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Research on classification of high spatial resolution remote sensing image based on SVM

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Abstract: Considering the high spatial resolution remote sensing image has huge amounts of data and complex spectral distribution and the characteristics of the space characteristics of the rich, in combination with support vector machine (SVM) in tackling small sample, nonlinear and high dimensional pattern recognition problems show unique advantages, in this chapter will experiment data by using support vector machine (SVM) for high spatial resolution remote sensing image classification.

1. Introduction

With the continuous improvement of the spatial resolution of remote sensing images, the detailed information contained in the images is more and more rich. Compared with the past low and medium spatial resolution images, the images can better represent the texture, shape and geometric structure information of the target.At the same time, the improvement of spatial resolution of remote sensing images is accompanied by the surge of data volume, which requires efficient automatic classification technology to replace the traditional manual visual interpretation to extract useful information from images.On the other hand, high spatial resolution remote sensing images contain a large amount of detailed information, resulting in unusually complex spectral distribution, which reduces the separability of ground objects in the spectral domain.In order to solve this problem, automatic classification technology needs to make full use of the hidden information in the image and make up for the deficiency of spectral features.

In this paper, considering the advantages of support vector machine in solving small sample, nonlinear and high-dimensional pattern recognition problems, this machine learning algorithm is used as a classifier to classify high spatial resolution remote sensing images from the perspective of spectral domain.According to the experimental results, it is not reliable to distinguish the ground object in the image only by the difference of spectral characteristics, and the different ground object with similar spectral characteristics will be confused.

2. Multi-classification problem of support vector machines

2.1 "one-to-many" approach

A one-to-many approach is more specifically a one-to-others approach.Assuming that there are N categories to be classified, the samples of one category are classified as positive samples for the first time, and the samples of the other n-1 categories are collectively classified as negative samples. Thus, a binary support vector machine is obtained, which can identify whether unknown data belongs to the category of positive samples.The rest of the n-1 classes and so on, resulting in N support vector machines corresponding to N classes.When the unknown data is classified, the unknown data are input into N support vector machines respectively to obtain the results of multiple classification.

2.2 "one-to-one" approach

The "one-on-one" method can also be called the voting method.Suppose there are N categories to be divided, take samples of any two categories, and set one type of sample as positive sample and the other as negative sample to get a binary support vector machine.And so on, we need to construct a binary support vector machine. When the unknown data is classified, the classification of the unknown data is judged by the binary support vector machine. Whenever a support vector machine judges the unknown data as a certain category, it votes on the category. Finally, the voting result is counted, and the category with the most votes is the category of the unknown data.

2.3 DAG method

The DAG method is proposed to address some shortcomings of the "one-to-one" method.The strategy adopted in the training stage is the same as the "one-to-one" method, that is, for the problem with N categories to be divided, a binary support vector machine is still constructed.When the unknown data is classified, it is realized by directed acyclic graph.

In view of the characteristics of the three methods to solve the multi-classification problem, this chapter adopts DAG method in the experimental part to obtain high classification accuracy and unique classification results.

3. Experimental data processing

3.1 Selection of experimental data

The experimental data were taken from a part of the high-spatial resolution remote sensing image taken by WorldView-2 satellite, the image size was, and the spatial resolution of the image was 0.5 meters. In the experiment, the spectral values of three visible bands, red, green and blue, were selected as the spectral characteristics of the image.The image is shown in Figure 1.

Figure. 1 Experimental image

3.2 Selection of training samples

Training samples were selected for the five types of objectives according to the following principles:

(1) The spatial distribution of training samples is relatively uniform to avoid overlapping areas.

(2) The training samples should be as representative as possible, that is, the quality of the samples should be high.

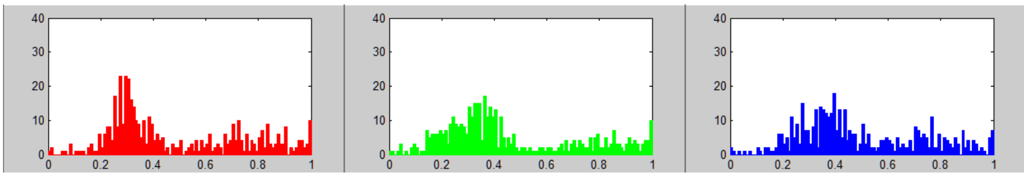
(3) The number of training samples is less than the total pixel number of the image, so as to test the ability of SVM to solve the classification in the case of small samples.

The number of training samples and populations for each category is shown in the following table.

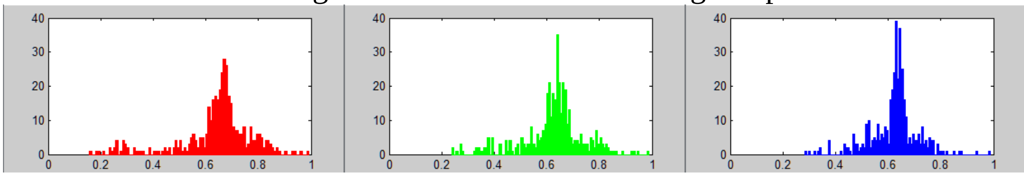
Table 1 The classification results

category	The training sample	The overall
building	820	66275
road	403	45475
vegetation	398	53027
shadow	374	21487
water	405	37516
OA	2400	223780

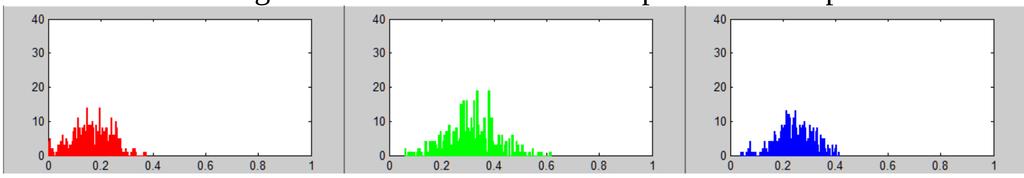
The histogram of spectral characteristics of each band of training samples of each category is shown in the figure below.



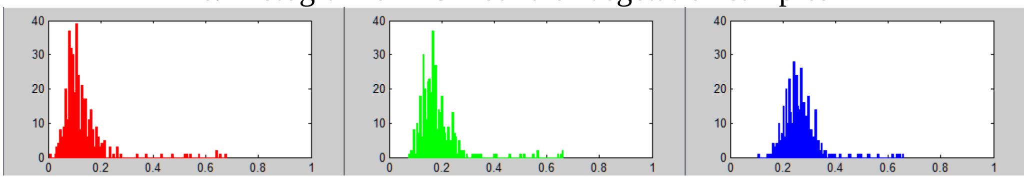
a. Histogram of RGB band of building samples



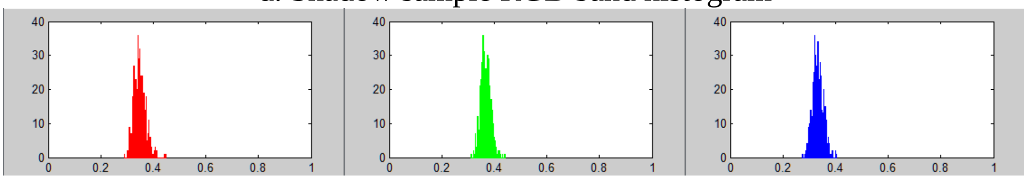
b. Histogram of RGB band of cement pavement samples



c. Histogram of RGB band of vegetation samples



d. Shadow sample RGB band histogram



e. Histogram of RGB band of water samples

Figure. 2 Histogram of samples classified in different bands

From the RGB band histogram of each sample, it can be found that: the distribution of spectral features of building samples is complex; Vegetation samples and shadow samples and water samples have more spectral features overlap; The difference of spectral characteristics between cement pavement samples and shadow samples is the largest.The spectral distribution of cement pavement samples and water samples is relatively independent.

3.3 Support vector machine classification

According to the comparison of three multi-classification strategies of support vector machines, it can be found that DAG avoids the phenomenon of classification overlap, unclassification and data set bias, and at the same time has higher classification efficiency.On the other hand, in order to improve the classification accuracy of DAG method, it is necessary to select the root node before classification.As can be seen from Fig. 2.8, there is a significant spectral gap between the training samples of cement road surface and shadow, which means that the support vector opportunity constructed with these two types of training samples has the highest classification accuracy, and the root node can minimize the accumulation of errors.

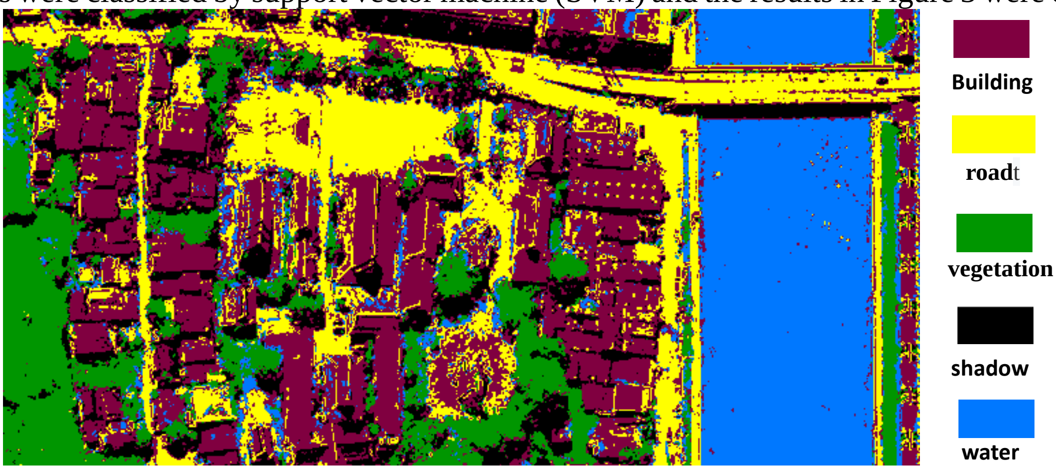
In view of the characteristics of the four kernel functions, the radial basis kernel function is selected as the kernel function of support vector machine.The radial basis kernel function has two parameters. One is the parameter in the kernel function, i.e., in Equation (23), which can be regarded as a parameter and denoted as; The other is the penalty factor, which is in Equation (20). For these two parameters, the parameter optimization method of particle swarm optimization (PSO) was used in this paper to optimize, and the optimal parameters obtained were shown in the table below.

Table 2 Classification accuracy table

category	building	road	vegetation	shadow	water
building	NaN	**C=1.046 g=49.613**	**C=6.674 g=50.677**	**C=4.174 g=7.190**	**C=1.040 g=20.846**
road	C=1.046 g=49.613	NaN	**C=0.771 g=16.967**	**C=0.100 g=64.749**	**C=7.472 g=33.329**
vegetation	C=6.674 g=50.677	C=0.771 g=16.967	NaN	**C=32.154 g=85.880**	**C=0.100 g=87.161**
shadow	C=4.174 g=7.190	C=0.100 g=64.749	C=32.154 g=85.880	NaN	**C=0.375 g=49.235**
water	C=1.040 g=20.846	C=7.472 g=33.329	C=0.100 g=87.161	C=0.375 g=49.235	NaN

4. Experimental Results

After the determination of multiple classification strategies and the optimization of parameters, the images were classified by support vector machine (SVM) and the results in Figure 3 were obtained



Classification accuracy =70.97%

Figure. 3 Classification results of spectral features

Buildings and cement pavements in these areas have close spectral characteristics that are difficult to distinguish by spectral characteristics.Similarly, light-colored vegetation is misclassified as a body of water, and the rippling locations in the water are misclassified as concrete pavements and buildings.These misclassification and salt-and-pepper noise phenomena in the classification results indicate that the classification results only relying on spectral features are not reliable, and other features are needed to supplement the spectral features to enhance the classification accuracy.

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