Modified Image Segmentation Method based on Region Growing and Region Merging

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Abstract: *Image segmentation is one of the basic concepts widely used in each and every fields of image processing. The entire process of the proposed work for image segmentation comprises of 3 phases: Threshold generation with Dynamic Modified Region Growing phase (DMRG), texture feature generation phase and region merging phase. by dynamically changing two thresholds, the given input image can be performed as DMRG, in which the cuckoo search optimization algorithm helps to optimize the two thresholds in modified region growing. after obtaining the region growth segmented image, the edges are detected with edge detection algorithm. In the second phase, the texture feature is extracted using entropy based operation from the input image. In region merging phase, the results obtained from the texture feature generation phase is combined with the results of DMRG phase and similar regions are merged by using a distance comparison between regions. The proposed work is implemented using Mat lab platform with several medical images. the performance of the proposed work is evaluated using the metrics sensitivity, specificity and accuracy. the results show that this proposed work provides very good accuracy for the segmentation process in images.*

Keywords: *DMRG, edge detection algorithm, cuckoo search algorithm, texture generation, region merging.*

Received September 10, 2014; accepted December 23, 2014

1. Introduction

Image segmentation is one of the basic problems encountered in times of earlier computer vision. Its ability to support recognition, description of data structure and detection of related objects [8] has allowed numerous researches of the past to be concentrated towards it [5]. Several researches have been carried out in the field of image processing to explore a number of automatic image segmentation techniques. The main goal of image segmentation is to partition an image into its constituent regions [25] and as a result, the effort of processing the image can be significantly decreased [9]. These partitions are the image objects that own similar texture or color. The image segmentation process results in a set of regions that jointly cover the image completely or produce a set of contours extracted from the image. The pixels of an image region are related through its characteristic or calculated properties like color, intensity and texture. The same characteristics make neighboring regions to be different [17]. The most frequent problem associated with image segmentation is the need of a goodness measure that can objectively evaluate its performance. The cause of this difficulty is the lack of absolute ground truth due to different manual segmentations of the same image [13]. Different technologies have enabled the image segmentation methods to be classified according to two basic properties, namely, the detection of discontinuities and the detection of similarities. Detection of discontinuities involves the partitioning of images depending on sudden intensity Changes. On the other hand, the detection of similarities utilize a set of predefined criterion to partition the image into regions of similarity [7]. Edge detection is an image segmentation algorithm that belongs to the former category of detecting discontinuities in gray level images. The latter category of detecting similarities includes image segmentation algorithms like thresholding, region growing and region splitting and merging. The thresholding method uses the basis range values that are applied to the intensity values of pixels to categorize regions [23]. Region merging, region splitting and a blend of region merging and splitting approaches are most commonly called as region-detection techniques. The fundamental techniques of region detection depend on the techniques of edge detection [27].

Automatic image segmentation play a vital role in object recognition [12], image compression, image editing, image searching and other tasks of machine vision. The industry and daily life applications of image segmentation include different facets like disease diagnosis that involve localization of tumors and other pathologies, measuring tissue volumes, computer-aided surgery and so on [19]. In addition to these tasks, automated segmentation could result in increased precision (intra-operator repeatability and inter-operator reproducibility), by eradicating the prejudice of the clinician [25]. In remote sensing applications, image segmentation allows the objects to be located from satellite imageries of roads, forests, etc. Face recognition techniques and finger print recognition techniques offer much support in providing security. But, there are also automatic image segmentation techniques that are already available for use like traffic control systems that include brake light detection [19]. When comparing manual tracing, the automatic image segmentation has the ability of saving enormous time and effort [25].

García-Ugarriza *et al*. [7] have presented a novel unsupervised automatic color image segmentation algorithm based on color edge detection and dynamic region growing/merging that utilizes color gradients, dynamic thresholding and texture modeling algorithms in a split and merge framework. Shaaban *et al*. [18] have introduced a new approach to color image segmentation that uses contour deformation and region-based segmentation in union. Shahab *et al.* [19] have introduced a modified chain code algorithm for segmentation. Peng *et al.* [15] have presented the automatic image segmentation problem in a region merging fashion. Starting with an over-segmented image that has several regions or super-pixels with homogeneous color detection, the image segmentation is carried out in an iterative manner through the merging of the regions, based on a statistical test. Lu J *et al.* [12] has proposed a robust, fully automatic segmentation method based on the modified edge-following technique. BeenChen *et al.* [3] have presented an algorithm for segmenting scaling in 2-D digital images. This algorithm was assumed to be the earliest method of localizing scaling directly in 2-D digital images. The Pulse-Coupled Neural Network (PCNN) is used far and wide in image segmentation. Gao C *et al.* [6] have presented an automatic image segmentation algorithm that works iteratively by making use of a modified PCNN. A novel dermoscopy image segmentation algorithm using a combination of a Self-Generating Neural Network (SGNN) and the Genetic Algorithm (GA) was introduced by [24]. In comparison to the conventional segmentation schemes, the proposed automatic scheme was found to decrease human errors and operating time with more robustness.

1.1. Previous Work

Segmentation is a very challenging task in medical image analysis. Brain tumor images varies in shapes, size, position and appearance. Over the last 15 years, many researches have been done on semi or fully automatic methods for segmenting brain tumors in MRI images. Fuzzy C-mean is a clustering algorithm introduced by Bezdek in the year 1981 [2]. This is based on minimizing an object function by updating membership function and cluster centers. The object function used here is the weighted sum of distance from cluster centers. The weighted mean of data is the cluster center. Iteration is continued till the operation between iterations exceeds a threshold. This method is time consuming. To overcome this problem Balafar *et al.* [1] proposed a method, in which the histogram of image instead of the pixel values are used as input data for clustering. Hence the size of the data decreases and clustering is done more quickly. This Fuzzy-Mean (FCM) method does not use spatial information while clustering. Therefore they do not provide a good result in noisy images. Tolias and Papas [24], attempted to incorporate spatial information in FCM. They proposed a method which spatially smoothes the membership function to enhance the results of FCM. Huang *et al.* [10] proposes an automated tissue segmentation of brain MRI images. By integrating both image edge geometry and voxel statistical homogeneity, they employed an edge-based geodesic active contour for segmentation. Judehemanth *et al.* [11] proposes a modified FCM algorithm. The computational rate is improved by modifying the cluster center and membership value. Pan *et al.* [14] provides a bayesian-analysis besed region growing algorithm. This method uses multislices Gaussian an anisotropic filters as a preprocessing filters to reduce noise.

2. Proposed Technique

In order to tackle the problems in segmentation work, a new image segmentation technique with cuckoo search based Dynamic Modified Region Growing (DMRG) and Region Merging is proposed. The entire process comprises of 3 phases:

1. Threshold generation DMRG with phase.
2. Texture feature generation phase
3. Region merging phase.

The block diagram for the proposed image segmentation method is illustrated in the Figure 1.

Initially DMRG process is carried out by dynamically changing the two thresholds. Intensity threshold and orientation threshold are the two thresholds that are changed dynamically in the DMRG process. From the dynamic changes of these two thresholds, the optimized best two thresholds to be used in the DMRG process can be identified by utilizing the cuckoo search algorithm. Finally, the region growth image is obtained by the MRG process by using the best two thresholds. From the region grown image, edges and the boundaries are detected from every objects, which results into a edge detected image. Then for the next phase, the original image is subjected to entropy based operation for the generation of texture feature image. in region merging phase, the results obtained from the texture feature generation phase are combined with the results of DMRG phase and similar regions are merged by using a distance comparison between regions.

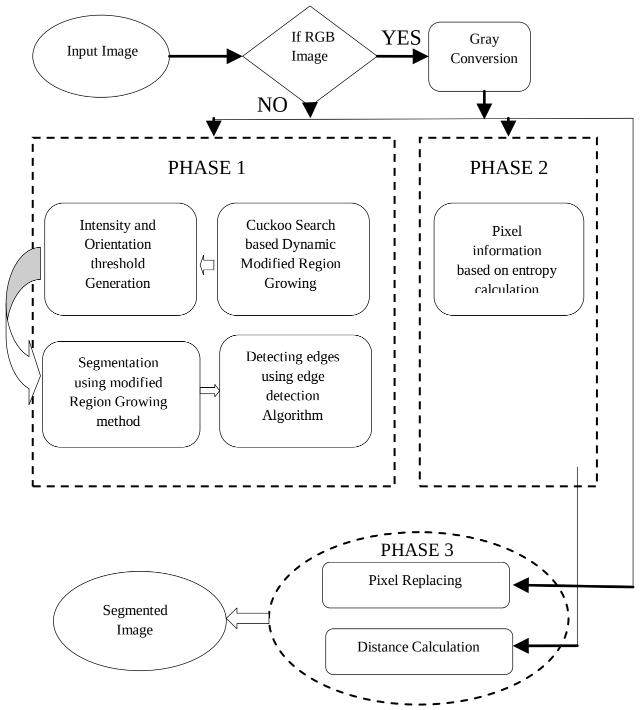

Figure 1. Block diagram for the proposed work.

2.1. Threshold Generation with Dynamic Modified Region Growing Phase

The input image may be a RGB image or a gray scale image. If the input image is RGB, it is converted to gray scale image. If the given input image is Gray, then no change is required. The gray image is represented as I_R.

Segmentation of image using MRG method: Region growing method is a popular technique for image segmentation which involves seed point selection. In the segmentation process, the neighboring pixels are compared with the initial seed points to check whether the neighboring pixels can be added to the region or not. Seed point selection is important task in the segmentation. Generally region growing method selects the seed points by setting the intensity threshold, which has drawbacks of noise or variation in intensity that leads to over-segmentation or holes. Moreover, the shadings of real images may not be differentiated by this method. To overcome these difficulties, we modify the Region growing method by considering intensity and orientation thresholds from the input images to utilize those features in the selection of seed points. The process of MRG method is given in steps which are shown below:

- *Step 1.* Calculate the gradient of the image I_R for both *x* axis and *y* axis (I_{RY}).
- *Step 2.* Form the gradient vector *GV* by combining the gradient values using the following equation:

$$GV = \frac{1}{1 + \left(I_{RX}^2 + I_{RY}^2 \right)} \tag{1}$$

- *Step 3.* Change the gradient vector values that are usually in radians into degrees to get the values of orientation.
- *Step 4.* Segregate the image into grids G_i.
- Step 5. Set intensity threshold (T_{IN}) and orientation threshold T_{OR}.
- *Step 6.* For every grid G_i, continue the following processes in step 7 until the number of grids reached total number of grids for an image.
- *Step 7.*
  a) Find the histogram *h* of each pixel in G_i.
  b) Determine the most frequent histogram of the G_i^{th} grid and denote it as F_h.
  c) Prefer any pixel, according to F_h and assign that pixel as seed point which has the intensity IN_p and Orientation OR_P.
  d) Consider the neighboring pixel having the intensity IN_R and orientation OR_n.
  e) Find the intensity and orientation difference of those pixels *p* and *n*.

i.e.,

$$D_{IN} = \left\| IN_P - IN_R \right\| \tag{2}$$

And

$$D_{OR} = \left\| IN_P - IN_R \right\| \tag{3}$$

  f) If $D_{IN} \leq T_{IN}$ and $D_{OR} \leq T_{OR}$, then add the corresponding pixel to the region and the region is grown, else move to step 7-h.
  g) Check whether all pixels are added to the region. If true go to step 6 otherwise go to step 7-h.
  h) Re-estimate the region and find the new seed points and do the process from step 7-a.
- *Step 8.* Stop the whole process.

Using this MRG process, the input images of gray color space are gets segmented.

Optimizing thresholds by Cuckoo search algorithm based on DMRG method: Cuckoo search algorithm is a meta-heuristic algorithm which was inspired by the breeding behavior of the cuckoos and ease to implement. In cuckoo search, there are a number of nests. Every cuckoo lays one egg at a time, and leaves its egg in a randomly selected nest. The best nests with high superiority of eggs will put back to the next generation. Each egg in a nest represents a solution, and a cuckoo egg represents a new solution. The number of available host's nests is allocated, and the egg laid by a cuckoo is found by the host bird.

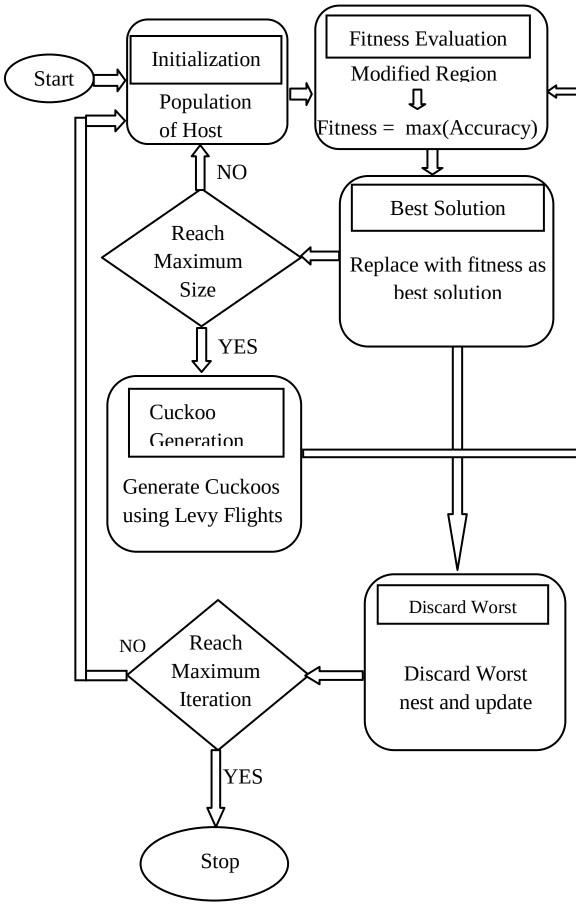

Figure 2. Process of Cuckoo search based on DMRG.

The process performs on some of the worst nest sets and the obtained solutions are leaved from out of calculations. This avoids the over-segmentation of images, which in turns reduce the time spent for the merging process. Thus, by getting the threshold values, the DMRG process is carried out. The process of Cuckoo search based on DMRG is given in the Figure 2.

Initialization: Primarily, the population of host nest hn_i, $i\hat{I}1, \ldots, S$ is randomly initiated. Here, S is the size of the population and s=10×Q where Q indicates the number of thresholds (i.e., Intensity threshold and orientation threshold), which in turns s=10×Q. Both the threshold's generation ranges are [0, 1].

Fitness Function (FF): From the population of host nests, the first nest (hn_1) is chosen and the *FF* of the nest is computed by using the Equation 4:

$$FF = max\ (accuracy) \tag{4}$$

To get the fitness value as given in Equation 4, the process of Modified Region Growing is performed for the first nest value (hn_i) of the two thresholds from the population. The best of fitness value is chosen from all the grids of the given image and this best solution is updated in the first nest by replacing the existing old solution. Then, all the host nests (hn_i) are updated by doing these processes by evaluating FF as in Equation 4. If the accuracy of new solution in the selected nest is better than the old solutions, it is replaced by the new solution (Cuckoo). Otherwise, the previous solution is kept as the best solution.

Generating new cuckoo: A cuckoo is picked at random and it generates new solutions using levy flights. Levy flights help to generate the solutions by random walks. After that the generated cuckoo is evaluated with the FF using MRG method for determining the best accuracy of the solutions.

Discard worst nest: The worst nests are discarded and the new ones are built. Afterwards, the best solutions are ranked based on their FF. Then the best solutions are identified and marked as optimal solutions.

Stopping Criterian: This process is repeated until the maximum iteration is reached. Finally, the best thresholds are obtained.

Thus, the intensity threshold (T_{IN}) and orientation threshold (T_{OR}) to segment the given input image is optimized using Cuckoo search and then these thresholds are only given to MRG method for obtaining the segmented image.

Detecting edges from the segmented image: The edges of the MRG based segmented images are detected by using edge detection algorithm. The process of edge detection algorithm is given below in detail:

1. *Smoothing*: Any noises presents in the image can be filter out by the smoothing process with the help of Gaussian filter. The Gaussian mask is made to slide over the image to manipulate a square of pixels at a time and which is smaller than the actual image size. The mask of the Gaussian filter with the standard deviation of σ=1.4 is given in the following Equation 5.

$$A = \frac{1}{159}\begin{bmatrix} 2 & 4 & 5 & 4 & 2 \\ 4 & 9 & 12 & 9 & 4 \\ 5 & 12 & 15 & 12 & 5 \\ 4 & 9 & 12 & 9 & 4 \\ 2 & 4 & 5 & 4 & 2 \end{bmatrix} \tag{5}$$

2. *Finding Gradients*: From the smoothed image, the gradients are found using Sobel operator. In Sobel operator a pair of 3x3 convolution masks is utilized to find the gradients in x and y axis directions. The gradients in x-axis direction are given in the Equation 6.

$$GX = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \tag{6}$$

The gradients in y-axis direction are given in the Equation 7.

$$G_Y = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} \tag{7}$$

The magnitude of the gradient is approximated using the following Equation 8 with the use of Equation 6 and Equation 7, which is also called as edge strength of the gradient.

$$|G| = |GX| + |GY| \tag{8}$$

The edges are difficult to find, where they are and the directions of the edges can be found using the Equation 9.

$$\theta = arctan\left(\frac{|GX|}{|GY|}\right) \tag{9}$$

3. *Non-Maximum Suppression*: To get the sharp edges from the blurred edges, this step is performed by considering only the local maxima of the gradients. The gradient direction θ is to be rounded nearest to 45^o, by its corresponding 8-connected neighborhood. The magnitude of the current pixel is compared with the magnitude of the pixel in the positive and negative gradient direction. If the magnitude of the current pixel is greatest value means, then only preserve that pixel magnitude value; otherwise suppress the particular pixel magnitude value.
4. *Thresholding*: The edge pixels that remains after the non-maximum suppression process are subjected to the thresholding process by choosing the thresholds in order to find the only true edges in the image. The edge pixels that are stronger than the high threshold are considered as strong edge pixels and the edge pixels that are weaker than the low threshold are suppressed. And also, the edge pixels between these two thresholds are taken as weak edge pixels.
5. *Edge Tracking*: Edge pixels are divided into connected Binary Large Objects (BLOB's) using 8-connected neighborhood. The BLOB's that have at least one of the strong edge pixels are preserved and the other BLOB's without strong edge pixels are suppressed.

Thus, from the MRG based segmented image, we can obtain the edge detected image by detecting only the edges from the image. Hence, from the optimized intensity and orientation thresholds, the given input image gets segmented with its detected edge and the output image is represented as I_{MRG}.

2.2. Texture Feature Generation

The texture feature is generated from the input image I_R The textured region consists of an uncertainty value associated with them, which facilitates a structure for merging the regions that have same characteristics. This required uncertainty of a random variable can be measured from the local entropy, which specifies the randomness related with the region of pixels. At first, the input I_R image gets quantized by uniformly dividing the image into small boxes of size 9 x 9 different levels. The entropy is calculated for each block in the image.

Entropy calculation: Let $\{S_1, S_2, \ldots, S_s\}$ be the pixels with the number of pixels s and its corresponding values be $A_1, A_2, \ldots, A_s$. The probability for a specific value A_j to occur is denoted as $p(A_j)$ and which contains $I(A_j)$ units of information. The unit of information is defined as in the Equation 10.

$$I\left(A_j\right) = log\frac{1}{P\left(A_j\right)} = -logP\left(A_j\right) \tag{10}$$

Thus, $I(A_j)$ of the whole pixel set in one block of image is found and then the entropy of each block of the image can be calculated as in the Equation 11.

$$E(s) = -\sum_{j=1}^{s} P\left(Aj\right)logP\left(Aj\right) \tag{11}$$

For generating the texture feature, after computing the entropy value of each block in an image, the resulting value is assigned to the center pixel of the block. Thus, we can obtain the texture feature from the image and the texture image is represented as I_T.

2.3. Region Merging

Both images from Modified region growing phase and texture feature generation phase are considered for Region merging. The region merging processes are subsequently given in detail:

- *Pixel Replacing*: The pixels in the foreground images of MRG image (output image from phase-I, I_{MRG}) and original input image (input gray image I_R) are considered for the process of pixel replacing. From the I_R image the gray pixels are taken and then the MRG image pixels are replaced by this gray pixels of I_R image. Thus the MRG image pixels get replaced by the gray pixels and the output image is represented as I_P.
- *Distance Calculation*: The distance between each pixels of pixel replaced MRG image, I_P and texture image I_T are calculated. For the distance evaluation, Euclidean distance measure is utilized. By this measure each and every pixel in these both set of images get evaluated as in Equation 12.

$$I\left(P,T\right) = \sum_{i=1}^{N} IPi - ITi \tag{12}$$

After calculating the distance between the pixels of pixel replaced MRG image, I_P and texture image I_T, one threshold value is set to merge the regions of these images. If the pixel distance is less than the threshold value means, those pixels are set as 0 and otherwise, the pixels are set as 1. Thus, the same pixel regions are merged based on the pixel distance evaluation with the pixel replaced MRG image, I_P and texture image I_T.

3. Results and Discussion

The proposed Cuckoo search with DMRG and texture feature based image Segmentation algorithm is experimented with several medical images in MATLAB platform. Four sample images are given in Figure 3. The results with the experimentation on these images are given below in detail.

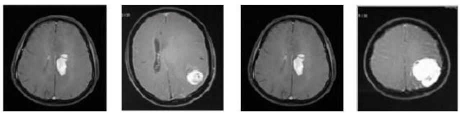

Figure 3. Sample input images.

For this experiment we use both RGB and gray scale images. Most of the medical images are gray scale images, but in general, medical images in RGB format is also available. Because of this reason, we need RGB to Gray scale conversion. Figure 4 shows RGB to gray scale converted images.

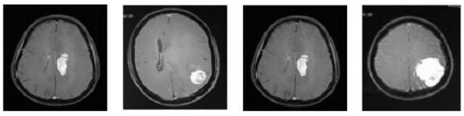

Figure 4. RGB to Gray scale converted images.

After the color conversion of images, dynamic region growing process is performed as the first phase of segmentation. In our work, we are using MRG method using two thresholds (Intensity and Orientation). The optimization of these thresholds is done by using cuckoo search algorithm. The best value is chosen by means of DMRG method for the fitness evaluation. As a result, we can obtain the optimized threshold values and based on these thresholds, the segmentation of the input image can be performed by using MRG method. The resultant output image of segmentation using MRG is given in Figure 5.

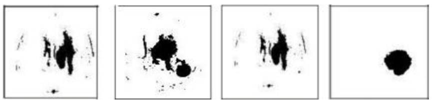

Figure 5. MRG image.

The edges of the MRG based segmented images are detected by using Gradient operator, which is then followed by Non-Maximum suppression, Thresholding and Edge tracking. The Edge detected images are shown in Figure 6.

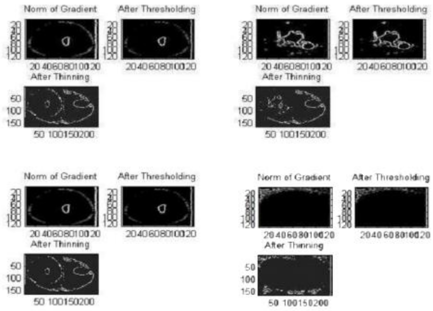

Figure 6. Edge detected images.

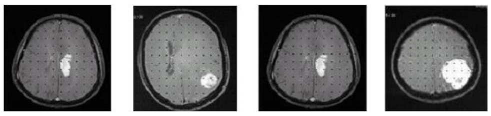

Figure 7. Resulting images after texture feature generation

The texture features were calculated using the Entropy measure and is shown in Figure 7. Finally, the region grown image and texture image are combined to get the region merge output image. The results of region merging process are shown in Figure 8.

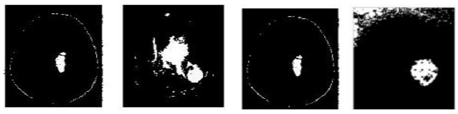

Figure 8. Region merging output.

3.1. Performance Evaluation

By utilizing the performance measures namely False Positive Rate (FPR), False Negative Rate (FNR), sensitivity, specificity and accuracy, the performance of the proposed work is estimated. The segmentation results for some images are given in the Table 1. In our work, totally 4 images are considered to provide the results of FPR, FNR, sensitivity, specificity and accuracy.

Table 1. Segmentation results of medical images with our proposed work.

Images	FPR	FNR	Sensitivity (in %)	Specificity (in %)	Accuracy (in %)
Image-1	0.0443	0.1039	89.6104	95.5674	95.4834
Image-2	0.0774	0.0481	95.189	92.2575	92.3096
Image-3	0.044	0.1167	88.3333	95.5959	95.4895
Image-4	0.0885	0.4293	91.1467	57.0707	90.7349

Corresponding graph for the above Table 2 is plotted in the graph and which is shown in Figures 9 and 10.

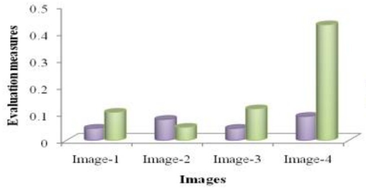

Figure 9. Graphical representation of evaluation measures FPR and FNR for the proposed work with some medical images.

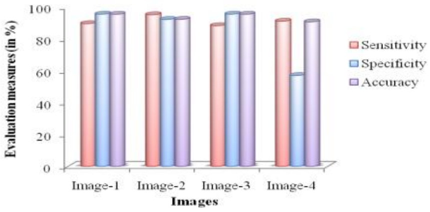

Figure 10. Graphical representation of sensitivity, specificity and accuracy for the proposed work with some medical images.

Table 2. Comparison results of proposed with existing works of image segmentation.

Methods	Accuracy (in %)
Modified FCM method [14]	92.45
Conventional FCM method [14]	92.55
Proposed method	93.50435

From the results of performance measures for our proposed work, the effectiveness of our work can be estimated. The results of four medical images are shown in Table 2 and its corresponding graph is shown in Figures 9 and 10, which are helpful to prove the effectiveness of our proposed work. The accuracy of image-1 is 95.4834%, which tells that our proposed work provides good segmentation results and also it can be proved by showing lesser values in both the FPR and FNR Rates (0.0443 and 0.1039). And another two performance values for that image-1 are sensitivity and specificity, which gives 89.6104% and 95.56745% of higher values, respectively. Likewise, all other three images facilitate very low values for the evaluation metrics FPR and FNR, in which images 1, 2, 3 and 4 gives 0.0774, 0.044 and 0.0885 of FPR values and 0.0481, 0.1167 and 0.4293 of FNR values respectively. The lower values in FPR and FNR lead to very good results of segmentation accuracy. By our proposed work, the higher accuracy values for images 4, 1, 2 and 3 are 95.4895 %, 95.4834%, 92.3096% and 90.7349%. And also the sensitivity and specificity values for these images are also high to provide the better segmentation results for our proposed work. In overall, our proposed work provides 91.0698% of Sensitivity, 85.1228% of Specificity and 93.5043% of Accuracy values.

3. Comparison Results

The existing works are also compared with the proposed work, in order to prove that our proposed work is better. For this, an existing algorithm [14] is taken for consideration in which, two methods were utilized, Conventional FCM based image segmentation and Modified FCM based image segmentation. The accuracy results are given in Table 2.

In Figure 11, the corresponding graphical representation for the Table 2 is given below.

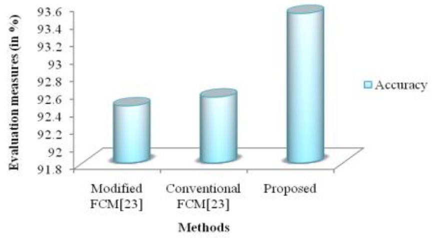

Figure 11. Comparison graph for existing methods and proposed methods.

From the results of comparison, it can be seen that our proposed work is better for image segmentation with medical images. The existing paper with reference [14] is taken for comparison result evaluation. In this paper [14], the authors have utilized two methods for segmentation. The methods are based on FCM, which are conventional FCM and modified FCM based image segmentation. The existing FCM based image segmentation has facilitated 92.55% of accuracy and the existing modified FCM based image segmentation has provided 92.45% of accuracy. This proposed work outperforms all these existing works by providing 93.5043% of accuracy for the image segmentation.

4. Conclusions

The proposed image segmentation method is primarily based on the threshold generation for DMRG, where the threshold is optimized using cuckoo search algorithm, texture feature generation and region merging. This algorithm has been tested using various medical images and the results were evaluated based on the performance measures sensitivity, specificity and accuracy. These measures reveal that this algorithm produces best result when compared to other methods.

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