

Face-Palm Identification System on Feature Level Fusion based on CCA

Zhifang Wang¹, Chao Liu¹, Taibin Shi² and Qun Ding¹

¹: Department of Electronic Engineering
Heilongjiang University
No.74, Xufu Road, Nangang District, Harbin
xiaofang @126.com;lcjnt@163.com;qunding@yahoo.cn

²: School of Basic Medical Sciences
Xinxiang Medical University
No.601, Jinsui Road, Hongqi District, Xinxiang
stb2873314@yahoo.com.c

Received December, 2012; revised May, 2013

ABSTRACT. *In recent years, multimodal biometrics recognition technology takes more attention by its higher safety and better performance. In this paper, we propose an efficient feature-level fusion algorithm for face and palm. We extract the features of face and palm by principal component analysis(PCA), and then use the canonical correlation analysis(CCA) to carry out feature fusion and get correlation characteristic features. The experiment results show that our method has the better performance than that of two unimodal biometrics and four feature fusion algorithms.*

Keywords: Multimodal biometrics, Feature level fusion, Canonical correlation analysis

1. **Introduction.** Unimodal biometric technology is a comprehensive utilization of various of biological characteristics of emerging biometric technology. However, the performance of unimodal biometrics systems has to contend with a variety of problems such as background noise, non-universal applicability, stable stability, inter-class similarities[1]. In order to solve these problems, multimodal biometrics technique emerge as times require. Multimodal biometric recognition technology mainly has following three advantages, higher reliability, wider applicability and stronger security. Because of its important theoretical research value and application prospect in the market, multimodal biometrics has become an important research direction of biometric recognition and attract more and more domestic and international research group engaged in research in this area.

According to the structure of the biological characteristic recognition system, multimodal biometric systems has four levels of fusion: pixel level, feature level, matching score level and decision level. Pixel level fusion[2, 3] directly in the original level of the acquisitioned. This scheme is the lowest level of the hierarchy to fusion, its advantage is that it can retain as much of the data that other fusion levels cannot provide, but the amount of data to be processed is too large, poor anti-interference ability and long process time, so cannot satisfy the real-time requirements. Matching score level fusion[4, 5] put the single features into the recognition model respectively, then get each matching score.

These scores can be combined to analyses synthetically to get the final decision. In all of the fusion levels, matching score level fusion is the most commonly used because it has small difficulty to implement relatively. But its performance depends on the individual characteristics of the recognition accuracy, ascending the space is lesser. Decision level fusion[6, 7] is a kind of high level, we obtained multiple recognition results after different features were processed independently, then get the final result through comprehensive fusion these results. This method is simple, but also depends on the individual characteristics of the recognition performance, the space to be improved is limited. Feature fusion can derive the most discriminative information from original multiple features sets and eliminate the redundant information resulting from the correlation between different feature sets. Feature level fusion can get optimal recognition result theoretically. At present, research mainly focus on the matching level and decision level.

Feature level fusion has two main method: serial rule and parallel rule [8, 9]. The former connects two groups of features as a longer vector. Weighted rule and sum rule are the typical methods of the latter. In addition, a novel parallel method are presented that represents two groups of feature vectors parallel into complex vector[10]. The algorithms canonical correlation analysis(CCA) use two groups of feature vectors as the effective discriminant information. This paper implements information fusion and eliminate the characteristics between the information redundancy effectively at the same time, this method provide a new thought of two group of features for classification.

Face recognition technology is a hot topic in the biometric recognition, it developed with the development of computer and network technology. Because of face recognition widely used in public security, secure authentication systems, credit card verification, file management, video conferencing, interactive systems, face recognition has become a hot research topic in the field of pattern and artificial intelligence. Although human can identify the face and expression easily, but it is an extremely difficult task for computer. It involves a lot of knowledge like pattern recognition, image processing and physiology, psychology and so on. Compared with the fingerprint, retina, iris and other human biometric recognition system, face recognition system more directly, user friendly, without any mental disorder, and can gets some information though facial expressions, posture analysis which other recognition system difficult to get.

Palmprint recognition is a new branch of biometric identification technology. Compared with other biometric technology, palmprint recognition has some unique advantages: palmprint information is not related to privacy issues; Rich information but also has the uniqueness and stability of low cost acquisition equipment. Face and palmprint recognition both have not infringe on the user and acceptable levels are high. The most important is this two kinds of biometric recognition method can use the same acquisition device. For example, using a low resolution of the camera can complete acquisition of face and palmprint image. At the same time, we can use a same method for feature extraction of face and palmprint recognition. So the features are compatible, we can analysis the integration at all levels. This paper will draw lessons from the newest achievement of the international biometric recognition, information fusion and image processing, information fusion problem analysis. Research on the face and palmprint biological feature fusion based on the face recognition and palmprint recognition.

Compared with other biological characteristics identification, palmprint recognition has the broad application prospect, face recognition is one of the most natural and most easy to accept the identification method. The two kinds of biological characteristics identification are both promising identity recognition technology. In this paper, we fuse the two feature sets in series. The rest of this paper is organized as follows: In the next section, we present the theory canonical correlation analysis and feature extraction of face and palm. In

section 3 fuse face and palm feature. In section 4, experimental results and comparison. At last, we conclude in section 5.

2. Canonical Correlation Analysis Theory. Canonical correlation analysis(CCA) is a method to extract the common feature of the collection of more than two samples. For example, we hope to establish a system which have the function that provide a picture and at the same time provide the corresponding name pronunciation. For a given image, the system need to answer the picture name through speech, or given a speech information, then the system provides the corresponding picture. This process can be viewed as a recession from the image to the voice, of course vice versa. Because the dimension of the image and voice are very large, regression analysis can not get very good results. So we can use the canonical correlation analysis mapping the input into the low feature space, then solve the problem of recession. The canonical correlation analysis was first proposed by Hotelling in 1935. It is looking for a linear transformation to make the correlation coefficient minimal in the two groups of multivariable. This kind of transformation will get the information maximum on the point of view of information.

CCA is multivariate statistical analysis which study two groups of random variable relationship between the statistical method[11]. Based on the idea of CCA, we set up the correlation criterion function between two groups of feature vectors, and calculate typical projection vector set of the two groups according to the criterion. Then combined canonical correlation characteristics are extracted for recognition. The framework of the multimodal biometric algorithm as figure 1.

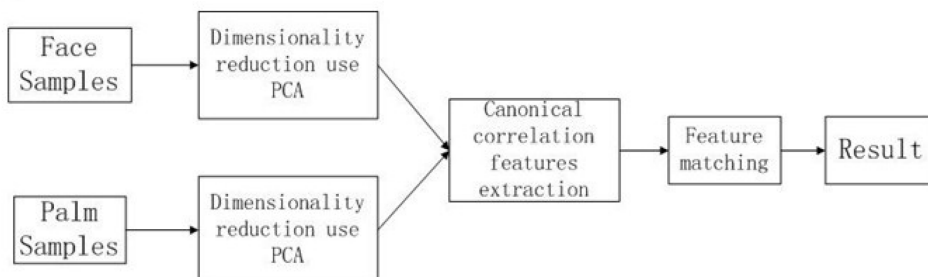


FIGURE 1. The framework of the proposed algorithm

2.1. Principle of CCA. Let $x \in R^{n_x}$ and $y \in R^{n_y}$ are two set of interrelated random vector. The purpose of the CCA method is to find the projection direction of a and b which make x and y have the maximum correlation coefficient $\rho(a, b)$ projection value $u = a^T x$ and $v = b^T y$ in the two projection direction, in which

$$\rho(a, b) = \frac{E(u, v)}{\sqrt{\text{var}(u)}\sqrt{\text{var}(v)}} \quad (1)$$

$$= \frac{a^T \text{cov}(x, y)}{\sqrt{a^T \text{var}(x)}\sqrt{b^T \text{var}(y)}} \quad (2)$$

Thus the study of the correlation between the two set of random variables simplified into the study a few of the correlations between the variables. $\text{var}(x)$ and $\text{var}(y)$ represent x and y of covariance matrix respectively. $\text{cov}(x, y)$ is their mutual covariance matrix, u and v are canonical correlation features.

In the process of multiple biometric feature fusion, due to the different of physical meaning and the range between biometrics information extracted, direct fusion is not much significance, but also may makes the feature information component gap influence weight on the recognition result greatly between different feature information fusion, affect the recognition performance and difficult to analysis the change on the recognition performance. In order to eliminate the unbalance and get good performance, we must to normalize the feature before fusion.

Normalization method must satisfy two conditions: the first one is the normalized matching score between sets can achieve a degree of uniformity. The normalized model tend to rely on the implementation of quantitative value distribution of one or several reference points, and then achieve the effect of overall distribution approximately uniform. The other one is the decision result before and after the normalization can not be changed, otherwise the score normalization is meaningless. Z-score model is the most commonly used at present, this kind of model using the arithmetic mean and variance of the given data to normalize the element in the set. After the normalization, the mean value is 0 and the standard deviation is 1. The formula of the Z-score is $X_k = \frac{A_k - \bar{A}_k}{\sigma_k}$ in which X_k as the normalized matching score, A_k is the matching before normalization. \bar{A}_k and σ_k are the mean and standard scores before the normalization. The Z-score normalization model can reach the good results for the set which its mean and standard is known.

2.2. Features extraction and transformation matrix calculation. Let x and y be the feature vectors extracted from face and palm. According to theory CCA, we first extract the canonical correlation features $u = a^T x$ and $v = b^T y$. Then, compute the associated feature z used for identification as follows:

$$z = \begin{pmatrix} u \\ v \end{pmatrix} = \begin{pmatrix} a^T x \\ b^T y \end{pmatrix} = \begin{pmatrix} x \\ y \end{pmatrix} \begin{pmatrix} a \\ b \end{pmatrix}^T \quad (3)$$

Let $V_{xx} = \text{var}(x)$, $V_{yy} = \text{var}(y)$, $V_{xy} = \text{cov}(x, y)$, $V_{yx} = \text{cov}(y, x)$, the equation (1) transformation for

$$\rho(a, b) = \frac{a^T V_{xx} b}{\sqrt{a^T V_{xx} a} \sqrt{b^T V_{yy} b}} \quad (4)$$

Use k and l to normalize a and b respectively, the quotient of equation is

$$\frac{kla^T V_{xx} b}{\sqrt{k^2 a^T V_{xx} a} \sqrt{l^2 b^T V_{yy} b}} = \frac{a^T V_{xx} b}{\sqrt{a^T V_{xx} a} \sqrt{b^T V_{yy} b}} \quad (5)$$

It is revealed that the extremum $\rho(a, b)$ has nothing to do with the size of a and b , only with their direction. Then the above problem can be turned into $\max_{ab} a^T V_{xy} b$. The constraint condition is $a^T V_{xx} a = 1$, $b^T V_{yy} b = 1$.

Based on Lagrange multipliers, computing $L = a^T V_{xx} b - \lambda_1 (a^T V_{xx} a - 1)/2 - \lambda_2 (b^T V_{yy} b - 1)/2$. Then, Derivation respectively for a and b

$$\begin{cases} \partial L / \partial a = V_{xy} b - \lambda_1 V_{xx} a = 0 \\ \partial L / \partial b = V_{yx} a - \lambda_2 V_{yy} b = 0 \end{cases} \quad (6)$$

Premultiplication with a^T and b^T , use constraint condition to get

$$\begin{cases} a^T V_{xy} b = \lambda_1 \\ b^T V_{yx} a = \lambda_2 \end{cases} \quad (7)$$

Because $V_{yx} = V_{xy}$, $\lambda_1 = \lambda_1^T = (a^T V_{xy} b)^T = b^T V_{yx} a = \lambda_2$. Let $\lambda_1 = \lambda_2 = \lambda$, then $\rho(a, b) = a^T V_{xy} b = b^T V_{yx} a = \lambda$. Equation(6) can be turned into

$$\begin{cases} V_{xy} b = \lambda V_{xx} a \\ V_{yx} a = \lambda V_{yy} b \end{cases} \quad (8)$$

$$\begin{cases} V_{xx}^{-1} V_{xy} V_{yy}^{-1} V_{yx} a = \lambda^2 a \\ V_{yy}^{-1} V_{yx} V_{xx}^{-1} V_{xy} b = \lambda^2 b \end{cases} \quad (9)$$

In this way, the calculation of canonical correlation can convert to calculate two generalized eigenvalue equation.

3. Face-Palm Feature Fusion. The field of pattern recognition exist the small sample size problem, especially the study of the human face and palm image recognition. The number of training samples is less than the face and palm pixel points. So the total population scatter matrix is singular matrix. One of the thought to solve the small size problem is dimension reduction. Firstly, reduce the dimension of the original samples X and Y to $k = V_{xx}$ and $l = V_{yy}$. In low Euclidean space the population covariance matrix is reversible. So, calculate the projection vector only in low Euclidean space. Here we use principle component analysis(PCA) [12] method to reduce dimension.

Principal component analysis is a statistical method of transform multiple indicators into several comprehensive index. In the field of face recognition, principle component analysis is also called the eigenface method. The basic idea of this method is regard the human face as a random variable, gets its orthogonal K-L vector using the discrete K-L transform. The large eigenvalues and the corresponding eigenvectors indicate the shape of the face, Then approximation and expression the face with these orthogonal vector. Identification method of eigenface can be simply stated that map the detected face image into the spanned eigenface subspace, then compare the distance with the known facial feature.

PCA comes from K-L transform which is the optimal orthogonal transformation in the sense of mean square error. The purpose of PCA is to find a set of optimal unit orthogonal vector base through linear transformation, reconstruct the original sample by linear combination with the minimum error between the reconstruction samples and the original samples. Principle component analysis is a kind of optimal orthogonal transform based on statistical characteristics, it has excellent properties. The new component orthogonal or uncorrelated after the transformation. Representation the size of the original vector variance with the part of the new component. The vector transform is more deterministic, more focused energy. The method have the very important application value in image compression and feature extraction.

For CCA concerned, in the null space of V_{xx} and V_{yy} does not exist effective related information. When V_{xx} and V_{yy} are singular, it will not lose any effect information in the premise of PCA dimensionality reduction. Remove the null space of V_{xx} and V_{yy} and then calculate the typical projection vector.

What has been discussed above the calculate of typical projection vector in small sample problem. In practical applications, small intrinsic often contain more interference information to the original samples, which is disadvantageous to classification. Therefore,

according to the needs of the problem, it necessary to convert the high dimension to $k = V_{xx}$ and $l = V_{yy}$, namely only retain the eigen vector corresponding big eigenvalue.

All the steps of our algorithm are summarized as follows:

Use the principal component analysis to reduce the dimension. The size of the face and palm image are 92×112 and 128×128 respectively. Project the image vector to the subspace, after the dimension reduction the were reduced to 80.

Calculate the canonical weight between the feature matrix of face and palm.

Calculate the final fusion feature through the feature matrix and canonical weight matrix.

Calculate the Euclidean distance between the different class to get the classification results.

4. Experiments and Analysis.

4.1. **Database.** The experiments are performed on ORL face database and PolyU multispectral palmprint database. ORL face database includes 40 people, 10 different image pose and expression variation per person. Multispectral palmprint images were collected from 250 volunteers, including 195 males and 55 females, the samples were collected in two separate sessions. In each session, the subject was asked to provide 6 images for each palm. In order to the number of samples accordance. We select 40 people, 10 different image per people from PolyU multispectral palmprint database. The first row and second row of figure 2 show the face images and palmprint images of two database respectively.

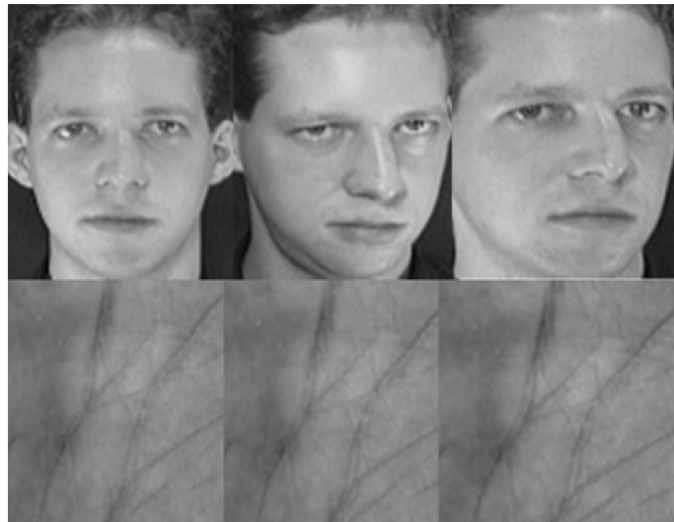


FIGURE 2. Examples of the sample image

4.2. **Experiment result.** We select five images per person as the training samples, the others are taken as the testing set. At first, we extract the features of face and palm samples respectively with principal component analysis (PCA). Our goal is to compare our algorithm with two unimodal biometrics based on PCA (face and palm), and other three fusion approaches: serial rule, weighted sum rule and combined Fisherface. And sum rule can be taken as a special case of weighted sum rule to experiment. 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 and therefore are used as the performance parameters of the proposed algorithm in this paper. Besides, equal error rate (EER) is also taken as a Comparable Performance Indicator.

We perform the series fusion rule and three parallel fusion rules(sum rule, weighted rule and complex field) using the same features of face and palm. Comparing other methods, our algorithm can be taken as the feature selector to extract the more discriminant feature. Table 1 and figure 3 proves our method has the better performance. Figure 3 shows the DET curves of different algorithms. Table 1 represents the compared results. From that, we can find two unimodal recognition methods have the higher EER in seven algorithms. EER of our fusion method based on CCA is the lowest than series rule and three parallel rules.

TABLE 1. EER comparison of different methods

Algorithm	EER
Palm with PCA	0.11
Face with PCA	0.09
Feature fusion in serial rule	0.085
Feature fusion in sum rule	0.082
Feature fusion in weighted rule	0.084
Feature fusion in complex field	0.086
Feature fusion in CCA	0.075

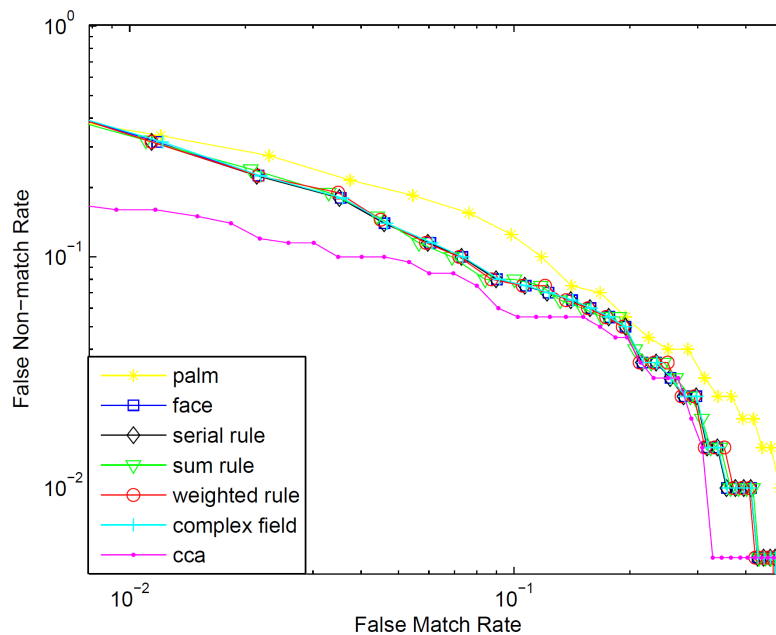


FIGURE 3. DET curves of different algorithms

5. Conclusions. In this paper, a feature level fusion algorithm of face and palm is proposed for personal identification. The algorithm use the idea of canonical correlation analysis(CCA), extract the correlation feature of face and palm for identification; And give a solution of the small sample problem,when the scatter of two groups feature vector are singular,reduce the dimension with principle component analysis(PCA) and then calculate the canonical correlation characteristics. The result show that our algorithm improve the recognition rate.

Acknowledgment. This work is supported by National Natural Science Foundation of China (no.61201399), China Postdoctoral Science Foundation (no.2012M511003), Project of Science and Technology of Heilongjiang Provincial Education Department(no.12521418), Youth Foundation of Heilongjiang University (no.201026), and Startup Fund for Doctor of Heilongjiang University.

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