

Study on a New Remote Sensing Image Classification Method and Its Application

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Abstract—For slower computation speed and lower classification accuracy of the traditional image classification methods, wavelet transform, multi-strategy, particle swarm optimization (PSO) algorithm and support vector machine (SVM) are introduced into image classification in order to propose a new remote sensing image classification (RIWMPS) method. First of all, wavelet transform method with multi-resolution characteristics is used to extract the features of remote sensing image. Then the steepest descent strategy, corrective decline strategy, random movement, aggregation strategy and diffusion strategy are used to improve the PSO algorithm to obtain an improved PSO (MSPSO) algorithm, which is used to optimize the parameters of the SVM model in order to construct an optimized SVM classifier for realizing remote sensing classification. Finally, the remote sensing image of Chongming Island is select to test the effectiveness of the RIWMPS method. The experiment results show that the RIWMPS method has higher classification efficiency and accuracy, and takes on better superiority and effectiveness. This study provides a new classification method for processing the remote sensing image.

1. INTRODUCTION

Image classification is a key technology to realize automatic image processing. The goal is to give one label for each pixel according to the pixel own property of remote sensing image and its correlation with the neighborhood pixel. In recent years, many scholars have studied and proposed many remote sensing image classification methods. The different processing methods can be divided into supervised classification method and unsupervised classification method. Unsupervised classification method relies on the system cluster, and a group of pixels are classified according to the similarity. The main algorithm includes ISODATA [1], principal component analysis [2], independent component analysis [3], K-means [4], genetic algorithm [5], differential evolution algorithm [6], etc. Due to the spatial resolution of the image and the phenomenon of the same object, this method often appears more wrong and missing classification phenomenon.

Supervised classification method is a common statistical decision classification with high accuracy. It mainly includes the minimum distance, neural network method, Bayes network, etc. [7–15]. SVM is a structural risk minimization principle method. It can improve the generalization ability by minimizing empirical risk and confidence interval [16–19]. However, it is difficult to determine the parameters of SVM. So researchers proposed some improved SVM classification methods. Adankon and Cheriet [20] proposed an additional criterion with the standard formulation of semi-supervised SVM (S3VM). Mylonas et al. [21] proposed an object-based classification scheme for remote sensing images. Patra and Bruzzone [22] proposed a novel iterative learning technique based on SOM neural network and

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SVM. Du et al. [23] proposed wavelet SVM classifier. Bruzzone et al. [24] proposed a novel modified TSVM classifier based on the transductive SVMs. Marconcini et al. [25] proposed a novel composite semisupervised SVM for image classification. Zhai et al. [26] proposed a new decision tree ensembles based on C4.5, Ada Boost and Boost Tree. Jing et al. [27] proposed a remote sensing image classification based on optimized SVM. Mallinis et al. [28] proposed a novel fuzzy decision tree. Xu et al. [29] proposed a method of reducing dimensions based on genetic algorithm and object-oriented classification based on SVM.

These image classification methods based on SVM and improved SVM model can better obtain classification effect, but they have low classification efficiency and prolonged classification time with increasing samples. With the progress of sensor technology, the amount of remote sensing data is significantly increased. The information is highly detailed, and the dimensions of data change greatly. SVM is difficult to meet the actual requirements of image classification. Wavelet transform is one of the tools which is used widely in current applied mathematics and engineering application. Therefore, wavelet transform is used to extract the texture features of image. Then the steepest descent strategy, corrective decline strategy, random movement, aggregation and diffusion strategies are used to improve PSO algorithm, which is used to optimize the parameters of SVM in order to propose a new remote sensing image classification method for improving the speed and accuracy of remote sensing image classification.

2. BASIC METHODS

2.1. Wavelet Transform

The concept of wavelet is proposed by a French engineer J. Morlet in 1974 [30]. By comparing the Fourier transform, wavelet transform, partial transformation of space (time) and frequency, the dilation and translation operation functions are used to analyze the functions or signals to solve these difficult problems that cannot be solved by Fourier. In order to apply the wavelet transform to process the image, a two-dimensional wavelet function and scaling function are required. A separable variable method with the two-dimensional wavelet function based on one-dimensional wavelet function and scaling function is used. On each wavelet, H is the horizontal direction, V the vertical direction, and D the diagonal direction. The scale function and wavelet function define a dilation and translation basis functions:

$$\phi_{j,m,n}(x, y) = 2^{j/2} \phi(2^j x - m, 2^j x - n) = \phi_{j,m}(x) \phi_{j,n}(y) \quad (1)$$

$$\varphi_{j,m,n}^H(x, y) = 2^{j/2} \varphi^H(2^j x - m, 2^j x - n) = \varphi_{j,m}(x) \phi_{j,n}(y) \quad (2)$$

$$\varphi_{j,m,n}^V(x, y) = 2^{j/2} \varphi^V(2^j x - m, 2^j x - n) = \phi_{j,m}(x) \varphi_{j,n}(y) \quad (3)$$

$$\varphi_{j,m,n}^D(x, y) = 2^{j/2} \varphi^D(2^j x - m, 2^j x - n) = \varphi_{j,m}(x) \varphi_{j,n}(y) \quad (4)$$

The wavelet transform can concentrate the energy of the original image on the small part of wavelet coefficients. Therefore, the decomposed wavelet coefficients have a high degree of local relevance in the horizontal, vertical and diagonal directions, which provide favorable conditions for feature extraction.

2.2. Particle Swarm Optimization Algorithm

The PSO algorithm [31] is a population-based search algorithm. In PSO algorithm, the positions of particles in search space are changed according to the tendency of individuals. Assuming that in a d -dimensional search space, a population has m particles, among which the i th particle is expressed as a d -dimensional vector $x_i = (x_{i1}, x_{i2}, \dots, x_{id})$, $i = 1, 2, \dots, m$. It means that the position in d -dimensional search space in the population is x_i . Its speed is also a d -dimensional vector, denoted as $v_i = (v_{i1}, v_{i2}, \dots, v_{id})$; the optimal location is $p_i = (p_{i1}, p_{i2}, \dots, p_{id})$; the optimal location of the whole population is $p_g = (p_{g1}, p_{g2}, \dots, p_{gd})$. The velocity updating and position updating of the particle are shown:

$$v_{id} = wv_{id} + c_1 r_1 (p_{id} - x_{id}) + c_2 r_2 (p_{gd} - x_{id}) \quad (5)$$

$$x_{id} = x_{id} + v_{id} \quad (6)$$

Among them, w is the inertia weight coefficient; c_1 and c_2 are two nonnegative constants, known as acceleration constant; r_1 and r_2 are two random numbers between $[0, 1]$.

2.3. Support Vector Machine

SVM is a supervised machine learning method based on structural risk minimization [32, 33]. It is to find one division plane with meeting the given requirement to keep the point of training set far away from the plane. It is used to solve the linear constraint quadratic programming problem by mapping the input space into a high dimensional inner product space. The kernel function in SVM is used to map the input space into a high-dimensional feature space. There are the linear kernel function, radial basis kernel function (RBF), Fourier kernel function, etc. For different systems in the process of classification, there is the optimal kernel function with the best effect. The radial basis function has wide application because of its simple expression form, good smoothness and analyticity. Therefore, the RBF is selected as the kernel function of SVM. The kernel function is described as follows.

$$K(x, x_i) = \exp\left(-\|x - x_i\|^2 / \sigma^2\right) \tag{7}$$

where x is a m -dimensional input vector, and x_i is the center of the i th radial basis function and has the same dimension with x .

3. A NEW CLASSIFICATION METHOD

In order to solve the existing problems in remote sensing image classification, a new classification method of remote sensing image (RIWMPS) based on wavelet transform, improved PSO and SVM is proposed in this paper. A flowchart is shown in Fig. 1.

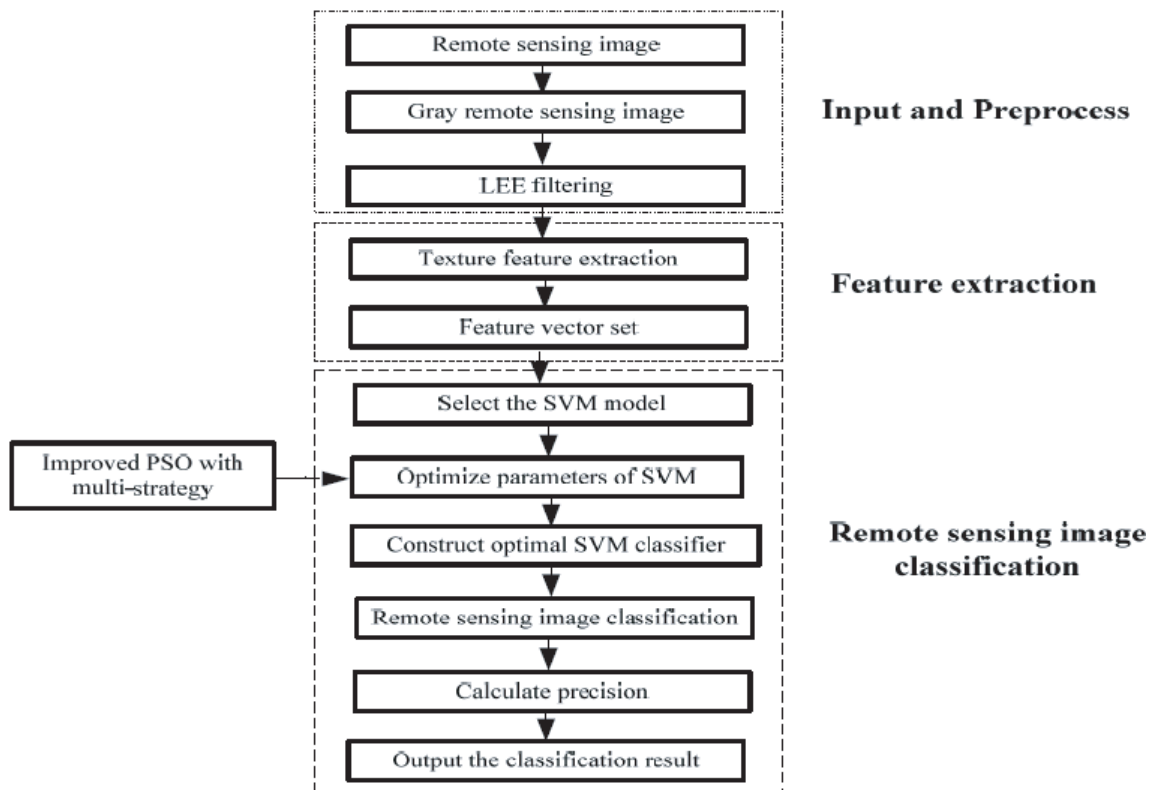


Figure 1. The flow chart of RIWMPS method.

3.1. Input and Preprocess the Remote Sensing Image

The remote sensing image of Chongming Island on August 2, 2003 is selected here. The radiation and geometry of remote sensing image are corrected. It is converted into a grayscale image. The number of determined samples is 3. The LEE filtering is selected to preprocess the grayscale image to obtain a preprocessed remote sensing image.

3.2. Texture Feature Extraction Method of Remote Sensing Image

The image contents include the visual features and semantic features of the color, texture, and shape. Among them, the texture feature is regarded as the most significant visual feature, which does not depend on the color or brightness to reflect the visual features of the homogeneous phenomena. The texture feature contains important information of the surface structure and the relation of the surrounding environment. The wavelet transform can concentrate the energy of the original image on a small part of the wavelet coefficients, so the wavelet transform is used to realize the feature extraction of remote sensing image.

3.3. Select the Key Parameters

In the theory of the SVM, the function of the penalty coefficient C is used to adjust the proportion of the confidence range and experience risk in the determined subspace to make the best classification ability of learning machine. For determined classification data, when the value of C is small, the penalty of the experience error is small. Otherwise, the complexity of the machine learning is low, and the experience risk of the machine learning is high, and vice versa. The function of the kernel parameter σ^2 is used to determine the corresponding relation between the mapping function and feature space. An appropriate σ^2 will be able to map the data into an appropriate feature space. However, the values of σ^2 and C are very difficult to be predetermined. It is critical how to effectively optimize the parameter values of SVM for the experience risk and classification ability of the SVM.

3.4. An Improved PSO Algorithm

The update formula of velocity in the PSO is the same for all particles [34–36]. The single search strategy will result in weak local search ability. Even when the particles are very close to the best position, they cannot quickly find the location. These will result in low convergence accuracy. In order to overcome these shortcomings, the steepest descent strategy, corrective descent strategy, random movement strategy, gathering and diffusion strategies are used to improve the PSO algorithm. A multi-strategy PSO (MSPSO) algorithm is proposed to improve the search strategy with the iteration of the particles. The idea of the MSPSO algorithm is described as follows. When the searched optimization location changes, the optimal particle uses the steepest descent and the corrective descent strategies to search for the local extremum, and the non-optimal particles use the gathering strategy to be close to the optimal particle. When the searched optimization location does not change, the optimal particle uses the random movement strategy to jump out the local extremum, and the non-optimal particles select the gathering strategy or diffusion strategy according to the searched optimal location. A flowchart of the MSPSO algorithm is shown in Fig. 2.

4. EXPERIMENT RESULT

4.1. Optimize Parameters of SVM

In the experiment, the data image set is selected from the publicly available data of Digital Globe. The data set contains 5 classes and 51 images, including training samples (28 images) and test samples (23 images). The correct rate of image classification is selected as the fitness functions of MSPSO and GA. The optimization process of MSPSO and GA on Matlab 7.0 is shown in Fig. 3.

As can be seen from Fig. 3, the fitness value (the correct rate of image classification) is 86%, which is found at the 6th generation using the MSPSO algorithm. The optimal fitness value (the correct rate of image classification) is only 73%, which is found at the 46th generation using the GA. So the MSPSO

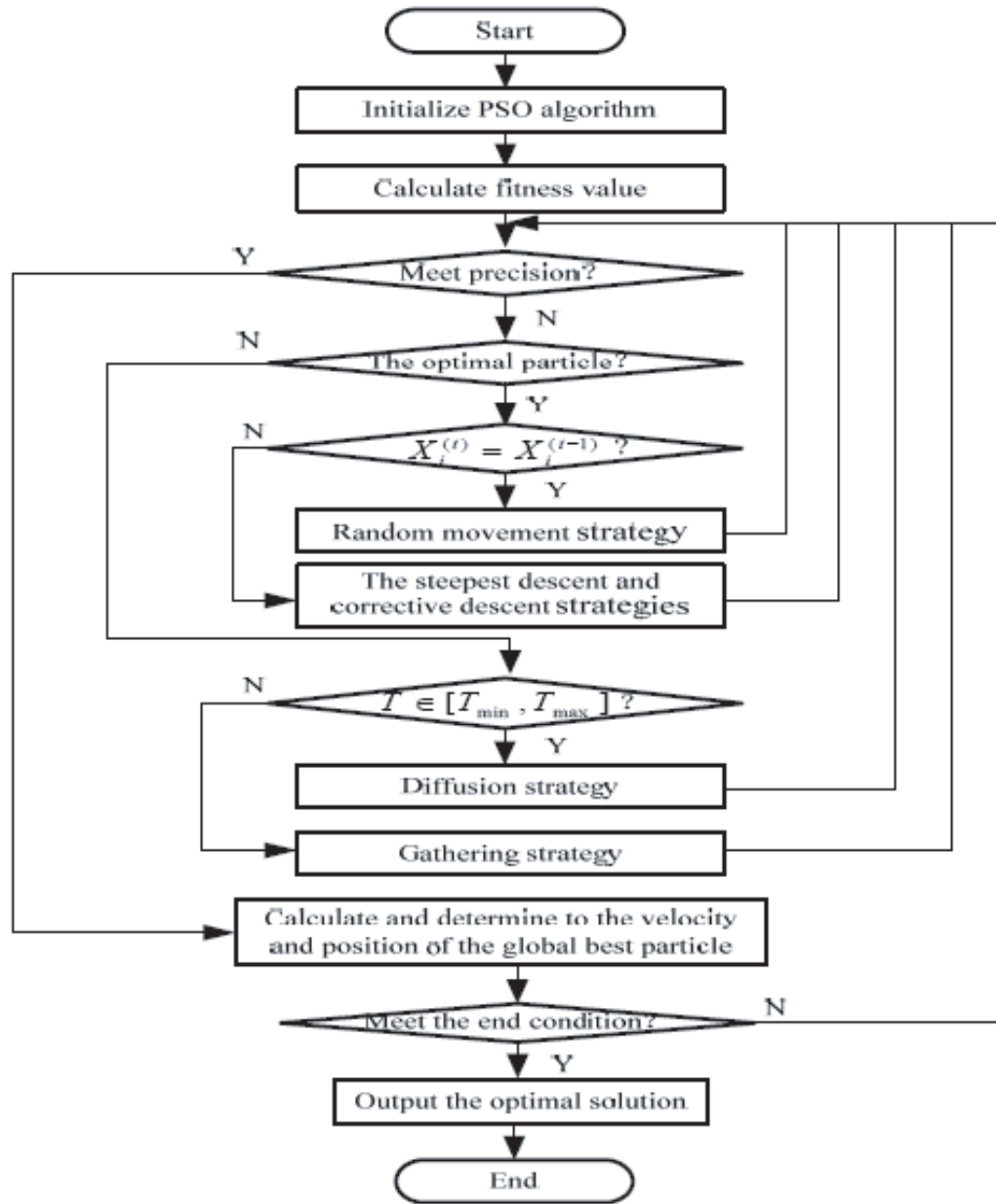


Figure 2. The flow of the MSPSO algorithm.

algorithm can obtain more optimal fitness value (the correct rate of image classification) than the GA in the experiment, and it has less evolution iteration. These results illustrate that the MSPSO algorithm can better optimize the parameters of SVM.

4.2. Test Classification Method and Analyze the Result

4.2.1. Experimental Data and Environment

In order to test the performance of the proposed classification method, the selected remote sensing image is TM multi-spectral satellite data of Shanghai Chongming Island wetland. The experiment image is radiometric corrected, geometric corrected and enhanced, so it can be used directly, shown in Fig. 4. The number of extracted features of remote sensing image is 26, and these features are basic features of the image. Three kinds of samples, housing, land and sea with different texture features, are selected

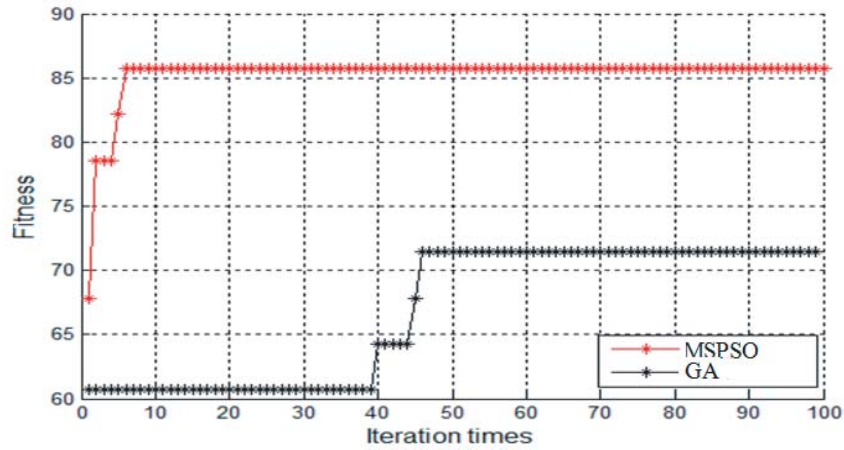


Figure 3. Optimize parameters of SVM based on MSPSO and GA.

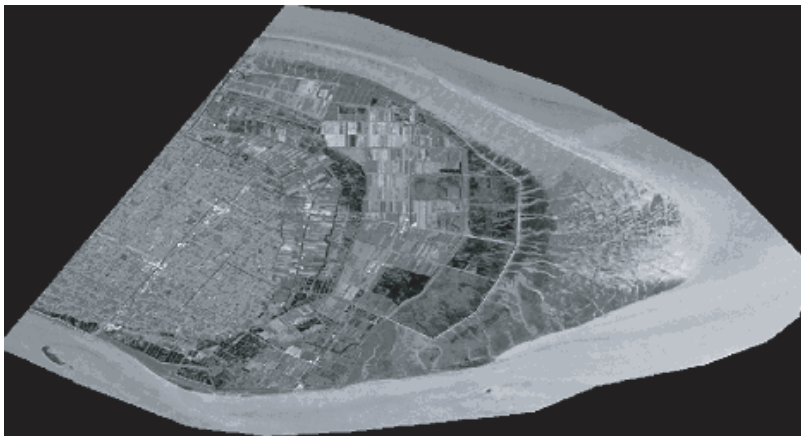


Figure 4. Remote sensing image of Chongming island.

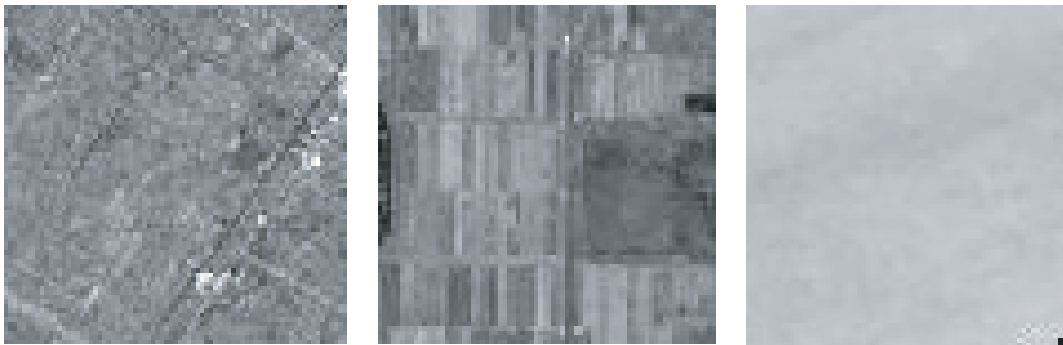


Figure 5. Three kinds of samples.

in this paper, shown in Fig. 5. The training sample and validation data sets are collected according to the remote sensing image and field investigation. A total of 50 sample images with 20×20 are randomly collected from three kinds of sample images respectively. There are 25 training samples and 25 testing samples.

4.2.2. Obtain and Analyze the Classification Result

In order to verify the effectiveness of the RIWMPS method, the classification method (GA-SVM) based on genetic algorithm (GA) and SVM and the classification method (GS-SVM) based on grid search (GS) and SVM are selected to realize the comparison experiment. The initial settings of GS-SVM, GA-SVM and RIWMPS are shown in Table 1.

Table 1. Initial value of the parameters of the algorithms.

Parameter \ Method	GS-SVM	GA-SVM	RIWMPS
Population size (M)	N/A	20	20
Iteration times (T_{max})	N/A	200	200
Parameter of SVM Cross Validation (v)	6	6	6
Scope of Parameter c	[0.1, 100]	[0.1, 100]	[0.1, 100]
Scope of Parameter g	[0.001, 1000]	[0.001, 1000]	[0.001, 1000]
Accelerated constant	N/A	N/A	$c_1 = c_2 = 2$
Inertia weight (w)	N/A	N/A	0.80
Modulus of elasticity	N/A	N/A	$r_1 = r_2 = 1$
Step length	$cstep = gstep = 1$	N/A	N/A

The average classification accuracy of texture is used to regard as the comparison result. The simulation result and comparison result are shown in Table 2 and Fig. 6–Fig. 9.

Table 2. Classification accuracy of the optimized SVM classifier.

Method	Sample	Correct	Wrong	accuracy
GS-SVM	75	68	7	90.67%
GA-SVM	75	70	4	94.67%
RIWMPS	75	71	3	96.00%

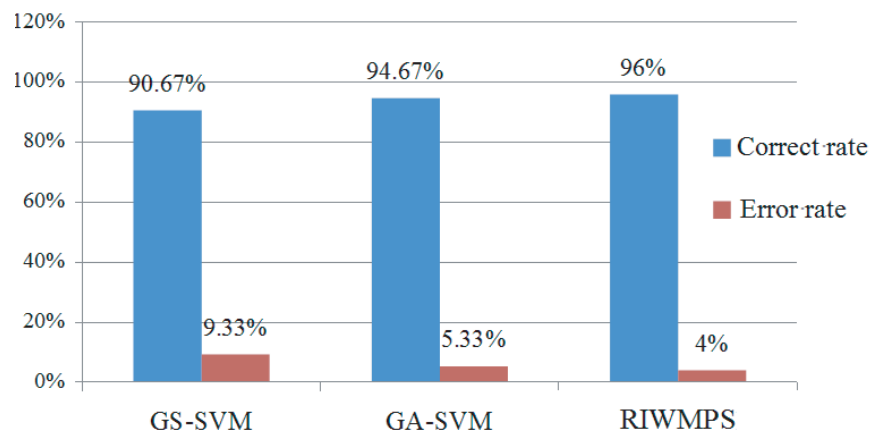


Figure 6. The comparison of classification result.

Figure 7 shows the comparison result with forecast classification and actual classification with 75 testing samples using GA-SVM classifier. Fig. 8 shows the comparison result with forecast classification

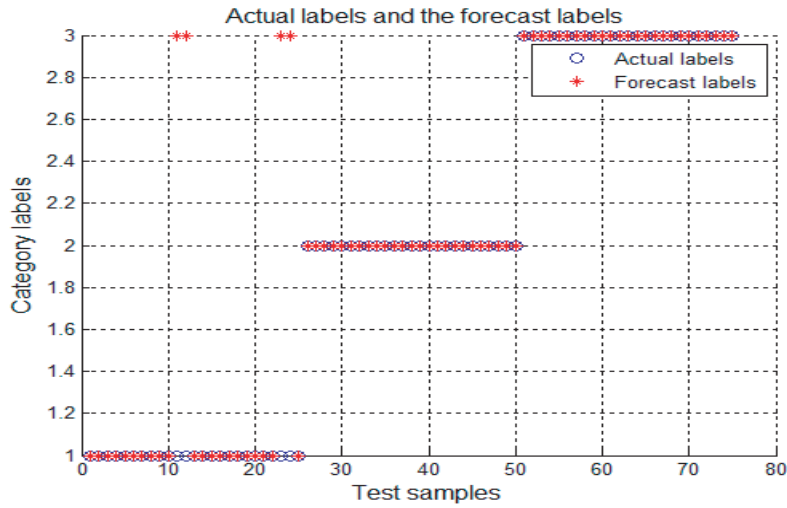


Figure 7. The comparison result by using GA-SVM classifier.

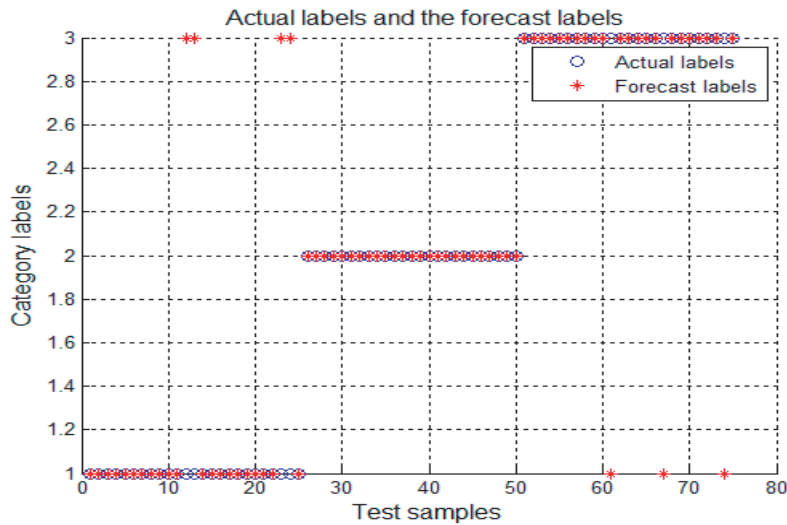


Figure 8. The comparison result by using GS-SVM classifier.

and actual classification with 75 testing samples using GS-SVM classifier. Fig. 9 shows the comparison result with forecast classification and actual classification with 75 testing samples using RIWMPS classifier. As can be seen from Fig. 6–Fig. 9 and Table 2, the GS-SVM classifier has 7 wrong classification samples, and the classification accuracy is 90.67%. The GA-SVM classifier has 4 wrong classification samples, and the classification accuracy is 94.67%. The proposed RIWMPS classifier has 3 wrong classification samples, and the classification accuracy is 96%. Therefore, it can be seen that under the same experiment conditions, the RIWMPS classifier has the highest classification accuracy, and the classification accuracy of RIWMPS classifier is improved about 5.3% compared to the classification accuracy of GS-SVM classifier. It is proved that the MSPSO algorithm can obtain the best values of parameters of SVM model.

In order to comprehensively analyze the effectiveness of the RIWMPS classifier, the classification accuracy of the improved SVM classifier is analyzed from the house, land and sea. The experimental result is shown in Table 3.

As can be seen from Table 3, the GS-SVM classifier has wrongly classified 4 house samples into land samples and 3 land samples into house samples; the GA-SVM classifier has wrongly classified 4

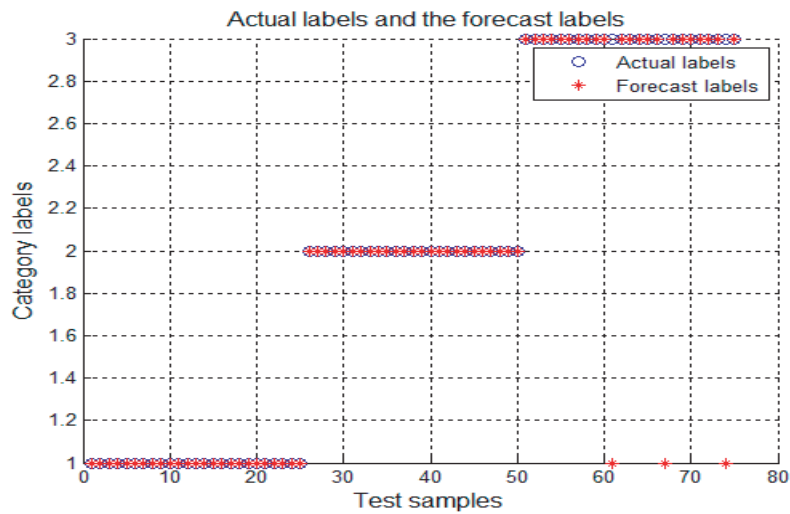


Figure 9. The comparison result by using RIWMPS classifier.

Table 3. The classification accuracy of the improve SVM classifier.

Type	Sample	GS-SVM	GA-SVM	RIWMPS	Average accuracy
House	25	84%	84%	88%	86%
Land	25	88%	100%	100%	96%
Sea	25	100%	100%	100%	100%

house samples into land samples; the RIWMPS classifier has wrongly classified 3 house samples into land samples. For sea samples, three improved SVM classifiers have correctly classified all samples. So it can be proved that the RIWMPS classifier can effectively improve the classification accuracy.

As can be known from comprehensive analyzing experimental result, the overall average classification accuracy of the RIWMPS classifier is 96%, which can obtain the best classification effect and classification accuracy. As can be found from the analysis, the classification accuracy of water and land is better. The main reason for easy distinguishing of the water and land is that they have obvious pixel features and relatively concentrated distributions. The classification accuracy of house is a bit lower than the classification accuracies of water and land. As can be known from the field inspection, the misclassification pixels are mainly focused on the house object, because the house is discrete distribution and not a single structure. And the bare land is mixed in house object, and the house and bare land are closely distributed together. For the pixels at the border of two types of surface features, these pixels often contain many kinds of target feature information because of the influence of the scattering of objects. The existing mixed pixels influenced the classification accuracy and caused the mistake classification.

5. CONCLUSION

The remote sensing image classification with fast speed and high precision is the premise to realize various practical application technologies of remote sensing image. In allusion to the existing defect of SVM model in the remote sensing image classification, wavelet transform, multi-strategy, PSO algorithm are introduced into remote sensing image classification to propose a new WMSPSV method. Test samples are used to classify and forecast for outputting the classification result. In the experiment result, the classification accuracies of the GS-SVM classifier, GA-SVM classifier and RIWMPS classifier are 90.67%, 94.67% and 96%, respectively. The result shows that the proposed RIWMPS classifier has

improved the classification accuracy of remote sensing image to a certain extent and proves that this method is an effective remote sensing image classification method with high classification accuracy. In the next work, we will concentrate on how to select the optimal texture feature vector and further improve the classification precision of remote sensing image.

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Conflict of Interest: The authors declare that they have no conflict of interest. This article does not contain any studies with human participants or animals performed by any of the authors. Informed consent was obtained from all individual participants included in the study.

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