Locally Linear Embedding for Dimensionality Reduction in Hyperspectral Image Classification

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The pixels of a hyperspectral image (HSI) can be demonstrated in an *n*-dimensional feature space, n being the number of spectral bands of the image (n>100 for a typical HSI). To overcome the curse of dimensionality and avoid overfitting especially when a large number of features are present, dimensionality reduction techniques (DRTs) are utilized in HSI analysis. In the past, many linear, as well as non-linear DRTs, have been introduced in order to transform high dimensional feature spaces into low dimensional spaces. Implementation of linear DRTs like principal component analysis, linear discriminant analysis and feature space discriminant analysis on HSIs has been successful, given that the datasets possess a predominant linear scatter. In cases where the datasets are highly non-linear, the aforementioned linear DRTs fail in terms of subsequent classification problems. In this research, locally linear embedding (LLE) has been utilized for dimensionality reduction in HSI classification. LLE is a manifold learning method which finds low dimensional global coordinates when the data lie on a manifold embedded in a high dimensional space. The specialty of this technique is executing linear dimensionality reduction at each data point (since locally, a manifold is seen linear) of the manifold and then combining these data points with a minimal discrepancy. In this work, the LLE algorithm has been tested on standard HSI datasets of Salinas, Pavia University and Indian Pines with the aid of mathematical and statistical concepts and the tools available in MATLAB®. Also, a comprehensive comparison is done on the classification accuracies between LLE and other linear DRTs with respect to the above datasets. The results show the dominant performance of LLE over the other techniques. The contribution of our work is generalizing the suitability of LLE for dimensionality reduction in the hyperspectral domain by testing the algorithm on standard HSI datasets.

Key words: Hyperspectral imaging, dimensionality reduction, locally linear embedding, non-linear, manifold learning