IMAGE SPECTRAL DATA CLASSIFICATION USING PIXEL-PURITY KERNEL GRAPH CUTS AND SUPPORT VECTOR MACHINES: A CASE STUDY OF VEGETATION IDENTIFICATION IN INDIAN PINE EXPERIMENTAL AREA

Mengfei Wang[1], Weijie Jia[1], Qingjie Liu[2], Fengxian Miao[3]

1. China Aero Geophysical Survey and Remote Sensing Center for Natural Resources, Beijing 100083, China
2. Institute of Remote Sensing and Digital Earth, Chinese Academy of Sciences, Beijing 100094, China
3. STATE Grid AC Engineering Construction Company, Beijing 100052, China

ABSTRACT

Salt and pepper phenomenon of pixel-based images classification, has a major negative impacts on the accuracy of Imaging Spectra classification. Various kernel-based methods, such as Kernel graph cuts (KGC) and support vector machine (SVM), are used to solve the nonlinear problems by mapping the original nonlinear data into higher dimensional space. Four experiment schemes, including Original-Pixel-SVM (OPSVM), Original-PKGC-SVM (OPKGCSVM), PCA-PKGC-SVM (PPKGCSVM), and MNF-PKGC-SVM (MPKGCSVM), are designed to class AVRIS in India Pine of USA for comparison of classification User Accuracy (UA), Producer Accuracy (PA), Overall Accuracy (OA) and Kappa index quantitatively. The average UAs of MPKGCSVM, PPKGCSVM, OPKGCSVM and OPSVM are 91.92%, 83.09%, 84.51% and 75.55%, the average PAs are 95.33%, 91.47%, 88.03% and 87.78% their OAs are 93.57%,88.99%,85.35% and 82.36%, their Kappa indexes are 0.92,0.85,0.83 and 0.79 respectively. From MPKGCSVM to OPSVM, the OA and Kappa indexes are improved 11.21% and 0.13 respectively. Therefore, PKGC reduce the salt-and-pepper effects of classification obviously, and improve the accuracy and robustness greatly. Besides, dimensionality reduction pre-processing before PKGA of HSI with Minimum noise fraction can enhance the performance of final classification than other transformations.

***Index Terms*—**Imaging Spectra, kernel graph cuts, support vector machine, classification accuracy

1. INTRODUCTION

Spectral classification, which gives each pixel of an image a label of a certain category, is an important basis for the application of cartography, target detection, agricultural monitoring, urban survey and national defense construction. Imaging spectral data classification is faced with huge dimensionality [1], data structure nonlinearity, spatial homogeneity/ heterogeneity[2] and other problems. Commonly used imaging spectral pixel level classifier including K-nearest neighbor classifier (KNN), Random Forest classifier (RF), a Bayesian classifier (BY) classifier, all need a big enough sample size to ensure its high classification performance, which is difficult to obtain in practical applications. In addition, there are many problems in spectral data classification such as data dimension disaster and salt-pepper noise, which seriously affect the final classification accuracy and the application of thematic information extraction. The development of new theories and methods such as feature mining, pattern recognition and machine learning has greatly promoted the development of hyperspectral data classification. The intelligence classifier, with the support vector machine (SVM)[3] as the representative, has further improved the generalization ability, can achieve high classification results in the case of a limited sample size, and gradually to the direction of development of intelligent parameter optimization[4], multi-nucleation, and multiple classifier combination.

Therefore, this paper proposes an image spectral support vector machine classification algorithm based on pixel purity kernel graph cuts (PKGCSVM). Experimental results show that PKGCSVM can effectively reduce the salt-pepper noise of traditional pixel classification and improve the classification accuracy of imaging spectral data.

2. THEORIES AND METHODS

2.1. The seed points of pixel purity segment

Spectral mixing is a common phenomenon in imaging spectra. Pixel purity index (PPI) algorithm based on hypothesis that all data of the imaging spectrum can be expressed as a linear combination of pure pixel spectra, can express the spectral characteristics of the main feature types in the image coverage area. The commonly used PPI calculation method is as follows: a large number of test vectors are generated randomly, and spectral points are projected to each test vector. According to the principle that end elements are projected to the middle of two mixed pixels on both sides of the vector, the number of times each pixel in the image is projected to the end element is recorded, and the point with the highest frequency is the pure end element. Pixel purity represents the hyperspectral statistical information of typical features and can be selected as the basis for the generation of initial seed points in image segmentation.

2.2. Kernel graph cuts

Graph segmentation (GC) theory[5]: determine the minimum segmentation of network flow by finding a set of edges with the minimum capacity and removing all edges in the set. KGC[6] introduced the kernel function into the energy function to establish a discriminant function guided by the kernel function. The kernel guided discriminant function is minimized by two step recursive optimization algorithm. The first step is to fix the partition mark and obtain the region parameter of the nuclear energy function. The second step uses graph cut optimization to obtain the optimal cut identity. Kernel function K mainly has polynomial, sigmoid kernel and Radial Basis Function (RBF) kernel Function. Many experiments show that RBF kernel has better image cut performance than other knernels.

2.3. Support vector machine

Support vector machineis a new statistical algorithm with high accuracy, fast computing speed and generalization ability, which has been widely used in the classification of remote sensing images in the past decade. SVM transforms the input space into a high-dimensional space through nonlinear transformation, and conducts linear regression in this high-dimensional space to obtain the optimal linear classification surface. For the imaging spectral training data set $SET_T=\{(x_1,y_1),\cdots,(x_n, y_n)\}$(among that, $x_i \in R_n$, $y_i \in \{1,-1\}$, $i=1,\cdots,n$), SVM is:

$$\min_{\omega,b,\xi} \quad \|\omega\|^2/2 + P\sum_{i=1}^{n}\xi_i^2 \qquad (1)$$

$$y_i(\omega^T x_i + b) \geq 1 - \xi_i \qquad (2)$$

Where, $P > 0$ is the penalty parameter, ξ is the deflated variable, ω as the weight vector and b as the threshold weight.

Existence of $x = \phi(x)$ transformation transform input space into high-dimensional space, can obtain hyperplane ($\omega \cdot x$) +b=0 in high-dimensional space plane, and correctly divide the training set. The kernel function $K(x_i, x) = (\phi(x_i)\cdot\phi(x))$ is the positive definite kernel. According to Largrange duality theory, the SVM decision function is obtained from:

$$f(x) = \mathrm{sgn}[\sum_{i=1}^{n} a_i^* y_i K(x_i, x) + b^*] \qquad (3)$$

In this paper, one-against-one (OAO) multi-classification method of RBF kernel function is used.

2.4. Imaging spectral cut classification of kernel transformation

Principle of the algorithm: Based on the pixel purity index of hyperspectral features, the algorithm of segmenting seed points established. Then, RBF kernel function is used to convert image data to the high dimension space, connect the minimum segmentation of image with graph cut, and establish regional energy term and boundary term. Then, by minimizing the energy function, the homogeneity region of remote sensing images with strong spatial and spectral correlation is segmented, and the pixel purity kernel graph cut algorithm (PKGC) is established. Particle swarm optimization support vector machine is used to classify the pixels in the segmented patches. By using the voting method, the category identification of homogeneous image patches was realized, and finally the classification algorithm of PKGCSVM was established.

The main steps of the algorithm include: (1) normalization processing of imaging spectral data; (2) using PCA or MNF transformation to complete dimensional reduction of imaging spectral data; (3) PPI was calculated to select the purest end elements; (4) KGC was used to segment the dimension reduced image with the pure end element as the seed, and the segmented spatial homogeneous patches were obtained; (5) select part of known hyperspectral sample data randomly and train SVM model, and the parameter optimization of SVM is completed by particle swarm optimization algorithm; (6) the trained SVM model was used to classify the pixels within the homogeneous patches; (7) based on maximum voting method, the category of each segmentation patch was determine.(8) complete the accuracy evaluation and performance comparison of classification results.

3. EXPERIMENT AND RESULT DISCUSSION

3.1. Experimental method

Airborne Visible Imaging Spectrometer (AVIRIS) of Indian Pine experimental area, Indiana, USA as experimental data (Fig.1a) to test the kernel graph cut and SVM classification algorithm in this paper. The image size is 145×145 pixels with a spectral range of 0.4-2.4 μm and a total of 220 bands. There are 16 ground objects in the original image, and 12 typical ground objects with large distribution area are selected as test objects (Figure 1b).Training and testing samples were randomly selected from them, in which each type of training samples contained 20 sample points, and the remaining samples of each type were test samples. The sample names, serial numbers, and numbers are shown in table 1.

Table 1. AVIRIS samples in Indian Pine

Classes	Name	Total sample number	Training sample number	Test sample number
C1	Corn-notill	401	20	381
C2	Corn-min	200	20	180
C3	Corn	33	20	13
C4	Grass/Pasture	143	20	123
C5	Grass/Trees	190	20	170
C6	Hay-	247	20	227

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C7	Soybeans-notill	356	20	336
C8	Soybeans-min	1152	20	1132
C9	Soybean-clean	113	20	93
C10	Wheat	35	20	15
C11	Woods	647	20	627
C12	Bldg-Grass-Tree-Drives	151	20	131

Four experimental schemes were designed to compare and verify the classification accuracy of imaging spectral data. Classical parameters such as User Accuracy (UA), Producer Accuracy (PA), Overall Accuracy (OA) and Kappa coefficient were adopted for quantitative evaluation.

(1) The first scheme: directly use the SVM of particle swarm parameter optimization to complete the pixel classification of the original image. Represented by OPSVM.

(2) The second scheme: PKGC is used to segment the original image firstly, and then particle swarm parameter optimized support vector machine is used to complete the classification of segmentation patches. Represented by OPKGCSVM.

(3) The third scheme: principal component transformation is used to conduct dimensionality reduction processing for the original image, then PKGC is used to segment the dimensionality reduction image, and finally, particle swarm parameter optimized support vector machine is used to complete the classification of segmentation patches. Represented by PPKGCSVM.

(4) The fourth scheme: the original image is processed with the minimum noise transform to reduce the dimensions; then, PKGC is used to segment the dimensionless image; finally, the particle swarm parameter optimized support vector machine is used to complete the classification of segmentation patches. Represented by MPKGCSVM.

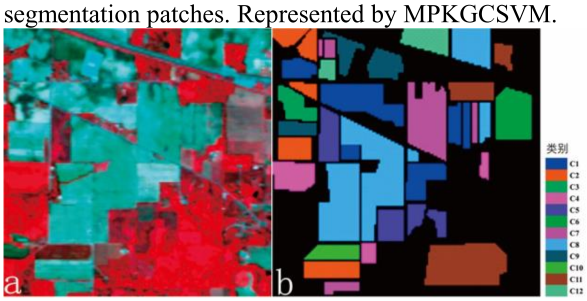

Figure 1. AVIRIS image and ground objects
a-AVIRIS of Indian Pine; b-Distribution of ground objects

3.2. Kernel graph cuts of imaging spectral data

In the last three schemes, the pixel purity kernel graph cuts algorithm (PKGC) is needed to segment the original imaging spectral data and dimensionality reduction data respectively. In the pixel purity detection algorithm, the size of the detection vector is 1000, and the largest size of the purest end element set is 50.The weighted coefficient in KGC segmentation is 0.6. In general, PKGC can effectively segment the sample features from the background and reduce the fragmentation within the features, thus maintaining homogeneity.

3.3. Classification accuracy analysis

The AVIRIS imaging spectra in the Indian Pine experimental area were classified by OPSVM, OPKGCSVM, PPKGCSVM and MPKGCSVM. Each scheme was executed for 10 times, and the average value and variance of such parameters as User Accuracy (UA), Producer Accuracy (PA), Overall Accuracy (OA) and Kappa coefficient were calculated, and the unit of classification Accuracy was percentage (%). The statistical curves of average classification accuracy and variance of UA and PA are shown in figure 2a and figure 2b.The overall OA and Kappa coefficients, statistical data and their comparison results are shown in table 2. The classification results of AVIRIS images are shown in figure 3.

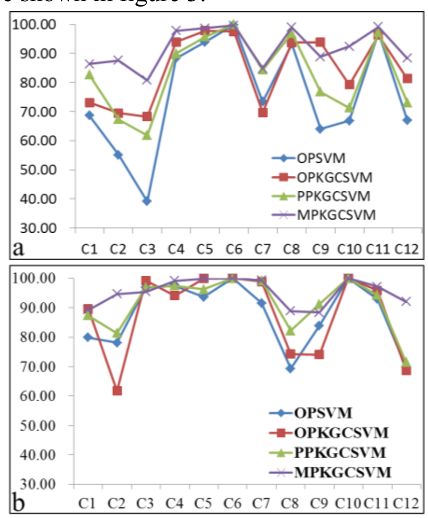

Figure 2. Comparison of User Accuracy and Producer Accuracy for AVIRIS classification
a-Comparison of User Accuracy; b-Comparison of Producer Accuracy

UA represents the conditional probability that any random sample taken from the classification result has the same type as the actual type. The statistical results show that: The accuracy mean of OPSVM is the lowest but the most stable, and the accuracy of MPKGCSVM is the highest, and the stability is slightly better than that of OPKGCSVM and PPKGCSVM algorithms. MPKGCSVM algorithm gives 10 types maximum UA from 12 types of ground object samples, and OPKGCSVM and PPKGCSVM algorithms each only give 1 type. PA represents the conditional probability that the classification result of the same place on the classification map is consistent with the real result relative to any random sample in the real result. The statistical results show that: The average PA values of the four methods were in the order of MPKGCSVM > PPKGCSVM > OPKGCSVM > OPSVM, and the stability results were in the order of OPSVM > MPKGCSVM > PPKGCSVM > OPKGCSVM. MPKGCSVM can achieve the highest mapping accuracy for 10 types of ground object samples, while OPKGCSVM only gives 2 types and PPKGCSVM only gives 1 type.

Table 2 OA and Kappa comparison of OPSVM, OPKGCSVM, PPKGCSVM and MPKGCSVM

Average± Variance	OPSVM	OPKGC SVM	PPKGC SVM	MPKGC SVM
OA（%)	82.36 ±1.99	85.35 ±2.06	88.99±1.96	93.57±1.86
Kappa	0.79 ±0.02	0.83 ±0.02	0.87±0.02	0.92±0.02

The OAs were ranked as MPKGCSVM > PPKGCSVM > OPSVM > OPKGCSVM, and all of them reached over 82%. The OA of MPKGCSVM was 11.21% higher than the traditional pixel based classification algorithm OPSVM.

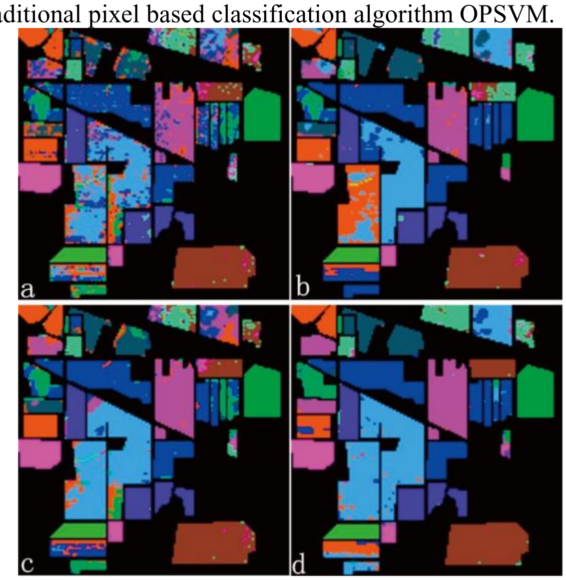

Figure 3. AVIRIS classification results with (a) OPSVM, (b) OPKGCSVM, (c)PPKGCSVM and (d) MPKGCSVM

As can be seen from the classification result (Fig.3)： Due to the lack of spatial information constraints in the pixel-level classification, there is a relatively serious salt-and-pepper noise in the classification result of OPSVM algorithm. By introducing spatial constraints, the OPKGCSVM algorithm greatly reduces the salt- and-pepper noise, effectively improves the classification accuracy, but at the same time causes the misclassified patches. PPKGCSVM and MPKGCSVM further reduce noises and misclassification patches by introducing hyperspectral PCA and MNF dimensionality reduction. However, in PPKGCSVM classification results, there are still misclassification phenomena, for example, part of C12 is misclassified as C4, and part of C8 is misclassified as C2 and C1. MPKGCSVM further improved the classification results in PPKGCSVM, and the ground object misclassification with large area no longer exists, mainly because MNF includes two time of PCA transformations, further enriching and optimizing the image space information.

The AVIRIS imaging spectral data in the Indian Pine experimental area reflect the information of 12 plants, and their spectral difference is relatively small. It is difficult to get ideal classification results by directly using the pixel - based OPSVM algorithm. OPKGCSVM algorithm can effectively improve the classification accuracy by combining KGC with kernel classification. PPKGCSVM and MPKGCSVM algorithms further utilize principal component analysis and minimum noise transform and other data dimensionality reduction means to conduct data aggregation and reorganization of imaging spectral data before segmentation and classification, thus further improving classification accuracy.

4. RESULT

In this paper, we propose a new method of dimensions reduction-nuclear space segmentation-SVM classification to solve the problem of salt-and-pepper noise in spectral data classification. Firstly, PCA/MNF was used to reduce the dimensionality of spectral data, and the core image segmentation algorithm of pixel purity index was used to complete the segmentation of homogeneous regions of images, and finally, the final classification was completed by the support vector machine. By introducing spatial dimensional homogeneity feature constraint of spectral data, the accuracy of classification is improved and the noise of pepper and salt classification is reduced.

The MPKGCSVM, PPKGCSVM, OPKGCSVM, OPSVM proposed were evaluated quantitatively by using quantitative indexes such as UA CA, OA and Kappa coefficient. The results show that MPKGCSVM has higher accuracy and more stable classification performance. Further sparse optimization and fusion of imaging spectral dimension and spatial dimension characteristics are the focus of subsequent research work.

5. ACKNOWLEDGEMENT

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6. REFERENCES

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