Abstract

In medical applications all effectual agents in patient health must be fast, even medical algorithms such as clustering ones. This paper aims to introduce a Fast FCM (FFCM) technique to segment brain MRI images. Elapsed time and iteration numbers is decreased efficiently using proposed FCM technique. Furthermore a gaussian function proposed to incorporate spatial information in the algorithm. Experimental results show that gaussian spatial FCM/FFCM (gsFCM/gsFFCM) manage nuisance factors efficiently. Consumed time by FFCM or gsFFCM is approximately half time of FCM or gsCM, nonetheless their qualities are comparable.

1. Introduction

Image Segmentation is the procedure of dividing an image into several homogenous regions. MRI segmentation techniques facilitate in extracting diverse brain tissues such as gray matter (GM), cerebrospinal fluid (CSF) and white matter (WM) popularly.[1]

In the last decades numerous methods were used to segmentation of medical images. Artificial neural networks (ANNs), Self-Organizing Maps (SOM), deformable models and region growing are image segmentation approaches. Among existing methods to medical image segmentation, fuzzy clustering ones have more applications than other segmentation approaches, because they can preserve lot of information about original image using fuzzy membership. [2]. However, in emergency medical applications FCM may not be fast enough to convergence toward solution and it spends much time. This paper presents a Fast FCM approach to image segmentation. Proposed FFCM relatively preserves quality of standard FCM nevertheless is faster in convergence to solution. FCM/FFCM by only one feature such as intensity vector, misclassifies images particularly noisy ones.[3] In order to develop robust FCM/FFCM algorithm, this paper presents a modified gaussian spatial FCM/FFCM (gsFCM/gsFFCM). Proposed gsFCM/gsFFCM provides well management in tissue boundaries, angles and small organs such as tumors compared with spatial FCM (sFCM) [2, 3].

Method

2.1 FCM clustering

FCM clustering, developed in 1970s and optimized later[2,3]. The FCM algorithm is an iterative optimization process that provides the following cost functions:

\[ J_u(V, u) = \sum_{i=1}^{c} \sum_{j=1}^{N} u_{ij}^p \left( \frac{1}{\sum_{k=1}^{c} \left( \frac{d_i(v_j, v_k)^2}{d_i(v_j, v_k)^2 + 

2.2 Fast FCM:FFCM

Standard FCM doesn’t have enough convergence speed especially in emergency situations. To update cluster centers, a hard membership can be assigned to pixels in each iteration step; however, segmentation is a fuzzy process. New approach to update cluster centers in each iteration is presented as follows:

1. For p-dimensional input data, rearrange \( u_{ij} \) to \( d_i \times d_j \) matrix; where \( d_i \), \( d_j \) are input dimensions.
2. Set new fuzzy membership as \( u_{ij}' \) and label matrix as \( L = \{ l_1, \ldots, l_c \} \); where \( L \) is the label matrix of \( c \) clusters in current iteration.
3. Set all data points which correspond to \( L \) label matrix as \( i \).
4. Define \( \text{Def}^* \) for each \( i \)-th cluster by equation 5:

\[ \text{Def}^* = \sum_{k=1}^{c} \frac{u_{ik}}{\text{Def}_{ik}} \]

where \( \text{Def}_{ik} \) is number of data points in \( i \)-th cluster.
5. Update control of \( i \)-th cluster by equation 5:

\[ u_{ij}' = \left( \frac{1}{\sum_{k=1}^{c} \left( \frac{d_i(v_j, v_k)^2}{d_i(v_j, v_k)^2 + \sigma^2} \right)^{1/(p-1)}} \right)^{1/(p-1)} \]

2.3 Gaussian Spatial Fast FCM

Correlation and continuity among neighboring pixels is one of the significant characteristics in the brain MRI image. Therefore spatial information incorporated in FCM by a linear filter[FCM/3]. Use of linear filter in sFCM has disadvantages on tissue boundaries, angles and small organs. In sFCM, one pixel which is anatomically a distinct tissue (for example a tumor or pathological lesion) has less chance to be classified in a unique cluster. In this paper to surmount on these disadvantages a variable weighing factor is reserved to incorporation of spatial information. Proposed spatial feature is based on a nonlinear function which handles gaussian spatial information on FCM/FFCM and denoted as gsFCM/gsFFCM. To exploit the spatial information on FCM/FFCM, the gaussian spatial function is defined as:

\[ x_i^s = \sum_{c} \sum_{j} \frac{1}{2 \sigma^2} e^{-\frac{d_i(v_j, v_k)^2}{2 \sigma^2}} \]

The improved spatial FCM/FFCM by the gaussian parameter with \( p \) and \( q \) are represented as gsFCM\(_p,q\) and gsFFCM\(_p,q.\)

The proposed gsFCM\(_p,q\) can be summarized as follows:

1. Select the number of clusters (\( c \)), fuzziness value (\( m \)), and initialize \( \mu^{(0)} \).
2. Update the membership matrix \( U \) by Eq.(6).
3. Update cluster center matrix \( v_{(i)} \) for gsFCM by Eq.(3) or Eq.(4).
4. Repeat steps 3 and 4 until \( \sum_{i} \sum_{j} u_{ij}^p \leq \epsilon \), where \( \epsilon \) is a small positive constant.

3. Cluster validity functions

Typically two types of fuzzy partition functions are used to evaluate the performance of clustering: partition coefficient \( V_p \) and partition entropy \( V_e \). To evaluate the various functions:

\[ V_p = \frac{\sum_{i=1}^{c} \sum_{j=1}^{N} u_{ij}^p}{\sum_{i=1}^{c} \sum_{j=1}^{N} u_{ij}^p} \]

\[ V_e = \left( -\frac{1}{\sum_{i=1}^{c} \sum_{j=1}^{N}} u_{ij}^p \log(u_{ij}) \right) \]

4. Result and discussion

To verify the effectiveness of the FCMC, gsFCM, and gsFFCM, techniques, experiments evaluated on both synthetic and real brain MRI images. Experimental results show that proposed FFCM and gsFFCM techniques by new rule, updates cluster centers efficiently. Images in the experiments are corrupted by additive gaussian noise therefore they are segmented by FCM, gsCM and gsCM techniques.

Moreover elapsed time and iteration numbers by presented FCMC/gsFFCM techniques were decreased significantly in comparison with FCM/gsCM techniques. Both FCM and gsFFCM elapsed time and iteration numbers are less than FCM and gsCM. In Fig 4 and Fig 5 simulation time and number of iteration steps of FCM techniques are represented respectively.

5. Conclusion

Standard FCM may not have required convergence gradient especially in emergency situations. Hence this paper proposed a Fast FCM technique. By the new approach, time and iteration numbers relatively decreased to half of FCM. Synthetic and real clinical MRI images were used in the experiments to evaluate the techniques. Furthermore a gaussian spatial function was adopted to incorporate spatial information in FCM/FFCM, then gsFCM / gsFFCM techniques were proposed which efficiently reduced the noise effects in segmented image. Also tissue boundaries and angles were well distinguished by proposed approaches. The optimum performance of the proposed FCM, gsCM and gsCM techniques were evaluated by quantitative validity functions.

References: