Signal Processing ∎ (∎∎∎∎) ∎∎∎–∎∎∎

Contents lists available at ScienceDirect

Signal Processing

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

Fast communication

Couple manifold discriminant analysis with bipartite graph embedding for low-resolution face recognition

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ARTICLE INFO

Article history:
Received 30 November 2015
Received in revised form
8 February 2016
Accepted 10 February 2016

Keywords:
Signal classification
Low-resolution
Face recognition
Couple manifold learning

ABSTRACT

This brief paper presents a novel method for low-resolution face recognition. We introduce a generalized bipartite graph to discretely approximate the underlying manifold structure of face sets with different resolutions. Unlike traditional graph-based methods that only construct the graph based on one sample set, the proposed method constructs the generalized bipartite graph on two heterogeneous sample sets and contains more completed information. Our method learns a couple of mappings that project the face sets with different dimensions into a unified feature space which favors the task of classification. Specifically, in this unified space, our method preserves within-class local geometrical structure according to the network topology of the generalized bipartite graph and maximizes between-class separability at the same time. Experimental results on two benchmark face databases demonstrate the effectiveness of our proposed algorithm.

1. Introduction

In real world applications, detected faces are often of low-resolution, which is a critical problem for surveillance circumstances. The low-resolution images lose some discriminative details across different persons which make the recognition task difficult. Intuitively, improving the quality of the low resolution images by super-resolution is a promising approach for achieving better performance. During the last decade, many super-resolution methods have been developed to recover the corresponding high-resolution image from a single low-resolution image. Simple and rapid interpolation methods, such as bilinear, bicube, and spline [1], are usually chosen for real-world systems. Recently, learning-based super-resolution methods attract more attention due to their outstanding performance. Chang et al. [2] propose a method stem from the geometric intuition, which maps the local geometry of the low-resolution patch space to the high-resolution one. Ma et al. [3] propose a novel face super-resolution method via local sparse representation upon classified over-complete dictionaries. Yang et al. [4] propose a coupled dictionary training method based on patch-wise sparse recovery [5]. Jiang et al. [6] propose an iterative neighbor embedding strategy to solve face super-resolution. Villena et al. [7] propose a variational Bayesian methodology for super-resolution image reconstruction which obtains good performance.

Another line of research that motivates us to solve the low resolution issue is to learn a common subspace shared by multiple feature spaces with different dimensions, such that samples from different feature spaces can be compared. Canonical Correlation Analysis (CCA) [8,9] is the most typical statistical approaches to obtain a common space for multiple heterogeneous spaces. CCA learns two transformations for two sets of variables by mutually maximizing the correlations between the projections onto the basis vectors. Couple Metric Learning (CML) [10] is another subspace learning-based approach which aims to learn two transform matrices to project the heterogeneous

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http://dx.doi.org/10.1016/j.sigpro.2016.02.009
0165-1684/© 2016 Published by Elsevier B.V.

Please cite this article as: X. Xing, K. Wang, Couple manifold discriminant analysis with bipartite graph embedding for low-resolution face recognition, Signal Processing (2016), http://dx.doi.org/10.1016/j.sigpro.2016.02.009

sample sets into a common subspace such that the distances between the projecting point pairs that have similar relations in the original heterogeneous sets are as small as possible. To learn a discriminant common space for heterogeneous sets, Discriminative Canonical Correlation Analysis (DCCA) [11] is proposed to extend CCA by maximizing the difference of within-class and between-class variations across different feature spaces. Couple Metric Learning with Separable Criteria (SCML) [12] and simultaneous discriminant analysis (SDA) [13] incorporate the label information into the separable criteria and employ discriminative information to improve the recognition performance of the CML method. However, the above-mentioned approaches do not consider the intrinsic manifold structure of the sample sets. The performance of these methods notably degrades when the distribution of the samples in each class is non-Gaussian or the samples in a class are multimodal. Locality Preserving Canonical Correlation Analysis (LPCCA) [14] tries to capture the local geometrical structure by forcing nearby points in each original feature space to be close in the latent space. However, LPCCA does not take the label information into account so it is not well suited for classification. Recently, graph discriminant analysis on multi-manifold (GDAMM) [15] and coupled discriminant multi-manifold analysis (CDMMA) [16] employ both the local geometrical structure and the label information to address the problem of low-resolution face recognition.

In this brief paper, we propose a new method for low-resolution face recognition called Couple Manifold Discriminant Analysis with Bipartite Graph Embedding (CMDA_BGE). We introduce generalized bipartite graph to discretely approximate the underlying manifold structure of heterogeneous sample sets. Unlike GDAMM and CDMMA which construct the graph based on one of the two heterogeneous sample sets, our proposed CMDA_BGE constructs the generalized bipartite graph on two heterogeneous sample sets and contains more completed information. CMDA_BGE preserves within-class local geometrical structure and maximizes between-class separability at the same time. The derivation of our CMDA_BGE is based on a novel pairwise interpretation of the Fisher discriminant analysis [17] in the couple subspace. Therefore, CMDA_BGE takes advantages of both the locality preserving power and the discriminating power to improve the performance of heterogeneous classification, especially for the heterogeneous datasets whose samples in a class are multimodal or obey non-Gaussian distribution.

2. Couple manifold discriminant analysis with bipartite graph embedding

2.1. Problem statement

Suppose that we are given two sets of sample points with different dimensions $X=\{x_i \in \mathbb{R}^{D_x}, i=1,\dots,N_x\}$, $Y=\{y_i \in \mathbb{R}^{D_y}, i=1,\dots,N_y\}$ and the associated class labels $l_i^x \in \{1,2,\dots,c\}$, $l_i^y \in \{1,2,\dots,c\}$, where c is the number of classes. Let n_l^x be the number of samples in class l from X, and n_l^y be the number of samples in class l from Y, we have $\sum_{l=1}^{c} n_l^x = N_x$ and $\sum_{l=1}^{c} n_l^y = N_y$. Moreover, for each heterogeneous set X or Y, data points from each class are sampled from a smooth manifold $\mathcal{M}_l^x \subseteq \mathbb{R}^{D_x}, l \in \{1,2,\dots,c\}$ or $\mathcal{M}_l^y \subseteq \mathbb{R}^{D_y}, l \in \{1,2,\dots,c\}$. Furthermore, we are given a similarity constraint set $\mathcal{S}$ in the form of two-tuples for the data points having similarity relation across heterogeneous sets. Thus, if $x_i \in X$ is similar with $y_j \in Y$, then $(i,j) \in \mathcal{S}$ (In our experiments, the low-resolution image and the corresponding high-resolution image have similarity relation). The objective of heterogeneous classification for data points residing on multiple manifolds with different dimensions is to learn a couple of mappings $P_x \in \mathbb{R}^{D_x \times d}$ and $P_y \in \mathbb{R}^{D_y \times d}$ of the heterogeneous manifolds to a unified Euclidean space $\mathbb{R}^d$ $(d < D_x, d < D_y)$ representing the similarity relation $\mathcal{S}$ of the heterogeneous sets, so that we can perform the affinity measure or classification for the heterogeneous points in this unified Euclidean space by the traditional Euclidean distance measure or the nearest neighbor approach.

2.2. Bipartite graph embedding

We usually have no prior knowledge about the underlying manifold structure of the sample set. In practice, we often construct a graph incorporating neighborhood information of the dataset to discretely approximate the local geometry of the data manifold. For the heterogeneous sets X and Y defined in Section 2.1, we can build an undirected bipartite graph [18,19] $G=((X,Y),\mathcal{S})$ to model the relationship between them, where X and Y are sets of heterogeneous vertices and each edge in $\mathcal{S}$ has one endpoint in X and one endpoint in Y. In order to further describe the local geometrical structure of the whole heterogeneous sets, we introduce a generalized bipartite graph $\hat{G}$ which incorporates neighborhood information about the heterogeneous sets.

The construction of the generalized bipartite graph is shown in Fig. 1. Specifically, in the first step, we put edges between the data points from the same class in the set X or Y (see the solid lines with arrows in Fig. 1). We also put an edge between the point pairs in the similarity constraint set $\mathcal{S}$ (see the connections across sets X and Y with solid lines). We compute the distance matrices D^x and D^y for each set X and Y, and define the distance matrix D^s for the point pairs in the similarity constraint set $\mathcal{S}$ as follows:

$$D_{i,j}^x = \begin{cases} 1 - \dfrac{x_i^T x_j}{\|x_i\| \|x_j\|} & \text{if } (i,j) \in E_x \\ \infty & \text{otherwise} \end{cases}, \tag{1}$$

$$D_{i,j}^y = \begin{cases} 1 - \dfrac{y_i^T y_j}{\|y_i\| \|y_j\|} & \text{if } (i,j) \in E_y \\ \infty & \text{otherwise} \end{cases}, \tag{2}$$

$$D_{i,j}^s = \begin{cases} 0 & \text{if } (i,j) \in \mathcal{S} \\ \infty & \text{otherwise} \end{cases}. \tag{3}$$

where E_x is a set of edges connecting the points from the same class in X and E_y is a set of edges connecting the points from the same class in Y. In fact, we have computed

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