Neurocomputing 122 (2013) 229–238

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

Fractional-order embedding multiset canonical correlations with applications to multi-feature fusion and recognition

Yun-Hao Yuan, Quan-Sen Sun*

School of Computer Science and Engineering, Nanjing University of Science & Technology, Nanjing 210094, P.R. China

ARTICLE INFO

Article history:
Received 24 January 2013
Received in revised form
15 May 2013
Accepted 8 June 2013
Communicated by Jinhui Tang
Available online 2 July 2013

Keywords:
Pattern recognition
Canonical correlation analysis
Multiset canonical correlations
Feature fusion
Multi-view learning

ABSTRACT

The sample covariance matrices in multiset canonical correlation analysis (MCCA) usually deviate from the true ones owing to noise and the limited number of training samples. In this paper, we thus re-estimate the covariance matrices by using the idea of fractional order embedding to respectively correct sample eigenvalues and singular values. Then, we define fractional-order within-set and between-set scatter matrices, which can significantly reduce the deviation of sample covariance matrices. At last, a novel multiset canonical correlation method is presented for multiset feature fusion, called fractional-order embedding multiset canonical correlations (FEMCCs). The proposed FEMCC method first performs joint feature extraction on multiple sets of feature vectors that are obtained from the same objects, and then fuse the extracted correlation features by a given fusion strategy to form discriminative feature vectors for classification tasks. The proposed method is applied to face recognition and object category classification and is examined using the AR, AT&T, and CMU PIE face image databases and the ETH-80 object database. Numerous experimental results demonstrate the effectiveness and robustness of the FEMCC fusion method.

1. Introduction

In many practical pattern recognition applications, the same objects are often represented in multiple different feature spaces (views). For instance, genes can be represented by the genetic activity feature and the text information feature [1] in bioinformatics. Since multiple feature representations from the same objects contain different characteristics and information of original data, it is very meaningful to fuse them to form discriminative feature vectors for classification tasks. At present, feature fusion has become an important research focus in the fields of pattern recognition and computer vision.

Conventional feature fusion methods, such as serial feature fusion [2], parallel feature fusion [3–6], are performed by simply concatenating or integrating multiple feature representations together. Although these fusion methods can improve the recognition performance to some extent, the correlation information between different feature sets, which has been demonstrated to be helpful information for recognition [7,8], has not been employed in these traditional methods. In Ref. [7], Sun et al. presented a new feature fusion method using canonical correlation analysis (CCA) [9] that can explicitly reveal the correlation information between two sets of features. The CCA-based method first extracts canonical correlation features (CCFs) from two sets of features, and then fuses these CCFs by given fusion strategies for recognition purpose. Many experimental results on handwritten numeral and face recognition show that the CCA-based fusion method is more powerful in contrast with conventional fusion methods. However, standard CCA is an unsupervised method, and thus it cannot preserve discriminant information of training samples in low-dimensional canonical subspaces. Later on, a variant of CCA called generalized CCA (GCCA) [10] is developed to exploit discriminant information in feature fusion. GCCA does not only consider the correlation between two-set features, but also the within-class information of training samples. The fused features are more discriminative in handwritten numeral classification. Moreover, the method of partial least squares (PLS) [11], which is closely related to CCA, has also been proposed for fusion of two feature sets [12]. The basic idea of the PLS-based fusion method is to find a pair of linear transformations such that the covariance between the projections of two sets of feature vectors can be maximized.

However, most of the foregoing methods can only fuse two sets of feature vectors for classification. For more than two sets of features, Fu et al. [8] presented a general subspace learning framework, in which the cumulative pairwise canonical correlation between each pair of feature sets is maximized after dimension normalization and subspace projection. Subsequently, Hou et al. [13] proposed a novel feature fusion method called multiple component analysis (MCA). In MCA, all sets of features can be fused into a higher-order covariance tensor and then orthogonal subspaces corresponding to each feature set are learned through higher-order singular value decomposition (HOSVD) [14].

* Corresponding author. Tel.: +86 25 84315142; fax: +86 25 84318156.
E-mail addresses: yyhzbh@163.com (Y.-H. Yuan), sunquansen@njust.edu.cn, yyhzbh@gmail.com (Q.-S. Sun).

0925-2312/$ - see front matter © 2013 Published by Elsevier B.V.
http://dx.doi.org/10.1016/j.neucom.2013.06.029

Recently, a multiset integrated canonical correlation analysis (MICCA) framework [15] is presented for feature fusion. This method defines a new correlation criterion using generalized correlation coefficient and fuses multiple sets of feature vectors by given strategies to form discriminative feature vectors for recognition tasks. Extensive experimental results on handwritten numerals classification have demonstrated the effectiveness and robustness of the MICCA method. Due to the lacking of supervised information, Yuan et al. [16] further developed the discriminative-analysis of multiset integrated canonical correlations (DMICCs), which introduces within-class information of training samples and improves the classification accuracy.

As a generalized extension of CCA, multiset canonical correlation analysis (MCCA) [17] is a powerful technique for analyzing linear relationships between multiple sets of random variables. Thus, MCCA is very suitable for multiset feature fusion. Currently, MCCA has been widely applied to many scientific fields, such as blind source separation [18], fMRI data analysis [19,20], remote sensing image analysis [21], and target recognition [22]. However, in MCCA, since within-set and between-set population covariance matrices are not known beforehand in real-world applications, their estimates have to be computed in a training sample space. In this case, sample covariance matrices usually deviate from true ones due to noise and the limited number of training samples. Meanwhile, Hendrikse et al. [23] have pointed out that, even though sample covariance matrices are unbiased estimates of true ones, their eigenvalues are also biased estimates of the eigenvalues of true covariance matrices and the leading sample eigenvalues differ greatly from the true ones if the number of samples is of the same order as the dimensionality of data. Clearly, the deviation has a negative effect on the learning of MCCA for multiset feature fusion.

In this paper, we re-estimate the within-set and between-set covariance matrices in MCCA by using the idea of fractional order embedding to respectively correct sample eigenvalues and singular values. Then, we define fractional-order within-set and between-set scatter matrices, which can significantly reduce the biased estimates of covariance matrices caused by noise and the limited number of training samples. On this basis, a novel multiset canonical correlation method is presented for multiset feature fusion, called fractional-order embedding multiset canonical correlations (FEMCCs). The proposed FEMCC method first performs joint feature extraction on multiple sets of feature vectors that are obtained from the same objects, and then fuse the extracted correlation features by a given strategy to form discriminative feature vectors for classification tasks. The proposed method is applied to face recognition and object category classification and is examined using the AR, AT&T, and CMU PIE face image databases and the ETH-80 object database. Many experimental results demonstrate the effectiveness and robustness of the FEMCC method.

2. Backgrounds and related work

2.1. Canonical correlation analysis (CCA)

In CCA, given two zero-mean random vectors $x\in R^p$ and $y\in R^q$, the objective of CCA is to compute a pair of projection directions, $\alpha\in R^p$ and $\beta\in R^q$, such that the correlation of canonical variates $\alpha^T x$ and $\beta^T y$ is maximized by

$$\rho(\alpha,\beta)=\frac{E(\alpha^T xy^T\beta)}{\sqrt{E(\alpha^T xx^T\alpha)\cdot E(\beta^T yy^T\beta)}}=\frac{\alpha^T S_{xy}\beta}{\sqrt{\alpha^T S_{xx}\alpha\cdot\beta^T S_{yy}\beta}},\tag{1}$$

where $E(\cdot)$ denotes the notation of expectation, S_{xx} and S_{yy} are, respectively, within-set covariance matrices of vectors x and y, and S_{xy} is the between-set covariance matrix between vectors x and y. Clearly, the canonical correlation criterion in (1) is affine-invariant to arbitrary scaling of α and β. According to this characteristic, CCA needs to normalize canonical transformations α and β by setting

$$\alpha^T S_{xx}\alpha=1,\quad \beta^T S_{yy}\beta=1.\tag{2}$$

On the foregoing basis, the first pair of projection directions, α_1 and β_1, are computed by maximizing the criterion (1) with constraints (2). After this, the kth pair of projection directions, α_k and β_k, where $2\le k\le r$ and $r=rank(S_{xy})$, are found by continually maximizing the criterion (1) with the following constraints (3).

$$\begin{cases}\alpha^T S_{xx}\alpha=1, & \beta^T S_{yy}\beta=1,\\ \alpha_j^T S_{xx}\alpha=0, & \beta_j^T S_{yy}\beta=0, \quad (j=1,2,\cdots k-1).\end{cases}\tag{3}$$

2.2. Multiset canonical correlation analysis (MCCA)

MCCA is an important technique which can analyze linear relationships between multiple sets of random variables. At present, MCCA has many different forms [17]. Thereinto, the following form (i.e., standard MCCA) is a natural and direct extension of CCA.

Given m sets of zero-mean random vectors $\{x_i\in R^{d_i}\}_{i=1}^m$, a set of projection directions $\{\alpha_i\in R^{d_i}\}_{i=1}^m$, called multiset canonical transformations (MCTs), is found to maximize the sum of pair-wise correlations between multiset canonical variates (MCVs) $\{\alpha_i^T x_i\}_{i=1}^m$ as

$$\rho(\alpha_1,\alpha_2,\cdots,\alpha_m)=\sum_{i=1}^m\sum_{j=1}^m\alpha_i^T S_{ij}\alpha_j,\tag{4}$$

where S_{ii} is the within-set covariance matrix of vector x_i, and $S_{ij}(i\neq j)$ is the between-set covariance matrix between vectors x_i and x_j.

In MCCA, multiset canonical variates are generally normalized such that $\alpha_i^T S_{ii}\alpha_i=1$, $i=1,2,\cdots,m$. With these constraints, MCCA can be formulated equivalently as

$$\begin{aligned}&\max\rho(\alpha_1,\alpha_2,\cdots,\alpha_m)=\sum_{i=1}^m\sum_{j=1}^m\alpha_i^T S_{ij}\alpha_j\\ &\text{s.t.}\ \ \alpha_i^T S_{ii}\alpha_i=1,\quad i=1,2,\cdots,m.\end{aligned}\tag{5}$$

By the Lagrange multiplier technique [17], we can obtain the first set of projection directions from the optimization problem in Eq. (5). Under conjugately orthogonal constraints and $\{\alpha_i^T S_{ii}\alpha_i=1\}_{i=1}^m$, MCCA can further produce multiple sets of projection directions by maximizing the criterion function in Eq. (4).

2.3. Multiset integrated canonical correlation analysis (MICCA)

MICCA aims at finding a projection matrix for each feature space in multiple different representations of the same patterns such that multiset integrated canonical correlations can be maximized in the transformed representations.

Specifically, suppose m sets of zero-mean random vectors $x_i\in R^{d_i}$, $i=1,2,\cdots,m$, are given. MICCA searches for a set of projection directions $\alpha_i\in R^{d_i}$, $i=1,2,\cdots,m$, to maximize the generalized correlation among the projected variables, i.e., $\alpha_1^T x_1,\alpha_2^T x_2,\cdots,\alpha_m^T x_m$, which can be formally written as

$$\rho(\alpha)=\max_{\alpha}\sqrt{1-\frac{\det(G(\alpha_1^T x_1,\alpha_2^T x_2,\cdots,\alpha_m^T x_m))}{\|\alpha_1^T x_1\|\cdot\|\alpha_2^T x_2\|\cdot\cdots\cdot\|\alpha_m^T x_m\|}},\tag{6}$$

where $G(\cdot)$ denotes a Gram matrix, $\det(\cdot)$ represents the determinant of a square matrix, $\|\cdot\|$ is the notation of 2-norm, and $\alpha^T=(\alpha_1^T,\alpha_2^T,\cdots,\alpha_m^T)$. In MICCA, ρ is referred to as multiset integrated canonical correlation coefficient (MICCCoe) and α is called multiset integrated canonical vector (MICVec). The kth MICCCoe is defined by the kth set of MICVecs $\alpha_{1k},\alpha_{2k},\cdots,\alpha_{mk}$, which are conjugately orthogonal to the previous ones. Since there is no closed-form