Bimodal Person Identification System

C. N. Dinakardas, S. Perumal Sankar, and Nisha George

Abstract—**Face recognition is one of the most important applications of computer vision in recent years. The developed multimodal biometric system possesses a number of unique qualities, starting from utilizing principal component analysis and Fisher's linear Discriminant methods for individual matcher's identity authentication and utilizes the novel feature fusion method to consolidate the results obtained from different biometric matchers. In this paper, we present a bimodal face-finger recognition system that fuses results from both Principal Component Analysis and Fisher face projections. The proposed approach is tested on a real database consisting of 500 images and shows promising results compared to other techniques. The main goal of bimodal identification system is to develop the security system for the areas that require high level of security. The Receiver Operating Characteristics also shows that the proposed method is superior compared to other techniques under study.**

Index Terms—**Fisher faces, principal component analysis, receiver operating characteristics curve.**

I. Introduction

Biometric information system is one of the finest examples of computer system that tries to imitate the decisions that humans make in their everyday life, specifically concerning people identification and matching tasks [1]. 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. Physiological biometric identifiers include fingerprints, hand geometry, ear patterns, eye patterns (iris and retina), facial features, and other physical characteristics. Behavioral identifiers include voice, signature, typing patterns, and others. Biometric authentication systems generally suffer from imprecision and difficulties in person recognition due to noisy input data, limited degrees of freedom, intra class variability, no universality, and other factors that affect the performance, security, and convenience of using such systems [2].

Several approaches have been proposed and developed for the multimodal biometric authentication system. In 1988 Kirby and Sirovich,[3] proposed the first automated face recognition system using a standard linear algebra technique. In 1998, a bimodal approach was proposed by Hong and Jain[4] for a PCA based face and a minutiae-based fingerprint identification system with a fusion method at the decision level. In the same year, Ross and Jain[5] proposed a multimodal system for face, fingerprint, and hand geometry, with three fusion methods at the matching score level, namely, sum rule, decision trees, and linear discriminant function, after score normalization

In 2003, Kumar *et al.* [6] proposed a multimodal approach for palm print and hand geometry, with fusion methods at the feature level by combining the feature vectors by concatenation, and the matching score level by using max rule... There were also some PCA-based multimodal biometric systems proposed in 2003. Wang *et al.*[7]. proposed a multimodal approach for a PCA-based face verification system and a key local variation-based iris verification system, with fusion methods at the matching score level by using unweighted and weighted sum rules, Fisher Discriminant analysis, and neural networks.Another face identification teqnique proposed by Draper *et al.* [8] based on Independent component analysis (ICA) or the discrete cosine transform (DCT) can be used in place of PCA within the eigenface technique. ICA and PCA have been compared to one another with contradicting results and consequently it is debatable which method is superior, or whether they both have their place within face recognition.

In 2005, Snelick *et al.* [9] developed a multimodal approach for face and fingerprint, with fusion methods at the score level. Ribaric *et al.* [10] presented a multimodal biometric system based on features extracted from fingerprint and palmprint data. Fusion is applied at the match score level after extracting the features by using PCA projection. In 2007, Natalia *et al.* [11] proposed an empirical recognition capacity under global PCA and ICA Encoding..In the same year, Jing *et al.* [12] proposed combining face and palmprint identification system based on pixel level fusion. Also the three normalized similarity scores using palm finger and face features and sum rule was proposed by Jain *et al.* [13] in the same year

In 2008, Jia Cui *et al.* [14], proposed a feature fusion combined with 2D fisher linear Discriminant analysis for face and iris images. Maruf *et al.*[15], proposed a rank-level fusion approach utilizing principal component analysis and FLD methods for individual matches, utilizing rank level fusion in 2009. In the same year, Sheetal *et al.* [16] proposed a a multimodal biometric recognition system integrating palm print, fingerprint and face based on score level fusion. The feature vectors are extracted independently from the pre-processed images of palmprint, fingerprint and face. In this fusion module performs score normalization and fusion of normalized scores by weighted sum rule. Also Nageshkumar *et al.*[17] integrated the palm print and face features which proposed to increase the robustness of the

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person authentication. The final decision is made by fusion at matching score level architecture in which features vectors are created independently for query measures and are then compared to the enrolment template, which are stored during database preparation

The goal of fusion is to determine the best set of experts in a given problem domain and devise an appropriate function that can optimally combine the decisions rendered by the individual experts. In this paper the features of the person face, and fingerprint are extracted using Fisherface and Principal Component Analysis (PCA) and are fused and the Euclidian similarity measure is used to recognize the person.

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

II. Bimodal Biometric System Design

In this section deals the development procedures of the proposed multimodal biometric system is explained. Each fusion method has its advantages. In real practice, fusion at match score level and decision level are usually employed since they are much more practical and simple. In this paper PCA and Fisherface techniques are used in this system for enrollment and recognition of biometric traits. A more detailed representation of the proposed system is shown in Fig. 1.

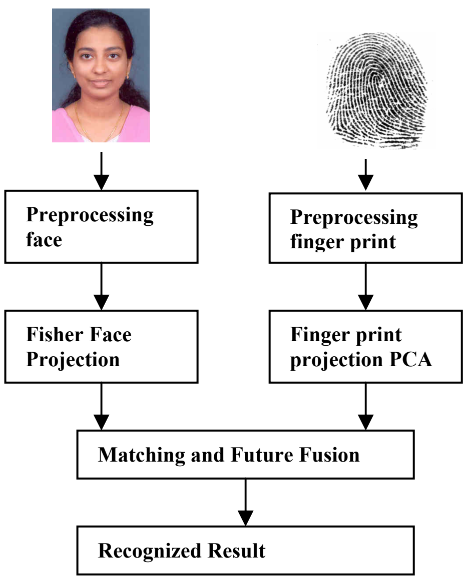

Fig. 1. Block diagram of the Proposed Bimodal Biometric Identification System

A. 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 [18], 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 [19] 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 $\overline{\omega}.\overline{x}$ 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 (1).

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

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

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

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

When the assumptions of LDA are satisfied, the above equation is equivalent to LDA. The vector $\vec{\omega}$ 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 $\vec{\omega}$. Generally, the data points to be discriminated are projected onto $\vec{\omega}$, 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,

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

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

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

B. 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.

PCA, mathematically defined as an orthogonal linear transformation [5] 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, 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 $\mathbf{X}$ is $\mathbf{X} = \mathbf{W\Sigma V^T}$, where $m \times m$ matrix, $\mathbf{W}$ 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 $\mathbf{V}$ is the matrix of eigenvectors of $\mathbf{X}^T\mathbf{X}$ .The PCA transformation that preserves dimensionality is then given by (3).

$$Y^T = X^T W = V\Sigma^T W^T W = V\Sigma^T \quad (3)$$

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 Y^T is simply a rotation of the corresponding row of X^T. The first column of 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, W_L; $Y = W_L{}^T X = \Sigma_L V^T$

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 as in (4)

$$C = XX^T,\ X.X^T = W\sum\sum{}^T W^T \quad (4)$$

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 Σ are the square roots of the eigenvalues of the matrix 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".

III. Experiment and Results

In this section the performance of the proposed multibiometric recognition is tested on a real time database consisting of 500 persons in whom the faces, fingerprint images of the persons are collected. 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 350 images. Face images are randomly sampled as training samples, and the remaining are left as test samples. The technique is also applied for fingerprint to collect 350 training samples. Then, each sample of the face database is randomly combined with one sample of the fingerprint database. We compare PCA techniques and the Fisherface + PCA technique in terms of sensitivity and specificity in terms of Receiver Operating Characteristics Curve (ROC). From the results shown in the graph of Fig. 2, it is clear that Fisherface+PCA works more efficiently than PCA.

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 multi biometric systems.

TABLE I: Classification Results

	Single mode PCA	Multimodal PCA	Proposed
Az	0.94470	0.96036	0.96096
S.D	0.01710	0.01413	0.01393
95% CI	0.91119	0.93268	0.93365

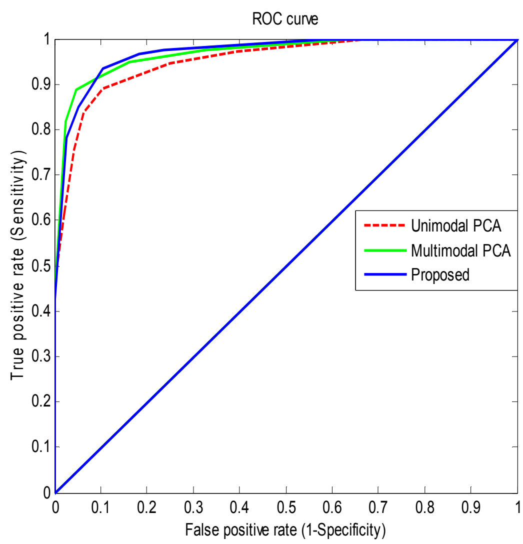

Fig. 2. Receiver Operating Characteristics Curve.

IV. Conclusion

We presented a multimodal system for person recognition. For the facial images the fisher face projections are extracted and used for recognition. Then, the PCA technique was applied for extracting the features of fingerprint images. For the multimodal system, we fused the features at the score level. We compared the single mode PCA and the multimodal PCA with the proposed PCA+Fisherface technique. Although all the techniques produced comparable results, the proposed approach with PCA and fisherface projections has the advantage that it has high classification accuracy. Better multimodal fusion technique can be used for better results in the biometric fusion. In the future, we will work on improving the performance of the proposed technique with improved results on a large database.

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References

[1] H. Mahoor, "A Multimodal Approach for Face Modeling and Recognition," *IEEE Transactions on Information Forensics And Security*, vol. 3, no. 3, september, pp: 431-440, 2008

[2] U. M. Bubeck and D. Sanchez, "Biometric authentication: Technology and evaluation," San Diego State Univ., San Diego, CA,. Tech. Rep, 2003

[3] M. Kirby and L. Sirovich, "Application of the Karhunen-Loève Procedure for the Characterization of Human Faces,"*IEEE Trans. PAMI,* 12, 1, pp. 103-108, 1990

[4] L. Hong and A. K. Jain, "Integrating faces and fingerprints for personal identification," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 20, no. 12, pp. 1295–1307, Dec. 1998.

[5] S. C. Dass, K. Nandakumar and A. K. Jain, "A principal approach to scorelevel fusion in Multimodal Biometrics System," *Proceedings of ABVPA*, 2005

[6] L. Hong and A. K. Jain, "Integrating faces and fingerprints for personal identification," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 20, no. 12, pp. 1295–1307, Dec. 1998.

[7] T. Wang, T. Tan, and A. K. Jain, "Combining face and iris biometrics for identity verification," in *Proc. 4th Int. Conf. Audio- Video-Based Biometric Person Authentication*, J. Kittler and M. Nixon, Eds., vol. LNCS 2688, pp. 805–813, 2003,

[8] B. A. Draper, K. Baek, M. S. Bartlett and J. R. Beveridge,"Recognizing faces with PCA and ICA," *Computer Vision andImage Understanding*, vol. 91, no. 1-2, pp. 115-137, 2003

[9] R. Snelick, U. Uludag, A. Mink, M. Indovina, and A. K. Jain, "Large scale evaluation of multimodal biometric authentication using state-of the-art systems," *IEEE Trans. Pattern Anal. Mach. Intell*., vol. 27, no. 3, pp. 450– 455, Mar. 2005.

[10] S. Ribaric, I. Fratric, "A biometric identification system based on eigenpalm and eigenfinger features," *IEEE Trans. Pattern Anal. Mach.Intell,* vol. 27, no. 11, pp. 1698–1709, 2005.

[11] Natalia A. Schmid and Francesco Nicolo, "Multimodal Biometric System Using Rank-Level Fusion Approach," *IEEE Trans. on Information Forensics and Security*, vol. 3, no. 3, pp. 867-878, September 2008

[12] X. Jing, Y. Yao, D. Zhang, and M. Li, "Face and palmprint pixel level fusionand Kernel DCV-RBF classifier for small sample biometrics recognition,"*Pattern Recognition,* vol. 40, no. 11, pp. 3209–3224, 2007.

[13] K. Nandakumar, A. Ross and A. K. Jain, *Handbook of Multibiometrics*. New York: Springer-Verlag, 2006

[14] Jia Cui, Jian-Ping li and Xiao-Jun Lu, "Study on Multi-Biometric Feature Fusion and Recognition Model," 978-1-4244-3425-1/*IEEE*, pp.66-69,2007

[15] Md. Maruf Monwar and Marina L. Gavrilova, "Multimodal Biometric System Using Rank-Level Fusion Approach," *IEEE Transactions on Systems, Man, and Cybernetics—Part B: Cybernetics*, vol. 39, no. 4, pp.512-528, August 2009

[16] Sheetal Chaudhary, and Rajender Nath, "A Multimodal Biometric Recognition System Based on Fusion of Palmprint, Fingerprint and Face," in *Proceedings of ICART in Communication and Computing,* pp. 596-600, 2009

[17] M. Nageshkumar, P. K. Mahesh and M. N. Shanmukha Swamy, "An Efficient Secure Multimodal Biometric Fusion Using Palmprint and Face Image," *IJCSI International Journal of Computer Science Issues*, vol. 2, 2009.

[18] T. Heseltine, N. Pears, J. Austin, and Z. Chen, "Face recognition: A comparison of appearance-based approaches," in *Proc. 7th Digit. Image Comput.: Tech. Appl.*, C. Sun, H. Talbot, S. Ourselin, and T. Adriaansen, (Eds.), Sydney, Australia, pp. 59–68, 2003.

[19] P. N. Belhumeur, J. P. Hespanha, and D. J. Kriegman, "Eigenfaces vs. fisherfaces: Recognition using class specific linear projection," *IEEE Trans. Pattern Anal. Mach. Intell*., vol. 19, no. 7, pp. 711–720, Jul. 1997.

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