Applied Soft Computing 34 (2015) 758–769

Contents lists available at ScienceDirect

Applied Soft Computing

journal homepage: www.elsevier.com/locate/asoc

Conditional spatial fuzzy C-means clustering algorithm for segmentation of MRI images

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ARTICLE INFO

Article history:
Received 7 July 2014
Received in revised form 13 April 2015
Accepted 2 May 2015
Available online 11 June 2015

Keywords:
Image segmentation
MRI brain image
Fuzzy C-means
Conditional spatial FCM

ABSTRACT

The fuzzy C-means (FCM) algorithm has got significant importance due to its unsupervised form of learning and more tolerant to variations and noise as compared to other methods in medical image segmentation. In this paper, we propose a conditional spatial fuzzy C-means (csFCM) clustering algorithm to improve the robustness of the conventional FCM algorithm. This is achieved through the incorporation of conditioning effects imposed by an auxiliary (conditional) variable corresponding to each pixel, which describes a level of involvement of the pixel in the constructed clusters, and spatial information into the membership functions. The problem of sensitivity to noise and intensity inhomogeneity in magnetic resonance imaging (MRI) data is effectively reduced by incorporating local and global spatial information into a weighted membership function. The experimental results on four volumes of simulated and one volume of real-patient MRI brain images, each one having 51 images, show that the csFCM algorithm has superior performance in terms of qualitative and quantitative studies such as, cluster validity functions, segmentation accuracy, tissue segmentation accuracy and receiver operating characteristic (ROC) curve on the image segmentation results than the k-means, FCM and some other recently proposed FCM-based algorithms.

1. Introduction

Image segmentation is an important step in medical imaging analysis [1]. The goal of segmentation is to partition an image into a set of disjoint regions that have similar characteristics such as intensity, colour and texture. In medical image segmentation, dissimilar image components are used for analysis of different structures, tissues and pathological regions. However, manual segmentation is a challenging and time consuming task and prone to error. Its success heavily depends on the expertise of the physician and thereby errors occur in the results and also augmented due to the intrinsic nature of the medical images. For example, in magnetic resonance imaging (MRI) brain images, different tissue regions have poorly outlined or blur edges and slender topological structures. This makes the process of MRI brain image segmentation into a challenging task. Moreover, accurate segmentation is also necessary for detecting and analysing the diseased regions in medical images. Therefore, computer aided segmentation is very significant to achieve effective results. For many clinical applications it is a classical problem to segment brain images into different tissue types, such as white matter (WM), grey matter (GM) and cerebrospinal fluid (CSF). A number of algorithms for segmentation of medical images such as, MRI images have been presented in the past. Among them, intensity thresholding, region-based segmentation, edge-based segmentation and classification-based segmentation are the most frequently used techniques [2–4].

In intensity thresholding, the threshold level is automatically determined from the grey-level histogram of the image. The distribution of intensities in medical images, especially in MRI images is usually very complex as stated above, and therefore, thresholding methods fail due to lack of determining optimal threshold. In addition, intensity thresholding methods have disadvantage of spatial uncertainty as the pixel location information is ignored [5]. The edge-based approaches first generate interrupted (scattered) contour lines around an object of interest using some edge detection algorithms. Next, these contour lines are joined based on some similarity criteria to detect the object of region of interest (ROI). However, these methods usually require computationally expensive post-processing to obtain hole free representation of the objects. The region growing methods extend the thresholding by integrating it with connectivity by means of an intensity similarity measure. These methods start with a seed point (pixel) for each region and during the region growing, pixels in the neighbourhood are added to the regions based on homogeneity criteria, resulting connected regions. However, they are sensitive to noise [6] and thus less suitable for medical image segmentation.

In classification-based segmentation method, the fuzzy C-means (FCM) clustering algorithm [7], is more effective with considerable amount of benefits. Unlike hard clustering methods, like k-means algorithm, etc., which assign pixels exclusively to one cluster, the FCM algorithm allows pixels to have relation with multiple clusters with varying degree of memberships and thus more reasonable in real applications. Although the FCM is a very popular unsupervised clustering method, it has some serious drawbacks as it does not consider the image spatial information and is therefore very sensitive to noise and imaging artefacts. It can also generate local optimal solution due to poor initialization. In order to make the FCM algorithm more robust to noise and outliers for image segmentation, many modified fuzzy clustering approaches have been reported in the past [8–21]. Pedrycz [8] introduced a conditional fuzzy C-means-based clustering method guided by an auxiliary or conditional

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http://dx.doi.org/10.1016/j.asoc.2015.05.038
1568-4946/

variable. The method reveals a structure within a family of patterns by considering their vicinity in a feature space along with the similarity of the values assumed by a certain conditional variable. Mohamed et al. [10] modified the FCM algorithm through the incorporation of the spatial information. They introduced the spatial information into the computation of similarity measure. The similarity measure is modified to drag a pixel closer to the cluster centre if it is in homogeneous region. The drawbacks of this algorithm are its sensitivity to the non-descriptive initial centres and its massively computational load. Ahmed et al. [11] introduced the local grey level information by modifying the objective function with another similarity measure for bias field estimation and segmentation of MRI data. This method is also expensive in terms of computational time. Many researchers subsequently modified the objective functions and developed several robust FCM variants for image segmentation [12–19]. These algorithms were shown to have better performance than the standard FCM algorithm. However, some of these methods depend on a fixed spatial factor which needs to be adjusted according to the real applications. In order to overcome the problem of over-smoothed edges, causes due to use of larger spatial window, adaptive selection mechanisms of the spatial parameters have been proposed [20–22]. The performances of these methods are superior and are able to reduce partly the blurring effects, which arise due to use of filtering and larger spatial window. Another major contribution with spatial information into the FCM membership function was suggested by Chuang et al. [23], known as sFCM algorithm. The spatial function is the summation of the membership function in the neighbourhood of each pixel under consideration. It represents the probability for a pixel to belong into a particular cluster. This spatial function is incorporated into a weighted membership function. The advantages of this method are; it yields regions more homogeneous than those of other methods and it removes the noisy spots and partly reduces the spurious blobs.

Recently, Qiu et al. [24] suggested a novel algorithm for fuzzy segmentation by introducing two fuzzifiers and a spatial constraint in the membership function. Benaichouche et al. [25] presented another improvement of the FCM clustering algorithm using particle swarm optimization (PSO) initialization, Mahalanobis distance and post segmentation correction. The first step introduced PSO initialization to overcome the trapping of the solution in local minima, the second step was concerned with the integration of the spatial grey level information and the Mahalanobis distance and the final step refined the segmentation results by reallocating the potentially misclassified pixels. Kannan et al. [26] introduced a class of robust non-Euclidean distance measure for the objective function to enhance the robustness of the original FCM clustering algorithm and to reduce noise and outliers. Liao et al. [27] proposed a fast spatial constrained fuzzy kernel FCM (FKFCM) algorithm for MRI brain image segmentation. The FKFCM algorithm first transforms the pixel intensities into a higher dimensional space using a kernel trick and then performs classification on the transformed data. Selvathi et al. [28] presented a modified version of spatial FCM algorithm for MRI image segmentation. This algorithm first uses wrapping-based curvelet transform to remove any noise in the image and then uses a spatial FCM algorithm to classify the pixels. Adhikari et al. [29] presented a method for MRI brain image segmentation by incorporating intensity inhomogeneity (IIH) and spatial information by using probabilistic FCM algorithm. The method works in two steps. First, it estimates the intensity inhomogeneity by fusing Gaussian surfaces and subsequently generates the IIH-corrected image. In the second step, it classifies the pixels of IIH-corrected image by a probabilistic FCM algorithm.

Most of the methods discussed so far suffer heavily due to presence of noise and another additional multiplicative noise factor called intensity inhomogeneity (IIH) or bias field in the MRI medical images. The IIH usually refers to the slow, non-anatomic intensity variations of the same tissue over the image domain and causes due to imperfection of the image acquisition devices, eddy current, poor magnetic field and patient movement, etc.

In this paper, we propose a conditional and spatial fuzzy C-means (csFCM) clustering algorithm that can effectively segment MRI brain images with the presence of noise and intensity inhomogeneity. Consequently, we have incorporated local spatial interaction among adjacent pixels in the fuzzy membership function in such a way that if the neighbouring pixels share similar characteristics, the centre pixel should have higher probability of grouping to the same cluster as of the neighbouring pixels. We have also introduced conditioning aspect into the clustering mechanism. The algorithm takes into consideration the conditioning variable associated with each pixel, which describes the level of involvement for construction of membership functions and different clusters. This is realized by introducing a weighted membership function.

The remaining part of the paper is organized as follows: Section 2 states the FCM algorithm, the proposed csFCM algorithm is explained in detail in Section 3. Section 4 illustrates the results and discussion of the algorithm with qualitative and quantitative evaluations on MRI data. Finally, a summary and some concluding remarks are given in Section 5.

2. The fuzzy C-means (FCM) algorithm

The fuzzy C-means (FCM) algorithm is a fuzzy clustering method based on the minimization of a quadratic criterion where clusters are represented by their respective centres. The FCM algorithm was proposed by Dunn in 1973 and improved by Bezdek [7] in 1981. For a set of N data patterns $\boldsymbol{X} = \{\boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_N\}$ the algorithm allows to partition the data space, by calculating the centres of classes $\boldsymbol{v}$ and the membership matrix $\boldsymbol{U}$, and by minimizing an objective function J_{fcm} with respect to these centres and membership degrees as follows:

$$J_{fcm} = \sum_{i=1}^{C}\sum_{k=1}^{N}\mu_{ik}^{m}\left\|x_k - v_i\right\|^2 \tag{1}$$

where N is the number of patterns, C is the number of clusters, m is any real number (>1), which controls the fuzziness of the resulting partition, and $m = 2$ is used in this study, μ_{ik} is the degree of fuzzy membership of pixel $\boldsymbol{x}_k$ in the ith cluster, and $||\cdot||$ is any norm expressing the similarity measure.

Typically, the Euclidean distance measure is usually used. The objective function is minimized when the large membership values are assigned to input patterns that are close to their nearest cluster centres and low membership values are assigned when they are far from the cluster centres.

Minimizing the objective function (1) with the following constraint

$$\sum_{i=1}^{C}\mu_{ik} = 1, \quad \text{we have - -}$$

$$\frac{\partial J_{fcm}}{\partial \mu_{ik}} = 0, \quad \text{and} \quad \frac{\partial J_{fcm}}{\partial v_i} = 0 \tag{2}$$

These lead to the following iterative solutions:

$$\boldsymbol{\mu}_{ik} = \frac{1}{\left\|x_k - v_i\right\|^{\frac{2}{m-1}} / \sum_{c=1}^{C}\left\|x_k - v_c\right\|^{\frac{2}{m-1}}} \tag{3}$$

and

$$v_i = \frac{\sum_{k=1}^{N}\boldsymbol{\mu}_{ik}^{m}x_k}{\sum_{k=1}^{N}\boldsymbol{\mu}_{ik}^{m}} \tag{4}$$

Algorithm 1. FCM

Input: set values for the number of clusters C, the degree of fuzziness $m = 2$ and the error ε.

1. Initialize randomly the centres of clusters $\boldsymbol{v}_i^{(0)}$
2. $j = 0$
3. **Repeat**
   a. $j = j + 1$
   b. Calculate the membership matrix $\boldsymbol{U}^{(j)}$ using the centres $\boldsymbol{v}_i^{(j-1)}$ as follows:
   $\boldsymbol{\mu}_{ik} = \frac{1}{\|x_k - v_i\|^{\frac{2}{m-1}} / \sum_{c=1}^{C}\|x_k - v_c\|^{\frac{2}{m-1}}}$
   c. Update the centres $\boldsymbol{v}_i^{(j)}$ using $\boldsymbol{U}^{(j)}$: $v_i = \frac{\sum_{k=1}^{N}\boldsymbol{\mu}_{ik}^{m}x_k}{\sum_{k=1}^{N}\boldsymbol{\mu}_{ik}^{m}}$
4. **Until** $\left\|\boldsymbol{v}_i^{(j)} - \boldsymbol{v}_i^{(j-1)}\right\| < \varepsilon$
5. **Return** the cluster centre $\boldsymbol{v}_i$ and the membership value μ_{ik}; $i = 1, 2, \ldots, C$; $k = 1, 2, \ldots, N$.

3. Conditional spatial fuzzy C-means (csFCM) clustering algorithm

In the present study, the segmentation process is modelled as a classification problem of pixel intensities into different homogeneous regions. In MRI image, neighbouring pixels have strong correlation and usually dependant on each other. The FCM algorithm, where the correlation between the neighbouring pixels is not considered, fails to generate accurate clusters. Thus, we have incorporated local spatial interaction among adjacent pixels in the fuzzy membership function in such a way that if the neighbouring pixels share similar characteristics, the centre pixel should have higher