Diagnosis of Brain Tumor through MRI Image Processing using Clustering with Bacterial Foraging Optimization Technique

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Abstract: MRI Imaging plays an important role in brain tumor for analysis, diagnosis and treatment planning. It is helpful for doctor to determine the previous steps of brain tumor. Because of the complex structure of the brain, detection of brain tumor using MRI images is difficult task. The automatic segmentation of brain tumor is still a challenging problem due to various type of tumor with different structure, shapes and size in morphological.

In this paper a method is presented for diagnosis of brain tumor through MRI Image Processing using Clustering with Bacterial Foraging Optimization Technique.

1. INTRODUCTION

For MRI segmentation numerous techniques have been developed. The most important four classes are region based, model based, threshold-based techniques and pixel classification. In region based segmentation techniques pixels are grouped into homogeneous regions and it segments the region of homogeneous properties and the connected regions are generated. Region growing can also be induced to separate the regions, graceful to noise. This all problems which are coming in region growing techniques can be removed by using hemitropic region-growing algorithm. The disadvantage is that it is expensive in computational time and memory. In model-based segmentation, advanced knowledge of the object like structure, position and situation is used to build a particular anatomic shape. Connected model are also constructs in a continuous manner. These are costly and tough to initialize. The threshold based techniques is one of the older method of segmentation. In this the object of the intensities in the image are differentiate with one or many thresholds intensity and are classified. These threshold techniques are global and local. These methods of segmentation cannot utilize the MRI information. Various method used for segmentation such as thresholding, k mean clustering, fuzzy c mean and biased corrected fuzzy c mean etc. We used biased corrected fuzzy c mean segmentation because it required less time and more accurate.

One of the major difficulties faced by brain MR image segmentation is the bias field in MR images, which arises from the fallibility in the radio-frequency coils. Bias field correction refers to a procedure to detect the bias field from the measured image so that its effect can be eliminated.

In this paper a method is presented which is a mixture of the Bias-Corrected Fuzzy C Means (BCFCM) and Bacterial Foraging Optimization technique. The aim is that to improve the segmentation accuracy high, PSNR value high and computational time should be reduced with segmentation technique. The remaining paper is organized as follows: The previous works and disadvantages are described in Section 2. Section 3 describes the details of proposed work. Experimental results are explained in section 4, conclusion is given in section 5 and references are mention in section 6.

2. PREVIOUS WORK AND ITS DISADVANTAGES

The brain consists of cells and mixture of tissues which can also been seen in the brain tumour image of MRI, so it's the most critical part to recognize the brain tumour exactly and efficiently. Charbel Fares et al (2011), regularly measure and assess the segmentation of an image algorithms. It will perform the segmentation algorithms and differentiate which is based on most important factors: exactness, image will be choices depend on stability, and parameter will be chosen depend on the stability. Ivana Despotovi (2013), introduced a FCM-based clustering techniques majorly for noise robust and spatially coherent image segmentation types. The information of the local image is mingle into both the sameness evaluate and the function of membership is to repay for the result of noisy. Neighborhood, based on the features which are a phase congruency was established to allow extra reliable image smoothing without segmentation.

The results will be segmented, method will be demonstrate efficiently protect the regions of homogeneity and is extra noise to robust than comparable to FCM-based methods. Maoguo Gong (2013), by introducing a kernel metric for segmentation of an image upgrade fuzzy C-means clustering algorithm and fuzzy factor will be a weighted. The factor of fuzzy which is depends on the distance space of all neighbouring pixels and the difference in the gray-level at the same time. It will determine the parameter of the modern algorithm adaptively by using selection rule which will be a fast bandwidth selection for all data points in the collection of group. The results of original images show that the algorithm is powerful and well planned for any type of noise. Jccattashree Aparajeeta (2015), it developed the modified fuzzy c mean for bias field estimation and segmentation of brain. Bias-corrected fuzzy c mean is very useful for noise and intensity inhomogeneity image segmentation. It has the low pass filter to guarantee the smooth bias field estimation.

The Previous work was skilful to diagnose the tumour but the accuracy and efficiency level of segmentation was not up to the mark and for correctly diagnose the tumour the processing time was very high. There was a possibility of a group of parts of tissues and the inner swelling to be categorized as a tumours region. Hence for brain tumour detection and segmentation in MRI images there is a need of computer aided techniques. There are many segmentation techniques which are used for MRI detection. But from most suitable technique for segmentation is BCFCM and to detect the tumor, we will combine BCFCM technique with the optimization technique BFO.

3. THE PROPOSED METHOD

The various steps of MR imaging like; pre-processing, feature extraction, segmentation, post-processing, etc. which is used for finding the tumor area of MRI-images. The proposed block diagram is shown in fig.3.

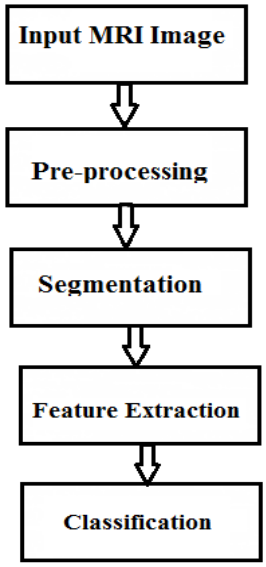


Fig. 3: The Proposed Methodology for Brain Tumor Detection

3.1 Pre-processing:

Median filter and average filter is a non-linear filtering technique used for noise removal. Median filtering is used to remove salt and pepper noise from the converted gray scale image. Average filtering is used to remove gaussion filter .It replaces the value of the center pixel with the median of the intensity values in the neighbourhood of that pixel. Median filters are particularly effective in the presence of impulse noise. Impulse noise is also called as salt and pepper noise because of its appearance as white and black dots covered on image.

3.2 Segmentation

Image segmentation is the process of partitioning a digital image into multiple segments to locate objects and boundaries in image. A label is assigned to every pixel in an image such that pixels with the same label share certain visual characteristics. Various method used for segmentation such as thresholding, k mean clustering, fuzzy c mean and biased corrected fuzzy c mean etc. We used biased corrected fuzzy c mean segmentation because it required less time and more accurate.

3.2.1 Biased Corrected Fuzzy C Mean Algorithm

The observed MRI signal modelled in term of gain field. The gain field is defined as a product of the true signal generated by the underlying anatomy and a spatially varying factor.

$$Y_K = X_K G_K \quad \forall K \in \{1.2 \dots \dots \dots N\} \qquad (1)$$

Where X_K and Y_K are the true and observed intensities at the k th voxel, respectively, $G_K$is the gain field at the k th voxel, and $_N$ is the total number of voxels in the MRI volume. If the gain field is known, then it is easily find the tissue class by applying a conventional intensity-based segmenter to the corrected data. Similarly, if the tissue classes are known, then we can estimate the gain field .We will show that by using an iterative algorithm based on fuzzy logic, we can estimate both.

It allows the labelling of a pixel to be affected by the labels in its immediate neighbourhood by using modified equation (1). The neighbourhood effect acts as a regularizer and biases the solution toward piecewise-homogeneous labelling. Such a

method is useful in segmenting scans corrupted by salt and pepper noise. The modified objective function is given by

$$j_m = \sum_{i=1}^{c}\sum_{k=1}^{N} u_{ik}^{p}\|X_r - V_r\|^2$$

$$+\frac{\propto}{N_R}\sum_{i=1}^{c}\sum_{k=1}^{N} u_{ik}^{p}\left(\sum_{X_r \in N_k}\|X_r - V_i\|^2\right) \qquad (2)$$

Formally, the optimization problem comes in the form

$$U, \{v_i\}_{i=1}^{c} \overset{min}{} \{\beta_k\}_{k=1}^{N} \quad J_m \quad \text{Subject to} \quad U \in u$$

The salient steps of the BCFCM algorithm are given below:
Initialization: Set!j to zero, Threshold= 1, initialize c and vi.
Algorithm :
1: Compute fuzzy membership and Possibilistic membership. Compute η_i.
2: Update Fuzzy membership and Possibilistic membership.
3: Update cluster prototype.
4: Estimate the bias field and compute kvnew − voldk.
5: Repeat step 3 − 5, until kvnew − voldk <Threshold.

3.3 Feature Extraction

Most commercial image retrieval system associates keyword or text with each image and require the user to entire a keyword or textual description of desired image. Features that commonly used in context-based retrieval include colour, shape and edge .When the input data to an is too large to be processed and it is suspected to be redundant, then it can be transformed into a reduced set of features .

Histogram is nothing but the graphical representation of an image. The histogram of a digital image with gray levels in the range [0, L-1] is a discrete function .The histogram of an image mostly represents the comparative frequency of the various gray levels in the image. This process is called feature selection. Extras the features from images in form of color map and edge map.

3.4 Bacterial Foraging Optimization Techniques

Optimization is the process of finding the best inputs in obtaining the maximum or minimum output with minimum cost. The procedure for optimization problem begins by choosing the design variable, and by formulating the constraints and objective functions. We used bacterial foraging optimization technique for brain tumor detection.The bacterial foraging optimization algorithm is a computational intelligence and Meta heuristics type. It was first proposed by Passino. Like another swarm algorithms such as artificial bee colony and firefly algorithm, it is also applied to get solutions for many engineering problems. The inspiration for this algorithm is taken from chemotaxis behaviour of bacteria E. coli and MX anthus. According to the gradient of chemicals in the environment, bacteria seek direction for food. Bacteria can tumble or swim according to its flagella. Using its swimming behaviour bacteria moves in different directions in order to get food. These Bacteria cells are treated like agents. Depending on the agent to agent interactions, agents may form a group or it may ignore each other. Bacteria Foraging Optimization Algorithm governed by four steps is given below:

3.4.1 Chemotaxis: This process simulates the movement of an E.coli cell through swimming and tumbling via flagella. The movement of an E.coli with the help of swimming and tumbling via flagella .An E.coli bacterium can move in two different ways. It can swim for some period of time in the same direction or it may tumble.
3.4.2 Swarming: Swarming is termed as group behaviour of E.coli bacteria in which the cells arrange themselves in a form of a ring by moving up the nutrient gradient. The cells when stimulated by a high level of succinate, release an attractant aspirate, which helps them to aggregate into groups and thus move as concentric patterns of swarms with high bacterial density.
3.4.3 Reproduction: Objective function is used to calculated health of bacteria. If the objective function yields a high value such bacteria are the least healthy bacteria and finally they die. The bacteria which yield lower value are the healthier ones which split into two separate bacteria, which are then placed in the same location. This is how the swarm size is constant.
3.4.4 Elimination and Dispersal: Gradual or sudden changes in the local environment like rise of temperature, where a bacterium population lives may kill or disperse a group of bacteria that are currently in a region with a high concentration of nutrient gradients.

The salient steps of the BFO algorithm are given below:

Step1: Give input image.
Step2: Match input image feature with database features.
Step3: Compute bacterial match value each image.
Step4: Calculate the maximum value i.e., $C_{max.}$

Step5: Compare with maximum index i.e.max_index.
Step6: repeat step 2, until max_index<= $C_{max.}$

4. EXPERIMENTAL RESULTS

The segmentation is performed of brain tumor by using Matlab 13 and the output is obtained for each stage. The MRI data base of brain tumor has collected from Neuron hospital, Dhantoli, Nagpur. For the segmentation purpose 10 MRI brain images are considered. The image is with the default size 0f 512 x512. The segmentation results of BCFCM with Optimized BFO for 10 MRI images are shown in fig. 4.1.

The statistical analysis of the proposed methodology is terms of the parameters like PSNR value (dB), average time (sec), segmentation accuracy (%).
PSNR in dB given by:

$$PSNR=10\log_{10}\frac{MAX^2}{MSE} \quad (3)$$

Where,

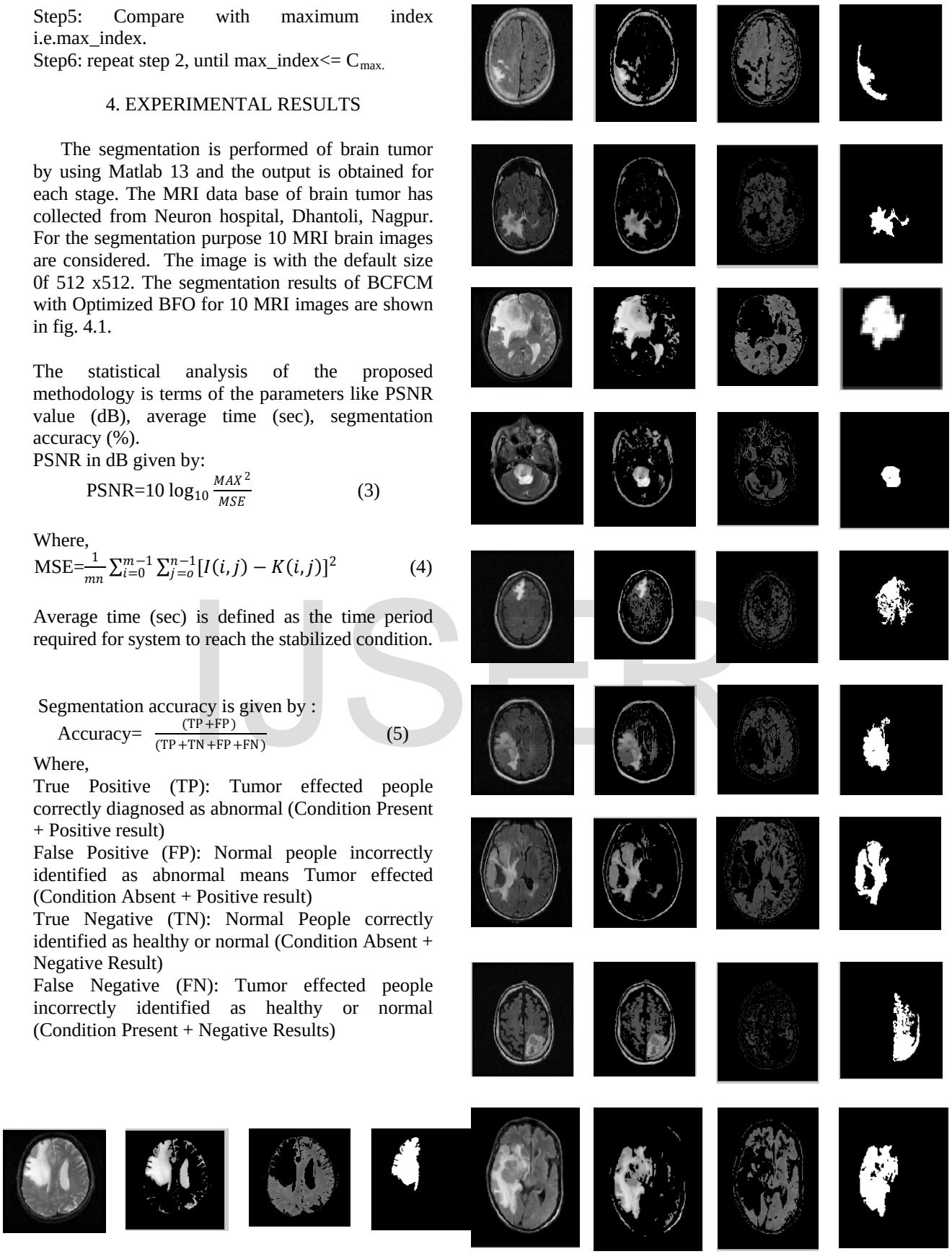
$$MSE=\frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=o}^{n-1}[I(i,j)-K(i,j)]^2 \quad (4)$$

Average time (sec) is defined as the time period required for system to reach the stabilized condition.

Segmentation accuracy is given by :

$$Accuracy=\frac{(TP+FP)}{(TP+TN+FP+FN)} \quad (5)$$

Where,
True Positive (TP): Tumor effected people correctly diagnosed as abnormal (Condition Present + Positive result)
False Positive (FP): Normal people incorrectly identified as abnormal means Tumor effected (Condition Absent + Positive result)
True Negative (TN): Normal People correctly identified as healthy or normal (Condition Absent + Negative Result)
False Negative (FN): Tumor effected people incorrectly identified as healthy or normal (Condition Present + Negative Results)



(a) (b)(i) (b)(ii) (c)

Fig. 4.1 Output of BCFCM:(a)Original Image (b)Segmented image using BCFCM (i)with white matter (ii)with gray matter (c)Segmented image using BCFCM with BFO

The performance analysis as shown is as shown in table 4.1

Table 4.1Comparison of FCM with PSO & BCFCM with BFO

S. N.	FCM WITH PSO		BCFCM WITH BFO	
	Average Time(sec)	*Segmentation Accuracy(%)*	*Average Time(sec)*	*Segmentation Accuracy(%)*
1	7.0083	96.1732	4.6234	98.0963
2	7.4831	96.2641	4.7410	97.8352
3	7.492	96.4554	4.8426	97.9052
4	7.1345	96.4103	4.7082	98.0108
5	7.8236	96.3181	4.7181	98.0492
6	7.9494	96.7875	4.6031	97.8742
7	8.0307	96.3735	4.7195	97.8792
8	7.0176	96.0754	4.5837	97.9219
9	7.0833	96.6919	4.5358	97.8747
10	7.0355	96.783	4.1585	98.0312

The PSNR value and percentage of tumor using method BCFCM with BFO technique is as shown in the table 4.2.

Table 4.2 PSNR & Percentage area of tumor using method BCFCM with BFO technique

S.N.	PSNR (dB)	Percentage(%) of area tumor
1	26.1236	9.6102
2	18.2231	3.7144
3	18.2671	6.7020
4	23.2587	14.1481
5	18.2671	4.4932
6	18.2231	4.4360
7	18.6466	7.8877
8	28.922	9.9014
9	21.9948	8.4797
10	17.0589	9.6102

5. CONCLUSION

In this paper segmentation of brain tumors using Biased Corrected Fuzzy C Mean (BCFCM) method is carriedout which required less time as well as more accurate than FCM algorithm. Then, for classification of brain tumor we used bacterial foraging optimization technique. Bacterial Foraging Algorithm is based on a computational intelligence technique that is not largely affected by the size and non-linearity of the problem and has converged to the optimal solution to many problems where the most analytical methods fail to converge and also has its advantages such as less computational burden, global convergence, less computational time requirement and can handle more number of objective function. Hence, diagnosis of brain tumor using clustering with BFO optimization technique is more efficient than other techniques.

6. References

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