



Fuzzy local discriminant embedding for image feature extraction [☆]



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ABSTRACT

In pattern recognition, feature extraction techniques have been widely employed to reduce the high dimensionality of data. In this paper, we propose a novel algorithm called fuzzy local discriminant embedding (FLDE) based on the unsupervised discriminant projection criterion and fuzzy set theory for image feature extraction and recognition. In the proposed method, a membership degree matrix is firstly calculated using the fuzzy k -nearest neighbor (FKNN) algorithm, and then the membership degree and the label information are incorporated into the definition of the weighted matrices to get the fuzzy local scatter and fuzzy nonlocal scatter. After characterizing the fuzzy nonlocal scatter and the fuzzy local scatter, a concise feature extraction criterion is derived via maximizing the ratio between them. Experimental results on the ORL, FERET, and CMU PIE face databases show the effectiveness of the proposed method.

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1. Introduction

Dimensionality reduction is to construct a meaningful low-dimensional representation of high-dimensional data. Since there are large volumes of high-dimensional data in numerous real-world applications, dimensionality reduction is a fundamental problem in many scientific fields. From the perspective of pattern recognition, dimensionality reduction is an effective means of revealing the distinctive features from the original data and improving the computational efficiency of pattern matching. The two most well-known linear methods are principal component analysis (PCA) [1] and linear discriminant analysis (LDA) [2,3].

PCA aims at finding a linear mapping that can preserve the total variance by maximizing the trace of feature covariance matrix. The optimal projections of PCA are the eigenvectors associated with the d largest eigenvalues of the data's covariance matrix. PCA is an unsupervised method, which may be unsuitable for classification tasks. Different from PCA which has nothing to do with the label information, LDA takes full consideration of the label information. LDA aims to find the optimal set of projection vectors that maximize the determinant of the between-class scatter matrix and at the same time minimize the determinant of the within-class scatter matrix. Despite the effectiveness of LDA in many applications, its success is still limited because the number of the available projection directions is lower than the number of classes. Furthermore, since

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the number of the dimension is often higher than the number of observations, an intrinsic limitation of traditional LDA is that it fails to work when the within-class scatter matrix is singular, which is known as the small sample size (SSS) problem [4]. In the past, many effective and efficient methods [5–9] have been explored to deal with this problem.

Recent studies have shown that large volumes of high-dimensional data possibly reside on a nonlinear sub-manifold. The two classical methods PCA and LDA may fail to discover the intrinsic manifold structure of the data since they mainly focus on discovering the global Euclidean structure of the data. In recent years, many useful manifold learning based methods have been developed to discover the intrinsic low-dimensional embedding of data. Among them, the most representative ones are isometric feature mapping (Isomap) [10], locally linear embedding (LLE) [11] and Laplacian Eigenmap (LE) [12]. These methods aim to preserve local structures in small neighborhoods and successfully derive the intrinsic structure of nonlinear manifold. However, they are implemented restrictedly on the training set and cannot give explicit maps on new test data points for recognition problems. In [13], Yan et al. presented a general framework for dimensionality reduction called graph embedding from which many algorithms, such as PCA, LDA, Isomap, LLE, and Laplacian eigenmap, can all be reformulated. In [14], He et al. proposed locality preserving projections (LPP), which builds a graph incorporating neighborhood information of the data set and aims to optimally preserve local structure in a certain sense. In contrast to most manifold learning algorithms, LPP possesses an obvious advantage that the map of LPP is explicit and is easy to compute. To boost the ability of locality preserving, Cai et al. proposed an orthogonal LPP [15]. By exploiting the label information to improve the discriminating ability of LPP, Li et al. proposed kernel class-wise LPP [16].

Motivated by the idea of classification-oriented multi-manifold learning, Yang et al. proposed an unsupervised discriminant projection (UDP) [17] algorithm. UDP characterizes the local scatter and the non-local scatter and looks for a linear projection that not only maximizes the non-local scatter and but also minimizes the local scatter simultaneously. This property contributes to make UDP more intuitive and more powerful than most of up-to-date methods. However, it must be noted that UDP is completely unsupervised with regard to the label information. It is generally believed that the label information can make the algorithm more discriminative. Moreover, a major drawback in UDP is that the affinity graphs are constructed based on the assumption that the membership degree of each sample to corresponding class is the same. Since the distances between the samples in local k -nearest neighborhood might also vary in a big range, the graph constructed in this way might have potential disadvantages that the weights are not in accordance with the natural relations of samples in actual applications. To better describe the relations in the samples, some fuzzy pattern recognition methods [18–25] are proposed in recent years. Kwak et al. [18] proposed a fuzzy fisher classifier based on fuzzy k -nearest neighbor (FKNN) [25] and the recognition rate is improved on different face databases. Laskaris et al. [19] suggested the fuzzy connectivity graph to represent the relative distribution of the data and got remarkable result for data clustering. Zhao et al. [21] introduced fuzzy gradual graphs to reflect the relationship between samples and achieve impressive pattern matching results. Ye et al. [23] designed a non-negative matrix factorization algorithm based on fuzzy k nearest neighbor graph and achieved reliable recognition performance for classification. Li et al. [24] presented a fuzzy maximum scatter difference (FMSD) algorithm by incorporating fuzzy theory into traditional MSD [9] algorithm and obtained promising result for face recognition. This testified the effectiveness of fuzzy pattern recognition method.

To overcome the limitations of UDP, we propose a novel supervised manifold learning method named as fuzzy local discriminant embedding (FLDE) in the paper. In FLDE, a membership degree matrix is firstly calculated using FKNN algorithm, and then the membership degree and the label information are incorporated into the definition of the weighting matrices. Significantly differing from the existing graph-based algorithms, two novel fuzzy affinity graphs are constructed in FLDE, where it is important to maintain the original neighbor relations and preserve the relationship degree of each sample corresponding to given classes. Besides, owing to taking advantage of the label information, the proposed algorithm can capture more valuable discriminative information in comparison with UDP.

The rest of this paper is organized as follows. In Section 2, we briefly review the related works. In Section 3, we introduce the new method in detail. In Section 4, experiments with face image data are presented to evaluate the effectiveness of the proposed algorithm. Conclusions are summarized in Section 5.

2. Related works

Let $X = [x_1, x_2, \dots, x_n]$ denote a set of n training data points in R^N , and $A \in R^{N \times d}$ ($d < N$) is a projection matrix. Using the matrix A , we can get the representation of x_i ($i = 1, 2, \dots, n$) in the d -dimensional space as: $y_i = A^T x_i$. In this section, we briefly review UDP and the fuzzy k -nearest neighbor algorithm.

2.1. UDP

UDP seeks to find a set of optimal projection vectors to maximize the ratio of the nonlocal scatter to the local scatter. For the convenience of discussion, we use two weighted adjacency graphs $G_L = \{V, E, H_1\}$ and $G_N = \{V, E, H_2\}$ to characterize the local scatter and the nonlocal scatter of the data respectively, where V denotes the set of vertices, E is the set of edges connecting the vertices, H_1 is the local weighted matrix with elements measuring the similarity of two points that are within a local area and H_2 is the nonlocal weighted matrix with elements measuring the similarity of two points that are outside a local area.

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