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Neighboring Weighted Fuzzy C-Means with Kernel Method for Image Segmentation and Its Application

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Abstract: Image segmentation plays a crucial role in many image applications. Fuzzy C-Means (FCM) is a powerful method to segment image and has been applied to many image segmentations successfully. However, on the one hand, traditional FCM algorithm is sensitive to the noise due to the fact that it only accounts for the pixel's value information, not takes the neighboring pixels' spatial information into consideration; on the other hand, its performance becomes poor when the input data are nonlinearly. To overcome the above mentioned problems, this study proposed a neighboring weighted FCM associated with kernel method algorithm (KNW-FCM) for image segmentation. The values of the coefficients within neighboring window are adaptively determined by the characteristics of the image itself. Furthermore, the original Euclidean distance in the traditional FCM is replaced by the kernel-induced distance. Additionally, as a real application, we apply the proposed algorithm to segment the microscopic image of harmful algae. Experimental results show that the proposed algorithm achieves better performance compared with other algorithms.

Key words: Image segmentation, fuzzy c-means, kernel method, harmful algae

INTRODUCTION

Image segmentation is one of the crucial steps in an image processing and analysis system and plays a vital role in the process of extracting the useful information from the images (Gonzalez and Woods, 2002). Fuzzy clustering is a partition method that divides data point into groups (clusters) according to the membership degree (Liu and Xu, 2008). Fuzzy C-Means (FCM), one of the most popular unsupervised fuzzy clustering algorithms, is widely used in pattern classification (Xing and Hu, 2008), medical image segmentation (Sikka *et al.*, 2009), etc. Compared with hard c-means algorithm (Gorriz *et al.*, 2006), FCM is able to preserve more information from the original image. However, standard FCM does not take into account spatial information which makes it very sensitive to noise and other image artifacts. Furthermore, its performance becomes poor when the input data are nonlinearly (Ma *et al.*, 2007). Based on the above analysis, this study proposed a method for image segmentation using modified FCM combined with kernel method. Moreover, as a real application, the proposed algorithm was applied to the segmentation of microscopic image of harmful algae.

TRADITIONAL FCM ALGORITHM

The FCM algorithm assigns pixels to each category by using fuzzy memberships.

Let $X = \{x_i, i = 1, 2,..., n|x_i \in \mathbb{R}^d\}$ denotes an image with n pixels to be partitioned into c clusters, where x_i represents features data. The algorithm is an iterative optimization that minimizes the objective function defined as follows:

$$J_m = \sum_{k=1}^{c}\sum_{i=1}^{n} u_{ki}^m \|x_i - v_k\|^2 \tag{1}$$

With the following constraints:

$$u_{ki} \in [0,1] | \sum_{k=1}^{c} u_{ki} = 1, \forall i, 0 < \sum_{i=1}^{n} u_{ki} < n, \forall k \tag{2}$$

where, u_{ki} represents the membership of pixel x_i in the kth cluster, v_k is the kth class center; $\|.\|$ denotes the Euclidean distance, m>1 is a weighting exponent on each fuzzy membership. The parameter m controls the fuzziness of the resulting partition. The membership functions and cluster centers are updated by the following expressions:

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$$u_{ki}=\sum_{l=1}^{c}\left(\frac{\|x_i-v_k\|}{\|x_i-v_l\|}\right)^{\frac{-2}{m-1}} \quad (3)$$

And:

$$v_k=\frac{\sum_{i=1}^{n}u_{ki}^{m}x_i}{\sum_{i=1}^{n}u_{ki}^{m}} \quad (4)$$

In implementation, matrix V is randomly initialize and then U and V are updated through an iterative process using Eq. 3-4, respectively.

MODIFIED FCM WITH KERNEL METHOD

Modified FCM algorithm: FCM clustering algorithm is a powerful tool for segmenting the images and has been applied successfully to the various applications. However, traditional FCM algorithm is sensitive to noise due to not taking spatial information into consideration. In order to overcome such drawback, many researchers have proposed the modified FCM algorithms. In this study, we proposed a modified fuzzy c-means algorithm which takes spatial information into account for segmenting images.

Given a digital image with the size of m×n:

$$I = (f(x, y)|f(x, y)\in[0, L-1], 0\le x\le m-1, 0\le y\le n-1) \quad (5)$$

where, f(x, y) represents gray value of the pixel at coordinates (x, y) in the image I; the maximum gray level of the image I denoted by L; N = m×n denotes the total pixel numbers in I.

Defined a square local window with the size of (2r+1)×(2r+1):

$$W = \{w(s, t)|(s, t\in\{-\gamma, -(\gamma-1),..., -1, 0, 1,... (r-1), r\})\} \quad (6)$$

where, w(s, t) is the window's coefficient (weighting value); r is called the radius of window. The value of r is equal to the pixel numbers from the most marginal pixels to central pixel either in row-wise or column-wise within the current window. As for a 3×3 window (r = 1) centered at (x, y), it has the form as follows:

$$W(x,y)=\begin{bmatrix} w(x-1,y-1) & w(x-1,y) & w(x-1,y+1)\\ w(x,y-1) & w(x,y) & w(x,y+1)\\ w(x+1,y-1) & w(x+1,y) & w(x+1,y+1)\end{bmatrix} \quad (7)$$

where, window's coefficient w(x+s, y+t)(s, t∈{-0, 0, 1}) is defined as:

$$w(x,y)=\frac{1}{2}$$

$$w(x+s,y+t)=\frac{d(x+s,y+t)}{2\sum_{s=-1}^{1}\sum_{t=-1}^{1}d(x+s,y+t)},(s,t)\neq(0,0) \quad (8)$$

where, d(x+s, y+t)(s, t∈{-1, 0, 1}) is the reciprocal of gray gradient and can be calculated as:

$$d(x+s,y+t)=\frac{1}{|f(x+s,y+t)-f(x,y)|+1},(s,t)\neq(0,0) \quad (9)$$

where, f(x+s, y+t)(s, t∈{-1, 0, 1}^(s, t) ≠ (0, 0)) is the gray value of pixel at (x+s, y+t) and has the form as:

$$f(x+s,y+t)=\begin{bmatrix} f(x-1,y-1) & f(x-1,y) & f(x-1,y+1)\\ f(x,y-1) & f(x,y) & f(x,y+1)\\ f(x+1,y-1) & f(x+1,y) & f(x+1,y+1)\end{bmatrix} \quad (10)$$

In order to avoid the denominator equals to zero in Eq. 9, it is worth noting that number 1 is added to the denominator.

According to Eq. 8 and 10, we obtain a weighting average image as:

$$f^*(x,y)=\sum_{s=-1}^{1}\sum_{t=-1}^{1}[f(x+s,y+t)\bullet w(x+s,y+t)] \quad (11)$$
$$0\le x\le m-1, 0\le y\le n-1$$

Based on the traditional FCM's objective function, the modified objective function can be written as:

$$J_m=\sum_{k=1}^{c}\sum_{i=1}^{N}u_{ki}^{m}\|f_i-v_k\|^2+\alpha\sum_{k=1}^{c}\sum_{i=1}^{N}u_{ki}^{m}\|f_i^*-v_k\|^2 \quad (12)$$

where, f_i (i = 1, 2,... N = m×n) is gray value of the pixel in the original image I; f^*_i (i = 1, 2,... N = m×n) is gray value of the pixel in the Locally Weighting Average (LWA) image which obtained via., Eq. 11 in advance; parameter α in the second term controls the effect of the penalty.

Similar to the standard FCM clustering algorithm, the membership functions and cluster centers of the modified FCM are updated by the following expressions:

$$u_{ki}=\frac{1}{\sum_{l=1}^{c}\left(\frac{\|f_i-v_k\|^2+\alpha\|f_i^*-v_k\|^2}{\|f_i-v_l\|^2+\alpha\|f_i^*-v_l\|^2}\right)^{(m-1)}} \quad (13)$$

And:

$$v_k=\frac{\sum_{i=1}^{N}u_{ki}^{m}(f_i+\alpha f_i^*)}{(1+\alpha)\sum_{i=1}^{N}u_{ki}^{m}} \quad (14)$$

The modified FCM algorithm (locally weighting average FCM clustering algorithm, called LWA-FCM) can be summarized as follows:

Step 1: Fix m>1 and $2\le c\le N$-1; set to a very small value; maximum iterative number n_{max}
Step 2: Initialize cluster centers $v_k^{(0)}$ (k = 1, 2,..., c)
Step 3: Compute the locally weighting average image using Eq. 11 in advance

Repeat:
Step 4: Compute/modify with by Eq. 13 and 14
Step 5: Update with the modified by Eq. 14

Until $(\|V^{(n+1)}-V^{(n)}\|\le\varepsilon$ or iterative number $n>n_{max}$.

Modified FCM combined with kernel method: Though FCM has been applied to numerous clustering problems, it still suffers from poor performance when boundaries among clusters in the input data are nonlinear. One alternative approach is to transform the input data into a feature space of a higher dimensionality using a nonlinear mapping function so that nonlinear problems in the input space can be linearly treated in the feature space (Ma *et al*., 2007; Kaur *et al*., 2013). One of the most popular data transformation methods adopted in recent studies is the kernel method. One of the advantageous features of the kernel method is that input data can be implicitly transformed into the feature space without knowledge of the mapping function. Furthermore, the dot product in the feature space can be calculated using a kernel function.

With the incorporation of the kernel method, the objective function of Eq. 1 in the feature space using the mapping function Φ can be rewritten as follow:

$$J_m^{\Phi}=\sum_{k=1}^{c}\sum_{i=1}^{N}u_{ki}^{m}\left\|\Phi(x_i)-\Phi(v_k)\right\|^2 \tag{15}$$

Through kernel substitution, the above objective function can be rewritten as:

$$J_m^{\Phi}=2\sum_{k=1}^{c}\sum_{i=1}^{N}u_{ki}^{m}(1-K(x_i,v_k)) \tag{16}$$

where, $K(x_i, v_k)$ is function kernel which generally takes the Gaussian Radial Basis Function (GRBF) kernel with the following form:

$$K(x,y)=\exp\left(\frac{-\|x-y\|^2}{\sigma^2}\right) \tag{17}$$

By using the lagrange multiplier to minimize the objective Eq. 15, the membership functions can be updated as follow:

$$u_{ki}=\frac{(1-K(x_i,v_k))^{-1/(m-1)}}{\sum_{l=1}^{c}(1-K(x_i,v_l))^{-1/(m-1)}} \tag{18}$$

And the cluster centers can be updated as follow:

$$v_k=\frac{\sum_{i=1}^{N}u_{ki}^{m}K(x_i,v_k)x_i}{\sum_{i=1}^{N}u_{ki}^{m}K(x_i,v_k)} \tag{19}$$

Similar to the kernelized version of Eq. 1, we kernelized Eq. 12 and obtain the following new objective function through the kernel-induced distance measure substitution:

$$J_m^{\Phi}=\sum_{k=1}^{c}\sum_{i=1}^{N}u_{ki}^{m}(1-K(f_i,v_k))+\alpha\sum_{k=1}^{c}\sum_{i=1}^{N}u_{ki}^{m}(1-K(f_i^{*},v_k)) \tag{20}$$

where, K(x, y) is still taken as GRBF, f^*_i and a are defined as before. f^*_i directly viewed a data point in the original space to be mapped by Φ and thus can be computed in advance.

Formally, the above optimization problem comes in the form:

$$\min_{U,\{v_i\}_{i=1}^{c}} J_m^{\Phi} \text{ subject to Eq. 2} \tag{21}$$

In a similar way to the standard FCM algorithm, the objective function J^{Φ}_m can be minimized under the constraint of U as stated in Eq. 2 and then the membership functions and cluster centers are updated by the following expressions:

$$u_{ki}=\frac{((1-K(f_i,v_k))+\alpha(1-K(\overline{f_i^{*}},v_k)))^{-1/(m-1)}}{\sum_{l=1}^{c}((1-K(f_i,v_l))+\alpha(1-K(\overline{f_i^{*}},v_l)))^{-1/(m-1)}} \tag{22}$$

$$v_k=\frac{\sum_{i=1}^{N}u_{ki}^{m}(K(f_i,v_k)f_i+\alpha K(\overline{f_i^{*}},v_k)\overline{f_i^{*}})}{\sum_{i=1}^{N}u_{ki}^{m}(K(f_i,v_k)+\alpha K(\overline{f_i^{*}},v_k))} \tag{23}$$

The modified FCM, neighboring weighted FCM with kernel method (KNW-FCM), can be summarized as follows:

Step 1: Fix $m>1$ and $2 \leq c \leq N-1$; set $\varepsilon>0$ to a very small value; maximum iterative number n_{max}
Step 2: Initialize cluster centers $v_k^{(0)}(k = 1, 2,..., c)$
Step 3: Compute the weighting average image in advance using Eq. 11

Repeat:
Step 4: Compute/modify μ_{ki} with v_k by Eq. 22 and 23
Step 5: Update v_k with the modified μ_{ki} by Eq. 23

Until ($\|V^{(\alpha+1)}-V^{(\alpha)}\| \leq \varepsilon$ or iterative number $n>n_{max}$).

EXPERIMENTAL RESULTS AND ANALYSIS

In order to evaluate the performance of our proposed method, we take the real microscopic images of harmful algae (The images are taken from http://hab.jnu.edu.cn/index.asp) as experimental input data.

Figure 1a shows an original microscopic image of harmful algae. Figure 1b-d display the segmentation results using traditional FCM algorithm, algorithm described in Kaur *et al.* (2013) and the proposed algorithm, respectively.

Figure 2a shows another original microscopic image of harmful algae. Figure 2b-d display the segmentation results using traditional FCM algorithm, algorithm described in Kaur *et al.* (2013) and the proposed algorithm, respectively.

From Fig. 1 and 2, we can see that the segmentation effects of both the algorithm presented in Kaur *et al.* (2013) and the KNW-FCM are better than that of traditional FCM algorithm. Furthermore, compared Fig. 1c with Fig. 1d and 2c with Fig. 2d, we know that the segmentation results obtained by the proposed method are more consistent and accurate than that of the algorithm in Kaur *et al.* (2013).

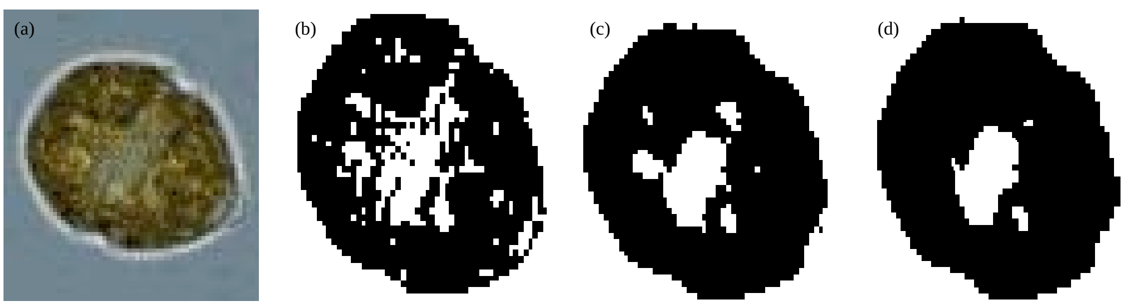

Fig. 1(a-d): Segmentation Results of Microscopic Image of Harmful Algae (a) Original image, (b) Segmentation using FCM, (c) Segmentation using algorithm presented in (Kaur *et al.*, 2013) and (d) Segmentation using proposed method

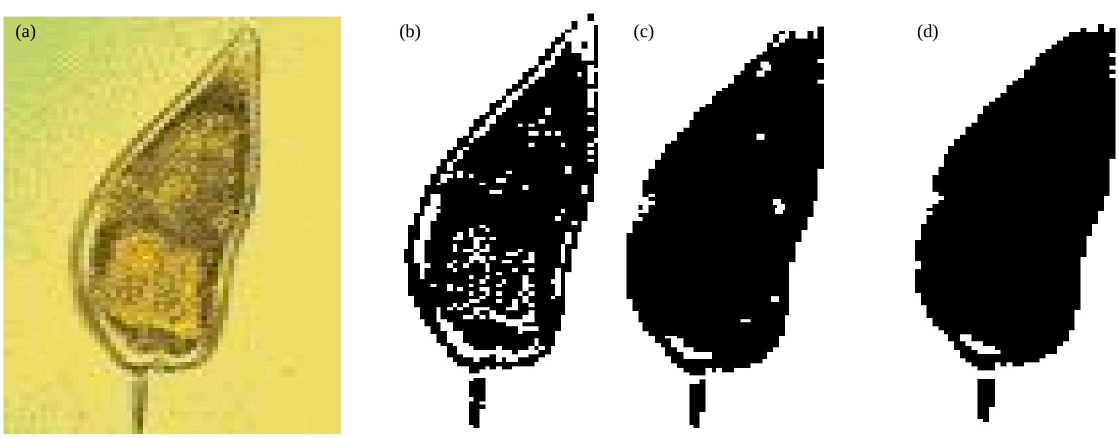

Fig. 2(a-d): Segmentation results of microscopic image of harmful algae (a) Original image, (b) Segmentation using FCM, (c) Segmentation using algorithm presented in (Kaur *et al.*, 2013) and (d) Segmentation using proposed method

CONCLUSION

In this study, we proposed a method for segmenting image. Firstly, we use neighboring weighted filter to modify the traditional FCM so as to improve the FCM's robustness to noise; Furthermore, we use the kernel-induced instance to replace the original Euclidean distance in the FCM algorithm so as to improve the algorithm's performance during processing the nonlinearly inputting data. Experimental results on two real microscopic images of harmful algae show that the propose algorithm outperforms than other two existing algorithms.

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