sum_{y=0} + \sum_{y=1})^{-1} (\overrightarrow{\mu_{y=1}} - \overrightarrow{\mu_{y=0}})$$

When the assumptions of LDA are satisfied, the above equation is equivalent to LDA. The vector $\overrightarrow{\omega}$ is the normal to the discriminant hyperplane. As an example, in a two dimensional problem, the line that best divides the two groups is perpendicular to $\overrightarrow{\omega}$.

Generally, the data points to be discriminated are projected onto $\overrightarrow{\omega}$, then the threshold that best separates the data is chosen from analysis of the one-dimensional distribution. There is no general rule for the threshold. However, if projections of points from both classes exhibit approximately the same distributions, the good choice would be hyperplane in the middle between projections of the two means,

$\overrightarrow{\omega} . \overrightarrow{\mu_{y=0}}$ and $\overrightarrow{\omega} . \overrightarrow{\mu_{y=1}}$.

In this case the parameter c in threshold condition $\overrightarrow{\omega} . \overrightarrow{x} < c$ can be found explicitly as in eq(2):

$$c = (\overrightarrow{\omega} . (\overrightarrow{\mu_{y=0}} + \overrightarrow{\mu_{y=1}})) / 2 \tag{2}$$

2.2. Principal Component Analysis

Principal Components Analysis is a method that reduces data dimensionality by performing a covariance analysis between factors. As such, it is suitable for data sets in multiple dimensions, such as a large experiment involving huge amount of data. PCA is an unsupervised technique and as such does not include label information of the data. Kirby and Sirovich[15] were among the first to apply principal component analysis (PCA) to face images, and showed that PCA is an optimal compression scheme that minimizes the mean squared error between the original images and their reconstructions for any given level of compression

PCA, mathematically defined as an orthogonal linear transformation [23] that transforms the data to a new coordinate system such that the greatest variance by any projection of the data comes to lie on the first coordinate (called the first principal component), the second greatest variance on the second coordinate, and so on.

Define a data matrix, $\mathbf{X}^T$, with zero empirical mean, where each of the *n* rows represents a different repetition of the experiment, and each of the *m* columns gives a particular kind of datum.

The singular value decomposition of **X** is $\mathbf{X} = \mathbf{W\Sigma V^T}$, where $m \times m$ matrix, **W** is the matrix of eigenvectors of $\mathbf{XX}^T$, matrix $\mathbf{\Sigma}$ is an $m \times n$ rectangular diagonal matrix with nonnegative real numbers on the diagonal, and the $n \times n$ matrix **V** is the matrix of eigenvectors of $\mathbf{X}^T\mathbf{X}$.

The PCA transformation that preserves dimensionality is then given by eq (3).

$$Y^T = X^T W = V\sum{}^T W^T W \quad = V\sum{}^T \tag{3}$$

V is not uniquely defined in the usual case when $m < n - 1$, but **Y** will usually still be uniquely defined. Since **W** is an orthogonal matrix, each row of $\mathbf{Y}^T$ is simply a rotation of the corresponding row of $\mathbf{X}^T$. The first column of $\mathbf{Y}^T$ is made up of the "scores" of the cases with respect to the "principal" component; the next column has the scores with respect to the "second principal" component, and so on. For reduced-dimensionality representation, project **X** down into the reduced space defined by only the first *L* singular vectors, $\mathbf{W}_L$,

$$Y = W_L{}^T X = \sum{}_L V^T$$

Where with $I_{L \times m}$ the $L \times m$ rectangular identity matrix. The matrix **W** of singular vectors of **X** is equivalently the matrix **W** of eigenvectors of the matrix of observed covariances $C = XX^T$,

$$X.X^T = W\sum\sum{}^T W^T \tag{4}$$

Given a set of points in Euclidean space, the first principal component corresponds to a line that passes through the multidimensional mean and minimizes the sum of squares of the distances of the points from the line. The second principal component corresponds to the same concept after all correlation with the first principal component has been subtracted from the points. The singular values in $\mathbf{\Sigma}$ are the square roots of the eigenvalues of the matrix $\mathbf{XX}^T$. Each eigenvalue is proportional to the portion of the "variance" that is correlated with each eigenvector. The sum of all the eigenvalues is equal to the sum of the squared distances of the points from their multidimensional mean. PCA essentially rotates the set of points around their mean in order to align with the principal components. This moves as much of the variance as possible (using an orthogonal transformation) into the first few dimensions. The values in the remaining dimensions, therefore, tend to be small and may be dropped with minimal loss of information. PCA is often used in this manner for dimensionality reduction. PCA has the distinction of being the optimal orthogonal transformation for keeping the subspace that has largest "variance". One characteristic of both PCA and LDA is that they produce spatially global feature vectors. In other words, the basis vectors produced by PCA and LDA are non-zero for almost all dimensions, implying that a change to a single input pixel will alter every dimension of its subspace projection.

2.3. Local Binary Pattern for Iris pattern

Local Binary Pattern (LBP) is an efficient method used for feature extraction and texture classification it was first introduced by Ojala et al in 1996 [19] , this was the first article to describe LBP. The LBP operator was introduced as a complementary measure for local image contrast, and it was developed as a grayscale invariant pattern measure adding complementary information to the amount of texture in images. LBP is ideally suited for applications requiring fast feature extraction and texture classificationLocal Binary Pattern (LBP) is a very efficient texture operator which labels the pixels of an image by thresholding the neighborhood of each pixel and considers the result as a binary number. Due to its discriminative power and computational simplicity, LBP texture operator has become a popular approach in various applications. . Local binary patterns are adopted for representing the textural characteristics of local sub-regions.It can be seen as a unifying approach to the traditionally divergent statistical and structural models of texture analysis. Each iris images can be considered as a composition of micro-patterns which can be effectively detected by the LBP operator .The LBP operator [18] forms labels for the image pixels by thresholding the 3 x 3 neighborhood of each pixel with the center value and considering the result as a binary number. The histogram of these $2^8 = 256$ different labels can then be used as a texture descriptor. The features of the iris pattern is extracted using the above procedure and is explained in Fig.2

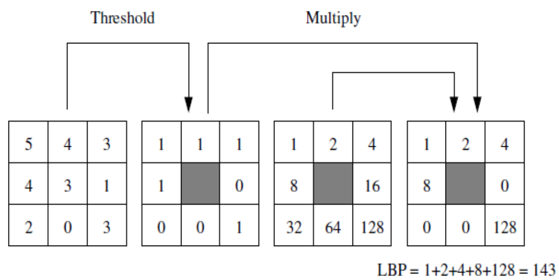

FIGURE 2: Calculating the Original LBP Code and A Contrast Measure.

3. Experiment and Results

In this section the performance of the proposed multibiometric recognition is tested on a real time database consisting of 50 pair of identical twins from whom the face, fingerprint and iris images of the persons are collected. The images are acquired in a resolution of 200x200 sizes. We have implemented our multibiometric system in MATLAB 7.10 on a Pentium-IV Windows XP workstation. To build our virtual multimodal database, we have chosen 100 images. Face images are randomly sampled as training samples, and the remaining are left as test samples. The technique is also applied for fingerprint and iris databases to collect training samples. Then, each sample of the face database is randomly combined with one sample of the fingerprint database and one sample of the iris database.

The performance of a biometric system can be shown as a Receiver Operating Characteristic (ROC) curve that plots the Genuine Accept Rate against the False Accept Rate (FAR) at different thresholds on the matching score. Fig. 5 shows the performance of the hybrid approach presented here.

We compare this performance with other approaches that does not utilize texture information for representing the fingerprint. As can be seen in the graph, the proposed hybrid approach outperforms over a wide range of FAR values.

The results obtained using various multibiometric systems were analyzed and the area under the ROC curve for each method using Real Time database are shown in Table 1., and it shows the area under the ROC curve (***Az***), Standard Deviation (*S.D*) and 95% Confidence Interval (*CI*) for each classifier. Results show that high performance was obtained by the proposed scheme when compared to other multibiometric systems.

	Single mode PCA	Multimodal PCA	Proposed
Az	0.94470	0.96036	0.96147
S.D	0.01710	0.01413	0.01370
95% CI	0.91119	0.93268	0.93419

TABLE 1: Classification Results.

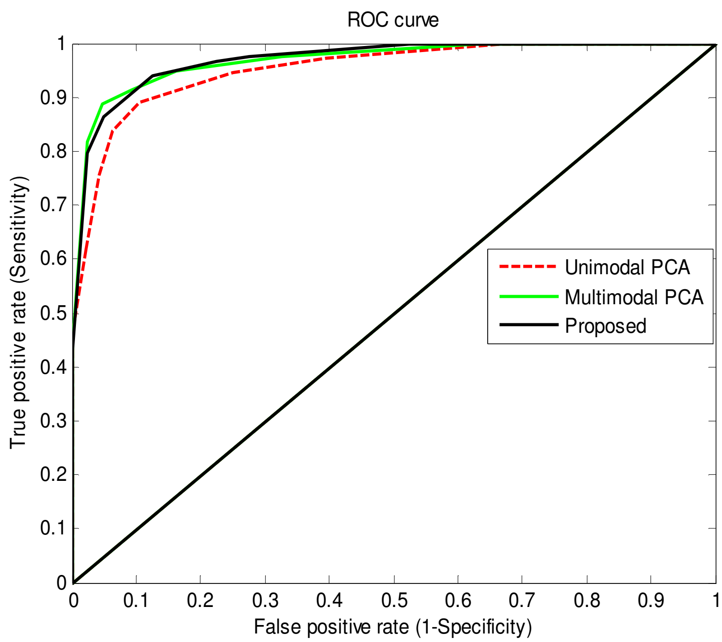

Figure 3. Receiver Operating Characteristics Curve.

4. CONCLUSION

This paper has presented a multimodal approach and comparison of three approaches in implementing a biometric system. Using a multimodal database we have investigated the relative merits of adopting a single classifier approach, an approach which uses a multimodal classifier configuration operating on a single modality and, finally, a multimodal biometric solution which combines different biometric samples in providing an identification decision. Our study has provided quantitative data to demonstrate the relative performance levels, in terms of ROC curve, attainable in each case, and we have shown how multimodal biometric solutions, while offering other additional advantages where appropriate, provide only modest improvements over an approach based on a multimodal classifier approach and a single modality, bringing some potentially significant benefits in terms of usability.

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