Journal of Information Hiding and Multimedia Signal Processing ©2018 ISSN 2073-4212
Ubiquitous International Volume **9**, Number **4**, July **2018**

A New Krill Herd Algorithm Based on SVM Method for Road Feature Extraction

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Received July 2004; revised December 2004

Abstract. *Scene complexity has a great effect on road feature extraction, such as shadow and obstructions. In order to extract high-precision road feature, we propose a new support vector machine (SVM) based on krill herb algorithm used for a fast road feature extraction. This new scheme includes three steps. First, image is smoothed and we use fuzzy c-means clustering method to segment images. Then, we use SVM to classify the road information. In this section, the krill herd (KH) algorithm, which has good nonlinear continuous space optimization performance and can better balance aggregation and divergence of the algorithm, will be applied into SVM to optimize the parameter penalty function C and the radial basis function δ^2. Third, after acquiring road classification results, we adopt discrimination function to distinguish to accuracy of extracted road. Finally, experiments show that our method is more effective and can get high precision road feature. The new SVM model has more advantages than conventional methods for line road, especially for small sample road recognition. It can accurately identify the linear characteristic of road type. The new method can extract a variety of road at the same time, and the extraction efficiency is higher.*
Keywords: Road feature extraction, SVM, KH, Fuzzy c-means clustering

1. **Introduction.** 1.With the development of satellite technology, remote sensing image has gradually become the important data source for road extraction [1]. Because the cost of human extraction is very high and time consuming, studying high precision resolution remote sensing image has great significance for road extraction.

For the high resolution remote sensing image, image characteristics and road target will become more and more rich with the improvement of image resolution. In addition, it can distinguish many narrow roads which are difficult to discern on the low resolution image. However, non-object noise also increases. Currently, there are two main problems on extracting road in high resolution remote sensing image: one is that straight line inside road has the same direction with road (such as road boundary); another is that straight line has the different direction with road (such as zebra crossing) [2]. The higher resolution is, the ground buildings are clear. The top or the shadow of the buildings often forms neighbors road parallel lines. Whats more, there are many cars and trees. These factors would result in difficult problems on road extraction.

Due to the complex and diversity of road in the real world, it partially solves the problems at some stage of road extraction (such as filtering [3], segmentation [4] in preprocessing stage, the extraction stage [5], split [6] and merge [7] in post-processing stage. Wang [8] proposed automated road extraction method from multi-resolution images using spectral information and texture. Saati [9] presented a method for automatic extraction of road center-lines from synthetic aperture radar (SAR) imagery. Xu [10] represented an adaptive approach for road extraction inspired by the mechanism of primary visual cortex, which was an improved support vector machine (SVM) based on the pooling of feature vectors, using an improved Gaussian radial basis function (RBF) kernel with tuning on synaptic gains. Gupta [11] proposed an efficient technique of road extraction from satellite images by using mathematical morphology, fuzzy and genetic Algorithm. The proposed algorithm has been performed to extract the rural roads exactly.

So we propose a new road extraction method based on improved SVM. Firstly, we use fuzzy c-means clustering method to segment high resolution images in preprocessing. Secondly, we use new SVM based on KH algorithm to classify the road information. Thirdly, after data preprocessing, we adopt relevant filtering methods and discrimination function to deal with the extracted road. Finally, we make comparison experiments to show our method that is more effective and can get high precision.

Image feature extraction and classifier design are the two main factors influencing the road recognition. Image feature extraction indicates that it obtains measurement and attributes benefit for identifying objects from image. Good characteristics are often able to describe the nature of things, which greatly improve the classification accuracy. Classifier design has stronger generalization ability for unknown samples. It can get good recognition effect by using classifier design with good characteristics and superior generalization performance. Therefore, we propose a new SVM based on KH algorithm for road extraction. First, we use fuzzy c-means clustering method to segment image and get different image blocks. Second, we make preprocessing and regularization for image blocks with irregular shape. In addition, we make data sampling after regularization. Third, we adopt new SVM to extract road from images and guarantee extraction accuracy. Figure 1 is the framework of our road extraction method.

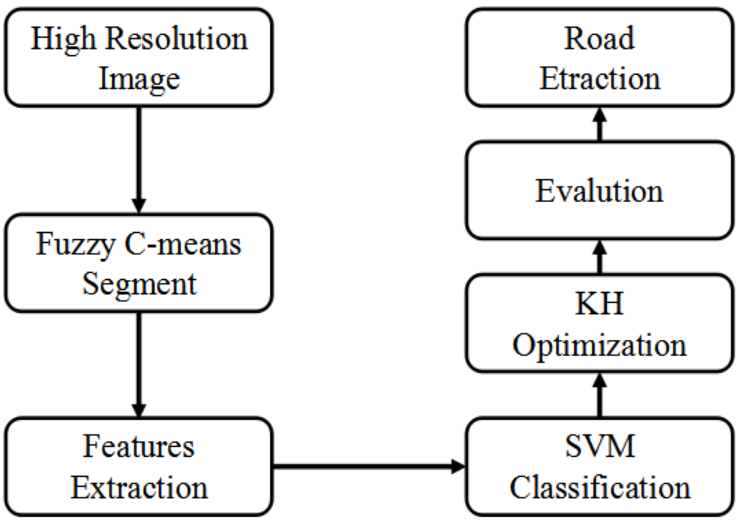


FIGURE 1. Framework of proposed road extraction method.

2. **Introduction of Fuzzy c-means clustering method and SVM.** In data set X, there are n samples, denoted as $x_k(k = 1, 2, \cdots, n)$. $V = (v_1, v_2, \cdots, v_c)$ is c cluster center set. u_{ik} is membership degree of the $k - th$ sample for the $i - th$ cluster. Let $U[u_{ik}]$ be the membership degree matrix, and it has the properties.

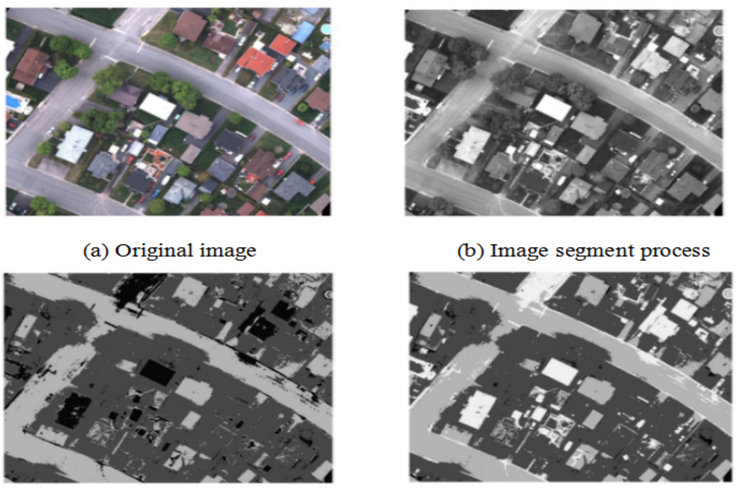
$$u_{ik} \in [0, 1], \forall k, \sum_{i=1}^{c} u_{ik} = 1. \forall i, 0 < \sum_{i=1}^{c} u_{ik} < n.$$

We define that objective function $W_m(U, V)$ is weighted square sum from sample to the cluster center.

$$W_m(U, V) = \sum_{k=1}^{N} \sum_{i=1}^{c} (u_{ik})^m (d_{ik})^2. \tag{1}$$

Where d_{ik} is the the distance between the $k - th$ sample and the $i - th$ cluster center. It can be written as $(d_{ik})^2 = ||x_k - v_i||^2 = (x_k - v_i)^T A(x_k - v_i)$. A is symmetric matrix. When $A = I$, d_{ik} is Euclidean distance. N is the total number of sample. C is cluster center number. U is fuzzy membership degree set of sample. V is cluster center set. $m \in [1, \infty]$ is fuzzy weighted exponent. W_m reflects intra-class compactness consistency in a certain differences. W_m is smaller, the cluster result is better.

So we adopt fuzzy c-means clustering method [12-14] to process the image segment. And we get the segment images as figure1. In order to illustrate the effectiveness of the proposed method, we do not consider the variations of illumination and weather including sunny or rainy in this paper.



(a) Original image (b) Image segment process

(c) Image segment process (d) Final result

FIGURE 2. Fuzzy c-means clustering segment results.

SVM is used widely in machine forecasting. It constructs the model as follows.

For the given data set $X = (x_i, y_i)|x_i \in R_n, y_n \in R, i = 1, 2, \cdots, n$, we construct a machine function.

$$f(x) = \omega \cdot \varphi(x) + b. \tag{2}$$

Where ω is the weight vector, b is polarization. $\varphi(x)$ maps input vector x of characteristic space. To reduce estimation risk, it introduces insensitive loss function ε and slack variable ξ, ξ_i^*. So SVM can be described as a quadratic programming problem.

$$minR(\omega,b)=\frac{1}{2}||\omega||^2+C\sum_{i=1}^{l}(\xi+\xi_i^*).\tag{3}$$

$$y_i-\omega\cdot\varphi(x)-b\le\varepsilon+\xi_i,\omega\cdot\varphi(x)+b-y_i\le\varepsilon+\xi_i.\tag{4}$$

Where $C>0$ is the penalty factor. It introduces Lagrange coefficients a_i and a_i^* into (2), so (2) can be transformed as a dual problem.

$$maxW=\frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l}(a_i-a_i^*)K(x_i,x_j)-\varepsilon\sum_{i=1}^{i}(a_i+a_i^*)\sum_{i=1}^{i}y(a_i-a_i^*).\tag{5}$$

Where $\sum_{i=1}^{l}(a_i-a_i^*)=0$. $K(x_i,x_j)=\varphi(x_i)$ is kernel function, which can affect the performance of the model with different values. In this paper, we use Radial Basis Function(RBF). Finally, we get SVM model function

$$f(x)=\sum_{i=1}^{l}(a_i-a_i^*)K(x_i-x_j)+b.\tag{6}$$

3. **New Krill Herd Algorithm Based on SVM Method for Road Feature Extraction.** Krill swarm optimization algorithm is one of simulation swarm intelligence algorithms by simulating the action of krill [15,16]. Each krill will be attracted or repelled by a certain range neighboring krill, so it can make local optimization. And the food center determined by fitness of krill would guide krill to make global optimization. In addition, the time interval needs to be adjusted, and the rest required parameters can be obtained from the research achievements of krill real ecological behavior. Meanwhile, krill swarm algorithm adopts Lagrangian model, therefore, the performance of krill swarm is superior to other optimization algorithm. The detailed processes of krill swarm algorithm are as follows:

1. Determine the Lagrangian model of krill swarm.

$$\frac{dX_i}{dt}=N_i+F_i+D_i.\tag{7}$$

   Where i is $i-th$ krill. X_i is the state of krill. N_i denotes velocity vector of induced movement. F_i is velocity vector of foraging behavior. D_i is random diffusion velocity vector.
2. 2)Motion induced by other krill individuals.

$$N_i^{new}=N^{max}(\alpha_i^{local}+\alpha_i^{target})+\omega_n N_t^{old}.\tag{8}$$

   Where $N_{max}=0.01m/s$ is the maximum velocity of the induced movement. $\omega_n\in(0,1)$ is the inertia weight of induced movement. N_i^{old} is the last velocity vector of induced movement. α_i^{local} is local influence of adjacent krill.

$$\alpha_i^{local}=\sum_{j=1}^{NN}\hat{K}_{i,j}\hat{X}_{i,j}.\tag{9}$$

$$\hat{K}_{i,j}=\frac{K_i-K_j}{K^{worst}-K^{best}}.\tag{10}$$

$$\hat{X}_{i,j}=\frac{X_i-X_j}{||X_j-X_i||+\varepsilon}.\tag{11}$$

Where K_i denotes fitness of $i-th$ krill. K_j is fitness of $j-th$ neighborhood krill. K^{best} and K^{worst} are the best fitness and the worst fitness respectively. X_i is the state of $i-th$ krill. X_j is the state of $j-th$ krill. ε is a small positive number to avoid singularity. NN is the number of adjacent krill, which can be determined by perception distance of each krill d_i. d_i can be expressed as:

$$d_i = \frac{1}{5N}\sum_{j=1}^{N}||X_i - X_j||. \tag{12}$$

Where N is the total number of krill. α_i^{target} is influence of the optimal krill as (13).

$$\alpha_i^{target} = 2(rand + \frac{1}{I_{max}})\hat{K}_{i,best}\hat{X}_{i,best}. \tag{13}$$

Where $rand$ is random number between 0 and 1. I is the current iterations number. I_{max} is the maximum iterations.

3. Foraging motion.

$$F_i^{new} = V_f(\beta_i^{food} + \beta_i^{best}) + \omega_f F_i^{old}. \tag{14}$$

Where $V_f = 0.02m/s$ is speed of foraging motion. $\omega_f \in (0,1)$ is inertia weight of foraging motion. β_i^{best} is the best previously visited position of the $i-th$ krill individual. F_i^{old} is the last velocity vector of foraging motion. β_i^{food} is influence of $i-th$ krill, which can be represented by:

$$X_{food} = \sum_{i=1}^{N}\frac{X_i}{K_i}/\sum_{j=1}^{N}\frac{1}{K_j}. \tag{15}$$

$$\beta_i^{food} = 2(1 - \frac{I}{I_{max}})\hat{K}_{i,food}\hat{X}_{i,food}. \tag{16}$$

So the influence of current $i-th$ krill is:

$$\beta_i^{best} = \hat{K}_{i,ibest}\hat{X}_{i,ibest}. \tag{17}$$

4. Stochastic diffusion process.

$$D_i^{new} = D^{max}(1 - \frac{I}{I_{max}})\delta. \tag{18}$$

Where $D^{max} \in (0.002, 0.01)m/s$ is the maximum speed of random diffusion. δ is the direction vector, which is subjected to (-1,1) uniform distribution.

5. Updating krill positions.

$$X_i^I = X_i^{I-1} + \Delta t(N_i^{new} + F_i^{new} + D_i^{new}). \tag{19}$$

Where Δt is time interval, selected according to the real situation. In this paper, $\Delta t = 1s$.

Generalization ability and machine precision of SVM are determined by penalty function C and parameter δ^2 in RBF. Because KH can better balance gather and divergence of the algorithm and it has better optimization performance. So we adopt KH to optimize C and δ^2. The detailed processes are as follows.

- Step1. Adopt normalization formula to handle original data. Then it accumulates normalized data for one time. Normalization formula is.

$$x^*_{i,j} = \frac{x_{i,j} - x_{min}}{x_{max} - x_{min}}. \tag{20}$$

Where $x_{i,j}$ is the $i - th$ row and $j - th$ column data. x_{max} and x_{min} denote maximum value and minimum value, respectively.
- Step2. Initialization. Set krill population size p_n, V_f, D^{max}, N^{max} and crossover probability p_c, maximum iteration NP. Randomly generate m krill individuals.
- Step3. Randomly generate p_n initial individual x_i. According to x_i, it calculates individual fitness value $fit_i = |y_i - \hat{y}_i|$, and determines current optimization krill position x_{best}.
- Step4. Each individual computes its motion vector by equations 6-9 and updates its position by equation 19.
- Step5. Update fitness function.
- Step6. Judge whether algorithm reaches maximum iteration. If NO, return step2. Otherwise, output optimization position x_{best} and put it into the SVM model.

We add the SVM based on KH into image after segment with fuzzy c-means clustering algorithm. Then, we will extract road information from high resolution image.

4. **Experiments and analysis.** In this section, we present some experiments to verify our method. This experiment is conducted in MATLABR2014a. Hardware environment is CPU 16GHz, Pentium(R) Dual-Core. We select seven types samples: water area, vegetation, residents, asphalt road, cement road, village road, construction road (we use number 1-7 to denote them.). Where the road is divided into four types. We use supervised classification for identification and selection data samples are shown in table 1. Image is shown in figure 3.

Table 1. Selected samples.

Type	Water area	Vegetation	Residents	Asphalt	Cement	Village	Construction
Training sample	2500	1500	1500	1200	1300	350	150
Testing sample	4000	4500	3000	2000	2000	500	250

We adopt binary coding, Markov distance method, parallel hexahedron, traditional SVM and our KH-SVM method to train and test the data [17-20]. And we record the classification costing time. RBF kernel function is as the objective function. Set $\lambda = 0.008$, penalty coefficient $C = 100$. Classification accuracy results are as in table 2.

Binary coding classification sets the data as 0 and 1 according to the band value whether is greater than average spectral value or not. It uses XOR function to compare and index and code spectroscopy data, then it gets image classification. Markov distance classification uses mathematical statistics in each class, it is a sensitive distance classifier similar to the maximum likelihood classification. Parallelepiped with simple decision rules classifies spectral data, determines the boundary in image data space forming a multidimensional parallelepiped. If the pixel value is between the low threshold and high threshold of classified band, it belongs to this category. If pixel is in several classes, then this pixel is classified into the last matching class. Traditional SVM uses the mean vector of each data to calculate Euclidean distance from each pixel to the mean vector. Each

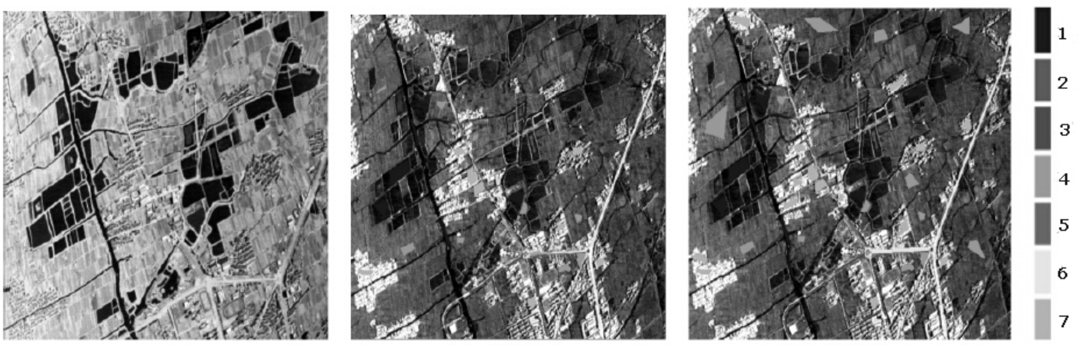
TABLE 2. Results of classification accuracy%.

Algorithm	Minimum distance	Binary coding	Parallel hexahedron	SVM	KH-SVM
Water area	98.56	94.35	97.49	95.77	99.29
Vegetation	60.64	78.67	95.14	86.66	88.73
Residents	26.51	53.25	46.57	61.93	81.39
Asphalt	45.42	33.56	0	62.23	77.19
Cement	69.08	53.77	0	61.56	73.01
Village	38.01	23.84	0	63.34	65.78
Construction	13.05	8.59	0	72.98	80.17
Overall accuracy	61.52	66.66	59.15	76.38	87.95
Kappa	0.5296	0.5858	0.4555	0.7192	0.8648

TABLE 3. Time comparison.

Algorithm	Minimum distance	Binary coding	Parallel hexahedron	SVM	KH-SVM
Time(s)	264	163	105	93	68

pixel is assigned to the nearest class. If pixel is not assigned to the nearest class and does not reach at the standard deviation and the distance threshold, these pixels may not be identified. Table 2 shows that parallelepiped method and the binary coding method take much less time, however, KH-SVM takes 68s which is the smallest as shown in table 3. KH-SVM has the overall highest precision and Kappa value. For the single precision, KH-SVM also has the better precision.



(a) Original image (b) Training samole (c) Testing sample

FIGURE 3. Testing image.

From figure 4, we can know that road recognition accuracy with KH-SVM is higher than other classification methods, especially for cement and asphalt road. It illustrates that Hyperspectral remote sensing image has information rich feature and KH-SVM has better identification ability on different type of roads. Binary coding method has a poor effect on rural road, resident, construction road. Markov distance method has poor recognizable on rural road, resident, construction road. Parallel hexahedron method has a bad

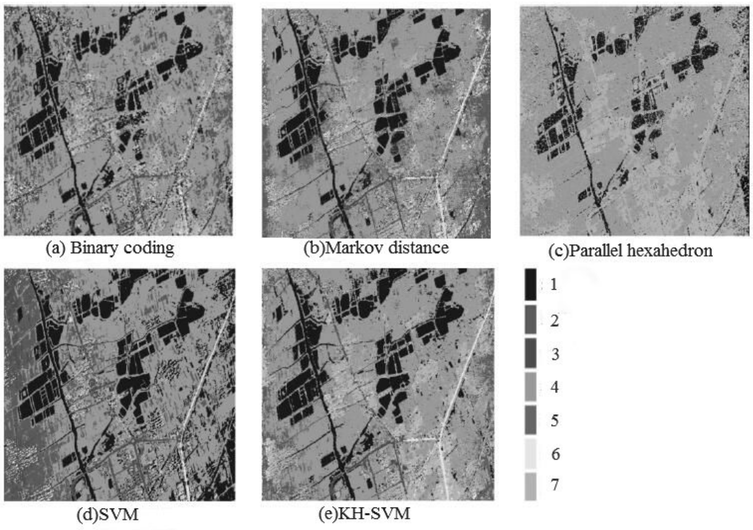


Figure 4. Classification results.

road extraction on rural road, resident and cement road. KH-SVM has a better overall classification effect, and road recognition effect is very clear.

5. **Conclusions.** In this paper, after analyzing SVM, it is concluded that the SVM has strong line road classification ability, it not only can accurately identify the structure of the road, but also can identify the material and type of road, such as rural road, cement road, construction road, asphalt and concrete road. We propose a new road extraction method based on improved SVM. Simulation experiments show that our new method has precise extraction results. In the future, we will study more advanced intelligence methods to extract road line.

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