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Complex kernel PCA for multimodal biometric recognition

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Abstract: This letter presents a novel multimodal biometric recognition algorithm based on complex kernel principle component analysis (CKPCA). CKPCA generalizes kernel principle component analysis (KPCA) method for complex field to perform feature fusion and classification. Iris and face are used as two distinct biometric modals to test our algorithm. Experimental results show that the proposed algorithm achieves much better performance than other conventional multimodal biometric algorithms.

Keywords: multimodal biometric recognition, feature fusion, complex field
Classification: Science and engineering for electronics

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1 Introduction

Along with match score level and decision level, one important branch of multimodal biometrics is to perform fusion in feature level which derives the most discriminative information from original multiple feature sets and eliminate the redundant information resulting from the correlation between different feature sets. In general, there are two basic modes for feature level fusion: serial rule [1] and weighted sum rule [2]. However, the serial rule based methods would increase computation cost due to the high dimension of the fusion features. And there is no general guiding principle to select the weighted value in practice for the weighted sum rule. Recently, Yang [3, 4] proposed the "combined Fisherface" method which involved the complex Fisher classifier for face recognition. Nevertheless, it only showed its advantage in multiple feature representation fusion of unimodal biometrics.

Aiming to the multimodal biometrics in feature level, this letter presents the complex kernel principle component analysis(CKPCA) based fusion algorithm which generalizes kernel principle component analysis(KPCA) [5] in complex filed. By combining two distinct features into a complex vector, the proposed algorithm achieves multimodal feature fusion with remarkable system performance. Furthermore, iris and face are used as two distinct biometric modals to test our algorithm. The key characteristics are as follows: (1) Two distinct feature sets are fused by a complex vector and construct a unitary space; (2) CKPCA is used to resolve the classification problem of the unitary space and ensure the availability of the proposed method; (3) Our algorithm employs z-score normalization model to eliminate the unbalance on the order of magnitude and the distribution of two feature sets, which makes the system more accurate.

2 Proposed algorithm

In this section, we propose the complex kernel principle component analysis (CKPCA) method and present the process of feature fusion and classification.

2.1 CKPCA

The initial motivation of CKPCA is to map the samples into a potentially much higher dimensional space by a nonlinear mapping and perform PCA in this nonlinear space. In our method, the sample space is a given subspace of complex field. Let C^d be the sample space, we define the inner product for C^d as follows

$$<\alpha, \beta> = \alpha^H \beta \quad \forall \alpha, \beta \in C^d \tag{1}$$

where H is the denotation of conjugate transpose. It can be easily proved that C^d is a unitary space as this inner product satisfies the following properties:

1. $<\alpha, \beta> = \overline{<\beta, \alpha>}$;

2. $<\alpha, \alpha> \geq 0$ where $<\alpha, \alpha> = 0 \Leftrightarrow \alpha = 0$;

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3. $< k_1\alpha_1 + k_2\alpha_2, \beta >= k_1 < \alpha_1, \beta > +k_2 < \alpha_2, \beta > \quad \forall \alpha_1, \alpha_2, \beta \in C^d$, where k_1, k_2 are any two real numbers.

First of all, a nonlinear mapping ϕ is used to map the sample space C^d into the nonlinear space F

$$\begin{array}{rccc} \phi: & C^d & \rightarrow & F \\ & x & \mapsto & \phi(x) \end{array} \tag{2}$$

Then perform PCA in the nonlinear space F. Suppose there are M training samples $x_1, x_2, \cdots, x_M$, we construct the total scatter matrix in the nonlinear space F

$$S_T = \frac{1}{M} \sum_{i=1}^{M} (\phi(x_i) - \bar{\phi})(\phi(x_i) - \bar{\phi})^H \tag{3}$$

where $\bar{\phi} = \frac{1}{M} \sum_{i=1}^{M} \phi(x_i)$. However, it is difficult to do so directly because of the high dimension of the nonlinear space F. Fortunately, kernel tricks can avoid this computation by the following rule

$$k(x_i, x_j) =< \phi(x_i), \phi(x_j) >= \phi(x_i)^H \phi(x_j) \tag{4}$$

where $k(\cdot)$ denotes the kernel function. In this method, the explicit mapping ϕ is not required. Three classes of kernel functions widely used in kernel classification are polynomial kernels, Gaussian kernels and sigmoid kernels. Our algorithm adopts polynomial kernel function which can be represented as

$$k(x_i, x_j) = (x_i \cdot x_j)^r \tag{5}$$

where r is a constant.

Our goal is to compute the eigenvalues and the corresponding eigenvectors of S_T. Singular value decomposition (SVD) technique is also adopted to reduce computational effort derived from the high dimensional nonlinear space F. Define the matrix $Q = [\phi(x_1), \phi(x_2), \cdots, \phi(x_M)]$, and form the matrix $\tilde{R} = Q^H Q$ whose elements can be computed as follows

$$\tilde{R}_{ij} = \phi(x_i)^H \phi(x_j) = k(x_i, x_j) \tag{6}$$

Then centralize $\tilde{R}$ as

$$R = \tilde{R} - 1_M \tilde{R} - \tilde{R} 1_M + 1_M \tilde{R} 1_M \tag{7}$$

where 1_M denotes a $M \times M$ matrix whose elements are all equal to $1/M$. From Eq. (6) and (7), it can be known that R is a semi-positive definite Hermite matrix. So the eigenvalues of R are all nonnegative real numbers [3]. Suppose $u_1, u_2, \cdots, u_n$ be the eigenvectors of R corresponding to n largest eigenvalues $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_n$. Then, by SVD technique, the eigenvectors $w_1, w_2, \cdots, w_n$ of S_T corresponding to n largest eigenvalues $\lambda_1, \lambda_2, \cdots, \lambda_n$ are

$$w_i = \frac{1}{\sqrt{\lambda_i}} Q u_i \quad i = 1, 2, \cdots, n \tag{8}$$

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By projecting the mapped vector $\phi(x)$ onto the eigenvector w_i, we can obtain the ith projection component

$$\begin{aligned} y_i &= w_i^H \phi(x) = \frac{1}{\sqrt{\lambda_i}} u_i^H Q^H \phi(x) \\ &= \frac{1}{\sqrt{\lambda_i}} u_i^H [k(x_1, x), k(x_2, x), \cdots, k(x_M, x)]^T \end{aligned} \tag{9}$$

So the CKPCA-transformed projection vector Y of the sample x is composed as $Y = (y_1, y_2, \cdots, y_n)^T$.

2.2 Feature fusion and classification

Let $a = (a_1, a_2, \cdots, a_{d_1})$ and $b = (b_1, b_2, \cdots, b_{d_2})$ be two feature vectors derived from two biometric modals respectively, CKPCA first combines them into a complex vector $x = a + ib$ (i is the denotation of imaginary unit). If the dimensions of a and b are not equal, pad the smaller dimensional one with zeros until its dimension is equal to the other's. Hence, the dimension of the fusion feature is $d = \max\{d_1, d_2\}$. Under the inner product as Eq. (1), the fusion feature vectors construct the unitary space C^d. Then we perform CKPCA in C^d as follows:

Step 1: Construct the kernel matrix $\tilde{R}$ using the polynomial kernel function based on Eq. (6);

Step 2: Centralize $\tilde{R}$ as R based on Eq. (7);

Step 3: Compute the eigenvectors $u_1, u_2, \cdots, u_n$ of R corresponding to the n largest eigenvalues $\lambda_1, \lambda_2, \cdots, \lambda_n$;

Step 4: transform the eigenvectors $w_1, w_2, \cdots, w_n$ of S_T based on Eq. (8);

Step 5: Project $\phi(x)$ onto w_i and calculate the projection vector Y based on Eq. (9).

Finally, the minimum distance is employed. Note that the measurement in unitary space can be defined as $||z|| = \sqrt{z^H z}$. Correspondingly, the distance between the complex vector z_1 and z_2 can be computed as

$$||z|| = \sqrt{(z_1 - z_2)^H (z_1 - z_2)} \tag{10}$$

Based on this distance, we can perform classification in unitary space.

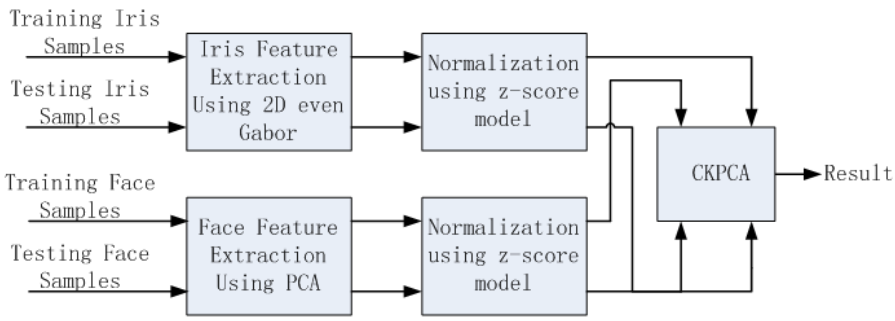

Fig. 1. The flow of the proposed algorithm

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3 Experiments

In this letter, iris and face are observed as two distinct biometric characteristics to test our algorithm. For iris, 2D even Gabor [6] is taken as the feature extractor. Principle component analysis (PCA) [7] extracts the statistical feature of face. In order to eliminate the differences in the order of magnitude and the distribution between two distinct feature sets derived from iris and face, we use z-score model [4] to normalize two feature sets before fusion. The flow of the above procedure is illustrated in Fig. 1.

Table I. Comparison result of EER (%)

Methods	Experiment I	Experiment II
Iris recognition	3.11	3.33
Face recognition	7.79	28.33
Serial rule	1.94	1.67
Sum rule	4.22	9.63
Weighted sum rule	2.5	5.54
Combined Fisherface	8.36	12.33
Our algorithm	0.06	2.22e-16

The experiments were performed on CASIA iris image database (ver.1.0) and two face databases (ORL database and Yale database). Two experiments were conducted: Experiment I fuses CASIA iris features with ORL face features, where $M = 40 \times 3$ and 4 samples per class were taken as the testing sets; Experiment II fuses CASIA iris features with Yale face features, where $M = 15 \times 3$ and 4 samples per class were selected as the testing sets. Our goal is to compare our algorithm with two unimodal biometrics characteristics (iris [6] and face [7]), and other three fusion approaches: serial rule, weighted sum rule and combined Fisherface [4]. And sum rule can be taken as a special case of weighted sum rule to experiment.

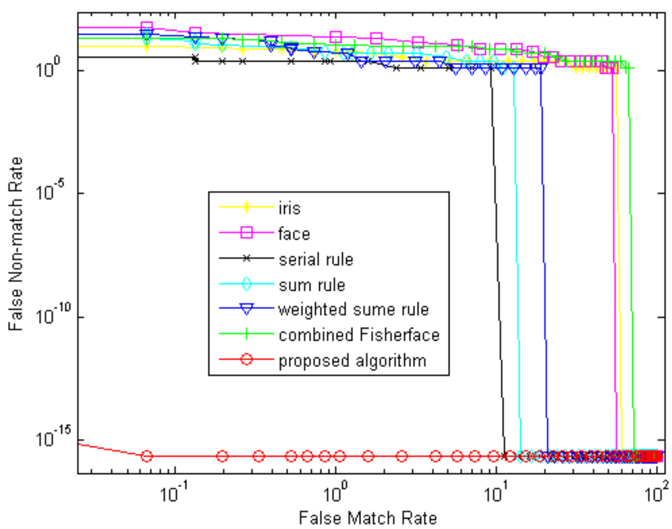

Fig. 2. DET curve of experiment I

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False match rate (FMR) and false non-match rate (FNMR) are more suitable to evaluate the performance of the algorithms in an off-line technology test [8] and therefore are used as the performance parameters of the proposed algorithm in this letter. Furthermore, equal error rate (EER) is taken as another parameter to evaluate the performance of our algorithm. Compared with serial rule, sum rule and weighted sum rule, CKPCA can be also considered as a feature selector to remove more redundancy of features before the fusion step. Besides, combined Fisherface focuses on the linear features of multiple representation of unimodal biometrics. However, potential nonlinear factors are imported in sample collection and feature extraction, such as illumination and distortion. CKPCA inherits the good distinguishability of nonlinear features from kernel tricks. So CKPCA is superior to complex Fisher. Fig. 2 and Fig. 3 show the DET curves of experiment I and experiment II respectively. And Tab. I gives the comparison result of EER. From these experiments, it can be obviously found that our algorithm not only exceeds the performance of unimodal biometrics, but also outperforms the other four fusion approaches.

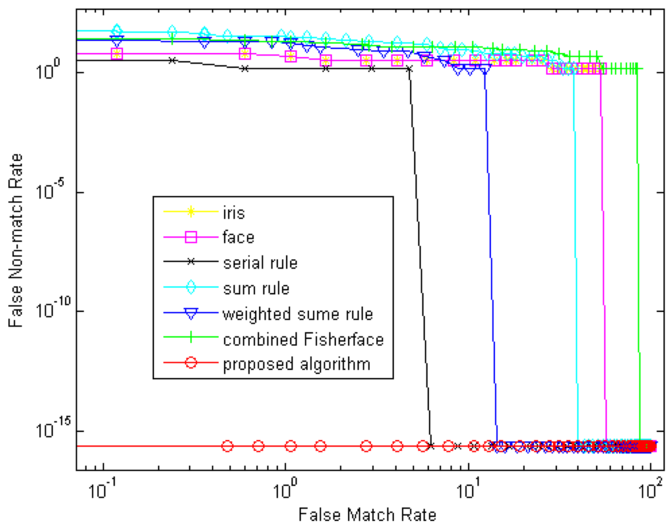

Fig. 3. DET curve of experiment II

4 Conclusion

A new multimodal biometric recognition algorithm based on CKPCA is presented. CKPCA combines two distinct feature vector sets into a complex vector set and obtain the projection vectors by performing PCA in the high dimension space of complex field. The experimental results demonstrate that the proposed algorithm outperforms two unimodal biometrics and other four conventional fusion schemes.

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