

Penalized Fuzzy C -Means Enabled Hybrid Region Growing in Segmenting Medical Images



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Abstract Segmentation is considered as one of the challenging and important processes in the field of digital image processing, and there are numerous applications like medical image analysis and satellite data processing where the digital image processing can be beneficial. Various algorithms have been developed by many researchers to analyze different medical images like MRI and X-rays. Nuclear image analysis and interpretation also a promising research topic in medical image analysis. For example, positron emission tomography (PET) image can be used to accurately localize disease to help doctors in providing the right treatment and saving valuable time. In recent years, there is a significant advancement in the biomedical imaging domain with the increasing accessibility of computational power as well as automated systems; medical image analysis has become one of the most interesting research areas. Microscopic image analysis is also valuable in the domain of medical imaging as well as medicine. For example, different cell determination, identification, and counting are an important and almost unavoidable step that assists to diagnose some precise diseases. Many computer vision and digital image analysis instances require a basic segmentation phase to find different objects or separate the test image into distinct segments, which can be treated homogeneous depending upon a given property, such as color and texture. Region growing and fuzzy C -Means are two efficient and popular segmentation techniques. In this chapter, we have proposed a hybrid scheme for image segmentation using fuzzy C -Means clustering, region growing method, and thresholding. The fuzzy C -Means (FCM) clustering is used as a preprocessing

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S. Bhattacharyya et al. (eds.), *Hybrid Machine Intelligence for Medical Image Analysis*, Studies in Computational Intelligence 841,
https://doi.org/10.1007/978-981-13-8930-6_3

step. It helps to process the image more accurately in further stages. To eliminate the noise sensitivity property of fuzzy *C*-Means (FCM), we have used the PFCM, i.e., penalized FCM clustering algorithm. In this work, to find the appropriate region, we have used the region growing segmentation technique coupled with the thresholding. In the proposed work, a similarity feature depending on pixel intensity is used. The threshold value can be calculated using different techniques, such as iterative approach, Otsu's technique, local thresholding, and manual selection, to determine the optimal threshold. The results are obtained and derived by applying the proposed method on different images obtained from publicly available benchmark datasets of human brain MRI images. Experimental results indicated that the PFCM supported hybrid model is far more superior in segmenting medical images than traditional image segmentation methods.

Keywords Medical images · MRI · PFCM · Hybrid region growing · Otsu's method · Local thresholding

1 Introduction

The image segmentation technique is focused on separating an image which is independent of domain. The prime goal of such an algorithm is to segment the image into some regions which are visually different and homogeneous in nature. The individual regions must be meaningful which is to be measured based on some attributes like texture or color. Segmentation helps in easy image analysis. Segmentation process segregates an image into different regions. The extent of the segregation level depends on the problem under consideration. Image segmentation is very useful in different domains and applied as a tool in various sectors like industry, health care, and various other domains. Segmentation is conceptually very simple and easy to implement. By observing an image, anyone can determine the different regions contained in an image. Any human being can easily determine whether an object is a building, or an animal, a person, a tree, or any background scene? Human vision is efficient enough to detect the area of interest. If we want to achieve the same thing by a computer algorithm, then it will be something tricky. It is little difficult to say or define a region. To perform the segmentation using a computer algorithm, one must specify some feature or properties that are used to distinguish one region from another. Another challenge is to find the number of regions in a given digital image. Many image segmentation algorithms depend on the discontinuity and similarity or homogeneity of the pixels to their local surroundings. There are two broad categories of segmentation methods. One is edge based. It is dependent on the discontinuity attribute. Another one is known as region-based method which is based on similarity or homogeneity. Thresholding-based image segmentation methods divide an image into separate segments depending upon a threshold value which can be computed locally or globally [1].

Clustering process divides an image in such a way that object with some similar characteristics falls in the same category. Similarity measure can be determined depending upon the problem. There are various clustering methods found in the literature. Clustering approaches can be broadly classified into two classes such as the hard clustering approach and the fuzzy clustering approach. Both of them have their own efficiency and drawbacks. The hard clustering technique compels each point to fall under one specific class resulting in a very crisp segmentation; i.e., every point falls under exactly one region. This method has a severe drawback and not applicable for some images with bad contrast, noise, poor resolution, etc. This method fails on those images and detects false segments.

Now fuzzy set theory [2] comes into picture. It basically works on the concept of partial membership. Fuzzy set-based clustering methods are frequently used as a part of soft segmentation technique and successfully applied on various segmentation processes on different datasets [3–10]. In this work, a penalized fuzzy C-Means clustering scheme is used to preprocess the image. After that, an integrated region growing and thresholding approach has been proposed that takes the preprocessed image as input and detects segments from this.

Seeded region growing (SRG) is a well-known segmentation technique proposed by Adams and Bischof [11]. It is hybrid in nature. This scheme begins by taking n initial seed points A_1, A_2, \dots, A_n , and, at each iteration, it increases the size of the region by incorporating a pixel x that satisfies the homogeneity criteria into its surrounding. The SRG scheme is robust, speedy, and not dependent on any controlling parameters [12]. Seed points are grown to construct a region, and at last, similar or small regions are merged to form an exact region for which we are interested about. In [12], seed points are generated by employing a tree method. The first scheme divides the image into some fixed rectangular regions first and then considers their centers as seeds. Next approach detects the edges of the subject and then finds the basic seed points along with their centroid. At last, the third method is an extension of the second method. In this scheme, a smoothing filter is employed to manage the noise. Tremeau and Borel [13] proposed a new scheme with both growing and merging technique, and this can be applied to the color image also. This algorithm first applies the region growing algorithm. It considers the color similarity and spatial proximity as the homogeneity measure. After that, the resulting regions are merged. In this step, only color similarity has taken into consideration.

Thresholding is an important and widely used method that basically works on the distribution of the gray level. In this method, the first goal is to identify and extract an object of interest from its background. To perform this job, the procedure depends on the arrangement of gray-level values or texture in different objects in the subject image. Two major factors on which most of the thresholding algorithms depend are: (i) frequency distribution of the one-dimensional (1D) gray levels (ii) the bi-dimensional (2D) co-occurrence matrix of the image under test. Various one-dimensional thresholding methods have been studied [14–22]. Parametric or nonparametric approaches can be taken to compute the threshold value [14, 17, 23]. In parametric approaches, the details of the gray levels in different regions are the key point for computing the threshold value. For example, in Wang and Haralick's

scheme [18], the pixel intensities of an image are segregated in two categories, e.g., edge pixels and non-edge pixels. Edge pixels are then divided into darker or brighter classes depending on their local surroundings and following this step histogram of these two classes are obtained. Then the threshold is computed from these two histograms, and the highest peaks of the histograms are considered as the threshold. On the other hand, moment preserving thresholding is an example of the parametric method. In this process, at first, segment the image into separate regions. Segmentation is performed depending on the criteria of equal moment which is to be satisfied by the actual and segmented image [16].

2 Penalized Fuzzy C-Means-Based Preprocessing

The fuzzy C -Means clustering approach forces every pixel to fall in some class by using fuzzy membership functions. Let $X = (x_1, x_2, \dots, x_N)$ represents an image where a count of pixels is denoted by N . Assume this image is to be segmented in c clusters. Here x_i represents the multispectral data. This algorithm optimizes the cost function by iterative process. The cost function is given in Eq. (1).

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

where u_{ij} denotes the associativity of a pixel x_j in the i th cluster and i th cluster center is given by v_i , $\|\cdot\|$ denotes a norm metric, and m is a constant. The fuzziness of the resulting segments is controlled by the parameter m . Here $m = 2$ is considered for this work.

In the FCM scheme, the distance of every pixel and the corresponding cluster center is the key factor for determining the probability. The membership functions along with the cluster centers are modified using the following equations:

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

And,

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

FCM process starts with some initial points for each cluster centers. The convergence of the process can be checked by either observing the change in the cluster centers or by the change occurred in the membership function. The original FCM algorithm can be applied to any images, but some major issues are associated with

it. For example, the image should be noise-free. It does not work well on noisy images. Moreover, any information about spatial context is not taken into consideration. Hence, this algorithm is not useful for noisy images and sensitive to some image artifacts.

One simplest and natural solution to the above-mentioned problem is that image can be smoothed before application of the FCM algorithm. For that purpose, we have to employ some filters. But conventional filters may lose some important image information. It can lose some vital information like edges. The balance between smoothing and clustering cannot be handled appropriately. To overcome this issue, many different techniques have been developed [4-9]. Tolia et al. [4] developed a method which was based on fuzzy rule and named the rule-based neighborhood enhancement system. This algorithm performs some post-processing on the obtained results to add spatial continuity in general FCM algorithm. In another method of the same authors [5], multi-resolution information was attached. Because of this operation, the spatial constraint is imposed on the image. Noordam et al. [6] suggested a new FCM method which is geometrically guided (GG-FCM). The main concept behind this algorithm was a semi-supervised FCM technique. In their proposed method, the membership values of neighboring play a major role to determine the condition of each pixel. Then the pixel is either included to or eliminated from the obtained cluster.

In the proposed work, a FCM algorithm with some modification to the conventional FCM clustering algorithm is applied for preprocessing. This process is called penalized FCM (PFCM) [24] algorithm. The penalty term is based on Neighborhood Expectation-Maximization (NEM) concept [25]. The penalty parameter considers the spatial dependence of the objects. The fitness parameter of the PFCM process is given in Eq. (4);

$$J_{\text{PFCM}} = \sum_{j=1}^N \sum_{i=1}^c u_{ij}^m \|x_j - v_i\|^2 + \gamma \sum_{j=1}^N \sum_{k=1}^N \sum_{i=1}^c u_{ij}^m (1 - u_{ik})^{m w_{jk}} \quad (4)$$

where w_{jk} is defined as Eq. (5). The parameter γ (≥ 0) is the controlling parameter to handle the consequence of the penalty term efficiently.

$$w_{jk} = \begin{cases} 1 & \text{if } x_j \text{ and } x_k \text{ are neighbours and } j \neq k \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

$$u_{ij} = \frac{1}{\sum_{l=1}^c \left(\frac{d^2(x_j, v_i) + \gamma \sum_{k=1}^n (1 - u_{ik})^q w_{jk}}{d^2(x_j, v_l) + \gamma \sum_{k=1}^n (1 - u_{lk})^q w_{jk}} \right)^{\frac{1}{q-1}}} \quad (6)$$

$$v_i = \frac{\sum_{k=1}^n (u_{ik})^q x_k}{\sum_{k=1}^n (u_{ik})^q} \quad (7)$$

In this work, images of interest first preprocessed using the above-mentioned penalized fuzzy *C*-Means algorithm. The resultant image will be given as an input to the hybrid region growing algorithm.

3 Thresholding

The main objective of thresholding method in digital image processing is to segregate image pixels into two or more values. Here, each pixel value is checked for the similarity with the pre-specified or predetermined threshold value T . If the value of the threshold is not correctly decided, then there can be following three scenarios may occur [1]

- The separated regions may not match with the actual one. It can be smaller or larger than the actual one.
- There can be some discontinuity in the detected image; i.e., they may not be connected.
- The resultant image may be over segmented, or it can be under segmented.

The value of the threshold can be calculated by various techniques. For example, we can determine the threshold value manually or we can use some of the well-known methods like iterative approach, Otsu's Method or local thresholding techniques.

4 Region Growing Process

The prime goal of the segmentation algorithms is to segregate an image into different regions. Thresholding achieves this goal by detecting edges. Edges are basically depended on the discontinuities in gray levels or in the color attributes. In contrast, region growing approach detects the regions directly without depending on the edges.

The initial step of the region growing process is to choose a set of seeds. Selection of seeds is dependent on the need of the user. In this approach, the initial seed can be chosen interactively. So a particular area of interest can be chosen separately. The initial region begins at the selected seed or the collection of seeds. The regions are increased by incorporating the surrounding seed points. Neighboring points can be incorporated depending on homogeneity criteria. There are various criteria depending on which regions can be grown like pixel intensity. Due to this fact, the information of the image is considered to be important. For example, the histogram of the image is very important where the intensity threshold value is considered to be the criteria because a suitable threshold can be useful for segmentation process [1].

The seed point can be chosen by many ways. For example, one can choose a seed point by taking a random position. In this proposed scheme, the seed point has been chosen interactively. The seed point can be chosen in such a way so that one can get a specific segment of interest. It will be very effective in different kind of

images; for example, medical image where a doctor may wish to separately analyze a portion of the image under test. In this work, we have combined the fuzzy C-Means, region growing method, and thresholding method. We have computed the threshold by using various techniques and used those values to determine the region [26].

5 Proposed System

5.1 Preprocessing

In this work, the subject image is first passed through the penalized fuzzy C-Means algorithm. For all the images under test, the value of the parameter γ is considered as 400 (unless otherwise stated). To select the value of this parameter, the experimental results are considered as the basis. Experiments proved that 400 is the most suitable value of this parameter that gives the most efficient and appropriate results. But if the image is noisy, then we may need to increase the value of this parameter. In this work, the spatial effect on a particular pixel is determined by the eight neighbors, and for that reasons, a 3×3 window of pixels is taken under consideration.

Algorithm: Penalized fuzzy C-Means algorithm [24]

Step 1: Set the cluster parameters

Step 2: Calculate the degree of the membership using Eq. (6)

Step 3: Determine the centroid of the clusters using Eq. (7)

Step 4: Go to step 2 and repeat the total procedure while it not converges

Now, after convergence of the process, defuzzification should be performed. This process is required for conversion on the fuzzy partition into crisp form.

5.2 Stack-Based Seeded Region Growing

At the very beginning, manual intervention is necessary for an initial selection of the seed. So it begins with a semiautomatic process. So the user needs to specify some feature of interest. After that, it is the responsibility of the region growing process to locate other points those are related with the same properties and incorporate them to form a larger region. This method proved to be very useful in several biomedical applications like detecting high-quality blood vessels in MRA and CTA data. To generate precise models for examining the vascular structures from X-rays or other radiological image sources, a pipeline of processing stages has been developed. These models are very useful to study the different branching patterns and various measurements.

Fig. 1 Four neighbors of the center pixel considered to grow the region

$x-1, y-1$	$x, y-1$	$x+1, y-1$
$x-1, y$	x, y	$x+1, y$
$x-1, y+1$	$x, y+1$	$x+1, y+1$

In this proposed work, two-dimensional SRG is implemented with the help of stacks. The stack is a very simple and elegant data structure. Moreover, data access is very simple, and therefore, surrounding pixel traversal around the seed location is simple. In this work, four neighbors are considered during the region growing process and the corresponding pseudocode is as follows (Fig. 1):

Algorithm: Seeded region growing (stack-based implementation)

Initialize the stack with default value

for every seed points considered

Push the location of the seed into the stack

While (some elements present in the stack)

pop location (of a pixel)

select the location of the pixel as a *Region*

Select the pixel as an already visited node

if homogeneity criteria/region growing attribute is similar for the immediate left neighbor of the pixel

if the pixel at the left neighbor is not visited

push the pixel (of the left neighbor) into the stack

if homogeneity property/region growing attribute matches for the pixel at location's right neighbor pixel

if the pixel at the right neighbor is not visited

push the pixel (of the right neighbor) into the stack

if homogeneity property/region growing attribute matches for the pixel at location's top neighbor pixel

if the pixel at the top neighbor is not visited

push the pixel (of the top neighbor) into the stack

if homogeneity property/region growing attribute matches for the pixel at location's bottom neighbor pixel

if the pixel at the bottom neighbor is not visited

push the pixel (of the bottom neighbor) into the stack

end

To include a neighbor inside the region, we have checked whether new region mean including that point is less than or equal to a predetermined threshold value. The threshold value is very difficult to choose. Various approaches have been studied to compute the threshold value and perform segmentation.

Here, the homogeneity criterion is based on the region mean. The new pixel becomes the part of the new region if the newly obtained region mean of the region is satisfying a particular threshold value. This threshold value can be selected in various ways like manual selection, Otsu's method, iterative method, and local thresholding.

The initial seed selection and the base condition on which the region growing process terminates are the two key factors that influence the performance of the region growing algorithm. Therefore, these things should be carefully chosen to achieve an efficient result and obtain the desired region. Generally, region growing process is based on some key factors like homogeneity of the region, contrast of the desired object from its background, strength of the region edges, size, texture, shape, and color. The proposed method has used a method based on region mean. The value of the homogeneity attribute is computed as given below:

Set the value of the `region_mean` with the seed value (i.e., pixel value of the seed point)

$$\begin{aligned} \text{new_region_mean} = & (\text{old_region_mean} * \text{no_of_points} \\ & + \text{pixel value of new entry}) / (\text{no_of_points} + 1) \quad (8) \end{aligned}$$

5.3 Thresholding

There are two basic categories are possible to generate from the image thresholding process:

1. Those pixels, to which, some attribute computed falls below a threshold and those at which the attribute computed from the image equals or exceeds a threshold.
2. Thresholding binarizes the image and can perform cell counts in digitized histological images.

As we have previously mentioned that, the threshold can be selected in various ways. In this proposed work, we have used local thresholding on experimental basis as it provides a better result. We have also tested our system by providing some manual inputs as threshold. After experiment, we found that threshold value 0.2 is working well for most of the images. The structuring element disk is used to test the integrated thresholding method. Other structuring elements are also tested, but the threshold value was not satisfactory for most of the images.

5.3.1 Manual Method

This is a simple approach in which the selection of the threshold value is arbitrary, i.e., any random can be given to test the system. Here the problem is, it completely dependent on the human and better result can be achieved after some attempts.

5.3.2 Iterative Method

In this case, the threshold value is calculated from the following algorithm:

Algorithm: Iterative thresholding method	
1	Initial estimate of T
2	Segmentation using T
3	G_1 , pixels having higher intensity than T
4	G_2 , pixels having lower (or equal to) intensity than T
5	Computation of the average intensities m_1 and m_2 of G_1 and G_2
6	New threshold value: $T_{\text{new}} = (m_1 + m_2)/2$
7	If $ T - T_{\text{new}} > \Delta T$, back to step 2, otherwise stop

This is a simple approach in which the selection of the threshold value is arbitrary, i.e., any random can be given to test the system. Here the problem is, it completely dependent on the human and better result can be achieved after some attempts.

5.3.3 Otsu's Method

In this method, the threshold that optimizes the weights in class variance is the key factor.

The main assumptions of this method are:

- (1) Images and the histogram of the images are considered to be bimodal.
- (2) Spatial coherence should not be used. Moreover, no other information about the object structure can be used.
- (3) Mainly statistics are stationary in nature, but addictiveness can be achieved locally.
- (4) Illumination should be uniform throughout the image. It is important to recognize the differences that arise from the bimodal brightness behavior.

Detailed description of this method can be found in [15].

5.3.4 Local Thresholding

Normally $T = T[i, j, \text{feat}(i, j), f(i, j)]$.

If T is a function which is only based on $f(i, j)$, then this type of threshold is considered as the global threshold.

If T is a function of both $f(x, y)$ and local features $\text{feat}(x, y)$, then this type of threshold is considered as the local threshold.

We have created a morphological structuring element. Different structuring elements are available like:

Arbitrary It is one of the flat-structuring elements. Here NHOOD is a parameter is used to determine the neighborhood. NHOOD is nothing but a matrix. It is a two-dimensional array consisting of only binary values. The location of the 1's is used to identify the neighborhood. This information is useful for morphological operations. The origin of NHOOD is the center element of the matrix which can be expressed as: $\text{floor}((\text{size}(\text{NHOOD}) + 1)/2)$ (Fig. 2).

Diamond It is also a flat-structuring element. It has diamond shape. Here R is a scalar parameter that denotes the Euclidean distance between different points enclosed within the diamond shape and origin of the SE. R cannot be negative, and it should be an integer scalar (Fig. 3).

Disk: This structuring element is also flat in nature. It has a disk-like shape. Here R is a scalar parameter that is used to specify the radius. R must be nonnegative integer because it used to specify the distance. N is a scalar parameter. It can take a value among 0, 4, 6 and 8 ($N > 0$). This structuring element can be approximately represented as a sequence of N lines which are periodic in nature. No approximation is required when $N = 0$. The members of the structuring element contain all pixels with centers within the distance R from the center. If no value is specified for the parameter N , then the default value is considered as 4 (Fig. 4).

Fig. 2 Arbitrary structuring element

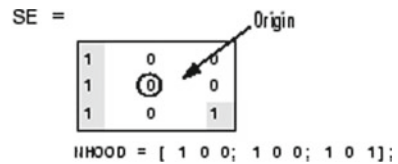


Fig. 3 Diamond structuring element

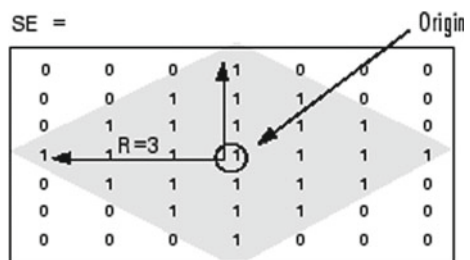


Fig. 4 Disk structuring element

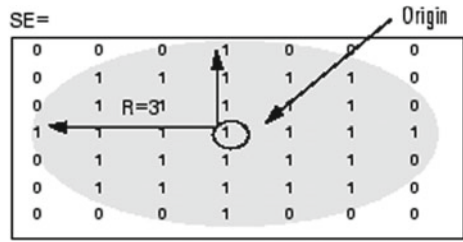


Fig. 5 Line structuring element

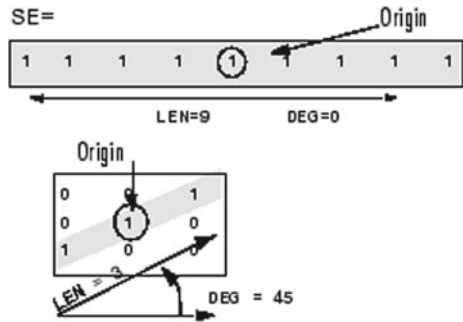
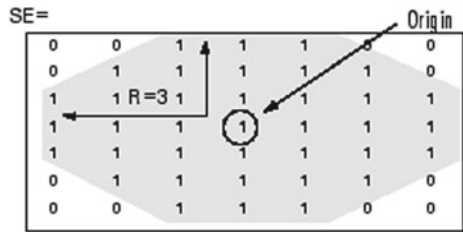


Fig. 6 Octagon structuring element



Line: This structuring element is also flat in nature. It possesses symmetric behavior measured from the origin. DEG is a scalar parameter that is used to represent the angle formed by the lines. The angle is computed in a counterclockwise where the baseline is the horizontal axis. LEN is also a scalar parameter. The separation length of the members of the SEs from the origin is given in Fig. 5.

Octagon: This structuring element is also flat in nature. It is octagonal in shape. Here R is a parameter which is used to specify the Euclidian distance between sides and the origin. Horizontal and vertical axes are used as the baseline of this computation. R must be an integer greater than or equal to 0. Moreover, R must be divisible by 3 (Fig. 6).

Pair: This structuring element is also flat in nature. It consists of two elements. One of them is placed at the center. OFFSET is a parameter that is used to represent the position of the second vector. OFFSET must consist of two elements, and it should be a vector of integers (Fig. 7).

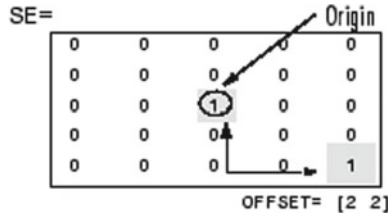


Fig. 7 Pair structuring element

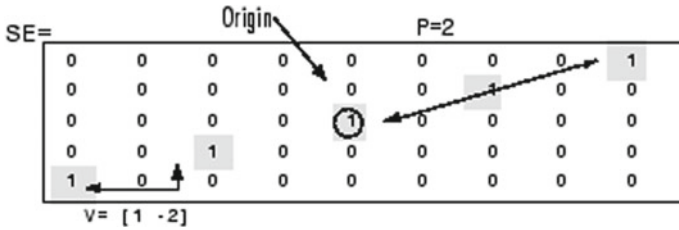


Fig. 8 Periodic line structuring element

Fig. 9 Rectangle structuring element

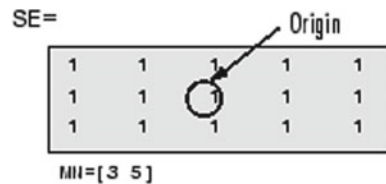
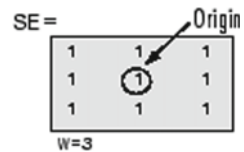


Fig. 10 Square structuring element



Periodic line: This structuring element is also flat in nature. It is built with of $2 * P + 1$ elements. V is a vector consists of two members. V is built with integral values offsets that represent. One of the SE members is located at the center. The other members are placed at $1 * V, -1 * V, 2 * V, -2 * V, 3 * V, -3 * V, \dots, P * V, -P * V$ (Fig. 8).

Rectangle: This structuring element is also flat in nature. It is rectangular in shape. Here MN is a vector that is used to specify the size. MN must be a vector consists of two elements. It must consist of integers greater than or equal to 0. The initial element of MN row count in the structuring element surrounding; the second element is the column count (Fig. 9).

Square: It is a square-shaped structuring element. Its width is denoted by W pixels. Here W must be an integer greater than or equal to 0 of type scalar (Fig. 10).

After creating a structuring element, top-hat filtering has been applied on the grayscale or binary input image. This operation is a morphological operation. Morphological opening of the image is performed and computed by the top-hat filtering and then subtracts the obtained result from the actual image. To perform the operation, a structuring element is needed. It should be a single-structuring element in nature. It cannot be an array that contains multiple structuring elements. After that, threshold value is computed (Fig. 11).

6 Results and Discussions

At the very beginning, the segmentation process is semiautomatic because of the seed selection. Then the image is preprocessed by PFCM algorithm followed by region growing and thresholding integrated method.

The MedPix Medical (radiological) image database [27] is used for the experimental results. MedPix is an online database of medical images and clinical topics, integrating images, and textual information including over 19,000 case scenarios and nearly 54,000 images. Different types of regions have been considered to the efficiency of the proposed approach.

The precision–recall is well-known and efficient way to measure the performance. Due to the simplicity of the implementation and efficiency, precision, recall, and F -Score are frequently used parameters. Here the main target is to define the optimal boundary. The precision can be demonstrated as the probability of correct detection of boundary pixel (for a detected boundary pixel) [28]. The probability that an exact boundary pixel is found is known as recall rate [29]. The harmonic mean of the precision and the recall values is represented as the F -Score [29]. Precision is given by Eq. (9), recall is given by Eq. (10), and F -score is given by Eq. (11).

$$\text{Precision} = \frac{\text{detected true boundary pixels}}{\text{detected all boundary pixels}} \quad (9)$$

$$\text{Recall} = \frac{\text{detected true boundary pixels}}{\text{all true boundary pixels}} \quad (10)$$

$$F\text{-Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (11)$$

The results in Table 1 as well as Figs. 12, 13, 14, 15 and 16, illustrate a comparative study of different metrics for the proposed method.

The proposed approach has better recall value than the values obtained using the direct application of the algorithm without preprocessing. The same phenomena are observed in the case of the F -score and precision results.

- In respect of the precision, the developed method is better and obtained higher values than that obtained using the direct application of the algorithm without preprocessing.

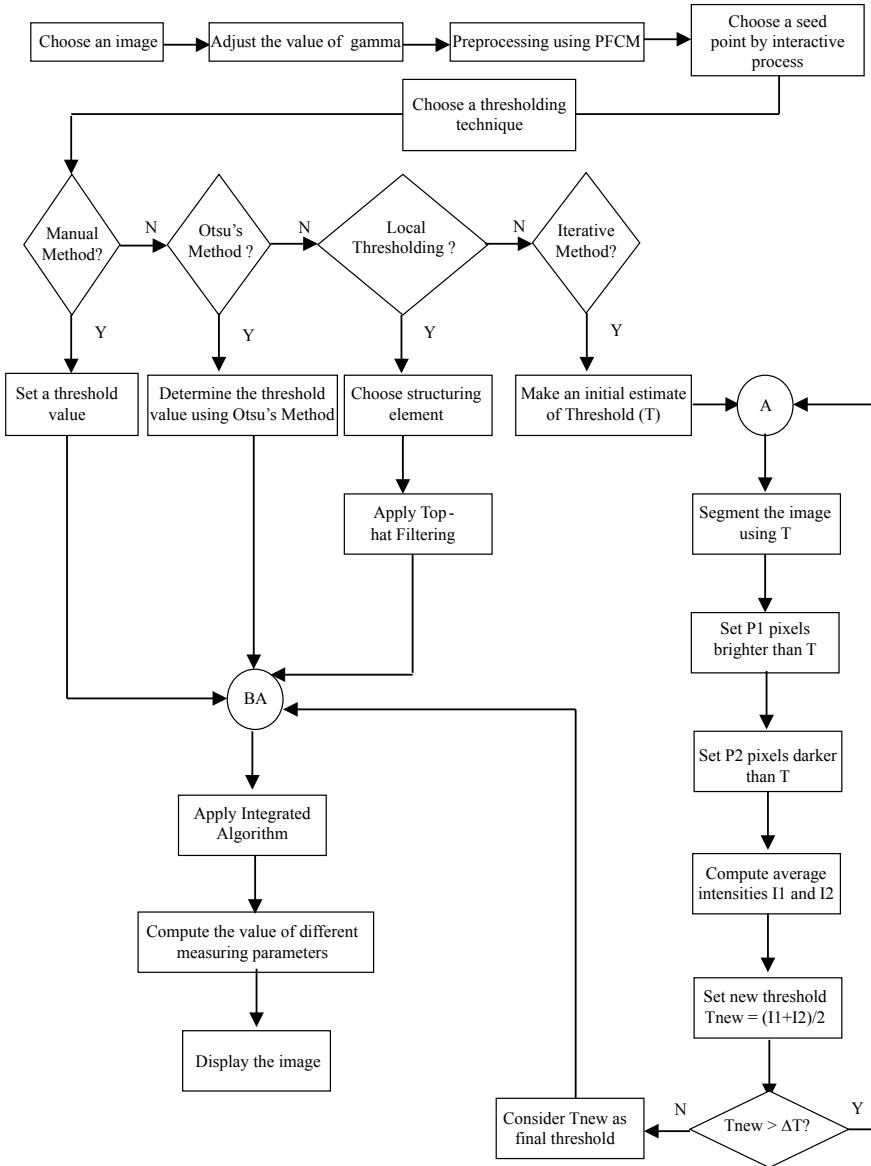


Fig. 11 Schematic diagram of the proposed approach

Table 1 Comparative analysis of the proposed work

S. No.	Proposed			Without PFCM		
	Precision	Recall	<i>F</i> -score	Precision	Recall	<i>F</i> -score
1	0.6489	0.62149	0.634899	0.663521	0.62145	0.641797
2	0.57145	0.86549	0.688385	0.56247	0.87456	0.684626
3	0.59126	0.888654	0.710076	0.65984	0.83214	0.736041
4	0.64254	0.88475	0.744439	0.63247	0.86231	0.72972
5	0.799658	0.89598	0.845083	0.79854	0.83745	0.817532
6	0.8945	0.8123	0.851421	0.7894	0.76589	0.777467
7	0.68745	0.78452	0.732784	0.64587	0.69875	0.67127
8	0.8456	0.9014	0.872609	0.8315	0.85697	0.844043
9	0.86548	0.76485	0.812059	0.8462	0.76842	0.805437
10	0.8456	0.963	0.90049	0.7984	0.912	0.851428
11	0.900145	0.874512	0.887143	0.8965	0.8759	0.88608
12	0.78946	0.886197	0.835036	0.86571	0.87413	0.8699
Average	0.75684	0.84526	0.79287	0.7492	0.815	0.77628

Fig. 12 Comparison between precision values

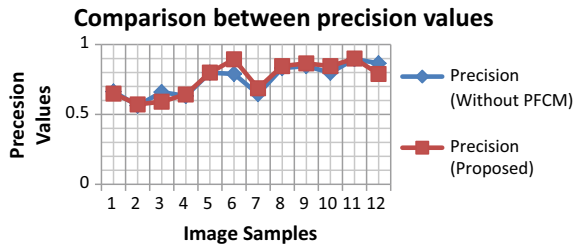


Fig. 13 Comparison between recall values

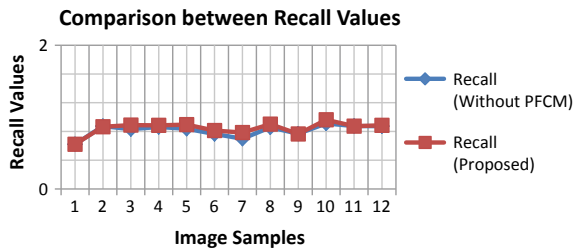


Fig. 14 Comparison between *F*-score values

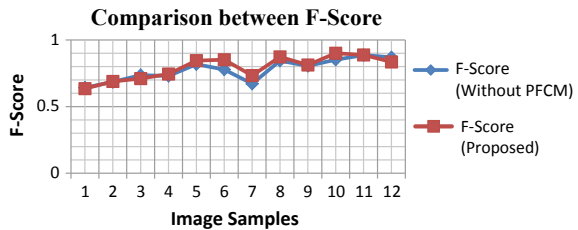


Fig. 15 Comparison among *F*-score, recall, and precision without preprocessing

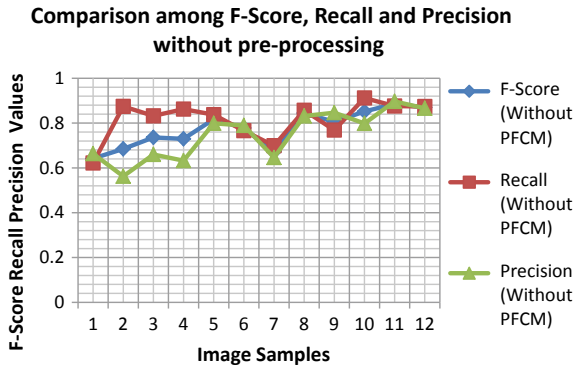
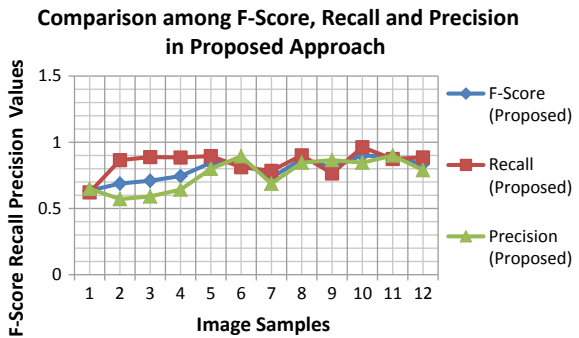


Fig. 16 Comparison among *F*-score, recall, and precision in the proposed approach



- The computed average values of the performance metrics establish the same and demonstrate that even the proposed method has superior average recall, precision, and *F*-Score values.
- It can be observed from the medical images under consideration that the proposed approach performs well in case of different images in terms of shape, parts of the body, etc.

Experimental results have been shown in Figs. 17 and 18. Both figures contain 12 test images where in Fig. 17 column a indicates the original image, column b indicates contour detected image, and column c indicates the image after segmentation where as in Fig. 18 column a indicates the preprocessed image, column b indicates contour detected image after preprocessing, and column c indicates the image after segmentation after preprocessing.

7 Conclusion

The proposed approach is employed to the biomedical images to exploit its capability to segment the images. It is a hybrid approach that uses the advantages of PFCM,

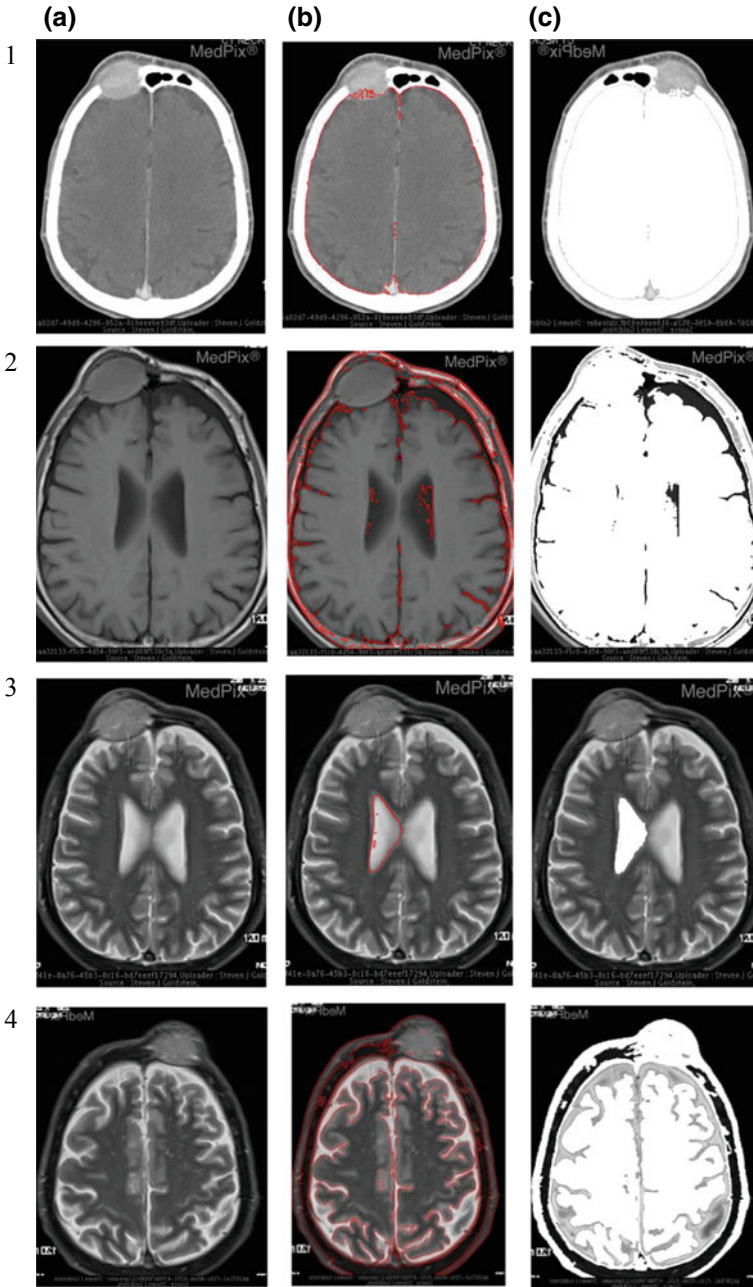


Fig. 17 a Original image, b contour detected image, c segmented image

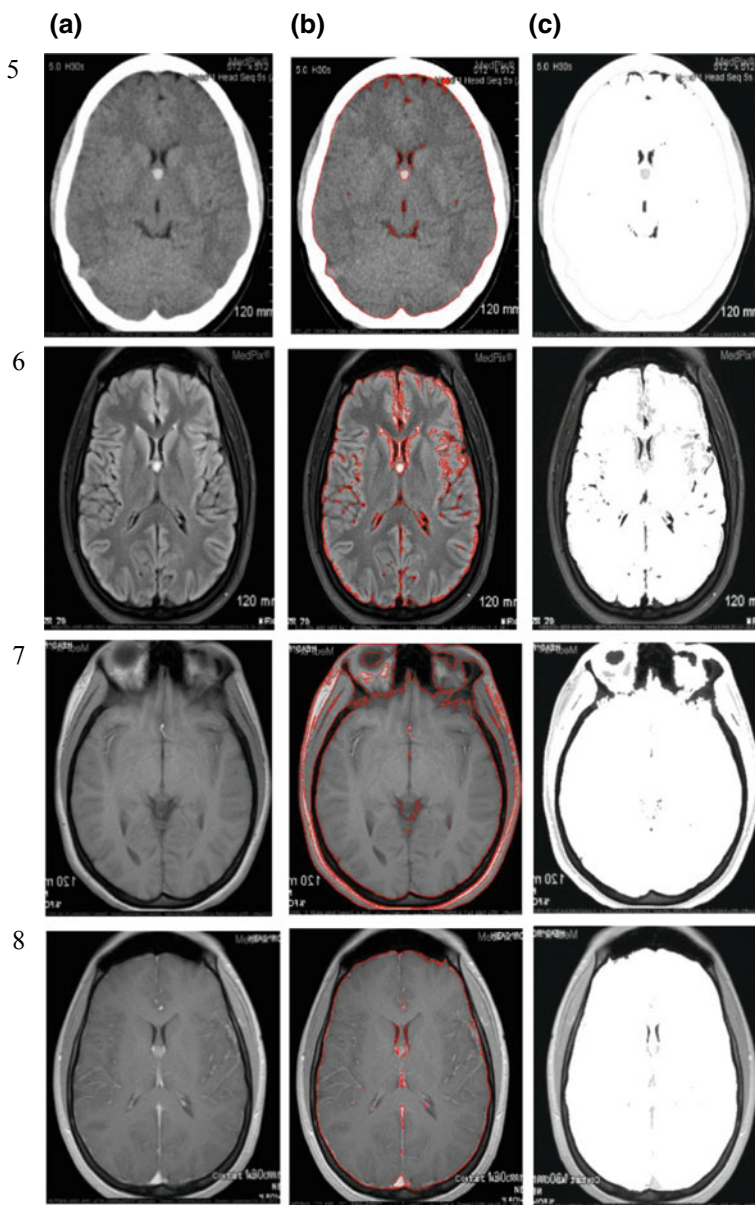


Fig. 17 (continued)

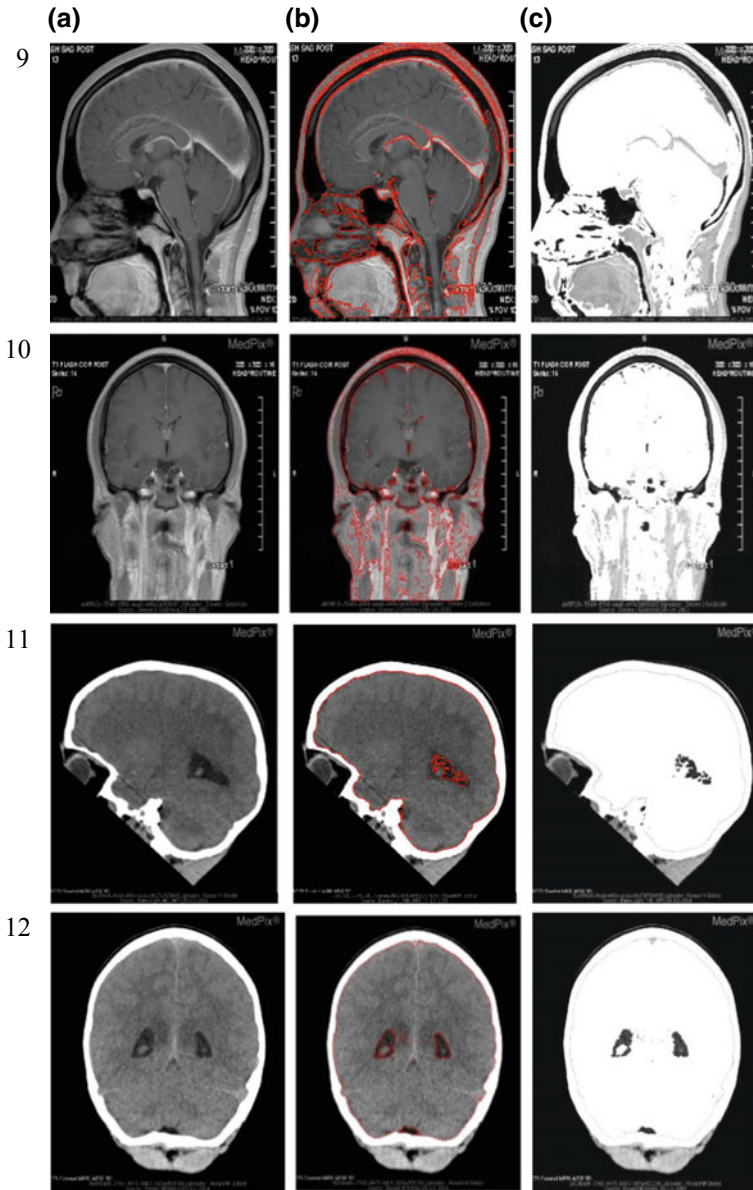


Fig. 17 (continued)

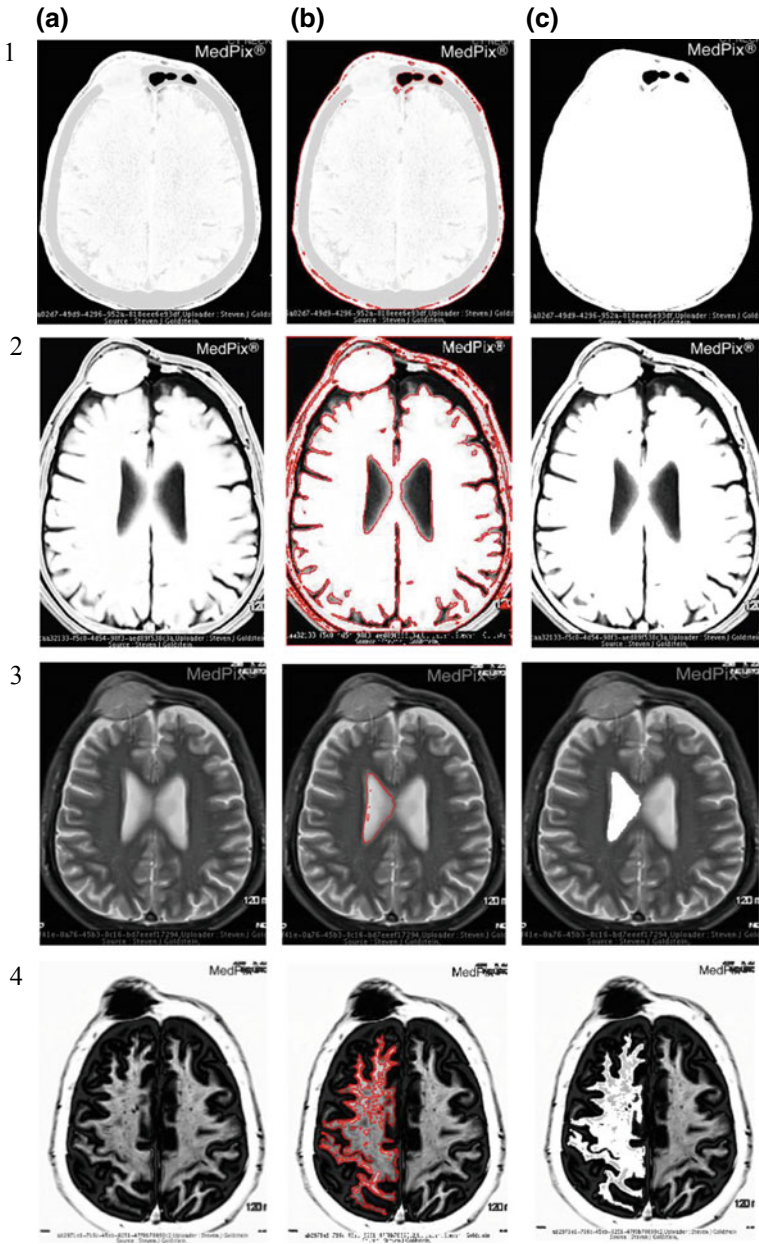


Fig. 18 a Preprocessed image, b contour detected image after preprocessing, c segmented image after preprocessing

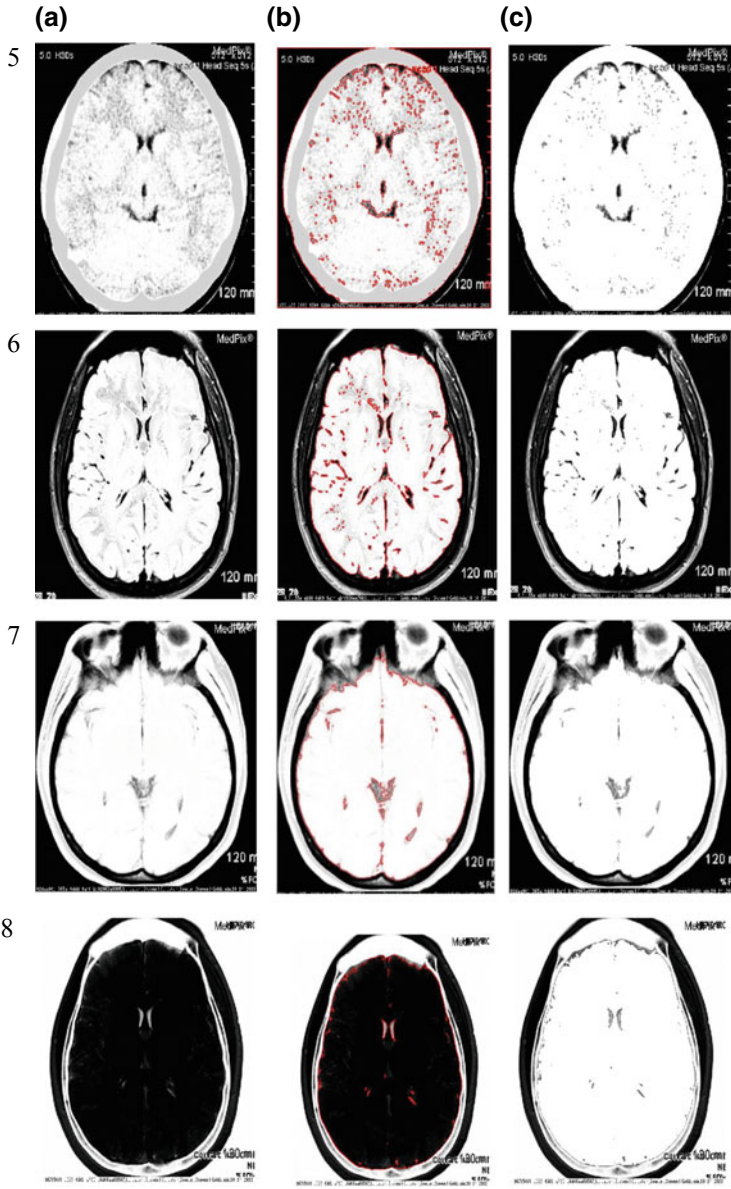


Fig. 18 (continued)

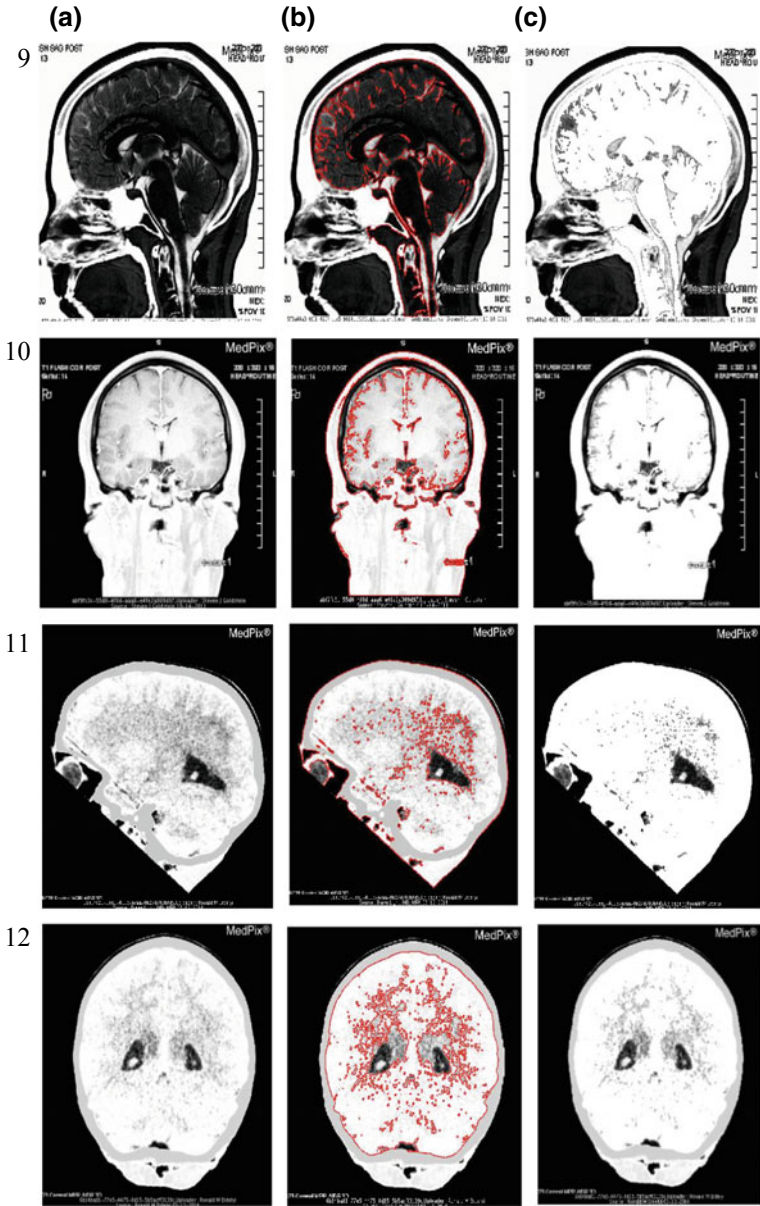


Fig. 18 (continued)

thresholding, and region growing methods to construct a better technique compared to the individual methods for image segmentation.

Moreover, this method provides a method by which medical practitioners can interact with the system manually. It can help users to choose a seed point according to their interest. The efficiency can be measured with three parameters (e.g., recall, precision, and F -score).

In the further work, semiautomatic methods can be implemented for different modalities like PET, fine and small blood vessels in magnetic resonance angiogram (MRA) or retinal images, and computed tomography angiography (CTA) volume data.

References

1. Kamdi, S., Krishna, R.K.: Image segmentation and region growing algorithm. *Int. J. Comput. Technol. Electron. Eng. (IJCTEE)* **2**(1), (2012)
2. Zadeh, L.A.: Fuzzy sets. *Inf. Control* **8**, 338–353 (1965)
3. Kwon, M.J., Han, Y.J., Shin, I.H., Park, H.W.: Hierarchical fuzzy segmentation of brain MR images. *Int. J. Imaging Syst. Technol.* **13**, 115–125 (2003)
4. Toliás, Y.A., Panas, S.M.: On applying spatial constraints in fuzzy image clustering using a fuzzy rule-based system. *IEEE Signal Process. Lett.* **5**, 245–247 (1998)
5. Toliás, Y.A., Panas, S.M.: Image segmentation by a fuzzy clustering algorithm using adaptive spatially constrained membership functions. *IEEE Trans. Syst. Man Cybern.* **28**, 359–369 (1998)
6. Noordam, J.C., van den Broek, W.H.A.M., Buydens, L.M.C.: Geometrically guided fuzzy C-means clustering for multivariate image segmentation. In: *Proceedings of International Conference on Pattern Recognition*, vol. 1 (2000), pp. 462–465
7. Ahmed, M.N., Yamany, S.M., Mohamed, N., Farag, A.A., Moriarty, T.: A modified fuzzy C-Means algorithm for bias field estimation and segmentation of MRI data. *IEEE Trans. Med. Imaging* **21**, 193–199 (2002)
8. Zhang, D.Q., Chen, S.C., Pan, Z.S., Tan, K.R.: Kernel-based fuzzy clustering incorporating spatial constraints for image segmentation. In: *Proceedings of International Conference on Machine Learning and Cybernetics*, vol. 4 (2003), pp. 2189–2192
9. Li, X., Li, L., Lu, H., Chen, D., Liang, Z.: Inhomogeneity correction for magnetic resonance images with fuzzy C-Mean algorithm. *Proc. SPIE Int. Soc. Opt. Eng.* **5032**, 995–1005 (2003)
10. Pham, D.L., Prince, J.L.: Adaptive fuzzy segmentation of magnetic resonance images. *IEEE Trans. Med. Imaging* **18**, 737–752 (1999)
11. Adams, R., Bischof, L.: Seeded region growing. In: *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 16. IEEE Computer Society, Los Alamitos California (1994), pp. 641–647
12. Fan, J., Zeng, G., Body, M., Hacid, M.: Seeded region growing: an extensive and comparative study. *Pattern Recogn.* **26**, 1139–1156 (2005) (Elsevier, Amsterdam)
13. Tremeau, A., Borel, N.: A region growing and merging algorithm to color image segmentation. *Pattern Recogn.* **30**, 1191–1203 (1997) (Elsevier, Amsterdam)
14. Tsai, D.M., Chen, Y.H.: A fast histogram-clustering approach for multilevel thresholding. *Pattern Recogn. Lett.* **13**(4), 245–252 (1992)
15. Otsu, N.: A threshold selection method from gray-level histogram. *IEEE Trans. Syst. Man Cybern.* **SMC-9**(1), 62–66 (1979)
16. Tsai, W.H.: Moment-preserving thresholding: a new approach. *Comput. Vis. Graphics Image Process.* **29**, 377–393 (1985)

17. Yen, J.C., Chang, F.J., Chang, S.: A new criterion for automatic multilevel thresholding. *IEEE Trans. Image Process.* **4**(3), 370–378 (1995)
18. Wang, S., Haralick, R.: Automatic multithreshold selection. *Comput. Vis. Graphics Image Process.* **25**, 46–67 (1984)
19. Sahoo, P.K., Soltani, S., Wong, A.K.C., Chen, Y.: A survey of thresholding techniques. *Comput. Vis. Graphics Image Process.* **41**, 233–260 (1988)
20. Pun, T.: A new method for gray-level picture thresholding using the entropy of the histogram. *Sig. Process.* **2**, 223–237 (1980)
21. Kapur, J.N., Sahoo, P.K., Wong, A.K.C.: A new method for gray-level picture thresholding using the entropy of the histogram. *Comput. Vis. Graphics Image Process.* **29**, 273–285 (1985)
22. Lee, S.U., Chung, S.Y.: A comparative performance study of several global thresholding techniques for segmentation. *Comput. Vis. Graphics Image Process.* **52**, 171–190 (1990)
23. Abutaleb, A.S.: Automatic thresholding of gray-level pictures using two-entropy. *Comput. Vis. Graphics Image Process.* **47**, 22–32 (1989)
24. Yang, Y., Huang, S.: Image segmentation by fuzzy C-means clustering algorithm with a novel penalty term. *Comput. Inf.* **26**, 17–31 (2007)
25. Ambroise, C., Govaert, G.: Convergence of an EM-Type algorithm for spatial clustering. *Pattern Recogn. Lett.* **19**, 919–927 (1998)
26. Hore S., et al.: An integrated interactive technique for image segmentation using stack based seeded region growing and thresholding. *IJECE* 6(6) (2016)
27. <https://medpix.nlm.nih.gov/home>. Last Accessed 15 Mar 2017
28. Buckland, M., Gey, F.: The relationship between recall and precision. *J. Am. Soc. Inf. Sci.* **45**, 12–19 (1994)
29. Dmw, P.: Evaluation: from precision, recall and F-factor to ROC, informedness, markedness & correlation. *J. Mach. Learn. Technol.* **2**, 37–63 (2007)