# Extraction model of forest features based on mutation and bidirectional particle swarm optimization

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**Abstract**

Although the existing forest feature extraction and classification model has a certain effect, but it still exists problems such as accuracy is not high, speed is slowly and so on. According to this problem, this paper proposed an extraction model of forest features based on mutation and bidirectional particle swarm optimization. First, we use mutation operators of genetic algorithm and the Sigmoid function of neural network to make a dynamic adjustment, in order to avoid the particles into a precocious state. Then according to this paper the original algorithm of the initial population is improved on the basis of the use of the two-way optimization strategy, and put forward the speed optimization strategy to help it get a local optimal solution timely when it appeared premature phenomenon and use the optimization strategy of particle effect to enhance the convergence accuracy. Finally the gauss perturbation theory is introduced to improve the convergence of the algorithm when the original algorithm falls into local optimum with optimize learning strategy to make it jump out. Through the simulation experiments, it shows that the proposed forest feature extraction model based on the variation feature subset and two-way optimized particle swarm algorithm with higher precision, better convergence performance.

*Keywords:* forest feature extraction, improved particle swarm algorithm, feature subset dynamically adjust, two-way optimization strategy

## 1 Introduction

Forest resources was not only the basis of natural resources and ecological environment construction, but also the main terrestrial ecosystems, which was irreplaceable for the sustainable development of economic, social and environmental [1]. Investigating and monitoring of the forest resources was an indispensable content for serious soil erosion, fragile ecological environment, ecological environment construction in the study area. It was the key to be timely and rapid access to information of vegetation coverage for ecological environment construction project [2]. Exploring the method to obtain more rapid and more accurate forest resources of thematic information which used to serve divide the forest types. Draw the forest map, inventory the forest resources, forecast the forest pest and fires, plan rationally, utilize and protect of the forest resources to provide the basis and foundation was the development trend to monitor the forest resources. Because there was a big difference between different forest types, we needed to build a quantitative inversion model for different forest types [3].

Experts and scholars had used a variety of methods to identify and classify the ground vegetation. Srinivasan had classified multi-source remote sensing data by using multi-source remote sensing data according to the various categories of spectrum model [4]. Firstly Franklin and Peddle classified the spectrum, texture and DEM with a linear classifier, and later presented the classification method of multiple data sources reasoning. The result was significantly better than using traditional statistical pattern recognition method [5]. Janssen etc. did a lot of research of how to fully use the image and the auxiliary data to classify and particularly be based on knowledge information to classify [6]. Foody etc classified the tropical forest types in Brazil MatoGrosso areas by applying artificial neural networks (ANN) method. The result showed that this method result was closer to the actual division and better than other traditional classification methods [7]. Townsend etc. proposed a classification method which applied multi-period multi-spectral satellite data to community Roanoke River floodplain forest wetland located northeastern of United States Carolina's into twenty-one forest community types and seven other important ecological. It had a accuracy of 96.6% by using fuzzy set theory evaluation [8]. Shujuan Diao researched thevegetation of Panzhihua areas based on spectral and spatial information characteristics of remote sensing images and the distribution of different vegetation classifiably and the classification accuracy was 90%, which increased by 10% compared with the maximum likelihood classification [9]. Zhijie Quan, etc used the self-organizing neural tree model to research the forest site classification classifiably, the result showed that the method had a classification speed, high accuracy, strong fault tolerance [10]. Junhun Teng etc. proposed an intelligent classification method of remotely sensing of mangrove vegetation information by extracting the

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spectral information of mangrove vegetation information [11]. Jiyuan Liu conducted a comprehensive classification study of vegetation in north-eastern China by the GIS technology. The result showed that the comprehensive classification method improves the classification accuracy of 18.3%compared with the traditional classification method of using the maximum likelihood classification for a single remote sensing image [12]. Weiguo Liu classified the vegetation of Helan Mountain region by experiment based on the relationship between environmental factor and vegetation distribution with the support of GIS and remote sensing technology [13]. Qiang Li etc. transformed smooth process model after the classification process into a constrained optimization problem, combined the smooth process of the classification result with the method of neural network, and proposed a integrated technology based on constraint satisfaction neural network classification and post-processing. Experiment showed that the method can significantly improve the division of forest types, classification accuracy of remote sensing applications for land use topics [14].

The paper proposed the forest feature extraction model based on variation feature subset and bidirectional optimization particle swarm algorithm which aiming at the forest feature extraction model. Also existed the problem of poor accuracy, optimized feature subset of the particle swarm algorithm by the mutation operation of genetic algorithm and optimized bidirectional for the initial population, finally used the best optimizing learning strategies to improve the optimization performance of the original algorithm.

## 2 The defect of particle swarm optimization

PSO algorithm groups considered each individual in a multi-dimensional search space is no mass and volume of the particles. The particles in the search space to a certain speed flight, and according to the iterative process of the most optimal value of itself and the groups constantly revised its forward direction and speed, thus forming a positive feedback mechanism optimization.

In a one-dimensional of goal search space, PSO random initialization m particles composed of a group (potential solution of the optimization problem) The position of the i particle can be expressed as, substituted into optimizing the fitness evaluation function can be drawn value, used to measure the merits. VI corresponding to the flight speed can be expressed as. In each iteration process, the particles update its velocity and position by tracking the two extremes. One extreme is the particle itself so far searched the optimal solution, that individual extreme Palest, expressed as {Pibest.1; Pibest.2, Pibest.D}. Another extreme value is a group of particles so far searched the optimal solution, that global minimum Pgbest, expressed as {Pgbest.1, Pgbest.2,…, Pgbest.D}. Its flow is shown below (Figure 1).

Specifically in the calculation of the $k$+1 iteration, the particle $i$ according to the Equations (1) and (2) to update the velocity and position, the speed is defined as Equation (3).

$$v_{id}^{k+1} = \omega \cdot [v_{id}^{k} + c_1 r_1 (p_{ibest.d}^{k} - x_{id}^{k}) + c_2 r_2 (p_{gbest.d}^{k} - x_{id}^{k})], \quad (1)$$

$$x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k}, \quad (2)$$

$$\begin{cases} if\ v_{id}^{k+1} > v_{\max}\ v_{id}^{k+1} = v_{\max} \\ if\ v_{id}^{k+1} < v_{\min}\ v_{id}^{k+1} = v_{\min} \end{cases}, \quad (3)$$

where $i$=1,2,…,$m$; $d$=1,2,…,$D$, $W$ is inertia weight. $C$1, $C$2 is accelerating factor, $R$1, $R$2 is uniformly distributed in [0,1] of a random number, $v_{max}$, $v_{min}$ is the particle maximum speed limit.

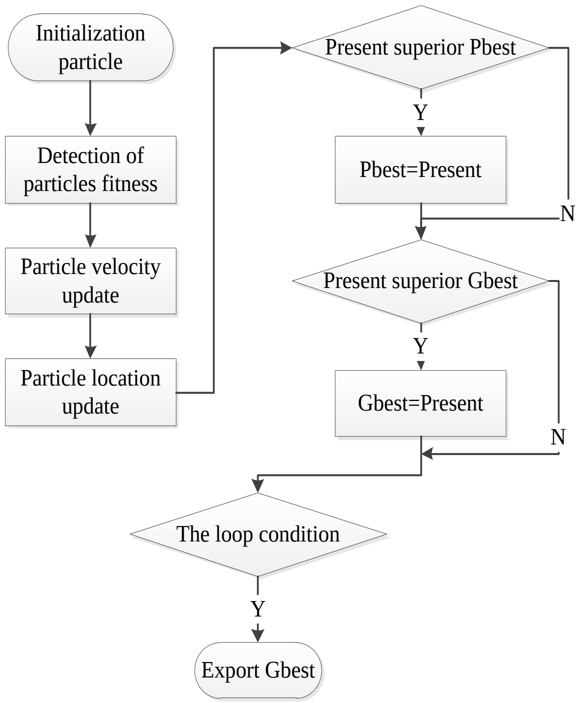


FIGURE 1 PSO flowchart

Advantages of PSO algorithm is simple and easy to implement of processes, not a lot of arguments. However, Particle Swarm is a significant difference with other computational intelligence methods is rarely necessary adjustments, but these settings are key parameters on the accuracy and efficiency of the algorithm has significant influence exists. Therefore, this article before using particle swarm forest feature extraction, the first of its optimized and improved.

## 3 Improved particle swarm algorithm based on feature subset optimization

### 3.1 THE PARTICLE SWARM OPTIMIZATION BASED ON FEATURE SUBSET MUTATION

Due to the existence of parameter settings, speed dynamic adjustment, particle swarm premature convergence and other issues in the particle swarm algorithm, the algorithm is easy to converge to local minima. Therefore, this paper introduces mutation combined with neural networks Sigmoid-type function to optimize the feature subset of particle swarm algorithm.

In the genetic algorithm, the mutation operator isto achieve a certain allele according to the mutation probability reversal binary character values. For a given bit string chromosomes, as follows:

$$o(p_m, x): a_i' = \begin{cases} 1-a_i, & if\ rand \le p_m \\ a_i, & else \end{cases}. \tag{4}$$

The new generation of individuals are $s_i' = a_1' a_2' ... a_l'$. So at different stages of evolution, particle swarm algorithm can be used to improve the performance by different algorithms variation, mutation strategy for its position and velocity:

$$\begin{cases} v_i^d = wv_i^d + \eta r_i^d (pbest_i^d - x_i^d) \\ x_i^d = x_i^d + v_{avg}^d N(0,1) \\ v_i^d = wv_i^d + \eta r_i^d (pbest_{rand}^d - x_i^d) \\ v_i^d = wv_i^d + \eta r_i^d (gbest_{rand}^d - x_i^d) \end{cases}, \tag{5}$$

in which $\eta$ is equivalent to the standard particle swarm algorithm acceleration factor $c_1$, $r_i^d$ is a random number for the interval [0,1] $N(0,1)$ is uniformly distributed random numbers for the standard normal distribution, the particles in the $d$ dimension is the current average speed $v_{avg}^d$ is calculated as follows:

$$v_{avg}^d = \sum_{i=1}^{m} \left| v_i^d \right| / m, \tag{6}$$

in which $m$ is the size of the population, $pbest_{rand}$ is a particle that is in order to adapt to the value of a randomly generated superior than $pbest_i$.

In summary, the improved particle swarm algorithm proposed in this paper use function $m(t)=p\times f(t)$ to adjust mutation probability dynamically, $p$ is a constant interval. Experiments show that if the parameter is too large, the algorithm does not converge, if the parameter is too small, algorithm will still fall into premature convergence, this section takes $p=1/5$.

From the image of sigmoid-type function, and $f(t)$ is an increasing function as the evolution of algebra increases gradually and eventually become one, that means mutation probability algorithm increases and tends to be a constant $p$. Specific steps are as follows:

1) Algorithm Initialization: Set inertia weight $w$, population size $m$, speed factor $c_1 \backslash c_2$, and the maximum evolution generation $T_{max}$, random initialization position $X_i$ and velocity $V_i$ of each particle population.

2) To calculate the adapted current value of each particle, record personal best for the current is $P_i = (p_{i1}, p_{i2}, ..., p_{iD})$ and global population is $P_g = (p_{g1}, p_{g2}, ..., p_{gD})$.

3) To determine the conditions of the termination of the algorithm, if met, the algorithm runs over, the global optimum $P_g$ is output.

4) If $rand \ge m(t)$, according to Equations (1) and (2) update the position of each particle; otherwise according to Equation (5) update the position $X_1$ of each particle. If the fitness value $X_i^{t+1} = (x_{i1}^{t+1}, x_{i2}^{t+1}, ..., x_{iD}^{t+1})$ of the new generation of particles $X_i^{t+1} = (x_{i1}^{t+1}, x_{i2}^{t+1}, ..., x_{iD}^{t+1})$, then $P_g = X_i^{t+1}$; if, then, go to (3).

Among them, $t$ is the current evolution of algebra, $rand$ is random number uniformly distributed on the interval [0, 1], $f$ stands for fitness function, constant $p$=1/5.

The introduction of improved PSO mutation in a subset of features in the late evolutionary diversity overcomes premature convergence of the algorithm into a defect. It not only improves the ability to get rid of multimodal function of local maximum, but also improve the convergence precision of single peak function.

### 3.2 BASED ON THE BIDIRECTIONAL OPTIMIZATION TO IMPROVE INITIAL POPULATION

In order to have a further improvement of the particle swarm optimization algorithm in feature extraction accuracy and convergence precision of forest, in this paper, optimized based on the feature subset. Again on the two-way optimization.

1) The speed optimization.

Aimed at particle swarm optimization to the late, slow flight, which results in the stagnation of global search ability of the phenomenon. This paper proposes a way to help the algorithm in a timely manner appeared premature phenomenon can jump out of local optimal solution, to ensure the diversity of particle population, to enhance the search precision of particle swarm optimization algorithm. First of all, set a threshold algorithm, and

$$D = \frac{P_{gD}}{\frac{1}{n}\sum_{i=1}^{n} P_{iD}}. \tag{7}$$

Among which, $P_{gD}$ is the optimal solution in the global, $P_{iD}$ for each particle in the dimension of individual optimal solution. N is the size of the population. So, when the population of particles and the more concentrated. The more easily trapped in local optimal solution. When D is the dmax, then $D \geq D_{\max}$, make part of the population to initialize particles.

So after the particles start to swarm search, if the particle concentration aim to a search area. The algorithm will lose the diversity of the population. Make PSO algorithm in local search and can't jump out to search the global optimal solution. At this time in the iteration process will automatically calculate the size of the threshold. When the population is more and more concentrated, the threshold is becoming more and more big, once $D \geq D_{\max}$, algorithm will automatically initialize part of the particle population randomly. So the initialized particles will jump out of local optimal predicament, ask them to have the global search ability, thus ensure the particles to the diversity of population, in order to search for better global optimal solution.

2) Effects of the degree of optimization between particles the paper improve the formula of basic particle swarm speed, the new Equation is:

$$v_{iD}^{t+1} = wv_{iD}^{t} + c_1 r_1 \left( p_{id} - x_{iD}^{t} \right) + c_2 r_2 \left( p_{gd} - x_{iD}^{t} \right) + c_3 r_3 \left( p_{jd} - x_{iD}^{t} \right), \tag{8}$$

$$x_{iD}^{t+1} = x_{iD}^{t} + v_{iD}^{t+1}. \tag{9}$$

In the new Equation $P_{jd}$ is an individual in the optimal solution in any random in addition to particles of *i*.

Through the two improvements, not only let basic particle swarm algorithm overcome local optimal solution of the problem of premature they faced easy to fall into well. But also increased the mutual contact between particles algorithm, let particle swarm algorithm be faster and more accurate search capability, not only strength convergence rate of particle swarm algorithm in the late local optimization process, but also enhanced its convergence precision.

### 3.3 THE OPTIMIZATION CONVERGENCE BASE ON LEARNING STRATEGY OPTIMIZATION

If populations are in a local optimum, they will take certain measures to jump out of local optimum; otherwise we are unable to find the global optimal solution. This paper use learning strategies jumping out when an optimization algorithm get into local optimum. The main principle of optimizing learning strategies is randomly select one dimension in the global optimal particle (setting the probability of each selected dimension is the same), for the selected the gauss perturbation of one dimension:

$$gBest^{d} = gBest^{d} + (X_{\max}^{d} - X_{\min}^{d}) \cdot Gaussian(\mu, \sigma^{2}). \tag{10}$$

Among which, $X_{\max}^{d}$ and $X_{\min}^{d}$ are separately on behalf of maximum and minimum values, all particles in the current population of each dimension; Gaussian disturbance mean is 0 and standard deviation is $\sigma$ which is also the optimal vector. $\sigma$ linear regressive with the increase of the number of iterations which is the same as neural network training strategy changing with time. The calculation method is shown.

$$\sigma = \sigma_{\max} - (\sigma_{\max} - \sigma_{\min}) \frac{gen}{MaxGen}. \tag{11}$$

Among which, $\sigma_{\max}$ and $\sigma_{\min}$. Represent the caps and collars of $\sigma$, on behalf of the scope of the ability to learn algorithm, *gen* is the current number of iterations, *MaxGen* is the total number of iterations of the algorithm. The research shows that when $\sigma_{\max}$ value as 1.0, $\sigma_{\min}$ value as 0.1, it can achieve good results for most test functions. So in this experiment we can value it like this: $\sigma_{\max} = 1.0,\ \sigma_{\min} = 0.1$.

## 4 Algorithm performance simulation

In order to verify the effectiveness of the improved algorithm proposed in this paper, we did some simulation experiments on it. First of all, we did some simulation experiments of improved particle swarm algorithm. Experimental parameters Settings: inertia weight $w$=0.8, accelerated factor $c_1$=$c_2$=2.05, population size $m$=20, Step factor F=0.6. Adopt Rosenbrock function, Restrigrin function and Griewank function to test it, results are as follows (Figures 2-5).

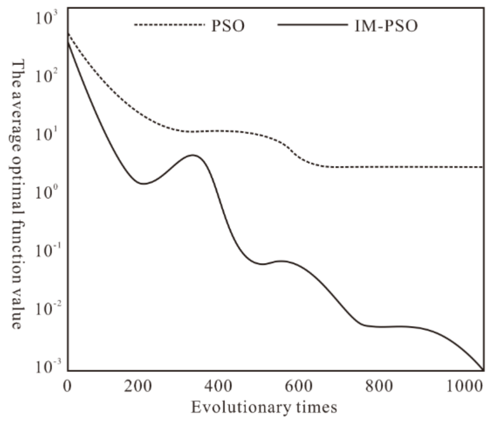


FIGURE 2 Rosenbrock function test results

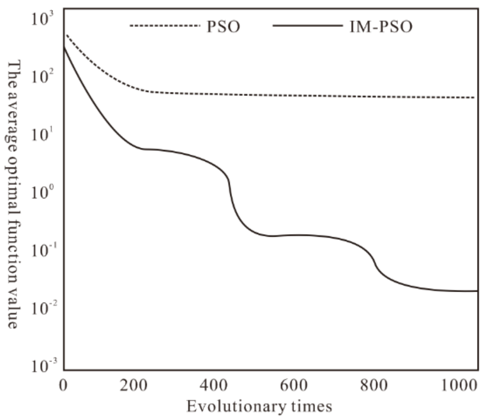


FIGURE 3 Restrigrin function test results

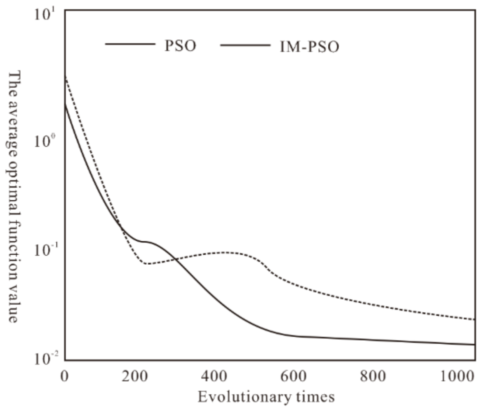


FIGURE 4 Griewank function test results

It is obvious that the performance of the improved particle swarm got a big promotion; significantly improved the global convergence speed and the convergence precision of the original algorithm had increased substantially.

Then, we did 500 times for the feature extraction of the forest simulation experiment with improved particle swarm optimization algorithm; statistics the error of the extracted features, the results are as follows (Table 1):

TABLE 1 Forest feature extraction error statistical comparison

| **Iterations** | **Error** | |
|---|---|---|
| | PSO | IM-PSO |
| **50** | 32.1% | 15.3% |
| **100** | 28.3% | 12.4% |
| **150** | 29.1% | 11.5% |
| **200** | 30.2% | 14.2% |
| **250** | 22.6% | 13.7% |
| **300** | 26.8% | 13.8% |
| **350** | 27.0% | 11.0% |
| **400** | 29.2% | 10.5% |
| **450** | 24.3% | 8.5% |
| **500** | 22.2% | 6.2% |

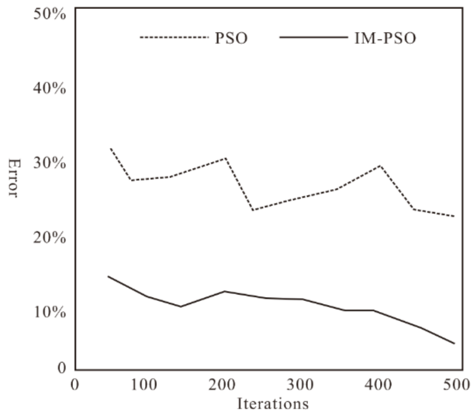


FIGURE 5 Simulation results of the feature extraction Forest

It can be seen from the simulation results, in this paper, when the feature extraction of forest based on the variation feature subset and two-way optimization of particle swarm optimization algorithm, the forest error smaller and the extraction accuracy higher.

## 4 Conclusions

In recent years, forest vegetation classification research get rapid development with the emergence of various new technologies, among them the improvement of classification accuracy is always a core problem which is difficult to solve. With the development of the artificial intelligence technology and the theory, the research and application of forest vegetation classification is also developing to intelligent direction. The forest feature extraction model based on the variation feature subset and two-way optimized particle swarm algorithm had been proposed from this paper, we can see it from the simulation results that the model has good convergence, fast convergence speed and the accuracy of feature extraction is higher.

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