Chapter 29
Medical Image Processing Using Soft Computing Techniques and Mathematical Morphology

Pratik Bhansali and Sandip Mehta

1 Introduction

Today, the mass information produced by medical imaging has considerably increased. All the medical examinations carried out like for the preparation of neurosurgical operations or for the study of cerebral pathologies (cerebrovascular accident, tumor, sclerosis in plate, etc.) can represent several hundreds of megabytes (100 Mo = more than 0.8 billion bits 0 or 1). Physicians and cognitive scientists need reliable tools to assist them in their decision-making and in interpreting the mass of information created.

The developments in magnetic resonance imaging (MRI) have allowed us to know and evaluate the different pathologies of human beings with a degree of detail never seen before. Many post-processing techniques have now been developed to efficiently visualize large volumes of data and study the functionality of certain organs, such as the brain, using the images generated by CT and MRI. Almost all postprocessing tools require a spatial coherence of the data. If the acquisitions are multiple in times, studying the same volume several times, it is necessary to ensure the spatial agreement of the voxels by means of image processing techniques.

To interpret image is to produce symbolic description of it, that is, to recognize and describe the different entities that make it up. Among the interpretation tools, segmentation (or tagging) is a vital link in many applications and quantitative analyses [1–4]. Segmentation is defined as the partitioning of an image into constituent regions (also called classes or subsets), which are homogeneous with respect to one or more

P. Bhansali (✉) · S. Mehta
Department of Electrical Engineering, Department of Electronics and Communication Engineering, Jodhpur Institute of Engineering & Technology, Jodhpur (Rajasthan), India
e-mail: pratik.bhansali01@gmail.com

S. Mehta
e-mail: sandip.mehta@jietjodhpur.ac.in

M. Shorif Uddin et al. (eds.), *Intelligent Energy Management Technologies*, Algorithms for Intelligent Systems,
https://doi.org/10.1007/978-981-15-8820-4_29

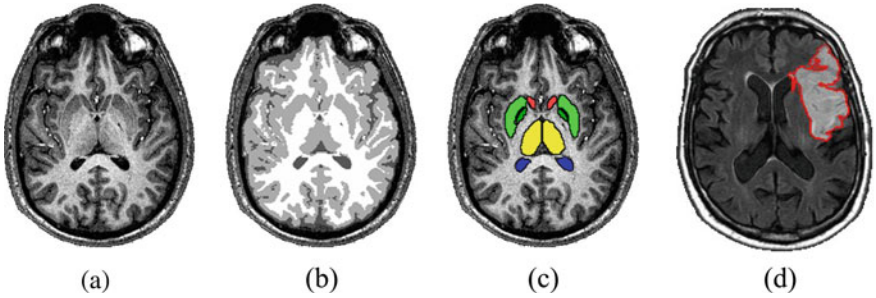


Fig. 1 MRI acquisition (image **a**), tissue segmentation (image **b**), segmentation into structures (image c) and segmentation of lesion (image **d**)

characteristics such as intensity, texture or functionality [5]. One of the typical use cases of segmentation is the distinction of neuroanatomical zones, in which it is used in order to separate areas of cerebral interest such as: hippocampus, frontal cortex, areas of language, among others [6, 7].

The goal is, for one or more images, to give each voxel a label to give a description. In cerebral MRI segmentation, we generally consider different level of descriptions (see Fig. 1).

Tissue segmentation, which aims to describe the composition of each voxel among the three main topics of the brain [8], the segmentation in structures, which describes the membership of each voxel with a known brain structure: thalamus, putamen, ventricular system, etc. and the segmentation of the cerebral lesions (tumors, multiple sclerosis, cerebral vascular accidents) in the clinical setting, which aims to study their location, volume, etc. Segmentation is, therefore, a central tool in both the clinical and the neuroscience fields.

2 Segmentation in Medical Imaging

In medical imaging, it is necessary to take measurements on acquired images. Whether anatomical or functional, the image provides accurate information about patient such as: level of tracer uptake, volumes of different organs or regions, depth of injury, etc. In many of these cases, the interest of the measure lies in a particular area of the image associated with an anatomical region. In order to be able to make these measurements, we use what we call segmentation techniques [9, 10].

Automatic image analysis and classification, in general, is based on the characteristics of the image. These are basically two: the signal strength of the pixels and their geometric arrangement in the image. Out of these characteristics, the intensity is probably the most used, along with the information of contours that gives us knowledge about the borders between the different objects of the image.

The techniques based on intensity base operation in the assumption that a type of fabric has a characteristic and own brightness. This is generally not true, so it is not possible to segment only by these techniques, requiring a postprocess to eliminate regions with an intensity similar to the object of interest that do not belong to it [11].

In the literature on MRI segmentation, the methods are usually divided into two categories: monospectral methods, if there is a single acquisition or modality of image, and multispectral, if they use one or several images with different characteristics but with geometric correspondence for the same anatomical volume [12, 13].

The difficulty of segmenting an image is due to the structural complexity of the MRI images and the contrast often insufficient to extract the structure of interest without any knowledge of priori neither on its form nor on its location. Thus a priori knowledge provided by the atlases probabilistic models will allow to better differentiate close anatomical structures contrast and spatial location [14].

Many approaches have been proposed to segment cerebral MRIs. They can be classified into two groups: methods supervised, requiring interaction with the user and unsupervised methods, where the parameter estimation is performed automatically.

3 Fuzzy C-Means

Fuzzy C-Means (FCM) is a fuzzy unsupervised classification algorithm, it introduces the basic concept of fuzzy set into class definition: every point in the dataset belongs to each cluster with a certain degree, and all clusters are characterized by their center of gravity. It uses a criterion of minimizing intraclass distances and maximizing interclass distances, but giving a certain degree of membership to each class for each pixel [15, 16].

This algorithm requires a prior knowledge of number of clusters and then generates the classes through an iterative process by minimizing an objective function. Thus, it makes possible to obtain a fuzzy partition of image by giving each pixel a degree of belonging to a given class [17]. The cluster with which a pixel is associated is the one with the highest degree of membership. The main steps of the Fuzzy C-means algorithm are:

1. The arbitrary fixation of a membership matrix.
2. The computation of class centroids.
3. The readjustment of the membership matrix according to the position of the centroids.
4. Calculation of the minimization criterion and return to Step 2 if there is no convergence of criteria.

4 Fuzzy C-Means-Based Segmentation

Let $X = \{x_1, x_2, x_3, \ldots x_N\}$ a set of N observations to classify in K classes where each observation $x_i(i = 1, 2, 3, \ldots..N)$ can be represented by a set of D attributes: $x_j = \left(x_{j1}, x_{j2}, x_{j3}, \ldots x_{jD}\right)^T$.

K Classes are represented by a vector of class centers

$V = (v_1, v_2, v_3, \ldots v_k)$, where $v_k = (v_{k1}, v_{k2}, \ldots, x_{kD})^T$, is the center of class k.

Each observation x_i is defined by its degree of belonging μ_{ik} to the class k, that $\mu_{ik} \in [0, 1]$. We can then define a partition matrix $U = [\mu_{ik}]$ of dimension $(N * K)$.

The FCM algorithm consists in partitioning the N observations into K classes in order to minimize the similarity of observations within each class. It results in the minimization of the following objective function:

$$J_{FCM}(U, V) = \sum_{k=1}^{K}\sum_{i=1}^{N} \mu_{ik}^{m} d^2(x_i, v_k) \tag{1}$$

Under constraints following:

$$0 < \sum_{i=1}^{N} \mu_{ik} < N, \sum_{k=1}^{K} \mu_{ik} = 1 \tag{2}$$

m: is the fuzzification factor or fuzzy factor such that $1 < m < \infty$.

$d(x_i, v_k) = x_i - v_k$ is the distance between the observation i and the center of the class k.

Generally the distance used is Euclidean:

$$d(x_i, v_k) = \sqrt{\sum_{j=1}^{D}\left(x_{ij} - v_{kj}\right)^2} \tag{3}$$

The first constraint ensures that no class should be empty and the second is a normalization constraint which ensures that the sum of the degrees of membership of each observation to all classes equal to 1.

Blurred partitioning is achieved by an iterative optimization of the objective function given by Eq. (1), with an update of membership levels and centers of classes as in the case of the K-means algorithm.

Update of the following degrees of membership:

$$= \frac{1}{\sum_{j=1}^{K}\left(\frac{d(x_i, v_k)}{d(x_i, v_k)}\right)^{\frac{2}{m-1}}} \tag{4}$$

Hence the formula for updating class centers:

$$v_k = \frac{\sum_{i=1}^{N} \mu_{ik}^m * x_i}{\sum_{i=1}^{N} \mu_{ik}^m} \tag{5}$$

In what follows, we present the algorithm of the FCM method:

(1) Set the parameters: K: number of classes; ε: threshold representing the convergence error (for example: = 0.001);m: degree of blur, usually taken as 2; Tmax: max iteration; t = 1

(2) Initialize the matrix membership degrees $_0$ by random values in the interval [0, 1]:

Calculate the matrix $_0$ by the relation (5)

Calculate the objective function $_0$ by the relation (1);

(3) Update the degree of membership matrix by the relation (4)

(4) Update the matrix (the centers) by the relation (5);

(5) Calculate objective function by the relation (1);

(6) Increment the value of t;

$$t = t + 1 \tag{6}$$

(7) Repeat steps 3–6 until you meet the stopping criterion which is:

$$(J_t - 1 - J_t) < \varepsilon_{\text{out}} \geq J\text{max} \tag{7}$$

Finally, a final step is necessary when the desired result is a non-blurred. This is called "defuzzification." When we do not want to highlight the pixels where the degrees of membership are approximately the same for each class, a natural way to proceed is to consider that the final class of a pixel is that for which degree of membership is maximal.

However, this algorithm that requires knowledge of the number of classes is not robust and its effectiveness depends strongly of the initialization stage of the class centers because the iterative process can easily provide a locally optimal solution. Thus to improve the results of the classification, several methods are adopted for optimizations of the result.

5 Particle Swarm Optimization

The clustering of images is a main task in the analysis and recognition of which intend to divide pixels of an image into different classes such that the pixels of same class are similar as possible and the pixels of diverse classes are also dissimilar as possible. In spite of the efforts devoted to this problem leading to abundant literature, it remains a very difficult task because of the lack of information, the distribution of the pixels as well as a single and precise definition of a cluster.

PSO algorithms have shown their effectiveness in solving optimization problems whose research space is large. Swarm particle optimization is a popular metaheuristic approach based on swarm intelligence. The particle swarm optimization algorithm launches the search with a population of solutions, where each is called "particle." The latter is characterized by a speed of movement and a position in the search space. During the search process, each particle moves to change its position in the search space based on its current speed, current position, and best position found in past iterations, and best position found by the searcher "Swarm." Its displacement allows it to update its position and speed of movement at each iteration.

6 PSO-Based Segmentation

First, the performance function (fitness) is defined to start with our PSO-based approach, which reflects the ability of individuals to adapt to the problem under consideration. This function, which the algorithm seeks to minimize, is closely dependent on the objective function.

Further, a particle is from the best overall solution and its best solution, the greater the variation in its velocity, in order to move the particle towards the best solutions.

The random variables p1 and p2 can be defined as follows:

p1 = c1 * r1, p2 = c2 * r1.

With r1 and r2 following a uniform law on [0…1]. c1 and c2 are constants that represent a positive acceleration, with c1 + c2 $\leq$ 4.

The algorithm runs as long as a convergence criterion has not been reached. This may be:

- A fixed number of iterations.
- Depending on the fitness.

When the speed variation is close to 0.

The movement of the agents is controlled in terms of $pbest$ and $gbest$. The speed of agent i is updated first taking into account the current position (px_i, py_i) with respect to its $pbest$:

$$v_{xi} = \begin{cases} vx_i - rand() * c_1 if px_i > pbestx_i \\ vx_i + rand() * c_2 if px_i < pbestx_i \end{cases} \tag{8}$$

Then it is updated with respect to $gbest$ according to:

$$v_{xi} = \begin{cases} vx_i - rand() * c_1 if px_i > gbestx \\ vx_i + rand() * c_2 if px_i < gbestx \end{cases} \tag{9}$$

The parameters c_1 and c_2 will be replaced by constant 2 which produced better results although they left as a future topic the investigation of their optimal value. In the simplified version of these simulations (Current Simplified Version), the agents updated their speeds by means of the equation:

$$v_{i,j} = v_{i,j} + 2 * rand() * \left(pbest_{i,j} - p_{ij}\right) + 2 * rand() * \left(gbest_j - p_{ij}\right) \tag{3}$$

where the subscript i, j denoted agent i and dimension j.

In this work, the fuzzy segmentation is considered as common optimization problem then PSO algorithm is used:

The objective function of each of the same function algorithm of the PSO method:

$$J_{FCM}(U, V) = \sum_{k=1}^{K} \sum_{i=1}^{N} \mu_{ik}^{m} d^2(x_i, v_k) \tag{10}$$

7 Morphological Operation for Postprocessing

Morphological techniques probe the given image with a small template or shape called structuring element (S.E.) [19]. The S.E. is sited at all possible locations in the image and it is then compared with corresponding pixels of neighborhood.

After applying both FCM- and PSO-based algorithms for the purpose of segmenting human brain MRI image morphological operations are applied to extract the region of interest, i.e., to the removal of nonbrain region form the segmented image.

Morphology process images with the help of previously chosen special shapes, which are generally smaller than the image and are called the structural element, which acts as an operator on an image to produce a result. The shape, size and orientation of the structural element are chosen based on prior knowledge taking into account the relevant geometric structures that are present in the image and the objective pursued with the morphological operation implemented.

Each structure element requires the definition of a point of origin (or reference) for its application as a morphological operator. This allows the structure element to be related in a particular way to the pixels of the image.

After applying FCM- and PSO-based clustering segmentation technique, the clustered information of the image achieved is further processed through morphological operation to achieve the desired region of interest, i.e., the brain image from the dataset of MRI chosen for segmentation.

First, an initial mask is created to filter the background of images with a threshold and then the small regions of binary images are filtered. The attributes of the image obtained are compared by the reference image to calculate the precision.

8 Results

The database is obtained from "Department of Telecommunications Brno University of Technology" form signal processing laboratory [20]. This database contains a set of actual medical images of MRI examination of several brain exams. There are total 12 sets of training data available, i.e., MRI image sets of 12 different patients. Each image set of a patient consists of 257 slices of image with resolution of 400 $\times$ 400 px and 16 bit grayscale bit depth. Each examination is composed with the set of sequences of modalities, where each sequence constitutes all the images. The number of sequences differs according to the examination.

The image sets contain not only original MRI images but also segmented labeled image slices of each patient done by the human expert with the accuracy of 99.540% + 0.07756 which acts as are ground truth, comparing to which we validate the accuracy of our segmentation methods. The simulation results on the random database images of patient number 9 after applying both the proposed methodologies are presented and then a comparative analysis on both visual and statistical ground is done to validate the work.

To find the accuracy of our simulated result, we use the contingency matrix that evaluates the performance of system by measuring the accuracy [21]:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{11}$$

A comparative visual analysis of both the methods, i.e., FCM- and PSO-based segmentation is presented on Image slice number 70, taken from image dataset of patient number 9 to showcase our methodology which can be implemented on all the image slices of the dataset. Here the initially defined clusters are varied to judge the preeminence of the proposed PSO-based approach for segmenting the brain image MRI.

Image slice no.: 'Image_70':

Method- "Fuzzy C Means"

(a) Cluster = 3

The above shown images in Fig. 2 from image (a) to image (h) revels the sequence of step by step appearance of results obtained as while performing Fuzzy C means.

Here the cluster no. is initialized to be three (3) and the process for segmenting the brain image is followed.

(b) Cluster = 4

The above shown images in Fig. 3, i.e., from image (a) to image (h) revel the sequence of step by step appearance of the result when the cluster number is initialized to be 4 and the process for segmenting the brain image is followed.

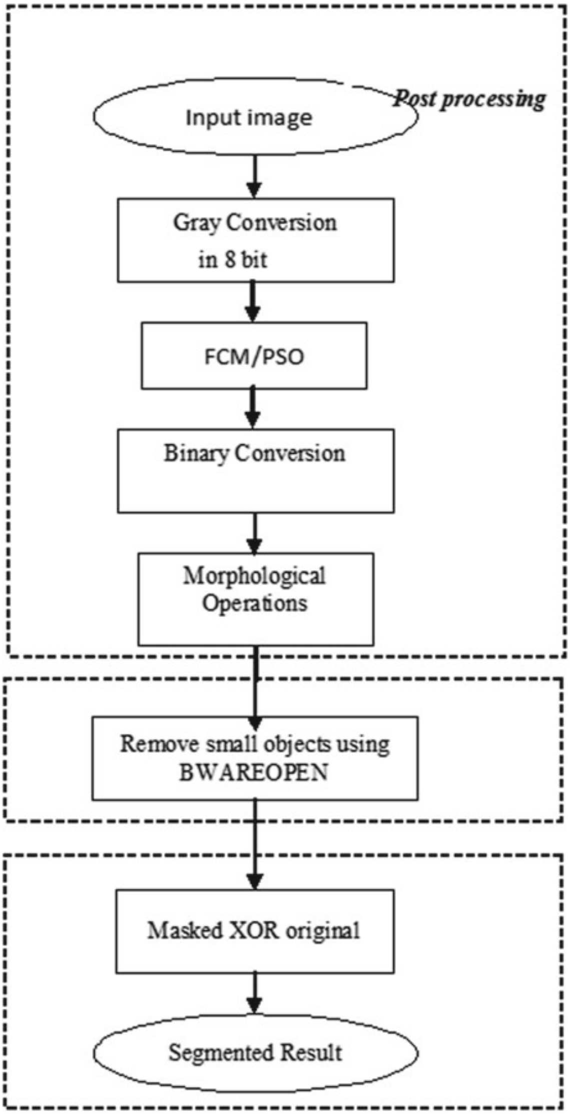


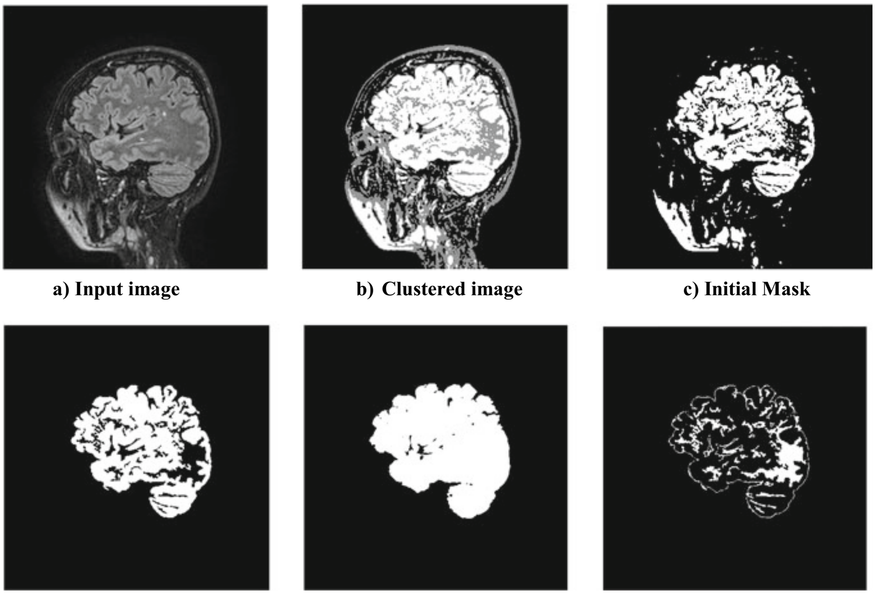
Fig. 2 Flow diagram for the proposed work

(c) Cluster = 5

The process is repeated by initializing the cluster number to be 5. The images in Fig. 4 from image (a) to image (h) revel the sequence of step by step appearance of the results obtained.

Method—"Particle Swarm Optimization (PSO)"

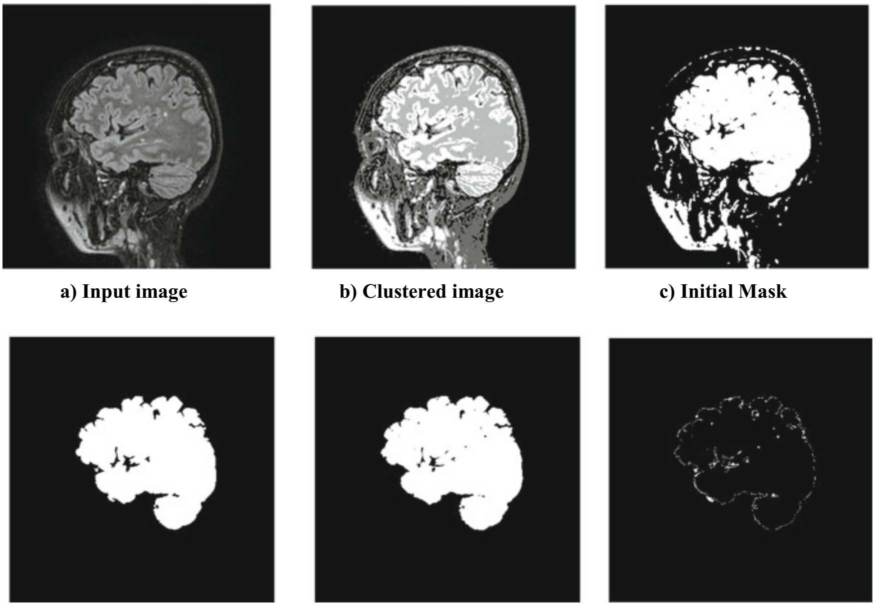
(a) Cluster = 3



a) Input image b) Clustered image c) Initial Mask

d) Segmented Brain Mask e) Segmentation By Human Expert f) Segmentation Error

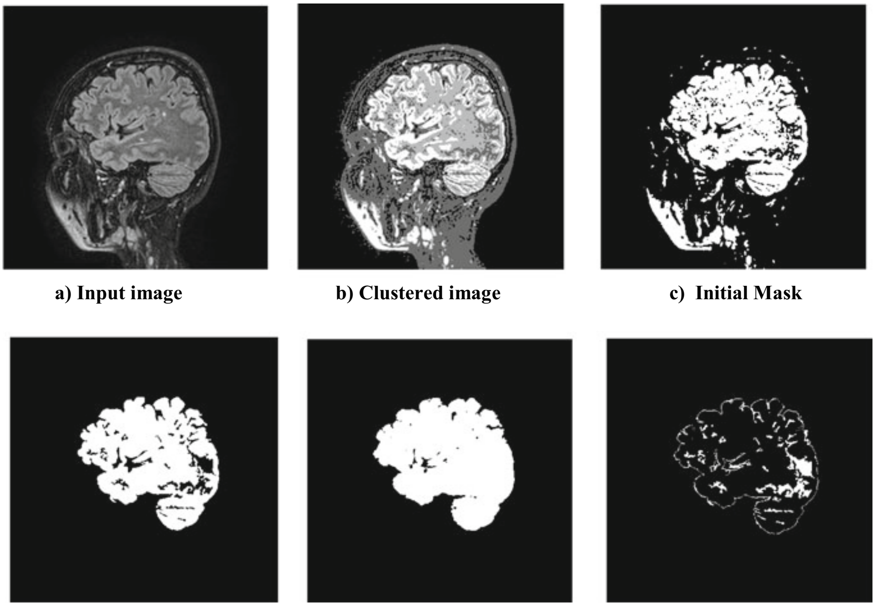
Fig. 3 Segmented brain image processed by FCM with cluster = 3



a) Input image b) Clustered image c) Initial Mask

d) Segmented Brain Mask e) Segmentation By Human Expert f) Segmentation Error

Fig. 4 Segmented brain image processed by FCM with cluster = 4



a) Input image **b) Clustered image** **c) Initial Mask**

d) Segmented Brain Mask **e) Segmentation By Human Expert** **f) Segmentation Error**

Fig. 5 Segmented brain image processed by FCM with cluster = 5

The above shown images in Fig. 5, i.e., from image (a) to image (h) revel the sequence of step by step appearance of the results obtained while performing PSO.

Here the cluster number is initialized to be 3 and the process of segmenting the brain image is followed.

(b) Cluster = 4

The process is repeated by initializing the cluster number to be The images in Fig. 6, i.e., from image (a) to image (h) revel the sequence of step by step appearance of results obtained.

(c) Cluster = 5

The process is repeated by initializing the cluster number to be 5 and the process for segmenting the brain image is followed.

Table 1 shows the comparative analysis of the accuracy obtained after applying both Fuzzy C Means and proposed PSO segmentation methods on different random image slices of patient number 9 and its variation with respect to the change in the initial cluster defined.

From the statistical evaluation shown in Table 1, a graph is plotted between cluster number and accuracy which shows the comparative behavior of FCM- and PSO-based segmentation approach on image no._70, i.e., "70" number slice of patient 9, which was also visually evaluated in the previous segment. The same can be followed for all the other image slices present in the dataset.

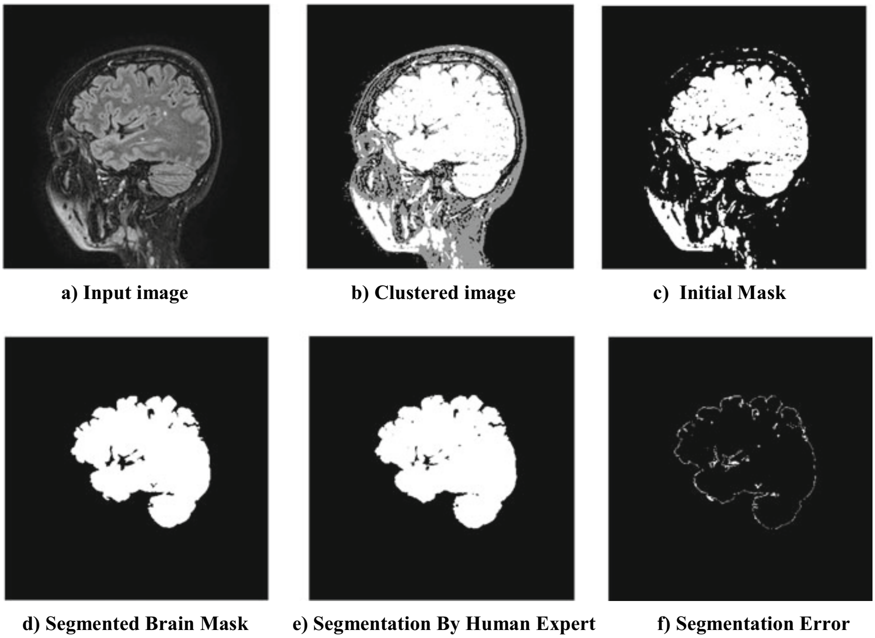


Fig. 6 Segmented brain image processed by PSO with cluster = 3

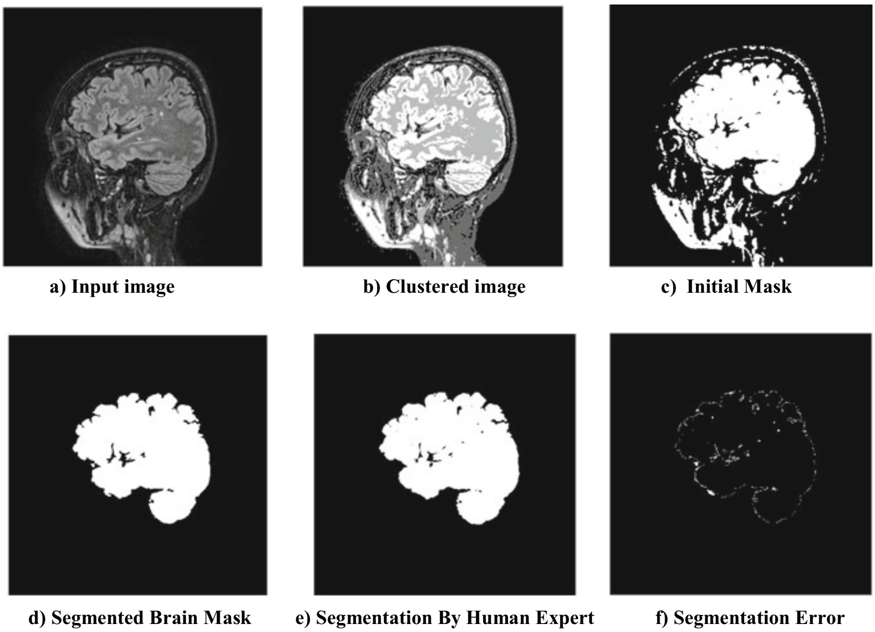


Fig. 7 Segmented brain image processed by PSO with cluster = 4

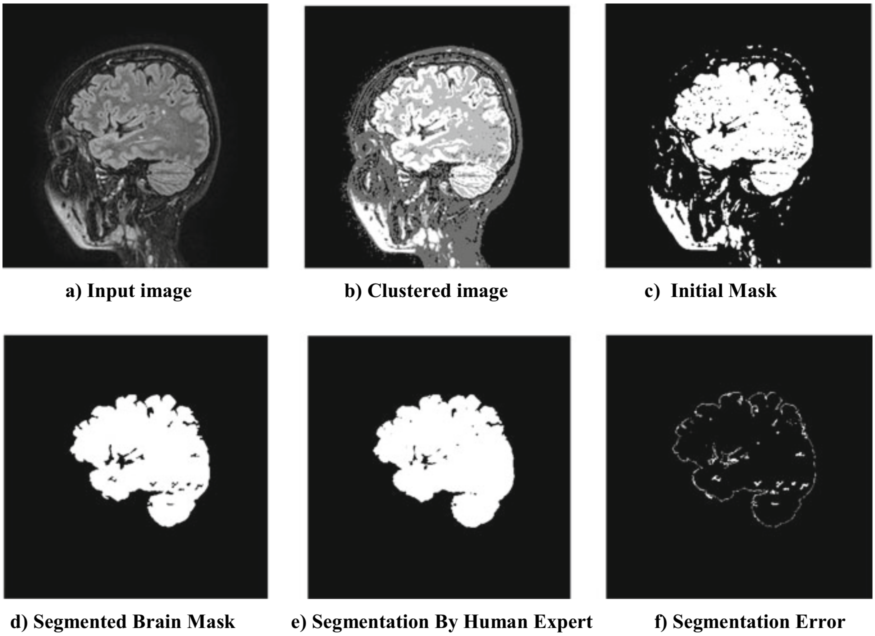


Fig. 8 Segmented brain image processed by PSO with cluster = 5

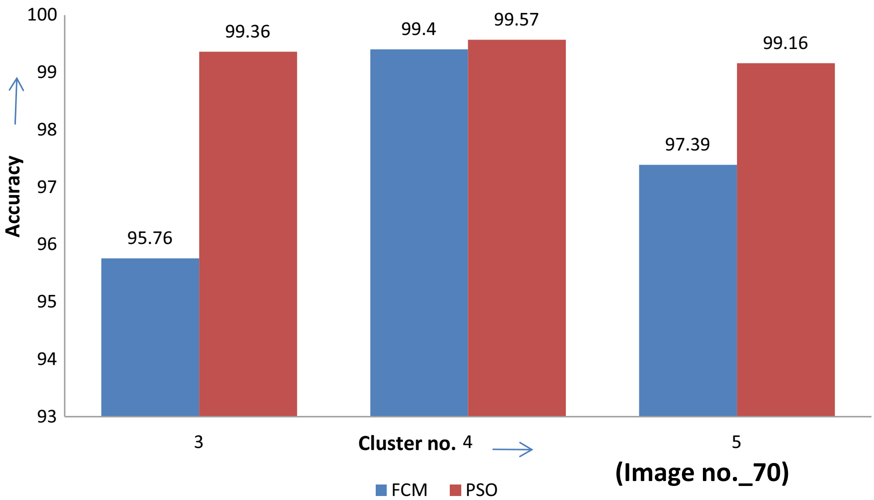


Fig. 9 Graphical Representation between cluster number and accuracy

Table 1 Result for patient number 9

S. no.	Image number	Cluster number	Accuracy	
			FCM	PSO
1	50	3	98.02	99.3
2		4	99.40	99.44
3		5	99.22	99.48
4	60	3	97.99	99.53
5		4	99.65	99.67
6		5	98.94	99.59
7	70	3	95.76	99.36
8		4	99.50	99.57
9		5	97.39	99.16
10	80	3	96.98	99.48
11		4	99.62	99.67
12		5	95.71	99.43
13	100	3	96.12	99.08
14		4	99.11	99.13
15		5	98.78	99.13
16	120	3	87.26	94.3
17		4	94.3	94.42
18		5	94.26	94.22
19	150	3	95.32	98.32
20		4	98.72	98.74
21		5	98.14	98.18
22	160	3	95.45	98.69
23		4	98.89	98.91
24		5	98.38	98.58
25	200	3	98.50	99.52
26		4	99.51	99.6
27		5	99.11	99.57

Conclusions and Future Scope of Work

The advancement in Image Processing techniques has opened a wide area of research especially in the application involving medical imaging where accuracy in diagnosing images plays a very important role. This paper has used two soft computing techniques, which involve FCM and PSO method followed by mathematical morphology to extract the region of interest from the brain MRI images.

The analysis on a patient's human brain MRI image having 257 different image slices has been done using MATLAB software. The preliminary results obtained from the proposed method may be used to achieve better results in terms of accuracy or segmented error of the MRI image. Further, it is evident from the study carried out that the use of the proposed PSO algorithm allows increasing the performance of the segmentation method under random variation of initial number of cluster. It is found that more stable outcome was obtained in terms of accuracy as compared to FCM method which gives unstable outcome with random variation of the initial number of cluster.

The proposed method applied on MRI database images which may be explored on different types of medical records like Ultrasonic images, X-Ray, CT scan, etc. However, further research and development is needed to improve the existing technique and introduce new possible solutions that may preserve the sharp edges in the template image.

References

1. Gonzalez RC, Woods RE (2002) Digital Image Processing. 3nd edition, Prentice Hall
2. Alasdair MC (2004) Introduction to Digital Image Processing with MATLAB. Cenage Learning
3. S Jayaraman, S Esakkirajan and T Veerakumar, "Digital Image Processing", Tata McGraw Hill, 2009
4. K. R. Castleman, "Digitial Image Processing", Pearson, 1996
5. Rogowska, J., 2000. Overview and Fundamentals of Medical Image Segmentation-5
6. Worth AJ, Makris N, CavinessJr VS, Kennedy DN (1997) Neuroanatomical segmentation in MRI: technological objectives. Int J Pattern Recognit Artif Intell 11(08):1161–1187
7. Despotović, I., Goossens, B. and Philips, W., "MRI segmentation of the human brain: challenges, methods, and applications". *Computational and mathematical methods in medicine, 2015*
8. Yazdani, Sepideh, RubiyahYusof, AmirhoseinRiazi, and AlirezaKarimian. "Magnetic resonance image tissue classification using an automatic method." *Diagnostic pathology* 9, no. 1, pp. 207, 2014
9. Pohle, R. and Toennies, K.D., "Segmentation of medical images using adaptive region growing". In *Medical Imaging* (pp. 1337–1346). International Society for Optics and Photonics, July 2001
10. Balafar MA, Ramli AR, Saripan MI, Mashohor S (2010) Review of brain MRI image segmentation methods. Artif Intell Rev 33(3):261–274
11. Lladó, X., Oliver, A., Cabezas, M., Freixenet, J., Vilanova, J.C., Quiles, A., Valls, L., Ramió-Torrentà, L. and Rovira, À.," Segmentation of multiple sclerosis lesions in brain MRI: a review of automated approaches". *Information Sciences*, *186*(1), pp. 164–185, 2012
12. Cabezas M, Oliver A, Lladó X, Freixenet J, Cuadra MB (2011) A review of atlas-based segmentation for magnetic resonance brain images. Comput Methods Programs Biomed 104(3):e158–e177
13. Balafar, M.A, " Fuzzy C-mean based brain MRI segmentation algorithms". *Artificial Intelligence Review*, pp. 1–9, 2014
14. Fedorov, Johnson, EswarDamaraju, Alexei Ozerin, Vince Calhoun and Sergey Plis. "End-to-end learning of brain tissue segmentation from imperfect labeling" International Joint Conference on Neural Networks (IJCNN), 2017
15. Bai Xiangzhi, Sun Chuxiong, Sun Changming (2019) Cell Segmentation Based On FOPSO Combined With Shape Information Improved Intuitionistic FCM. IEEE Journal of Biomedical and Health Informatics 23(1):449–459
16. Tao Lei, XiaohongJia, Yanning Zhang, Senior Member, IEEE, Lifeng He, Senior Member, IEEE, Hongying. "Significantly Fast and Robust Fuzzy C-Means Clustering Algorithm Based

on Morphological Reconstruction and Membership Filtering" IEEE TRANSACTIONS ON FUZZY SYSTEMS,vol- 26, no.- 5, pp: 3027 – 3041, 2018
17. Hiba Amin Mohammed Ali, Mohamed A.A. Ahmed, Eltahir Mohamed Hussein "MRI Brain Tumor Segmentation Based on Multimodal Clustering and Level Set Method" International Conference on Computer, Control, Electrical, and Electronics Engineering (ICCCEEE), 2018
18. Kennedy J (2011) Particle swarm optimization. In: Encyclopedia of machine learning, pp 760–766. Springer US
19. Reinoso O, Sebastián JM, Aracil R, Torres F (2001) Morphological operations with subpixel resolution on digital images. Machine Graphics and Vision 10(1):89–102
20. Signal Processing Laboratory, Department of Telecommunications Brno University of Technology, 2011. http://splab.cz/en/research/konference-a-workshopy/challenge-2013/challenge-3-brain-tissue-analysis
21. Robert S, Mustofa AA, Christy Atika Sari, De Rosal Ignatius Moses Setiadi, Eko Hari Rachmawanto (2018) MRI Image Segmentation using Morphological Enhancement and Noise Removal based on Fuzzy C-means.5th International Conference on Information Technology, Computer, and Electrical Engineering (ICITACEE)