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An Effective K-L Information Based Hyper Tangent Fuzzy C-Means For Segmenting Brain Magnetic Resonance Images

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Abstract

This paper introduces effective fuzzy clustering algorithm, which is based on the concepts of K-L (Kullback-Leibler) information and hyper tangent induced distance measure. In this work, we try to give the solutions for the problems in brain medical images such as partial volume effect and heavy noise using effective K-L information based FCM. The partial volume effect in brain image heavily affects the detection of the intracranial boundary and also blurs the intensity distinction between tissue classes at the border of the two tissues. To avoid the deterioration of image quality, it is necessary to reduce the partial volume effect, heavy noise and outliers in brain MRI. Thus, the novel effective K-L information based FCM is proposed in this paper to deal the above problems in segmenting brain MRI. In order to prove the effectiveness of proposed method, the simulated brain images are executed by the existed and proposed methods. Silhouette method cluster validity method is used to measure segmentation accuracy of the methods.

Keywords: Fuzzy clustering, brain MRI, Image segmentation, Cluster validity, hyper tangent function

Introduction

Image segmentation [1, 6, 20, 21] is an essential step in image analysis. It is a partition of the image into set of non-overlapping regions based on some attributes like intensity, color or texture etc. Image segmentation can be used for different tasks like navigation of robots, extracting malign tissues from body scans, detection of cancerous cells, and identification of an airport from remote sensing data. Clustering algorithm is one of the techniques used in image segmentation. Clustering algorithms are classified as hard clustering, K-means clustering and soft clustering or fuzzy clustering. Fuzzy clustering techniques [23] classify pixels with great extent of accuracy and it is basically suitable for decision oriented applications like tissue classification & tumor detection etc. Fuzzy clustering algorithms include FCM (fuzzy C means) algorithm, GK (Gustafson-Kessel), GMD (Gaussian mixture decomposition), FCV (Fuzzy C varieties), and etc. One of the most commonly used algorithms is FCM [5, 18, 19] algorithm since it can preserve much more information from the image itself than other approaches. FCM assigns pixels to each class by means of membership function. But in case of noisy images it does not take into account the spatial information, which makes it sensitive to noise and other image artifacts. In this work, we try to deal the problems in brain medical images such as partial volume effect and heavy noise using novel K-L information [8] based FCM. The partial volume effect in brain image heavily affects the detection of the intracranial boundary and also blurs the intensity distinction between tissue classes at the border of the two tissues. To avoid the deterioration of image quality, it is necessary to reduce the partial volume effect, heavy noise and outliers in brain MRI [12].

In order to overcome the outlier points and partial volume effect in complex datasets, several K-L FCM techniques had been proposed in this literature. Hidetomo Ichihashi [7] proposed the new FCM algorithm based on the Mahalanobis distance with the entropy regularization. This algorithm same as the EM algorithm, it can be derived from a modified FCM with regularization by K-L information. Hidetomo Ichihashi [8] extended K-L information based FCM algorithm. In addition, this method includes Gustafson and Kessel's constraint for giving valid results for noisy data. In order to improve the partition with a flexible cluster shape in the original input data space, Hidetomo Ichihashi [9] has developed a Kernelized K-L information based FCM algorithm. Nuno Vasconcelos [17] has proposed single Gaussian K-L kernel approach that replaces the standard SVM kernels for having the best performance in speaker verification and the method is mostly outperforming than the Fisher kernel based SVM's. The information theoretic model based on K-L information has been proposed by Kenneth et al [15] for analyzing the ecological data.

However, the previous extensions of FCM and EFCM have not endeavor many problems like heavy noise and outlier as much as in medical image applications. Especially, they are not enough robust to outliers and noise in the environment of complex brain medical images. In order to overcome the drawbacks of the existed algorithm, this paper concerns on developing the effective novel K-L information based FCM for segmentation of brain MRI which is affected by heavy noise, outliers and partial volume effects.

This paper is organized as follows: Section 2 gives basic idea about the paper. In section 3, the new effective K-L information based FCM method is proposed and the effectiveness of proposed method is proved in section 4 through experimental study. Section 5 concludes the work.

Basics

A. Fuzzy C- Means algorithm

Fuzzy C-means [10, 11] is an effective clustering algorithm for fuzzy clustering. Fuzzy clustering algorithm developed by Dunn [4] in 1973 and later extended by Bezdek in 1981 [2]. It is based on minimization of the following objective function [3]:

$$J = \sum_{i=1}^{N} \sum_{k=1}^{K} m_{ik}^{f} \|x_i - c_k\|^2, 1 \leq f < \infty \tag{1}$$

Where f is any real number greater than 1, m_{ik} is the degree of membership of x_i in the cluster k, x_i is the i^{th} of d – dimensional measured data, c_k is the d – dimension center of the cluster and $\|x_i - c_k\|^2$is the Euclidean distance expressing the similarity between any measured data and the center. Fuzzy partitioning is carried out through an iterative optimization of the objective function shown above, with the update of membership m_{ik} and the cluster c_k by

$$m_{ik} = \frac{1}{\sum_{k=1}^{K} \left[\frac{\|x_i - c_k\|}{\|x_i - c_j\|}\right]^{2/f-1}} \tag{2}$$

$$c_k = \frac{\sum_{i=1}^{m} x_i m_{ik}^{f}}{\sum_{i=1}^{m} m_{ik}^{f}} \tag{3}$$

This iteration will stop when $max_{ij}\left\{\left|m_{ik}^{(t+1)} - m_{ik}^{(k)}\right|\right\} < \varepsilon$ where ε is a termination criterion between 0 and 1 whereas t is the iteration steps. This procedure converges to a local minimum or a saddle point of J. Though it works well on noise free data, FCM fails to segment images corrupted by noise, outliers and other imaging artifacts mainly due to disregard of spatial contextual information in image.

B. K-L information

Kullback-Leibler (K-L) information is a measure of distance between two distributions of a random variable. The K-L information in U relative to P (which is also referred to as the cross entropy of U relative to P) is defined in the discrete case by

$$KL(M, P) = \sum_{i=1}^{N} \sum_{k=1}^{K} m_{ik} \log\left(\frac{m_{ik}}{p_k}\right) \tag{4}$$

K-L information measure is constructed using two distributions m_{ik} and p_k. It is a measurement commonly associated with information theoretic settings, where m_{ik} represents the membership of given dataset and p_k represents an approximation of m_{ik}.

C. Kernel Induced distance Function

Let the nonlinear transformation function $\emptyset: X \rightarrow F$ maps the data into a high dimensional feature space F. A kernel [22, 24] in feature space can be represented as $K(x, y) = \langle \emptyset(x), \emptyset(y) \rangle$

Hence, the kernelized distance measure between two patterns x and y is given by

$$\|\emptyset(x) - \emptyset(y)\|^2 = \left(\emptyset(x) - \emptyset(y)\right)^T \left(\emptyset(x) - \emptyset(y)\right) \tag{5}$$

$$\|\emptyset(x) - \emptyset(y)\|^2 = K(x, x) - 2K(x, y) + K(y, y) \tag{6}$$

Suppose *K(x,x)=1, K(y,y)=1*the above relation reduced to

$$\|\emptyset(x) - \emptyset(y)\|^2 = 2(1 - K(x, y)) \tag{7}$$

K-L Information Based Hyper tangent Fuzzy C-Means [KLHFCM]

In this section, we propose modified K-L information based FCM algorithm that reducing the heavy noise and partial volume effect. Thus, the proposed objective function J_{KLHFCM} is given as follows.

$$J_{KLHFCM}(M, C) = 2\sum_{i=1}^{N}\sum_{k=1}^{K} m_{ik}^{f}\left[1 - H(y_i, c_k)\right] + \frac{N}{\varepsilon}\sum_{i=1}^{N}\sum_{k=1}^{K} m_{ik}\, log\frac{m_{ik}}{p_k} \tag{8}$$

The eq. (8) is minimized subject to the constraints

$$\sum_{k=1}^{K} m_{ik} = 1, \forall i \tag{9}$$

$$\sum_{k=1}^{K} p_k = 1 \tag{10}$$

A. Membership evaluation

To obtain the membership grade, the objective function (8) is minimized by using the Lagrange multiplier method. The Lagrangian function of eq. (8) is

$$L_{KLHFCM}(M, C) = 2\sum_{i=1}^{N}\sum_{k=1}^{K} m_{ik}\left[1 - H(y_i, c_k)\right] + \frac{2N}{\varepsilon}\sum_{i=1}^{N}\sum_{k=1}^{K} m_{ik}\, log\frac{m_{ik}}{p_k} - \sum_{i=1}^{N}\alpha_i\left(\sum_{k=1}^{K} m_{ik} - 1\right) - \delta\left[\sum_{k=1}^{K} p_k - 1\right] \tag{11}$$

$$\frac{\partial L}{\partial m_{ik}} = 2\left[1 - H(y_i, c_k)\right] + 2\frac{N}{\varepsilon}\left[m_{ik} \times \frac{p_k}{m_{ik}} \times \frac{1}{p_k} + log\frac{m_{ik}}{p_k}\right] - \alpha_i = 0 \tag{12}$$

$$\left[1 - H(y_i, c_k)\right] + \frac{N}{\varepsilon}\left[1 + log\frac{m_{ik}}{p_k}\right] = \alpha_i \tag{13}$$

$$m_{ik} = p_k exp\left(\left[\alpha_i - \left[1 - H(y_i, c_k)\right]\right]\frac{\varepsilon}{N} - 1\right) \tag{14}$$

$$m_{ik} = p_k exp\left(\frac{\varepsilon}{N}\alpha_i - 1\right) exp\left(-\frac{\varepsilon}{N}\left[1 - H(y_i, c_k)\right]\right) \tag{15}$$

Since $\sum_{k=1}^{K} m_{ik} = 1$,

$$exp\left(\frac{\varepsilon}{N}\alpha_i - 1\right) = \frac{1}{\sum_{k-1}^{K} p_k exp\left(-\frac{\varepsilon}{N}\left[1 - H(y_i, c_k)\right]\right)} \tag{16}$$

Substituting (16) in (15) the zero-gradient condition for the membership grade estimator can be given as

$$m_{ik} = \frac{p_k exp\left(-\frac{\varepsilon}{N}[1-H(y_i,c_k)]\right)}{\sum_{k-1}^{K} p_k exp\left(-\frac{\varepsilon}{N}[1-H(y_i,c_k)]\right)} \quad (17)$$

B. Cluster center updating

Differentiating (8) partially with respect to c_k

$$\frac{\partial J}{\partial c_k} = 2\sum_{i=1}^{N} sech^2\left(-\frac{\|y_i-c_k\|^2}{\delta^2}\right)\left(-2\frac{y_i-c_k}{\delta^2}\right) \quad (18)$$

Simplifying this equation, we will get updating cluster center equation as

$$c_k = \frac{\sum_{i=1}^{N} m_{ik}^{f}\left[H(y_i,c_k)T(y_i,c_k)\frac{1}{\delta^2}\right]y_i}{\sum_{i=1}^{N} m_{ik}^{f}\left[H(y_i,c_k)T(y_i,c_k)\frac{1}{\delta^2}\right]} \quad (19)$$

where $T(y_i, c_k) = 1 + \tanh\left(-\frac{\|y_i-c_k\|^2}{\delta^2}\right)$

C. Estimation of p_k value

$$\frac{\partial L}{\partial p_k} = \frac{2N}{\in}\sum_{i=1}^{N} m_{ik}\frac{p_k}{m_{ik}} \times \frac{-m_{ik}}{{p_k}^2} - \delta = 0 \quad (20)$$

$$\frac{1}{p_k}\sum_{i=1}^{N} m_{ik} = \frac{\in\delta}{2N} \quad (21)$$

Since $\sum_{k=1}^{K} p_k = 1$

$$p_k = \frac{\sum_{i=1}^{N} m_{ik}}{\sum_{i=1}^{N}\sum_{k=1}^{K} m_{ik}} \quad (22)$$

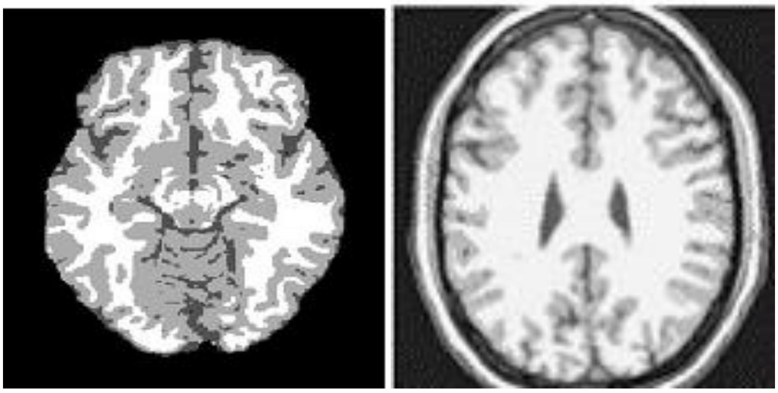
The value of p_k indicates the volume or ratio of the data in the k^{th} fuzzy cluster.

Experimental Work

This section presents the simulated brain MRI experiments and evaluation of the experimental results. Based on the experiment settings, the results of simulated brain MRI image segmentation using our proposed methods and existed methods are obtained. For experimental purpose two simulated brain MRIs are used in this section. The simulated brain MRI images were obtained using 3T Siemens Trio scanner. The first image consists of 640x400 and the total number of image pixels is 256000 with resolution of each pixel 1x1mm^2, and Axial 2D (TR/TE:1830ms/4.43ms) using a fast magnetization prepared rapid acquisition gradient echo pulse sequence. This testing image is contaminated with 9% of Gaussian noise and 3% of spatial inhomogeneity. And the second simulated brain slice consists of 640x400 pixels and the total number of image pixels is 256000 and pixel size is 1x1mm^2, *TR*/*TE* = 30/8.9 ms. They are dirtied with 10% of Gaussian noise.

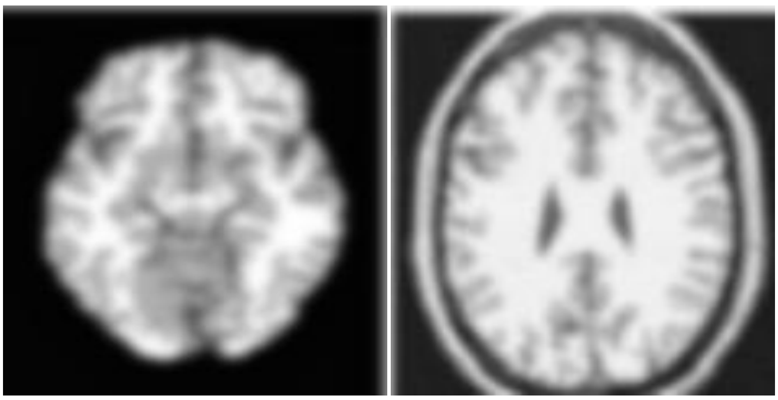
This section describes some experimental results to compare the segmentation performance of the following algorithms, Fuzzy C-Means (FCM), Kernelized Fuzzy

C-Means (KFCM) [25], Fuzzy C-Means Entropy Regularization Maximization (FCMERM) [16], and proposed method. Figs. 3-6 (*a*-*b*) show the segmentation results of existed methods and proposed method. As shown in Figs. 3-5 (*a*-*b*), existed methods fail to reduce the Gaussian noise from corrupted images, while our proposed method succeeded well in correcting and classifying the data as shown in Fig. 4(*a*-*b*). From the images, we can see that FCM is affected by the noise badly, while proposed method almost eliminates all the effect of noises.



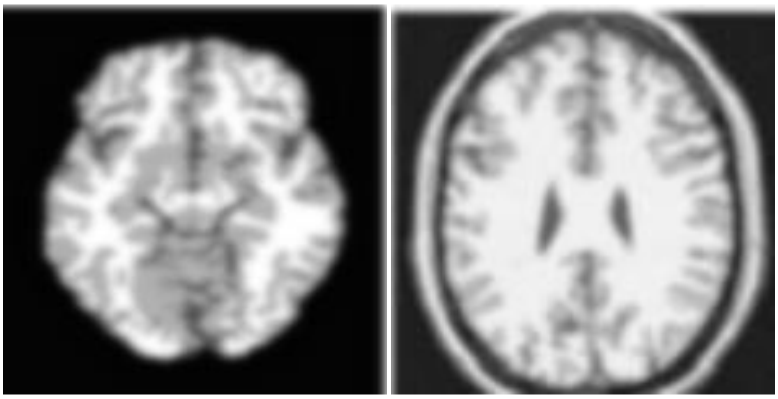
(a) (b)

Figure 1: (a) Simulated brain Image-1 (b) Simulated brain Image-2



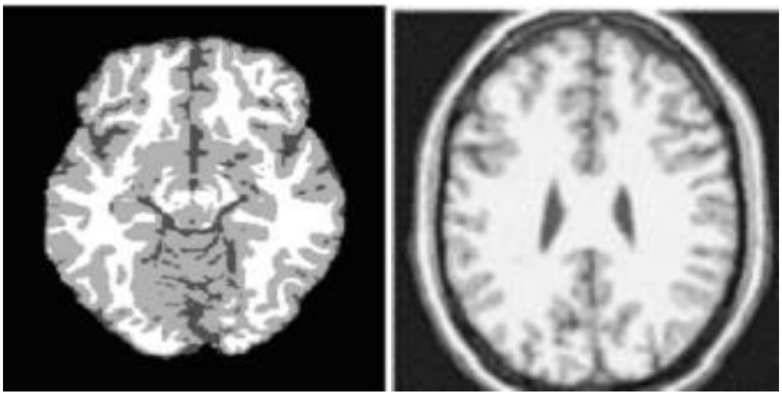
(a) (b)

Figure 2: (a) Corrupted Image-1 (b) Corrupted Image-2



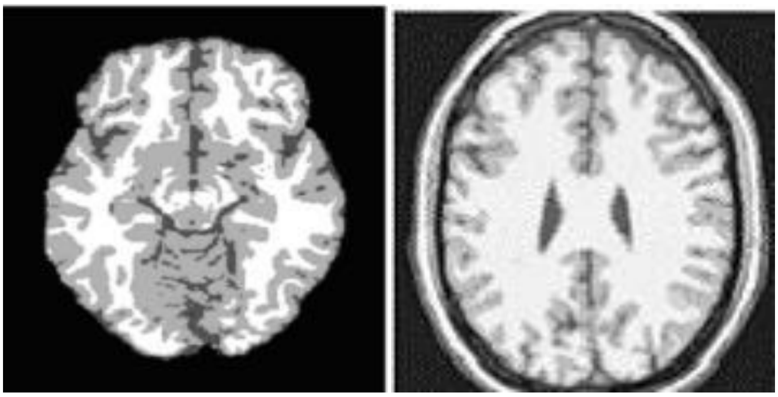
(a) (b)

Figure 3: (a) Segmented Image-1 by FCM (b) Segmented Image-2 by FCM



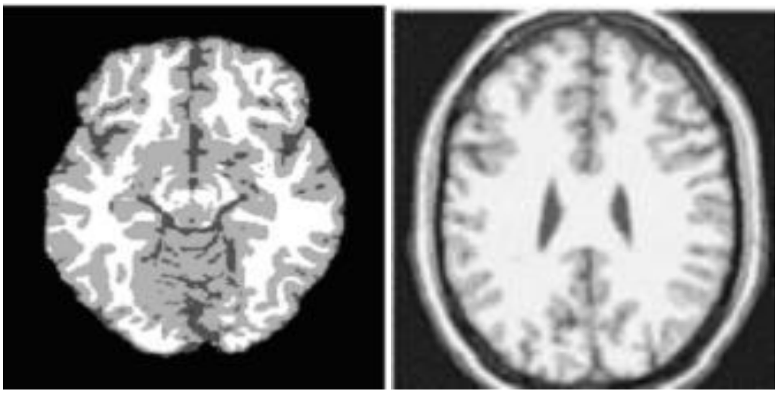
(a) (b)

Figure 4: (a) Segmented Image-1 by KFCM (b) Segmented Image-2 by KFCM



(a) (b)

Figure 5: (a) Segmented Image-1 by FCMERM (b) Segmented Image-2 by FCMERM



(a) (b)

Figure 6: (a) Segmented Image-1 by KLHFCM (b) Segmented Image-2 by KLHFCM

Table 1 gives the segmentation accuracy of the four algorithms on two different noisy training images, where segmentation accuracy is defined using silhouette value in (S R Kannan [13, 14]). These silhouette average values measure the degree of confidence in the clustering assignment of a particular observation, with well-clustered observations having values near 1 and poorly clustered observations having values near -1.

Table 1: Segmentation accuracies for simulated brain MRIs

Name of Algorithms	Silhouette Accuracy
FCM	54%
KFCM	67%
FCMERM	77%
KLHFCM	89%

From Table 1, the best clustering validity 89% was obtained by proposed method KLHFCM during the experimental work on brain image data. It is clear from Fig. 6(*a-b*) that our proposed method KLHFCM has completely succeeded in correcting and classifying the brain data and almost the method has eliminated completely the effect of noise in images. From the above given resulted images, the proposed method is superior to those obtained by using existed algorithm.

Conclusion

In this work, we introduced effective Fuzzy C-Means method by incorporating the concept of concepts of K-L information term and Hyper tangent function for segmenting brain MRIs. The new optimal method was used to deal partial volume effect and heavy noise presented in brain MRIs. In order to prove the effectiveness of proposed method, the existed and proposed methods were executed on two simulated brain MRIs. Comparative analysis was carried out both visually and quantitatively.

Segmentation accuracy was measured by Silhouette cluster validity method. From the comparative analysis, it was shown that our proposed method is promising technique for segmentation of not only brain MRI but all medical images and for finding meaningful structure in complex data also.

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