Available online at www.sciencedirect.com
ScienceDirect
August 2017, 24(4): 34–39
www.sciencedirect.com/science/journal/10058885
The Journal of China Universities of Posts and Telecommunications
http://jcupt.bupt.edu.cn

Correlation-based identification approach for multimodal biometric fusion

Ma Xin (✉), Jing Xiaojun

School of Information and Communication Engineering, Beijing University of Posts and Telecommunications, Beijing 100876, China

Abstract

Information fusion is a key step in multimodal biometric systems. The feature-level fusion is more effective than the score-level and decision-level method owing to the fact that the original feature set contains richer information about the biometric data. In this paper, we present a multiset generalized canonical discriminant projection (MGCDP) method for feature-level multimodal biometric information fusion, which maximizes the correlation of the intra-class features while minimizes the correlation of the between-class. In addition, the serial MGCDP (S-MGCDP) and parallel MGCDP (P-MGCDP) strategy were also proposed, which can fuse more than two kinds of biometric information, so as to achieve better identification effect. Experiments performed on various biometric databases shows that MGCDP method outperforms other state-of-the-art feature-level information fusion approaches.

Keywords correlation analysis, multimodal biometric information, information fusion

1 Introduction

Biometric refers to the use of the physical characteristics of the human body as the identity of the technology, which essentially is a pattern recognition technology through special identity. At present, the most widely used biometric technology mainly relies on a single biometric information, such as face, fingerprint, palm vein, voice, iris, etc. Because the use of these methods alone may result in poor recognition rates, therefore, the use of multimodal biometric fusion technology for identification has become the focus of research in this field.

Multimodal biometric fusion technology can be divided into feature-level, score-level and decision-level mode. In feature-level mode, data obtained from multi-sensor is used to compute a single feature vector. In score-level mode, each sensor provides a matching score indicating the proximity of the feature vector with the corresponding template vector. In decision-level mode, each sensor can capture multimodal biometric information and the resulting feature vectors individually classified into accept or reject class [1–2].

The feature-level fusion method is more effective than the score-level and decision-level method in multimodal biometric recognition, the reason is that it fuse more original biometric information into a single vector before dimensional reduction procedure [3]. Traditional parallel [4] and serial [5] strategy provide the technical support for feature-level fusion. The serial fusion strategy is simply connecting two original feature vectors, so the dimension of fused new feature vector is the sum of the two original vectors. The parallel fusion strategy convert two original feature vector into a complex vector, therefore the dimension of fused new vector is equal to the maximal dimension in original feature vector.

In recent years, the application of canonical correlation analysis (CCA) in multimodal biometric field attracted a growing number of researchers [6]. CCA convert the correlation of random vectors into a pair of variables, which are uncorrelated. The kernel CCA (KCCA) method [7] using non-linear method project two non-separable sets to a high dimensional linear separable

Received date: 22-03-2017
Corresponding author: Ma Xin, E-mail: xinma@bupt.edu.cn
DOI: 10.1016/S1005-8885(17)60221-8

space. The discriminative CCA (DCCA) method [8] takes into account the feature between intra-class samples and between-class samples, it minimizes the difference of intra-class while maximizes the difference of between-class. The generalized CCA (GCCA) method [9] makes use of both the supervised information and the intra-class distribution matrix information.

In this paper, we propose MGCDP method for multimodal biometric information fusion, which maximizes the correlation of the intra-class features within the modal while minimizing the correlation of the between-class between the modal.

2 Basic concept of CCA

CCA is an effective multi class data processing method, which is widely used in the analysis of the relationship between the two sets of data. Assuming that there are two sets of data matrix $\boldsymbol{X}\in\mathbb{R}^{p\times n}$ and $\boldsymbol{Y}\in\mathbb{R}^{q\times n}$, the dimensions of $\boldsymbol{X}$ and $\boldsymbol{Y}$ are p and q respectively, and all of them contain n training feature vectors. CCA is to find a set of optimal direction vector $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$, so that maximum the correlation between $\boldsymbol{a}_1=\boldsymbol{\alpha}^{\mathrm{T}}\boldsymbol{X}$ and $\boldsymbol{b}_1=\boldsymbol{\beta}^{\mathrm{T}}\boldsymbol{Y}$. After determining the first set of canonical vector $(\boldsymbol{a}_1,\boldsymbol{b}_1)$, CCA will continue to search the second pairs of canonical vector $(\boldsymbol{a}_2,\boldsymbol{b}_2)$, in which $\boldsymbol{a}_2=\boldsymbol{\alpha}^{\mathrm{T}}\boldsymbol{X}$ and $\boldsymbol{b}_2=\boldsymbol{\beta}^{\mathrm{T}}\boldsymbol{Y}$ not only uncorrelated with $(\boldsymbol{a}_1,\boldsymbol{b}_1)$, but also is the largest correlation between $\boldsymbol{a}_2$ and $\boldsymbol{b}_2$. In the same way, CCA can iteratively find all the d groups of canonical vector $(\boldsymbol{a}_d,\boldsymbol{b}_d)$.

If the sample space $\Omega=\{\xi\,|\,\xi\in\mathbb{R}^n\}$ has two vectors with mean value of zero $\boldsymbol{X}=\{\boldsymbol{x}\,|\,\boldsymbol{x}\in\mathbb{R}^p\}$ and $\boldsymbol{Y}=\{\boldsymbol{y}\,|\,\boldsymbol{y}\in\mathbb{R}^q\}$, where $\boldsymbol{x}$ and $\boldsymbol{y}$ are different biometric modal sample from same person ξ, assume that $\boldsymbol{S}_{\mathrm{XX}}\in\mathbb{R}^{p\times p}$ and $\boldsymbol{S}_{YY}\in\mathbb{R}^{q\times q}$ are covariance matrix of the unimodal $\boldsymbol{X}$ and $\boldsymbol{Y}$ respectively, and that $\boldsymbol{S}_{\mathrm{XY}}\in\mathbb{R}^{p\times q}$ is covariance matrix of the multimodal $\boldsymbol{X}$ and $\boldsymbol{Y}$, (note that $\boldsymbol{S}_{\mathrm{XY}}=\boldsymbol{S}_{\mathrm{YX}}^{\mathrm{T}}$), then the covariance matrix $\boldsymbol{S}$ contains all feature information of the person ξ:

$$\boldsymbol{S}=\begin{bmatrix}\mathrm{var}(\boldsymbol{x}) & \mathrm{cov}(\boldsymbol{x},\boldsymbol{y})\\ \mathrm{cov}(\boldsymbol{y},\boldsymbol{x}) & \mathrm{var}(\boldsymbol{y})\end{bmatrix}=\begin{bmatrix}\boldsymbol{S}_{\mathrm{XX}} & \boldsymbol{S}_{\mathrm{XY}}\\ \boldsymbol{S}_{\mathrm{YX}} & \boldsymbol{S}_{\mathrm{YY}}\end{bmatrix} \tag{1}$$

Let $\boldsymbol{\alpha}\in\mathbb{R}^p$ and $\boldsymbol{\beta}\in\mathbb{R}^q$ are two non-zero vector, then the linear combination of $\boldsymbol{x}$ and $\boldsymbol{y}$ can be expressed as:

$$\boldsymbol{\alpha}^{\mathrm{T}}\boldsymbol{x}=a_1x_1+a_2x_2+\ldots+a_px_p \tag{2}$$

$$\boldsymbol{\beta}^{\mathrm{T}}\boldsymbol{y}=b_1y_1+b_2y_2+\ldots+b_qy_q \tag{3}$$

In order to maximize the correlation between $\boldsymbol{\alpha}^{\mathrm{T}}\boldsymbol{x}$ and $\boldsymbol{\beta}^{\mathrm{T}}\boldsymbol{y}$, CCA uses Eq. (4) to find the projection in $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ directions:

In order to maximize the correlation between $\boldsymbol{\alpha}^{\mathrm{T}}\boldsymbol{x}$ and $\boldsymbol{\beta}^{\mathrm{T}}\boldsymbol{y}$, CCA uses Eq. (4) to find the projection in $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ directions:

$$J(\boldsymbol{\alpha},\boldsymbol{\beta})=\frac{\mathrm{cov}(\boldsymbol{\alpha}^{\mathrm{T}}\boldsymbol{x},\boldsymbol{\beta}^{\mathrm{T}}\boldsymbol{y})}{\sqrt{\mathrm{var}(\boldsymbol{\alpha}^{\mathrm{T}}\boldsymbol{x})\mathrm{var}(\boldsymbol{\beta}^{\mathrm{T}}\boldsymbol{y})}} \tag{4}$$

Because:

$$\mathrm{var}(\boldsymbol{\alpha}^{\mathrm{T}}\boldsymbol{x})=\boldsymbol{\alpha}^{\mathrm{T}}\mathrm{var}(\boldsymbol{x})\boldsymbol{\alpha}=\boldsymbol{\alpha}^{\mathrm{T}}\boldsymbol{S}_{\mathrm{XX}}\boldsymbol{\alpha} \tag{5}$$

$$\mathrm{var}(\boldsymbol{\beta}^{\mathrm{T}}\boldsymbol{y})=\boldsymbol{\beta}^{\mathrm{T}}\mathrm{var}(\boldsymbol{y})\boldsymbol{\beta}=\boldsymbol{\beta}^{\mathrm{T}}\boldsymbol{S}_{\mathrm{YY}}\boldsymbol{\beta} \tag{6}$$

$$\mathrm{cov}(\boldsymbol{\alpha}^{\mathrm{T}}\boldsymbol{x},\boldsymbol{\beta}^{\mathrm{T}}\boldsymbol{y})=\boldsymbol{\alpha}^{\mathrm{T}}\mathrm{cov}(\boldsymbol{x},\boldsymbol{y})\boldsymbol{\beta}=\boldsymbol{\alpha}^{\mathrm{T}}\boldsymbol{S}_{\mathrm{XY}}\boldsymbol{\beta} \tag{7}$$

Therefore, the optimization criterion of CCA is:

$$J(\boldsymbol{\alpha},\boldsymbol{\beta})=\frac{\boldsymbol{\alpha}^{\mathrm{T}}\boldsymbol{S}_{\mathrm{XY}}\boldsymbol{\beta}}{\sqrt{\boldsymbol{\alpha}^{\mathrm{T}}\boldsymbol{S}_{\mathrm{XX}}\boldsymbol{\alpha}\boldsymbol{\beta}^{\mathrm{T}}\boldsymbol{S}_{\mathrm{YY}}\boldsymbol{\beta}}} \tag{8}$$

The goal of Eq. (8) is to find linear combinations of $\tilde{\boldsymbol{X}}=(a_1,a_2,\ldots,a_d)^{\mathrm{T}}\boldsymbol{X}=\boldsymbol{W}_{\mathrm{X}}^{\mathrm{T}}\boldsymbol{X}$ and $\tilde{\boldsymbol{Y}}=(b_1,b_2,\ldots,b_d)^{\mathrm{T}}\boldsymbol{Y}=\boldsymbol{W}_{\mathrm{Y}}^{\mathrm{T}}\boldsymbol{Y}$. In this case, $\mathrm{cov}(\tilde{\boldsymbol{X}},\tilde{\boldsymbol{Y}})=\boldsymbol{W}_{\mathrm{X}}^{\mathrm{T}}\boldsymbol{S}_{\mathrm{XY}}\boldsymbol{W}_{\mathrm{Y}}$, $\mathrm{var}(\tilde{\boldsymbol{X}})=\boldsymbol{W}_{\mathrm{X}}^{\mathrm{T}}\boldsymbol{S}_{\mathrm{XX}}\boldsymbol{W}_{\mathrm{X}}$, and $\mathrm{var}(\tilde{\boldsymbol{Y}})=\boldsymbol{W}_{\mathrm{Y}}^{\mathrm{T}}\boldsymbol{S}_{\mathrm{YY}}\boldsymbol{W}_{\mathrm{Y}}$. By using the Lagrange multiplier method to solve the optimization problem of the covariance between $\tilde{\boldsymbol{X}}$ and $\tilde{\boldsymbol{Y}}$, under the condition of $\mathrm{var}(\tilde{\boldsymbol{X}})=\mathrm{var}(\tilde{\boldsymbol{Y}})=\boldsymbol{I}$, the projection matrix $\boldsymbol{W}_{\mathrm{X}}$ and $\boldsymbol{W}_{\mathrm{Y}}$ can be determined by:

$$\left.\begin{aligned}\boldsymbol{S}_{\mathrm{XX}}^{-1}\boldsymbol{S}_{\mathrm{XY}}\boldsymbol{S}_{\mathrm{YY}}^{-1}\boldsymbol{S}_{\mathrm{YX}}\widehat{\boldsymbol{W}}_{\mathrm{X}}=\boldsymbol{R}^2\widehat{\boldsymbol{W}}_{\mathrm{X}}\\ \boldsymbol{S}_{\mathrm{YY}}^{-1}\boldsymbol{S}_{\mathrm{YX}}\boldsymbol{S}_{\mathrm{XX}}^{-1}\boldsymbol{S}_{\mathrm{XY}}\widehat{\boldsymbol{W}}_{\mathrm{Y}}=\boldsymbol{R}^2\widehat{\boldsymbol{W}}_{\mathrm{Y}}\end{aligned}\right\} \tag{9}$$

where the $\widehat{\boldsymbol{W}}_{\mathrm{X}}$ and $\widehat{\boldsymbol{W}}_{\mathrm{Y}}$ are eigenvectors, and the $\boldsymbol{R}^2$ is the diagonal matrix of eigenvalues.

3 MGCDP method

Based on the basic concept of CCA, we propose the MGCDP method for multimodal biometric information fusion, which maximizes the correlation of the intra-class features within the modal while minimizing the correlation of the between-class between the modals.

Assume the biometric feature set $\boldsymbol{X}$ contains n samples (n feature vectors) from C classes, each class contains k_i feature vector, let n_i denotes the ith class, $\boldsymbol{x}_{ij}$ denotes the jth feature vector from the n_i class, $\boldsymbol{X}=\bigcup_{i=1}^{C}\boldsymbol{n}_i=\bigcup_{i=1}^{C}\bigcup_{j=1}^{k_i}\boldsymbol{x}_{ij}$. Let $\boldsymbol{u}_i$ denotes the mean of $\boldsymbol{x}_{ij}$ in