ROBUST FUZZY-C-MEANS FOR IMAGE SEGMENTATION

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Abstract: Fuzzy-c-means (FCM) algorithm is widely used for magnetic resonance (MR) image segmentation. However, conventional FCM is sensitive to noise because it does not consider the spatial information in the image. To overcome the above problem, an FCM algorithm with spatial information is presented in this paper. The algorithm is realized by integrating spatial contextual information into the membership function to make the method less sensitive to noise. The new spatial information term is defined as the summation of the membership function in the neighborhood of pixel under consideration weighted by a parameter α to control the neighborhood effect. This new method is applied to both synthetic images and MR data. Experimental results show that the presented method is more robust to noise than the conventional FCM and yields homogenous labeling.

1 INTRODUCTION

Magnetic resonance (MR) image segmentation is often required for computer-aided diagnostic and image analysis. Several approaches have been investigated for automating this crucial and difficult task in image processing (Leemput). The fuzzy-c-means (FCM) clustering algorithm classifies pixels with similar features into clusters and it has been highly effective for MR image segmentation (Chen(a), Yang, Bezdek(a), Lyer). Its success is due to the introduction of fuzziness in the classification process for image segmentation and the ability to preserve more information from the original image. However, conventional FCM takes care to pixels features and does not consider their location or any spatial information (Pham). Consequently, noisy image influence badly the performance of the FCM. Recently, many researchers try to incorporate spatial information in the conventional FCM. Ahmed et al. [Ahmed] modified the objective function of FCM to allow the labeling of a pixel to be influenced by the labels in its immediate neighborhood. The main disadvantage of this method is the necessity to compute the neighborhood term in each iteration which is very time-consuming. To overcome this problem, Chen and Zhang (Chen (b)) proposed two algorithms based on the mean-filtered image and median-filtered image which can be computed in advance to replace the neighborhood term in the above method. However, both methods can be applied only for single feature. Shen et al. [Shen] introduced two influential factors in segmentation which are the difference between neighboring pixels and their relative location in the image. In this paper, we improve the conventional FCM by incorporating spatial contextual information into the membership function. The membership function of a pixel is modified to consider the clusters distribution of its immediate neighborhood weighted by a parameter α to control the neighborhood effect. This scheme aims to improve the effectiveness of the conventional FCM to resist to noise. The rest of this paper is organized as follows. In Section 2, the conventional and the improved FCM are introduced. The experimental results of the comparative study are presented in Section 3. Finally, Section 4 gives our conclusions and some issues for future work.

2 PROPOSED METHOD

In this section we introduce the principle of the conventional FCM and the proposed FCM.

2.1 Conventional FCM

The Fuzzy-c-means (FCM) algorithm assigns pixels

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to each cluster by using fuzzy memberships. Let X= $\{x_i, i=1,2.....,N| x_i \in R^d\}$ denote an image with N pixels to be partitioned into c clusters, where x_i represents feature data and d is its size. The algorithm is an iterative optimization of the objective function defined as follows (Bezdek(a)):

$$J_m = \sum_{k=1}^{c}\sum_{i=1}^{N} u_{ki}^{m} \|x_i - v_k\|^2 \quad (1)$$

With the following constraints:

$$\sum_{k=1}^{c} u_{ki} = 1, \forall i\,;\ 0 \le u_{ki} \le 1, \forall k, i;\ \sum_{i=1}^{N} u_{ki} > 0, \quad \forall k \quad (2)$$

where u_{ki} represents the membership of x_i in the k^{th} cluster, v_k is the k^{th} class center, $\|\cdot\|$ denotes the Euclidean norm, 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:

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

and

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

The termination criterion is fixed as follows:

$$\|V_{new} - V_{old}\| < \epsilon \quad (5)$$

where V is a vector of cluster centers and ϵ is a threshold that can be set by the user.

2.2 Improved FCM

Neighboring pixels in image has nearly similar features. To incorporate this spatial information, a spatial term is defined as:

$$S_{ij} = \frac{\alpha}{|w_j|} \times \sum_{k \epsilon w_j} u_{ik} \quad (6)$$

where w_j represents the set of neighbors located in a n×n window centered on the pixel x_j. Therefore, along all cases a 3×3 window was used throughout this work. The parameter α is a tradeoff between robustness to noise and preserving image details. The spatial term S_{ij} is incorporated into the membership function as follows:

$$u'_{ij} = \frac{u_{ij} + S_{ij}}{\sum_{l=1}^{c} u_{lj} + S_{lj}} \quad (7)$$

When a pixel belongs to the same cluster as the majority of its neighbors, the spatial term just fortifies its original membership. However, for noisy pixel, each surrounding pixels try to pull it toward its cluster and its weight is reduced by the labels of its neigbhors. The improved FCM is robust to noise and then denoted RFCM. The classification process is a two-pass step in each iteration. The first step is identical to the classification process in the conventional FCM which computes the membership function. In the second step, the spatial information term is computed for each pixel by considering its immediate neighbors weighted by a parameter α and the original membership function is modified in the objective function defined by equation (1).

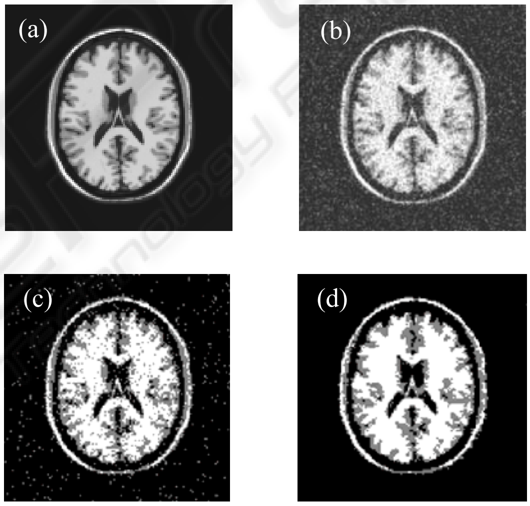

Figure 1: (a) MR T1 image (b) image with Gaussian noise. Segmented image by (c) FCM; (d) RFCM (α=0.27).

The algorithm is stopped when the difference between two cluster centers at two successive iterations is less than a threshold (=2×10^{-5}). To quantitatively evaluate the performance of the methods, we use two most known cluster validity functions based on fuzzy partition. These two validity functions are the partition coefficient V_{pc} (Bezdek(b)) and the partition entropy V_{pe} (Bezdek(c)). They are defined by:

$$V_{pc} = \frac{\sum_j^N \sum_i^c {u_{ij}}^2}{N} \quad (8)$$

$$V_{pe} = \frac{-\sum_j^N \sum_i^c [u_{ij} \log u_{ij}]}{N} \quad (9)$$

The idea of these validity functions is that the partition with less fuzziness corresponds to better performance. Thus, the best clustering is achieved when the value V_{pc} is maximal or V_{pe} is minimal.

3 RESULTS AND DISCUSSION

In this section, segmentation results are illustrated on digital MR phantoms and synthetic images. The MR phantoms simulated the same features of the T1-weighted MR image. The main advantage of using digital phantoms to validate segmentation methods is the prior knowledge of the images characteristics and parameters such as noise or others images artifacts (Goldszal). In all the examples, α varies between 0.1 and 1.2 and images were added with a Gaussian noise (μ=0, σ=0.1). Generaly, interesting tissues in brain are gray matter (GM), white matter (WM) and cerebrospinal fluid (CSF). The MR phantom image was divided into four clusters: GM, WM, CSF and background. However, CSF and background have in general the same gray level, so clusters number will be reduced to three. In addition, synthetic image with two classes is used as 'ground truth' for evaluation. The first class corresponds to the gray level 0 whereas the second class corresponds to the gray level 90. Figure 1 (a) and (b) represent respectively the original image and the image corrupted by additive Gaussian noise. Figure 1 (c) shows the segmentation result obtained by using FCM and figure 1 (d) shows the result of RFCM. The RFCM successfully segment MR image into three classes and outperforms the FCM. Segmentation result of FCM presents some spurious blobs of GM inside WM and background. The RFCM with higher value of α has a smoothing effect and it reduces spurious blobs but it can blur some fine details in the image which can lose much of its sharpness. Figure 2 (a) and (b) shows respectively the original synthetic image and the degraded noisy image. The RFCM correctly classify noisy pixels into clusters. The FCM did not totally recover from noise, but successfully segmented the image. The segmentation accuracy (SA) measures are summarized in table 1. SA is measured for different noise levels as follows:

$$\mathrm{SA} = \frac{\text{Number of correctly classified pixels}}{\text{Total number of pixels}} \times 100 \qquad (10)$$

From table 1, it can be observed that at 3% noise level RFCM slightly outperform FCM. From where we deduce that FCM is still competitive against RFCM under light noise conditions.When the noise level increases from 3% to 9%, the accuracy of FCM decreases from 86% to around 72% and the accuracy of RFCM decreases from 96% to around 95%.

Table 1: A summary of the accuracy (SA %) and the CPU time of the two clustering methods on the phantom data with different noise level: FCM and RFCM.

	3%	5%	7%	9%
Accuracy %				
FCM	86.26	85.78	84.50	72.20
RFCM	96.74	96.56	96.47	95.60
CPU time (sec)				
FCM	0.92	0.68	0.67	1.35
RFCM	6.66	5.08	5.10	8.09

Besides the accuracy, computation cost among the two methods is given in Table1. Because FCM is based only on the gray level histogram of the data, the CPU time of FCM is significantly lower than those by RFCM in the same platform. Table 2 summarizes cluster validity value of the two algorithms. In majority of cases, RFCM is superior to FCM according to validity function. A further experiment on real MRI image is given from a brain image with tumor. The used image is a T2-weighted MRI enhanced by contrast agent. Figure 3 (a) shows the original image with additive noise. The segmentation results are shown in Figure 3 (b) and (c). Tumor in Figure 3 (a) is not considered as an additional tissue class because it appears like CSF. Since no ground truth for this image is available, visual inspection shows that RFCM suppresses most spurious blobs than FCM. Linear low-pass filtering gives poor results as it yields even more edge blurring and detail loss. However, method incorporating spatial relationship directly in the classification process can produce more meaningful clusters.

4 CONCLUSIONS

In this work, we proposed an improved fuzzy-c-means clustering algorithm which is robust to noise. We modified the membership function in order to incorporate spatial information. Pixel is classified into its particular cluster by taking into account its immediate neighbors membership function weighted by a parameter α to control the neighborhood effect. Thus, spurious blobs due to the presence of noise are eliminated and the algorithm gives more homogenous regions than other clustering methods.

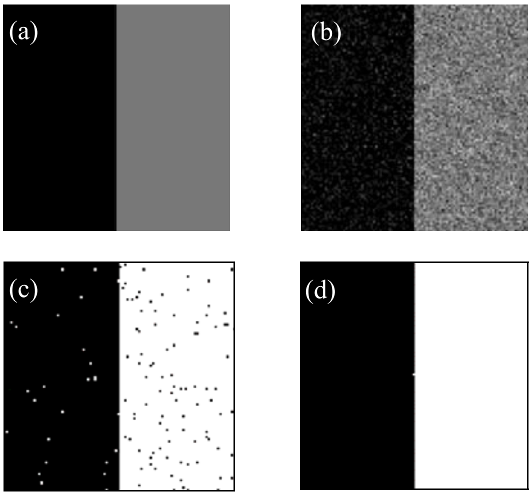

Figure 2: (a) Original image; (b)image with Gaussian noise, segmented image by (c) FCM; (d) FCM(α=0.97).

Table 2: The clustering results of three images using various FCM techniques.

Images	Methods	Vpc	Vpe
Original MR image	FCM	0.871	0.267
	RFCM	0.967	0.040
Gaussian noise added MR image	FCM	0.828	0.288
	RFCM	0.939	0.081
Salt and pepper added MR image	FCM	0.928	0.138
	RFCM	0.979	0.037
Mixed noise added MR image	FCM	0.804	0.334
	RFCM	0.943	0.097

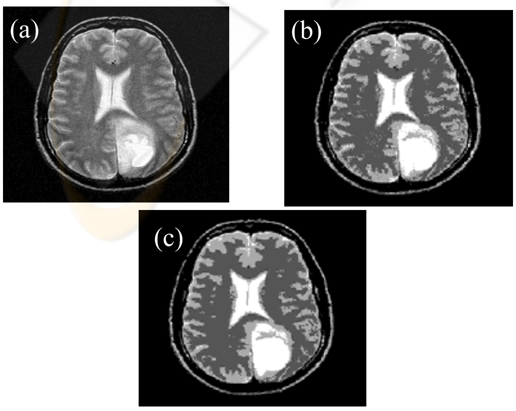

Figure 3: (a) MR image with additive noise. Segmented image by (b) FCM; (c) RFCM(α = 0.25).

The proposed method seems to be more robust to noise and it yields more homogenous labeling. However, this method has a drawback of blurring some fine details along the clustering process especially for high value of the parameter α. Thus, further works will emphasis on segmenting noisy image by incorporation spatial information and preserving image details.

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