GROUND OBJECT CLASSIFICATION ALGORITHM BASED ON ZHUHAI-1 SATELLIEHYPERSPECTRALIMAGE

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ABSTRACT: With the increasing resolution of satellite and aerial remote sensing images, much more useful spectral and spatial information can be obtained from hyperspectral images than before. This paper proposed a feature classification method based on machine learning and an integration model to classify ground objects in Zhuhai-1 OHS hyperspectral satellite images precisely and robustly. Firstly, principal component analysis was used to reduce the dimension of the data. Secondly, the classification model was established by the combination of undersampling, binary classification model and multi classification model. Then, random forest, AdaBoost and neural network classification algorithms were used to train the training data. Finally, based on the idea of voting method, the classification models were integrated into a new classification model, and comparisons were made between the classification of these single algorithms and the integration model. The principal component analysis on the hyperspectral images shows that the first two bands of these images almost contain 95% information. Therefore, the classification on the first two bands not only can maintain the accuracy, but also can reduce the amount of data for image classification processing and saving classification time effectively. Among the three single classification algorithms, the best one is the random forest classification model with an accuracy of 0.656 and a kappa value of 0.472. While the integration model can give a better classification result than the three-single classification algorithms, with an accuracy of 0.660 and the kappa value of 0.481, the integration model is in fact can improve the accuracy of the classification on Zhuhai-1 satellite hyperspectral images.

1. INTRODUCTION

For remote sensing information extraction, the ground object classification of remote sensing images is a key technologie. In the field of machine vision, this process is equivalent to semantic segmentation (Li et al, 2018; Zhao et al, 2016). The traditional classification method is based on the image features extracted by human. The commonly used human described features include Color histograms, Texture features, and Histogram of Oriented gradients(HOG), scale-invariant feature transform （SIFT) (Lowe ,2004)and others. Rapid advances in Machine learning and deep learning in recent years have also provided more methods for remote sensing image classification, such as random forest(Ifeanyi et al,2020), Support Vector Machine(SVM)(Maulik et al,2011), Adaboost(WANG et al,2017), K-means(Halberstadt et al,2020), Sparse representation(Zhang et al,2021), Convolutional Neural Network (Kainz et al,2017) , Deep Belief Network (DBN)(Wang et al,2020) , migration learning (Liao et al,2020) etc. .

In this paper, the sample data of remote sensing image provided by Zhuhai-1 OHS hyperspectral satellite is used to study the classify the ground objects. The OHS hyperspectral satellite has 32 bands with a spectral resolution of 2.5 nm and can obtain hyperspectral remote sensing images. Traditional remote sensing images simply distinguish different types of objects. Hyperspectral images can also give specific properties of different objects, such as plants, buildings, water bodies and bare soil. But opportunities often come with challenges, according to the Hughes effect, the classification accuracy of hyperspectral remote sensing image will decrease with the increase of spectral band number. In order to improve the accuracy, two methods are usually used to reduce the dimension: sub-band selection and feature extraction. The former selects the most effective bands from the original bands according to certain evaluation criteria, such as SFS, SBS and others. The latter transforms the high-dimensional data in the original band space into the low-dimensional data in the feature space by means of mapping and transformation, such as Principal Component Analysis(PCA)(Zu et al, 2019) ,Independent Component Analysis(ICA)(Xian-chuan et al,2012), Wavelet Transform(WT)(Deeba et al,2021) ,etc.

In this paper, the original remote sensing image data from Zhuhai-1 OHS hyperspectral satellite are firstly reduced by PCA algorithm. On this basis, in view of the problem that the difference of data amount will affect classification greatly, a classifier is constructed by combining the sub-sampling with the binary classification model and the multi-classification model with three classification algorithms of random forest, Adaboost and neural network, respectively, finally, based on the idea of voting method, the classification model is integrated into a new classification model to realize the classification of ground objects.

2. METHODOLOGY AND PRINCIPLES

2.1 PCA

When it comes to dimensionality reduction, PCA algorithm is often selected to carry out the operation. Data dimensionality reduction is the use of lower dimensions to represent higher latitudes. For PCA, that is, the original n-dimensional features on the basis of the reconstruction of new orthogonal features, that is to extract the principal components. The method of construction is to choose the direction with the greatest variance in the original data as the first new coordinate axis in the original high-dimensional space, and the second new coordinate axis is to choose the plane orthogonal to the first coordinate axis to make the variance maximum, and the plane with the largest variance in the plane orthogonal to the 1 and 2 axes is the third and so on. Finally, a new set of orthogonal axes is obtained. It can be observed that the front k axes of the new axis obtained in this way contain most of the variance, while the remaining axes contain almost zero variance, therefore, we can only retain the dimensionality that contains most of the variance, and ignore the dimensionality that contains almost zero variance. By this method, we can reduce the dimensionality of data features.

The method based on eigenvalues decomposition covariance matrix can be used to implement PCA. The key idea is that a set of eigenvectors of matrix A must be two orthogonal, and the eigenmatrix V could be expressed in the following form:

$$Av = \lambda v \tag{1}$$

The λ is the eigenvalue of the eigenvector V. A set of orthogonal unit vectors of matrix A can be obtained by orthogonalizing a set of eigenvectors of matrix A. Suppose the eigenvectors of matrix A can form matrix Q, then matrix A can be transformed into the following formula:

$$A = Q\Sigma Q^{-1} \ . \tag{2}$$

It is a diagonal matrix of the elements on the diagonal formed by the eigenvalues. The breakdown is as follows:
Input: Dataset is $X = \{x_1, x_2, x_3, ..., x_n\}$, the dimension reduction target is k dimension.

1) De-averaging (de-centralizing) , where each feature subtracts its own average.

2) Computing covariance matrix by

$$\frac{1}{n} XX^T \tag{3}$$

3) Use eigenvalue decomposition to obtain the eigenvalues and eigenvectors of the covariance matrix

4) Constructing eigenvector matrix P, the row vector of P is composed of k eigenvectors corresponding to the largest K eigenvalues.

5) Finally

$$Y = PX \tag{4}$$

Y is the result of data set X reduced to K dimension IE by PCA algorithm.

2.2 Random Forests

The basic unit of a random forest is a decision tree. The basic idea is an algorithm that integrates multiple decision trees through the idea of ensemble learning. For an input sample, random forest will construct n decision trees. Each decision tree is a classifier, so that N classification results can be obtained. These n categories are then integrated by voting to obtain the final output. The trees in the forest are independent of each other, and the vast majority of the trees make all-encompassing predictions that make up the noise and do not affect the final outcome. Only a small number of good trees will be able to make good predictions beyond the noise.

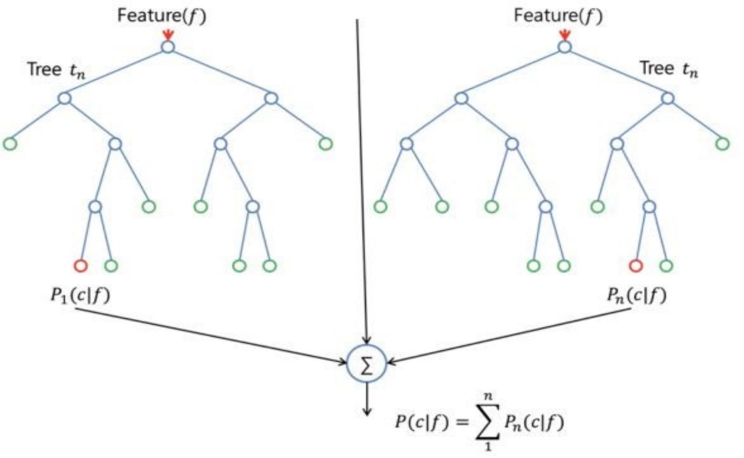

Fig.1 Structure of Random Forest Classifier

The random forest generates the decision tree according to certain rules, the rules are as follows:

1) For a training set of size N, Each tree randomly and reactively samples n training samples from the training set as the training set of the tree(this sampling method is called bootstrap sample method) ; the training set of each tree is a different training set with repeated training samples.

2) Get the feature dimension of the sample, suppose it is M, choose the constant m (guarantee m is much less than M) m feature subsets are selected randomly from M features. Every time the tree is split, the best one is selected from the m features

3) The trees are not pruned, and each tree is guaranteed to grow to the maximum.

The two randomness in 1) and 2) are the “Random” of a random forest. Because of the introduction of randomness, the random forest has good anti-noise ability, and is not easy to fall into over-fitting, which can greatly improve the classification performance of the random forest. There are two factors related to the effect of random forest classification (error rate) : the correlation of any two trees in the forest and the classification ability of each tree in the forest, the smaller the correlation and the stronger the classification ability of each tree, the lower the error rate throughout the forest. Decreasing the number of feature selection m will decrease the correlation and classification ability of the tree, and increasing m will increase the correlation and classification ability. Therefore, it is necessary to choose a suitable m to keep the balance.

2.3 Adaboost

The idea of iteration forms the basis of Adaboost algorithm. In the Nth iteration of Adaboost, the N^{th} weak classifier will be trained, and it has N-1 weak classifier trained in the first N-1 iteration and all parameters will not change, the N weak classifiers will jointly participate in the next iteration. The main aim of training the N^{th} weak classifier is to divide the data that the first N-1 weak classifiers did not divide correctly. The results of all weak classifiers constitute the final output of Adaboost classifier. Consider that the goal of the nth classifier is not to ensure that the previously paired data can also be paired at the same time, but more likely to be paired with the n-1st unpaired data. In other words, each weak classifier in Adaboost only focuses on one part of the whole data set, and each has its own point of greatest concern, so the final result must consider all weak classifiers, not just one .Because each weak classifier has different concern data, the classification error rate is not consistent. When the final result is obtained, the weight is calculated according to the classification error rate of the weak classifier. The law of computation is that the error rate of the weak classifier is lower, the more powerful it is. Finally, the weighted voting is carried out according to the weight of the weak classifier

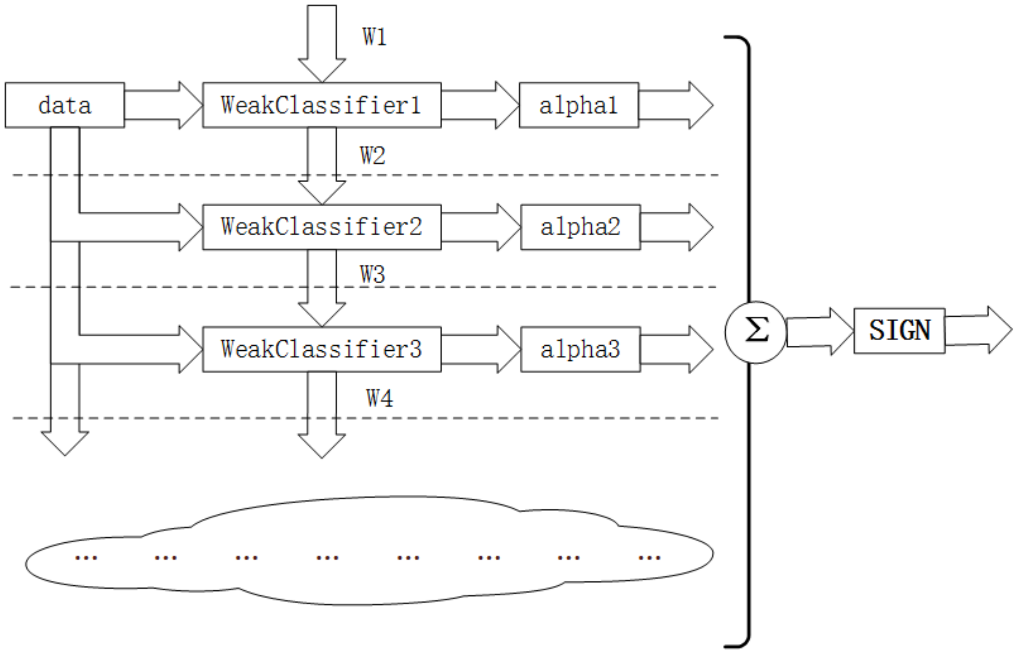

Fig.2 Structure of Adaboost Classifier

The overall structure of a typical Adaboost classifier is shown in Fig.2. The dotted line in the graph marks out the iterative effect of different rounds. Each iteration contain not only the previous structure, but also a new row of structure, that is, only the structure shown in line 1 is included, and on the second iteration, in addition to Line 1, the structure of Line 2 is included, and so on. Finally, the final output of the Adaboost classifier is obtained by the final summation and symbolic functions of all the weak classifiers. The "Cloud" at the bottom of the diagram represents the omission of the iterative structure.

Here are a few things to do in iteration i:
1) Add a weak classifier and a weak classifier weight, named WeakClassifier (i) and Alpha (i).

2) Train the weak classifier WeakClassifier (I). Corresponding dataset data with data weight W (I) , and its classification error rate is obtained, so the weak classifier weight alpha (i) is calculated

3) The final prediction output is obtained by weighted voting on all previous weak classifiers, and then the classification error rate of this prediction output is calculated. If the classification error rate is higher than the set threshold, then the weight of the updated data gets w (i + 1) and iteration i + 1. If the set threshold is higher than the classification error rate, then the iteration is over and the Adaboost classifier is constructed.

2.4Neural Networks

The goal of the neural network model is to simulate the neural network of the human brain. It has strong adaptive learning ability, can process data in large-scale parallel and has good robustness. But the neural network can't be controlled by the object of the system parameter changes and outside interference, can handle complex multi-input, multi-output nonlinear system. There are three main components of a neural network: First, the weight, which represents the strength of the connections between neurons, and the weight, which represents the probability. Second, the bias, the bias setting is to guarantee the flexibility of classification and improve the accuracy of classification by adjusting the proportion of discarded local information. Third, the activation function, if the value of a neuron can vary from negative to positive, then we can't decide whether we need to activate the neuron, and that's where the activation function helps us solve the problem. If linear mapping alone can't solve complex problems, the activation function mainly limits the output amplitude of the neuron to a certain range through the function of nonlinear mapping. Common activation functions are Sigmoid, Softmax, Tanh, ReLU, and so on, they have their own advantages and disadvantages and scope of application.

There are many varieties of Neural Network, such as probabilistic Neural Network, Back Propagation (BP) Neural Network, Convolutional Neural Network (CNN), Long Short-term Memory Network (LSTM) and so on. The simplest and most authentic neural network is the Muti-Layer Perception (MLP) .

The input layer, the hidden layer and the output layer constitute the MLP. The units in each layer of the MLP neural network are connected to all the units in the adjacent layer, and there is no connection between the units in the same layer. The structure of the MLP neural network is shown in Fig.3. There is a connection between the Layer and every two cells (neurons or output/input cells) preceding the Layer, representing a weight.

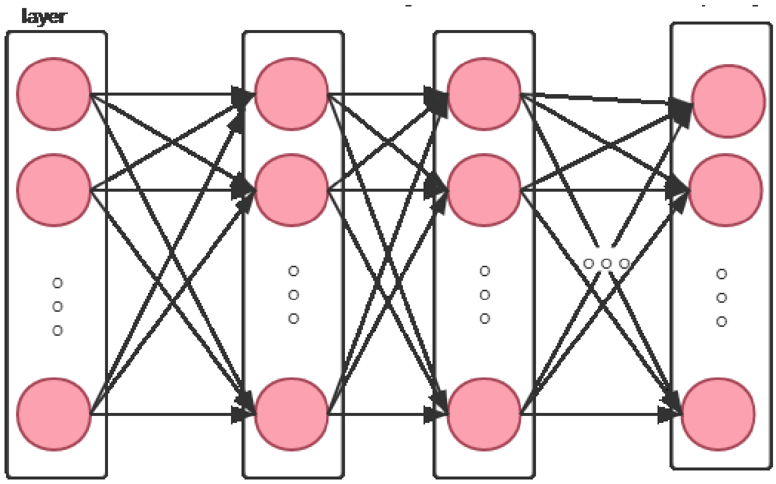

Fig.3 Structure of Multilayer Fully Connected Neural Network

For a single neuron in an MLP, the output of the previous layer is the input of the current layer。 Using the sum of the product of the weights and the inputs, plus the offset values, we get z as the input to the activation function, which outputs the value to the next layer, there is no difference between Z's calculation and regression.

3. ALGOTITHM DESIGN AND EXPERIMENTS

3.1Data Dimensionality Reduction

This data is taken from the image sample data provided by the Zhuhai-1 OHS hyperspectral satellite. The OHS hyperspectral satellite almost has the advantage of recording images of ground objects with continuous spectral information. However, it will increase the time and space complexity of image processing if we use different band images to classify objects directly. If the original data is directly used for classification, the amount of data is too large, and there is no way to complete the classification better. So before processing the data, the PCA algorithm is used to reduce the dimension of the remote sensing image data. By calculation, the first band of the remote sensing image has the largest eigenvalue, the last band has the smallest eigenvalue, and the first two bands account for 95% of the total eigenvalue, only the first two bands of remote sensing image data are used for ground object classification.

Having successfully reduced the dimensions of remote sensing data, the classification of ground features has been officially started, noting that bare land, vegetation, water bodies and buildings are to be classified, and that not all of these four categories are to be classified as background, so there are five features in all. The data contained in one pixel in the image is divided into one data, and the corresponding data volume of each feature in the 90 remote sensing images and corresponding mask images of the training set is counted, we found that the amount of data associated with each feature varied greatly. The largest of the four categories was vegetation, with 6,308,184 data points, while the smallest bare soil had only 110,062 data points, and the remaining buildings and water bodies had 3,585,512 and 1,350,551 data points, respectively, with 11,145,691 background data points, if we use the original data directly for classification training, it will cause great error. So here we use 4 binary classification and 1 multi-classification to classify, 4 binary classification is to judge whether the data belongs to 4 categories in turn, if not, then it belongs to the background data, in order to avoid when classifying, when multiple binary classification models are judged as target data at the same time, multi-classification results are used to verify the results. At the same time, using the idea of undersampling, for the binary classification model, the training data is all the data in the category to be judged as the target data, at the same time from the other three categories of data and background data from the number of data not exceeding the total number of data in that category, recorded as background data; for multi-classification model, the training data includes all the data of all 4 categories and the same amount of background data as the total. The training data of 5 groups are stored in TXT file, as shown in Fig.4. The first two numbers in each row are the first two band values of the remote sensing image, and the third data is the label. For binary models, the "obj" and "backg" labels indicate whether the data is the target data or the background data; for multiple classification models, the labels "vegetation" stands for vegetation, "build" stands for building, "water" stands for water, "soil" stands for bare soil, and "background" stands for background

503,572,obj
512,574,obj
507,570,obj
508,582,backg
512,583,backg
524,596,backg
516,603,backg
513,602,backg
509,601,backg
510,593,backg

Fig.4 Sample Dataset Schematic Diagram

3.2Classification Algorithms

After the completion of the Data pre-processing, the official start of the ground features classification. In this paper, random forest, Adaboost and MLP are used to classify the remote sensing images:

1)The data were pre-processed by random forest training, and will get four binary classifiers and one multiple classifier. The binary classifiers will be used to judge whether it was plant, building, water and bare soil.

2)These five classifiers will be used for ground object classification of remote sensing images. The classification rule is that, if all binary classifiers are judged as the background, then it is the background; if only one binary classifier is confirmed as the target, then the data is confirmed as the corresponding category of the classifier; If more than one binary classifier is confirmed as the target, then the result is judged by multiple classifiers. If more than one classifier is judged by one of the four major categories, then it is confirmed as the category, and if more than one classifier is judged by the background, then the result is the corresponding category of the first two classifiers that are judged as the target.

3）Taking into account the spatial continuity of the distribution of objects. So, the algorithm can improve the accuracy of terrain classification by using the 8 neighborhood pixels of the center pixel to constrain the prediction result of the classifier. Specifically, if more than half of the predicted results of a pixel's 8-neighborhood pixel classifier are the same, it is placed as the final classification result of the pixel's random forest classifier.

4）By this method, Adaboost and MLP are used to repeat the operations of (1)-(3) respectively to get the classification results.

5） The results predicted by the three classifiers are aggregated by voting, and The final category is the one with the most votes.

3.3Categorical Results

In this paper, the accuracy rate and Kappa coefficient are selected as the evaluation criteria to evaluate the feasibility and practicability of the algorithm: the accuracy rate is the ratio of the total number of pixels in all true surface classification to the total number of pixels classified; the Kappa coefficient is usually used for consistency checking. It is calculated as follows:

$$\mathrm{k}appa = \frac{p_0 - p_e}{1 - p_e} \tag{5}$$

In this equation p0 is the accuracy rate, and

$$p_e = \frac{\sum_i^n r_i * e_i}{al^2} \tag{6}$$

al means total number of pixels, n is the number of divisions, ri represents the total number of true pixels in category i and e_i represents the total number of pixels classified as category i.

The target remote sensing data are classified by three classification algorithms: Random Forest, Adaboost and neural network, and the integration algorithm of the three algorithms:

Table 1 Comparison of Results By Category

	Accuracy Rate	Kappa
Random Forest	0.656	0.472
Adaboost	0.646	0.458
Neural network	0.623	0.429
Integration algorithm	0.660	0.481

According to the results, we can see that the random forest classification model is the best among the three classification models, its accuracy rate is 0.656, kappa value is 0.472, the accuracy rate is improved to 0.660, kappa value is 0.481. The accuracy of ground object classification can be improved more effectively by using model integration. At the same time, we can see that the classification result of the algorithm has medium consistency with the correct classification.

4. CONCLUSION

Aiming at the hyperspectral remote sensing image acquired by OHS hyperspectral satellite, a method of ground object classification based on machine learning and model integration is proposed. In this paper, the PCA transform is used to Dimensionality reduction of hyperspectral image. Then this paper constructed a classifier using random forest, Adaboost and neural network. It is concluded that the first two bands can be used to represent 95% of the eigenvalues by PCA. Therefore, In the process of ground object classification of remote sensing image, we can classify them using only the first two bands. It can reduce the workload and improve the speed of classification while ensuring sufficient accuracy, so as not to offset. The classification accuracy and Kappa coefficient of the algorithm will be improved by the integration method. In the process of classification, the misclassification and omission classification of targets can also be obvious. However this paper only integrates the three classification methods. In the future, more and better classification methods will be selected for integration, which is the next step to be done.

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