摘 要

计算机视觉和模式识别领域越来越多的涉及到高维复杂数据的有效降维问题，具有重要的理论意义和使用价值。随着机器学习等领域的快速发展，降维算法快速涌现，如线性降维方法近邻保持嵌入（NPE）以及非线性降维方法局部线性嵌入（LLE）等。然而，这些方法都存在邻域选择与权重计算分离，算法效果依赖参数等不足，为它们的实际应用带来了影响。

针对高维复杂数据的有效降维，特别是无监督条件下的非线性降维问题，本文在调研和分析已有典型线性降维方法基础上，重点研究了近年来出现的稀疏表示在数据降维上的应用，提出了稀疏保持嵌入（SPE）线性降维方法和稀疏线性嵌入（SLE）非线性降维方法。本文的主要研究结果概括如下：

1. 对典型的线性降维方法进行了实验对比

以人脸识别为应用案例，对主成分分析（PCA）等五种典型的线性降维方法进行了实验对比，系统分析了它们的性能情况及其优缺点。

2. 对基于稀疏表示的人脸识别方法进行了实验验证

已有文献认为稀疏表示分类器（SRC）的特色之一是只要特征维数大于某个阈值，那么其识别性能基本不依赖于特征表示。本文实验验证了 SRC 确实在更大程度上不依赖于特征表示。

3. 独立于现有工作，提出了一种稀疏保持嵌入（SPE）线性降维方法

本文将稀疏表示引入线性降维，提出了一种稀疏保持嵌入（SPE）线性降维方法。SPE 利用稀疏性描述数据局部结构，通过保持稀疏性学习得到低维子空间。与 NPE 等方法相比，SPE 将邻域选择与权重计算同时进行，通过较大稀疏系数对应的样本自动确定近邻关系，并包含了辨别信息。实验表明 SPE 优于目前典型的无监督线性降维方法。

4. 独立于现有工作，提出了一种稀疏线性嵌入（SLE）非线性降维方法

LLE 等非线性降维方法存在邻域选择依赖于参数设置、邻域选择与权重计算分离等不足，而且无法进行多类流形分析。为了弥补上述算法的不足，本文提出了一种稀疏线性嵌入（SLE）非线性降维方法。SLE 利用稀疏表示代替 LLE 中的邻域选择与权重计算，从而在保持局部结构的同时保持一定的全局非线性结构，实验结果表明 SLE 不仅能处理单流形数据，还可以处理 LLE 等传统方法不能处理的多流形数据。

上述研究工作表明，无论是线性还是非线性降维方法，均可通过引入稀疏表示来确定适合特定问题的近邻关系和连接权重，从而获得更佳的降维效果。

关键词：数据降维；线性降维；子空间学习；稀疏表示；人脸识别；流形学习；非线性降维

Research on Sparse Representation based Dimensionality Reduction

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Dimensionality reduction is a fundamental problem in many real-world applications such as image processing and pattern recognition, where data are often very high-dimensional. The pattern recognition community has witnessed a variety of methods for dimensionality reduction in recent years. Among them linear methods Locality Preserving Projections (LPP), Neighborhood Preserving Embedding (NPE), and nonlinear methods Locally Linear Embedding (LLE), Laplacian Eigenmaps (LE), Isometric Mapping (Isomap) are most popular. However, all five methods share some weaknesses, such as the need for a parameter which can essentially affect the performance of the algorithm, and the separation of the neighborhood selection and weight computation process.

Motivated by the discriminating power of sparse representation, we address the shortcomings of above mentioned dimensionality reduction algorithms and present a new method for linear dimensionality reduction, called Sparsity Preserving Embedding (SPE), along with a new method for nonlinear dimensionality reduction, called Sparsely Linear Embedding (SLE). On the whole, the contributions of this dissertation are summarized as follows:

1. A comparative study of popular linear dimensionality reduction algorithms. We compare five typical linear dimensionality algorithms on face recognition tasks. A systematic analysis is provided based on the experimental results.

2. Experimental verification on spares representation based face recognition. One characteristic of Spare Representation Classifier (SRC) lies in its robustness to features. We compare SRC with Nearest Neighbor Classifier (NN) on four different features. Experimental results demonstrate that SRC is robust to features to some extent.

3. Propose a new linear dimensionality reduction algorithm independently, called Sparsity Preserving Embedding (SPE). SPE is motivated by that each sample can be represented as sparse linear combination of all training samples via solving a ℓ_1 minimization problem, and the deduced sparse coefficients can be used to characterize relationships among samples. Unlike conventional local methods Locality Preserving Projections (LPP) and Neighborhood Preserving Embedding (NPE) whose local neighborhood is determined by selecting close points in the Euclidean space, the "local neighborhood" of SPE is automatically determined by samples corresponding to few large coefficients while seeking a sparse representation for each sample. Also, SPE works in a parameter-free way and needs no manual setting. Extensive experiments on face recognition demonstrate the superiority of SPE over traditional unsupervised methods Eigenfaces, Laplacianfaces, NPE, and comparable performance to supervised method Fisherfaces.

4. Propose a new method for nonlinear dimensionality reduction independently, called

Sparsely Linear Embedding (SLE). The underlying philosophy of SLE is that each sample can be reconstructed by the sparse linear superposition of the training data. The sparse reconstruction coefficients, used to characterize the relationships among samples, are derived by solving an ℓ_1 optimization problem. Compared to conventional local methods LLE, LE and Isomap, SLE combines the neighborhood selection process and the weight computation process in one step. The “local neighborhood” of SLE is automatically determined by samples corresponding to few large coefficients. Also, SLE works in a parameter-free way and needs no manual setting. Another advantage of SLE is that small coefficients of SLE connect samples of different manifolds and ensure the connectivity of the adjacent graph. Thus, SLE possesses the capability to conduct multiple manifolds analyses, which are impossible for LLE, LE and Isomap. Experiments on Multi-pose Face database, Rotated Images and COIL-20 database demonstrate the effectiveness of SLE to deal with both single manifold data and multiple manifolds data.

The above research work demonstrates that for both linear and nonlinear dimensionality reduction methods, we can utilize sparse representation to determine reliable neighborhood relationships and corresponding adjacency weights for specific datasets, and further obtain more favorable results.

Keywords: Sparse Representation, Dimensionality Reduction, Subspace Learning, Manifold Learning, Unsupervised Learning, Face Recognition