Multiple Manifold Learning in Pattern Recognition

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Manifold learning is a prevalent topic in pattern recognition and computer vision research. It is a technique used to address the problem of dimensionality reduction by mapping a set of high dimensional data into a low dimensional space, while preserving the intrinsic structure of the data. Manifold learning techniques can be broadly categorized relative to global and local techniques. Isometric feature mapping (ISOMAP) [1] is a well-known global manifold learning algorithm and Locally Linear Embedding (LLE) [2, 3], Laplacian Eigenmaps (LE) [4] and Hessian Eigen Maps (HE) [5] are methods that employ local manifold learning techniques. Due to their computational efficiency, local non-linear manifold learning algorithms have gained prominence.

These existing manifold learning techniques operate assuming that the original data with multiple classes lies on a single manifold. In pattern recognition, we often come across situations, where the data belonging to multiple classes do not lie on a single manifold. In other words, if the original data set has data belonging to multiple classes, data belong to each class lie on a particular manifold.

LLE is widely used in solving image classification and object recognition problems. However, the classical LLE algorithm is not capable of learning multiple manifolds in a given dataset. Thus, finding a multi-manifold learning algorithm based on LLE is significant for the advancement of LLE based pattern recognition applications. A multi-manifold learning technique based on the ISOMAP was proposed in [6] and some linear approaches for multi-manifold learning are also considered in [7, 8, 9]. ISOMAP is global technique and [7, 8, 9] are linear techniques. Thus, they are not applicable to LLE.

We propose LLE-based multiple manifold learning method (MM-LLE), which is a local non-linear multi-manifold form learning that preserves the class structure of the data. To achieve this, the proposed MM-LLE algorithm differs from LLE in several ways. In contrast to LLE, we use a supervised form of neighborhood selection in the first phase of the algorithm. Secondly, we use the nearness of manifolds in a multi-manifold space as a measure to find the optimum number of dimensions of the same space. Such a nearness measure makes it possible to obtain high classification accuracy.

The proposed algorithm was compared with four other well-known manifold learning algorithms. We have shown that the proposed MM-LLE algorithm outperforms the other four algorithms in terms of the recognition rate.

ADVISOR: Dr. J. F. Peters
References


