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A Novel Histogram-Based Fuzzy Clustering Method for Multispectral Image Segmentation

Guoying Liu, Hongyu Zhou and Jing Lv

Department of Computer and Information Engineering, Anyang Normal University, Anyang 455002, China

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Abstract: Fuzzy C-Means (FCM) clustering has been widely used in remote sensing and computer vision. However, when dealing with multispectral images, the conventional FCM regards spectral responses of all bands on each pixel as a feature vector and conducts image clustering by searching cluster centers in a multi-dimensional space. It is rather time-consuming due to the fact that it has to visit each pixel many rounds during the iteration procedure. Besides, it is sensitive to noise, which mainly results from its ignorance spatial information. In order to overcome these problems, a novel histogram-based fuzzy clustering method is presented in this paper. The proposed method clusters each band independently and fuses the results to form the final segmentation map. On each band, a spatial-spectral image is computed previously, and then the histogram of this image is exploited to find the initial clusters, which is followed by a clustering procedure directly performed on the histogram instead of image pixels. The experimental results over remote sensing images show that the proposed method can achieve more accurate results but uses less time.

1. Introduction

Fuzzy C-Means (FCM) is one of the most widely used techniques for image segmentation. It was first proposed by Dunn [1] and later extended by Bezdek [2]. FCM has robust characteristics for ambiguity and is able to retain more original image information than hard or crisp methods [3]. However, it is rather time-consuming when dealing with multispectral images, because it has to visit each pixel multiple rounds during the iteration procedure. Besides, it is also sensitive to noise because of its ignorance spatial information.

A variety of improved approaches were proposed to incorporate the spatial information into the original FCM, such as fuzzy local information C-Means (FLICM) [3], Enhanced Fuzzy C-Means Clustering (EnFCM) [4], HMRF-FCM [5], Zhang's method [6], and our proposed methods [7-9]. All of them tried to improve the traditional FCM by introducing spatial information in different ways and achieved some excellent results in their intended realms. Among them, EnFCM has the best time efficiency because it performs the clustering procedure on the gray-level histogram of a newly generated image, which is a linearly-weighted sum image formed from the original image and its local neighbor average image. Due to the fact that the number of gray levels is generally much smaller than the size of the image, the execution time is significantly reduced. Unfortunately, this method is only suitable for segmenting gray-level image. For multispectral image, it has to convert it into a gray-level one previously, which may results much losses of important information. Recently, Saman Ghaffarian and Salar Ghaffarian [10] proposed an automatic histogram-based FCM method (AHFCM), which provides an available way to deal with multispectral images by independently clustering each band in advance and fusing band-wise results to form an initial cluster for another final clustering procedure. However, this method still follows the steps of the traditional FCM to execute fuzzy clustering, which is rather time-consuming. Besides, it does not take any spatial information into account, which makes it still sensitive to noise.

In this paper, we attempt to combine the merits of EnFCM and AHFCM together and present a novel histogram-based fuzzy c-means clustering method for multispectral image segmentation, called MsHFCM. It inherits the merits of AHFCM to independently cluster each spectral band and fuse the labels to form the final result. For the sake of retaining more details, MsHFCM uses the fusion result as the final result without an extensive fuzzy clustering procedure. Besides, the proposed method inherits the merits of EnFCM to incorporate spatial information by a newly precomputed gray-spatial image and the clustering method is performed on the histogram of the newly generated image.

2. Histogram-based fuzzy c-means clustering method for multispectral image segmentation

In this section, we present a novel histogram-based fuzzy c-means clustering method for multispectral image segmentation (MsHFCM). The framework is described in Fig. 1. For each band, a gray-spatial image is first obtained from the original data and the original image by taking the first component of the principles of the Gabor feature image. Then, the histogram of the gray-spatial image is calculated, based on which the histogram-based FCM is performed. Finally, the clustering result can be obtained by fusing all labels from all spectral bands.

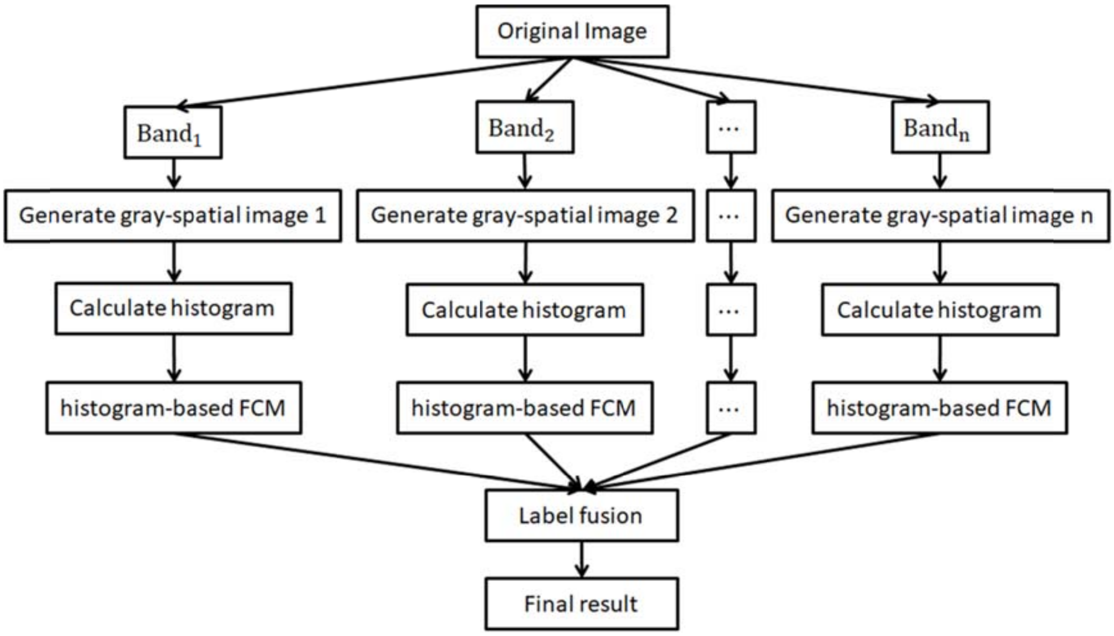

Figure 1 Framework of the clustering procedure.

2.1 Calculation of gray-spatial image based on Gabor filter bank

Gabor filters are used to exploit spatial information. Each filter has a real and an imaginary component representing orthogonal directions. The 2-D Gabor filter is defined as

$$g(x,y;\lambda,\theta,\psi,\sigma,\gamma) = \exp\left(-\frac{x'^2+\gamma y'^2}{2\sigma^2}\right)\exp\left(i\left(2\pi\frac{x'}{\lambda}+\psi\right)\right) \qquad (1)$$

where

$$\begin{cases} x' = xcos(\theta) + ysin(\theta) \\ y' = -xcos(\theta) + ysin(\theta) \end{cases}.$$

In this equation, λ represents the wavelength of the sinusoidal factor, θ is the orientation of the normal to the parallel of the Gabor function, σ represents the sigma of the Gaussian envelope, and γ is the spatial aspect ratio which specifies the ellipticity of the support of the Gabor function. For each pixel, the magnitude over all orientations is considered. In this paper, the parameters are set $\lambda \in \{2,4,6,8\}$, $\theta \in \{0,45,90,135\}$, $\sigma = \lambda$ and $\gamma = 0.25$. This generates $4 \times 4 \times 1 \times 1 = 16$ different configurations of Gabor filters. After applying to the gray-level image on each band, 16 Gabor images are generated. We pick out the first component of the principles of the Gabor features to form the spatial image ζ^{b}. Then, the gray-spatial image I_{new}^{b} is obtained by

$$I_{new}^{b} = \frac{I^{b} + a\zeta^{b}}{1+a} \tag{2}$$

where a is used to control the effect of the spatial image, and the term I^{b} is the b^{th} band of the original image I.

2.2 Histogram-based FCM

2.2.1 Histogram-based initialization

Let $H^{b} = \left[H_{1}^{b}, H_{2}^{b}, \cdots, H_{256}^{b}\right]^{T}$ be the histogram of I_{new}^{b}. We determine the initial clusters by seeking the local peaks of H^{b}. First of all, the discrete difference of H^{b} is calculated in advance, which is denoted as D^{b}. Then, a point $g(1 \le g \le 256)$ is a peak point if it satisfies:

$$D^{b}(g) = 0; D^{b}(g-1) > 0; D^{b}(g+1) < 0. \tag{3}$$

All peak points are employed as the initial cluster centers of the following fuzzy clustering procedure. In this paper, we perform a smooth filter on H^{b} before calculating its difference to reduce the impact of image noise. Besides, two points with a distance smaller than a predefined threshold will be merged.

2.2.2 Histogram-based FCM

The objective function of the histogram-based FCM is defined as

$$J_{m} = \sum_{g=1}^{256} \sum_{k=1}^{K} H^{b}(g) u_{gk}^{m} (g - v_{k})^{2} \tag{4}$$

where v_{k} is the prototype of the k^{th} cluster, u_{gk} ($\sum_{k=1}^{K} u_{gk} = 1$) represents the fuzzy membership of gray value g with respect to cluster k. By minimizing (4), u_{gk} and v_{k} can be estimated:

$$u_{gk} = \frac{(g-v_{k})^{-\frac{2}{m-1}}}{\sum_{k=1}^{K}(g-v_{k})^{-\frac{2}{m-1}}}, v_{k} = \frac{\sum_{g=1}^{256} g H^{b}(g) u_{gk}^{m}}{\sum_{g=1}^{256} H^{b}(g) u_{gk}^{m}}. \tag{5}$$

The iterative procedure of the histogram-based FCM is summarizes as follows: (a) Set values of K, m and ϵ; (b) Initialize the cluster centers v_{k} by using method described in 2.2.1; (c) Set the loop counter $ite = 0$; (d) Calculate the membership matrix $U^{ite+1} = \{u_{gk}\}_{256\times K}$ and cluster centers by (5); (e) If $\max\{U^{ite} - U^{ite+1}\} < \epsilon$ then stop, otherwise, set $ite = ite + 1$ and go to Step (d).

3. Experimental Results

Many images are tested to evaluate the performance of the proposed MsHFCM algorithm. We demonstrate its effectiveness using only one remote sensing image, which was acquired by an unmanned aerial vehicle of Phantom 4 Advanced over an area of South Anyang, China, on Nov. 15,

2016. The test image is shown in Fig. 2(a) with size of 563×1000.

The test image includes three different land cover types, namely wheat area, farmland ridges, and road, and its ground truth image is shown in Fig. 2(b). In the test image, wheat area is rich of textures, while farmland ridge has very similar spectral response to the road, which highly increases the difficulty of clustering.

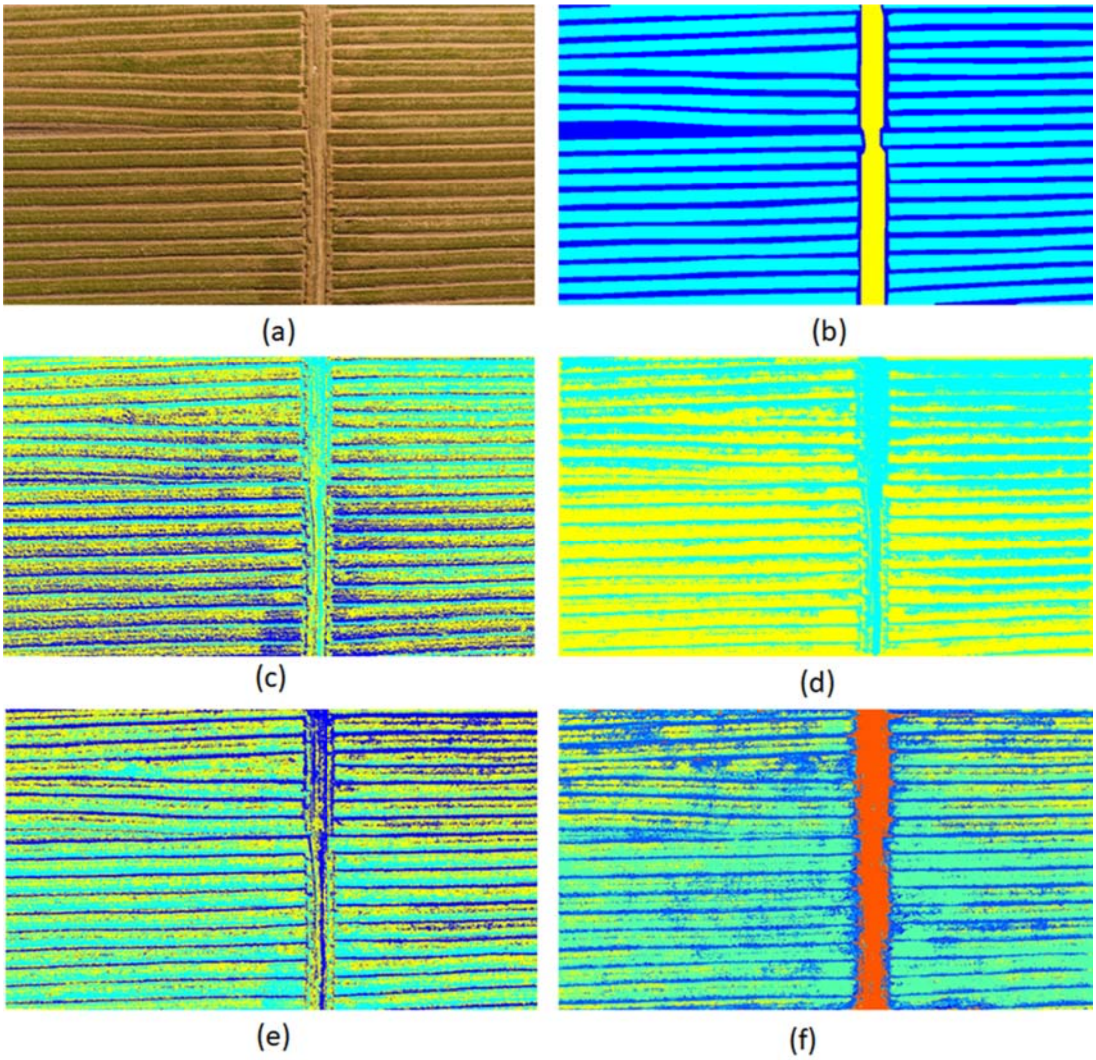

Figure 2 Results of image segmentation: (a) remote sensing image; (b) ground truth image; (c)–(f) are results of FCM, EnFCM, AHFCM and MsHFCM, respectively.

Table 1 Comparison of different algorithms

	FCM	EnFCM	AHFCM	MsHFCM
RI	0.5720	0.5539	0.5731	**0.6024**
Time (seconds)	9.3575	**1.6057**	12.0873	6.0117

We compare the efficiency and accuracy of MsHFCM with three fuzzy algorithms, FCM, EnFCM, and AHFCM. The segmentation results of FCM, EnFCM, AHFCM, and MsHFCM are shown in Fig.2(c)-(f), respectively. It is easy to find that the result of the proposed method is more coincident with the ground truth image than the competitors. It is mainly because the gray-spatial image used in MsHFCM has the ability to incorporate more useful information.

Besides, we evaluate these algorithms with respect to two indicators: random index (RI) [12] and time consumed. RI takes a value between 0 and 1, with the values close to 0 indicating a bad segmentation result, and the values close to 1 indicating a good result. All indicators are recorded in Table 1. As can be seen from the table, the proposed method used less time but achieved the best accuracy. It is due to the fact that the histogram-based method greatly accelerates the clustering procedure. Such a result clearly illustrates the success of the basic idea of proposed method to combine the merits of EnFCM and AHFCM.

4. Conclusions

This paper presents a novel histogram-based FCM algorithm. It inherits the merits of AHFCM to independently cluster each spectral band and fuse the labels to form the final result. It also inherits the merits of EnFCM to incorporate spatial information by a newly precomputed gray-spatial image and execute histogram-based clustering for the sake of time efficiency. Experimental results have shown the superiority of the proposed method.

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