Indian Journal of Science and Technology, *Vol 9(45), DOI: 10.17485/ijst/2016/v9i45/99962, December 2016*
ISSN (Print) : 0974-6846
ISSN (Online) : 0974-5645

Combined Spatial FCM Clustering and Swarm Intelligence for Medical Image Segmentation

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Abstract

Objectives: The development of image processing tools for medical image processing has recently generated lot of interest. Medical image segmentation is one such area of focus for many researchers over the years. **Methods/Statistical Analysis**: In this work we have proposed an algorithm which is a combination of Fuzzy C-Means Clustering (FCM) with spatial constraints which is called spatial FCM (SFCM) and swarm intelligence optimization methods for medical image segmentation. The swarm intelligence algorithm that we have considered in this work is the Artificial Bee Colony (ABC) optimization. **Findings:** The algorithm is applied to brain MRI image segmentation and compared with other existing algorithm and the validation of the algorithm is evaluated by cluster a validity function which is an indication of how good a clustering result is. The results show that the combined algorithm i.e. ABCSFCM has better performance and improve the cluster validity functions as compared to SFCM. **Applications/Improvements:** The result is quite promising and although the proposed algorithm is tested on brain MRI image it can be extended to other problems of interest. The other variants of FCM and other natured inspired optimization are worth investigating for further improvements.

Keywords: ABC, ABCSFCM, MRI, SFCM, Segmentation

1. Introduction

With the increase in the reliability of medical images for diagnosis a new direction of research for image processing is found. Recent trend is towards the Computer Assisted Diagnosis (CAD) for automated diagnosis of diseases or anomalies. Many different medical image modalities are available for diagnosis purposes such as Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET) scan, Computed Tomography (CT) scan etc. Using these images an expert knowledge is required to analyze the image for inference. However the process is manual and the accuracy is compromised because of the nature of the process. With the advances in medical image analysis algorithms the whole process can be automated and the expert opinion may not be required. The aim of developing CAD is to assist the expert in improving the diagnosis by helping the expert with the CAD tools.

MRI is one of the most popular imaging techniques used in the diagnosis of diseases in different parts of the body. For brain related diseases MRI is the commonly used technique. Unlike other imaging modalities, MRI gives the perfect result as well as no biological hazards. In this work we have design an algorithm for segmentation of the areas of the brain MRI for detection, diagnosis and treatment monitoring purposes. Segmentation[1] is a process of classifying regions in an image with similar characteristics. There are many methods available for image segmentation and clustering based segmentation

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algorithms are also very popular. The challenging task of brain MRI image segmentation is to produce a method that can be fully automated with high accuracy and robust segmentation results. The most popular clustering algorithm is the fuzzy based clustering algorithm Fuzzy C-Means (FCM) algorithm[2,3]. In our approach we have one variant of FCM which is called Spatial FCM (SFCM)[4]. The detail of the algorithm is briefly explained in the subsequent sections. In this paper we have also considered swarm intelligence based optimization algorithms for improving the segmentation results obtained by SFCM. We have combine Artificial Bee Colony (ABC) optimization algorithm and SFCM to obtain a better segmentation result. We have chosen ABC because of its superiority to other algorithms like Genetic Algorithm (GA), Particle Swarm Optimization (PSO), etc. The main contribution of the present work is towards the development of fusion algorithms to improve the brain MRI segmentation problems. However the algorithm can be extended to other segmentation related problems.

Some of the contributions by different authors in the area of brain MRI segmentation are briefly discussed below.

The authors[5] gives a comprehensive review about segmentation of brain MRI by giving detail analysis and comparison of different methods. A review of FCM based segmentation algorithms for brain MRI segmentation is presented by the authors[6]. Different variants of FCM such as Fuzzy Probabilistic FCM (FPCM), Fast Generalized FCM (FGFCM) and other methods that are modified versions of the standard FCM that defines a new objective function of the algorithm which are obtained by involving the neighborhood pixel information. One effective variant of FCM is the SFCM proposed in the research work by the authors[4]. The spatial information is incorporated in the membership function of the clustering. It was shown that SFCM has shown certain advantages over FCM in obtaining more homogenous regions in the segmented image. The algorithm is also less sensitive to noise. SFCM can be integrated with level set methods for automated medical segmentation as proposed in the research work[7]. A hybrid clustering technique for brain tumor segmentation is proposed[8] in which K-means clustering technique is combined with FCM to obtain a computationally fast and high accuracy segmentation result. Recently a new variant of SFCM was proposed[9] for image segmentation in which the objective function of the minimization problem is based on the energy level minimization.

A new direction in medical image segmentation using swarm intelligence and FCM can be found in that[10-12]. The author's proposed Genetic Algorithm (GA) based optimization algorithm to obtain more accurate cluster centers in FCM. The authors[13] tried to study the fine structures of the brain MRI image by obtaining edge detection from the output of the segmented image. The combination of other swam intelligence like PSO and ABC with FCM for medical image segmentation can be found in the[14-16]. A recent work[17] have proposed PSO for brain tumor detection through image segmentation.

2. Spatial FCM (SFCM)

The FCM algorithm assigns pixels to different cluster based on the fuzzy membership function of the pixels to belong in a particular cluster. It is an iterative optimization algorithm that minimizes an objective function.

Let us consider an image arranged in a one dimensional matrix as X=[x_1,x_2.........x_N], where x_i represents pixel intensity value or feature value and N is the total number pixels in the image. The aim of FCM is to partition the pixels in to c clusters. The cost function in the standard FCM is defined as

$$J = \sum_{j=1}^{N} \sum_{i=1}^{c} u_{ij}^{m} \|x_j - v_i\|^2 \tag{1}$$

where u_{ij} represents the membership value of pixel x_j to belong in i^{th} cluster, v_i is the cluster center, $\|\cdot\|$ is norm metric and m is a constant that controls the partition result. The membership values and the cluster centers are updated according to equation (2) and (3) respectively.

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{\|x_j - v_i\|}{\|x_j - v_k\|} \right)^{\frac{2}{(m-1)}}} \tag{2}$$

$$v_i = \frac{\sum_{j=1}^{N} u_{ij}^{m} x_j}{\sum_{j=1}^{N} u_{ij}^{m}} \tag{3}$$

The correlation between neighborhood pixels is exploited in SFCM. It is highly possible that the neighborhood pixels possesses same feature value and belong to the same cluster. This concept is considered in the standard FCM. The spatial information is exploited in SFCM by defining a spatial function[4] as in equation (4).

$$\boldsymbol{h}_{ij} = \sum_{k \in NB(x_j)} u_{ik} \tag{4}$$

Where NB(x_j) is square window define on the image centered on the pixel x_j. The size of the window can 3X3 or 5x5 but in this we have considered only 5x5 windows. The spatial h_{ij} is defined as the probability that a pixel x_j belongs to the ith cluster. This value indicates higher value of a pixel in a cluster if the majority of the neighborhood pixels belong to that cluster. The standard FCM is modified by incorporating the spatial function in the membership function. The modified membership function is defined in equation (5) which is reproduced from [4].

$$u'_{ij} = \frac{u_{ij}^{p} \boldsymbol{h}_{ij}^{q}}{\sum_{k=1}^{c} u_{kj}^{p} \boldsymbol{h}_{kj}^{q}} \tag{5}$$

where p and q are control parameters that decides the importance the original membership function and the spatial function. The spatial FCM with parameters p and q is denoted by SFCM$_{p,q}$. When p=1 and q=0 SFCM degenerates to conventional FCM.

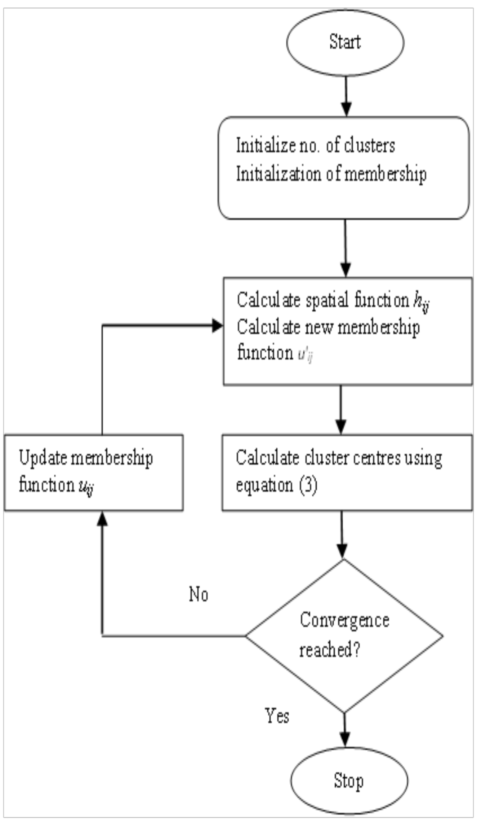


Figure 1. Flow chart of SFCM.

The spatial FCM performs in two pass iteration. In the first pass the membership values are calculated using the conventional FCM. This membership values are utilized in the calculation of the spatial function. In the second pass new membership function is calculated using equation (2). After the condition for convergence is achieved the iteration is stopped. The threshold can be set as the difference between two cluster centers at two successive iterations. After the iteration is completed defuzzification process is initiated by assigning each pixel to a cluster for which the membership function is maximal. The summary of SFCM is show in the flowchart in Figure 1.

3. ABCSFCM

In this section a brief description of swarm based optimization algorithm ABC and the combination of ABC with FCM i.e. ABCFCM is presented.

3.1 ABC Algorithm

Artificial Bee Colony Algorithm (ABC) is an optimization algorithm proposed and developed by[18] by mimicking the food source searching mechanism of honey bees. It was first applied in numerical optimization problems in the work[19]. Later ABC algorithm has been applied successfully in many engineering and scientific problems.

The algorithm is inspired by the working behavior of real bees in searching a food source and sharing the information about the food sources with the other bees in the hive. The quality of the food source is determined by the nectar amount of the food source. According to the work nature the bees are divided into groups: employed bee, onlooker bee and scout bees. The employed bees searches for food sources and memorised a good food source position by calculating the nectar amount. After completion of the entire task by the employed bees the information about the food source position is shared with the onlooker bees. The onlooker bees chose a food source from the nectar amount information. It modifies the food source position and checks the nectar information. A better food source position is memorised. If the employed bees abandoned the food source they become scout bees and join the searching process. The ABC algorithm is summarised in Figure 2.

3.2 ABCSFCM Algorithm

The ABC algorithm is used in combination with SFCM to obtain optimized cluster centres. Therefore the solutions of the problem are the cluster centres. The food source represents the cluster centres and the quality of the solution i.e. the cluster centres are checked using a fitness function. The fitness function of our problem is same as the cost function of standard FCM as defined in (1). Hence in ABCSFCM the pixels are assigned to a cluster based on the fuzzy membership value and the segregation of the region is done by the ABC algorithm by outputting an optimized cluster centre.

Initialization the population of solution (cluster centres)
cycle=1
repeat
 employed bee phase()
  {
   employed bees start new food source search
   Evaluate fitness and apply greedy selection
   Calculate probabilities P_i for the i[th] solution using equation(6)
  }
 onlooker bee phase()
 {
  Using P_i onlooker bees select food sources and evaluate them.
  Apply greedy selection process for the onlookers
 }
if abandoned solution exists for the scout
then a new random solution replaces it
  the best solution found so far is memorize
  cycle= cycle+1
untilcycle =maximum cycle number

Figure 2. ABC algorithm.

The selection of i[th] solution for the employed bees and the onlooker bees is done based on the probability value P_i calculated using equation (6).

$$p_i = \frac{f(g_i)}{\sum_{m=1}^{s} f(g_m)} \tag{6}$$

where g_i is the position of the i[th] solution and $f(g_i)$ represents the quality of the solution. The new food position or the solution in the next iteration (k+1) is updated using (7).

$$g_i(k+1) = g_i(k) + \phi_i\left(g_i(k) - g_{m(k)}\right) \tag{7}$$

m : randomly chosen index different from i.
ϕ_i : a random number in the interval [-1, +1].

The whole operation of ABCSFCM is summarized in Figure 3.

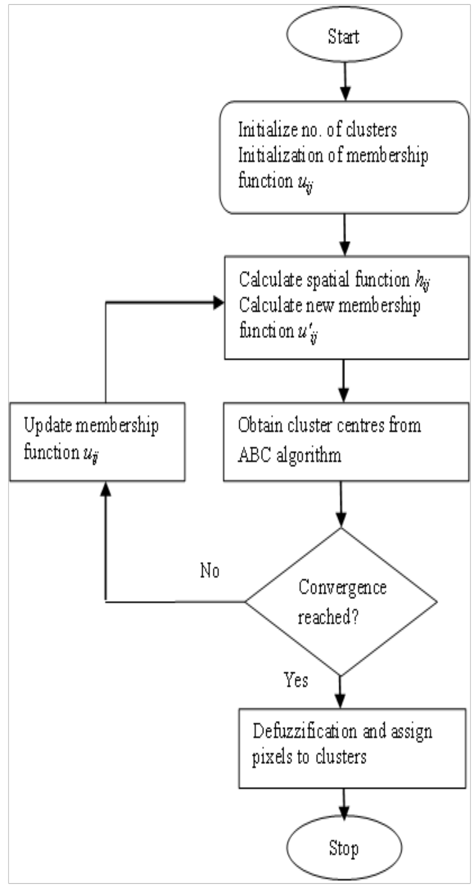


Figure 3. ABCSFCM algorithm.

4. Results and Discussion

In this section the simulation result of the algorithms are presented. For evaluation purposes we have use two brain MRI images which was used in the earlier works[4,16]. The output performance of clustering of different algorithms can be checked by using some cluster validity functions. We have use three cluster validity functions viz. the fuzzy partition coefficient V_{pc} [20], the fuzzy partition entropy V_{pe} [21] and the validity function V_{xb} [22] which are defined below.

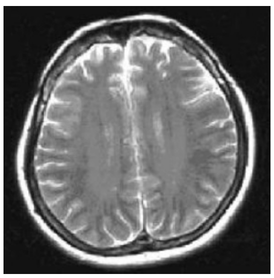
$$V_{pc} = \frac{\sum_j^N \sum_i^c u_{ij}^2}{N} \tag{8}$$

$$V_{pe} = \frac{-\sum_j^N \sum_i^c [u_{ij} \log u_{ij}]}{N} \tag{9}$$

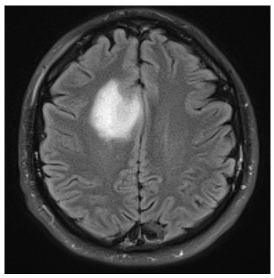
$$V_{xb} = \frac{-\sum_j^N \sum_i^c u_{ij} \|x_j - v_i\|^2}{N * (min_{i \neq k}\{\|v_k - v_i\|^2\})} \tag{10}$$

The fuzzy partition validity functions V_{pc} and V_{pe} indicate the level of fuzziness for better performance. The best clustering result is achieved when V_{pc} is maximal or V_{pe} is minimal. The validity function V_{xb} gives the connection between fuzzy partition and feature property of the image. This property makes V_{xb} more important than V_{pc} and V_{pe}. A good clustering result is obtained when V_{xb} is minimum.

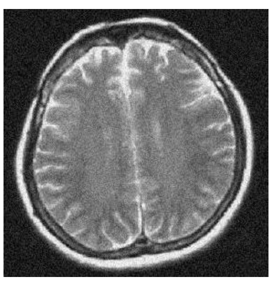
The image data used for analysis are shown in Figure 4. We have taken two original MRI images and two other images which are corrupted by adding uniform random noise of magnitude between [-50, 50] as indicated in Figure 4. We have partition the image into four different clusters. The number of cluster can be varied depending upon the problem to be investigated. Our aim is show the effectiveness of the proposed ABCSFCM so the choice of cluster size does not matter much.



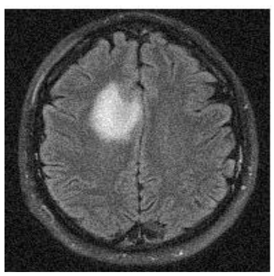
(a)



(b)



(c)



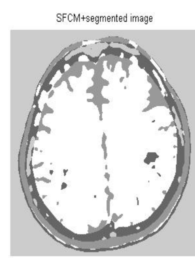
(d)

Figure 4. (a) MRI image 1 (b) MRI image 2 (c) MRI image 1 corrupted with uniform random noise (d) MRI image 2 corrupted with uniform random noise.

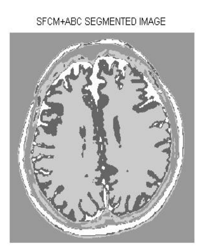
The segmentation results of the original MRI image 1 are shown in Figure 5. We have compare five different variants of FCM i.e. FCM, SFCM$_{1,1}$, SFCM$_{0,2}$, ABCSFCM$_{1,1}$ and ABCSFCM$_{0,2}$. It can be observed form Figure 5 that the fine details of the original image is preserved in the segmentation results obtained using the ABCSFCM. The incorporation of spatial information in standard FCM has already proved superior in the earlier study[4]. Now this experiment shows the better performance of the proposed combination of ABC and SFCM over the simple SFCM. This result is further validated by the values of validity functions given in Table 1. The experiment is repeated for another set of images which is the corrupted original MRI image 1. Before proceeding with segmentation the corrupted image is passed through a Weiner filter for preprocessing i.e. to reduce effect of noise. Even though a preprocessing filter is used the segmentation results is little deteriorated in comparison with the original image. The segmentation results for this corrupted image are shown in Figure 6. It also shows the superior performance of ABCSFCM over other algorithms. From Figure 5 and 6 we can also observed that the choice of the parameters *p* and *q* affects the performance of segmentation in the case SFCM variants. In this work we have chosen the values of *p* and *q* following the works[4]. The convergence of the ABCSFCM and SFCM algorithm is shown in Figure 7. The curve is the convergence of the fitness function defined in equation (1) w.r.t. the no. of iterations. The ABCSFCM is far better convergence rate compared to SFCM and it attains minimum value of the cost function.

(a) FCM

(b) SFCM$_{1,}$



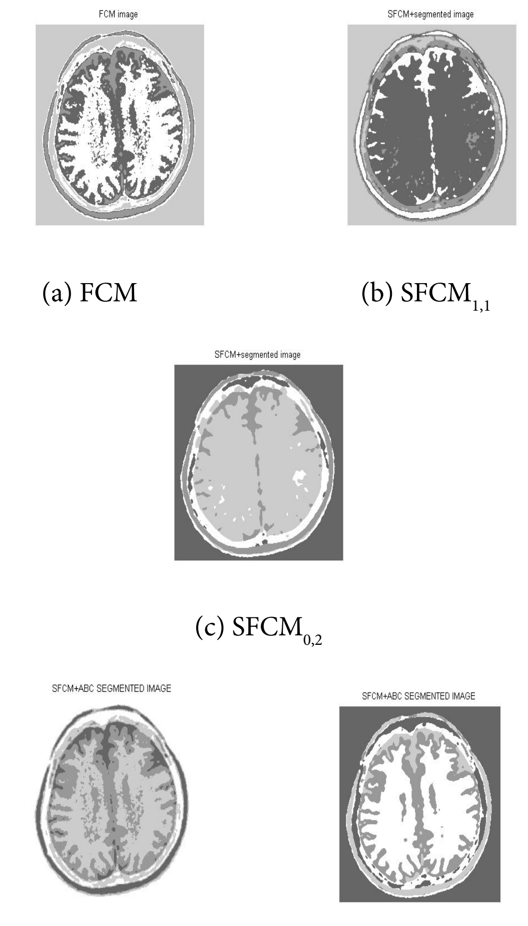
(c) SFCM$_{0,2}$



(d) ABCSFCM$_{1,1}$

(e) ABCSFCM$_{0,2}$

Figure 5. Segmentation results of MRI image1 using (a) FCM (b) SFCM$_{1,1}$ (c) SFCM$_{0,2}$ (d) ABCSFCM$_{1,1}$ (e) ABCSFCM$_{0,2.}$



(a) FCM (b) $SFCM_{1,1}$

(c) $SFCM_{0,2}$

(d) $SFCM_{1,1}$ (e) $SFCM_{0,2}$

Figure 6. Segmentation results of MRI image1 using (a) FCM (b) $SFCM_{1,1}$ (c) $SFCM_{0,2}$ (d) $ABCSFCM_{1,1}$ (e) $ABCSFCM_{0,2}$.

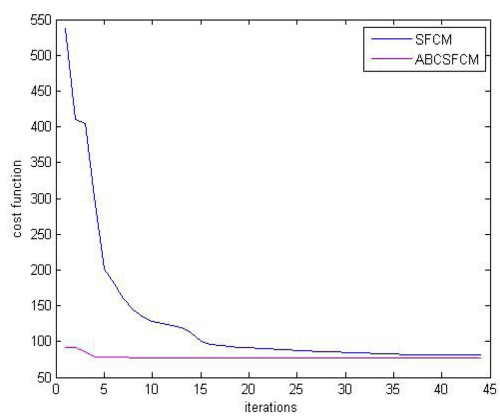


Figure 7. Convergence of cost function of $SFCM_{1,1}$ and $ABCSFCM_{1,1}$.

The comparison of the performance parameters in terms of the validity functions is given in Table 1. The comparison is given for the two images i.e. original MRI image1 and original image 2 also the corrupt version of the two images. It is quite evident that in all the experiments performed ABCSFCM has better performance in terms of the validity functions V_{pe} and V_{xb}. The better performance in terms of V_{xb} is more important because it has more significance than the other two functions.

Table 1. Cluster validity functions of different clustering techniques

Images	Methods	V_{pc}	V_{pe}	V_{xb} (x 10^{-3})
Image1	FCM	0.814	0.1380	3.53
	$SFCM_{1,1}$	**0.910**	0.0585	1.84
	$SFCM_{0,2}$	0.877	0.0930	3.17
	$ABCSFCM_{1,1}$	0.895	**0.0430**	**0.91**
	$ABCSFCM_{0,2}$	0.838	0.0750	1.43
Image1 corrupted with noise	FCM	0.819	0.1490	3.85
	$SFCM_{1,1}$	**0.910**	0.0606	1.94
	$SFCM_{0,2}$	0.872	0.0973	3.33
	$ABCSFCM_{1,1}$	0.875	**0.0580**	**1.09**
	$ABCSFCM_{0,2}$	0.824	0.0810	1.38
Image2	FCM	0.891	0.092	1.69
	$SFCM_{1,1}$	**0.952**	0.0366	0.71
	$SFCM_{0,2}$	0.923	0.0566	0.96
	$ABCSFCM_{1,1}$	0.912	**0.029**	**0.49**
	$ABCSFCM_{0,2}$	0.862	0.042	0.53
Image2 corrupted with noise	FCM	0.821	0.148	2.76
	$SFCM_{1,1}$	**0.925**	0.0577	1.14
	$SFCM_{0,2}$	0.881	0.0882	1.57
	$ABCSFCM_{1,1}$	0.820	**0.051**	**0.76**
	$ABCSFCM_{0,2}$	0.775	0.082	0.90

5. Conclusion

The paper presents a novel idea of combining SFCM and swarm intelligence algorithm ABC for medical image segmentation problem. The experimental analysis of the proposed method is carried out in the segmentation of brain MRI images. The performance of the algorithm is compared with previously existing variants of FCM. The performance is also evaluated by using three cluster validity functions. The results indicate that by incorporating optimization algorithms like ABC the performance of SFCM is improved. One may argue that by using swarm intelligence optimization algorithms the speed of the algorithm is compromised. However for CAD systems accuracy is preferred over speed. The ABCSFCM achieves

26.5 % reduction in V_{pe} and 50.5 % reduction in V_{xb} for the original image. Hence we can conclude that reliability of the proposed combined method i.e. ABCSFCM is high as compared to SFCM.

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