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2D-LPP: A two-dimensional extension of locality preserving projections

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Abstract

We consider the problem of locality preserving projections (LPP) in two-dimensional sense. Recently, LPP was proposed for dimensionality reduction, which can detect the intrinsic manifold structure of data and preserve the local information. As far as matrix data, such as images, are concerned, they are often vectorized for LPP algorithm to find the intrinsic manifold structure. While the dimension of matrix data is usually very high, LPP cannot be implemented because of the singularity of matrix. In this paper, we propose a method called two-dimensional locality preserving projections (2D-LPP) for image recognition, which is based directly on 2D image matrices rather than 1D vectors as conventional LPP does. From an algebraic procedure, we induce that 2D-LPP is related to two other linear projection methods, which are based directly on image matrix: 2D-PCA and 2D-LDA. 2D-PCA and 2D-LDA preserve the Euclidean structure of image space, while 2D-LPP finds an embedding that preserves local information and detects the intrinsic image manifold structure. To evaluate the performance of 2D-LPP, several experiments are conducted on the ORL face database, the Yale face database and a digit dataset. The high recognition rates and speed show that 2D-LPP achieves better performance than 2D-PCA and 2D-LDA. Experiments even show that conducting PCA after 2D-LPP achieves higher recognition than LPP at the same dimension of feature spaces.

Keywords: Locality preserving projection (LPP); Two-dimensional projection; Linear projection; Dimensionality reduction

1. Introduction

In pattern recognition, the process of identifying unlabeled test data, which are from the same group of identities in training set is called identification. Identification is actually a problem of pattern classification [8]. When the data have high dimension, such as image data, identification (recognition) becomes very hard.

Due to the wide application of image recognition, many methods have been developed for it over the past few decades. Appearance-based methods are among those well studied. While they are often confronted with dimensionality reduction problems because the dimension of vector representation of an (m × n) image is too high to allow fast and good recognition. Two of the most fundamental dimensionality reduction methods are principal component analysis (PCA) [25] and linear discriminant analysis (LDA) [2]. And now two new techniques, namely 2D-PCA [27] and Laplacianfaces [13], have appeared in recent literature.

PCA [25] aims to find a linear mapping, which preserves total variance by maximizing the trace of feature variance. The optimal mapping is the leading eigenvectors of the data's total variance matrix associated with the leading eigenvalues. The details and theoretical foundations of PCA could be found in [14]. While PCA does not sufficiently use the class label of given data, Chen and Sun [5] proposed a class-information-incorporated PCA (CIPCA) in feature extraction to make use of class label information for discrimination. Moreover, PCA cannot preserve local information due to pursuing maximal variance. Tan and Chen [23] proposed adaptively weighted sub-pattern PCA (Aw-SpPCA), which operates on sub-patterns partitioned from an original whole pattern and separately extracts features from them, then different contributions of each part are endowed to a classification

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task. To reduce the effect of large variations of poses and/or illuminations, Kim et al. [15] proposed a second-order mixture-of-eigenfaces method that combines the second-order eigenface method and the mixture-of-eigenfaces method. Each mixture of multiple eigenface sets is obtained from expectation-maximization (EM) learning [7].

LDA [2] pursues a linear mapping, which preserves discriminant information by maximizing between-class scatter meanwhile minimizing within-class scatter. So LDA contains the most discriminant information in the training set rather than the test set. Given a sufficient training sample, LDA is superior to PCA. While for a small sample size problem, PCA can outperform LDA because LDA is sensitive to the training data set [19]. Recently, Yang et al. [26] proposed a complete kernel Fisher discriminant analysis (CKFD) algorithm, which makes full use of regular and irregular discriminant information for recognition.

Compared with traditional PCA, 2D-PCA [27] extracts image features directly from 2D image matrices rather than 1D vectors so the image matrices do not need to be transformed into vectors. An image covariance matrix is constructed from the original image matrices for feature extraction. The optimal projection axes are its orthogonal eigenvectors corresponding to its largest eigenvalues. Due to the smaller size of image variance matrix than original variance matrix, 2D-PCA requires less time to extract image features and achieves a better recognition rate. Li and Yuan [17] extended the idea of using directly image matrix for LDA and presented 2D-LDA. Image between-class variance matrix and image with-class variance matrix were constructed for 2D-LDA. Even now $(2D)^2PCA$ [28] and $(2D)^2FLD$ [21] have been proposed, which investigated two-directional two-dimensional projections along not only in row direction but also in column direction to further reduce the dimension of feature space.

Laplacianfaces [13] is based on a technique called locality preserving projections (LPP) [12], which finds an embedding that preserves local information, and obtains a face subspace that best detects the essential face manifold structure. They construct a similarity matrix of data points, and then minimize the sum of square difference of feature weighted by the similarity matrix elements. The optimal projection axes best preserve the local structure of the underlying distribution in the L^2 sense. From analysis they found that LPP is connected with PCA and LDA. LPP can be seen as a generalization of LDA. He et al. [10] utilized the idea of LPP for document representation and indexing and constructed the algorithm of locality preserving indexing (LPI). However, LPI is sensitive to the number of dimensionality. Cai and He [4] improved it by iteratively computing the mutually orthogonal basis functions which respect the local geometrical structure. The algorithm (called Orthogonal LPI) is insensitive to the number of dimensions, which makes it an efficient data preprocessing method for text clustering, classification, retrieval, etc. Min et al. [20] proposed locality pursuit embedding (LPE), which is similar to LPP, to produce a linear embedding that respects the local geometrical structure described by the Euclidean distances. Zheng et al. [29] applied the idea of LPP for image database clustering and constructed the algorithm locality preserving clustering (LPC), in which they well-handled the pseudo solutions and the trivial solution of LPP and a renormalization step is added to improve the robustness of the algorithm. He [9] and Lu and He [18] proposed incremental LPP for image retrieval, which is a semi-supervised subspace learning algorithm that makes use of relevance feedbacks to enhance the performance of an image retrieval system from both short- and long-term perspectives. Cheng et al. [6] proposed supervised kernel LPP (SKLPP) for face recognition, in which geometric relations are preserved according to prior class-label information and complex nonlinear variations of real face images are represented by nonlinear kernel mapping.

There are lots of other methods, which pursue dimensionality reduction and image recognition in the literature, such as kernel PCA [26], ICA [1], NMF [16], Isomap [24], Laplacian Eigenmaps [3] and LLE [22]. Kernel PCA and ICA both can outperform PCA but their computational complexities are high. Non-negative matrix factorization (NMF) learns the parts of objects by its use of non-negativity constraints, which leads to a parts-based representation of objects. The solutions of NMF can only be achieved by iterative algorithm. Isomap is a variant of MDS, which uses the geodesic distance rather than Euclidean distance between points. It seeks to preserve the intrinsic distances of neighborhood points. Laplacian Eigenmaps shows some similarity to Laplacianfaces [12,13]. It is only a nonlinear embedding of training data and it is difficult to know data outside of training set. Locally linear embedding (LLE) is a nonlinear technique investigating the nonlinear structure of a manifold, which only discovers the intrinsic structure of training samples and is hard to extend to holistic space for recognition. Recently, He et al. [11] incorporated the idea of LLE into LPP and constructed the algorithm of neighborhood preserving embedding (NPE).

Nonlinear methods and kernel-based methods require more expensive computation for higher recognition rate. 2D-PCA and 2D-LDA are simple in computational complexity, which only see the Euclidean structure of image space. LPP can find an embedding that preserves local information. But if the training samples are insufficient and data dimension is high especially for image data, LPP cannot be used directly due to singularity of matrices. Motivated by the idea of 2D-PCA, which operates directly on image matrix, we investigated LPP in two-dimensional sense based directly on image matrices, which is called two-dimensional locality preserving projections (2D-LPP). Its speed and recognition performance are evaluated.

The rest of this paper is organized as follows: 2D-PCA, 2D-LDA and LPP methods are retrospected in Section 2; In Section 3, 2D-LPP is demonstrated in detail;