International Journal of Emerging Technology in Computer Science & Electronics (IJETCSE)
ISSN: 0976-1353 Volume 27 Issue 3 – SEPTEMBER 2020.

AUTOMATIC BRAIN TUMOR DISCRIMINATION ON MR IMAGES USING HISTOGRAM OPTIMIZED TREE SEED ALGORITHM

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***Abstract*— Recent trends in signal processing gives out a prominent hope in medical field. This work aims to make use of image analysis for extraction of prominent information from brain. The usage of data level information in the form of histogram will enable the processing to be more powerful than other available techniques. Despite the available four types of histogram, the histogram with dynamic range of intensity values will make the visualization of images a much understanding one. For such dynamic range histogram, gaussian filters are used. The best suited values for histogram are found out using Tree-Seed Optimization algorithm, which is very helpful in demarcation of brain tumor from MR images. The efficiency of the planned technique is tested with standard performance metrics. The proposed method yields an accuracy of 97.8%**

***Index Terms*— Segmentation, Histogram, Tree-seed Algorithm**

I. Introduction

MRI is most commonly used to detect brain tumor size, shape and location of the tumor. Brain tumor is nothing but abnormal cells inside the brain. There is of different types of brain tumor. Some of the tumors are not cancerous(benign) and some are cancerous(malignant)[1].Its treatment depends on the extent and form and type of the tumor inside the brain. There are two categories of brain tumors, primary and secondary brain tumors. Primary brain tumors cause due to normal cells gets mutations in DNA. This mutation grows and increases the cells and damages the healthy cells. This causes the large number of abnormal cells; the tumor is formed. Secondary brain tumors occur in people having a family history of Cancer[2].The spinal cord tumor is a tumor that starts inside the brain or spinal cord. This year an estimation of 23,820 adults will be diagnosed for primary cancerous tumors of brain. Also, children of below age 15 abut 3,720 will get diagnosed for primary cancerous tumors of brain[3].There is a high-level chance of brain tumor by exposing ionizing radiation to a person. Radiation therapy used to treat cancers, radiation exposure released by atomic bombs are the examples of ionizing radiation[4].The removal of tumor in brain is mostly by surgery. Radiotherapy also called as radiation therapy is used to kill the cancer cells and stops growing the tumor by using high power rays. The available medical techniques used to detect brain tumor are X-Ray, computed tomography(CT) and positron emission tomography(PET). The killing of cancer cells by using drugs is called chemotherapy. The symptoms of brain tumor are headache, vomiting and seizures[5].

II. Literature Survey

In this section noticeable works on brain tumor segmentation was discussed. In his work Hassan Khotan Lou et.al had proposed the segmentation method based on by combining deformable model and spatial relations[6],it leads to dissection of tumors. Jun jiang et.al had proposed a scheme to paradigm a graph by knowledge of the people and patient features set of MR images and using the chart cut to reach the segmentation[7].A CNN-model which combines efficiently the 2D long range and 3D short range and also network architecture with modality- specific sub-networks had proposed in this work by Pawel Mlynarskia et.al [8].In this work Lubna Farhi et.al proposes an algorithm that performs autonomous stochastic segmentation of tumor in MR images by combining uniform separation and histogram energies[9].A brain tumor segmentation is built on integrating the fully convolutional neural networks(FCNNs) and conditional random fields(CRFs) to obtain the segmentation results had been proposed by Xiaomei Zhao[10].In this work Tiejun Yang et.al proposed an automatic segmentation method integrating small kernels two path convolutional neural network(SM-TPCNN)and random forests(RF)[11].In this work Guotai Wanget.al had analysed the different doubts for CNN based 2D and 3D medicinal image segmentation task at both pixel and edifice level and also besides proposed a test-time augmentation based aleatoric uncertainty to detect the effect of dissimilar transformations of contribution image on the output segmentation[12].In this work Jie Chang et.al have designed a two-pathway model with middling and max pooling sheets in dissimilar path[13]. The involvement of max pooling will create a trade-off between segmentation accuracy and computational complexity and has to be carefully dealt. In this work Mikael Agn et .al proposed a contrast adaptive multiplicative model for entire brain segmentation with a new three-dimensional regularization model of tumor form by means of convolutional limited Boltzmann machine[14]. Disadvantage are the method does not match atlas with segmentation structures and also the method consumes about a time duration 40 minutes which is relatively larger. Chaiyanan Sompong, Sartra Wongthanavasu proposed a outline of two models to advance the brain segmentation image transformation and segmentation algorithm [15].Disadvantage is GLCM-CA offers the non-promising outcomes in the white matter areas having parallel intensities in tumor region and it has more complication for calculating the patch mass distance. Mustafa servet kiran presents a work to implement a new intellectual optimizer based on the relation among trees and seeds for constant optimization

III. PROPOSED WORK

A plentiful research works on tree seed algorithm and its applications were carried on various fields. A few prominent works are discussed in this section. The extraordinary properties of tree-seed algorithm in designing an optimization approach for well performing RBFN(Radial basis function network) was proposed by Muneeswaran in 2016. The algorithm generates a best solution of the network parameters. The network designed in such a way was used by the same author to segment gall bladder region from an ultrasound image. The designed segmentation algorithm using TSA-optimized RBFN achieved excellent results. The TSA algorithm has also become more popular in image pre-processing in which an adaptive filter that suits the need of a Beltrami-regularization parameter was meaningfully designed in the year 2017. The filter designed was applied on ultrasound B-mode images and parameters such as SSIM and PSNR were calculated. In the same line, a pre-processing method inclusive of local contrast and histogram equalization procedure together with the operation of TSA was executed to enhance mammogram images. In the field of image compression, the landmark of TSA was introduced in the year 2019, by designing a metaheuristic filter using TSA for image compression applications.

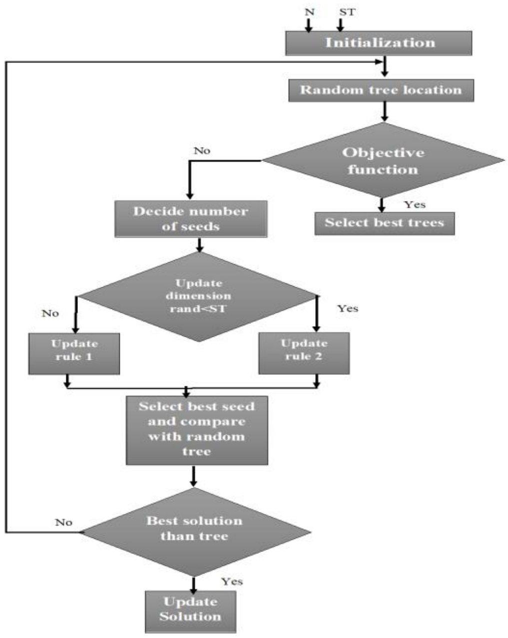


Figure 1: RBFN

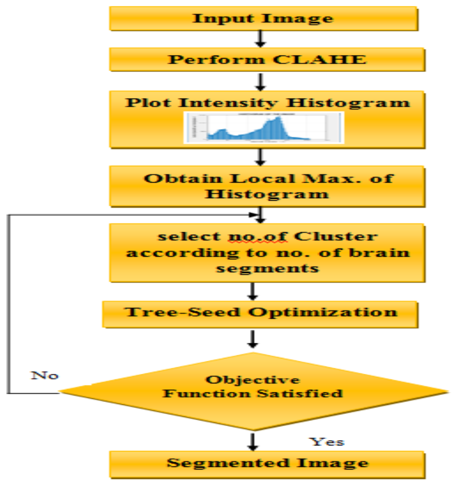


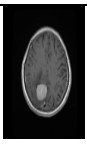
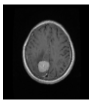
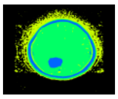
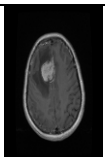
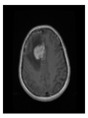
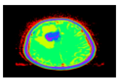
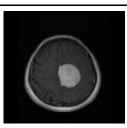
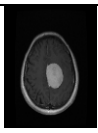
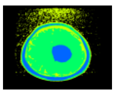
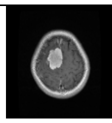
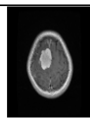
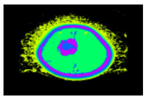
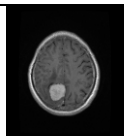
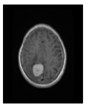
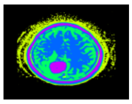
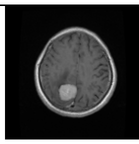
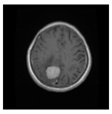
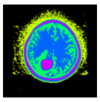
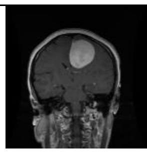
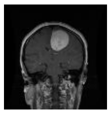
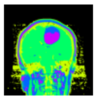
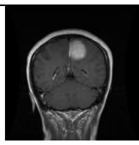
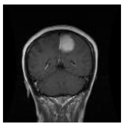
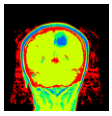
Figure 2: Proposed Segmentation

IV. IMPLEMENTATION

The Computational platform for implementing the segmentation algorithm comprises of the system components as MATLAB 2017 a installed on a Windows 10 operating system with AMD Ryzen 3 2200 with Radeon Vega Mobile Gfx and 4 GB RAM. Table 1 illustrates the sample selection of best solutions and fitness values for sample 30 iterations for input image 1 and input image 2. The best fitness value for input image 1 was obtained in third iteration whereas for the input image 2 only in the 12-iterationfitness value was obtained beyond that the solution does not improve as it is the global best solution. The visual efficacy of the segmentation algorithm is shown in fig. in which the left most column represents the sample image sequence, input image used proceeded with gaussian smoothened image and segmented image respectively. It is obvious that any medical imaging modality will suffer quality loss due to addition of noise and in such cases preferably a suitable filtering technique has to be chosen to remove such artefacts. In our proposed work the gaussian filter is used to remove the high frequency components that attempts to introduce noise. Then the histogram adaptiveness process will be done to gaussian smoothened image. By using the segments obtained from the histogram, the tree seed algorithm will find the optimum best values for better segmentation and its shown in fig. A sample histogram bin calculation and tree seed convergence curve for input image 1 and input image 2 was also shown in fig.

Iteration and ST	Input Image 1		Input Image 2	
	Best solution (10)	Fitness Value	Best solution (10)	Fitness Value
1 ST : 0.60	9	0.0044	8	0.0038
2 ST : 0.60	9	0.0044	1	0.0020
3 ST : 0.60	1	0.0037	10	0.0019
4 ST : 0.60	10	0.0037	4	0.0018
5 ST :	1	0.0037	4	0.0018

0.60				
6 ST : 0.60	1	0.0037	4	0.0018
7 ST : 0.60	1	0.0037	2	0.0017
8 ST : 0.60	1	0.0037	7	0.0016
9 ST : 0.60	1	0.0037	3	0.0014
10 ST : 0.60	1	0.0037	7	0.0013
11 ST : 0.60	1	0.0037	7	0.0013
12 ST : 0.60	1	0.0037	3	0.0013
13 ST : 0.60	1	0.0037	7	0.0012
14 ST : 0.60	1	0.0037	7	0.0012
15 ST : 0.60	1	0.0037	3	0.0012
16 ST : 0.60	1	0.0037	3	0.0012
17 ST : 0.60	1	0.0037	3	0.0012
18 ST : 0.60	1	0.0037	3	0.0012
19 ST : 0.60	1	0.0037	1	0.0012
20 ST : 0.60	1	0.0037	1	0.0012
21 ST : 0.60	1	0.0037	1	0.0012
22 ST : 0.60	1	0.0037	1	0.0012
23 ST : 0.60	1	0.0037	1	0.0012
24 ST : 0.60	1	0.0037	1	0.0012
25 ST : 0.60	1	0.0037	1	0.0012

Input Image No	Input Image	Smoothened Image	Output Image
Input Image 1			
Input Image 2			
Input Image 3			
Input Image 4			
Input Image 5			
Input Image 6			
Input Image 7			
Input Image 8			

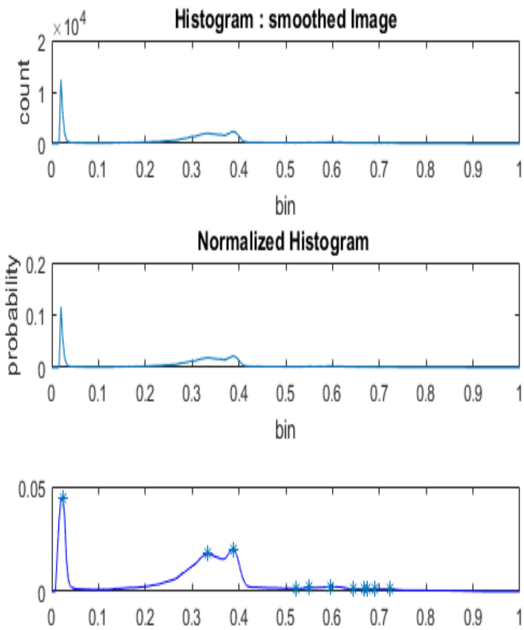


Figure 3: Sample Histogram Equalization Input Image 1

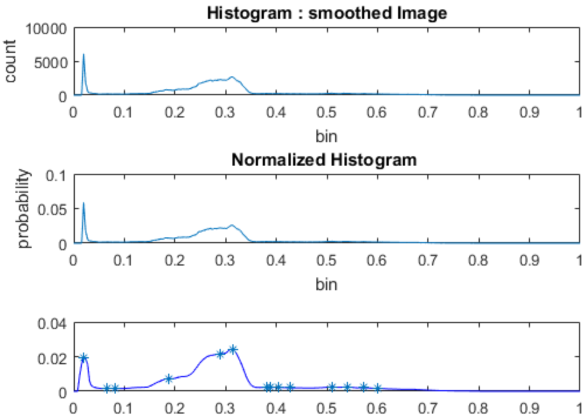


Figure 4: Sample Histogram Equalization Input Image 2

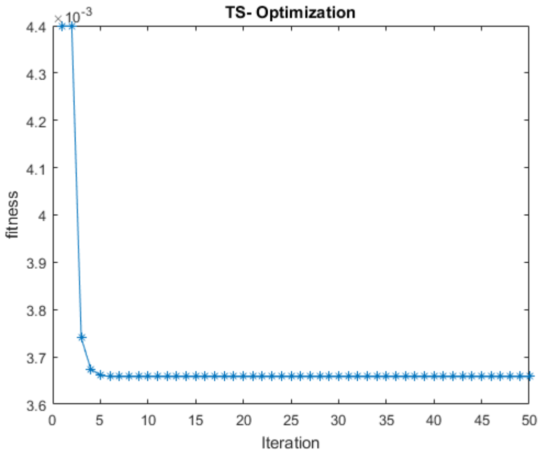


Figure 5: Sample Tree-Seed Algorithm Performance

V. CONCLUSION

This work illustrates the impact of selecting the best segment of histogram values for delineating the tumour region with exact preciseness. The visual quality of the algorithm is checked with quality parameters such as accuracy, sensitivity and specificity. The convergence curve shown in the figure shows that the tree seed algorithm rapidly segments the brain tumour region by viable selection of parameters with minimum computational complexity. Our future work includes modification of the tree seed algorithmic parameters and also including textural features of the image to improve the segmentation process and also tissue characterization. The proposed method has no manual intervention and can be helpful for diagnosis of brain related diseases effectively in an earlier aspect saving the human life.

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