A Novel Method for Hyper Spectral Image Classification using CNN based Laplacian Eigen map Pixels Distribution Flow

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Abstract—The problems of under classification, in hyperspectral imagery (HSI) and the high complexity of computing Eigen value problem for searching the nearest neighbouring pixel still exist in the nonlinear dimensionality reduction with LE-PD for classification. Therefore, this paper proposes an innovative graphical method namely CNN (Condensed Nearest Neighbour) based LEPD flow to solve the above two problems. First, data reduction and KNN (K Nearest Neighbour) is introduced in the LEPD construction to preliminarily reduce the dimension of HSI data. It aims to improve the speed of nearest neighbour searching. Then, based on the KNN graph, we get a connection matrix consisting of useful points for classification. After graph construction, the adjustment of mapping should be done for better visualization of results and finally the image is classified using threshold methods based on the KNN classification map with CNN extracted prototypes. The experimental result shows that 88% classification accuracy and provides better classification results and high computational speed.

I. INTRODUCTION

The classification problem is very important in the processing of hyperspectral imagery (HSI), because the classification results greatly benefit realistic applications, such as environment monitoring, vegetation mapping, geological surveying and land use analysis. Manifold learning methods are more suitable for HSI data because of the nonlinear structure of HSI data that originates from multi-scattering and the heterogeneity of pixels. Therefore, we focus our research on dimensionality reduction with manifold learning methods. Different manifold learning methods have been presented such as Isometric Mapping (Isomap), Locally Linear Embedding (LLE), and Principal Component Analysis (PCA). Applications of ISOMAP [2], [3] and LLE [4], [5] in hyperspectral image have been proposed recently, and there also have some improved works on ISOMAP in hyperspectral image classification [6]–[8]. Recently, a spectral graph technique namely Laplacian Eigenmap Pixels Distribution Flow (LEPD) is proposed [1]. It combines both the spatial and spectral characteristics. In this method, the most prominent advantage is that it is more robust than other algorithms when outliers exist in the data [9], [10]. However, two problems still have never been addressed.

1) The spatial features in HSI data are neglected. HSI data consists of an ensemble of images, and each pixel represents a spatial location in the image scene. Factors such as terrain, soil composition, illuminations, and in spatial resolution limits cause the spectral responses of ground objects in the same class vary with spatial locations. Therefore, the processing of HSI data should consider the effects of spatial variations in spectral signatures. However, in LEPD method, the classification results for large scale images results in under classification problem.

2) Applying LEPD flow increases the computational complexity. High performance computing schemes have been proposed, but the complex computing models and the expensive cost make it unsuitable for engineering applications.

The paper is organized as follows: Section II describes CNN data reduction algorithm. Section III focuses on CNN based KNN graph construction. Section IV gives the adjustment of mapping and section V presents the image classification using CNN extracted prototypes. Section VI describes the experimental results and discussions.

A. A General framework for data reduction

The CNN based Laplacian method is a new approach for nonlinear dimensionality reduction and it is related to spectral graph theory. In this method, *k* is a user-defined constant, and an unlabeled vector is classified by assigning the label which is most frequent among the *k* training samples nearest to that query point. Data reduction is one of the most important problems for work with huge data sets. Usually, only some of the data points are needed for accurate classification. Those data are called the *prototypes* and can be found as follows:

1) *Class-outliers*, are training data's that are classified incorrectly by
2) K-NN (for a given *k*). Class outliers with *k*NN produce noise. They can be detected and separated for future analysis.
3) *Prototypes* that are useful points for the classification decision
4) *Absorbed points* that can be correctly classified by k-NN using prototypes and can be removed from the training set.

Selection of class-outliers: A training example surrounded by examples of other classes is called a class outlier. Causes of class outliers include:

- random error
- Insufficient training examples of the class which we have taken.
- missing important features (the classes are separated in some other dimensions which we do not know)
- Too many training examples of other classes.

II. CNN ALGORITHM

In this paper, an enhanced CNN based KNN method is proposed to solve these two problems. Condensed nearest neighbor (CNN, the Hart algorithm) is an algorithm designed to reduce the data set for k-NN classification. It selects the set of prototypes U from the training data, such that 1NN with U can classify the examples almost as accurately as 1NN does with the whole data set. Three types of points: prototypes, class-outliers, and absorbed points. Given a training set X, CNN works iteratively:

1) Scan all elements of X; looking for an element x whose nearest prototype from U has a different label than x.
2) Remove x from X and add it to U
3) Repeat the scan until no more prototypes are added to U.

Use U instead of X for classification. The examples that are not prototypes are called "absorbed" points. It is efficient to scan the training examples in order of decreasing border ratio. The border ratio of a training example x is defined as

$$a(x) = ||x'-y|| / ||x-y|$$

Where ||x-y|| is the distance to the closest example y having a different color than x, and ||x'-y|| is the distance from y to its closest example x' with the same label as x. The border ratio is in the interval [0, 1] because ||x'-y|| never exceeds ||x-y||. This ordering gives preference to the borders of the classes for inclusion in the set of prototypes U. A point of a different label than x is called external to x.

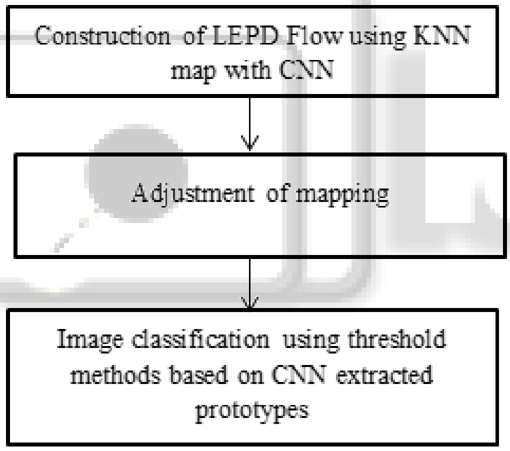

Fig. 1: Flowchart for CNN based Laplacian method

III. CNN BASED KNN GRAPH CONSTRUCTION

This CNN Based KNN graph construction consists of five steps. The algorithm (as described in [II]) is as follows:

Step1: Go through the training set, removing each point in turn, and checking whether it is recognized as the correct class or not

- If it is, then put it back in the set
- If not, then it is an outlier, and should not be put back

Step2: Make a new database, and add a random point.

Step3: Pick any point from the original set, and see if it is recognized as the correct class based on the points in the new database, using kNN with k = 1

- If it is, then it is an absorbed point, and can be left out of the new database

Step4: Proceed through the original set like this.

- If not, then it should be removed from the original set, and added to the new database of prototypes

Step5: Repeat steps 3 and 4 until no new prototypes are added.

IV. ADJUSTMENT OF MAPPING

Manifold learning algorithm can retain some aspects of the original space such as isometric measure, local similarity and representation of local linear subspace in the low-dimensional embedding space, Using this additional constraint, we can easily control the mapping results. If there is no such additional constraints, it will result in unexpected rotation, translation, scale or else. Necessary adjustment should be done for a stable flow.

For example, if the original image is rectangular and the result of the mapping is irregular quadrilateral, we need to adjust all of mapping results to rectangle and fix four vertexes according to the position corresponding to original image. This kind of adjustment allows not only better visualization of the results, but also the comparisons of mapping results with an appropriate measurement.

Actually the adjustment is not difficulty to be implemented. As mapping result is irregular quadrilateral, we can use the similar of correcting the distorted image which often used in digital image processing. We first rotate all points in the mapping result so that two special points corresponding to two vertexes of bottom edge of the original image are located on horizontal axis, and then extend the mapping result to a certain scale in order to process the result expediently. The sketch map is shown in Fig 2, where top left figure is the mapping result without adjustment, which is converted into original rectangular form by using some basic steps in digital image processing like Scaling, translation, rotation etc.

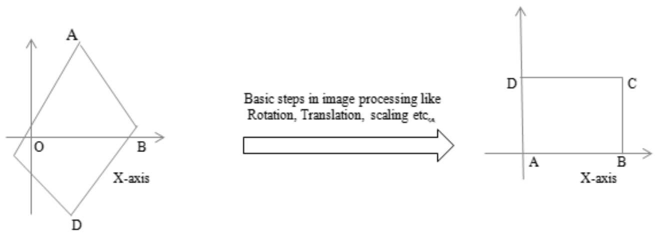

Fig. 2: Adjustment of manifold mapping

If we want to adjust the angle (shown in top right figure of Fig. 7) to right-angle for arbitrary x_{ij} of the result where (I, j) is the representative of x-coordinate and y-coordinate in current result, one can transform the coordinates of as follows:

$$\begin{cases} i' = i - \frac{l}{h} \times j \\ j' = j \end{cases}$$

where *l and h* are indicated in top right figure of Fig. 2. We can obtain bottom right figure of Fig. 2 by the above transform, then transform three remainder angles of mapping result to right-angle, and scale the coordinates to the corresponding size of original image, as shown in bottom left figure of Fig. 2.

V. IMAGE CLASSIFICATION

A. USING SINGLE THRESHOLD

For small scale problem, we can easily find out partition borders for classification with single threshold. We can find out the pixels as boundary points used for classification, because the average distance between these pixels and their neighbour is much larger than that of other points. As we have already adjusted the mapping results of the flow and all of these mapping results have significant coordinates, single threshold can be selected for the red framed segment shown in the fig 3.

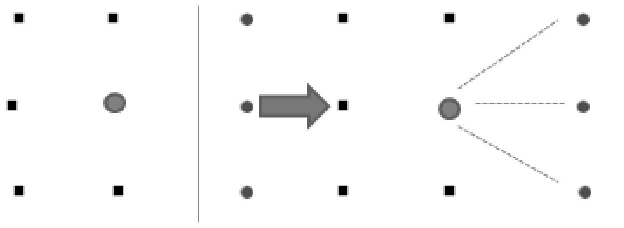

Fig. 3: Selection sketch map of boundary points used for classification.

Fig. 3 shows the selection sketch map of boundary points used for classification. In Fig. 3, left figure shows the location of object point (Red dashed circle) and its neighbour points in the image. We will determine whether the object point is a boundary point or not. In the right figure of Fig. 10, if there are three points (Blue circles) far away enough from the object point in plot of mapping result, this point is recognized as a boundary point, thus the borderline (the blue line in the left figure of Fig. 10) can be reflected. Usually, the distance is no less than 2 or $(2)^{1/2}$, which is two times of the original distance. In this paper, the average distance of 8 neighbour of the object point is considered, and single threshold is selected as about two times of the average distance, which is $1+(2)^{1/2}$.

B. USING MULTIPLE THRESHOLD

The method described above performs well when process small scale region of hyperspectral image, single threshold can find out the boundary points used for high accuracy classification. But for the entire image of 145 145 pixels, single threshold cannot get useful boundary points which are not connected with each other.

According to the analysis above, the existing method used is multiple threshold method. Firstly, using a big threshold when there exists some small regions that have been separated out by the boundary points as shown in Fig. 15; we label these regions and remove them. Then we decrease the threshold and separate each region which has been marked with boundary points, until most of points in interior part of mapping result have been selected as boundary points. In our experiment, if the number of points of a region is smaller than 1000 according to the prior knowledge of hyperspectral image data, we consider it is small.

When a region contains many points (more than 10^3), the region needs further segmentation with single threshold. In the final result, over-classification still exists. The proposed method in this paper avoids the problem of over classification by reducing the data for large scale images and gives more accuracy compared to the existing method. This method introduces a data reduction technique namely condensed nearest neighbour and it should be done along with KNN, so that only useful points are used for image classification. It is mainly used in the case of large scale with high dimension images, and the problems in the existing method are avoided.

VI. EXPERIMENTAL RESULTS AND DISCUSSIONS

The hyperspectral image of Indian pines vegetation was used for the experiment and recorded by AVIRIS sensor. These data sets and the corresponding results are discussed here.

The Indian Pines image of a vegetation area was recorded by the AVIRIS sensor over the Indian Pines site in North western Indiana. The image has spatial dimensions of 145 by 145 pixels, with a spatial resolution of 20 m/pixel. We discarded the 20 water absorption bands (104-108,150–163, and 220), and a 200-band image was used for the experiments. The reference data contain sixteen classes of interest: Alfalfa, Corn-notill, Corn-min, Corn, Grass/Pasture, Grass/Trees, Grass/pasture-mowed, Hay-windrowed, Oats, Soybeans-notill, Soybeans-min, Soybean-clean, Wheat, Woods, Bldg-Grass-Tree-Drives, Stone-steel towers.

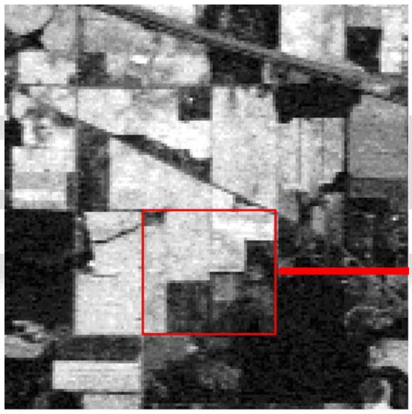

Fig. 4(a): Indian pines hyperspectral image

Fig 4(a) is the 171st band of Indian pines image of dimension 145 x 145 pixels that we select for further experiment. The region with red frame corresponds to the dimension of 46 x 41 pixels and it can be easily classified using single threshold method.

(b)

(b) Reference data: Corn-notill, Corn-min, Corn, Soybeans-notill, Soybeans- min, Soybeans-clean, Alfalfa, Grass/pasture, Grass/trees, Grass/pasture-mowed, Hay-windrowed, Oats, Wheat, Woods, Bldg-Grass-Tree-Drives, Stone-steel towers.

A. SIMULATION RESULTS

The simulation result of Indian pines image is shown in the fig 5(a).It labels and remove the green, blue and magenta color patterns and the scattered plot of labelled pattern is shown in fig 5(b).

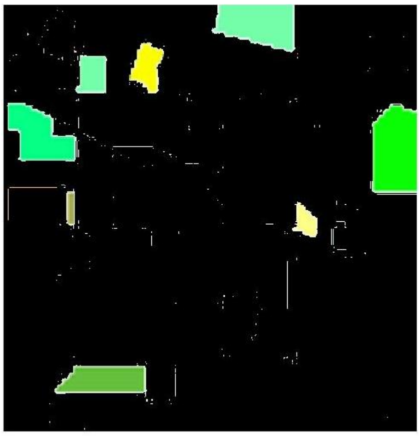

Fig. 5: Classification results of Indian Pines (a) The result of our method

The class-specific accuracy achieved in our method is recorded in Table I and compared with the existing method. The classification result of entire Indian Pines hyperspectral image is acceptable, and there are few pixels that are not found in most classes.

Method	LEPD Method	Our Method
Classification accuracy	67.45%	88.89%

Table. 1: Overall Classification Accuracies of Indian Pines using different methods

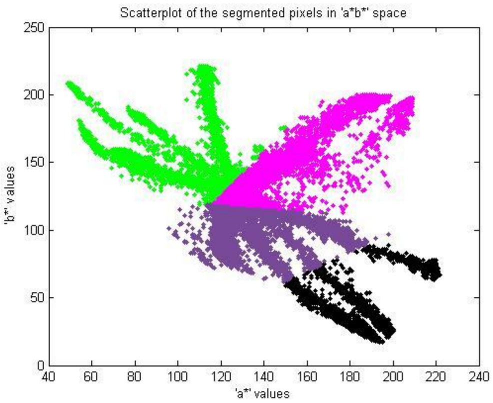

Fig. 5(b): Scattered plot of the labelled data

VII. CONCLUSION

We have developed a CNN Based LE PD-Flow algorithm for classification of hyperspectral image data. A framework of K nearest neighbour is constructed, and the spatial characteristic is introduced to compute the JSPCD for selection of neighborhood. Although pixel characteristics of hyperspectral image are the only factor for effective classification, we use spatial characteristics in JSPCD to solve two problems unexpected. One is the dimensions of the output space, which is restricted to 2, the same as the common dimension of an image. The other is the meaning of mapping result in LE PD-Flow, and our result is accord with the spatial distribution of pixels in original image and has a good visual effect. Experimental results have shown that the proposed method improves the classification accuracies and provides classification maps with more homogeneous regions compared with normal LEPD Flow.

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