Research on Classification and Recognition Algorithm of the High-resolution Remote Sensing Image on Chinese Ancient Villages

Zheng Jin, Liu Su, Zou Kunlin, Wu Wanneng, Sun Wei

Abstract— **As an important carrier of the Chinese traditional cultural heritage, the ancient villages are gradually disappearing. Fortunately, many experts and scholars at home and abroad are paying more and more attention on the ancient villages' protection with the help of high-resolution remote sensing images. Considering that the surface features in the images are so diverse and complex, a new classification and recognition algorithm toward the high-resolution remote sensing images is proposed in this paper. The proposed algorithm is mainly based on the ensemble learning thought. With the algorithm, the image is firstly processed with multi-scale and multi-feature segmentation, and then the spectral and texture features are extracted as the input element of the classification and recognition process. Finally, the eventual classification and recognition results are decided by the ensemble classifier which is constructed by multiple SVM (Support Vector Machine) basic classifiers trained with the AdaBoost algorithm. The verification experiments indicated that the proposed algorithm has an obviously better effect than the traditional methods.**

Index Terms— **Ancient village protection, High-resolution remote sensing image, Multi-scale and multi-feature segmentation, Ensemble learning.**

I. INTRODUCTION

The ancient village, the so-called folk Ecological Museum [1], is the gene pool of Chinese national culture [2]. However, its former prosperity has been gradually disappearing due to the passage of time, poor repair and the modern economy impacts. Besides that, the ancient villages are usually located in the remote environment and rugged terrain. In recent years, as the domestic and foreign experts have paid great attention to the ancient villages in our country, the ancient village protection is becoming increasingly urgent [3-6].

At present, the ancient village conservation is mostly planned with traditional ways and means, which mainly collect and analyze the basic data under current situation from the perceptual point of view. Unfortunately, their processing speed and accuracy are both poor. So the ancient village conservation planning cannot make a scientific analysis when taking a comprehensive consideration of the relevant data's interaction impact. As the ancient village protection is a really long-term and dynamic system engineering, it needs a dynamic control and adjustment in the whole process. Therefore, it requires the departments of planning, design and management to promptly grasp the various dynamic data with a reflection of the current situation and to serve them as the protection and management evidence for the administrator departments. So, it is difficult for the traditional method to meet the needs of the developing situation. And it is urgent to explore new technologies and methods to solve the problems encountered in the protection planning and management of the ancient villages.

As many new theories and methods in the domain of pattern recognition and artificial intelligence are proposed, as well as the continual exploration to the human vision mechanism, scholars at home and abroad have made lots of progress in the research of high-resolution remote sensing image classification and recognition, from the initial pixel-based statistical classifications gradually penetrating into the intelligent object-oriented automatic classification. For instance, Thias-Sanz etc. [7] proposed a bridge detection algorithm for the small-format high-resolution panchromatic remote images based on the texture feature and geometrical model, using neural network to classify the pixels. Although effective, it is not suitable for the extraction of the large-format and cross-river bridges. Chini etc. [8] did the change detection analysis for the artificial structure of the high-resolution satellite remote sensing image by the classification method based on statistics and neural network. It is found that the parallel classification method based on neural network classification accuracy is higher than the former. Melgani and Bruzzone etc. [9] used the SVM algorithm to classify the hyperspectral remote sensing image data respectively considering one to one, one-to-many and other cases. The experimental results showed that all of the classification accuracy, stability and robustness under the SVM method are better than both the RBF neural network and the K-nearest neighbor classification method.

In order to make the computer classify and recognize the remote sensing images better in line with the human visual information processing mechanism and ways of thinking, researchers have attempted and explored to introduce the thought of expert system, visual model, classifier combination and so on. Mathieu etc. [10] completed the feature classification for the New Zealand region's villages and towns through the object-level analysis of the remote image. Yi etc. introduced the words package model into the remote image as a guide, then analyzed the semantic relationships between the

This work was supported in part by the National Nature Science Foundation of China (NSFC 61673163, 61203207), the Young Core Instructor Foundation of Hunan Provincial Institutions of Higher Education, Hunan provincial natural science foundation of China (2016JJ3045), and Changsha science and technology program (k1501009-11).**Zheng Jin**, School of Architecture, Hunan University, Changsha, Hunan 410082, China, +86-0731-88822224.

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visual words according the PLSA model, and further completed the classification and identification of the high-resolution remote image. Mo etc. [11] took the high-resolution remote sensing image data IKONOS as a major data source, and then automatically extracted the land cover and land use information in the rural-urban area of Zhuzhou City, China, through the multi-scale segmentation and the object-oriented image analysis method based on fuzzy logic classification.

However, the existing target recognition methods of the high-resolution remote sensing images can only be used to detect one certain unnatural object, such as the roads, buildings, airports, bridges, ports, oil depots, ships and so on. In other words, a lack of traditional methods can universally detect different kinds of target features in the images. To better meet the practical application demands and expand the development prospect of the high-resolution remote image, some research focuses are emerging, such as that: how to build a highly efficient intelligent classification recognition algorithm, how to comprehensively consider the abundant information features in the image, how to convert the visual cognition to computer rules, how to further effectively analyze different kinds of target information in the remote image and so on.

II. The Preprocessing of the High-resolution Remote Sensing Image on Ancient Villages

As some force majeure, including satellite disturbance, atmospheric conditions, sensors etc., are inevitably produced in the remote image capture process, it tends to generate random errors which would results into the image degradation in the aspects of intensity, frequency and space. The degradation effect mainly contains the contrast decrease, edge blur and geometry distortion, which would affect the analysis and decision-making in the subsequent application of the images. The information contained in the high-resolution remote images is especially abundant. If they are not preprocessed suitably, it may bring a lot of problems such as a large number of the generated false features, the lost real characteristics, the feature information errors and so on. To improve the SNR (Signal Noise Ratio) of the images and make sure the exact extraction and identification of the remote image target, the restore operation toward the image is necessary, which is namely the preprocessing of the remote image.

In this paper, three high-resolution remote sensing images will be selected as the experimental research materials, as shown in Figure 1.

Experimental image I: a 0.16m resolution of low altitude UAV (unmanned aerial vehicle) image in Taiping Town, Lushan County, China, captured in April 20, 2013, as shown in Figure 2.1 (a).

(a)

(b)

(c)

Figure 1 The original experimental images.

Experimental image II：a GoogleEarth image of Gong Jia Wan, Huaihua City, Hunan Province, China, captured in September 2009, with the angle of view 1.04km and a size of 1315×679, as shown in Figure 1 (b).

Experimental image III：a GoogleEarth image of a paddy fields village, Chenxi County, Hunan Province, captured in September 2009, with the angle of view 774 meters and a size of 1341×687, as shown in Figure 1 (c).

III. The Classification with Ensemble Learning Method

According to the diversity of the ground objects and the complexity of the space distribution in the ancient villages high-resolution remote sensing images, as well as considering the limitations of a single classification algorithm and the complementarity between different classification methods, a multi-classifier fusion method based on the ensemble learning thought can be introduced to classify and recognize the high-resolution remote sensing images on the ancient villages. The proposed method would improve the quality of classification and recognition, and further optimize the results.

A. *Ensemble learning*

Ensemble Learning is a machine learning paradigm which firstly study on the same problem by a limited number of learning devices， and then integrate the outputs of each learning device following some certain rules. It conforms to the human thinking habit as well as significantly improve the generalization ability of the system algorithm, which has been widely used in many fields, such as speech recognition, text classification, intrusion detection, image retrieval and so on[12].

According to the type of training algorithm, it can be divided into isomorphic integration and heterogeneous integration [13, 14]. Homogeneous ensemble learning is based on a single learner, which generates different basic learner according to the construction strategy. However, heterogeneous ensemble learning is based on different learning algorithms, using the difference between different learning algorithms to obtain different basic learners. Due to the inherent mechanism of the learning algorithm, it is difficult to provide a reasonable and unified measurement analysis of integration effect, and the use of different learning algorithms will result in an increase in the overall complexity of the integrated learning. Therefore, most of the current ensemble learning researches are focusing on the isomorphic ensemble learning.

Multi-classifier ensemble learning is a typical application of the ensemble learning on classification problems, which improves the classification performance of a single classifier by fusing the predictive output of several homogeneous or heterogeneous classifiers. According to the ensemble learning system, it can be known that multi-classifier integration is usually composed of two stages [12]: the base classifier construction (learning stage) and base classifiers combination (application stage), whose basic framework is as shown in Figure 2.

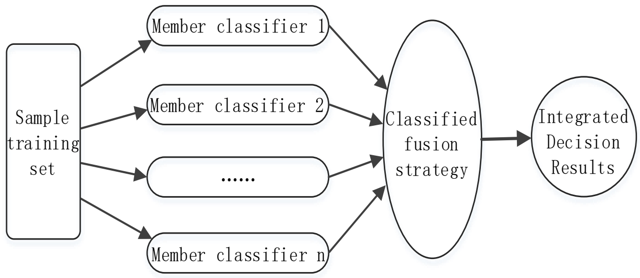


Figure 2 Basic framework of multiple classifier ensembles.

B. *The principle of the algorithm*

SVM (Support Vector Machine) was originally developed from solving two types of classification problems, whose essence is taking the easily mistaken training examples as a breakthrough to solve the problem. The main idea of classification is taking the "hard to distinguish and easily mistaken" sample as support point of classification surface, and then optimize the classification discriminant surface to make the biggest distance of support surface of positive and negative categories. As for the limited training sample data in high dimensional feature space, the classifier also has strong generalization ability while even a small sample is selected as a support vector to design the classifier. The structure of the algorithm is automatic optimal generation, which can reduce the test time and effectively solve the small sample problem.

As the SVM has a good performance, its application is gradually extended to the multi-class classification, which can be combined with several two-class classification SVM under certain criterion [13]. But there are still some problems to be solved in the rules of the combination, such as that the classification performance is not as outstanding as two-class problems solving. Besides that, the implementation of the multi-class classification is more complex. However, the architecture of multi classifier ensemble provides a powerful theoretical idea to the improvement of classification and generalization performance for SVM in multi-class classification problems.

AdaBoost algorithm is one of the most popular types among the Boosting algorithm clusters, and it is very simple to construct a member classifier with it. It also can obtain a very high precision when doing the integrated classification decision [14]. Considering the limitation of the experimental sample set in this paper, the multi-classifier fusion classification recognition algorithm based on the base classifier of SVM and AdaBoost construction method will be used to recognize and classify the elements of the ancient village of high-resolution remote sensing image.

The algorithm is based on the iterative idea of AdaBoost algorithm to train the SVM based classifier with the RBF as the kernel function: assumed a weight distribution D_t on the training set X_{tr}. In the *t*th iteration, assumed that each training session is assigned a weight of $D_t(x_i)$. According to the weight distribution of D_t, randomly select a sample $X_{tr}^{(t)}$ from the X_{tr} and take the sample (the input of SVM) as the base learning algorithm to train a base classifier C_t and calculate the classification error ε_t. Use this error to measure the performance of the base classifier C_t and update the weight distribution of the training samples. After a certain iteration cycle or when a predetermined precision is achieved, *T* base classifiers would be obtained. Carry on the fusion operation by weighted majority voting rule and then finally a strong classifier with a better decision performance is obtained.

C. *Algorithm description*

Given training sample set $X_{tr}=\{(x_i,y_i)\}_{i=1}^{N}$ and the iteration number (weak classifier number) T. Given initial weight $D_1=\{w_{1i}=1/N\}$, ($i=1,2,\cdots,N$) to each training individual (x_i,y_i) in the training set X_{tr}.

1) According to the weight distribution of D_t, conduct *N* times random sampling with replacement from the training set X_{tr} and a new training set is gotten as $X_{tr}^{(t)}=\{(x_i^{(t)},y_i^{(t)})\}_{i=1}^{N}$;

2) Take $X_{tr}^{(t)}$ as the input of a given base classification algorithm RBF-SVM and train it to get a base classifier C_t;

3) Calculate the classification error ε_t of base classifier C_t on the training sample set;

$$\varepsilon_t=P(C_t(x_i)\neq y_i)=\sum_{i=1}^{N}w_{ti} \tag{1}$$

4) If $\varepsilon_t>0.5$, set $D_{t+1}=\{w_{(t+1)i}=1/N\}$ and go to step 1; Otherwise, reset the weight of the RBF-SVM based classifier α_t;

$$\alpha_t=\frac{1}{2}\ln[(1-\varepsilon_t)/\varepsilon_t] \tag{2}$$

5) Update the weight distribution of training samples D_t

$$D_{t+1}=\{w_{(t+1)i}=\frac{w_{ti}\exp(-\alpha_t y_i C_t(x_i))}{Z_t}\} \tag{3}$$

where Z_t is the normalized factor normalization factor, which makes D_{t+1} a probability distribution

$$Z_t=\sum_{j=1}^{N}w_{tj}\exp(-\alpha_t y_j C_t(x_j)) \tag{4}$$

6) If $t=T$ or when the specified accuracy is achieved, output the final strong classifier $C(x)$ according to the majority voting fusion rule

$$C(x)=\arg\max(\sum_{t=1}^{T}\alpha_t C_t(x)) \tag{5}$$

IV. Experimental Results and Analysis

To analyze the performance of the classification and recognition algorithm proposed in this paper (the multi-classifier ensemble classification algorithm), the nearest neighbor and neural networks classification methods are selected as the comparative references in the comparative experiments, which are performed based on ENVI5.0 platform.

Algorithm validation and accuracy assessment are the fundamental problems of the remote sensing data processing and classification, which are the important steps when comparing different classification algorithms. When evaluating the remote sensing images' classification accuracy, the confusion Matrix is the most commonly used. It is a specific measurement which compares both the classification result and the actual predicted value. By comparing the actual classification and the predicted classification results of the surface area, the relationship between the actual class and predicted class can be recorded.

If given N zones, with the output class C, so the confusion matrix M is:

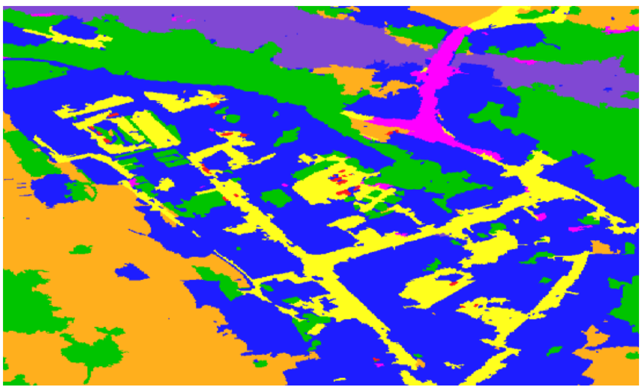
$$M = \{m_{ij}\} \tag{6}$$

where the m_{ij} represents the total number of the real class i in which the area is recognized as a category j. The greater the value of the diagonal elements in the confusion matrix is, the higher the reliability of the classification results are. Similarly, the greater the value of the non-diagonal elements in the confusion matrix is, the more serious the error classification is. According to it, the main indicators of the classification accuracy include production accuracy, user accuracy, the overall accuracy and *Kappa* coefficient [7]. In this paper, the *Kappa* coefficient which is more comprehensive to reflect the overall accuracy is selected as an evaluation metric. A greater *Kappa* coefficient indicates a higher classification accuracy of the corresponding classification methods.

$$Kappa = \frac{N\sum_{i=1}^{C} m_{ii} - \sum_{i=1}^{C}(\sum_{j=1}^{C} m_{ij} * \sum_{j=1}^{C} m_{ji})}{N^2 - \sum_{i=1}^{C}(\sum_{j=1}^{C} m_{ij} * \sum_{j=1}^{C} m_{ji})} \tag{7}$$

A. The first group of experiments

The experimental image I, the Taiping town picture, is firstly adopted in the experiment. Three small parts are further selected to be processed with different algorithms. And the classification and recognition effects are respectively shown in Figure 3, Figure 4, and Figure 5.



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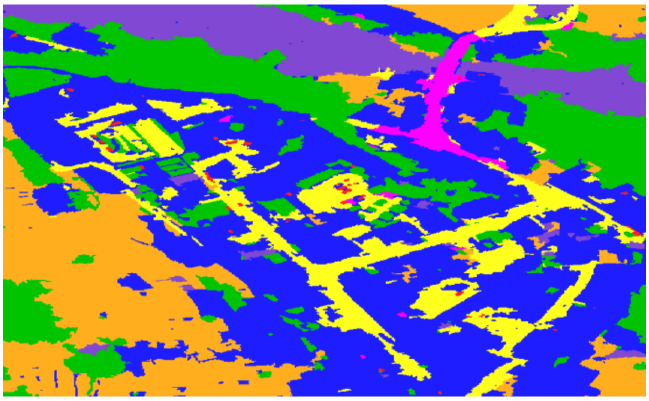

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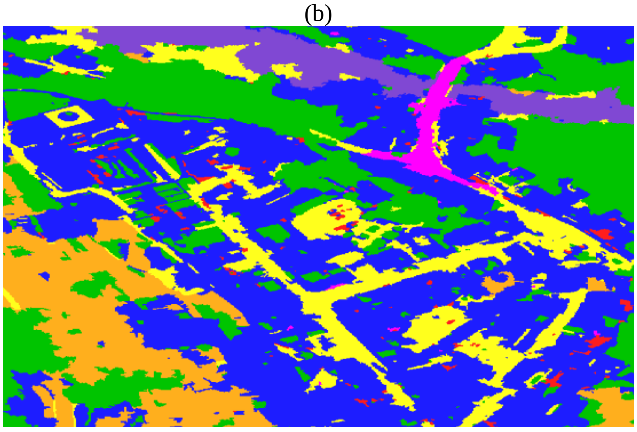

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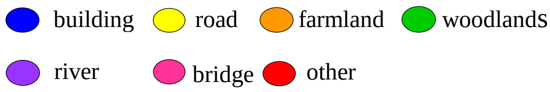


Figure 3. The classification and recognition results of the 1st Taiping town image: (a) Classification and recognition algorithm proposed in this paper; (b) Neural network classification; (c) Nearest neighbor classification.

For the Figure 3, the algorithm parameters of each method should be set as follows.

(1) The parameters of the proposed algorithm in this paper should be set as:

T: 30; *N*: 20; *Gamma*: 2.5; *Penalty Parameter*: 600.

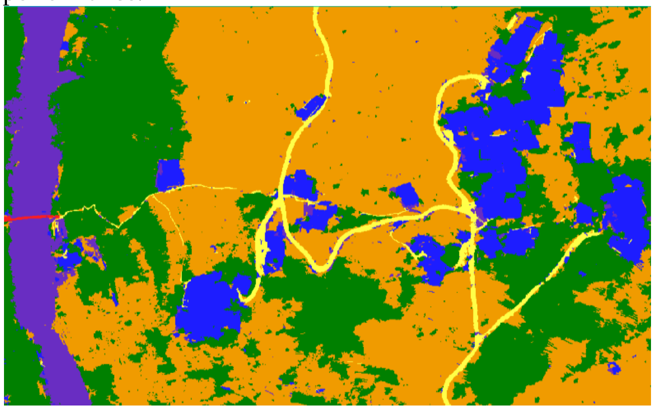
(2) The parameters of the neural network classification algorithm should be set as:

Number of Hidden Layers: 1; *Number of Training Iterations*: 600.

(3) The parameters of the nearest neighbor classification algorithm should be set as:

Neighbors: 6; *Threshold*: 5.0.

As the modern roads are similar to the modern buildings on material texture, it usually leads to a misclassification error between the roads and buildings. Besides that, part of road would be misclassified as bridge as a result of the connection error between them. In the experiment, it is found that the nearest neighbor classification algorithm misclassifies the part of farmland as building, and the modern building as road, the phenomenon of which is relatively serious. And some flood land would be classified as road because the similarity of the flood land and road. Similarly, with the neural network classification method, the classification error between the farmland and building is relatively large, and the error also exists among the part of road, building and farmland. In comparison, the classification and recognition algorithm proposed in this paper can avoid the above misclassification to a large extent. According to the *Kappa* coefficient as shown in Table 1, the classification and recognition algorithm proposed in this paper has an obvious improvement compared with the neural network method and the nearest neighbor method. So the proposed algorithm has a better classification performance.



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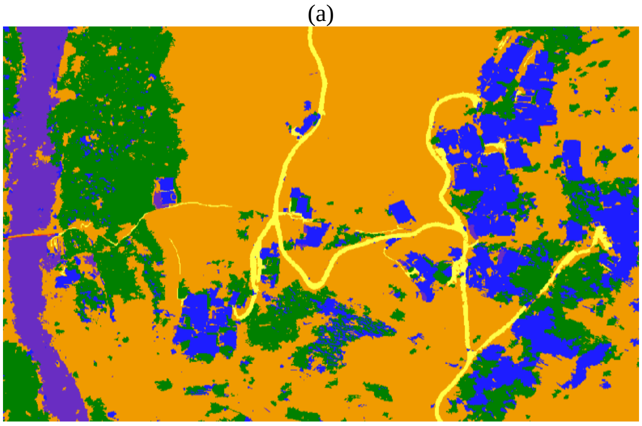

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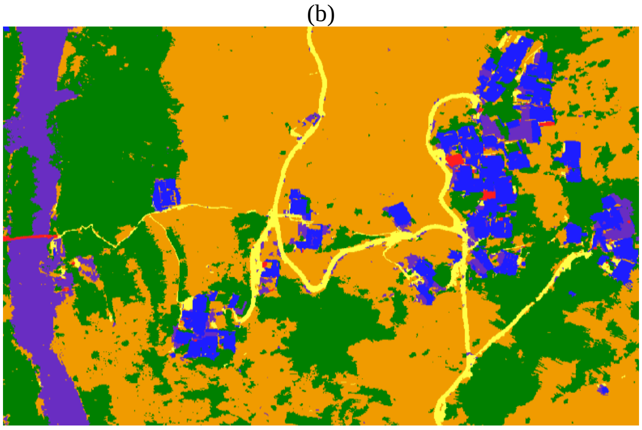


(c)

Figure 4. The classification and recognition results of the 2nd Taiping town image: (a) Classification and recognition algorithm proposed in this paper; (b) Neural network classification; (c) Nearest neighbor classification.

For the Figure 4, the algorithm parameters of each method should be set as follows.

(1) The parameters of the proposed algorithm in this paper should be set as:

T: 30; *N*: 20; Gamma: 0.3; *Penalty Parameter*: 500.

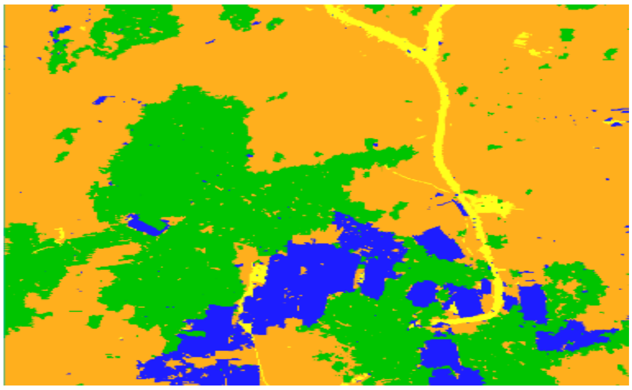
(2) The parameters of the neural network classification algorithm should be set as:

Number of Hidden Layers: 1; *Number of Training Iterations*: 600.

(3) The parameters of the nearest neighbor classification algorithm should be set as:

Neighbors: 3; *Threshold*: 3.5.

The experimental results indicate that the classification and recognition algorithm proposed in this paper effectively avoid the following phenomenon: the nearest neighbor classification method misclassifies the river as woodland and the jungle is misclassified as building with the neural network method. As shown in Table 1, the *Kappa* value of the proposed method is obviously higher than the contrast method. So with this, the classification accuracy is relatively improved, the overall recognition results are close to the actual distribution.



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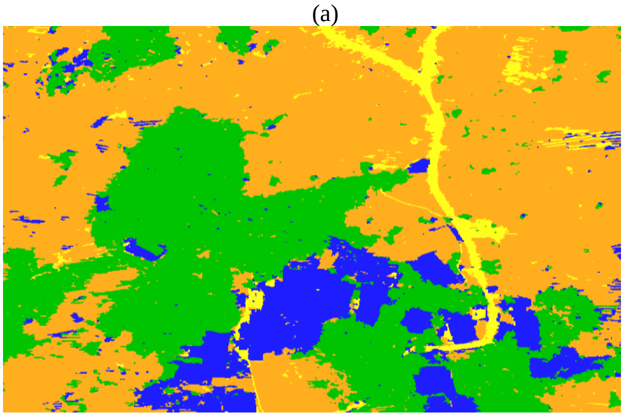

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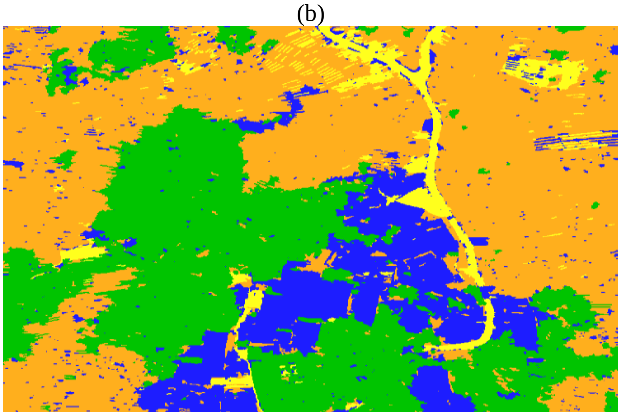


(c)

Figure 5. The classification and recognition results of the 3rd Taiping town image: (a) Classification and recognition algorithm proposed in this paper; (b) Neural network classification; (c) Nearest neighbor classification.

For the Figure 5, the algorithm parameters of each method should be set as follows.

(1) The parameters of the proposed algorithm in this paper should be set as:

T: 30; *N*: 20; *Gamma*: 0.02; *Penalty Parameter*: 500.

(2) The parameters of the neural network classification algorithm should be set as:

Number of Hidden Layers: 1; *Number of Training Iterations*: 600.

(3) The parameters of the nearest neighbor classification

algorithm should be set as:

Neighbors: 3; *Threshold*: 2.7.

In Figure 5, the housing distribution is clustered, meanwhile the farmland and forest land occupy a relatively large proportion of the image. But with the traditional nearest neighbor classification method, a lot of mistakes would appear. When neural network is used, the classification precision can be relatively improved, but farmland and woodland areas would still be misrecognized as building. Fortunately, with the classification and recognition algorithm proposed in this paper, the classification result is relatively close to the actual distribution.

Table 1. The *Kappa* coefficient of the Taiping Town ROI images

Classification recognition method	Figure 3	Figure 4	Figure 5
Nearest neighbor classification	0.492	0.476	0.406
Neural network classification	0.623	0.774	0.720
Classification and recognition algorithm proposed in this paper	0.820	0.875	0.872

B. The second group of experiments

For the Figure 6, the algorithm parameters of each method should be set as follows.

(1) The parameters of the proposed algorithm in this paper should be set as:

T: 30; *N*: 25; *Gamma*: 0.03; *Penalty Parameter*: 600.

(2) The parameters of the neural network classification algorithm should be set as:

Number *of Hidden Layers*: 1; *Number of Training Iterations*: 500.

(3) The parameters of the nearest neighbor classification algorithm should be set as:

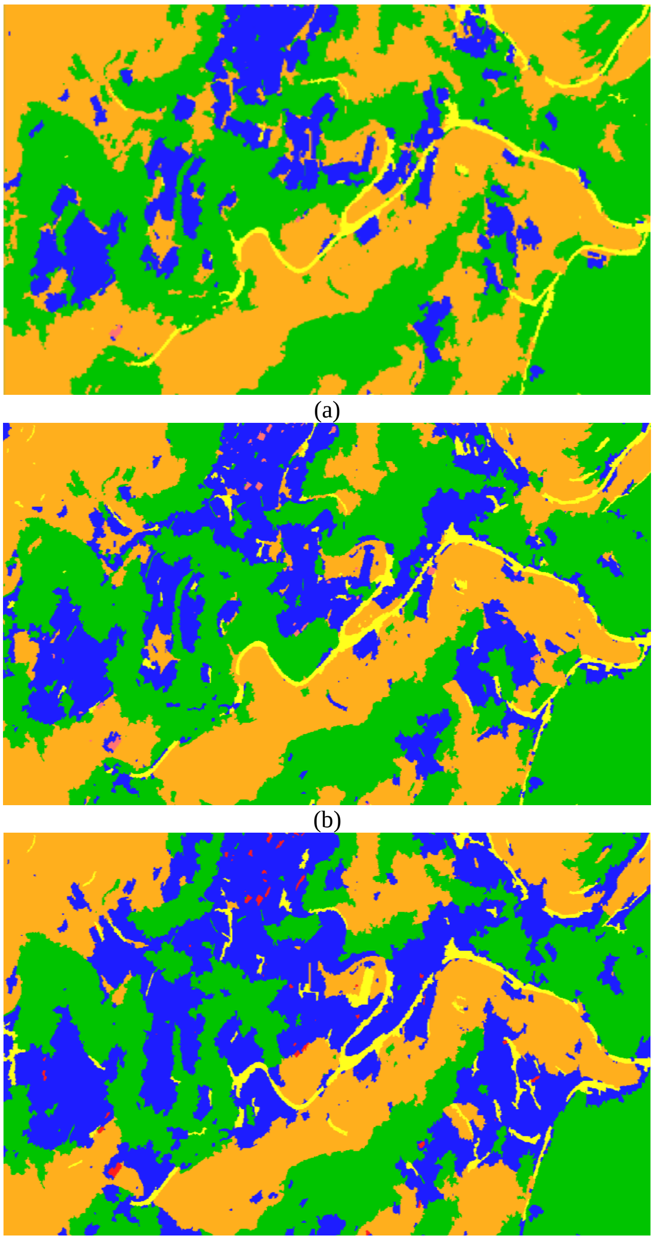
Neighbors: 3; *Threshold*: 1.2.

In this group of experiments, it is relatively serious that the nearest neighbor classification method would misclassify the farmland as building. Although the neural network classification method has an improvement to a certain extent, the classification accuracy is still low when comparing with the classified recognition method in this paper. As the *Kappa* coefficient in Table 2 showed that the proposed algorithm's classification accuracy had improved 49.1% and 21% when compared to the nearest neighbor classification method and the neural network classification method, respectively.

Table 2 The Kappa coefficient of Gong Jia Wan experimental image

	Nearest neighbor classification	Neural network classification	Classification and recognition algorithm proposed in this paper
Figure 6	0.413	0.695	0.904

From the Figure 6, it is serious that the nearest neighbor classification method would misclassify the farmland as building. Although the neural network classification recognition method has an improvement to a certain extent than the former, the classification accuracy is still very low when comparing to the proposed classified recognition method in this paper. According to the *Kappa* coefficient in Table 2, the proposed algorithm in this paper has a significantly improved performance compared with the former two.



(a)

(b)

(c)

Figure 6 The classification and recognition results of the Gong Jia Wan experimental image: (a) Classification and recognition algorithm proposed in this paper; (b) Neural network classification; (c) Nearest neighbor classification.

C. The third group of the experiments

For the Figure 7, the algorithm parameters of each method should be set as follows.

(1) The parameters of the proposed algorithm in this paper should be set as:

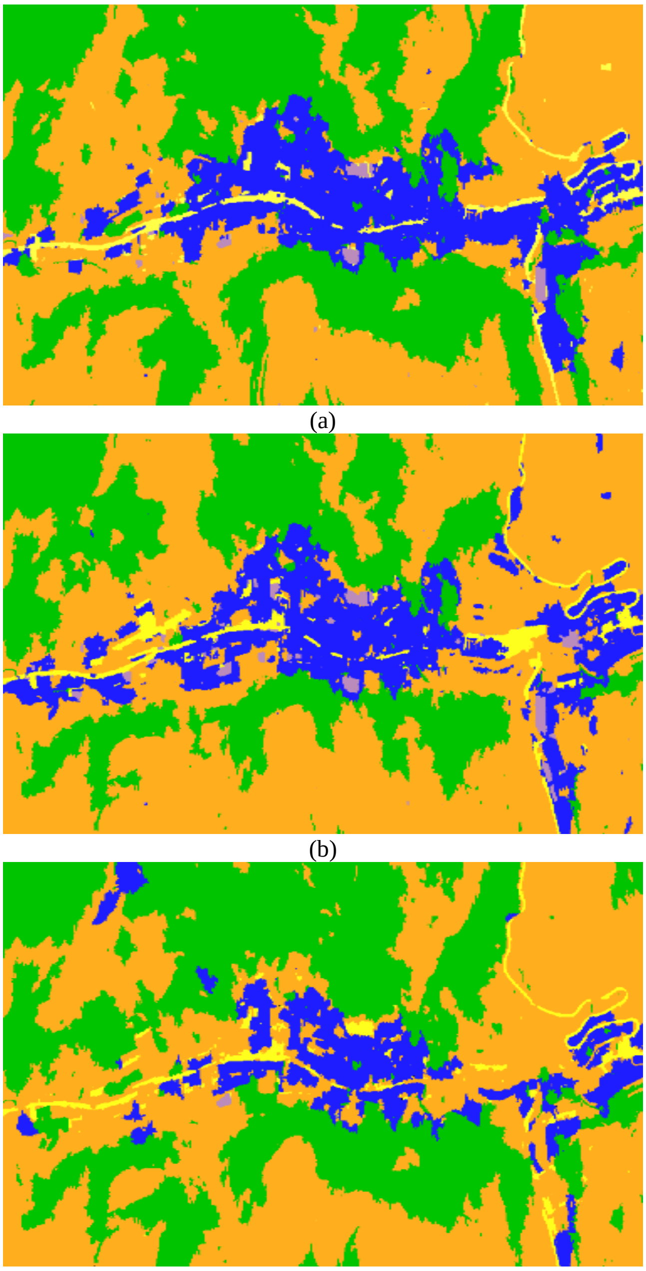
T: 30; *N*: 25; *Gamma*: 0.04; *Penalty Parameter*: 700.

(2) The parameters of the neural network classification algorithm should be set as:

Number of Hidden Layers: 1; *Number of Training Iterations*: 500.

(3) The parameters of the nearest neighbor classification algorithm should be set as:

Neighbors: 3; *Threshold*: 1.7.



(a) (b) (c)

Figure 7. The classification and recognition results of the large paddy fields experimental image: (a) Classification and recognition algorithm proposed in this paper; (b) Neural network classification; (c) Nearest neighbor classification.

In this set of experiments, the results of all the three classification methods are relatively close to the actual distribution of the feature images to a certain extent. However, the nearest neighbor method would mistakenly classify some farmlands as buildings, and a large number of buildings have been recognized as farmlands. For the neural network classification method, it is a little serious that the buildings are identified as farmlands.

As the housing distribution is gathered, country road is narrow, and the distribution without rules, coupled with the shooting angle influence, some roads are usually blocked by architecture and jungle occlusion. Table 3 shows the Kappa coefficient of the proposed classification and recognition algorithm proposed in this paper has increased by 37.9% compared to the nearest neighbor classification method, significantly improving a lot compared to the previous two methods.

Table 3 The *Kappa* coefficient of the large paddy field experimental image

	Nearest neighbor classification	Neural network classification	Classification and recognition algorithm proposed in this paper
Figure 7	0.512	0.780	0.891

V. CONCLUSION

In this paper, the classification and recognition algorithms of the high-resolution remote sensing image on Chinese ancient villages are analyzed. As the surface features in the remote sensing images are so diverse and complex, the traditional algorithms such as the Neural Network and Nearest-neighbor algorithm can hardly universally detect different kinds of target objects. To better meet these practical application demands, a new method based on the ensemble learning and multi-classifier fusion in the pattern recognition fields is proposed in this paper. The main analysis thought has been along with the procedure as "remote sensing image preprocessing - image segmentation - classification and recognition". Finally, after a series of classification and recognition comparative experiments toward three original images, the proposed algorithm based on the multi-classifier ensemble learning thought has an obviously better effect than the Neural Network and the Nearest-neighbor classification methods, according to the Kappa coefficient shown in Table 1, 2 and 3.

REFERENCES

[1] Shen Li. Ancient Villages: scattered China's Pearl. Culture Monthly, 2013, (2): 8-11.

[2] Cheng Tianci. Ancient Villages, the more security, the more a cultural gene pool. Farmers Daily, 2013-11-09 (005).

[3] Zhu Fengzhao. Under the space-time dimension to the analysis of ancient village protection. Technology rich Wizard, 2011, (17): 116-174.

[4] Wang Jihong. The New Thinking of Ancient Village Conservation and Development. Chinese Science and Technology Expo, 2011, (25): 236.

[5] Gao Feng. The protection of ancient villages without delay. Village committee director, 2012, (17): 25.

[6] Pan Lusheng. Ancient Village Conservation and Development. Folk Cultural Forum, 2013, (1): 22-24.

[7] Chen Zhong. High resolution remote sensing image classification technology research. Ph.D. Thesis. Beijing: Institute of remote sensing applications, Chinese Academy of Sciences, 2006.

[8] Thias-Sanz R., Lomenie N., Arbeau J. B. Using Textural and Geometric Information for an Automatic Bridge Detection System. Proc. Of ACIVS, Brussels, Belgium, 2004: 325-332.

[9] M. Chini, F. Pacifici, W. J. Emery et al. Comparing Statistical and Neural Net-work Methods Applied to Very High Resolution Satellite Images Showing Changes in Man-Made Structures at Rocky Flats. IEEE Transactions on Geoscience and Remote Sensing, 2008, 46(6): 1812-1821.

[10] F. Melgani, L. Bruzzone. Classification of Hyperspectral Remote Sensing Images with Support Vector Machines. IEEE Transactions on Geoscience and Remote Sensing, 2004, 42(8): 1778-1790.

[11] R. Mathieu, J. Aryal, A. K. Chong. Object-based Classification of IKONOS Imagery for Mapping Large-scale Vegetation Communities in Urban Areas. Sensors, 2007, 7(11): 2860-2880.

[12] Xia Junshi. Hyperspectral remote sensing image classification based on integrated study. Ph.D. Thesis. Xuzhou: China University of mining, 2013.

[13] Mao Shasha Integrated classification algorithm greedy optimization and projection transform. Ph.D. Thesis. Xi'an: Xi'an Electronic Science and Technology University, 2014.

[14] Cheng Lili. Support vector machine ensemble learning algorithm research. Ph.D. Thesis. Harbin: Harbin Institute of Technology, 2009.