Research on Hyperspectral Remote Sensing Image Classification Method based on CS and SVM Improved Algorithm

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Abstract: Hyperspectral remote sensing image classification is a main application of hyperspectral. Due to the large number of bands and large amount of data in hyperspectral remote sensing image, the classification accuracy is not high and the classification time is long in the process of hyperspectral classification. In this paper, the methods of supervised classification and unsupervised classification of hyperspectral classification are studied comprehensively, and an improved SVM classification method is proposed to solve the problems existing in the classification process of SVM. Although this method can improve the accuracy of classification, it cannot solve the problem of large data processing. Therefore, this paper applies the compressed sensing theory to the improved SVM method, which can realize the classification of hyperspectral remote sensing images on the basis of sparse basis, thus not only increasing the classification accuracy, but also reducing the computational load. Simulation results show that the algorithm has better classification characteristics.

Keywords: Compressed sensing; SCV. hyperspectral; Sparse matrix

1. Introduction

Remote sensing technology was born in the early part of last century. The early remote sensing technology developed from aerial photography, and with the development of aviation technology, space technology, computer technology and the manufacturing technology of various electronic components, it was not until the 1960s that a relatively complete exploration science was formed. Due to the limitations of filming methods and data transmission conditions, the development of remote sensing technology is rather tortuous and slow. Only when the basic science and technology on which remote sensing relies develops synchronously can it achieve significant development.

Compared with traditional remote sensing images, hyperspectral remote sensing images are characterized by the fusion of spatial information and spectral information, which greatly enhances the information representation ability of hyperspectral images. The application of hyperspectral data mainly focuses on the classification and recognition of interested objects by using the rich spectral features it provides. Specifically, carry the spectral characteristics of hyperspectral remote sensing image information can reflect the subject specific features of the object, by means of statistical methods and the corresponding computer algorithm, for each pixel spectrum qualitative quantitative analysis, supplemented by effective feature extraction method, accurate analytical hyperspectral image spectrum characteristics of each pixel, concluded the characteristic information of the pixels inside your subject features efficient intelligent identification of the foreground object. There are two main categories of hyperspectral classification methods: hyperspectral classification method based on spectral matching algorithm and hyperspectral classification method based on data statistics algorithm.

Common supervised algorithms include decision tree algorithm, support vector machine algorithm, bayesian algorithm and neural network correlation algorithm. The Decision Tree algorithm mainly calculates the entropy value between samples through a Tree structure, and makes a judgment at each node. Each branch of the node represents a choice, and a node can have many branches, but the binary Decision Tree is the most commonly used. Each leaf node represents a result of the decision tree, which is determined by the sample label in the previous supervised sample.

Many of the above methods can be applied to hyperspectral images, but there are many inherent problems in hyperspectral images, which are determined by the immaturity of hyperspectral imager technology and the reflection spectrum of the subject.

The hyperspectral image data is very serious "with different spectrum" and "foreign body with spectrum" phenomenon, namely the same categories of subject in the spectrum of different shooting conditions exist obvious differences and different categories of subject under the interference of environment or under the condition of high resolution with very similar spectral curve. In addition, the non-linearity and redundancy of hyperspectral image data are very high, and many frequency bands are greatly affected by the external environment, so that all these frequency bands need to be filtered out in practical tasks.

The above problems reflect the high degree of non-linearity, correlation and redundancy of hyperspectral images. With the development of relevant preparation technology of hyperspectral imager, the dimension and data volume of hyperspectral data will continue to increase, which requires the correlation algorithm to improve accuracy and efficiency on the premise of satisfying the large data volume. Therefore, this paper designs an improved algorithm based on CS and SVM, which has the characteristics of high precision and high efficiency.

2. Compressed Sensing Theory

In 2006, a new theoretical framework, Compressive Sensing (CS) theory, was developed. Within less than 10 years, the shannon-nyquist sampling theorem has been continuously improved. Each of its research results is likely to bring revolutionary progress to the field of signal processing, with broad development prospects and application space. The core idea is to assume that the signal can be sparse. As long as the signal is sparse or compressible, the low-dimensional observation signal can recover and reconstruct the high-dimensional original signal well, which brings a new direction to the large-scale image sampling and processing. Shannon - which is different from traditional Nyquist sampling theorem, the compressed sensing theory broke through the Nyquist sampling theorem, the limitation on the size of the signal bandwidth, at the same time points out that the signal has the characteristics of information sampling directly, proposes a new signal collection and transmission mechanism, which is directly on the sparse or compressible signal sampling and data compression processing, discard redundant data information, and then USES the appropriate reconstruction algorithm in the compressed data were collected from optimization to reconstruct the original signal, to realize accurate reconstruction from the low sampling.

As a brand new image acquisition mechanism, the compressed sensing theory is different from the traditional sampling method and has the following characteristics: first, the signal sparsity is no longer limited by the bandwidth, but depends on the sparsity of the signal itself, that is, the content and structure of important information represented in the signal. 2. The signal sampling and compression process shall be completed simultaneously; 3. While retaining the complete key information, less measurement values are obtained after sparse representation; 4. Able to reconstruct the original signal from a small number of measured values with high quality and fully express the signal structure. However, compared with the common image compression processing mechanism, the difference lies in that the simple image compression mechanism needs to meet certain preconditions, and the redundant data should be discarded to reduce the information and ensure the image quality. However, the compressive sensing theory does not need to meet the criteria of Nyquist sampling theorem, so it directly performs the signal sampling compression processing.

Under the overall framework of compressed sensing theory, its sampling rate is no longer limited by the size of signal bandwidth, but determined by the structure and content of important information in the signal. It mainly includes three key technologies: signal sparse representation, measurement matrix design, signal reconstruction algorithm design. Signal sparsity is the basic prerequisite for satisfying the theoretical framework of compressed sensing. Sparsity plays an important role in the field of signal processing. Signal sparsity can more intuitively and effectively express the essential information of signals than signal bandwidth.

3. SVM and SVM Improved Algorithm

SVM (support vector machine) is a new generation of machine learning theory developed on the basis of statistical learning theory. Based on limited sample information, it seeks the best compromise between the complexity of the model and the learning ability, so as to obtain the best promotion ability. SVM has a solid theoretical basis and strong generalization ability, so it shows its unique advantages in solving small-sample, nonlinear and high-dimensional model problems [5]. In hyperspectral data processing, the remarkable advantages and good effects of SVM have been fully demonstrated, and have been widely used in the fields of band selection, data compression, spectral classification, spectral end element selection, spectral dismixing, sub-pixel positioning and anomaly detection.

From the perspective of classification, SVM theory is a generalized linear classifier, which is evolved from the linear classifier by introducing structural risk minimization principle, optimization theory and kernel function. The original

SVM theory is used to deal with two kinds of classification problems. The classification principle can be summarized as follows: to find a classification hyperplane so that the two types of sample points in the training sample can be separated and as far as possible from the plane.

The successful application of nuclear technology improves the classification performance of SVM. After introducing the concept of kernel function, the basic idea of SVM can be summarized as follows: firstly, the input space is transformed into a high-dimensional space by nonlinear transformation, and then the optimal linear classification surface is obtained in this new space, and such nonlinear transformation is realized by defining appropriate inner product function. Common kernel functions include linear kernel function, polynomial kernel function and gaussian kernel function.

Among many SVM development types, SVM improved algorithm is widely used for its efficient classification and regression function. More importantly, the mathematical model of SVM improved algorithm is an optimization problem of the sum of squares of error cost functions with only equality constraints. Its solution can be carried out in a linear system with efficient classification and regression functions, so it is widely used in various fields. The mathematical form of SVM improved algorithm is described as follows:

First, the hyperspectral image nonlinear transformation is input into the high-dimensional space, as shown in equation (1).

$$\min_{p,b,q}(p,q)=\frac{1}{2}\|w\|^2+\frac{\gamma}{2}\sum_{i=1}^{n}q_i^2 \qquad (1)$$

Find out its critical condition, as shown in equation (2).

$$s.t.y_i=<w,\varphi(x_i)>+b+q_i$$
$$i=1,2,......n,\gamma>0 \qquad (2)$$

The corresponding dual problem can be solved, as shown in equation (3).

$$\min_{p,b,q,a} L(w,b,q,\alpha)=J(w,q)-\sum^{n}\{\langle w,\varphi(x_i)\rangle+b+q_i-y_i\} \quad (3)$$

The optimal KKT condition is shown in equation (4).

$$\begin{bmatrix} 0 & 1_v^T \\ 1_v & \frac{1}{\gamma} \end{bmatrix}\begin{bmatrix} b \\ \alpha \end{bmatrix}=\begin{bmatrix} 0 \\ y \end{bmatrix} \qquad (4)$$

4. Research on Improved Algorithm based on CS and SVM

The SVM improved algorithm transforms the solution of QP problem in SVM into the solution of linear equation. More importantly, all the training data in the SVM improved algorithm model are support vectors, which not only ignore the sparsity of the model, but also reduce the robustness of the model. When constructing SVM improved algorithm model based on training data, there may be redundant data in the training data, which does not play a great role in the accuracy of the model, but these redundant data reduce the operation efficiency of the model. To solve this problem, CS is introduced in this section to propose an improved SVM algorithm based on sparse samples.

According to CS theory basic on that signal in sparse or frame is sparse, and when it comes to meet RIP measurement matrix properties measurement signal is to reconstruct the original signal, projection shows that measured signal contains enough refactoring information, in other words, is a small amount of sample enough to reflect the information contained in a complete sample. Before establishing the SVM improved algorithm model, CS is used to sample the training data to obtain its corresponding sparse sample data, and then the SVM improved algorithm model is established with the sparse sample data. In this algorithm, compared with the traditional CS, there is no need to realize the reconstruction signal, only the sparse signal obtained meets the condition that the signal can be reconstructed.

In this section, the sparse signal corresponding to the training sample s is obtained according to the OMP algorithm. Sparse samples were obtained according to sparse signals, and then the regression model was constructed according to the improved SVM algorithm. Where, the calculation formula of sparsity is (5).

$$Sparsity=\left(1\text{-}\frac{\mathrm{m}}{\mathrm{M}}\right)\times 100\% \qquad (5)$$

Where, m is the number after sparse, and m is the real number.

The improved algorithm based on CS and SVM is as follows:

Step 1: design the measurement matrix, set different sparsity, and obtain the sparse signal corresponding to the training sample according to the OMP algorithm;

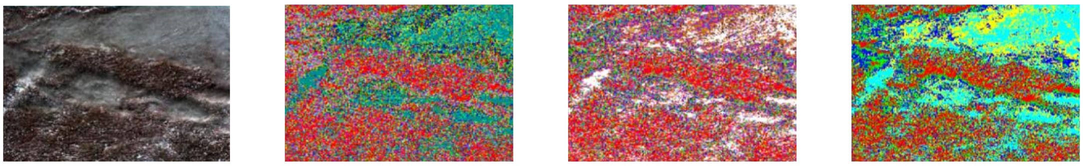
Step 2: obtain sparse samples; According to the sparse signal, the corresponding sample values in the training samples are obtained.

Step 3: obtain SVM improved algorithm model, and establish SVM improved algorithm model based on sparse samples;

Step 4: get the predicted value, and make regression prediction according to the improved algorithm model based on CS and SVM.

5. Experimental Analysis and Results

The data of the simulation experiment were HIS data of hj-1a satellite launched in September 2008. In this paper, the hyperspectral remote sensing data of HIS level 2 product in yichun, heilongjiang province was taken as the data source, and the number of bands was 255. In this paper, the 34th band of hyperspectral images numbered L1A0002851779 was selected for experiment. Among them, figure 1 (a) is the original graph, figure 1 (b) is the classification graph of adaptive correlation estimation (ACE) classification algorithm, figure 1 (c) is the classification graph of support vector machine (SVM) classification algorithm, and figure 1 (d) is the classification graph of this algorithm.



a. The original image | b. Adaptive | c. SVM classification | d. This algorithm Correlation estimation classification chart classification

Figure 1. Classification results of hyperspectral remote sensing images

As can be seen from figure 1, the algorithm in this paper is superior to the first two algorithms in accuracy. Through many experiments, a variety of classification algorithm comparison, verify the effectiveness of the classification algorithm. This paper compares different algorithms by running time, classification accuracy and Kappa coefficient. See table 1 for details.

Table 1. Comparison of classification algorithms

Classification algorithm	Running time (S)	Classification accuracy (%)	Kappa
Adaptive, Coherence, estimation	22	81.87	0.7896
Support vector machine classification	31	85.12	0.7931
This algorithm	18	87.13	0.8015

Simulation results show that this algorithm has certain application value in terms of running time and classification accuracy because of the former two algorithms and can effectively serve for hyperspectral remote sensing image classification.

6. Conclusion

At first, this paper studied the characteristics of hyperspectral remote sensing image, on the basis of the compression perception theory and classification of hyperspectral remote sensing image to do the research, an improved SVM classification algorithm is proposed, and then according to this algorithm the problem of low efficiency of the process of the experiment, the compressed sensing theory is introduced into the improved SVM classification algorithm, thus effectively solves the classification of the highlights in the process of remote sensing image classification algorithm is complex, classified by the large amount of data, training data capacity requirement is high. Simulation results show that the proposed algorithm improves the classification efficiency and accuracy compared with adaptive coherent estimation and SVM.

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