Hyperspectral Remote Sensing Images Classification Method Based on Learned Dictionary

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Abstract. A novel hyperspectral image classification method based on learned dictionary is presented in this paper. Firstly, the sampled image pixel and its classification vector are combined as sample pair. Secondly, defined as a sample vector, the sample pair are used for sparse coding and dictionaries learning. Then, the sparse association between sample pairs is established efficiently. Finally, defined as prior knowledge, the sparse association is used to guide the classification of input image. The whole dictionary learning process can be achieved offline, and improve the speed of the algorithm. Several experiments show that the method can get good classification results.

Introduction

Recently developed sparse representation defines the image as the sparse linear combination of basis atoms in the dictionary. When the image pixels projected onto the atoms of the feature subspace, only a few processing active at the same time. Then the image classification is based on the composition of sparse dictionary atoms. Hyperspectral image classification method based on sparse representation has been a considerable amount of research papers[1]. Chen et.al[2] proposed an algorithm relies on the observation that a hyperspectral pixel can be sparsely representation by a linear combination of a few training samples from a structured dictionary. The sparse representation of an unknown pixels is expressed as a sparse vector whose nonzero entries correspond to the weights of the selected training samples. The algorithm directly uses a small number of samples as atoms, and proposes joint sparsity model which fully considers the spatial information. Liu et.al[3] proposed a novel classification method based on sparse representation, which considers the spatial correlation and the spatial information of training data to improve the accuracy. The experiments results show that the method can improve the classification results. Song et.al[4] proposed a novel algorithm based on sparse representation and spectral information. During dictionary learning, the sparse representation coefficient of each pixel is calculated according to the learning dictionary. As a result, sparse representation feature is obtained. Finally, based on the sparse representation feature and spectral information, the random forest is constructed, then the classification results is got via voting mechanism. Experiments justify the effectiveness of the algorithm.

To make full use of the prior knowledge of samples, improve classification accuracy and speed, this paper refers to Yang's super-resolution method based on sparse representation[5], and presents a novel classification method based on learned dictionary. Firstly, this method unifies image pixel and its classification information as a sample, which is used for sparse dictionary learning. Then, the corresponding sparse association between image pixel and its classification information is sufficiently constructed, and the same sparse representation coefficient between them is guaranteed; According to the learned dictionary, the sparse representation coefficient of input image pixel is calculated, and guiding classification. Several experiments show that the method can get good classification results. The main innovation points include:

(1) A novel processing framework for hyperspetral image classification is presented. The image pixel and its classification information are unified as a sample pair, which is used for sparse coding, and training learning dictionary. the method sufficiently builds the sparse association between image

pixel and its classification information, which is defined as prior knowledge to guide the classification of input image.

(2) Improving the computing speed. Dictionary learning processing can be achieved offline, solving the problem of the number of samples influence on the speed of classification algorithm.

Sparse Representation

The key idea of sparse coding assumes that natural signals can be commonly expressed, or represented efficiently as a linear combination of atom signals, where only few coefficients are non-zero. The sparse coding of an observed signal *x* can be expressed as[6, 7]:

(1)

Where the coefficient is the sparse representation of *x*, is the error tolerance and is called dictionary, and is called atom of *D*. The function is referred as the l_p-norm, usually .

Donoho has proven the transformation from l_0-norm to l_1-norm and vice versa, when enough sparity[6]. The sparse coding problem of Eq.1 can be described in several ways. For example, we can seek the minimal error possible at a given level of sparsity :

(2)

We can also use a regularization parameter to balance the minimal error and sparsity:

(3)

The fundamental problem of sparse representation is the selection of dictionary. There are generally two kinds of methods: analytic-based and synthetic-based (learning-based). The dictionary of analytic-based model is also called implict dictionary, which mainly includes Wavelets, Contourlet, Curvelet, etc. This kind of dictionary is fixed structured with a fast numerical implementation, but certainly in lack of adaptivity. The dictionary of learning-based is inferred by machine learning techniques from some examples with flexible structure and highly adaptability. It is typically called learned dictionary, which can get sophisticated representation and fine performance. The method has stronger adaptivity, and gets finer sparse representation witch better performance. More details about dictionary are shown in papers[8, 9].

Classification Algorithm based on Learned Dictionary

In this paper, the pixel and its classification information are unified as a sample for image classification. The main ideas: firstly, the classification information of pixel is referred as a vector; The characteristic value of pixel and its classification information are unified as one vector for sparse coding, which is used for learning dictionary, while keeping the same sparse representation coefficient between them; finally, based on learned dictionary, the sparse representation coefficient of input pixel is used to estimate the classification.

Dictionary learning. Given the hyperspctral image pixel samples , its sparse representation based on the dictionary (the column is called its atom):

(4)

To unify the image pixel and its classification information for dictionary learning, the sample pairs (is referred as the classification set of image pixels) are defined. The goal of sparse representation is to estimate the dictionary using the samples *P*. The method unifies the image pixel and its classification information into the same sparse representation framework, where they have the same sparse representation coefficient. The objective function can be expressed as:

(5)

Where and are learned dictionary of image pixels and its classification information respectively, *A* is the sparse representation coefficient. *N* and *M* are the matrix dimension of and repectively. They are referred as the coefficient to balance the effects of the number of training samples on the whole sparse coding framework. Eq.5 can be simplified to:

s.t. , (6)

In the field of signal and image processing, the optimization problem of Eq.6 is the hot issue in the recent years. Its purpose is to train learning dictionary *D* using the sample *Z*. The current commonly used algorithms contain: general PCA, Method of Optimal Directions (MOD), K-SVD, etc[10, 11].

Classification. Based on the learned dictionary , the sparse coding problem of input image pixel can be defined as:

(7)

Given the sparse representation coefficient of , its classification can be got based on the learned dictionary :

(8)

Eq.7 and Eq.8 imply an important hypothesis: input image pixel and its classification have the same sparse representation coefficient, where the idea of the hypothesis is similar with Yang's super-resolution method[5]. During the processing of dictionary learning, Eq.6 shows the method unifies the image pixel and its classification into sample pair, which are used for training the dictionary and in the same framework of sparse coding. The method ensures that they have the same sparse representation coefficient. In the same way, in the same framework with the processing of dictionary learning, input image pixel and its classification should have the same sparse representation coefficient.

Optimization of the algorithm. The optimization problems of Eq.6 need a lot of computing resources. In this section, we will optimize the above model.

(1) Dictionary initialization. Randomly selecting samples as the initial over-complete dictionary. In this way, the method fully considers the prior information of samples, and enhances robustness of the algorithm. However, norm is non-convex optimization problem. Usually, norm is adopted in Eq.5. Where, is the regularization parameter, which is used to balance the precision of sparse representation and sparsity. This paper set its value to 0.01.

(2) Representation of classification information. [0,1] is equally splitted by *m* classification, where the numerial interval is 1/*m*. *m* classification can be defined: . While, this method has poor robustness, and the error rate of classification is higher. This paper uses *m* vector to represent the type of classification:

(9)

The position of the value 1 of the vector is used to judge the type of classification. Considering the calculation error, the position of the maximum number of the vector is used for judging the type of classification.

(3) Normalizing image pixel vector and classification vector. To improve the stability of sparse coding algorithm, before processing, each vector should be averaged and normalized.

Experiments

To evaluate the effect of the classification algorithm, two experiments are done using two groups of hyperspectral remote sensing image data sets, and the results is compared with SVM method[12]. Experiments use commonly used classification comparison evaluation index: OA(Over Accuracy) and Kappa coefficient. To make the algorithms have comparable, samples are randomly divided into two parts as the training sets and test data sets. All the experiments in this way are done five times, and the results are averaged, the better results in italic.

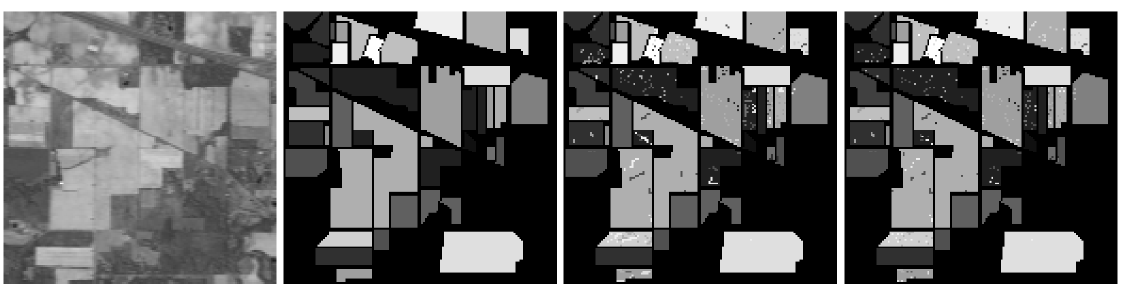
Experiment 1. This experiment adopts the hyperspectral remote sensing image gathered by AVIRIS sensor over the Indian Pines test site in June, 1992[13]. The Indian Pines scene contains two-third agriculture, and one-third forest or other natural perennial vegetation. The test scene has 220 bands, with the wavelength range 0.4-2.5. The whole image comprises 145 lines by 145 samples, with spatial resolution 20 meters. The number of bands is reduced to 200 by removing bands covering the region of water absorption. The nine classes are used as test samples which have 9234 sample pixels shown in Table 1.

Table 1 Statistical table of typical ground objects in Indian Pines test site

Type	Name	Value	Sum of Samples
1	Corn-notill	2	1428
2	Corn-mintill	3	830
3	Grass-pasture	5	483
4	Grass-trees	6	730
5	Hay-windrowed	8	478
6	Soybean-notill	10	972
7	Soybean-mintill	11	2455
8	Soybean-clean	12	593
9	Woods	14	1265

Table 2 Comparison results of classification methods

Method	SVM	Our Method
OA(%)	87.4	*89.7*
Kappa	0.862	*0.891*



(a) test site (b) distribution (c) SVM method (d) Our method

Fig.1 Results of classification methods

1000 sample pixels are randomly selected as test data, other as sample data for learning dictionary. The results of two algorithms are shown in Table 2. Fig.1 shows the classification figures. The results show: (1) OA is increased to 89.7% by our method from 87.4% based on SVM method; (2) Kappa is increased to 0.891 by our method from 0.862 with SVM method.

Experiment 2. This experiment adopts the hyperspectral remote sensing image gathered by AVIRIS sensor over the Salinas scene test site[13]. The whole image comprises 512 lines by 217 samples, with spatial resolution 3.7 meters. The number of bands is reduced to 204 from total 220 bands by removing bands covering the region of water absorption. The sixteen classes are used as test samples for experiment, which have 54129 sample pixels shown in Table 3.

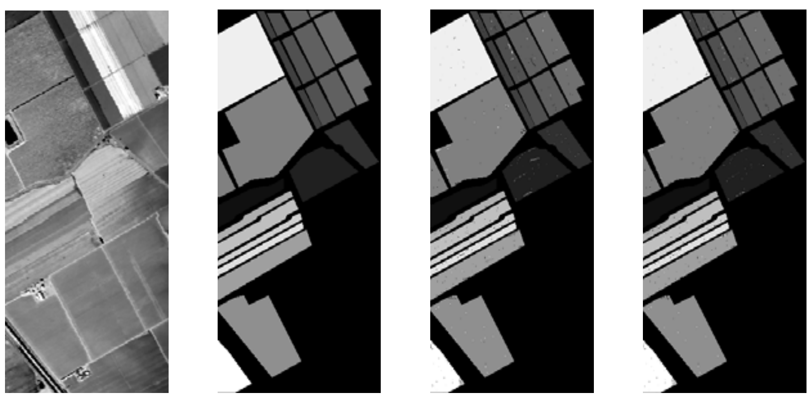
Table 3 tatistical table of typical ground objects in Salinas scene test site

Type	Name	Sum of Samples

1	Brocoli_green_weeds_1	2009
2	Brocoli_green_weeds_2	3726
3	Fallow	1976
4	Fallow_rough_plow	1394
5	Fallow_smooth	2678
6	Stubble	3959
7	Celery	3579
8	Grapes_untrained	11271
9	Soil_vinyard_develop	6203
10	Corn_senesced_green_weeds	3278
11	Lettuce_romaine_4wk	1068
12	Lettuce_romaine_5wk	1927
13	Lettuce_romaine_6wk	916
14	Lettuce_romaine_7wk	1070
15	Vinyard_untrained	7268
16	Vinyard_vertical_trellis	1807

Table 4 Comparison results of classification methods

Method	SVM	Our method
OA(%)	84.2	*87.5*
Kappa	0.832	*0.870*



(a) test site (b) distribution (c) SVM method (d) Our method

Fig.2 Results of classification methods

5000 sample pixels are randomly selected as test data, other as sample data for learning dictionary.

The results of two algorithms are shown in Table 4. Fig.2 shows the classification figures. The results show: (1) OA is increased to 87.5% by our method from 84.2% based on SVM method; (2) Kappa is increased to 0.870 by our method from 0.832 with SVM method.

Summary

A novel hyperspectral image classification method based on sparse learned dictionary is presented. Referring to the Yang's method, the method unifies the image sample pixel and its classification as sample for training learned dictionary, and keeping the same sparse model. The sparse association between them is build, and is referred as prior knowledge to guide the classification processing. Several experiments show our method can get good results. However, the spatial information is not fully considered, that is also one of our key future works.

References

[1] Plaza, J.A. Benediktsson, J.W. Boardman, and J. Brazile, Recent advances in techniques for hyperspectral image processing, Remote Sensing of Environment. (2009) S110-S2.

[2] Y. Chen, N.M. Nasrabadi, T.D. Tran, Hyperspectral Image Classification Using Dictionary-Based Sparse Representation, IEEE Transactions on Geoscience and Remote Sensing. 49 (2011) 3973-3985.

[3] L. Jian-jun, W. Ze-bin, W. Zhi-hui, X. Liang, and S. Le, Spatial Correlation Constrained Sparse Representation for Hyperspectral Image Classification, Journal of Electronics&Information Technology. 34 (2012) 2666-2671.

[4] S. Xiang-fa, J. Li-cheng, Classification of Hyperspectral Remote Sensing Image Based on Sparse Representation and Spectral Information, Journal of Electronics & Information Technology. 34 (2012) 268-272.

[5] J. Yang, J. Wright, T. Huang, and Y. Ma, Image Super-Resolution via Sparse Representation, IEEE Transactions on Image Processing. 19 (2010) 2861-2873.

[6] D.L. Donoho, For Most Large Underdetermined Systems of Equations, the Minimal l1-norm near-solution approximates the sparsest near-solution, Communications on Pure and Applied Mathematics. 59 (2006) 907-934.

[7] J.A. Tropp, S.J. Wright, Computational methods for sparse solution of linear inverse problems, Proceedings of the IEEE. Special issue on Application of Sparse Representation and Compressive Sensing. 98 (2010) 948-58.

[8] M. Elad, M.A.T. Figueiredo, M. Yi, On the role of sparse and redundant representations in image processing, Process of the IEEE. 98 (2010) 972-982.

[9] R. Rubinstein, A.M. Bruckstein, M. Elad, Dictionaries for sparse representation modeling, Process of IEEE, Special issue on Applications of Sparse Representation and Compressive Sensing. 98 (2010) 1045-1057.

[10] J.A. Tropp, A.C. Gilbert, M.J. Strauss, Algorithms for simultaneous sparse approximation, part I: Greedy pursuit, Signal Processing, special issue "Sparse approximations in signal and image processing". 86 (2006) 572-588.

[11] M. Aharon, M. Elad, A.M. Bruckstein, K-SVD: An algorithm for designing overcomplete dictionaries for sparse representation, IEEE Transactions on Signal Processing. 54 (2006) 4311-22.

[12] F. Melgani, L. Bruzzone, Classification of hyperspectral remote sensing images with support vector machine, IEEE Transactions on Geoscience and Remote Sensing. 42 (2004) 1778-1790.

[13] AVIRIS NW Indiana’s Indian Pines 1992 Data Set on. http://cobweb.ecn.purdue.edu/biehl/MultiSpec/documentation.html.