J. Meas. Sci. Instrum., 2025, 16(2): 216-223.
DOI: 10.62756/jmsi.1674-8042.2025021
http://jmsi.publish.founderss.cn
jmsi@nuc.edu.cn

An EnFCM remote sensing image forest land extraction method based on PCA multi-feature fusion

ZHU Shengyang[1], WANG Xiaopeng[1*], WEI Tongyi[1], FAN Weiwei[1], SONG Yubo[2]

1. School of Electronics and Information Engineering, Lanzhou Jiaotong University, Lanzhou 730070, China;
2. Institute of Mechanical and Electrical Technology, Lanzhou Jiaotong University, Lanzhou 730070, China

***Corresponding author:** WANG Xiaopeng (wangxiaopeng@mail.lzjtu.cn)

Received: September 20, 2023 **Revised:** November 11, 2023 **Accepted:** December 5, 2023

Abstract: The traditional EnFCM (Enhanced fuzzy C-means) algorithm only considers the grey-scale features in image segmentation, resulting in less than satisfactory results when the algorithm is used for remote sensing woodland image segmentation and extraction. An EnFCM remote sensing forest land extraction method based on PCA multi-feature fusion was proposed. Firstly, histogram equalization was applied to improve the image contrast. Secondly, the texture and edge features of the image were extracted, and a multi-feature fused pixel image was generated using the PCA technique. Moreover, the fused feature was used as a feature constraint to measure the difference of pixels instead of a single grey-scale feature. Finally, an improved feature distance metric calculated the similarity between the pixel points and the cluster center to complete the cluster segmentation. The experimental results showed that the error was between 1.5% and 4.0% compared with the forested area counted by experts' hand-drawing, which could obtain a high accuracy segmentation and extraction result.

Key words: image segmentation; forest land extraction; PCA transform; multi-feature fusion; EnFCM algorithm

0 Introduction

Image segmentation is widely used in many fields. The commonly used image segmentation algorithms include threshold-based, edge-based, and clustering-based methods. The clustering algorithm is more suitable for segmenting images with large data volume and complex features like remote sensing images due to the ambiguity of the pixel points when performing image segmentation[1,2]. The traditional FCM algorithm only considers the single grey-scale information of the image during image segmentation, ignoring the spatial information of the image, resulting in poor segmentation performance and low noise immunity[3]. Many scholars have introduced spatial information into the FCM objective function. Ahmed et al.[4] proposed the FCM-S clustering algorithm with spatial constraints by adding the neighboring pixel information around the central pixel to the FCM objective function, which has improved noise immunity compared to FCM. However, the algorithm needs to calculate the corresponding neighboring pixel information at each iteration with high time complexity. Chen et al.[5] used the mean and median filtering pixels to replace the central pixels in the objective function and obtained FCM-S1 and FCM-S2 algorithms. This algorithm reduces the time required for iteration and improves the noise resistance.

The traditional clustering algorithms are based on a single pixel. Szil et al.[6] proposed an enhanced FCM clustering algorithm EnFCM by defining a linearly weighted and filtered image and performing clustering segmentation on the grey-scale histogram of that image. However, only the neighborhood information of the image is considered when constructing the filtered image without considering the spatial information of the image, and the segmentation accuracy of the image decreases significantly when the image contains a large amount of pretzel noise. Most of the improved FCM algorithms require the introduction of a corresponding parameter, and this parameter needs to be set artificially. Krinidis et al.[7] proposed an image segmentation algorithm FLICM based on fuzzy clustering of local spatial information. By constructing a new fuzzy factor to improve the robustness of the FCM algorithm, and without the need to manually set parameters, more image details can be retained, and segmentation accuracy can be improved. Zhao et al.[8] proposed the neighborhood-weighted FCM image segmentation algorithm NWFCM, which replaced the Euclidean distance in the traditional FCM algorithm with the neighborhood-weighted distance and calculated the neighborhood weights through the sample grey-scale values. The segmentation accuracy is improved, but the segmentation accuracy is significantly reduced when the central pixel is a noisy point.

Remotely sensed woodland images have rich feature sets, such as texture, edge, and spatial features, but traditional clustering algorithms mostly consider only single grey-scale features in segmentation, resulting in low segmentation accuracy of remotely sensed images. A fusion multi-feature improved EnFCN clustering segmentation method was proposed. Multiple features were used instead of single gray feature as the feature constraint of EnFCM clustering algorithm to improve segmentation accuracy and anti-noise ability. The new feature distance measure was used to replace the original Euclidean space distance, which had a better segmentation effect for images with complex features.

1 EnFCM algorithm

The EnFCM algorithm takes a weighted average of each pixel in the original image and the pixels in its neighborhood to obtain the processed image.

$$\zeta_i = \frac{1}{1+\alpha}\left(x_i + \frac{\alpha}{N_R}\sum_{r\in N_i} x_r\right), \tag{1}$$

where ζ_i is the gray value of the ith pixel in the processed image; N_i is the neighborhood region centered on x_i; N_R is the total number of pixels in N_i; α is the weighting factor indicating the degree of influence of the neighborhood pixels on the central pixel.

Define objective functions as

$$J = \sum_{i=1}^{L}\sum_{j=1}^{c} r_i u_{ij}^m d_{ij}^2. \tag{2}$$

The EnFCM algorithm is a cluster segmentation on the grey-scale histogram, which effectively reduces the algorithm's running time. However, only the neighborhood information is considered when constructing the image, and the spatial information is ignored, making the algorithm less noise resistant. The EnFCM algorithm, which fuses multiple features, is proposed to address the existing problems.

2 Multi-feature fusion EnFCM

2.1 Feature extraction

Remotely sensed woodland images are rich in multi-features. Among them, texture features are more stable than other features and can suppress the phenomenon of the same spectrum of different objects and different spectrum of the same object. The edge features are the places where the attributes of the image area change abruptly and contain rich information. In this paper, the image texture and edge features were extracted and studied.

2.1.1 Texture feature extraction

The local binary pattern (LBP) algorithm is used to extract texture features from images[9]. The initial LBP operator is defined in the 3×3 neighborhood; later, the algorithm changes the range to 8 points in the circular neighborhood for comparison, and the central pixel in the neighborhood range is used as the threshold.

Compare the gray values of adjacent pixels. If the adjacent pixel is greater than this threshold, the position of the corresponding pixel is marked as 1, and vice versa. Finally, all the pixel points in the region are compared to produce an 8-bit binary-free number, which is the LBP value of the central pixel of the window and used to reflect the texture information of the region. The specific steps are as follows.

Step 1 Divide the image into several $N \times N$ regions and calculate the LBP value corresponding to each pixel in the region.

Step 2 Histogram statistics of each region are carried out to obtain the histogram of $N \times N$ image regions.

Step 3 Normalize the histogram for all image areas.

Step 4 The normalized histograms of all regions are added together to obtain the texture feature image of the whole image.

2.1.2 Edge feature extraction

Morphological expansion and erosion operations were used to extract image edge feature maps[10]. Assuming that the original image is f, and the structural element is b, the corresponding feature image extraction algorithm is

$$G(f) = (f \oplus b) - (f \Theta b), \tag{3}$$

where $\oplus$ is the expansion operation; Θ is the corrosion operation, and $Z(f)$ is the resulting edge image.

2.2 PCA multi-feature fusion

Multi-feature fusion is the process of extracting multiple features from an image and transforming them into feature vectors, and then reorganizing or replacing these vectors to form a new composite image[11,12]. A mathematical transformation-based PCA technique was used to fuse multiple features of an image. It used a positive transformation to transform the correlated data in the original data variables into several more essential variables that were independent of each other and retain more information about the original data. And then these variables were reorganized to obtain a new composite variable[13-15]. PCA multi-feature fusion process is shown in Fig. 1. First, the extracted texture and edge features are normalized. Then, the PCA technique is used to decompose the principal components of the equalized image, and three principal components can be obtained in order from the largest to the smallest to complete the histogram matching between the feature image and the corresponding principal components (Through a large number of simulation experiments, the texture and edge features of the image are matched with the second and third principal components, respectively). And after the matching was completed, the corresponding principal components were replaced by the extracted features. Finally, the multi-feature pixel image $G(f)$ was reconstructed by PCA inverse transform. The detailed process is as follows.

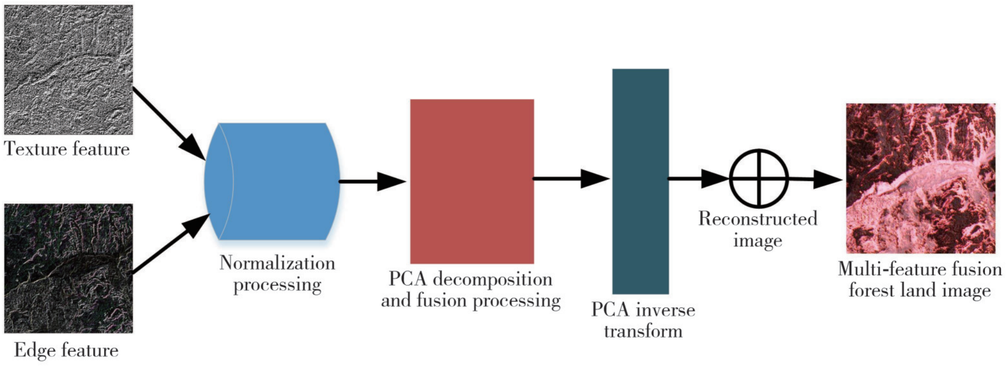


Fig. 1 Schematic diagram of PCA multi-feature fusion process

Step 1 Read the equalized remote sensing image and obtain the corresponding matrix noted as *mul*, size as $r \times c*band$; read the texture feature matrix ($r \times c$) noted as mat1; read the edge feature matrix ($r \times c$) noted as mat2, and then normalize between 0 and 1, respectively. The formula is shown as

$$mul' = mul/255. \tag{4}$$

Step 2 Transform the *mul* matrix into a $r \times c \times 3$ matrix, denoted as *muls*; find the correlation matrix of *mul*, denoted as *correlation*; find the eigenvalues *cvalue* and the eigenvectors *cvector* to obtain the corresponding principal component matrix, denoted as *pc*; transform the resulting principal component matrix into a $r \times c \times 3$ matrix, denoted as *pcs*, where *correlation* and *pc* are defined as

$$correlation = (mul^{\mathrm{T}} \times mul)/(r \times c), \tag{5}$$

$$pc = muls \times cvector. \tag{6}$$

Step 3 The *cvalue* obtained in the previous step is arranged from smallest to largest, and after flipping left and right, the first channel corresponding to *pcs* is the first principal component, and so on. And the normalized texture feature (mat1) and edge feature (mat2) are histogram-matched with the second and third principal components, respectively.

Step 4 After the matching is completed, the corresponding principal component matrices are replaced by mat1 and mat2, respectively, and then the matrix *pcs* is transformed into a $r \times c \times 3$ matrix, which is then multiplied with the transpose of the feature vectors to obtain the reconstructed fused image.

$$G(f) = pcs \times cvector^{\mathrm{T}}. \tag{7}$$

2.3 Improved EnFCM algorithm

The traditional distance metric represents the variability between pixels through grey-scale features. In order to improve the segmentation accuracy of images, the local standard variance distance was introduced as the feature distance and to replace the original Euclidean distance metric. The local variance can reflect the maximum and minimum values within the local neighborhood and measure the similarity between pixels. The definition is

$$\Phi_i = \frac{1}{1+\alpha}\left(x_i + \frac{\alpha}{N_R}\sum_{r \in N_i} x_r\right), \tag{8}$$

where Φ is the image obtained after pre-processing $G(f)$. The proposed method corresponds to the objective functions, i.e.,

$$J_* = \sum_{i=1}^{L}\sum_{j=1}^{c} r_i u_{ij}^m \left(d_{ij}^*\right)^2, \tag{9}$$

$$d_{ij}^* = \frac{1}{1+\beta}\left(d_{ij} + \beta d_t^2\right), \tag{10}$$

$$d_t^2 = \frac{1}{n-1}\sum_{i=1}^{n}\left(\Phi_i - \frac{1}{n}\sum_{i=1}^{n}\Phi_i\right)^2, \tag{11}$$

where β is a constant parameter used to control the role of the distance term which is the weight of each of the two types of distance (in this paper $\beta=0.6$); d_{ij} is the Euclidean distance from the pixel to the cluster centre, $d_{ij}=\|\Phi_i-v_j\|$; d_t is the local neighborhood feature distance introduced by the local standard variance; r_i is the number of pixels corresponding to gray level i in image Φ, satisfying $d_{ij}=\|\Phi_i-v_j\|$; L is the number of gray levels in the image, and n is the sum of the number of pixels of all gray levels, that is, the total number of pixels.

The optimal solution to the above objective function J_* can be obtained by

$$u_{ij}=\frac{\|\Phi_i-v_j\|^{\frac{-2}{m-1}}}{\sum_{k=1}^{c}\|\Phi_i-v_k\|^{\frac{-2}{m-1}}}, \tag{12}$$

$$v_j=\frac{\sum_{i=1}^{L}r_i u_{ij}^m\Phi_i}{\sum_{i=1}^{L}r_i u_{ij}^m}. \tag{13}$$

Eqs. (12) and (13) satisfy the constraint $\sum_{j=1}^{c}u_{ij}=1$. Although it has the same form as EnFCM, the algorithm introduces image space information and incorporates texture, edge, and grey-scale features of the image.

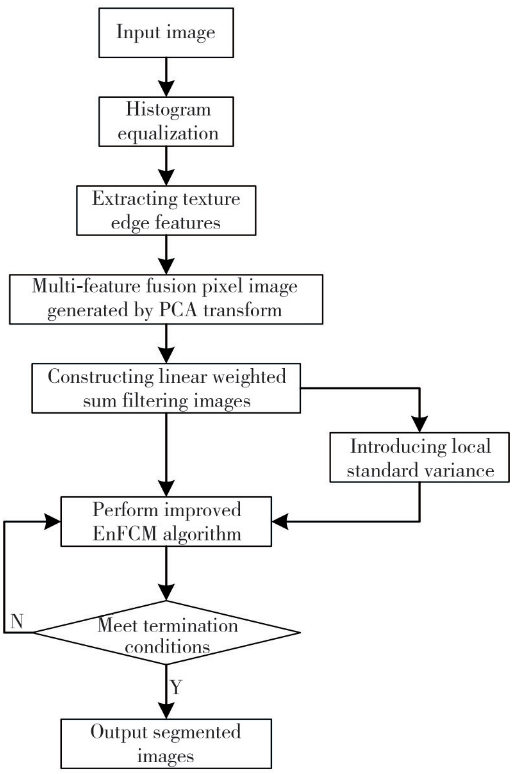


Fig. 2 Algorithm flow diagram

2.4 Algorithm implementation process

Step 1 Equalize and enhance input images to improve image contrast.

Step 2 Extract image texture and edge features.

Step 3 By using PCA decomposition and reconstruction, the extracted features are fused with gray features, and the pixel image with multi-feature fusion is obtained.

Step 4 An improved EnFCM algorithm is executed on a multi-feature fused pixel image and the output results.

3 Results and discussion

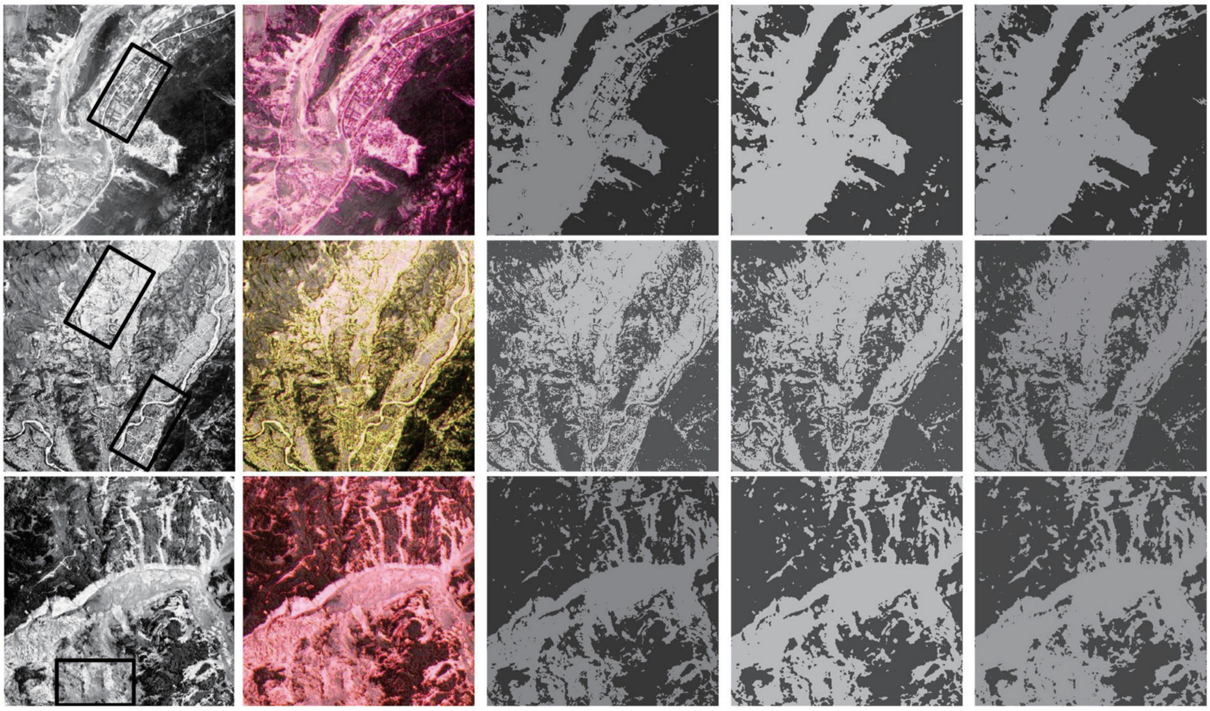
3.1 Experimental results

In order to verify the effectiveness of the method for woodland extraction, three remote sensing images, as in Fig.3, are selected for experimental analysis. The data are all from Google Earth, and they are Beichuan Old Town (size: 604×604, scale: 1∶6 000), Lushan, Sichuan (size: 433×433, scale: 1∶ 10 000), and Tangjiashan (size: 490×490, scale 1∶6 000) from left to right. Fig.4 shows EnFCM segmentation results integrating different features. The rectangular box area in Fig.4 corresponds to the non-forest area, which should be the light-colored part after clustering segmentation. Fig.4 (c) has a more obvious mis-segmentation phenomenon compared with Fig.4 (d), which indicates that when the original EnFCM is used to segment the fused multi-feature image and the single gray-scale feature image, respectively, the multi-feature segmentation effect is better than the single gray-scale feature.

I II III

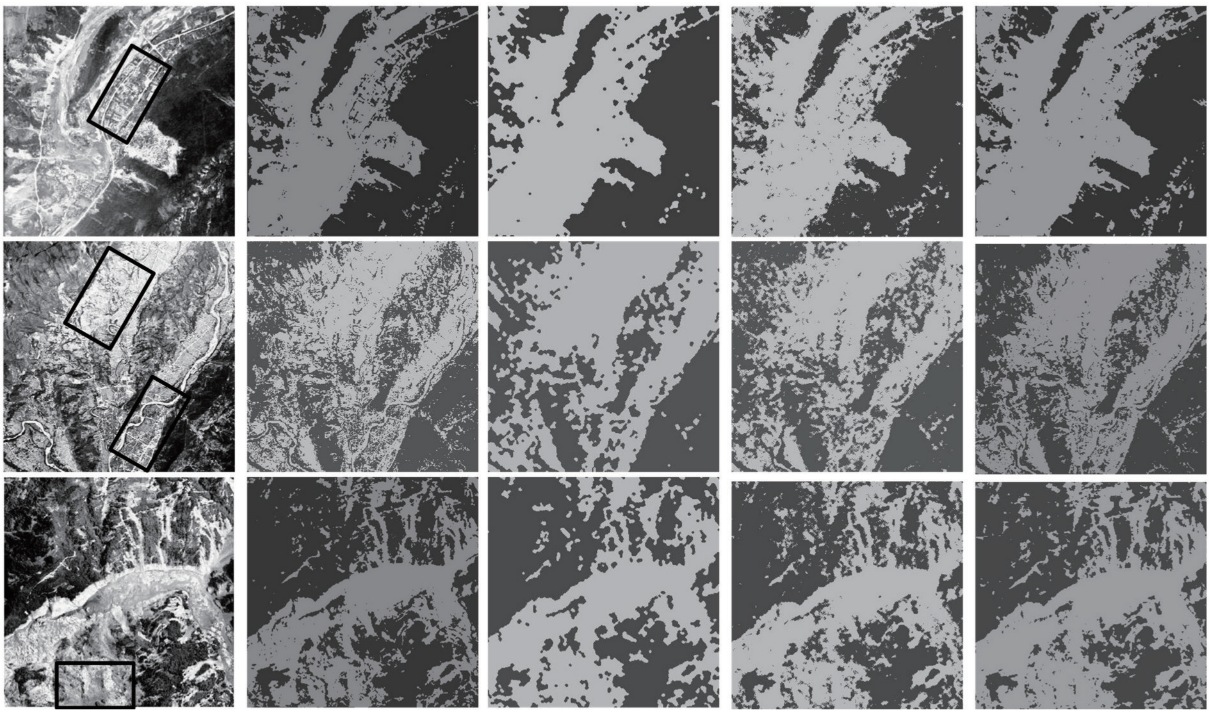
Fig. 3 Schematic diagram of remote sensing image

However, compared with Fig.4 (d) and 4 (e), the former segments the non-target area as the target area in a more significant proportion, indicating that the improved EnFCM is better than the former traditional EnFCM algorithm. In order to further verify the effect of this method on remote sensing woodland image segmentation and extraction, the results are compared with the EnFCM algorithm, enhanced spatially constrained FCM (HMRF-FCM) algorithm based on the hidden Markov random field model[16], and adaptive fuzzy local information C-mean clustering algorithm (ADFLICM) [17]. The results are shown in Fig. 5. The black rectangular boxed area in Fig.5 (a) is the non-woodland area. It can be seen that the EnFCM algorithm mis-segments the non-target area in the rectangular box as the target area with a more significant proportion of over-segmentation. The HMRF-FCM algorithm has under-segmentation, and the segmentation effect at the boundary is significantly reduced. The ADFLICM algorithm segmentation results are more disturbed by noise and have more outliers. In contrast, the proposed method has a better segmentation effect and less mis-segmentation.



(a) Single feature equalization image (b) Multiple feature image (c) Single feature EnFCM (d) Multi-feature EnFCM (e) Method of this paper

Fig. 4 Shematic diagram of EnFCM segmentation results integrating different features



(a) Equalization image (b) EnFCM (c) HMRF-FCM (d) ADFLICM (e) Method of this paper

Fig. 5 Comparison algorithm segmentation extraction result diagram

3.2 Effect analysis

The mean absolute error (MAE) and normalized mean square error (NMSE) are used to quantitatively analyze the extraction accuracy of woodland segmentation and compare the segmentation results with the area belonging to the woodland area in the expert hand map (Fig.6). That is, the percentages of woodland pixels in the total pixels of the original image in the cluster segmentation map and the expert hand-drawn map are calculated, respectively.

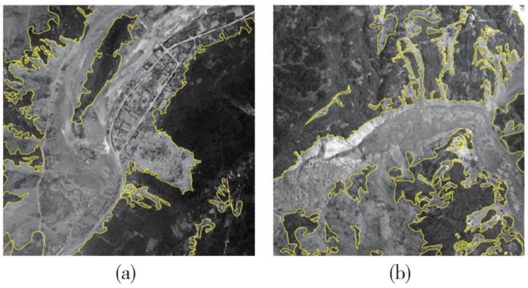


Fig 6 Expert hand-painted schematic diagram of Fig. 3(Ⅰ)(a) and Fig. 3(Ⅲ)(b)

MAE represents the deviation of the segmented image from the original image. The smaller the value, the higher the segmentation accuracy.

$$MAE = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left| I(i,j) - I'(i,j) \right|}{MN}, \quad (14)$$

where M and N are the width and height of the image, respectively; $I(i,j)$ and $I'(i,j)$ are the grey scale values of the corresponding pixels in the original and the segmented image, respectively.

NMSE is a measure based on energy normalization. The smaller the value, the higher the segmentation accuracy.

$$NMSE = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left[I(i,j) - I'(i,j) \right]^2}{\sum_{i=1}^{M}\sum_{j=1}^{N}\left[I(i,j) \right]^2}. \quad (15)$$

As shown in Tables 1 and 2, the MAE and NMSE values of the proposed method are the lowest, indicating that both MAE and NMSE indicators are better than other algorithms, and the variation is smaller compared to other algorithms, among which the EnFCM algorithm segmentation effect is the worst.

Table 1 MAE evaluation of segmentation results

Remote sensing image	MAE/%			
	EnFCM	HMRF-FCM	ADFLICM	Proposed method
Fig.3(Ⅰ)	12.49	9.32	10.56	2.14
Fig.3(Ⅲ)	22.24	15.58	13.86	4.96

Table 2 NMSE evaluation of segmentation results

Remote sensing image	NMSE/%			
	EnFCM	HMRF-FCM	ADFLICM	Proposed method
Fig.3(Ⅰ)	16.96	12.13	15.08	6.92
Fig.3(Ⅲ)	28.56	21.05	20.60	12.92

The percentage of woodland areas is shown in Table 3.

Table 3 Percentage of forest land area

Remote sensing image	Percentage of forest land area/%				
	EnFCM	HMRF-FCM	ADFLICM	Proposed method	Expert hand-painted results
Fig.3(Ⅰ)	53.13	47.07	48.44	44.29	40.91
Fig.3(Ⅲ)	60.26	51.65	51.38	46.94	45.37

The result of forest land extraction by this method is the closest to the result of expert hand painting. The error of Fig. 3(Ⅰ) is less than 4.0%, and the error of Fig.3(Ⅲ) is less than 2.0%, followed by HMRF-FCM and ADFLICM algorithm, and finally EnFCM algorithm. The results showed that the proposed method was better than other methods, with better segmentation performance and high accuracy.

4 Conclusions

In order to improve the segmentation and extraction accuracy of woodland areas in remote sensing images, an EnFCM remote sensing woodland extraction method based on PCA multi-feature fusion was proposed. Firstly, the texture and edge features of the image were extracted, and the texture and edge features were incorporated into the EnFCM algorithm through PCA technology. The fused features were used to measure the difference between pixels instead of single grey-scale features to solve the influence of the traditional EnFCM algorithm in image segmentation, which only considered single grey-scale features on the segmentation accuracy. Secondly, the feature distance was introduced to measure the similarity between the pixel points and the clustering center to improve the segmentation. The second was the introduction of feature distance to measure the similarity between pixels and clustering centers, which improved the segmentation accuracy. The comparison experiment of EnFCM, ADFLICM, and HMRF-FCM further verified the effectiveness of the proposed method.

Acknowledgement

This work was supported by National Natural Science Foundation of China (No. 61761027); Gansu Young Doctor's Fund for Higher Education Institutions (No.2021QB-053)

Declaration of conflicting interests

The authors have no conflict of interests related to this publication.

References

[1] LI D R, DING L, SHAO Z F. Application-oriented real-time remote sensing service technology. National Remote Sensing Bulletin, 2021, 25(1): 15-24.

[2] WANG Z K, QIN P L, ZENG J C. Multi-scale feature enhancement network based on large kernel convolution and dense object refinement for remote sensing images. Journal of North University of China (Natural Science Edition), 2024, 45(5): 628-637.

[3] BEZDEK J C. Pattern recognition with fuzzy objective function algorithms. Cham: Springer US, 1981.

[4] AHMED M N, YAMANY S M, MOHAMED N, et al. A modified fuzzy C-means algorithm for bias field estimation and segmentation of MRI data. IEEE Transactions on Medical Imaging, 2002, 21(3): 193-199.

[5] CHEN S C, ZHANG D Q. Robust image segmentation using FCM with spatial constraints based on new kernel-induced distance measure. IEEE Transactions on Systems, Man, and Cybernetics Part B, Cybernetics, 2004, 34(4): 1907-1916.

[6] SZILAGYI L, BENYO Z, SZILAGYI S M, et al. MR brain image segmentation using an enhanced fuzzy C-means algorithm//The 25th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, September 17-21, 2003, Cancun, Mexico. New York: IEEE, 2003: 724-726.

[7] KRINIDIS S, CHATZIS V. A robust fuzzy local information C-means clustering algorithm. IEEE Transactions on Image Processing, 2010, 19(5): 1328-1337.

[8] ZHAO Z X, CHENG L Z, CHENG G Q. Neighbourhood weighted fuzzy C-means clustering algorithm for image segmentation. IET Image Processing, 2014, 8(3): 150-161.

[9] WEI X P, YU X C, ZHANG P Q. CNN hyperspectral image classification combined with local binary pattern. Journal of Remote Sensing, 2020, 24(8): 1000-1009.

[10] YANG W T, WANG X P, FANG C. Salience adaptive morphological structuring element construction method based on minimum spanning tree. Journal of Measurement Science and Instrumentation, 2021, 12(1): 36-43.

[11] LI J, HUANG X, GAMBA P, et al. Multiple feature learning for hyperspectral image classification. IEEE Transactions on Geoscience and Remote Sensing, 2015, 53(3): 1592-1606.

[12] WANG P X, ZHANG Z J, YANG H. Target classification method in infrared images via combination of multi-feature fusion and extreme learning machine. Infrared and Laser Engineering, 2022, 51(6): 506-511.

[13] HE D, LIU R Y. Ultra-short-term wind power prediction using ANN ensemble based on PCA//The 7th International Power Electronics and Motion Control Conference, June 2-5, 2012, Harbin, China. New York: IEEE, 2012: 2108-2112.

[14] JIANG Q C, YAN X F. Parallel PCA-KPCA for nonlinear process monitoring. Control Engineering Practice, 2018, 80: 17-25.

[15] ZHANG X, HE L, ZHANG J, et al. Determination of key canopy parameters for mass mechanical apple harvesting using supervised machine learning and principal component analysis (PCA). Biosystems Engineering, 2020, 193: 247-263.

[16] CHATZIS S P, VARVARIGOU T A. A fuzzy clustering approach toward hidden Markov random field models for enhanced spatially constrained image segmentation. IEEE Transactions on Fuzzy Systems, 2008, 16(5): 1351-1361.

[17] ZHANG H, WANG Q M, SHI W Z, et al. A novel adaptive fuzzy local information *C*-means clustering algorithm for remotely sensed imagery classification. IEEE Transactions on Geoscience and Remote Sensing, 2017, 55(9): 5057-5068.

[18] DING J G, GUO J H. Principal component analysis combined with random forest algorithm for hot strip width prediction. Journal of Northeastern University (Natural Science Edition), 2021, 42(9): 1268-1274.

一种基于PCA多特征融合的EnFCM遥感图像林地提取方法

朱生阳[1], 王小鹏[1*], 魏统艺[1], 樊炜玮[1], 宋宇博[2]

1. 兰州交通大学 电子与信息工程学院, 甘肃 兰州 730070;
2. 兰州交通大学 机电技术研究所, 甘肃 兰州 730070

摘　要: 传统EnFCM(Enhanced fuzzy C-means)算法在图像分割时只考虑图像的灰度特征, 导致该算法用于遥感林地图像分割提取时结果不够理想。本文提出一种基于PCA多特征融合的EnFCM遥感林地提取方法。首先, 对图像进行直方图均衡化处理, 提高图像对比度。其次, 提取图像的纹理及边缘特征, 利用PCA技术生成多特征融合的像素图像, 以该融合特征替代单一灰度特征作为衡量像素差异的特征约束。最后, 利用改进的特征距离度量公式计算像素点与聚类中心的相似性, 完成聚类分割。实验结果表明, 与专家手绘统计的林地面积相比, 误差在1.5%-4.0%之间, 可以得到较高精度的分割提取结果。

关键词: 图像分割; 林地提取; PCA变换; 多特征融合; EnFCM算法

引用格式: ZHU Shengyang, WANG Xiaopeng, WEI Tongyi, et al. An EnFCM remote sensing image forest land extraction method based on PCA multi-feature fusion. Journal of Measurement Science and Instrumentation, 2025, 16(2): 216-223. DOI: 10.62756/jmsi.1674-8042.2025021