An Improved Fuzzy C-means Algorithm for MR Brain Image Segmentation

Khalid Abdel wahab ali qora

Mathematics and Computer Science Department
Faculty of Science ,Beni Suef University ,Egypt

Prof.Dr.E.A.Zanaty

Mathematics and Computer Science Department
Faculty of Science ,Sohag University ,Egypt

Abstract
Segmentation is an important aspect of medical image processing, where Clustering approach is widely used in biomedical applications. Brain image segmentation is one of the most important parts of clinical diagnostic tools.Fuzzy C- Means (FCM) algorithm proved to be superior over the other clustering approaches in terms of segmentation efficiency. But the major drawback of the FCM algorithm is the unknown number of clusters that assumed randomly. The effectiveness of the FCM algorithm in terms of Unknown number of clusters is improved by using metaheuristic algorithm to converges to the best number of clusters based on Xie-Beni validation index. In this paper, Xie-Beni index is used to choose the best number of clusters for FCM resulted after comparing all values of the index have been chosen using the metaheuristic algorithm which means the best segmentation result.

Keywords:
metaheuristic; swarm; MRI; segmentation; fuzzy c-means; Pso;

1. **Introduction**

Segmentation plays an integral part in partitioning an image into sub-regions on a particular application. The image might be having certain characteristics like that gray level gray level, color intensity, texture information, depth or motion based on the measurement. Image segmentation is an important task in image processing and computer vision applications. It can be considered as the first step in image processing and pattern recognition [1]. Image segmentation refers to the process of partitioning an image into many regions of pixels corresponding to different objects or parts of objects according to some homogeneity criteria (e.g. pixel intensity ,color ,or texture)[2]. The traditional methods used for the medical image segmentation are Clustering, threshold, region based Segmentation, edge based methods and ANN Image Segmentation [3].

Image segmentation methods are of three categories: edge based methods, region based methods, and pixel based methods .K-Means clustering is technical way in pixel-based methods [4].

Each region is homogeneous and the union of adjacent regions is not homogeneous. Several techniques for image segmentation have been proposed in literature [1,5]. In general, these techniques are classified into four categories: thresholding, edge based, region growing and clustering techniques [6].

Bezdek introduced Fuzzy C-Means clustering method in 1981, extend from Hard C-Mean clustering method. FCM is an unsupervised clustering algorithm that is applied to wide range of problems connected with feature of analysis, clustering and classifier design. FCM is widely applied in agricultural engineering, astronomy, chemistry, geology, image analysis, medical diagnosis. [7].

Image segmentation can be considered as a clustering problem where the features characterizing each pixel correspond to a pattern, and each image region corresponds to a cluster [2]. The FCM algorithm, which was first proposed by Dunn [8] and extended as the general FCM clustering algorithm by Bezdek [7], is the most widely used fuzzy clustering method for MR brain images segmentation because of its simplicity and applicability [9–11]. However, the application of the standard FCM algorithm to image segmentation, especially to brain MRI often performs inefficiently since the performance of FCM extremely depends on the initialization of cluster centers, where the random selection in these centers makes the algorithm falling into local optimal solution easily [10,12]. On the other hand FCM is very sensitive to MR image artifacts [10], such as noise, intensity inhomogeneity, and artifacts due to image acquisition [13].

1.1 Fuzzy c-means algorithm

FCM algorithm and cluster validity indices The FCM algorithm assigns pixels to each category by using fuzzy memberships. Let $O = \{o_1, o_2, o_3, \ldots o_n\}$ denotes an image with n pixels to be partitioned into $c(2 \le c \le \sqrt{n})$ classes (clusters), where o_i represents the feature value of pixel i, the most commonly used feature is the gray-level

Manuscript received April 5, 2018
Manuscript revised April 20, 2018

value. The algorithm is an iterative optimization that minimizes the objective function defined as follows [14]:

$$J=\sum_{k=1}^{c}\sum_{i=1}^{n}u_{ki}^{m}\|O_i-Z_k\|^2 \quad (1)$$

Such that :

$$\forall i \in \{1 \ldots . n\}, \forall k \in \{1 \ldots . c\},$$

$$\sum_{k=1}^{c}u_{ki}=1\ ;\ \ 0\le u_{ki}\le 1\ ;\sum_{i=1}^{n}u_{ki}>0 \quad (2)$$

where u_{ki} represents the membership of pixel O_i in the k-th cluster, Z_k is the k-th cluster center. $\|.\|$ denotes the Euclidean distance. The parameter m(m > 1) controls the fuzziness of the resulting partition. The membership functions and cluster centers are updated by Eq.3 and Eq.4 respectively

$$c_i=\frac{\sum_{j=1}^{n}u_{ij}{}^{m}x_j}{\sum_{j=1}^{n}u_{ij}{}^{m}} \quad (3)$$

$$u_{ij}=\frac{1}{\sum_{k=1}^{c}\left(\frac{d_{ij}}{d_{kj}}\right)^{2/(m-1)}} \quad (4)$$

1.2 Metaheuristic Algorithm

This algorithm[15] aims to achieve rapid convergence rate and high accuracy to find the optimal value in the optimization problem. suppose a group of birds is searching for food in an area, only one piece of food is available. Birds do not have any knowledge about the location of food. A flying bird has a position and velocity at any time t. through in searching for food, the bird change its position and velocity. The velocity changes based on his past experience and also the feedbacks received from its neighbor. Each solution is considered as bird. All birds have fitness value. The fitness value can be calculated using objective function. all birds preserve their individual best performance and best performance of the group.

Each bird adjust its position and velocity according to the following equations.

$$v_{i+1}=a\,v_i+b\,r_1(xbest_i-x_i)+c\,r_2(xglobal_i-x_i) \quad (5)$$

$$x_{i+1}=x_i+A\sin(\theta)+v_{i+1} \qquad 0\le\theta\le 2\pi,\ A\in[0,2] \quad (6)$$

Where x_i and v_i are the position and velocity of the bird at time i. $xbest_i$ and $xglobal_i$ represent the individual best performance and best performance of the group. during an evolutionary algorithm , the maintenance of population diversity is important. Therefore , standard deviation used in the algorithm to control the diversity of the population of birds.

Definition: (population position standard deviation)

If birds of a population $S=(X_1, X_2, X_3, \ldots, X_N)$ get their positions $X_1(t), \ldots\ X_N(t)$ at generation t and $X_i(t)$ can be expressed as a vector $(X_{i1}(t), X_{i2}(t), \ldots, X_{iD}(t))$, i=1,2,….., N, let $\bar{X}(t)=(\bar{X}^1(t), \bar{X}^2(t), \ldots, \bar{X}^D(t))$, and $\bar{X}^J(t)={}^1/_N\sum_{i=1}^{N}X_{ij}(t)$.

The population position standard deviation for generation t can be computed by

Std-positon (t)=$(std^1(t), std^2(t), \ldots, std^D(t))$,

$$std^j(t)=\sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(X_{ij}(t)-\bar{X}^j(t)\right)^2} \quad (7)$$

Then with respect to searching locally, a new solution generated according to the equation:

$$X_L=X_{i+1}+\sin(\theta)\ \ ,\ \ 0\le\theta\le 2\pi \quad (8)$$

The procedure of the algorithm is :

1. Objective function f(x), $x=[x_1, x_2, \ldots, x_3]^T$.
2. Randomly Initialize the birds population x_i, $1\le i\le n$ and v_i .
3. Initialize the parameters of the equations (5) and (6).
4. Compute the standard deviation for populations using equation (7).
5. While (iter $\le$ Max number of iterations)
6. Generate new solutions by equations (5) and (6) for each bird in the population.
7. For each bird , generate local solution using equation (8) .
8. If (iter %10 = = 0)

Using equation (3) compute the standard deviation for every dimension, if the value is less than before , compute new solution using (5) and (6) but change random value A to be one of {2A,3A,4A,5A} in equation (6) in this dimension and the other dimensions use the (5) and (6) without change.

9. Rank the birds and determine the best solution
10. End while

1.3 Validation index

Xie-Beni index [12] to be studied is defined as

$$\frac{\sum_{k=1}^{c}\sum_{i=1}^{n}u_{ki}^{m}\|O_i-Z_k\|^2}{n\ min_{i\ne j}\|Z_i-Z_j\|^2}$$

As one of the best known fuzzy clustering methods the fuzzy C-means (FCM) algorithm has received much attention, but some cluster validity criterions have to be required to evaluate the quality of clustering algorithm because FCM is a sort of unsupervised clustering algorithm. In order to give more accurate partitions of data, many researchers have studied this validity problem. the validation functions can be divided into two main classes according to whether the separation index is involved. One is compact index within the clusters, such as partition coefficient [16], partition entropy [17], proportion exponent [18], and the other is combined index (including fuzzy partitions and cluster centers), such as Fukuyama and Sugeno index [19], compactness and separation index [20] and Xie-Beni index [21]. The paper focuses on the Xie-Beni index. Although it can provide more reliable response over a wide range of choice for the number of clusters and fuzzy weighting exponent, Xie-Beni index has intrinsic drawback that is validation index monotonically decreases when the number of clusters gets very large and close to data points [21]

2. The proposed Algorithm

The proposed algorithm aims to achieve high accuracy to find the optimal value of the clusters number in the segmentation problem for brain image MRI. suppose a group of birds is searching for food in an area, only one piece of food is available. Birds do not have any knowledge about the location of food. A flying bird has a position and velocity at any time t. through in searching for food, the bird change its position and velocity. The velocity changes based on his past experience and also the feedbacks received from its neighbor. Each solution is considered as bird. All birds have fitness value. The fitness value can be calculated using objective function. all birds preserve their individual best performance and best performance of the group.

The procedure of the algorithm is :

The specific steps for FCM:

Step 1: initialize the population compute the position and velocity for every bird, set the number of clusters c (2≤c☐ n) for each bird and fuzzy index m (m>1), initializing the matrix of membership for each bird (or initializing cluster centers), set the maximum iterations n, compute the standard deviation for the number of clusters.

Step 2: calculate various cluster centers (or the matrix of membership).

Step 3: calculate the matrix of membership (or various cluster centers).

Step 4:compute the Xie-Beni index for every bird. Find the best value that correspond to certain value of number of clusters, then compute the new velocity and position for every bird. compute local solution.

Step 5:use value of standard deviation to compute the dispersion.

Step 5:rank the birds

Step 6: repeat step 2 and step 3, until the completion of the maximum number of iterations. It can also set a convergence precision as the condition for a loop terminates.

Table 1

Algorithm	C (number of clusters)	Index(Minimum)
Proposed	8	1.256
FCM	5	1.897
Proposed	5	3.421
FCM	4	4.073
Proposed	7	1.410
FCM	8	1.899
Proposed	8	2.135
FCM	5	2.010
Proposed	6	3.946
FCM	2	2.526
Proposed	7	3.109
FCM	5	3.854

3. analysis

this paper examined the proposed algorithm using MRI for brain image and compare it with FCM . And the results describe the effectiveness of the proposed algorithm if the number of clusters will not be large because of the limits of Xie-Beni. Computing the index for FCM and compare it with the index of the best value indicate that the proposed gives accurate results.

4. Conclusion

By analyzing the advantage and disadvantage of the FCM, algorithm based on Metaheuristic algorithm that is proposed

in this paper. improved FCM has accurate convergence , it is likely to trap out of the local optimum, and can guarantee converge to the global optimum. Proposed algorithm used standard deviation to measure the dispersion to increase it every 10 generations by generating new solution away from the current solutions. experiment was tested on 4 benchmark functions. From the experimental results of these functions, it can be seen that the Proposed algorithm performed much better than PSO on the most of selected problems. Although Proposed algorithm needs more time to perform convergence. Further research will focus on using Proposed algorithm with Fuzzy c-means algorithm to optimize its work.

References

[1] H. D. CHENG, X. H. JIANG, Y. SUN, and Jing Li WANG, Color image segmentation: Advances and prospects, Pattern Recognition, 34:2259–2281, 2001.

[2] A. K. JAIN, M. N. MURTY, and P. J. FLYNN, Data clustering: A review. ACM Comput. Surv., 31(3):264–323, 1999.

[3] Paresh Chandra et.al., "MRI image Segmentation using level set method and implement an medical diagnosis system", Computer science & Engineering: An international journal(CSEIJ).Vol.1, No.5,2011.

[4] Y. ZHANG A V. DEY and M. ZHONG B, A review on image segmentation techniques with remote sensing perspective, In Proceedings of the International Society for

Photogrammetry and Remote Sensing Symposium (ISPRS),38, pp. 31–42, 2010.
[5] Tsai,C.S., Chang,C.C., "An Improvement to image segment based on Human Visual system for object based coding", Fundamentainformaticae, Vol.58,No.2,2004.
[6] Rafael C. GONZALEZ and Richard E. WOODS, Digital Image Processing (3rd Edition), PrenticeHall, Inc., Upper Saddle River, NJ, USA, 2006.
[7] J. C. DUNN, A fuzzy relative of the isodata process and its use in detecting compact well- separated clusters, Journal of Cybernetics, 3(3):32–57, 1973.
[8] James C. BEZDEK, Pattern Recognition with Fuzzy Objective Function Algorithms, Kluwer Academic Publishers, Norwell, MA, USA, 1981.
[9] S. R. KANNAN, S. RAMATHILAGAM, R. DEVI, and E. HINES, Strong fuzzy c-means in medical image data analysis, J. Syst. Softw., 85(11):2425–2438, November 2012.
[10] [10] A. N. BENAICHOUCHE, H. OULHADJ, and P. IARRY, Improved spatial fuzzy c-means clustering for image segmentation using pso initialization , mahalanobis distance and post-segmentation correction, Digit. Signal Process., 23(5):1390–1400, September 2013.
[11] Maoguo GONG, Yan LIANG, Jiao SHI, Wenping MA, and Jingjing MA, Fuzzy c-means clustering with local information and kernel metric for image segmentation, IEEE Transactions on Image Processing, 22(2):573–584, 2013.
[12] ZHOU Xian-cheng. Image segmentation based on modified particle swarm optimization and fuzzy c-means clustering, In Second International Conference on Intelligent Computation Technology and Automation, ICICTA,1, pp. 611–616, 2009.
[13] N. FORGHANI, M. FOROUZANFAR, and E. FOROUZANFAR, Mri fuzzy segmentation of brain tissue using ifcm algorithm with particle swarm optimization, In 22nd international symposium on Computer and information sciences, pp. 1–4, 2007.
[14] JiayinKANG, LequanMIN, QingxianLUAN, XiaoLI, andJinzhuLIU, Novelmodifiedfuzzyc-means algorithm with applications, Digital Signal Processing, 19(2):309 – 319, 2009.
[15] Khalid Abdel wahab , Prof.Dr.E.A.Zanaty “A Novel Metaheuristic Algorithm based on Wave Function” , IJCSNS International Journal of Computer Science and Network Security, VOL.18 No.3, March 2018
[16] J.C. Bezdek, “Cluster validity with fuzzy sets,” J. Cybernet, vol.3, pp. 58 - 73, 1973.
[17] J.C.Bezdek, “Mathematical models for systematics and taxonomy,” in Proc. 8th Int. Conf. Numerical Taxonomy, G. Estabrook, Ed., Freeman, San Franscisco, CA, pp. 143 – 166, 1975.
[18] M.P. Windham, “Cluster validity for fuzzy clustering algorithms,” Fuzzy Sets and Syst., vol. 5, pp177 - 185, 1981.
[19] Y. Fukuyama and M. Sugeno, “A new method of choosing the number of clusters for the fuzzy c-means method,” in Pro. 5th Fuzzy Syst. Symp., pp.247 - 250, 1989 (in Japanese).
[20] B.L.M.R. Rezae and J. Reiber, “A new cluster validity index for the fuzzy c-means,” Pattern Recognition Letters, vol. 19, pp. 237 - 246, 1998.
[21] X. Xie and G. Beni, “A Validity Measure for Fuzzy Clustering,” IEEE Trans. Pattern Analysis and Machine Intelligence (PAMI), vol. 13, no. 8, pp.841 - 847, 1991.