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Fuzzy C-mean based brain MRI segmentation algorithms

M. A. Balafar

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Abstract Brain image segmentation is one of the most important parts of clinical diagnostic tools. Fuzzy C-mean (FCM) is one of the most popular clustering based segmentation methods. In this paper, a review of the FCM based segmentation algorithms for brain MRI images is presented. The review covers algorithms for FCM based segmentation algorithms, their comparative evaluations based on reported results and the result of experiments for neighborhood based extensions for FCM.

Keywords FCM · MRI · Brain

1 Introduction

FCM is a clustering algorithm introduced by James (1981). It is based on minimizing an object function by iteratively updating membership function and cluster centers. The object function is the weighted sum of distance of data from cluster centers. For each cluster, the membership of a data to the cluster is considered as weight for that data. The membership function bounds a data to each cluster. To do that, a membership matrix is formed whose factors are numbers between 0 and 1, and represents the degree of membership of a data to a cluster. The center of a cluster is weighted mean of data. Iteration is continued until optimization between iterations exceeds a threshold. When pixel values are used as input for FCM, the size of data is large. Therefore, FCM becomes time consuming. Fast FCM is proposed to overcome this problem (Yong et al. 2004; Balafar et al. 2010). In this method, the histogram of the image instead of the pixel values is used as input data for clustering. Therefore, the size of the input data roughly decreases and clustering is done more quickly.

Usually, the intensity of input image is used as input for clustering and in noisy images, intensity is not reliable, as a result, this algorithm does not have a good result in noisy images (Balafar 2011a,b; Balafar et al. 2011) and those with in-homogeneity (Hall et al. 1992;

M. A. Balafar (✉)
Department of Computer, Faculty of Engineering, University of Tabriz, Tabriz, East Azerbaijan, Iran
e-mail: balafarila@yahoo.com

Balafar et al. 2010). Many algorithms are introduced to make FCM robust against noise and in homogeneity; but most of them need to be improved (Acton and Mukherjee 2000; Zhang and Chen 2004; Dave 1991; Tolias and Panas 1998; Balafar et al. 2010, 2008a,b).

The Possibilistic C-Means Algorithm (PCM) is proposed by Krishnapuram and Keller (1993) to add possibility to FCM objective function. The authors claim PCM is more robust against noise. Fuzzy-Possibilistic C-Means (FPCM) is introduced by Boudouda (2005) which combines the object function of FCM and PCM to make PCM more robust against noise, overlapping and coincidence. Fuzzy degree is used to assign each pixel to a class in which its membership function value is maximum and possibilistic degree is used for other pixels (Boudouda et al. 2005). FPCM spends more time than FCM to compute more complex object function, fuzzy degree and decision based on that.

FCM initializes its membership function randomly and at different times may give different results. As a result, initialization is other area in which FCM may be improved. The initialization of membership values for FCM is proposed Boudouda et al. (2005). In addition, FCM with initialized cluster centers is proposed by Zou et al. (2008). The sample space is divided into grids and a list of grids with high density is made. From the list, the highest density grid is chosen iteratively. Afterwards, the selected grid and grids with similar properties to selected one are deleted from list. This process is repeated until the list is empty. At last, cluster centers are initialized at the centers of selected grids. Initialization needs time and makes FCM more time consuming.

FCM does not use spatial information in clustering process. Therefore, it is not robust against noise and other imaging artifacts. Many researchers attempted to incorporate spatial information into FCM process (Tolias and Panas 1998; Pham and Prince 1999; Liew et al. 2000; Balafar et al. 2010,a,b). Tolias and Panas (1998) proposed a spatial constraint rule-based system which spatially smoothes membership function to enhance the results of FCM. This method spends more time for membership smoothing. Pham (2002) proposed a modified objective function by incorporating a spatial penalty and named his method robust FCM (RFCM). However, the modified objective function causes complex variation in the membership function (Shen et al. 2005).

Ahmed et al. (2002) proposed other modification for the objective function which allows pixel to be labeled by the influence of its neighborhood labels. Its method is known as FCM_S. FCM_S is less sensitive to noise and in-homogeneity in compare to original FCM but due to using linear neighborhood it may cause blurring. Zhang and Chen (2004) proposed spatially constrained kernelized FCM-SKFCM. They replaced the similarity measurement in the objective function by a kernel-induced distance and incorporated a different penalty term in the objective function which contains spatial neighborhood information. All these methods which modify the objective function, yield computation issues due to modifying most equations along with the modification of the objective function In addition, they cannot use FCM functions which are well-realized with many tools such as MATLAB.

Shen et al. (2005) proposed improved FCM (IFCM) which attempts to overcome blurring problem of FCM_S. IFCM adds neighborhood attraction to the distance of a pixel from a class centre. They used intensity and distance attractions. In both attractions, they take weighted average of neighboring pixels membership. In intensity attraction, they take difference in intensity of considered pixel from each neighbor pixel as a weight for averaging. In distance attraction, they take distance of considered pixel from each neighbor pixel as a weight for averaging.

In each iteration, FCM_S and IFCM spend more time than FCM to compute neighbourhood term for each pixel. Chen and Zhang (2004) proposed two methods, FCM_S1 and

FCM_S2, which are faster. For each pixel, these methods replace the neighborhood term of FCM_S with respected pixel from mean-filtered and median-filtered of input image.

Szilágyi et al. (2003) proposed enhanced fuzzy C-mean (EnFCM) algorithm which is faster than previous algorithms. First, the average image is obtained by applying average filter on input image. Then, a linearly-weighted sum of original image and obtained average image is obtained. In order to speed up the clustering process, the grey level histogram instead of pixel values of the result image is used as input for clustering. The quality of method is comparable to that of FCM_S (Szilágyi et al. 2003) but it is faster.

Chuang et al. (2006) present a method namely FCMSI which incorporates the sum of the memberships at the neighborhood of each pixel into the membership value of that pixel.

However, EnFCM still shares a common challenge in to specify the parameter which controls the trade-off between the original image and the filtered image. The parameter usually is determined by experience or by trial-and-error experiments (Liew et al. 2000; Chen and Zhang 2004; Szilágyi et al. 2003). The parameter is determined globally for the input image, and local information is not considered. Cai et al. (2007) proposed the fast generalized fuzzy C-means (FGFCM) algorithm for fast and robust image segmentation. In FGFCM, a locality parameter replaces the previous global one. Local spatial and grey level relationship automatically is used to determine new parameter.

In Wang et al. (2008), a modified fuzzy C-means (FCM) algorithm for MRI brain image segmentation is presented which incorporates both the local and the non-local neighborhood information into clustering process to increase the robustness of algorithm against noise.

In Karan Sikka et al. (2009), a fully automated brain MR image segmentation algorithm under modified FCM framework is proposed. An entropy driven homomorphic filter is used for in-homogeneity correction. A method namely histogram-based local peak merger using adaptive window is proposed to initialize cluster centers. Image is clustered using a modified fuzzy C-mean (MFCM) method which uses the neighborhood information. After clustering, the membership values of a number of pixels, called ambiguous pixels in the proximity of the boundaries of two clusters, are too close (difference is <0.15). The normal FCM or MFCM classifies such pixels into cluster in which their membership function value are maximum which may lead to misclassification. In order to overcome this problem, a new technique called neighborhood-based membership ambiguity correction (NMAC) is proposed which incorporates spatial information in order to smooth the boundaries between different tissue clusters.

2 Background-spatial based extensions of FCM

2.1 FCM_S

Ahmed et al. proposed FCM_S, a modification to the standard FCM by incorporating neighborhood information in the object function.

$$J_q = \sum_{i=1}^{n}\sum_{j=1}^{m} u_{ij}^{q} d(x_i, \theta_j) + \frac{\alpha}{N_R}\sum_{i=1}^{n}\sum_{j=1}^{m} u_{ij}^{q}\sum_{r\in N_i} d(x_r, \theta_j) \tag{1}$$

where d is distance between data x_i and centre of the cluster j, θ_j and U is the fuzzy membership of data x_i to cluster with centre θ_j. q specifies the degree of fuzziness in the clustering and α is the weight of neighborhood information. N_R is the number of neighbors in a window around x_i, N_i is the set of neighbors and x_r represents the neighbor of x_i.

The membership and centre of clusters are obtained by following equations:

$$U_{ij} = 1/\sum_{k=1}^{m}\left[(d(x_i,\theta_j)^{2^2}\right] + \frac{\alpha}{N_R}\sum_{r\in N_i} d(x_r,\theta_j) \bigg/ \left[\left(d(x_i,\theta_k)^2 + \frac{\alpha}{N_R}\sum_{r\in N_i} d(x_r,\theta_k)^2\right)^{(1/1-1)}\right] \tag{2}$$

$$\theta_j = \sum_{i=1}^{N} U_{ij}^q \left(x_i + \frac{\alpha}{N_R}\sum_{r\in N_i} x_r\right). \tag{3}$$

A shortcoming of FCM_S is that the neighbor term is computed in iteration which is time consuming.

2.2 FCM_S1

In order to overcome FCM-S shortcoming, FCM-S1 is introduced. The neighborhood term is calculated before the clustering process. The mean-filtered of input image is obtained prior to clustering and is used as neighborhood information. The objective function is revised as follow:

$$J_q = \sum_{i=1}^{n}\sum_{j=1}^{m} u_{ij}^q d(x_i,\theta_j) + \alpha \sum_{i=1}^{n}\sum_{j=1}^{m} u_{ij}^q d(\bar{x}_i,\theta_j) \tag{4}$$

where $\bar{x}_i$ is the average of neighbors of pixel x_i. The Equations (2)–(3) are modified as follow:

$$U_{ij} = 1/\sum_{k=1}^{m} [(d(x_i,\theta_j)^2 + \alpha(d(\bar{x}_i,\theta_j)^2]. \quad /[(d(x_i,\theta_k)^2 + \alpha(d(\bar{x}_i,\theta_k)^2])^{(1/1-1)} \tag{5}$$

$$\theta_j = \sum_{i=1}^{N} U_{ij}^q (x_i + \bar{x}_i)/(1+\alpha)\sum_{i=1}^{N} U_{ij}^q. \tag{6}$$

2.3 FCM_EN

In order to speed up the clustering process for the input image, Szilágyi introduced a new extension named FCM_EN. In this extension, instead of using neighborhood information in iteration process, a linearly-weighted sum image of the original image and its average image is used as the input image for clustering. That is:

$$S_i = \frac{1}{1+\beta}(X_i + \beta \bar{X}_i) \tag{7}$$

The β is the weight of neighborhood information. The grey-level histogram of the sum image S is used as input for clustering.

2.4 FGFCM

In order to overcome shortcomings of FCM-EN in adapting the common crucial parameter β, FGFCM is proposed. A parameter S_{ir} is introduced which incorporates both the local spatial information (called Ss_ir) and the local grey-level information (called Sg_ir) as follow:

$$S_{ir} = \left\{ \begin{array}{ll} S_{s\_ir} * S_{g\_ij}, & i \neq r \\ 0, & i = r \end{array} \right\} \tag{8}$$

where rth pixel is a neighbor of pixel x_i. Ss_ir represents the distance of the pixel x_i from neighbor pixels as follows:

$$S_{s\_ir} = \exp\left(\frac{-\max(|x_i - x_r|, |y_i - y_r|)}{\beta_s}\right) \tag{9}$$

where (x_r, y_r) is rth neighbor pixel, β_s is the weight of spatial information. Sg_ir represents the difference between grey-level of pixel x_i from that of its neighbors as follows:

$$S_{g\_ir} = \exp\left(\frac{-||I_i - I_r||^2}{\beta_g * \sigma_i^2}\right) \tag{10}$$

where σ_i is defined as follow:

$$\sigma_i = \sqrt{\frac{\sum_{r \in N_i} ||I_i - I_r||^2}{|N_i|}} \tag{11}$$

where I_i is grey value of the pixel x_i and Ir is that of rth neighbor. The parameter σ_i is the average grey-level difference between the pixel x_i and its neighbor pixels. It represents local grey homogeneity degree. The input image for clustering is generated as follow:

$$x_i = \frac{\sum_{r \in N_i} S_{ir} I_r}{\sum_{r \in N_i} I_r} \tag{12}$$

By replacing new generated image with input of FCM_EN, a fast and robust extension for FCM is introduced.

2.5 Modified FCM based on the local and the non-local neighborhood information

In order to make FCM more robust against noise, the distance measurement is modified as follows:

$$D(x_j, v_i) = \alpha_j d_{\mathrm{nl}}^2(x_j, v_i) + (1 - \alpha_j) d_l^2(x_j, v_i) \tag{13}$$

where d_{l} and d_{nl} are the distance measurement influenced by local and non-local information, α_j is the weighting factor controlling the trade-off between them and η_i is the neighborhood of pixel x_i. The x_i is influenced by a pixel in N_i as much as the pixel is close to the centre pixel. The d_{l} is defined as follow:

$$d_l^2(x_j, v_i) = \frac{\sum_{x_k \in \eta_j} w_l(x_k, x_j) d^2(x_k, v_i)}{\sum_{x_k \in \eta_j} w_l(x_k, x_j)} \tag{14}$$

$\omega_{\mathrm{l}}(x_k, x_j)$ is the weight of each pixel in η_i and defined as

$$w_l(x_k, x_j) = e^{-\frac{|x_k - x_j|}{\delta^2}} \tag{15}$$

Where δ is the variance of pixel values in N_i. The d_{nl} is defined as follow:

$$d_{nl}^2(x_j, v_i) = \sum_{x_k \in I} w_{nl}(x_k, x_j) d^2(x_k, v_i) \tag{16}$$

where $W_{nl}(x_k, x_j)$ is the weight of each pixel in averaging and defined by

$$w_{nl}(x_k, x_j) = \frac{1}{Z(x_j)} e^{-\frac{|v(\eta_k) - v(\eta_j)|}{h^2}} \tag{17}$$

The values of samples in η_i is denoted by $v\ (\eta_i)$, a vector of intensities. The more η_j is similar to η_i, the more pixel x_i is influenced by pixel x_j. The similarity of η_i and η_j is defined by similarity of $v\ (\eta_i)$ and $v\ (\eta_j)$, which is measured by Euclidean distance. $Z(x_j)$ is a normalizing factor and defined as follow:

$$Z(x_j) = \sum_{x_k \in I} e^{-\frac{|v(\eta_i) - v(\eta_j)|}{h^2}} \tag{18}$$

where the parameter h controls the decay of exponential function.

3 Literature review

The reported results and the result of experiments for neighborhood based extensions for FCM are presented. Three main brain tissues are considered which corresponds to grey matter (GM), white matter (WM) and cerebral spinal fluid (CSF). In order to investigate their effectiveness, the results of the algorithms are compared quantitatively.

3.1 Phantom based brain images

In Wang et al. (2008), a modified FCM algorithm which incorporates both the local and the non-local neighborhood information into clustering process (NonlocalFCM) and FCM extensions (FCM_S, FCM_SI, FGFCM) are applied on a simulated T1-weighted normal MRI brain volume in variant noise levels.

Standard FCM and the extensions are applied on a slice of simulated image from Brainweb with 9% noise. The proposed algorithm eliminates the effect of noise, while the competing algorithms cannot do that and their results are affected by the noise.

The effect of neighborhood size on the algorithms performance is investigated. FCMSI, FGFCM and FCMS with larger neighborhood size (5×5) is used, although the noise reducing effect of the algorithms increase, the edge blurring effect of the algorithms especially FCMS are obvious. The proposed algorithm outperforms other algorithms in term of overlap degree. As the neighborhood window size increases, the segmentation performance of FGFCM and FCMS is degraded which may be due to blurring and degrading of image details and fine structures. Also, the proposed algorithm with variant neighborhood and search window sizes is applied on the simulated image volumes. The proposed algorithm even with the larger neighborhood and search window has not blurring effect.

Also, the algorithms are applied on whole image volumes with variant noise levels. Average similarity index for FCM-S, FGFCM, NOnlocalFCM and FCM-SI with variant noise levels are: 3% noise level (0.954, 0.9575, 0.958 and 0.955), 5% noise level (0.938, 0.938, 0.9404 and 0.937), 7% noise level (0.92, 0.915, 0.924 and 0.9) and 9% noise level (0.9, 0.893, 0.914, 0.88). NonlocalFCM, in all noise levels, produces highest similarity indices.

The algorithms present the same performance at low noise level. While, the proposed algorithm significantly outperforms the other competing methods when the level of noise increases.

There are not any reported results for FCM-S1, and FCM-EN. Therefore, these methods are implemented and applied on a simulated T1-weighted normal MRI brain volume in variant noise level. Average similarity index for different methods with variant noise levels (3, 5, 7 and 9%) are: FCM-S1 (0.951, 0.9415, 0.93 and 0.913), FCM-EN (0.941, 0.934, 0.925 and 0.913).

In Shen et al. (2005), FCM, RFCM, and IFCM are applied to the noisy images. In order to evaluate the methods, Incorrect segmentation (*InC*) is used which represents the total percentage of false segmentation. Average similarity index for different methods with variant noise levels (0, 1, 3, 5, 7, 9, 11, 13 and 18%) are: FCM (0.2, 0.4, 0.8, 1, 1.4, 1.6, 1.7, 1.8 and 15.8), RFCM (0.2, 0.4, 0.8, 1, 1.5, 2.7, 14, 14 and 18), and IFCM (0.2, 0.4, 0.8, 1, 1.5, 2.8, 14.2, 14.5 and 18). As the level of noise increases, *InC* for all methods increases. Under 3% noise level, the results for all three methods were close. Above 3% noise, IFCM reduced *InC* significantly and was the most convincing in segmentation. RFCM and FCM exhibit similar results; however, RFCM exhibited more robustness to noise.

Both IFCM and NonlocalFCM use neighbourhood information but they use different definition for non-local neighbourhood. IFCM utilizes grey-level and distance attraction to specify the neighbourhood of a pixel but the other uses the grey level deference between a pixel and its neighbouring pixels to define neighbourhood relation between them. The two mentioned methods are compared with different state-of-art methods. Both methods significantly outperform utilized state-of-art methods at high noise levels.

In Karan Sikka et al. (2009), A fully automated brain MR image segmentation algorithm under modified FCM framework is proposed (improved MFCM). The proposed method is compared with conventional MFCM and Yale University's BioImage Suite (Bioimage suite) which present in FMRIB's Software Library (FSL) (Smith 2004) developed by Oxford University. The methods are applied on simulated brain image volume from BrainWeb with noise levels from 0–9% and inhomogeneity of 0 and 40% for each of studied noise levels. Three indexes: sensitivity (ρ), specificity (σ) (Karan Sikka et al. 2009) and similarity index (τ) (Karan Sikka et al. 2009) are used for quantitative evaluation of competing methods. Between three indexes, similarity index is the most influential one. Quantitative evaluation begins with investigating the effect of post processing with NMAC. The MRI image volume is segmented using the proposed method with and without NMAC post processing. The proposed method with NMAC outperforms without NMAC case.

$\tau = 0.92$ for GM is reported as the result of applying FSL tools on an image with 3% noise and 40% in-homogeneity. The proposed algorithm is applied on the same image. The result is 0.951. In other words, the proposed method outperforms FSL tools for studied image.

In order to consider most of the practically observed cases, the performance of three competing methods over 12 cases with a wide range of image modalities are compared. The proposed method outperforms MFCM in almost all the cases. While FSL tools exceptionally show better performance in terms of ρ values for WM. However, the proposed method outperforms competing methods for more than 70% of the cases.

Improved MFCM uses the neighbourhood information as previous mentioned methods. The method is an extension for MFCM. Like previous mentioned methods, the method evaluated at different noise levels. In addition, it is evaluated at different inhomogeneity levels.

3.2 Real images

In Cai et al. (2007), a fast and robust fuzzy *c*-means clustering algorithm incorporating local information (FGFCM) and FCM extensions (FCM_S1, FCM_S2, EnFCM) are applied on a real *brain MR* slice. The effect of neighborhood size on the algorithms is investigated.

FCM_S1, FCM_S2 and EnFCM heavily blur the segmentation result with increasing neighborhood size to 5*5, while such blurring is not visible in the segmentation result of FGFCM. Also, FGFCM performs better in preserving details. This means FGFCM is more suitable in case more spatial information or larger local window is necessary. Also, the performance of algorithms is compared quantitatively. FGFCM outperforms the competing algorithms.

In Wang et al. (2008), a modified FCM algorithm which incorporates both the local and the non-local neighborhood information into clustering process (NonlocalFCM) and FCM extensions (FCM_S, FCM_SI, FGFCM) are compared. NonlocalFCM is applied on a real T1-weighted normal MRI brain volume (IBSR_18, size of 256 × 256 × 128). The authors reported 5.98 and 81.90% for the average similarities of WM and GM. There are not any reported results for FCM extensions (FCM-S, FCM-S1, FCM-EN and FGFCM). Therefore, these methods are implemented and applied on 20 normal data volumes with T1-weighted sequence. The MRI images are obtained from the IBSR by the Centre for Morphometric Analysis at Massachusetts General Hospital. Average similarity index for different methods are: FCM-S = 0.7517, FCM-S1 = 0.7573, FCM-EN = 0.7581 and FGFCM = 0.7597.

In Shen et al. (2005), applied IFCM on 20 normal volumes. The average similarity index were 0.53 (gray matter) and 0.64 (white matter).

All three methods, FGFCM, NonlocalFCM and IFCM use neighbourhood information. Both NonlocalFCM and IFCM use non-local neighbourhood but with different definition. FGFCM uses local information to balance the effect of pixel value and its neighbourhood in clustering process. The authors claim less blurring and better detail preserving for FGFCM due to incorporating local information. They mention FGFCM is suite for large window size.

4 Conclusion

In this paper a critical review for FCM based brain segmentation is presented. Also, current spatial based extensions for FCM is presented in detail. This paper presents a review of most recent works in this area and contains database, similarity index, and state-of-art methods which different works has been used. Also the results achieved by different works.

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