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Discriminant structure embedding for image recognition

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ABSTRACT

Neighborhood preserving embedding (NPE) has been widely used to learn the intrinsic structure of data. However, it may impair the local topology and ignore the diversity of data. In this paper, we present a dimensionality reduction approach, namely discriminant neighborhood structure embedding (DNSE). DNSE constructs an adjacency graph to characterize the diversity of data and combines NPE to learn the local intrinsic geometric structure, which well characterizes both similarity and diversity. Finally, the global structure, which is obtained by LDA, is integrated with the aforementioned local structure to build the objective function. Experiments on the four image databases illustrate the effectiveness of the proposed approach.

1. Introduction

Dimensionality reduction (DR) is one of the fundamental problems in pattern recognition, machine learning, and face recognition areas. It aims to extract the low-dimensional representation that can well characterize the meaningful structure hidden in the high-dimensional data and be useful for subsequent analysis such as data clustering, classification and representation. Two of the most popular linear techniques for this purpose are principal component analysis (PCA) [1] and linear discriminant analysis (LDA) [2].

PCA is an unsupervised method and projects the data along the direction of maximal variance. LDA is a supervised method and seeks the project axes on which the data points of different classes are far from each other while requiring data points of the same class to be close to each other. PCA and LDA have proven their effectiveness in several applications. However, methods based on PCA and LDA techniques are optimal under Gaussian assumption and mainly capture the global structure that may impair the local geometrical structure of data [3–6].

Many previous approaches have demonstrated that local geometrical structure is very important for dimensionality reduction and image classification [7–9]. The local geometrical structure of data can be effectively captured by manifold learning approaches [5,7,9–12]. Two of the most popular manifold learning approaches are locality preserving projection (LPP) [8], which is a linear approximation of the Laplacian eigenmaps (LE) [13], and neighborhoods preserving embedding (NPE) [9], which is a linear approximation of the locally linear embedding (LLE) [4]. Although their motivations are different, they both map nearby points in the high-dimensional space to nearby data in the low-dimensional space and mainly characterize the similarity of data [14,15]. Motivated by LPP and NPE, many discriminant approaches have been developed for feature extraction, such as margin fisher analysis (MFA) [16], local fisher discriminant analysis (LFDA) [17], maximum margin projection (MMP) [18], locality sensitive discriminant analysis (LSDA) [19], discriminant locality alignment (DLA) [21], neighborhood minmax projection (NMMP) [20] and discriminant locally linear embedding (DLLE) [22]. These approaches cannot ensure that the basis vectors shall be combined for a low-dimensional representation in non-subtractive way which is a computational theory of object recognition. To overcome this shortcoming, many approaches have been developed by imposing non-negative constraints to reinforce the performance. These non-negative approaches [23–25] characterize the part-based geometric properties of data and mainly capture the local geometrical structure of data.

In real-world applications, such as face recognition and image recognition, the intrinsic geometric structure of data is unknown and complex. Thus, only global or local geometric structure may not be sufficient to represent the intrinsic structure of data [26–28]. Following this idea, Chen et al. [26] proposed LapLDA by integrating LPP into the objective function of LDA. Cai et al. [29] proposed semi-supervised discriminant analysis (SDA), which was extended by Nie et al. [30], by integrating the local intrinsic structure of the labeled and unlabeled data into the objective

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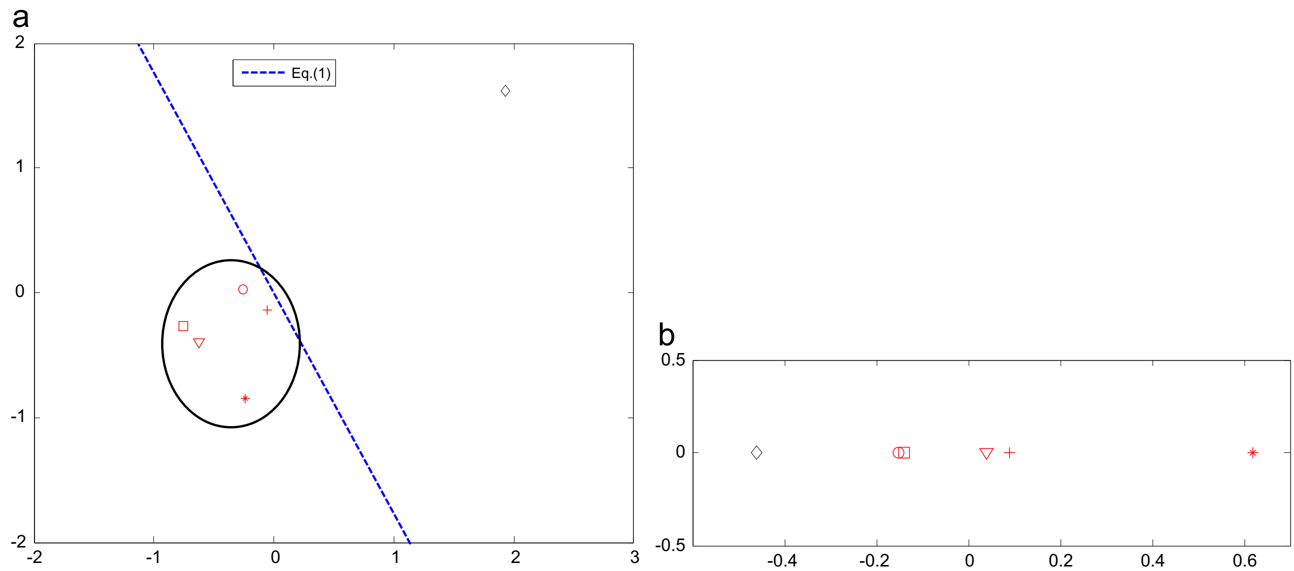

Fig. 1. (a) Two-dimensional data and one-dimensional embedding spaces obtained by Eq. (1); (b) one-dimensional embedded results obtained by Eq. (1).

function of LDA. Li et al. [31] proposed locally linear discriminant embedding (LLDE) by combining NPE and MMC (maximum margin criterion). It is generally considered that LPP or NPE has the *local topology preserving property*: a pair of graph nodes with high mutual similarities (i.e., small distance) is embedded nearby in the embedding space, whereas a pair of graph nodes with small mutual similarities (i.e., large distance) is embedded far-way in the embedding space [15]. However, local intrinsic structure of data characterized by LPP and NPE characterizes the similarity of data and ignores the diversity that is important for image classification and also characterizes the local geometric of data [15,27,28,32–37] due to the uneven distribution of data in real world applications. This results in inexact local topology representation of data.

In this paper, we propose a novel linear dimensionality reduction approach, called discriminant neighborhood structure embedding (DNSE), for feature extraction. To be specific, we construct an adjacency graph to characterize the diversity of data, and employ NPE to capture the similarity of data. Thus, we can well preserve the local topology of data. Finally, we combine the global structure, which is learned by LDA, with the aforementioned topology of data to form the objective function of DNSE. Experiments on four image databases illustrate the effectiveness of DNSE.

The remainder of this paper is organized as follows. Section 2 analyzes NPE and LDA. Section 3 presents DNSE. Some experimental results are reported in Section 3.1. The conclusions are drawn in Section 4.

2. Problem statements

2.1. NPE

NPE is a useful linear manifold learning method for dimensionality reduction and preserves the local geometric reconstruction relationship of data. Given training data $X=[x_1\ x_2\ \cdots\ x_N]\in R^{d\times N}$, NPE seeks to find the projection vector α by solving the following objective function [9].

$$\min_{\alpha}\ \alpha^T XMX^T\alpha \tag{1}$$

where $M=(I_N-W)^T(I_N-W)$, I_N denotes the N-dimensional identity matrix. The elements W_{ij} in weight matrix W denote the coefficients of reconstructing x_i from its neighbors $\{x_j\}$ and are calculated as in Refs. [4,9].

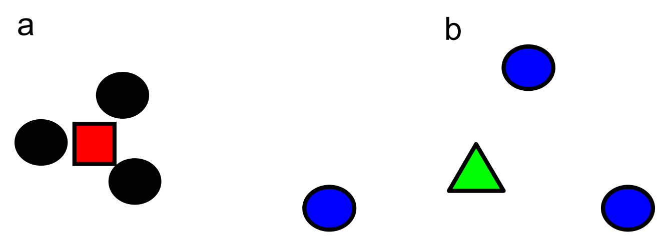

Fig. 2. Some data points. (a) Points lie in a compact region; (b) points lie on a sparse region.

The objective function (1) preserves the local reconstruction relationship and characterizes the similarity of data. However, it results in the following disadvantages in real-world applications.

- The objective function (1) results in unstable local intrinsic structure representation. The objective function (1) maps nearby data points in the high-dimensional space to a subspace in which they are close to each other [15]. In the ideal case, the nearby data points are mapped to a single point in the low-dimensional space. Moreover, in real applications, the distribution of training data is usually uneven, thus the k nearest neighbors of some data may lie in a compact region while the k nearest neighbors of the other data may lie in a sparse region. If we always map neighbor points to nearby points with the low-dimensional representation, we may ignore the geometric structure embedded in the nearby data points, which lie in sparse region and characterize the diversity of data. In summary, Eq. (1) only characterizes the similarity of data and ignores the diversity of data, which can be learned by maximizing the variance of data [32–34]. In many real cases, the intrinsic structure of data is unknown and complex, and only similarity or diversity may not be sufficient to represent the intrinsic structure of data in the low-dimensional space.
- The objective function (1) may impair the local topology of data. NPE cannot ensure that the smaller the distance between nearby points is, the larger the value of the weighted coefficient is in the objective function (1). Moreover, in the objective function (1), the large distance dominates the optimal solution of Eq. (1). Therefore, Eq. (1) may not guarantee that the smaller the distance between nearby data points is, the closer they are embedded in the low-dimensional space, leading to many violations of local topology preserving at small distance data