Guided kernel fuzzy c-means clustering with spatial information for remote-sensing image segmentation

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Abstract: Fuzzy C-means (FCM) has widely been applied to computer vision, which emerged as an important tool for segmenting the structure of image data. However, the effectiveness of this technique lies in its inability to preserve edges and suppress noise, often leading to unsatisfactory segmentations. To solve this problem, we derive a modified FCM algorithm by using guided filter. The first key concept of our method is its linear translation-variant filtering process, which exploits edge-preserving smoothing property to preserve the edge structures in segmentation. The second is that this technique improves the robustness to noise by incorporating the spatial information into the objective function, which are obtained by the mean output of guided filtering. The main advantages of the proposed method are that it exhibits robustness to edge-preserving and noise and it can enhance the segmentation accuracy. Experimental results on both synthetic and real remote-sensing images suggest that the proposed method behaves well in segmentation performance.

1. Introduction

Image segmentation is the process of partitioning an image into meaningful regions, which has emerged as an interesting alternative for diverse applications in computer vision. In remote sensing, a segmentation method should leverage the advances made in data acquisition, specifically the spectral and spatial resolution capability [1]. Fuzzy c-means (FCM) is one of the most widely used methods in image segmentation, and it is generally more flexible than the corresponding hard-clustering algorithms [2-14]. Among FCM based methods, the kernelized fuzzy C-means (KFCM) algorithms have received an enormous amount of attention [7-15]. The KFCM algorithms maps image points from the input space to a higher dimensional feature space using a kernel function. Although good performances have been achieved in the development of FCM-based algorithms, the edge-preserving denoising remains a largely unsolved problem. The main difficulty with image segmentation in this way is that these techniques are very sensitive to noise and are hard to maintains the clear image edges [4, 8, 11, 13, 15].

Filtering has been widely used in computer graphics, imaging and vision for many different applications. In particular, the guided filter [15] is one of several popular algorithms for edge-preserving smoothing whose computational complexity does not depend on the filter size. It can effectively smooth the region with noise and produce visually pleasing edge profiles. Guided filter gives better output near the edges than that of bilateral filter. So, it is an important technique for various image processing and computer vision applications such as feature extraction and target recognition. Considering one of segmentation tasks is to suppress noise and emphasize important structure features, we conduct fuzzy clustering by incorporating guided filtering into the objective function of KFCM in the processing of image segmentation. Our intuition is that if guided filter can effectively suppress gradient-reversal artifacts and produce visually pleasing edge profiles, we can get more accurate segmentation when segmenting image with KFCM. Experimental results demonstrate the effectiveness of the proposed algorithm.

The rest of this paper is organized as follows. Some related works are described in Section II. Section III includes details on the guided segmentation algorithm. Experimental results of the proposed algorithm are given in Section IV. Concluding remarks are provided in the final section.

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2. Generalized Fuzzy C-Means Clustering Algorithm

2.1 Fuzzy C-Means

Fuzzy C-Means (FCM) is a method of clustering which allows one piece of data to belong to two or more clusters, which assigns a degree of membership for every class using a fuzzy membership [2]. Basically, the FCM method includes three basic operators: the fuzzy membership function, partition matrix and the objective function. Given the cluster number C and a dataset $X = \{x_i\}_{i=1}^{N}$, the method iterates to minimize following objective function

$$J(U,V) = \sum_{i=1}^{N}\sum_{j=1}^{C} u_{ij}^{m} \left\| x_i - v_j \right\|^2, \text{ s.t. } \sum_{j=1}^{C} u_{ij} = 1 \ \forall i, \tag{1}$$

where m is any real number greater than 1, $\|\cdot\|$ stands for the Euclidean norm, U is the membership function containing u_{ik} and $V = [v_j]$ denotes cluster centers. Using the Lagrange multiplier method, we may obtain a local minimum for J if we update U and V alternatingly according to the algorithm

$$v_j^{(k+1)} := \frac{\sum_{i=1}^{N} (u_{ij}^{(k)})^m x_i}{\sum_{i=1}^{N} (u_{ij}^{(k)})^m}, \tag{2}$$

$$u_{ij}^{(k+1)} := \left(\sum_{l=1}^{C} \left(\frac{\left\| x_i - v_j^{(k+1)} \right\|}{\left\| x_i - v_l^{(k+1)} \right\|} \right)^{\frac{2}{m-1}} \right)^{-1}. \tag{3}$$

2.2 Kernelized Fuzzy C-Means

To capture nonlinear relationships among data, kernel tricks perform an arbitrary nonlinear mapping Φ from the original feature space to a space of higher dimensionality $\Phi : X \to F(x \to \Phi(x))$ [9, 10]. The kernel method then takes advantage of the fact that dot products in the kernel space can be expressed by a Mercer kernel K given by $K(x, y) = \Phi(x)^{\mathrm{T}} \Phi(y)$ [10]. This trick has been widely used in clustering, as shown in support vector clustering and fuzzy c-means algorithms. In this section, we describe a kernelized FCM (KFCM) algorithm with objective function as follows [9]:

$$J(U,V) = \sum_{i=1}^{N}\sum_{j=1}^{C} u_{ij}^{m} \left\| \Phi(x_i) - \Phi(v_j) \right\|^2, \text{ s.t. } \sum_{j=1}^{C} u_{ij} = 1 \ \forall i, \tag{4}$$

where symbol $\|\cdot\|$ is the Euclidean norm, and Φ is an implicit nonlinear map. Through the kernel substitution, we get

$$\begin{aligned} \left\| \Phi(x_i) - \Phi(v_j) \right\|^2 &= (\Phi(x_i) - \Phi(v_j))^{\mathrm{T}} (\Phi(x_i) - \Phi(v_j)) \\ &= \Phi(x_i)^{\mathrm{T}} \Phi(x_i) - \Phi(v_j)^{\mathrm{T}} \Phi(x_i) \\ &\quad - \Phi(x_i)^{\mathrm{T}} \Phi(v_j) + \Phi(v_j)^{\mathrm{T}} \Phi(v_j) \\ &= K(x_i, x_i) + K(v_j, v_j) - 2K(x_i, v_j). \end{aligned} \tag{5}$$

Consider the Gaussian kernel

$$K(x_i, v_j) = \exp\left(-\frac{\left\| x_i - v_j \right\|^2}{\sigma} \right), \tag{6}$$

Eq. (5) can be rewritten as $2(1 - K(x_i, v_j))$. From Eqs. (4-6), the objective function of KFCM can be simplified to

$$J = 2\sum_{i=1}^{N}\sum_{j=1}^{C} u_{ij}^m (1 - K(x_i, v_j)). \tag{7}$$

In a similar way to the standard FCM algorithm, the objective function J can be minimized under the constraint of U. The optimization of the membership function U and cluster centers V involve the use of the technique of Lagrange multipliers which leads to the expression

$$u_{ij} = \frac{1}{\sum_{l=1}^{C}\left(\frac{1 - K(x_i, v_j)}{1 - K(x_i, v_l)} \right)^{1/(m-1)}}, \tag{8}$$

$$v_j = \frac{\sum_{i=1}^{N} u_{ij}^m K(x_i, v_j) x_i}{\sum_{i=1}^{N} u_{ij}^m K(x_i, v_j)}. \tag{9}$$

3. Guided Kernel Fuzzy C-Means Clustering with Spatial Information

Guided filter [16] is defined as a general linear translation-variant filtering process, which involves a guidance image I, an input image p, and an output image q. The key assumption of the guided filter is that q is a linear transform of I:

$$q_i = a_k I_i + b_k, \ \forall i \in w_k, \tag{10}$$

where i is the index of a pixel, and w_k is a window which centered at the pixel k with a radius r. To determine the linear coefficients (a_k, b_k), the objective function that minimizes the difference between q and the filter input p in window w_k is given by

$$E(a_k, b_k) = \sum_{i \in w_k} ((a_k I_i + b_k - p_i)^2 + \varepsilon a_k^2), \tag{11}$$

where ε is a regularization parameter controlling the degree of smoothness. The solution of Eq. (11) is obtained by linear regression

$$a_k = \frac{\frac{1}{|w|}\sum_{i \in w_k} I_i p_i - \mu_k \overline{p}_k}{\sigma_k^2 + \varepsilon}, \tag{12}$$

$$b_k = \overline{p}_k - a_k \mu_k. \tag{13}$$

Here, μ_k and σ_k are the mean and variance of I in the window k. The final output of guided filter is

$$q_i = \overline{a}_i I_i + \overline{b}_i, \tag{14}$$

where $\overline{a}_i$ and $\overline{b}$ are the average of a and b respectively on the window w_i centered at i.

In order to arm guided filter with the fuzzy clustering by incorporating spatial information, we

design our guided kernel fuzzy c-means clustering with spatial information (GKFCMS). We show that the processing of the original image by the guided smoothing technique can efficiently eliminate noise and superfluous structure. Following the strategy of [8], the objective function of GKFCMS algorithm is minimized using the following alternate iterations:

$$u_{ij} = \frac{\left(\left(1\text{-}K(x_i, v_j)\right) + \alpha\left(1 - K(\bar{G}(x_i), v_j)\right)\right)^{-1/(m-1)}}{\sum_{l=1}^{C}\left(\left(1\text{-}K(x_i, v_l)\right) + \alpha\left(1 - K(\bar{G}(x_i), v_l)\right)\right)^{-1/(m-1)}}, \tag{15}$$

$$v_j = \frac{\sum_{i=1}^{N} u_{ij}^m \left(K(x_i, v_j)x_i + \alpha K(\bar{G}(x_i), v_j)\bar{\phi}(x_i)\right)}{\sum_{i=1}^{N} u_{ij}^m \left(K(x_i, v_j) + \alpha K(\bar{G}(x_i), v_j)\right)}, \tag{16}$$

where $G(x_k)$ denotes the guided filtering of a dataset $X = \{x_i\}_{i=1}^{N}$, $\bar{G}(x_k)$ is the mean values of $G(x_k)$.

4. Experimental Results

4.1 General Setting

To evaluate and compare the performance of the proposed GKFCMS with that of other FCM-based methods, the RFCM [5], KGFCMS [12] and ARKFCM [14] methods have been considered. We carry out segmentation experiments on one synthetic image and two real images. In this paper, we use the segmentation accuracy (SA) [17] as the evaluation indices. SA is defined as the sum of correctly classified pixels divided by the total number of pixels:

$$SA = \sum_{i=1}^{c} \frac{A_i \cap C_i}{\sum_{j=1}^{c} C_j} \tag{17}$$

where c is the number of clusters, A_i denotes the pixels belonging to the ith class found by algorithm, and C_i denotes the pixels belonging to the ith class in the reference segmented image.

4.2 Synthetic Image

In this section, we conduct some experiments to compare the segmentation performance on the synthetic image. The advantage for using synthetic images rather than real image data for validating segmentation methods is that synthetic data includes prior knowledge of the true types and control over image parameters such as modality and noise.

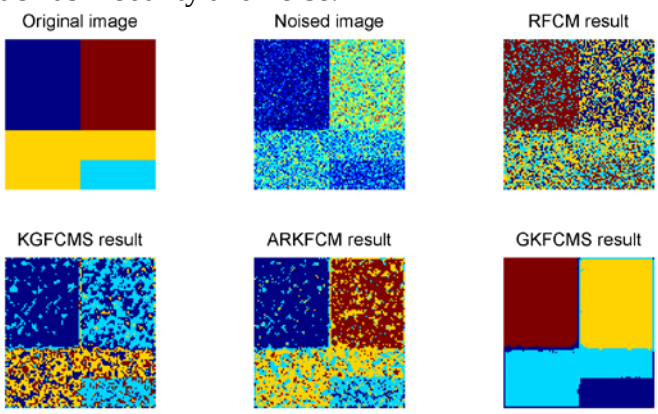

Fig.1. Comparison of segmentation results on synthetic image corrupted by Gaussian noise with 0.01 variance

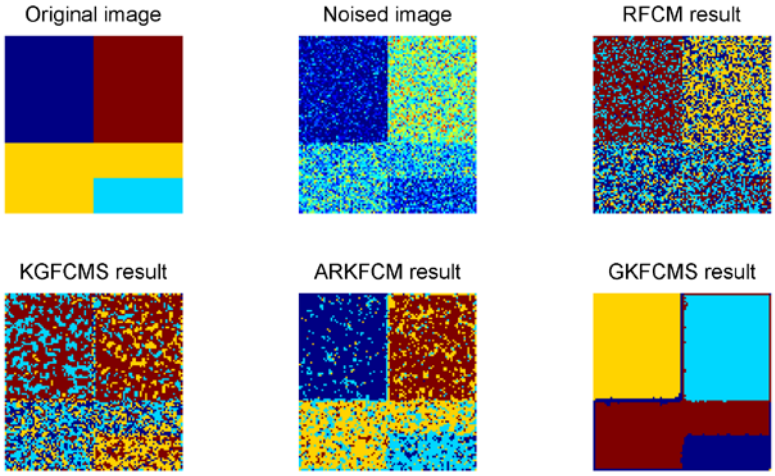

Fig.2. Comparison of segmentation results on synthetic image corrupted by Gaussian noise with 0.02 variance

The synthetic image is shown in the top left of Figs. (1-3), which contains a four-class pattern. In Figs. (1-3), we test the algorithms' performance when the synthetic image corrupted by Gaussian noise with 0.01, 0.02 and 0.05 variance, respectively. What we can see in Figs. (1-3) is that RFCM, KGFCMS and ARKFCM are sensitive to noise, and the boundaries between different regions are not well defined. The results achieved by GKFCMS show that the region uniformity is good and the boundaries between regions are clear, while nearly all pixels are classified correctly so that the algorithm turns out to be robust to Gaussian noise. The segmentation accuracies in terms of SA obtained by considered methods for corrupted synthetic images are listed in Table 1. The SA of GKFCMS is significantly closer to 1 than the other algorithms. This suggests that the proposed algorithm outperforms the compared algorithms on this kind of test data.

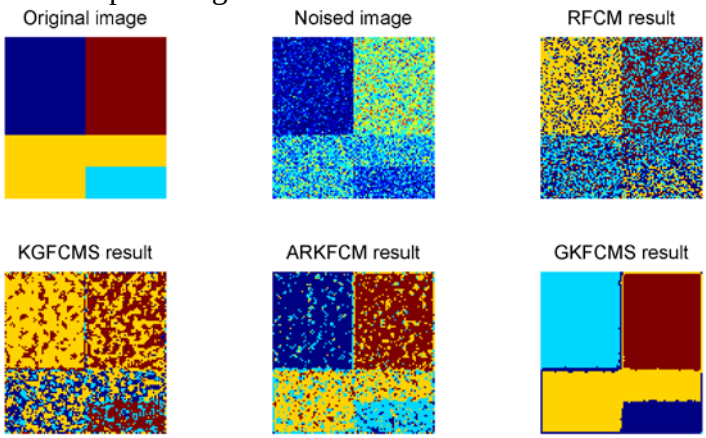

Fig.3. Comparison of segmentation results on synthetic image corrupted by Gaussian noise with 0.05 variance

Table 1 SAs of different methods on synthetic image corrupted by Gaussian noise

Variance	RFCM	KGFCMS	ARKFCM	GKFCMS
0.01	0.5459	0.5781	0.7381	0.9488
0.02	0.5326	0.4614	0.7454	0.9487
0.05	0.5366	0.4426	0.7716	0.9491

4.3 Real Image

Fig. 4 shows a comparison of segmentation results on a remote-sensing image (airport). The results of GKFCMS demonstrate that the region uniformity is good and the boundaries between regions are clear. The superiority of the proposed GKFCMS is observable in this figure.

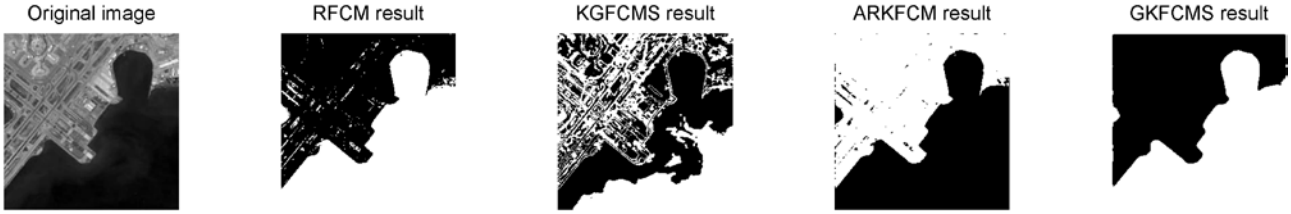

Fig.4. Segmentation results on remote-sensing image (airport)

Fig.5. Segmentation results on remote-sensing image (bridge)

Fig. 5 presents a comparison of segmentation results between RFCM, KGFCMS, ARKFCM and GKFCMS methods, when applied on a remote-sensing image (bridge). Visually, RFCM, KGFCMS and ARKFCM cannot correctly classify the images, while GKFCMS acquire satisfying segmentation results. In this case, it could be observed from the results that GKFCMS could detect the main objects in the test image more effective than the other methods, and the boundaries between the true regions obtained by GKFCMS are well defined.

The segmentation results of seven different compared algorithms on the third real remote-sensing image (river) are shown in Fig. 6. In this test image, GKFCMS maintains the clear image edges and the more details. Although there are still some isolated pixels, the region uniformity and the boundary localization of the GKFCMS are both satisfactory.

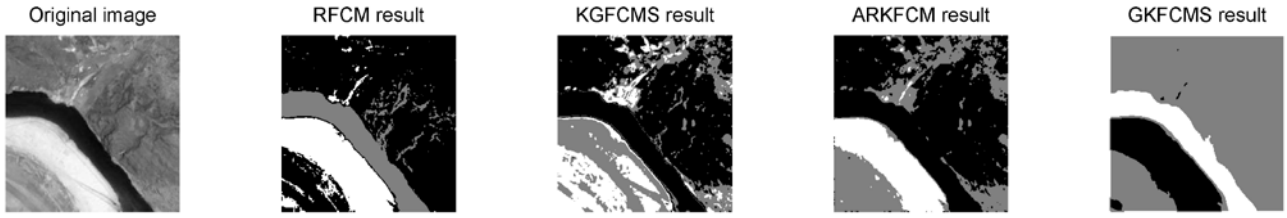

Fig.6. Segmentation results on remote-sensing image (river)

5. Conclusion

In computer vision, image segmentation based on the fuzzy clustering is an important problem. In this study, we have introduced a new, robust and efficient method to segment remote-sensing images. The proposed algorithm takes advantage of the guided filter and the spatial information, which makes it capable of image segmentation whose structures are corrupted by noise. Although the number of clusters must be given a priori, the results obtained from our method are acceptable. Although the number of clusters must be given a priori, the results obtained from our method are acceptable. Our further and ongoing works include complex scene classification in our algorithms, adaptive determination for the clustering number and other applications.

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