RESEARCH ARTICLE OPEN ACCESS

Multimodal Biometrics Recognition by Dimensionality Diminution Method

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ABSTRACT
Multimodal biometric system utilizes two or more character modalities, e.g., face, ear, and fingerprint, Signature, plamprint to improve the recognition accuracy of conventional unimodal methods. We propose a new dimensionality reduction method called Dimension Diminish Projection (DDP) in this paper. DDP can not only preserve local information by capturing the intra-modal geometry, but also extract between-class relevant structures for classification effectively. Experimental results show that our proposed method performs better than other algorithms including PCA, LDA and MFA.
Keywords: PCA, Multimodal biometrics, Dimensionality Diminution, Face & Palmprint recognition.

I. INTRODUCTION

Biometrics is an emerging technology [1] that is used to identify people by their physical and/or behavioral characteristics and, so, inherently requires that the person to be identified is physically present at the point of identification. The physical characteristics of an individual that can be used in biometric identification/verification systems are fingerprint, hand geometry, palm print [2], face [3], iris, retina, and ear; the behavioral characteristics are signature, lip movement, speech, keystroke dynamics, gesture, and gait [1]. Biometric systems based on a single biometric characteristic are referred to as unimodal systems. They are usually more cost-efficient than multimodal biometric systems. However, a single physical or behavioral characteristic of an individual can sometimes fail to be sufficient for identification. For this reason, multimodal biometric systems that integrate two or more different biometric characteristics are being developed to provide an acceptable performance, to increase the reliability of decisions, and to increase robustness to fraudulent technologies [4]. Hong et al. [5] developed a prototype multimodal biometric system, which integrates faces and fingerprints at the identification stage. Ribaric and Fratric [6] presented a multimodal biometric system based on features extracted from fingerprint and palmprint data.

Recently, subspace methods, which select low dimensional features to represent raw data, have been widely studied in biometrics researches [7, 8]. It is shown that subspace selection is one of the most important steps for entire biometric systems. These methods which carry out fusion at feature level obtain the low-dimensional features integrated the information of all modalities.

In this paper, we propose a new dimensionality reduction method called Dimension Diminish

Projection (DDP) for multimodal biometric recognition. The rest of this paper is organized as follows: Section 2 describes the proposed algorithm DDP. In Section 3, experimental results on the face and palmprint databases are presented. We conclude this paper in section 4.

II. DIMENSIONALITY DIMINISH PROJECTION

To take face images as an example, there are two kinds of face difference: intra-class face difference and extra-class difference. The intra-class difference contains transformation difference such as illumination, pose changes while the extra-class difference contains intrinsic difference (identity changes), transformation difference.

In this section, DDP is proposed as a new dimensionality reduction method, which can be used to extract features from multimodal biometric data. It modeling intra-class metric matrix to characterize the distribution of transformation difference and extra-class metric matrix to characterize the distribution of intrinsic difference. Figure 1 shows the block diagram of the proposed system for multimodal biometrics system. It is well known that the manifold or distribution of one face (or palm print) under variations such as viewpoint, deformation, and illumination is highly nonlinear and nonconvex [11]. However, we can recover the nonlinear structure by locally linear fits [12]. We adopt linearization extension of locally linear embedding (LLE) [13] to model the intra- class metric matrix. LLE can preserve the local geometry of the faces in the same class. Because of the high-dimensional raw data, the step of preprocessing is recommended for compressing the raw data. In this work, we adopt a straightforward image projection technique, Two-Dimensional Principal Component Analysis (2DPCA) [9] for initial dimension reduce.

2.1 Two-Dimensional Principal Component Analysis

Two-dimensional principal component analysis (2DPCA) is developed for image feature extraction. As opposed to conventional PCA, 2DPCA is based on 2D matrices rather than 1D vectors. That is, the image matrix does not need to be previously transformed into a vector. In contrast to the covariance matrix of PCA, the size of the image covariance matrix using 2DPCA is much smaller. As a result, 2DPCA has two important advantages over PCA. First, it is easier to evaluate the covariance matrix accurately. Second, less time is required to determine the corresponding eigenvectors. Let P denote an n-dimensional unitary column vector. Our idea is to project image A, an m´n random matrix, onto P by the following linear transformation:

$$B = AP. \quad (1)$$

Thus, we obtain an m-dimensional projected vector B, which is called the projected feature vector of image A. The projection vector P can be determined by solving eigenvector of image covariance (scatter) matrix Gt corresponding to the largest eigenvalue [10],

Where G E[(A E(A))T (A E(A))] .We can evaluate Gt directly using the training image samples. Suppose that there are M training image samples in total, the jth training image is denoted by an m´n matrix Aj (j=1, 2.M), and the average image of all training samples is denoted by A.

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2.3 Modeling of intra-class metric matrix

Modalities, the images are compressed and sorted by its feature vectors x. Denote the multimodal biometric data set m n X x xN R = [, ,]Î ´ 1r *K* r , and each datum xi r belongs to one class, each of which has two or more modalities. The data X is the training data set, on which the DDP algorithm is developed. The system obtains a transformation matrix U ÎRm´d that maps the set X of N points to the set d n
Y y yN R = [, ,]Î ´ 1rK r , such that Y=UTX, where d<m.

Given the testing set P, we can project it to the subspace via the transformation matrix U as Q=UTP. Finally, we classify the dimension-reduced testing data Q in the subspace by matching with the corresponding training data Y.

III. EXPERIMENTS & RESULTS

In this section, the performance of DDP was evaluated on the ORL face databases and the PolyU palmprint database [14]. Our system can be extended to include more modalities. There are 10 different images of 40 distinct subjects contained in ORL database. For some of the subjects, the images were taken at different times, varying lighting slightly, facial expressions and facial details.. The size of each image is 92×112, 8-bit grey levels. The PolyU palmprint database contains 7752 grayscale images corresponding to 386 different palms. We select 25 individuals and for each individual select 10 face images and 10 palmprint images, 5 for training and the other 5 for testing. That is, we have 125 images for training and 125 images for testing in one modal. We compared DDP with the performances of other methods including PCA [8], LDA, and MFA [15][18]. In the preprocessing step, we take d=5 (5 projection vectors), for the face image size of 92×112, then the dimension after 2DPCA is reduced to 560. The nearest extra-class neighbors parameter k in DDP is chosen as k=4 and 5, so we can obtain 2 results DDP4 and DDP5. Table 1 gives the recognition rates with the corresponding reduced dimensions of the employed algorithms on ORL and PolyU database. Figure 2 shows the average recognition rates versus subspace dimensions in multimodal tests. We can see that the proposed algorithm DDP performed much better than other algorithms. The performances of DDP4 and DDP5 are nearly the same.

We also take another experiment on the variance of d (number of projection vectors). Table 2 gives the recognition rates and recognition time.

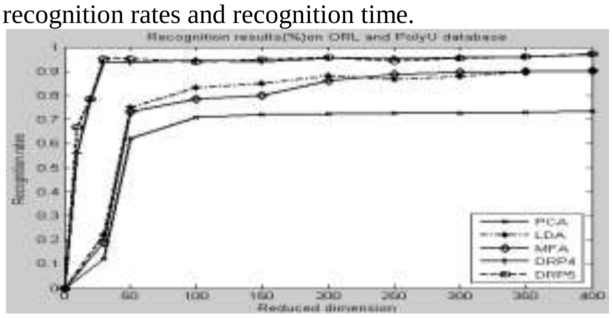

Fig 1: Recognition results on the ORL and PolyU database

Table 1: Recognition Results (%) On The Orl And Polyu Dataset

Method	Recognition Rate (%)	Dimension (d)
PCA	73.6	400
LDA	83.2	200
MFA	89.6	350
DDP	93.6	30
DDP	95.2	30

Table 2: Recognition Results (%) Versus The Number Of Projection Vectors On The Orl And Polyu Data Set.

d	Recognition Rate (%)	Recognition Time(s)	Dimension
3	78.2	5.41	100
5	93.6	9.65	30
10	95.8	26.34	30

IV. CONCLUSION

In this paper, a new dimensionality reduction method called Dimension Diminish Projection (DDP) is proposed for multimodal biometric recognition. DDP preserves local information by capturing the intra-modal geometry and extract between-class relevant structures which is useful for classification. Experimental results have shown the effectiveness and the advantages of the proposed method.

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