Hyperspectral Image Classification by Means of Suprepixel Representation with KNN

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Hyperspectral Image Classification by Means of Suprepixel Representation with KNN

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Abstract In real-world application, especially in remote sensing based on image processing hyperspectral imaging (HSI) shows promising results. Superpixel-based image segmentation is the powerful tool in hyperspectral image processing. Series of neighboring pixels composes superpixel which may belong to different classes but can be regarded as homogenous region. Extraction of more representative feature is considered to be most important thing in hyperspectral imaging. Training and testing samples that are more representative are found by proposing a new method for selecting two k values for representing optimal superpixels. This paper starts with superpixel shifting as first step and followed by KNN classifier. Which is performed by pixels with minimal spectral features in HSI are clustered together in the same superpixel. Followed by spatial-spectral feature is extraction by a domain transformation from spectral to spatial. For each superpixel, training and test samples are selected to eliminate classification within the same class. An average distance between test and training samples are used for determining class label. Finally, by the results from most common hyperspectral images Indian pines, Salinas, Pavia show that this method shows a better classification performance.

Keywords Hyperspectral image classification · Superpixel segmentation · K-nearest neighbor classification (KNN)

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1 Introduction

In the field of remote sensing, there is an endless development of spectral resolution which has been achieved by spontaneous research in hyperspectral imaging. For earth observation and space exploration, hyperspectral images play a major role. Number of spectral bands is extended to several hundreds. With their reflectance the material present in the pixel detected. The collected information are recorded by the hyperspectral sensors by series of images. The scene of observation's reflected solar radiation provides the spatial distribution. Narrow and contiguous spectral bands image acquisition are made possible only through rapid development in hyperspectral imaging and remote sensor technology. Reliable and rich spectral information can be given by HSI and has been used widely in remote sensing field. Extra computing burden and Hughes phenomena are felt over high dimensionality of hyperspectral imaging. Chaos theory and Manifold learning are said to be some classical method for nonlinear HIS dimension reduction used for feature extraction in HSI. Most of these methods perform classification of HIS images only based on spectral information which may not give satisfactory results.

Nowadays, in feature extraction process, some spatial-spectral feature-based classification methods have been carried out that uses contextual information into account for classification process. For HSI classification process, one of a popular method to be used is KNN classifier. A label is assigned simply to the test sample that occurs most frequently in its KNN so it is said to be nonparametric classifier. The inter-sample relationship cannot be accurately described in the input by a solo Euclidean distance subspace which has been implied by Manifold [1]. The following major steps are followed in the proposed method for KNN representation of superpixels (KNNRS). On the first three principle components of hyperspectral, an entropy rate superpixel (ERS) segmentation technique is executed initially. Secondly for extracting the spectral-spatial features, a filtering method based on edge preserving has been adopted effectively to remove the texture and noise removal from the image. For different superpixels, different numbers of training and test samples can be selected by using KNN method. Existence of pixels that belong to dissimilar classes may occur in one superpixel region is the main problem addressed which is main objective of the paper. With minimal distance, the superpixel region is assigned with label by calculating the average distance among the selecting testing and training samples.

2 Literature Survey

Benediktsson et al. [2] described that for high-spatial resolutions urban areas, hyperspectral data classification has been concerned. Mathematical morphology has been used for preprocessing of hyperspectral images. For separation of bright and dark structures in the proposed approach, morphological opening and closing functions have been used. For original image starting with single, by using repetitive use of opening and closing structure elements that have high dimensions a morphological profile was created. Wang et al. [1] designate that for terrestrial laser scanning point clouds classification in a precise and efficient manner of a significant necessity is to mine shape features valuably. It is still a challenging task to analyze noisy and unstable TLS point and get robust and discriminative features. For classification of TLS point clouds for the cluttered and urban scenes, hierarchical and multi-scale outline were presented by the authors. Multi-scale and hierarchical point clusters (MHPC) were discussed by the authors.

Lefevre, Aptoula, Courty, [3] conveys by means of manifold learning and morphological features a new method of spectral classification of hyperspectral images was presented by the authors. The investigational indications were earlierly on the attention of class-wise orderings were followed and the issue was mentioned. A superior performance model has been demonstrated by the authors by comparing extended morphological profiles Pavia dataset to the proposed method.

3 Related Work

A. *Feature extraction using recursive filtering (RF)*

The domain transform recursive filter (DTRF) by preserving sharp edges and boundaries eliminates noise and texture in an image and it is a real-time EPF. Transformation of a signal to domain transformed signal

$$Z_m = I_0 + \sum_{m=1}^{n} (1 + \frac{r_s}{r_r} |I_m - I_{m-1})$$

$I_m = m$th input signal; $Z_m = m$th domain transformed signal; $r_s =$ spatial parameter of the filter; $r_r =$ range parameter of the filter; pixels that lie on identical flank of sturdy edge and those lie on different sides of strong edge are nearby and far coordinates, respectively, in the transformation domain. Then comes the processing of transformed signal by RF as follows

$$K_m = \left(1 - f^l\right) I_m + f^l K_{m-1}$$

where $f^l =$ feedback coefficient; $l =$ measure of distance between two neighbor samples; $K_m =$ transform domain by which the signals sharp edges are preserved the propagation chain will be stopped as increase in l results in making f^l zero. Output from the *mth* signal is filtered by K_m.

$$f = \exp\left(\frac{-\sqrt{2}}{r_x}\right) \epsilon [0, 1]$$

On each dimension, a one-dimensional filtering should be performed on every two-dimensional image. By performing one-dimension filtering on images with three iterations shows satisfactory results [4].

For processing images 1D field transformation RF is agreed for three iterations.

B. *Superpixel image segmentation*

In computer vision based on graph theory the superpixel segmentation algorithms have been widely used [5]. Based on different spatial structures the size and shape of each superpixel can be adaptively changed. The number of superpixels can be given by the following equation

$$I = \bigcup_{i=0}^{N} Y_i, \, and \, Y_i \cap Y_j = \emptyset, \, (i \neq j)$$

Y_i = ith superpixel; with ERS segmentation algorithm the superpixels are generated. Initially, the graph $G = (V, E)$ was constructed where V and E represent the corresponding to pixels of image by which adjacent pixels pairwise similarities can be measured. The original graph is divided into N connected subgraphs by selecting subset of edges $M \subseteq B$. A balancing term $B(N)$ and an entropy rate term $E(N)$ were introduced to obtain homogenous and compact superpixels into the superpixel segmentation [6].

$$E(N) = -\sum_{m} \mathrm{sd}_m \sum_{n} p_{m,n}(N) \log\big(p_{m,n}(N)\big)$$

$$B(N) = E(C_N) - CC_N = -\sum_{i} PC_N(i) \log(PC_N(i)) - CC_N$$

where $p_{m,n}$ = transition probabilities; sd_m = stationary distribution; CC_N = the number of connected components in the graph;C_N = cluster membership distribution; The superpixel segmentations detached function is presented as follows:

$$\max N\{E(N) + \mathrm{sd}B(N)\} \text{ subject to } M \subseteq B$$

Entropy rate term and balancing contributes the weight controlling by sd > *0.* To solve the optimization problem efficiently, a greedy algorithm has been used.

4 Proposed System

In this paper, a classification method based on KNNRS with spectral-spatial has been introduced. This method consists of four parts

- Hyperspectral image partitioning into superpixels;

- Feature extraction of HSI by domain transform RF;
- For each superpixel, the training and testing samples that are most representative are selected by using the KNN;
- Based on decision function decision function the class labels of superpixels are obtained.

Tessellation of an image into “superpixels” has become a basic thing for many kinds of object recognition, segmentation, etc. In advancement to rectangular patch, the patches are aligned better with edge intensities [7]. The superpixel partitioning problem is formulated with optimized graph cuts and minimized energy framework. Regular superpixels are explicitly encouraged by our energy function [8] (Fig. 1).

Superpixel segmentation was initially introduced by Ren and Malik [9] in which a perceptually meaningful connection of pixels that similar in color or other feature in a group. Many algorithmic approaches are proposed in subsequent year [10, 11].

KNN-based superpixels representation: Pixels with similar structural information are clustered together in the same superpixel which is referred as superpixel segmentation method [13, 14]. Training samples that are more representative for each class is given by selection of k_1 by which within class variations are effectively overcome.

Detailed description is given by the following equation.

Training samples $X^i = X_1^i, X_2^i, X_3^i \ldots\ldots..X_j^i$

$$X_j^i = \text{belongs to } jth \text{ class}$$

$J =$ number of training samples.

$$Y_n = y_{n,1}, y_{n,2}, \ldots\ldots y_{n}, k_n$$

$k_n =$ pixels count in *nth* superpixel

Due to spectral mixing samples belonging to similar session shows spectral variations even due to environmental factors such as cloud and shadow [5]. And the Euclidean distance $E\left(y_{n,i}, X_j^i\right)$ and mean $E_{\text{mean}}\left(y_{n,i}, X^i\right)$ are given by

$$E\left(y_{n,i}, X_j^i\right) = \left\|y_{n,i} - X_j^i\right\|_2^2$$

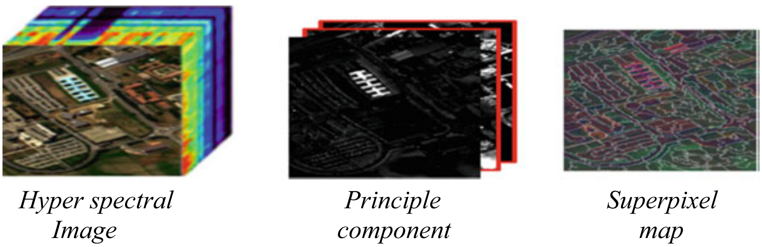


Fig. 1 Input HSI image its principle component and superpixel map

$$E_{\text{mean}}\left(y_{n,i}, X^i\right)\frac{\sum \hat{E}\left(y_{n,i}, X^i\right)}{k_1}$$

Test samples that are most representative in each superpixel is adopted by k_2 selection rule instead of using all the pixels in each superpixel. Distance for discrimination is given by the following equation [12, 16].

$$d\left(y_{n,i}, X^i\right)\frac{\sum \hat{E}\left(Y_n, X^i\right)}{k_2}$$

By K selection method pixels with same distance are in one superpixel region [15]. The resulting distance for the test superpixel Y_n used for discrimination is described as

$$d\left(Y_n, X^i\right) = d\left(y_{n,i}, X^i\right)$$

Labeling based on distance: in this step, the superpixel $\mathbf{Y}n$ that gives the minimal distance is assigned with the label as follows:

$$\text{Class}(Y_n) = \arg \min_{i=1,2,\ldots.C} d\left(y_{n,i}, X^i\right)$$

5 Result

For this experiment Salinas C and Indian pine hyperspectral images have been chosen for classification purpose. Airborne visible/infrared imaging spectrometer sensor was used for acquisition of images. Salinas image has 224 spectral bands with 217 × 512 as pixel size with 3.7 m resolution. The image was acquired in Salinas valley, California at October 8, 1998. Indian pines image has 220 spectral bands with 125 × 125 pixels. Acquired at November 1992 (Figs. 2 and 3: Tables 1, 2 and 3).

6 Conclusion

The work for HSI transformation a KNN-based representation of superpixels (KNNRS) which is a novel method has been proposed. First spectral and special features are extracted by RF by which the complete spatial information in superpixels are used by which Edge and boundary features are enhanced effectively. For each superpixel, the representative training and test samples are selected by KNN algorithm. In the proposed method on real hyperspectral database, higher classification accuracy is obtained in limited number of training samples. The main limitation of

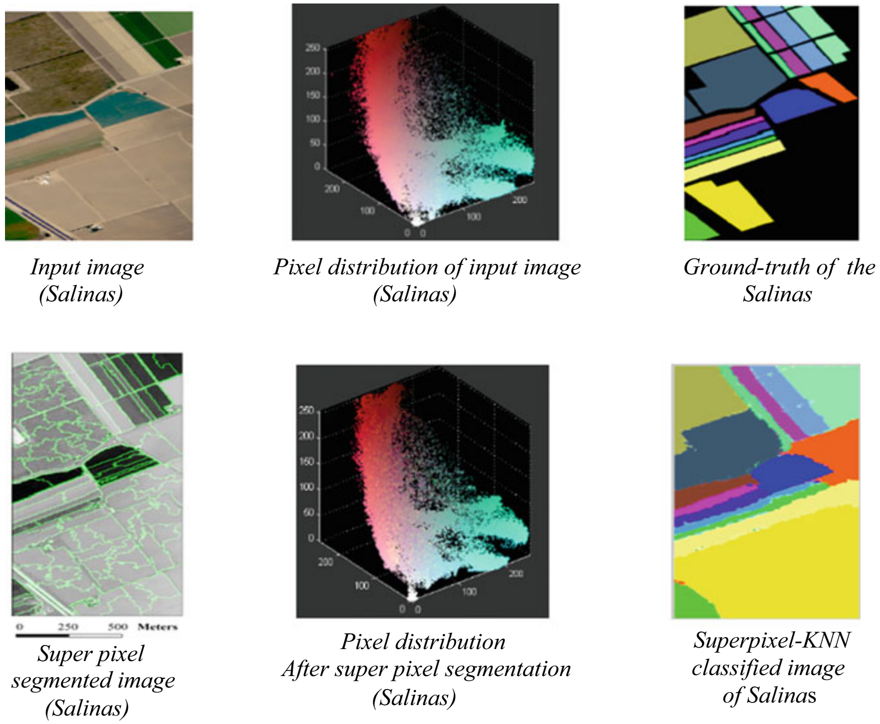
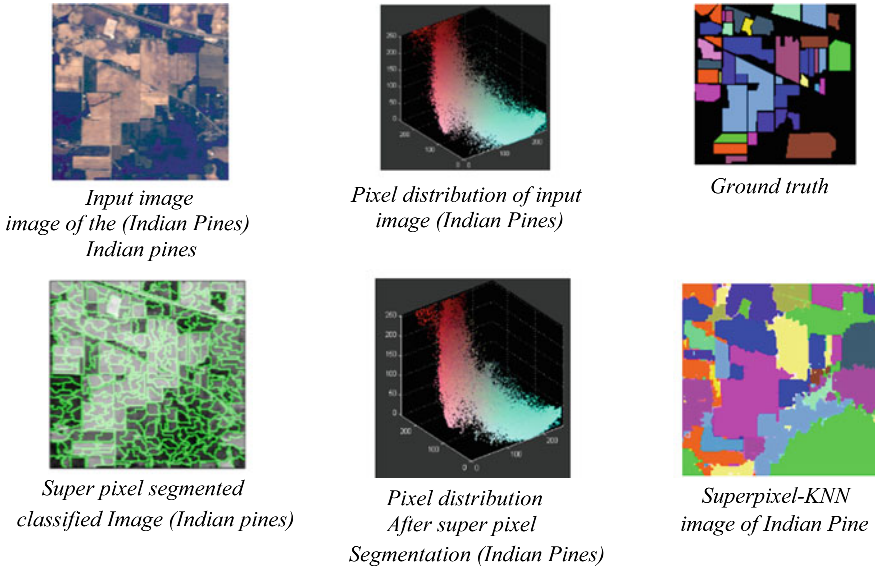


Fig. 2 Various stages of hyperspecral image classification—input image, pixel distribution, ground truth image, superpixel segmentation, and finally classification of Salinas image

this method is the performance of segmentation decides the performance of classification. Classification may not be efficient when pixels of different class lie in same pixel region. Another challenging problem is the computational burden of KNN operation. Still the system shows a better performance compares to state of art methods.



Input image image of the (Indian Pines) Indian pines

Pixel distribution of input image (Indian Pines)

Ground truth

Super pixel segmented classified Image (Indian pines)

Pixel distribution After super pixel Segmentation (Indian Pines)

Superpixel-KNN image of Indian Pine

Fig. 3 Various stages of hyperspecral image classification—input image, pixel distribution, ground truth image, superpixel segmentation, and finally classification of Indian pines image

Table 1 Details of Hyperspectral data used

Class	Indian pines	Salinas	Pavia University
	16	16	9
Band	200	204	103
Size	145 × 145	512 × 217	610 × 340
Sensor	AVIRIS	AVIRIS	ROSIS
Resolution (m)	20	3.7	1.3
Sample	10,249	54,129	42,776

Table 2 Train and test samples in Indian pines image

Class	Name	Training		Test	
		2%	0.2%	98%	99.8%
1	Weeds_1	40	4	1969	2005
2	Weeds_2	76	8	3650	3718
3	Fallow	38	4	1938	1972
4	Fallow_P	26	3	1368	1391
5	Fallow_S	52	5	2626	2673
6	Stubble	79	8	3880	3951
7	Celery	70	7	3509	3572

(continued)

Table 2 (continued)

Class	Name	Training		Test	
		2%	0.2%	98%	99.8%
8	Grapes	225	21	11,046	11,250
9	Soil	124	11	6079	6192
10	Corn	21	3	1047	3275
11	Lettuce_4wk	21	3	1047	1065
12	Lettuce_5wk	38	4	1889	1923
13	Lettuce_6wk	18	2	898	914
14	Lettuce_7wk	20	2	1050	1068
15	Vinyard_U	140	13	7128	7255
16	Vinyard_T	36	4	1771	1803
Total		1024	102	53,105	54,027

Table 3 Train and test samples in Indian pines image

Class	Name	Training		Test	
		10%	1%	90%	99%
1	Alfalfa	10	3	36	43
2	Corn_N	143	14	1285	1414
3	Corn_M	83	8	747	822
4	Corn	34	3	203	234
5	Grass_M	48	6	435	477
6	Grass_T	23	7	707	723
7	Grass_p	2	2	26	26
8	Hay_W	28	5	450	473
9	Oats	2	2	18	18
10	Soyabean_N	150	10	822	962
11	Soyabean_M	246	24	2209	2431
12	Soyabean_C	60	6	533	587
13	Wheat	21	2	184	203
14	Woods	127	13	1138	1252
15	Building	35	4	351	382
16	Stones	10	3	83	90
Total		1022	112	9227	10,137

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