Neurocomputing ∎ (∎∎∎∎) ∎∎∎–∎∎∎

Contents lists available at ScienceDirect

Neurocomputing

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

Multi-view Sparsity Preserving Projection for dimension reduction

Huibing Wang [a,b], Lin Feng [a,b,*], Laihang Yu [a], Jing Zhang [a]

[a] School of Computer Science and Technology, Faculty of Electronic Information and Electrical Engineering, Dalian University of Technology, Dalian 116024, China
[b] School of Innovation and Entrepreneurship, Dalian University of Technology, Dalian 116024, China

ARTICLE INFO

Article history:
Received 22 January 2016
Received in revised form
17 July 2016
Accepted 28 July 2016
Communicated by Steven Hoi

Keywords:
Multi-view
Dimension reduction
Sparse subspace learning
Multi-view Sparsity Preserving Projection
Sparse representation

ABSTRACT

In the past decade, we have witnessed a surge of interests of learning a low-dimensional subspace for dimension reduction (DR). However, facing with features from multiple views, most DR methods fail to integrate compatible and complementary information from multi-view features to construct low-dimensional subspace. Meanwhile, multi-view features always locate in different dimensional spaces which challenges multi-view subspace learning. Therefore, how to learn one common subspace which can exploit information from multi-view features is of vital importance but challenging. To address this issue, we propose a multi-view sparse subspace learning method called Multi-view Sparsity Preserving Projection (MvSPP) in this paper. MvSPP seeks to find a set of linear transforms to project multi-view features into one common low-dimensional subspace where multi-view sparse reconstructive weights are preserved as much as possible. Therefore, MvSPP can avoid incorrect sparse correlations which are caused by the global property of sparse representation from one single view. A co-regularization scheme is designed to integrate multi-view features to seek one common subspace which is consistent across multiple views. An iterative alternating strategy is presented to obtain the optimal solution of MvSPP. Various experiments on multi-view datasets show the excellent performance of this novel method.

1. Introduction

In recent years, along with the arrival of information age, one sample has been described at different viewpoints [1,2] because more useful information exists in multiple views than in a single one. For example, one image can be represented by multi-view features (as Fig. 1), such as Gist, Local Binary Patterns (LBP) [3] and Edge Direction Histogram (EDH) [4]. Although features from different views reflect various properties of one same sample, they contain compatible and complementary information which can improve the performances of most traditional methods.

In many application domains, such as image retrieval [5,6], text categorization [7] and face recognition [8–10], most features which are extracted from multiple views always locate in high-dimensional spaces. Direct manipulations on these features are time consuming and computationally expensive [11]. To tackle this problem, researchers have developed a variety of DR methods to find appropriate low-dimensional subspaces by preserving some certain properties of samples. Principle Component Analysis (PCA) [12] and Linear Discriminant Analysis (LDA) [13] are two most popular ones which are widely utilized in various applications. PCA is an unsupervised method which maximizes the global variance of data to obtain the low-dimensional subspace. Although it is simple and convenient, PCA lacks discriminative ability since it cannot take label information into consideration. LDA is a supervised DR method which makes full use of label information. It constructs the subspace by maximizing the ratio between the trace of between-class scatter and the trace of within-class scatter. However, both PCA and LDA only maintain the global Euclidean structure while neglecting the local correlations between samples. Locality Preserving Projections (LPP) [14] aims to find an optimal subspace which can preserve the correlations between adjacent samples as much as possible. Neighborhood Preserving Embedding (NPE) [15], Locality Sensitive Discriminant Analysis (LSDA) [16] and Marginal Fisher Analysis (MFA) [17] are all local methods which construct low-dimensional subspaces by different means. Unlike these linear methods above, many manifold learning methods [18–20] have been developed, which promise to be useful for dealing with the nonlinear high-dimensional data which lie on or near a submanifold of the observation space. Locally Linear Embedding (LLE) [18], Laplacian Eigenmaps (LE) [19] and Local Tangent Space Alignment (LTSA) [20] are representative manifold learning methods which have attracted wide attentions. Sparse subspace learning (SSL) [21–24] is a novel family of DR methods which considers sparse relationships between samples. Among all

* Corresponding author at: School of Computer Science and Technology, Faculty of Electronic Information and Electrical Engineering, Dalian University of Technology, Dalian 116024, China.

http://dx.doi.org/10.1016/j.neucom.2016.07.044

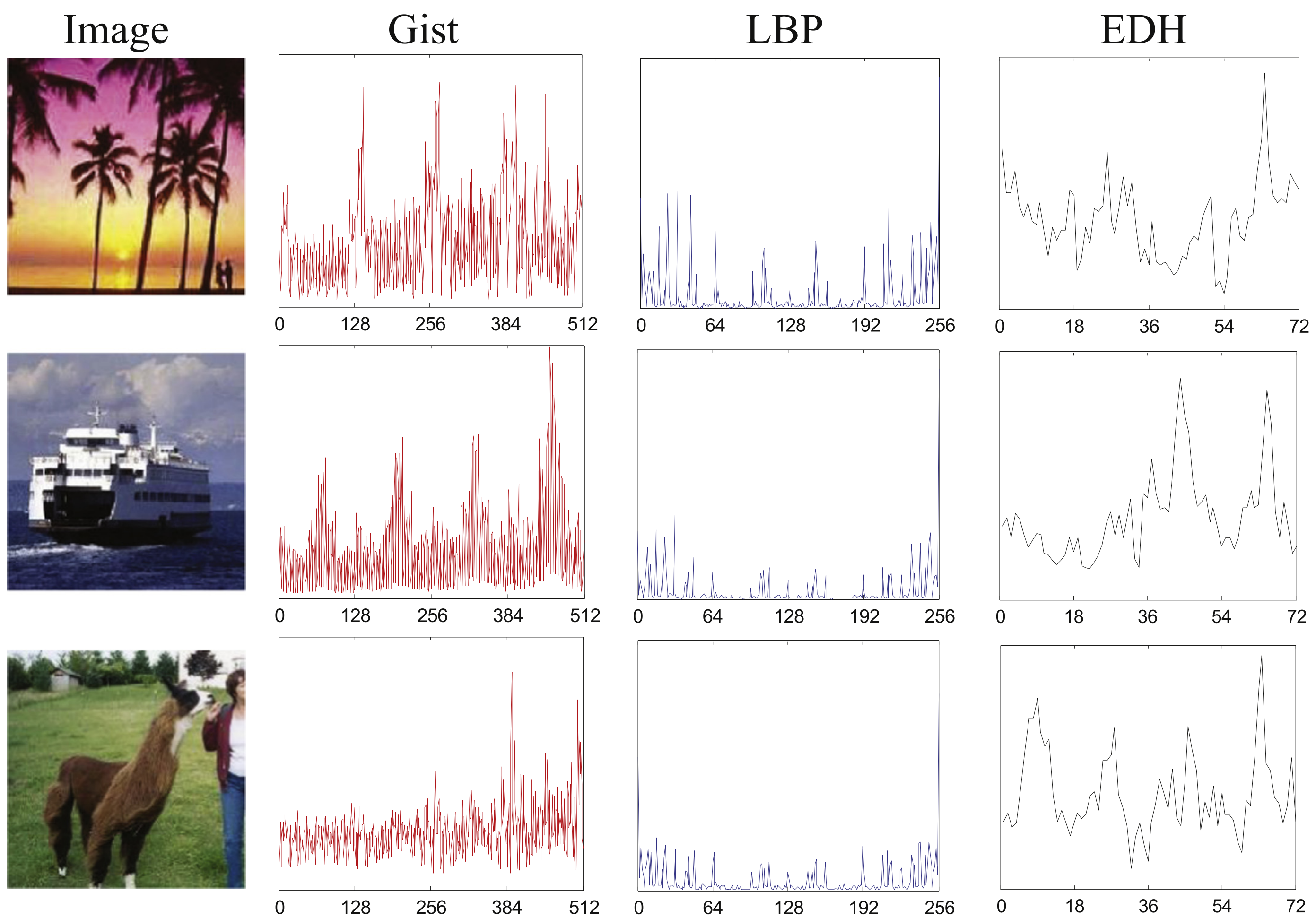

Fig. 1. Complementary characteristics of multi-view features in representing the images.

SSL methods, Sparsity Preserving Projections (SPP) [10] is one of the most influential methods. It preserves the sparse reconstructive weights (SRWs) which are calculated by sparse representation (SR) [25]. Although many DR methods are proposed, most DR methods fail to integrate compatible and complementary information from multi-view features to construct the low-dimensional subspace.

The past decade has also seen significant development of multi-view methods in various fields. A plenty of studies [26–30] focus on incorporating the multi-view setting with independent views to obtain better clustering performances. Chaudhuri [26] proposed a multi-view clustering method by using Canonical Correlation Analysis (CCA) [27]. It utilizes CCA to project multi-view data into the subspace to get an easier clustering problem, and then apply standard clustering algorithms in this space. Kumar [28] developed a multi-view spectral clustering framework which achieves this goal by co-regularizing a clustering hypotheses, and proposed two co-regularization schemes to accomplish this. Xu [29] presented a new Multi-view Self-Paced Learning (MSPL) for clustering. A novel probabilistic smoothed weighting scheme is designed in MSPL. Some researchers devote themselves to expanding single-view DR algorithms to multi-view setting. Multiview Spectral Embedding (MSE) [31] incorporates conventional spectral-embedding algorithms with multi-view data to find the low-dimensional representations of original multi-view data. However, MSE only exploits multi-view graph Laplacian matrices and abandons multi-view samples in the process of constructing the subspace. Multi-view Discriminant Analysis (MvDA) [32] is proposed to extend LDA to a multi-view setting. It can project features from multiple views to one discriminative common space. Yu [33] proposed a multi-view features fusion method to construct low-dimensional subspace. Both intraclass and interclass geometries are taken into consideration so that the discriminability is effectively preserved.

1.1. Motivation

For many real-world applications, dimension reduction is a necessary tool because the dimensions of samples are higher and higher. As an important family of DR, sparse subspace learning methods have attracted wide attentions due to their excellent performances. With the wide applications of multi-view data, a multi-view SSL method is necessary to fill the blank of this field. Although some multi-view methods are proposed, the following 2 aspects have not been investigated comprehensively and thoroughly:

(1) How to fully exploit the sparse reconstructive weights (SRWs) from multiple views and construct a common sparse subspace for multi-view features: Single-view SRWs can reflect sparse relationships between features, which always contain incorrect correlations due to the global property of SR. They can cause negative impacts on single-view sparse subspace learning method. Maintaining multi-view SRWs can improve the discriminative ability of the learned subspace. However, existing multi-view DR methods have not taken this issue into consideration.
(2) How to integrate multi-view features from different dimensional spaces into one unified framework: Although multi-