International Journal of Signal Processing, Image Processing and Pattern Recognition
Vol.8, No.8 (2015), pp.361-372
http://dx.doi.org/10.14257/ijsip.2015.8.8.37

Research on Corn Region Extraction of Remote Sensing Image Based on Fusion of PSO Parameters Optimization and Adaboost_SVM

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Abstract

High resolution remote sensing image contains abundant information, and the amount of data expands rapidly, it is challenge and advantage to the corn information extraction. For high resolution images, the spectral characteristics are the most important characteristics, but remote sensing classification only according to the spectral ignores the texture information as positive factors. This paper introduced texture features, establishes joint spectrum - texture feature set. Support Vector Machine (SVM) classification method relies on the selected parameters, this paper used Particle swarm optimization (PSO) to optimize penalty and kernel function parameters. Under the condition of a large number of high resolution remote sensing data, the increase of samples will influence the algorithm efficiency greatly. This paper improved SVM, namely Adaboost_SVM, extracted corn planting information. The method can be used as support for corn area prediction and yield estimation. The experimental results show that the proposed method improves extraction accuracy, improves efficiency compared with classic algorithms significantly.

Keywords: *remote sensing, region extraction, PSO, parameter optimization, Adaboost_SVM*

1. Introduction

With many years' development, remote sensing technology, such as sensors, platform construction, information processing, and remote sensing application has been developed rapidly, used in various fields widely, for example, global climate change, desertification, sea ice melting and drift phenomenon. It already gets human attention widely by remote sensing observation, plays a major role in the fields of fire, earthquake, crops diseases, insect pests and meteorological disaster prediction and evaluation, becomes an indispensable way in resource investigation, crop planting area estimation and yield estimation.

Agricultural remote sensing information extraction is premise in remote sensing applications, many methods have been improved and explored to improve the automatic classification precision and reduce running speed of the algorithm constantly. The corn area is very wide in northern China, and the corn is related to the healthy development of national economy as an important economic crop. Corn planting area extraction is an important application of agriculture remote sensing field, which provides data support for planting area prediction and yield estimation. In practice, corn is a king of season crop, with short growth cycle and great species diversity, spectral information is very complex because of intercropping. Classification accuracy is affected severely only according to spectral information, the texture of corn area is different from that of villages and other

ISSN: 2005-4254 IJSIP

vegetables, corn area is regular rules commonly, so this paper extracts the texture information as a supplement, which improves the accuracy of information extraction.

In general, remote sensing image classification methods can be divided into supervised classification and unsupervised classification. Unsupervised classification without a priori knowledge, classifies objects according to the statistical characteristics and the distribution of natural point group, mainly including k-means, ISODATA, etc. The lack of these methods is that classification accuracy is low, and classification results are rough. It doesn't fit for high resolution remote sensing image, causes loss of remote sensing information, so commonly used in coarse classification. Supervised classification is used as high precision statistics discriminant classification, uses training samples with prior knowledge to identify other unknown pixels. The key is the choice of training samples. Sample quality is related to classification accuracy.

With the development of the remote sensing classification research, many new means, such as artificial neural network [1-3], support vector machine [4-6], and random forest [7-8], meet the requirements of complex multispectral data. SVM, as an important classification algorithm, roots in the handling of data classification problem, mainly for binary classification problems. In engineering application, the kernel parameters and penalty parameters determine the strengths and weaknesses of the SVM performance to a large degree [9]. Kernel parameters affects the mapping function and, in turn, affects the complexity of the samples subspace, finally affects the classifier performance. Penalty parameters are used in data subspace to the adjust confidence interval range of learning machine [10]. All of these explain that the selection of the penalty parameters and kernel parameters are very important. At present there are many ways to choose the parameters, such as experimental method, grid method, and gradient descent method, etc. These above methods optimize two parameters as a parameter, process is complicated.

The experimental process block diagram is shown as Figure 1.

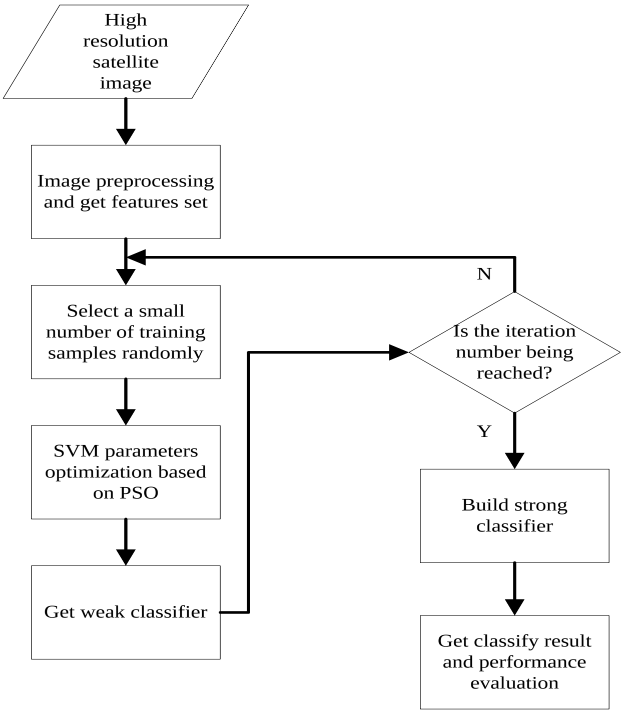


Figure 1. Experimental Process Block Diagram

2. Related Theory Research

With the development of sensing technology and satellite technology, remote sensing technology had great development, every day huge amounts of remote sensing images with multispectral resolution and temporal resolution can be gotten. High spatial resolution sensing images are important data source of various fields, classification research of high resolution remote sensing image could always be popular direction. Up to now, classification algorithms emerge in endlessly, such as unsupervised classification(k-means[11]and ISODATA), supervised classification（maximum likelihood [12], artificial neural network, decision tree, support vector machine [13-16], and random forests), and Combination classification techniques (semi-supervised and fusion of supervised and unsupervised classification) and so on.

Although a large number of remote sensing classification techniques have been developed in recent decades [17], most methods only utilize spectral variables, while spatial information has more or less been ignored. Spectrum-based classification approaches are conceptually simple and easy to be implemented, but neglect the spatial components, which are inherited in real-world remote sensing imagery [18]. This issue becomes severe with the availability of high resolution remote sensing imagery. With improvement of spatial resolution, images are likely to have higher within-class spectral variability. As a result, less than satisfactory results have been reached with spectral classifiers [19].

Literature [20] proposed that texture information can improve the spatial resolution image classification to a large degree. At the same time, single feature representation methods can't descript all of the information, thus he developed multiple features fusion method. M. Fauvel [21] used morphological properties to describe spatial information, and combined spectrum characteristics, overcomes the disadvantage of single feature classification, and improves the classification precision of pixel scale greatly. Y. Tarabalka [22] used the spectrum - spatial information, such as clustering method to segment images, and votes to optimize classification results based on pixel level in the same region. M.Fauvel and Y. Tarabalka [23] combined morphological properties and multiple classifier methods to improve the classification results, at the same time showed that the texture information and spectral information are important to image classification.

2.1. Support vector machine

Support vector machine (SVM) is based on VC dimension theory and structure risk minimum principle of statistical learning theory. According to the complexity of the model with limited samples information (*i.e.*, learning accuracy of particular training sample) and learning ability (*i.e.*, identification of any samples without error) it seeks the best compromise. The basic idea is to find an optimal classification plane between two classes.

K is kernel function, its main types are ones as follows:

Linearity: $K(x, x_i) = x^T x_i$

RBF: $K(x, x_i) = \exp(-\gamma \|x - x_i\|^2), \gamma > 0$

Polynomial: $K(x, x_i) = (\gamma x^T x_i + r)^p, \gamma > 0$

Sigmoid: $K(x, x_i) = \tanh(\gamma x^T x_i + r)$.

Common binary classification SVM model contains four steps as follows:

Step1: Suppose train sample set: $T = \{(x_1, y_1), \cdots, (x_l, y_l)\} \in (X \times Y)^l$

Step2: Select Proper kernel function and parameters of punishment, structure and solve the optimization problems:

$$\min_{\alpha} \frac{1}{2}\sum_{i=1}^{j}\sum_{j=1}^{l} y_i y_j K(x_i, x_j) - \sum_{j=1}^{l}\alpha_j \quad s.t.\sum_{i=1}^{l} y_i \alpha_i = 0, \quad 0 \le \alpha_i \le C, i = 1, \cdots l \tag{1}$$

Then get optimal solution: $\vec{\alpha} = (\alpha_1^*, \cdots \alpha_l^*)^T$.

Step3: Select a positive component of the optimal solution $0 < \alpha_j^* < C$, calculate threshold:

$$b^* = y_j - \sum_{i=1}^{l} y_i \alpha_i^* K(x_i - x_j) \tag{2}$$

Step4: Construct the decision function: $f(x) = \mathrm{sgn}(\sum_{i=1}^{l} y_i \alpha_i^* K(x, x_j) + b^*)$. (3)

2.2. Particle Swarm Optimization

PSO is an evolutionary computation method, was firstly proposed by Eberhart and Kennedy in 1995, can be applied to the study towards the behavior of preying birds. The basic idea is to find the optimal solution through collaboration and information sharing between individuals in the group. Firstly, we initialize a group of random particles, then, find the optimal solution based on iterations. In each iteration, particles track two update "extreme", find the two optimal values, update the speed and position. Update equations as follows:

$$v_i(k+1) = \omega \cdot v_i(k) + c_1 r_1(k)(p_{best,i}(k) - x_i(k)) + c_2 r_2(k)(g_{best}(k) - x_i(k)) \tag{4}$$

$$x_i(k+1) = x_i(k) + v_i(k+1) \tag{5}$$

Where, v_i is particle's velocity, x_i is particle's position. $p_{best,i}$ is the past optimal value of ith particle, g_{best} is the optimum position of all of the particles. c is the acceleration constant, r is random factor between 0 and 1.

Of course, other methods can be used to do Parameter optimization, for example, Genetic algorithm (GA), the experimental results will be shown in part 3 based on the first experimental data. Genetic algorithm contains three important parameters: the population size, crossover rate and mutation rate, parameter settings have not fixed rule. Because of probability type and the huge computation, there is a certain risk to fall into a local optimal solution, search speed is too slow. Compared with genetic algorithm, PSO algorithm can complete the operation as long as you can work out the update speed, but with the increase of the iterations the consumption of time will multiply.

2.3. Adaptive Boost Strategy

This is an active learning method. Its core idea is that through adjusting the weights of sample distribution and weak classifier automatically, several key weak classifiers are extracted from weak classifier space, integrated into a weak classifier group, namely the strong classifier. Theoretical research proves that strong classifier error rate will be zero as long as each weak classifier classification error rate is below 50% and the number of weak classifier is close to ∞. In corn planting information extraction, it is necessary to construct weak SVM classifier group (strong classifier) based on the samples of few number and brief characteristics, in order to simplify the process parameters optimization. This mentality is feasible in theory completely. Algorithm is described as follows:

Step 1: Randomly select training data from the sample space group, initialize data distribution weights $D_k(i) = 1/m$, initialize the parameters of particle swarm optimization algorithm.

Step 2: When training the kth weak classifier, train SVM weak classifiers and predict output data based on training data and optimization parameters, then get prediction error of $g(k)$ and $e(k)=\sum_i D_k(i)$ $i=1,2,\cdots,m(g(k)\neq y)$. Where, $g(k)$ is the prediction result, y is the expectation result.

Step 3: Compute forecast sequence weight according to $e(k)$, $\alpha(k)=0.5\ln(\frac{1-e(k)}{e(k)})$ (6)

Step 4: Adjust test data weight of the next iteration according to $\alpha(k)$,

$$D_{k+1}(i)=\frac{D_k(i)}{B_k}\exp[-\alpha(k)y_i g_k(i)], i=1,2,\cdots,m. \tag{7}$$

Step 5: Train K weak classifiers $f(g_k,\alpha_k)$ and construct strong classifier

$$h(x)=sign(\sum_{k=1}^{K}\alpha_k f(g_k,\alpha_k)). \tag{8}$$

3. Experiment Process and Result Analysis

3.1. Experiment Data

Experimental data is derived from the fusion results based on multi-spectrum images (B - G - R - NIR) and panchromatic image (pan). The spatial resolution is 2 meters. To keep consistent experimental conditions, this text selects two images from the same scene data set, geographic location is corn main planting territory in Gaoling, shaanxi province. Remote sensing images include corn, non-corn plants, and urban. Here, we study the corn crop planting area information extraction, the corn area as interested area, other area as background. Images size are 1308*1337、472*422 respectively. In order to adapt to the human eye visual sensitive features, the paper selects three bands (G - R - NIR) to establish false color images, as shown in Figure 5 (a) and Figure 6 (a). All of the experiments are based on a windows 7 operation system with a Intel Core i5-2.30GHz processor and 4.0 GB RAM.

3.2. Feature Extraction and Selection

3.2.1. Spectrum Features: Spectrum features are described as pixel grey value, reflect the spectral information of objects. For corn, band selection should be conducive to the human eye determination and extraction of interested area. According to experience, for the experimental area of multispectral images, selecting NIR, R, G three bands grayscale to build false color images is more effective to artificial interpretation. So automatic classification technology chooses the above three features as feature set. Furthermore, the normalized difference vegetation index (NDVI) is one of the most important features, this uses the red and near infrared band to distinguish plants from others, which are defined as follows:

$$NDVI=\frac{NIR - R}{NIR+R} \tag{9}$$

3.2.2. Texture Features: The texture feature analysis methods are divided into structure analysis, statistical analysis, spectrum analysis and model analysis, but the most popular is the gray level co-occurrence matrix (GCLM) of statistical analysis. The text can calculate many statistical characteristics based on GCLM. Marceau shows that the difference of texture statistical features affects the result 7%. They contain a certain degree of correlation, similar, because different texture statistics features are suitable for different images, so some scholars study and choose several common statistics. Bamldi thinks, the important statistical characteristics of image analysis are energy, entropy, homogeneous degree and the contrast degree. Harlow and Conners adopt energy, entropy, contrast, homogeneous degree and the correlation five characteristics for texture analysis. This text adopts energy, entropy, homogeneity and the contrast degree. First of all, color remote sensing images are turned into grayscale image, the grayscale are compressed, levels of 256 quantified as 16. Four different directions (0, 45, 90, 145) are chosen, each eigenvector of the matrix is calculated respectively, the mean of each variable is computed as the texture feature vector.

Entropy is the measurement of information contained in the image, which measures the grayscale distribution random characteristics and represents the complexity of the image texture. The greater the entropy value, the more complex the texture.

$$Entropy = -\sum_i \sum_j P(i,j) \log P(i,j) \tag{10}$$

Homogeneity is used to analyze the image uniformity, the higher it's value, the smaller the gray difference, the more uniform the pair of pixel.

$$Homogeneity = \sum_i \sum_j \frac{1}{1+(i-j)^2} P(i,j) \tag{11}$$

Contrast degree reflects the definition of image and texture grooving depth. The more clear visual effects, the greater the contrast.

$$Contrast = \sum_i \sum_j (i-j)^2 P(i,j) \tag{12}$$

Studies show that the dimension of the feature vector affects the algorithm efficiency to a great extent. Although vector dimension is not very large in this text, reducing the dimension of the feature set can improve the efficiency of algorithm, have practical significance. This paper putted into use cross validation to determine feature importance [24-25], as Figure 2 shows. According to experimental result, select R,NIR,NDVI, homogeneity and contrast degree to build feature set. It's worth mentioning that although the degree of dimension reduction is small, it isn't disregardful in operational process. When the characteristic dimension is very large, this step has significant practical significance.

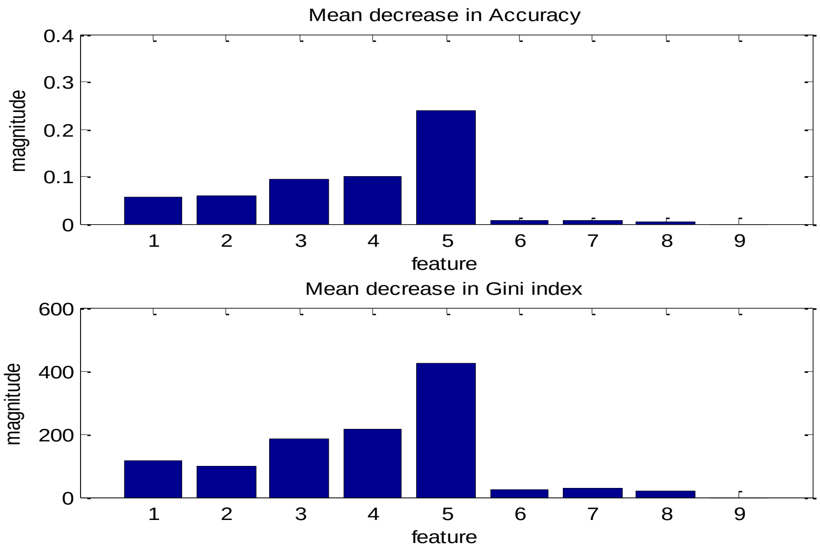


Figure 2. Importance of Every Feature

In Figure 2, the numbers of x axle represent feature, which are B,R,G,NIR,NDVI, entropy, homogeneity, energy and contrast degree respectively. According to importance of features, we select G, NIR, NDVI, entropy and contrast degree to execute supervised classification.

3.2.3 Adaboost_SVM Classifier based on PSO: In this text, the experiments are based on LIBSVM which is simple, rapid, effective, developed by Professor Lin. Internationally, SVM is used in pattern recognition, methods and parameters selection have no unified mode, algorithm parameter selection only rely on experience, experiment contrast, search in a wide range of or cross test to a large extent, etc. So it’s a time-consuming work, the effect is not the best necessarily. With the constantly emerging of the intelligent algorithm, genetic algorithms and particle swarm optimization algorithms provide new ways for the SVM parameter optimization. We compare two different algorithms under the condition of the same samples and the same features, to obtain image optimization algorithm which is suitable for remote sensing images, to help build a classifier. It is worth mentioning that with the number of samples increase, the optimization process takes much more time. Therefore, under the condition of small sample, train weak classifier, and then construct strong classifier is very important to improve the classification accuracy and efficiency.

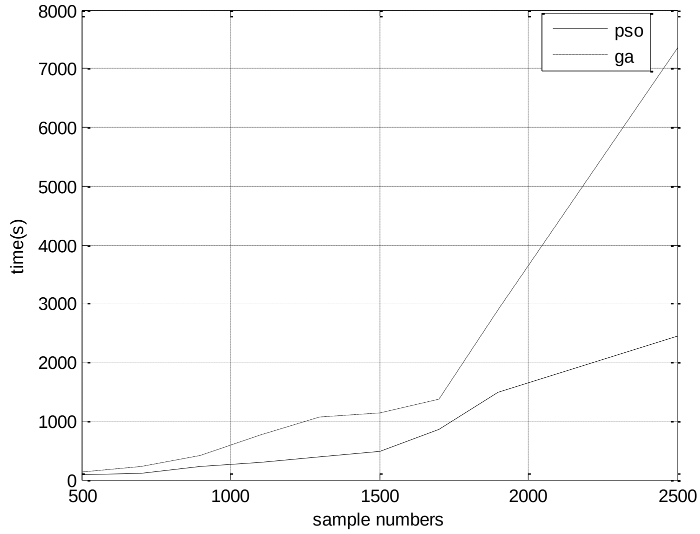
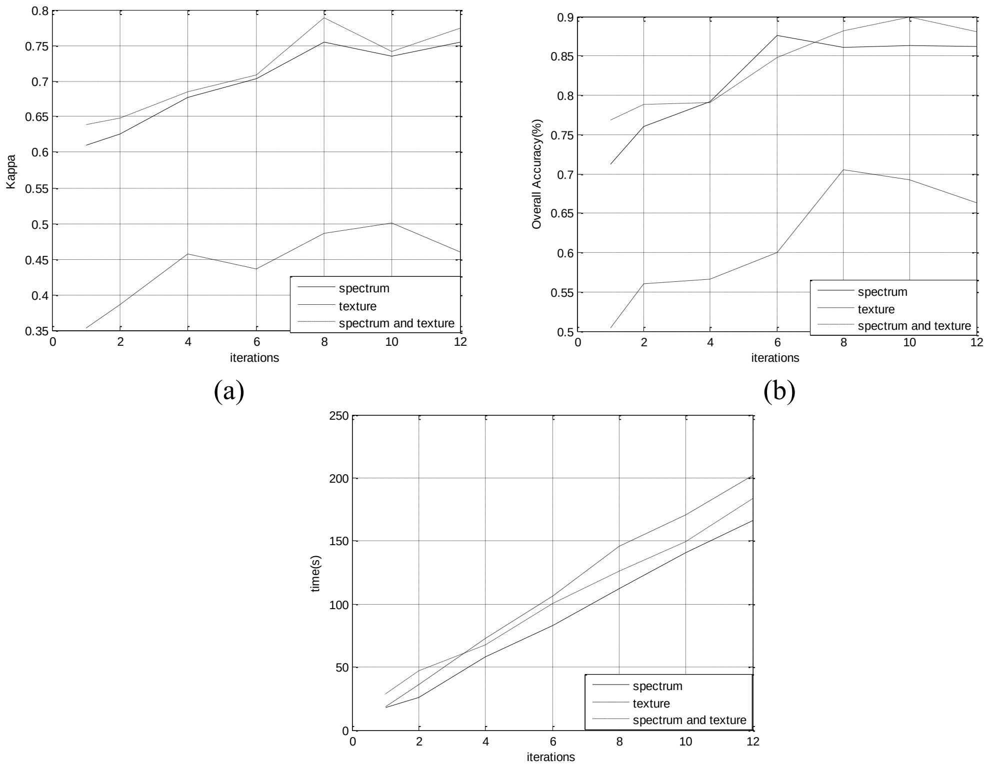


Figure 3. The Computational Cost with PSO and GA

In this paper, the samples number is 500, this can be considered as very few samples for whole image. To strengthen contrast, for the following three situations: spectral characteristics, texture characteristics and spectral and texture, construct weak classifier group respectively, implement Adaboost_SVM classifier.

3.2.4. Experiment Results: This section implements experiments for the two images, compare results with others which are acquired by other classical classification methods. For the first dataset of experiment, the number of weak classifier will affect the final classification performance, including the accuracy and efficiency. So this text selects different number of weak classifier, such as 1, 2, 4, 6, 8, 10, 12, according to the experience, constructs Adaboost_SVM respectively.



(c)

Figure 4. Classification Performance Indexes with Three Different Situations, Kappa Index (a), Overall Accuracy (b), Runtime (c)

Figure 4 presents the Kappa×iterations curves, overall accuracy×iterations curves, runtime×iterations curves for above three situations.

$$Kappa = \frac{(TP+TN)M-(TP+FP)(TP+FN)+(TN+FN)(TN+FP)}{M^2-(TP+FP)(TP+FN)+(TN+FN)(TN+FP)} \tag{13}$$

$$OA = \frac{TP+TN}{M} \tag{14}$$

$$M = TP+TN+FN+FP \tag{15}$$

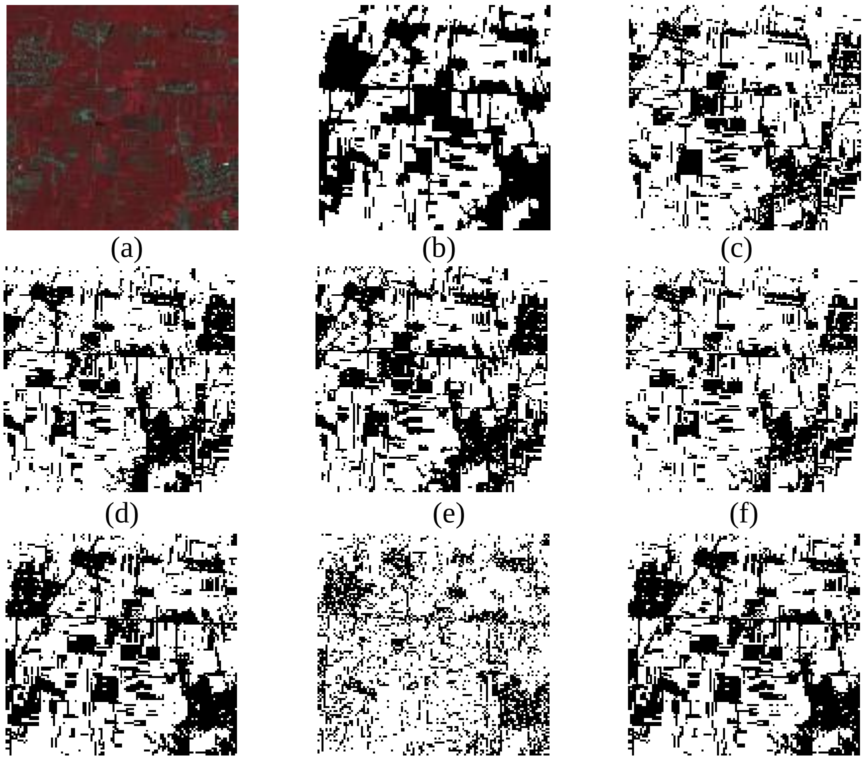
With the increase of iterations gradually, kappa index and overall accuracy(OA) increase slightly, but after 8 iterations, decline. Under the background of experiments, the spectral characteristics is more beneficial than the texture features to classification accuracy, This also presents similarity with Figure 2 which shows the importance degree of characteristics. The introduction of texture characteristics improves the classification accuracy to a certain extent. Check all of indexes, when the iteration is 8, the index parameters are close to the optimal value. Therefore in the subsequent process, indexes which are based on it are compared with the indexes obtained by the classical classification method. The classical methods contains Mahalanobis Distance Classification(Mahal Dist)、Parallelepiped Classification(Parallel)、Maximum Likelihood Classification(Max Likeli) and Minimum Distance Classification(Mini Dist). The comparison results are shown in Figure 5 and Table 1.

Table 1 lists confusion matrixes of classification and other indicators. True Positive (TP) is defined as an entity labeled as “corn” that also corresponds to “corn” in the reference data. True Negative (TN) is an entity that belongs to “non-corn” in both the detection results and the reference data. False Positive (FP) is defined as an entity labeled as "corn" that corresponds to "non-corn" in the reference. False Negative (FN) is the exact opposite of the FP case. Except for kappa index and OA, the metrics Producer's Accuracy (PA) and user's Accuracy (UA) were computed using the equations as follows:

$$PA = \frac{TP}{TP + FN} \tag{16}$$

$$UA = \frac{TP}{TP + FP} \tag{17}$$

The results of the proposed algorithm are superior to the others markedly. For the first remote sensing image with PSO+Adaboost_SVM(spectrum and texture), KAPPA, UA and OA are 0.7562,0.8677 and 0.881 respectively.



(a) (b) (c) (d) (e) (f) (g) (h) (i)

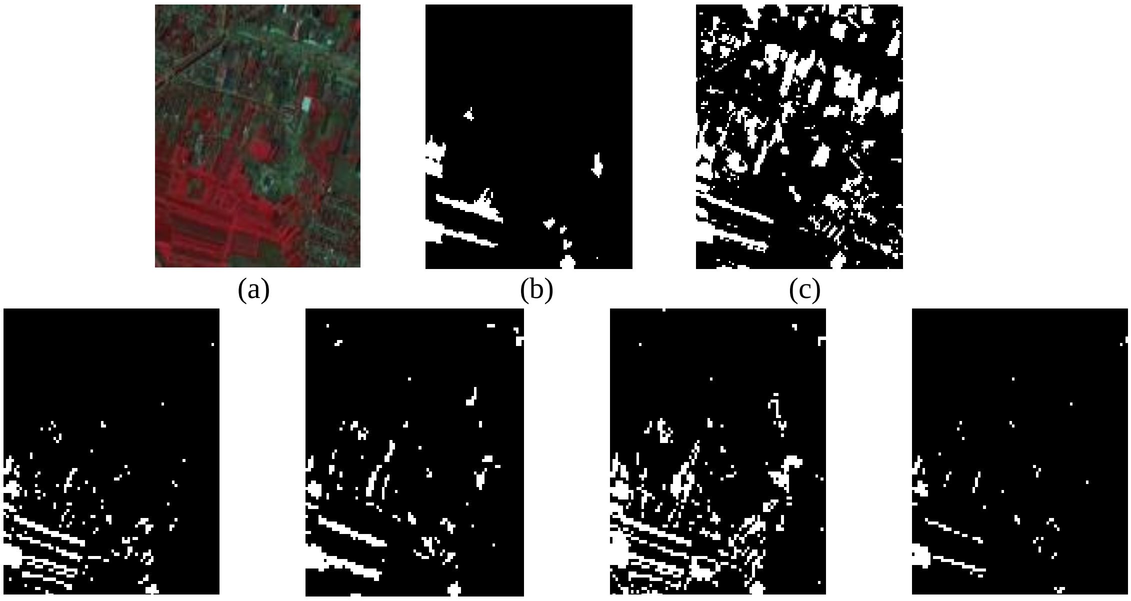
Figure 5. Classification results of the first data with different methods,False color image(a),Ground truth(b), Mahal Dist(c), Parallel(d), Max Likeli(e), Mini Dist(f), PSO+Adaboost_SVM(spectrum)(g), PSO+Adaboost_SVM(texture)(h) and PSO+Adaboost_SVM(spectrum and texture)(i)

Table 1. Classification Precision of the First Data with Different Methods

Method	TP	TN	FP	FN	KAPPA	UA	PA	OA
Mahal Dist	674921	269862	499943	304070	0.411	0.5745	0.6894	0.5402
Parallel	646629	291221	478584	332362	0.396	0.5747	0.6605	0.5363
Max Likeli	596386	333046	436759	382605	0.421	0.5773	0.6092	0.5315
Mini Dist	690334	248099	521706	288657	0.284	0.5696	0.7051	0.5366
PSO+Adaboost_SVM(spectrum)	920843	617771	152034	58148	0.7529	0.8583	**0.9406**	0.8798

PSO+Adaboost_SVM(texture)	872868	368944	400861	106123	0.4267	0.6853	0.8916	0.7101
PSO+Adaboost_SVM(spectrum and texture)	909508	631138	138667	69483	**0.7562**	**0.8677**	0.929	**0.881**

The final simulation results of the second data are shown in Figure 6. Classification precision parameters are listed in Table 2. In view of terrain features, corn planting area is relatively small. After many experiments, texture feature's contribution to the classification results is small. In some cases, it cannot even get normal results. For PSO+Adaboost_SVM(spectrum and texture), KAPPA, UA and OA are 0.4878,0.7446 and 0.9667 respectively. Because of the objective condition of second data, OA is relatively high, but kappa index is very low. The non-corn area accounts for a large proportion, this masks the shortcoming of insufficient information to a certain extent.



(a) (b) (c)

(d) (e) (f) (g)

Figure 6. Classification results of the second data with different methods, False color image(a),Ground truth(b), Mahal Dist(c), Parallel(d), Max Likeli(e), Mini Dist(f) and PSO+Adaboost_SVM(spectrum and texture)(g)

Table 2. Classification Precision of the Second Data with Different Methods

Method	TP	TN	FP	FN	KAPPA	UA	PA	OA
Mahal Dist	5831	156276	34089	2988	0.1797	0.1460	0.6611	0.8138
Parallel	5012	184349	6016	3807	0.4794	0.4544	0.5683	0.9506
Max Likeli	4721	183171	7194	4098	0.4261	0.3962	0.5353	0.9433
Mini Dist	5955	173887	16478	2864	0.3390	0.2654	**0.6752**	0.9028
PSO+Adaboost_SVM(spectrum and texture)	3351	189216	1149	5468	**0.4878**	**0.7446**	0.3799	**0.9667**

4. Conclusion

The paper extracted corn area information in remote sensing images, which is also the realization of binary classification problem. We realized information extraction process of instant parameters optimization, sample training and classification, constructed weak classifiers of less samples and brief features, optimized classifier parameters and established Adaboost_SVM classifiers. According to the above experimental results and analysis, the proposed method gets a relatively good performance for remote sensing images. According to the experimental data, this paper used the PSO algorithm to optimize parameters of weak classifiers and compared a variety of methods. Experiments show that classification precision is better than typical supervised classification methods, parameter optimization and the training process take much less time than the traditional SVM classification method.

5. Expectation

The proposed research method can realize the image information extraction of a variety of different crops, and even more land cover types. More, the object-oriented as a new effective method, processing method can be introduced into agricultural remote sensing field, serves better for agricultural production.

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