Fast and Robust Fuzzy C-Means Algorithms for Automated Brain MR Image Segmentation

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INTRODUCTION

By definition, image segmentation represents the partitioning of an image into nonoverlapping, consistent regions, which appear to be homogeneous with respect to some criteria concerning gray level intensity and/or texture.

The fuzzy c-means (FCM) algorithm is one of the most widely used method for data clustering, and probably also for brain image segmentation (Bezdek & Pal., 1991). However, in this latter case, standard FCM is not efficient by itself, as it is unable to deal with that relevant property of images that neighbor pixels are strongly correlated. Ignoring this specificity leads to strong noise sensitivity and several other imaging artifacts.

Recently, several solutions were given to improve the performance of segmentation. Most of them involve using local spatial information: the own gray level of a pixel is not the only information that contributes to its assignment to the chosen cluster. Its neighbors also have their influence while getting a label. Pham and Prince (1999) modified the FCM objective function by including a spatial penalty, enabling the iterative algorithm to estimate spatially smooth membership functions. Ahmed, Yamany, Mohamed, Farag, and Moriarty (2002) introduced a neighborhood averaging additive term into the objective function of FCM, calling the algorithm bias corrected FCM (BCFCM). This approach has its own merits in bias field estimation, but it computes the neighborhood term in every iteration step, giving the algorithm a serious computational load. Moreover, the zero gradient condition at the estimation of the bias term produces a significant amount of misclassifications (Siyal & Yu, 2005). Chuang, Tzeng, Chen, Wu, and Chen (2006) proposed averaging the fuzzy membership function values and reassigning them according to a tradeoff between the original and averaged membership values. This approach can produce accurate clustering if the tradeoff is well adjusted empirically, but it is enormously time consuming. In order to reduce the execution time, Szilágyi, Benyó, Szilágyi, and Adam (2003), and Chen and Zhang (2004) proposed to evaluate the neighborhoods of each pixel as a prefiltering step, and perform FCM afterwards. The averaging and median filters, followed by FCM clustering, are referred to as FCM_S1 and FCM_S2, respectively (Chen & Zhang, 2004). Szilágyi et al. (2003) also pointed out that once having the neighbors evaluated, and thus for each pixel having extracted a one-dimensional feature vector, FCM can be performed on the basis of the gray level histogram, clustering the gray levels instead of the pixels, which significantly reduces the computational load, as the number of gray levels is generally smaller by orders of magnitude. This latter quick approach, combined with an averaging prefilter, is referred to as enhanced FCM (EnFCM) (Cai, Chen, & Zhang, 2007). All BCFCM, FCM_S1, and EnFCM suffer from the presence of a parameter denoted by α, which controls the strength of the averaging effect, balances between the original and averaged image, and whose ideal value unfortunately can be found only experimentally. Another drawback is the fact that averaging and median filtering, besides eliminating salt-and-pepper noises, also blurs relevant edges. Due to these shortcomings, Cai et al. (2007) introduced a new local similarity measure, combining spatial and gray level distances, and applied it as an alternative prefiltering to EnFCM, having this approach named fast generalized FCM (FGFCM). This approach is able to extract local information causing less blur then the averaging or median filter, but still has an experimentally adjusted parameter λ_g, which controls the effect of gray level differences.

Another remarkable approach, proposed by Pham (2003), modifies the objective function of FCM by the means of an edge field, in order to eliminate the filters that produce edge blurring. This method is also significantly time consuming, because the estimation of the edge field, which is performed as an additional step in each iteration, has no analytical solution.

In this article, we propose a novel method for MR brain image segmentation that simultaneously aims high accuracy in image segmentation, low noise sensitivity, and high processing speed.

BACKGROUND

The Standard Fuzzy C-Means Algorithm

The fuzzy c-means algorithm has successful applications in a wide variety of clustering problems. The traditional FCM partitions a set of object data into a number of c clusters based on the minimization of a quadratic objective function. When applied to segment gray level images, FCM clusters the intensity level of all pixels (x_k, $k = 1 \ldots n$), which are scalar values. The objective function to be minimized is:

$$J_{FCM} = \sum_{i=1}^{c} \sum_{k=1}^{n} u_{ik}^{m} (x_k - v_i)^2 \qquad (1)$$

where $m > 1$ is the fuzzyfication parameter, v_i represents the prototype value of cluster i, $u_{ik} \in [0,1]$ is the fuzzy membership function showing the degree to which pixel k belongs to cluster i. According to the definition of fuzzy sets, for any pixel k, we have $\sum_{i=1}^{c} u_{ik} = 1$. The minimization of the objective function is reached by alternately applying the optimization of J_{FCM} over $\{u_{ik}\}$ with v_i fixed, $i = 1 \ldots c$, and the optimization of J_{FCM} over $\{v_i\}$ with u_{ik} fixed, $i = 1 \ldots c$, $k = 1 \ldots n$ (Hathaway, Bezdek, & Hu, 2000). During each cycle, the optimal values are computed from the zero gradient conditions, and obtained as follows:

$$u_{ik}^{*} = \frac{(x_k - v_i)^{-2/(m-1)}}{\sum_{j=1}^{c} (x_k - v_j)^{-2/(m-1)}} \qquad (2)$$

and

$$v_i^{*} = \frac{\sum_{k=1}^{n} u_{ik}^{m} x_k}{\sum_{k=1}^{n} u_{ik}^{m}} \qquad (3)$$

After adequate initialization of centroids v_i, (2) and (3) are applied alternately until the norm of the variation of vector **v** is less than a previously set small value ε. FCM has invaluable merits in making optimal clusters, but in image processing it has severe deficiencies. The most important one is the fact that it fails to take into consideration the position of pixels, which is also relevant information in image segmentation. This drawback led to introduction of spatial constraints into fuzzy clustering.

Fuzzy Clustering Using Spatial Constraints

Ahmed et al. (2002) proposed a modification to the objective function of FCM, in order to allow the labeling of a pixel to be influenced by its immediate neighbors. This neighboring effect acts like a regularizer that biases the solution to a piecewise homogeneous labeling. The objective function of BCFCM is:

$$J_{BCFCM} = \sum_{i=1}^{c} \sum_{k=1}^{n} \left[u_{ik}^{m} (x_k - v_i)^2 + \frac{\alpha}{n_k} \sum_{r \in N_k} u_{ik}^{m} (x_r - v_i)^2 \right] \qquad (4)$$

where x_r represents the gray level of pixels situated in the neighborhood N_k of pixel k, and n_k is the cardinality of N_k. The parameter α controls the intensity of the neighboring effect, and unfortunately its optimal value can be found only experimentally. Having the neighbors computed in every computation cycle, this iterative algorithm performs extremely slowly.

Chen and Zhang (2004) reduced the time complexity of BCFCM, by previously computing the neighboring averaging term or replacing it by a median filtered term, calling these algorithms FCM_S1 and FCM_S2, respectively. These algorithms outperformed BCFCM, at least from the point of view of time complexity.