Brain MRI Segmentation for Lesion Detection Using Clustering with Fire-Fly Algorithm

Pramita Manna and Tapas Si

Abstract This paper presents brain MRI segmentation for lesion detection using fire-fly based hard-clustering algorithm. First, MR images are denoised using median filter and denoised images are segmented using fire-fly based clustering algorithm. After segmentation, lesioned regions are extracted from segmented MR images. The performance of the proposed method is evaluated using quantitative measurement index. A comparative study is made with *k*-means and Fuzzy c-means algorithms. The experiment results demonstrate that the proposed method performs better than other two methods.

Keywords Magnetic resonance imaging · Brain · Lesion · Clustering · Fire-fly algorithm · Segmentation

1 Introduction

Multimodal Magnetic Resonance Image (MRI) [1, 2] of brain segmentation is an important medical image processing tasks for disease diagnosis. Lesion in brain's MRI detection is very much important for the diagnosis as well as treatment of the patients. There are several types modalities in MRI such as T1-weighted (T1W1), T2-weighted (T2W2), proton density weighted, Fluid Attenuated Inversion Recovery (FLAIR) etc. [1]. In brain's MRI, there are several objects like white matter, gray matter, Cerebral Spinal Fluid(CSF), bone, scalp, background, and lesions (if present) [3]. So, many research contributions are given in lesion detection

P. Manna (✉) · T. Si
Department of Computer Science and Engineering, Bankura Unnayani Institute of Engineering, Bankura, West Bengal, India
e-mail: mannapramita@gmail.com
URL: http://www.buie.ac.in

T. Si
e-mail: c2.tapas@gmail.com

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during past several years. Sindhumol et al. [4] presented Multi Signal Wevelet Independent Component Analysis (MW-ICA) that is applied on Automated Brain Tissue Classification. El-Sayed et al. [5] proposed a hybrid intelligent machine learning technique for computer-aided detection system for automatic brain tumor detection using MR images. Fuzzy automatic and accurate method is suggested by Harati et al. [6] for tumor segmentation in brain images that is improved by fuzzy connectedness algorithm. Brain MRI segmentation technique based on Fuzzy C-Means (FCM) clustering algorithm proposed by Shen et al. [7] using Neighborhood attraction with neural network optimization. Hall et al. [8] segmented brain MR images using an ANN and the performance is compared with FCM. Li et al. [9] presented a knowledge-based classification and tissue labeling approach to segment magnetic resonance images brain using FCM algorithm. Si et al. [10] proposed Grammatical Swarm based clustering algorithm for detection of tumors in brain MRI. Sivaramakrishnan et al. [11] proposed an intelligent system designed to diagnose tumor through mammograms, using image processing techniques along with intelligent optimization tools, such as Fire-Fly Algorithm (FFA), Enhanced BEE Colony Optimization (EBCO), and Artificial Neural Network. In article [12], clustering and classification based approaches are applied for identifying tumor in brain's MRI. The main objective of this paper is to apply Fire-fly algorithm [13] based hard-clustering [14] technique for lesion detection in brain's MRI.

2 Materials and Methods

In this paper, a new segmentation method using Fire-fly algorithm based clustering technique for lesion detection in brain MRI is proposed. The flowchart of the proposed method is given in Fig. 1.

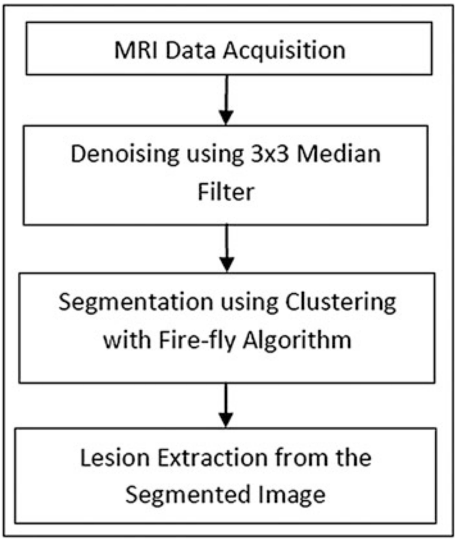
2.1 MRI Data Acquisition

Two Axial T2 MRI images of human brain have been used for application. All the images are generated by 1.5-T GE Medical MR imaging machine. The slice thickness is 5.0 mm, the gap between two slices is 1.5 mm. Each MR image has a resolution of 256 × 256.

2.2 Denoising

Segmentation process faces difficulties due to presence of noise in the images and the noises are removed from images using median filter having neighborhood size

Fig. 1 Flowchart of the proposed method



3×3. The median is calculated by first sorting all the pixel values from the window (pattern of neighbors) into numerical order, and then replacing the pixel being considered with the middle (median) pixel value.

2.3 *Segmentation Using Clustering with Fire-Fly Algorithm*

Clustering is a unsupervised learning method used to partition the data into groups or clusters [15]. *k*-means algorithm [16] is a well-known hard-clustering algorithm to partition the data into K number of clusters. Let $y_i = (y_{i1}, y_{i2}, \ldots, y_{in})$ is the *i*th features in data set having $\mathcal{N}$ number of data. In *k*-means algorithm, the initial cluster centers are randomly selected from the data set itself and the Euclidean distance of *i*th data point from the kth centers are calculated using the following equation:

$$\mathcal{D}_{\mathrm{ik}} = d(\mathrm{y}_i, \mathrm{m}_k) = \left[\sum_{i=1}^{d} (y_{il} - m_{\mathrm{kl}})^2\right]^{\frac{1}{2}} \tag{1}$$

The data are then assigned to the closest cluster using following equation:

$$k = \arg \min_{\forall k \in \mathcal{K}} (\mathcal{D}_{ik}) \tag{2}$$

where κ is the number of clusters in the data set.

The objective function of k-means algorithm is defined as following:

$$J = \sum_{k=1}^{\mathcal{K}} \sum_{y_i \in \boldsymbol{c}_k} \| y_i - m_{\mathrm{k}} \|^2 \tag{3}$$

The major drawback of k-means algorithm is that it gets stuck in the local optima due to selection of the initial cluster's centers from the data itself. These drawback is overcome By using evolutionary algorithm [15] and Swarm Intelligent algorithms like Particle Swarm Optimizer [17], Fire-fly algorithm [14] in hard-clustering technique. In this work, Fire-fly based hard-clustering technique is used to segment the MR images. The Fire-fly algorithm is a nature inspired technique. Flashing light of fireflies is important to communicate (attract) their partner. Flashes are unique for a specific species. Females are attracted by male (individual) of same species. Light intensity (I) at a fixed distance (r) follows the inverse square law that means $I \propto \frac{1}{r^2}$. Fire-fly algorithm follows three rules: (a) All fireflies are unisex and they are attracted to each other by their sex. (b) Attractiveness is proportional to the brightness. Less brighter fire-fly moves toward the more brighter fire-fly one. Fire-fly will move randomly if there is no brighter fire-fly than itself (c) Brightness of a fire-fly is measured by the objective function. The distance between ith and jth fireflies at x_i and x_j respectively, is the Euclidean distance

$$r_{ij} = \| x_i - x_j \| = \sqrt{\sum_{k=1}^{d} \left(x_{ik} - x_{jk}\right)^2} \tag{4}$$

where x_{ik} is the kth component of position x_i of ith fire-fly. The movement of a fire-fly i is attracted to another more brighter fire-fly j is measured by

$$x_i = x_i + \beta_0 e^{-\gamma r_{ij}^2} \left(x_j - x_i\right) + \alpha \left(\text{rand} - \frac{1}{2} \right) \tag{5}$$

$$\beta(r) = \beta_0 e^{-\gamma r^2} \tag{6}$$

β_0 is the attractiveness at $r = 0$ and is the light absorption coefficient.

The complete Fire-fly algorithm is given in Table 1.

Fire-fly based Clustering Algorithm (CFA) Each fire-fly $\boldsymbol{x_i}$ is constructed as $x_i = (m_{i1}, \ldots, m_{ij}, \ldots, m_{iNc})$ where $\boldsymbol{m_{ij}}$ indicates to the jth cluster center of the ith fire-fly. This paper adopted fitness function from the article [17] which is comprised of three different objective functions to achieve better clustering solutions and it is defined as following:

$$f(x_i, y_i) = w_1 \cdot \bar{d}_{\max}(y_i, x_i) + w_2 \cdot (y_{\max} - d_{\min}(x_i)) + w_3 \cdot Q_{ei} \tag{7}$$

Table 1 Fire-fly algorithm

Fire-fly algorithm
1. Objective function $f(x)$, $x = (x_1, x_2, \ldots, x_d)^T$
2. Generate initial population of fire flies x_i, ($i = 1, 2, \ldots, n$)
3. Light intensity I_i at x_i is determined by f(x_i)
4. light absorption coefficient γ
5. While (t <= Max Generation)
6. for $i = 1{:}n$
7. for $j = 1{:}n$
8. if ($I_j > I_i$), move fireflies i towards j in D-dimension, end if
9. Attractiveness varies with distance r via exp[$-r$]
10. Evaluate new solutions and update light intensity
11. end for j
12. end for i
13. Find the current best
14. end while

where $y_{\max}$ is maximum pixel value (i.e., 255) in the image set. y_i is a matrix representing assignment of pixels to clusters of ith Fire-fly. Here, w_1, w_2, and w_3 are user defined constants. Also, maximum average is defined by the following equation:

$$\bar{d}_{\max}(y_i, x_i) = \max_{j=1,\ldots,Nc} \sum_{\forall y_p \in c_{ij}} d\left(y_p, m_{ij}\right) / \left|c_{ij}\right| \tag{8}$$

where $\left|c_{ij}\right|$ is the cardinality of the set c_{ij}.

The minimum inter-cluster distance is calculated by the following equation:

$$d_{\min}(x_i) = \min_{l_1, l_2, l_1 \neq l_2} d(m_{il_1}, m_{il_2}) \tag{9}$$

The Quantization error Q_e is defined by following equation:

$$Q_e = \frac{1}{Nc} \left\{ \sum_{j=1}^{Nc} \sum_{\forall y_p \in c_j} d\left(y_p, m_j\right) / \left|c_j\right| \right\} \tag{10}$$

The euclidean distance $d\left(y_p, m_j\right)$ is calculated as following:

$$d\left(y_p, m_j\right) = \sqrt{\sum_{k=1}^{n_b} \left(y_{pk} - m_{jk}\right)^2} \tag{11}$$

2.4 Performance Measurement

Davies–Bouldin (DB) Index: The Davies–Bouldin (DB) Index [18] is the ratio of sum of within-cluster distance to between-cluster separation and it is calculated by the following equation:

$$\mathrm{DB} = \frac{1}{\mathcal{K}} \sum_{i=1}^{\mathcal{K}} \max_{\substack{i \neq j \\ 1 \leq i,j \leq \mathcal{K}}} \left\{ \frac{S(m_i) + S(m_j)}{d(m_i + m_j)} \right\} \tag{12}$$

The DB Index minimizes the within-cluster distance $S(m_i)$ and maximizes the between-cluster separation $d(m_i, m_j)$. For a given image and κ value, low DB Index indicates better clustering.

2.5 Parameter Settings

The parameters of CFA are set as following: number of cluster (κ) = 4, population size (NP) = 50, $X_{\max} = 255$, $X_{\min} = 0$, $\alpha = \beta = \gamma = 1$, $w_1 = w_2 = w_3 = 0.33$, maximum number of iterations = 100. Total number of function evaluations = 5000. In k-means and FCM, the maximum number of function evaluations is set to 5000 to make a fair comparison with CFA.

3 Results and Discussion

The proposed method is applied on two Axial T2 MR images given in Fig. 2(a), (c). The original MR images contain noise and the noise is removed by the median filter and the denoised images are given in Fig. 2(b), (d) respectively. After denoising, the Fire-fly based clustering algorithm is used to segment the images and the segmented images are given in Fig. 3. Finally, the lesions are extracted from the segmented images and the lesions are given in Fig. 4. The quantitative performance of the CFA, k-Means and FCM methods are measured using DB Index. The lower

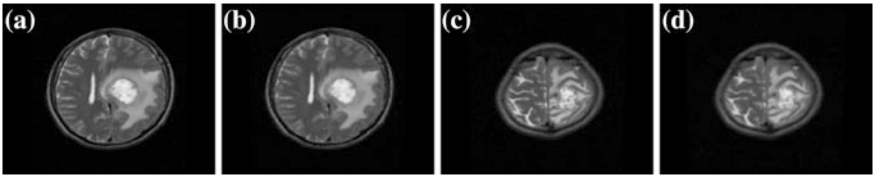


Fig. 2 Original MR images (**a**, **c**) and their denoised versions (**b**, **d**)

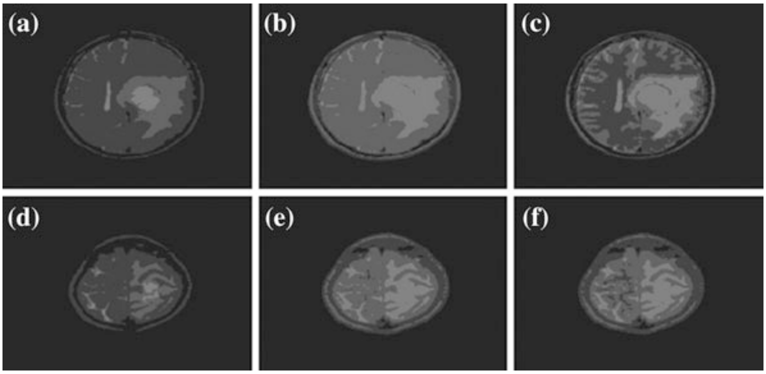


Fig. 3 Segmented MR images. *1st column* CFA, *2nd column* *k*-means, *3rd column* FCM

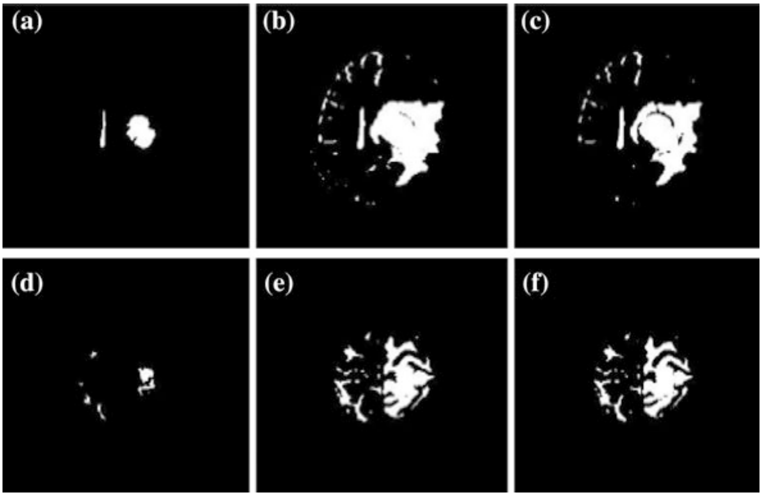


Fig. 4 Extracted lesions from segmented MR images. *1st column* CFA, *2nd column* *k*-means, *3rd column* FCM

DB-Index value indicates the good performance. The mean and standard deviation of DB-Index values over 30 independent runs are 0.1346(±0.0218), 0.1364 (±0.0112) and 0.1548(±0.0100) for CFA, *k*-means and FCM respectively for Fig. 2(b) whereas 0.1317(±0.0219), 0.1375(±0.0005) and 0.1405(±4.74e−08) are obtained respectively for Fig. 2(d). The mean values of DB Index achieved from CFA algorithm are lower than that of *k*-means and FCM algorithms for both images. From the visual analysis of the extracted lesions in Fig. 4, it is observed that lesions are better detected using CFA algorithm than other algorithms. In *k*-means and FCM-based segmentation methods, portions of other objects are also detected with lesions. Hence, lesions are not well detected. Whereas, very small parts of other objects are detected along with lesions using CFA. This occurs due to similar intensities in lesions and other objects in the MR images. The experimental results show that the Fire-fly algorithm based cluster technique can be used in segmentation for lesion detection in brain MRI.

4 Conclusions

This paper presents a new segmentation method for lesion detection in brain MRI using hard-clustering technique with Fire-Fly algorithm. In the proposed method, MR images are denoised using median filter. Then, Fire-Fly based clustering algorithm is used to segment the MR images. Finally, lesions are extracted from the segmented images. The experimental results show that the proposed method can be applied in lesion segmentation in brain MRI. In future, different type of distance measures can be used in Fire-fly based clustering algorithm to improve the performance.

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Conflict of Interest The authors declare that they have no conflict of interest.

Informed Consent Informed consent was obtained from all individual participants included in the study.

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