Ant Colony Optimization Technique on Brain Tumor Detection using Segmentation based on Machine learning Approaches.

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Abstract

Problem Statement: Tumor is detected by a radiologist with help of MRI, which is an intricate process. Most of the brain tumor detection methods provide concrete information about the brain tumor and they lack in providing a precise result on existence of a tumor. As a result, a formal consultation with a radiologist is mandatory, which becomes a surplus expenditure in case of a healthy patient. The objective of this research work is to develop a supporting system that would aid the radiologist to have the aforementioned result which reduces the time taken in brain tumor detection.

Approach: The proposed method consists of four processing stages. In first stage, the MRI (Magnetic Resonance Imaging) Brain Image is acquired from MRI Brain Image data set. In second stage the acquired MRI Image is given to the Pre-Processing stage, where the film artifacts (labels) are removed. In third stage, the high frequency components are removed from MRI Image using various filtering techniques. Finally, this study investigates the most effective optimization method, known as Ant Colony Optimization (ACO) is considered in this proposed research work.

Result: The proposed methods reduce the time complexity for brain tumor detection which also includes more accuracy.

Conclusion: In this research work the MRI brain image is considered as input. The end users themselves examine the MRI report by normal vitalization without consulting a radiologist.

Keywords: - Pre-processing, Enhancement, Median filter, Adaptive filter, Weighted Median filter, Ant Colony Optimization

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I. INTRODUCTION

To Access the real medical images like MRI, PET (Positron Emission Tomography) or CT (Computer Tomography) scan and to take up a research is a very complex because of privacy issues and heavy technical hurdles[16]. The purpose of this study is to compare Automatic Brain Tumor Detection methods through MRI Brain Images.

MRI Images were transformed to a Linux Network through LAN (Local Area Network) Kovai Medical Center Hospital (KMCH) India. All images had 1 mm slice thickness with 1×1 mm in plane resolution. Out of these systems, the 0.5T intra-operative Magnetic Resonance Scanner of the Kovai Medical Center and Hospital (KMCH, Sigma SP, GE Medical Systems) offers the possibility to acquire 256*256*58(0.86mm, 0.86mm, 2.5 mm) T1 weighted images with the fast spin echo protocol (TR=400, TE=16 ms, FOV=220*220 mm) in 3 minutes and 40 sec. The quality of every 256*256 slice acquired intra-operatively is fairly similar to images acquired with a 1.5T Conventional Scanner, but the major drawback of intra-operative image is that slice remains thick (2.5 mm)[17].

A grayscale Image can be specified by giving a large matrix whose entries are numbers between 0 and 255, with 0 to black and 255 to white.

II. PRE-PROCESSING

Pre-processing functions involve in those operations that are normally required prior to the main data analysis and extraction of information and are generally grouped as radiometric or geometric corrections. Radiometric corrections incorporate correcting the data for sensor irregularities and unwanted sensor or atmospheric noise [10].

A. Removal of Film Artifacts

The film artifacts are removed using Tracking Algorithm. Initially the Tracking algorithm is proposed to remove film artifacts such as labels and X-ray marks from the MRI Image[9].

Starting from the first row and first column of the MRI Image, the intensity value of the pixel is copied into a new two-dimensional array (256x256) when the following conditions are satisfied. Initially a flag value is assigned as zero. If the intensity value is zero then it is copied to the new image. If the intensity value is greater than zero, it is copied to a new image and the flag value is set as one.

Again the next value is assessed; if it is a non-zero value then that value is stored in a new array; if it is zero, the flag value is set as zero and the remaining pixels in that row are skipped. The next iteration is started with the next row. In this manner, only the brain region is copied into the new array; thus the film artifacts are removed from the MRI Image.

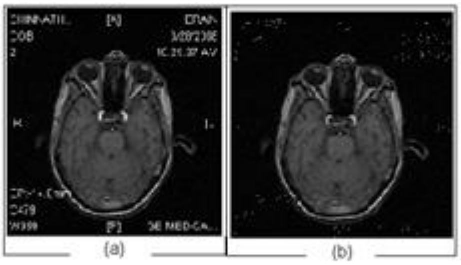

Fig. 1. (a) Original MRI Brain Image (b) Removal of film-artifacts

III. ENHANCEMENT

Image enhancement techniques inquire about how to improve the visual appearance of images from Magnetic Resonance Image (MRI) and the contrast enhancing brain volumes were linearly aligned. The enhancement activities are removal of film artifacts and labels, for filtering the Images [7]. The proposed system describes the information of Enhancement using three types of filters such as (a) Median Filter, (b) Weighted Median Filter and (c) Adaptive Filter for removing high frequency components[8].

A. Median Filter

Median Filter can remove the noise, the high frequency components from MRI without disturbing the edges, bandwidth etc and it is used to reduce salt and pepper noise. This technique calculates the median of the surrounding pixels to determine the new (denoised) value of the pixel. A median is calculated by sorting all pixel values by their size, then selecting the median value as the new value for the pixel.

20	21	20
20	50	22
21	20	21

20	21	20
20	21	22
21	20	21

Fig. 2. Median Filtering

Let us evaluate above Fig. 2., 3x3 windows there are nine pixels, the pixel intensity values are 20, 20, 20, 20, 21, 21, 21, 22, and 50. The values are arranged in ascending order such as 20, 20, 20, 20, 21, 21, 21, 22, and 50. The median is equal to 21. The center pixel value is replaced with 21. This procedure is followed for all the pixels in the image to smoothen the entire MRI Image.

For each pixel, 3x3, 5x5, 7x7, 9x9 and 11x11 Windows of Neighborhood Pixels are extracted and the median value is calculated for the window. The intensity value of the center pixel is replaced with the median value. High Resolution Image is obtained when the process is repeated.

The tumor pixels in the foreground region are white in color their Intensity is 0 to 255 and the background region is normally black in color their intensity is 0 to 10. The Contrast of the region is defined by,

$$C = (f-b) / (f+b)$$

where f is the mean gray-level value of the foreground and b is the mean gray-level value of the background.

Table I shows the performance analysis of the Median Filter in that the Sliding Window of 3x3, 5x5, 7x7, 9x9 and 11x11 of Mean gray level of foreground, Mean gray level of Background and contrast values are computed.

Table I Performance Analysis of Median Filter

Sliding Window	Mean gray level of foreground	Mean gray level of	Contrast Value

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size		Background	
3×3	93.154	4.049	0.9167
5× 5	95.414	4.267	0.9144
7×7	95.475	4.305	0.9137
9 ×9	94.835	4.284	0.9136
11 ×11	93.869	4.243	0.9135

The contrast value for various sliding window sizes of 3x3, 5x5, 7x7, 9x9 and 11x11 is calculated using mean gray level of foreground and background.

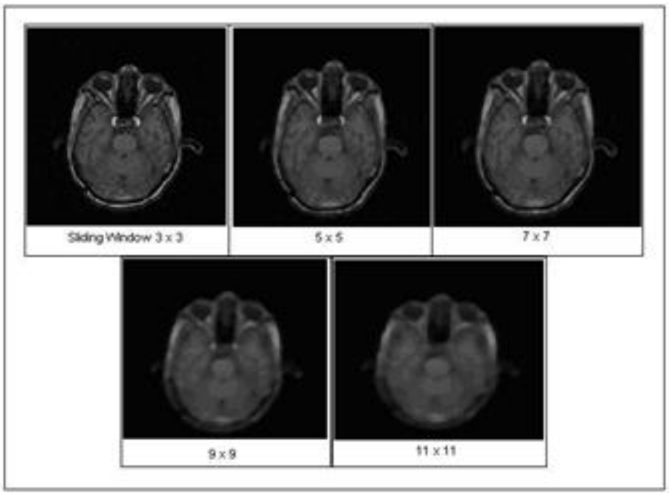


Fig. 3. Median Filter of 3x3, 5x5, 7x7, 9x9, and 11x11 of Sliding Window Concept

The above Fig. 3 shows, 3×3, 5×5, 7×7, 9×9 and 11×11 windows are analyzed, in which 3×3 window is chosen based on the high contrast than 5×5, 7×7, 9×9 and 11×11.

B. Weighted Median Filter

The Weighted Median Filter is to eliminate high frequency component noise from MRI Image without disturbing the edges. The Weighted Median Filter is same as Median Filter but here, giving Weights to the pixels. If the intensity value is less than 50, a weight 0.1 is multiplied with the intensity value Else If the intensity value ranges from 51-100, a weight 0.2 is multiplied with the intensity value Else If the intensity value ranges from 101-150, a weight 0.3 is multiplied with the intensity value then calculates the median values.

This Enhancement stage, the Weighted Median Filtering is applied for each pixel of 3×3, 5×5, 7×7, 9×9 and 11×11 window and neighborhood pixels are extracted and analyzed the mean gray value of foreground, mean value of background and contrast value. If all the weights are equal, then the Weighted Median is the same as the Median Filter.

The tumor pixels in the foreground region are white in color their Intensity is 0 to 255 and the background region is normally black in color their intensity is 0 to 10[15]. The Contrast of the region is defined by,

C = (f-b) / (f+b)

where f is the mean gray-level value of the foreground and b is the mean gray-level value of the background.

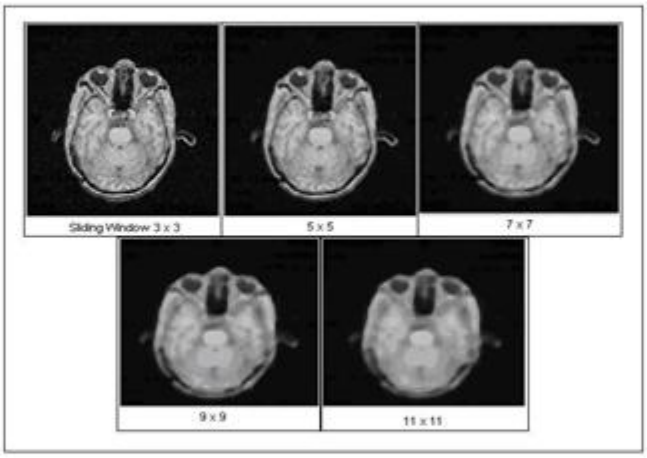
Table II shows the performance analysis of the Weighted Median Filter in that the Sliding Window of 3x3, 5x5, 7x7, 9x9 and 11x11 of Mean gray level of foreground, Mean gray level of background and contrast values are computed.

Table II

Table 2. Performance Analysis of Weighted Median Filter

Sliding window	Mean gray level of foreground	Mean gray level of Background	Contrast Value
3×3	92.5059	4.2789	0.9116
5× 5	95.1252	4.5236	0.9092
7×7	95.2662	4.5717	0.9084
9 ×9	94.1861	4.5462	0.9079
11 ×11	92.5125	4.4779	0.9077

The contrast value for various pixel size of 3x3, 5x5, 7x7, 9x9 and 11x11 are calculated using mean gray level of foreground and background.



The Fig .4 shows the Performances Analysis of Weighted Median Filter.

C. Adaptive Filter

An adaptive filter is a filter that Self-adjusts its transfer function according to an optimizing algorithm [8]. A new type of adaptive filter is developed for impulsive noise reduction of an Image without the degradation of an original Image.

The Contrast of the region is defined by,

C = (f-b) / (f+b)

where f is the mean gray-level value of the foreground and b is the mean gray-level value of the background.

Table III shows the performance analysis of the Adaptive Filter in that the Sliding Window of 3x3, 5x5, 7x7, 9x9 and 11x11 of Mean gray level of foreground, Mean gray level of Background and contrast values are computed.

Table III

Performance Analysis of Adaptive Filter

Sliding Window	Mean gray level of foreground	Mean gray level of Background	Contrast Value
3×3	88.2121	3.3551	0.9267
5× 5	96.4823	3.6145	0.9278
7×7	95.9038	3.6561	0.9266
9 ×9	96.1042	3.7143	0.9256
11 ×11	96.1785	3.7485	0.9250

The below Fig 6 shows Performance Analysis of Adaptive Filter 3×3, 5×5, 7×7, 9×9 and 11×11 windows are analyzed in that 3×3 window is chosen based on the high contrast than 5×5, 7×7, 9×9 and 11×11.

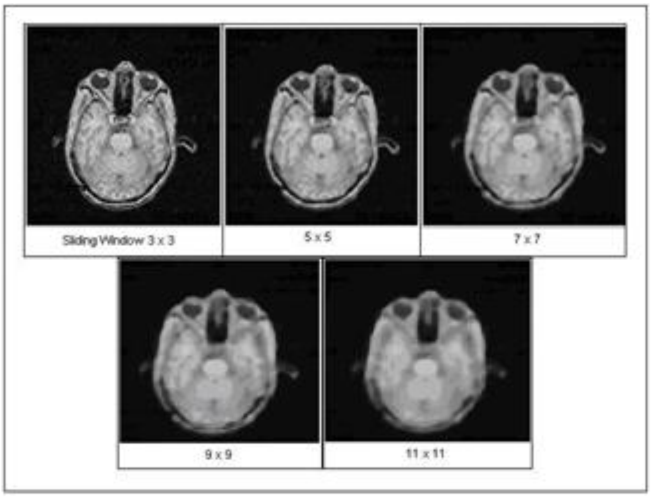


Fig. 5. Adaptive Filter of 3x3, 5x5, 7x7, 9x9, and 11x11 of Sliding Window Concept

IV. PERFORMANCE EVALUATION

The Average Signal-to-Noise Ratio (ASNR) and Peak Signal-to-Noise Ratio (PSNR) values are computed using following filtering techniques such as Median Filter, Weighted Median Filter and Adaptive Filter [11].

The PSNR and ASNR are used to evaluate the enhancement performance. The noise level is measured by the standard derivation (σ) of the original MRI Image.

$\sigma = \text{sqrt}((1 / N) \sum i\ (bi - b)2),\ i=1,\ldots,N$

where b is the mean gray level value of the original image and bi is the gray level value of a surrounding region, and N is the total number of pixels in the surrounding region.

The PSNR and the ASNR are defined as follows:

$PSNR = (p - b) / \sigma$

$ASNR = (f - b) / \sigma$

where p is the maximum gray level value and f is the average gray level value of an enhanced image.

If the values of the two indices are larger, the proposed preprocessing and enhancement method performance is better. The proposed method produces 0.924 and 0.929 for the PSNR and the ASNR respectively. The IV Table shows compares the performance of the proposed algorithm with the existing methods.

The Signal-to-Noise Ratio can be used as an optimal parameter to analyze the performance of the enhancement techniques. The statistical result shows that the proposed method performs better than the existing methods.

A. Experiment and Result

Peak Signal-to-Noise Ratio (PSNR)

Average Signal-to-Noise Ratio (ASNR)

The Contrast and Contrast Improvement index is needed to Compute ASNR and PSNR.

1. Contrast Improvement Index(CII)
2. Contrast

Contrast Improvement Index (CII)

$CII = C_{Processed} / C_{Original}$

where C processed and C original are the contrasts for a Brain Image in the processed and original images.

C processed and C original = Contrasts of MRI

$CII = C_{Processed} / C_{Original}$

$= 0.9167 / 0.9267$

$= 1.0000$

The noise level is measured by the standard derivation σ of the original MRI Image,

σ = sqrt ((1 / N) ∑i (bi – b)2), i=1,…,N

where bi = Gray level of a background region and N = total number of pixels in the surrounding background region (NB)

$\sigma = \sqrt{(1/ 20753)} \sum_i (75011- 3.6145)$

$= \sqrt{(1/ 20753)} \sum_i (75007)$

$= \sqrt{(4.8185)} \sum_i (75007)$

Contrast is the act of distinguishing by comparing differences,

C = (f-b) / (f + b)

where f = mean gray -level value of the foreground and b= mean gray-level value of the background.

Noise level= standard derivation (σ) of the background

The PSNR and the ASNR are defined as follows:

PSNR = (p – b) / σ

ASNR = (f – b) / σ

where FG – Gray level Foreground, BG – Gray Level Background, C – Contrast, NF - Total number of pixel in the surrounding Foreground Region, NB - Total number of pixel in the surrounding Background Region, b- Background, F- Foreground

Table IV

Performance Analysis of Enhancement Techniques

S No	Filters	PSNR	SNR
1	Median	0.911	0.909
2	Weighted Median	0.924	0.929
3	Adaptive	0.904	0.907

The PSNR and ASNR values calculated for Median Filter, Weighted Median Filter and Adaptive Filter.

V. Ant Colony Optimization

Ant Colony Optimization (ACO) is a population-based approach first designed by Marco Dorigo and coworkers, inspired by the behavior of Ant Colonies [1]. Individuals ants are simple insects with limited memory and capable of performing simple actions. However, the collective and comprehensive behavior of ants offers intelligent solutions to problems such as finding the shortest paths from the nest to a food source. Ants foraging for food lay down quantities of a volatile chemical substance named pheromone, marking their path that it follows [2].

The probability that an ant chooses a path increases with the number of ants choosing the path at previous times and with the strength of the pheromone concentration laid. The goal of this method is to find out the optimum label of the image that minimizes the posterior energy function value. Initially assign the values of number of iterations (N), number of Ants (K), initial pheromone value (T0)[5].

A. Pheromone Initialization

For each kernel assign the initial pheromone value T0 and for each ant select a random kernel, which has not been selected previously. A flag value is assigned for each pixel to know whether the kernels are already been selected or not with respective to the ant. Initially the flag value is assigned as zero; once the kernel is selected the flag is changed to one. This procedure is followed for all the ants. For each ant a separate column is maintained for flag values.

B. Local Pheromone Update

Update the pheromone values for all the selected kernels using the following equation:

$TLP = (1 - \rho) * Told + \rho * T0$

where Told and TLP are the old and locally updated pheromone values and ρ is rate of pheromone evaporation parameter in local update, ranges from (0,1) i.e., $0 < \rho < 1$. Calculate the posterior energy function value for all the selected kernels by the ants.

C. Global Pheromone Update

Compare the posterior energy function value for all the selected kernels from each ant, select the maximum value from the set, which is known as 'Local Maximum' (Lmax) or 'Iterations best' solution. This value is again compared with the 'Global Maximum' (Gmax). If local maximum is greater than global maximum, then the global maximum is assigned the current local maximum value. Then the kernel, which has this local maximum value, is selected and its pheromone is updated using the following equation:

$$TGP = (1 - \alpha) * TLP + \alpha * \Delta TLP$$

where TLP and TGP are the local and globally updated pheromone values and α is rate of pheromone evaporation parameter in global update, ranges from [0,1] i.e., $0 < \alpha < 1$ and Δ is equal to (1 / Gmax). For the remaining kernels their pheromone is updated as:

$$TGP = (1 - \alpha) * TLP$$

here, the Δ is assumed as 0. Thus the pheromones are updated globally. The kernel, which generates the Gmax, is traced and the spatial co-ordinate of the center pixel is stored. This procedure is repeated till all the ants have visited the kernels. The entire procedure can be repeated for number of times (NI). For the next iteration the ants are placed at the neighborhood kernels with highest probability of pheromone. At the final iteration, the co-ordinate of the image pixel that maximizes the posterior energy function value is considered.

VI. Implementation of ACO with FCM

After completing all the processes the generated output is given to the FCM as input [4][12]. The optimal value of ACO through MRI Brain Image is given as an input for FCM. The aim of FCM is to find cluster centers (centroids) that minimize dissimilarity function [3][13].

The membership matrix (U) is randomly initialized as

where i is the number of cluster

j is the image data point

$$\sum_{i=1}^{c} U_{ij}=1;$$

The dissimilarity function can be calculated with this equation

$$C_i = \sum_{i=1}^{c} J_i = \sum_{i=1}^{c}\sum_{j=1}^{n} U_{ij}{}^{n} d_{ij}{}^{2}$$

where Uij is between 0 and 1

Ci is the centroid of cluster i

dij is the Euclidean distance between ith and centriod (Ci) and jth data point

M is a weighiting exponent.

To calculate Euclidean distance (dij)

Euclidean distance (dij) = Cluster center pixels - current neuron

Dij = CCp – Cn

where CCp is the Cluster center pixels

Cn is the current neuron

i.e. Number of clusters is computed as

C = (N/2)1/2

N= no. of pixels in image

To find the Minimum dissimilarity function can be computed as

$$U_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{d_{ij}}{d_{kj}} \right)^{2/(m-1)}}$$

where dij=|| xi -cj|| and dkj=|| xi –ck||

xi is the ith of d- dimensional data

cj is the d-dimensional center of the cluster

||**|| is the similarity between any measured data and center

so these iteration will stop when the condition

Max ij { | Uij(k+1)-Uijk | } <€ is satisfied

where € is a termination criterion between 0 and 1

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K is the iteration step

The step of the FCM Algorithm has been listed

Step 1: Initialise U = Uij matrix

Step 2: At K step initialize centre vector C (k) = C j taken from ACO Clustering Algorithm

Step 3: Update U (k), U (k+1), then compute the dissimilarity function

If $\| U^{(k+1)} - U^{(k)} \| < €$ then stop.

$$U_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{d_{ij}}{d_{kj}} \right)^{2/(m-1)}}$$

In the first step, the algorithm selects the initial cluster from ACO Clustering Algorithm. Then, in later step after several iteration of the algorithm, the final result converges to actual cluster of ACO with FCM [6]. The aim of ACO with FCM is to detect the suspicious region from the background region in the MRI brain Image. If the Maximum Adaptive threshold is used to compare the current neuron value. If the current value is less than the Adaptive Thresholds neglects the region set to black and the suspicious region is look like bright [14].

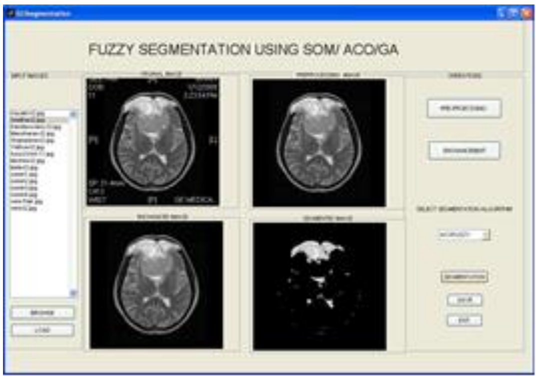

Fig. 6. Tumor Detection using various segmentation Methods ACO, GA and HSOM

VII CONCLUSION & FUTURE ENHANCEMENT

This research work highlights and emphasizes the Pre-Processing and Enhancement of the proposed method to remove the Film Artifacts using Tracking Algorithm. The MRI Images where considered for Enhancement stage and removes high frequency components. In this paper filtering techniques are considered to remove high frequency components from MRI Brain Image. The performance of the systems is investigated based on the Computational result. As a result of investigation and comparison Weighted Median Filter is better than compared with other filtering techniques. The merit of using Weighted Median Filter is to remove the noise without disturbing the edges. From this research work the proposed Ant Colony Optimization algorithm gives 82% tumor pixel values when compared with other segmentation techniques. From these visualization results a normal end user can able to easily understand the results with respect to brain tumor without any domain knowledge.

There is immense scope for extracting the ideas to a wider variety of application of brain tumor detection.

1. The program needs to be compiled to run in an independent environment and algorithms need to be optimized in order to reduce the time consuming and performing and increase in accuracy.

2. The program could be developed in ability of access to host computer or hospital via ICT to get patients information and images.

3. More discriminative futures could be identified to reduce the error rate.

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