SOCIETY FOR SCIENCE AND EDUCATION
UNITED KINGDOM

JBEMi JOURNAL OF BIOMEDICAL ENGINEERING AND MEDICAL IMAGING

ISSN: 2055-1266
VOLUME 3 ISSUE 2

MRI Segmentation based on Multiobjective Fuzzy Clustering

Olfa Mohamed Limam
Institut Supérieur d'Informatique, University Tunis EL Manar, Tunis, Tunisie
limemolfa@yahoo.fr

ABSTRACT

Brain image segmentation has a major role in medical image analysis for better interpretation of complex medical diagnosis such as tumor detection. The challenge of brain tumor detection is to detect accurately the tumor portion inside the brain image. In this work, we propose a multiobjective clustering framework to separate tumor regions from a brain image based on the neighbor nearest strategy. Applied to magnetic resonance image brain, our method provides an accurate identification of brain tumor.

Keywords: Brain tumor detection, fuzzy clustering, multiobjective optimization, neighbor nearest strategy.

1 Introduction

Brain tumor detection is a challenging task in medical image processing [1]. Brain tumor detection problem is termed as clustering problem while it consists in partitioning a given image into different regions [3]. Therefore, it is obvious to apply clustering for the distinction of tumor tissues from other healthy tissues for medical images [4].

Most conventional clustering methods assign each pixel to a one single region. While, boundaries between regions are not clearly defined [4]. So, fuzzy clustering is more appropriate to detect tumor in brain images [5]. Fuzzy clustering has been widely applied for brain image segmentation [6]. Li et al. [7], Pham and Prince [8] used FCM algorithm. Maksoud et al. [9] used K-means clustering technique combined with FCM algorithm. Udupa and Pnuam [10] used the fuzzy connectedness for abnormal tissue segmentation. However, these methods are very sensitive to noise. Hence, hybrid methods was applied in order to get desired results. Menon et al. [11] and Alsmadi [12] combined FCM with artificial bee colony algorithm. However, single fuzzy clustering is not recommended since single validity index fails to cope with different types of data sets. Moreover, the wrong choice of a single clustering measure may conduct to unsatisfying segmentation results [5]. Then, several multiobjective approaches have been proposed to segment brain images [13]. Acharya et al. [14] used simulated annealing for classification of cancer data sets. Three cluster validity indices are optimized namely XB, PBM, and FCM indices, to accurately reflect tissue clusters. Mukhopadhyay et al. [15] used NSGA-II to optimize the same three objective functions. Saha and Bandyopadhyay [16] proposed a genetic clustering technique and in [17] they proposed variable length genetic clustering technique to segment brain image data sets.

DOI: 10.14738/jbemi.32.1959
Publication Date: 12th April 2016
URL: http://dx.doi.org/10.14738/jbemi. 32.1959

However, most multiobjective fuzzy clustering techniques are developed for brain image segmentation and not for tumor detection and optimized with at most two objective functions. In previous work, Limam [18] proposed a multiobjective fuzzy genetic clustering technique optimizing two objective functions, the spatial compactness and the spatial separateness of clusters for brain tumor detection.

In this work, we propose a multiobjective fuzzy clustering method for brain tumor detection using three objective functions based on different data properties, namely, the fuzzy neighbor nearest connectedness, the fuzzy variance cluster and the external c cluster validity index Minkowski score. Our method generates an ensemble of Pareto solutions and we use the Minkowski score to select the final segmented image. Therefore, this paper develops a new multiobjective fuzzy clustering approach for brain tumor detection in MRI images to accurately diagnose the region of cancer. The main problem of works is that the quantitative results done by different works for their proposed methods are tested on different datasets rather than a common standard dataset. Also, the absence of a standard measure to compare classification accuracy of algorithms .

This paper is organized as follows. Section 2 details our proposed method. Section 3 illustrates the experimental study. Section 4 presents a conclusion.

2 The Multiobjective Fuzzy Clustering Method

The different steps of our proposed method are detailed in the following sections.

2.1 Color features

In order to improve the quality of the resulting segmentation, color features are used [19]. The standard RGB color space is used by our proposed algorithm.

2.2 Pattern proximity

The Euclidean distance is used to calculate the pattern proximity [20]. In general, the distance between two pixels x: $(x_1, \ldots, x_n)$ and y: $(y_1, \ldots, y_n)$ in an Euclidean n-space is given by

$$d(x,y) = |x-y| = \sqrt{\sum_{i=1}^{n} |x_i - y_i|^2} \tag{1}$$

2.3 Multiobjective fuzzy clustering algorithm

NSGA-II is adopted as the underlying multiobjective framework for fuzzy clustering. NSGA-II inputs arguments are the population size, an upper bound of the number of clusters, the data set, and a maximum number of generations. At the beginning of the algorithm, an initial potential solutions should be defined.

2.3.1 Initialization Step

In NSGA-II based clustering, chromosomes encodes the centers of the partitions. So, in the initial NSGA population, initial centers are encoded using FCM in order to provide more accurate solutions. FCM produces C cluster centers and a C x N membership matrix U(x).

2.3.2 Fitness Functions Computation

Three cluster validity measure are used to quantify the quality of each obtained chromosome. The fuzzy neighbor nearest connectedness index, fuzzy variance of clusters and Minkowski index, are simultaneously optimized and computed for each chromosome. To compute the objective functions, we extract the centers encoded in a given chromosome. The fuzzy neighbor nearest connectedness NN_c index, is defined by

$$NN_c = \sum_{i=1}^{C} \frac{\sigma_i}{n_i} = \sum_{i=1}^{C} \frac{\sum_{k=1}^{N} f_{ik}{}^{m} D(v_i, x_k)}{\sum_{k=1}^{N} f_{ik}{}^{m}} \quad (2)$$

where m the fuzzy exponent , $D(v_i, x_k)$ defines the Euclidean distance between i^{th} cluster center and k^{th} data point, σ_i denotes the variation of clusters and n_i the fuzzy cardinality of the i^{th} cluster is given by:

$$n_i = \sum_{k=1}^{N} f_{ik}{}^{m}, 1 \le i \le C. \quad (3)$$

The conditional membership function of a pixel f_{ik} is defined as

$$f_{ik} = \frac{u_{ik} h_{ik}}{\sum_{j=1}^{C} u_{jk} h_{jk}}, \quad (4)$$

where the membership degree u_{ik} is defined as

$$u_{ik} = \frac{1}{\sum_{j=1}^{C} \left(\frac{D(v_i, x_k)}{D(v_j, x_k)} \right)^{\frac{2}{m-1}}} \quad (5)$$

and h_{ik} , the level of pixel x_k belonging to the i^{th} cluster based on its neighborhood in a spatial domain, is defined as follows:

$$h_{ik} = \sum_{k \in Nb(x_k)} g_{ik}, \quad (6)$$

with

$$g_{ik} = \begin{Bmatrix} 1 & if \quad u_{ik} = \max\{u_{lk}\},\ for \quad l = 1, ..., C \\ 0 & otherwise \end{Bmatrix} \quad (7)$$

where $NB(x_k)$ represents a square neighborhood having pixel x_k in its center. We used a pixel Window of 3x3. The fuzzy variance of clusters V is given by

$$V = \sum_{i=1}^{C} \sum_{i=1, j \neq i}^{C} f_{ij}^{\ m} \ D(v_i, v_j). \tag{8}$$

where $D(v_i, v_j)$ the Euclidean distance between clusters v_i and v_j .

The external cluster validity index Minkowksi score (MS), measuring the agreement between the true clustering T and the obtained clustering U, is given by:

$$MS(T,U) = \sqrt{\frac{n_{01} + n_{10}}{n_{11} + n_{10}}} \tag{9}$$

where n_{11} is the total number points assigned to the same clusters in both T and U, n_{01} the total number of pairs of points that are assigned only in the same cluster of U and n_{10} the total number of pairs of points that are assigned to the same cluster of T but in a different cluster of U. Hence, the fuzzy neighbor nearest connectedness measure NN_c should be minimized, the fuzzy variance V should be maximized and the Minkowski score MS should be minimized, as follows:

$$\begin{cases} \text{Min } NN_c \\ \text{Max } V \\ \text{Min } MS \end{cases}$$

2.3.3 Genetic Operators

Crowded binary tournament selection is adopted to generate the mating set of chromosomes, conventional crossover and mutation are utilized. The NSGA-II final step is its elitism operation, where the Pareto solutions among the parent and child populations are propagated to the next generation. The NSGA based clustering algorithm provides a set of solutions on the final Pareto optimal front.

2.4 Optimal solution

The final part of the multiobjective fuzzy clustering algorithm is chosen as the best solution from a set of solutions based on a validity measure MS index [21]. The best partition corresponds to the minimum value of MS index [21].

3 Experiments and Analysis

Segmentation results are analyzed based on a visual experimental study applied to three simulated brain tumor image data sets illustrating different tumor locations. The following Figures present different tumor types inside the brain stem. The simulated brain MR images can be downloaded from Brainweb [22].

The evolutionary parameters of our method are set as follows: the population size is 20, the number of generations is equal to 20, the crossover probability is 0.8 and mutation probability is set to be 0.01. The number of clusters used are between 2 and 16 and the fuzzy factor m is set to 2. The (a) parts of Figures

(1), (2) and (3) show the original MRI brain tumor images and the (b) parts show the segmented images generated by our method.

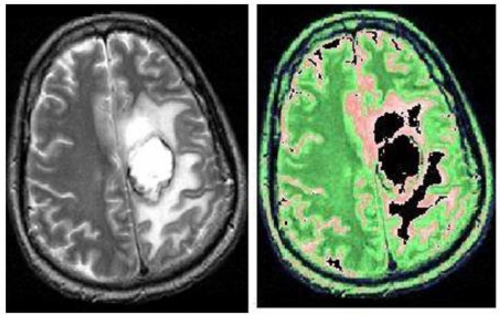

Figure 1 (a) Original MRI brain tumor image (b) Image segmented by our method

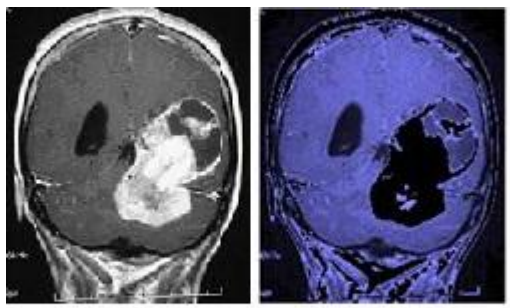

Figure 2 (a) Original MRI brain tumor image (b) Image segmented by our method

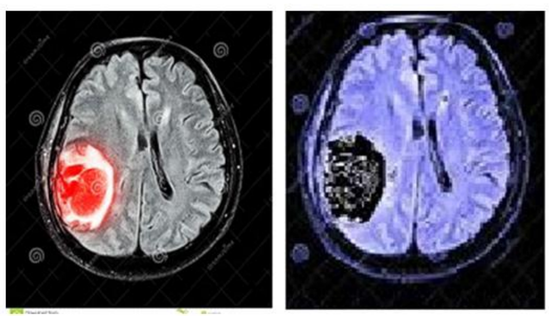

Figure 3 (a) Original MRI brain tumor image (b) Image segmented by our method

In previous Figures, our method succeeds to locate the tumor part of the brain and clearly separates

it from the other parts of the brain. Results shows that for the different images, our method makes a clear identification of the tumor portion in the brain.

4 Conclusion

This paper presents a multiobjective fuzzy clustering method that optimizes three objectives. A visual comparison applied to MRI brain image was conducted in order to show the effectiveness of our proposed method to detect brain tumor images. Our proposed approach can be extended to detect other types of tumors in other medical imagery types.

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