A METHOD TO DETECT BRAIN TUMOUR USING BOUNDING BOX AND ANISOTROPIC FILTER

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Abstract - Brain tumors may be characterized as either primary or secondary. Primary brain tumors are those which arise initially in the central nervous system (CNS) or its adjacent structures. In contrast, secondary tumors arise outside of the CNS and secondarily metastasize to the brain or its adjacent structures. The basic principle behind FBB: a change detection principle, where a region of change (D) is detected on a test image (I), when compared with a reference image (R). Brain Tumor is a fatal disease which cannot be confidently detected without MRI. To pave the way for morphological operation on MRI image, the image was first filtered using Anisotropic Diffusion Filter to reduce contrast between consecutive pixels. Anisotropic Diffusion Filter used for capturing the diseased MRI images through plotting and comparing them with their nearest neighbors. Filtering technique is used for filtering the tumor images out of good ones using pixels. Bounding box is based upon change detection principle, where a region of change (D) is detected on a test image (I), when compared with a reference image (R). The goal of our approach is to justify bounding box algorithm separately and with which is based on Anisotropic Diffusion Filter.

Keywords- MRI ,tumor, lobes, voxel, coronal ,sagittal, gray matter ,white matter, cerebrospinal

1. INTRODUCTION

A brain tumor is a collection (or mass) of abnormal cells in the brain. A tumor can cause cancer, which is a leading cause of death and is responsible for approximately 13% of all deaths worldwide. The incidence of cancer is increasing at a dangerous rate in the world. Therefore it is very important to detect tumors in the first stage. Great knowledge and experience are required on radiology to detect exact tumors in medical imaging. MRI is the most flexible of our diagnostic imaging methods, with the ability to show a wide range of parameters in the living subject and provide excellent spatial resolution. Brain Tumor Detection Form There are several stages in magnetic resonance imaging (MRI). Segmentation is considered a necessary but difficult step in classical imaging classification and analysis. Therefore, it is very important that the MRI images should be split correctly before asking the computer for precise diagnosis. This review presents an overview of magnetic resonance imaging

(MRI) based medical image analysis for brain tumor studies.
Brain 1.1

Together, the brain and spinal cord (the central nervous system (CNS)) control the physical and psychological functions of our body. Normally our brain consists of three major parts:

1. Cerebrum. It controls thinking, learning, troubleshooting, emotions, speech, reading, writing, and voluntary movement.
2. Cerebellum It controls movement, balance, and currency.
3. Brain stem. It connects the brain to the spinal cord, and regulates vital functions in the human body, such as motor, sensory pathway, cardiac, reservoir and reflection [1].

1.1 Image Database

The feasibility of the proposed technique is tried on 12 T2 weighted MR brain images collected from medical college

2. BRAIN MRI CLASSIFICATION USING DWT & PCA

Classify the colors in a*b* color space has K means clustering. Since the image has 3 colors create 3 clusters. .

The datasets consists of T2-weighted MR brain images in axial plane and 256 £ 256 in-plane resolution, which were downloaded from the website of Harvard Medical School (URL: http://med.harvard.edu/AANLIB/), ASIS dataset (URL: http:// www.oasis-brains.org/), and ADNI dataset (URL: http://adni.loni.uc-la.edu/). Selected T2 model since T2 images are of higher-contrast and clearer vision compared to T1 and PET modalities.

The abnormal brain MR images of the dataset consist of the following diseases: glioma, meningioma, Alzheimer's disease, Alzheimer’s disease plus visual agnosia, Pick's disease, sarcoma, and Huntington's disease.

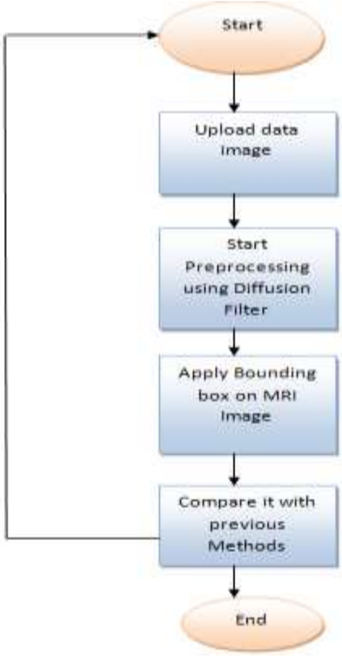
2.1 Axis Of Symmetry (X-Image Size, Y-Energy Function)

In FBB, after finding the axis of symmetry on an axial MR slice, the right (or the left) half supplies as the reference image R the left (or the right) half serves as the test image I.

It utilizes a novel score function that can identify the region of change D with two very quick searches– one along the vertical direction of the image and the other along the horizontal direction.

The changing region D is restricted to be an axis-parallel rectangle that is essentially aims for circumscribing the abnormality.

3. FLOW CHART OF PROPOSED WORK METHODOLOGY



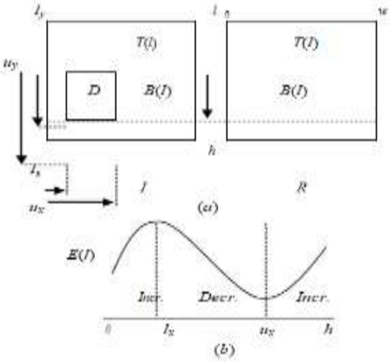
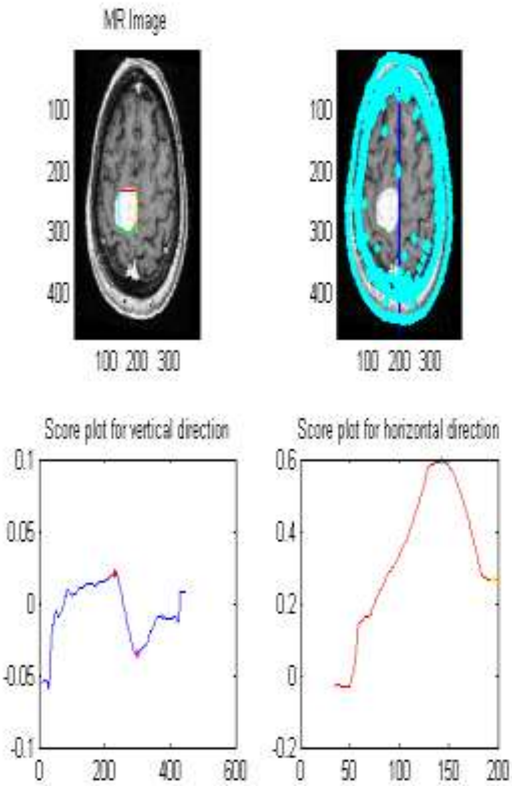
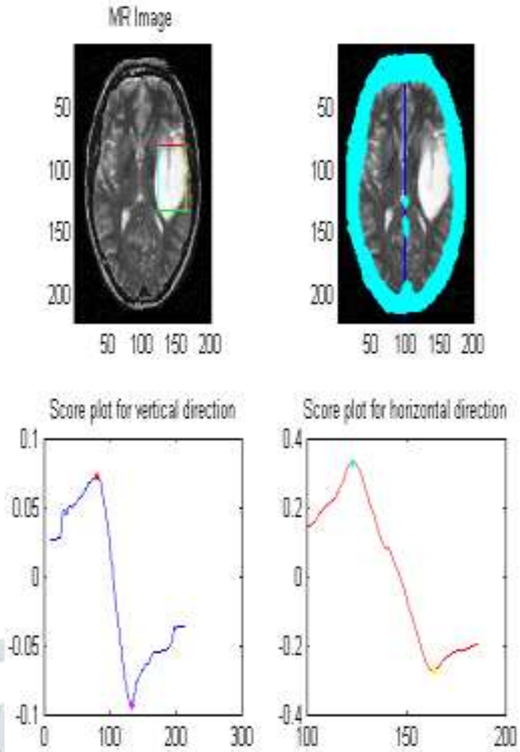


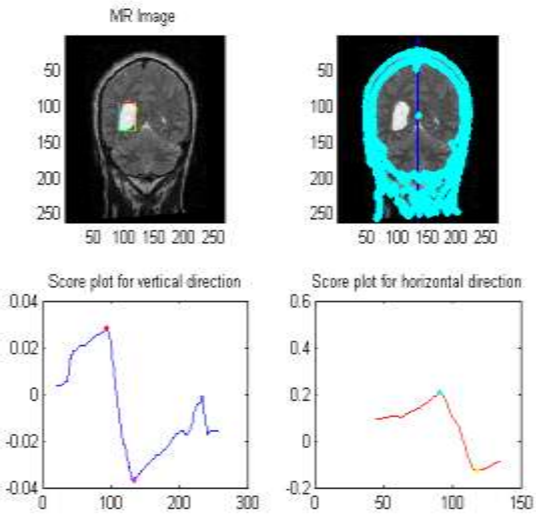
Fig. 1 (a) Finding anomaly *D* from test image *I* using reference image *R*. 1(b): Energy function plot



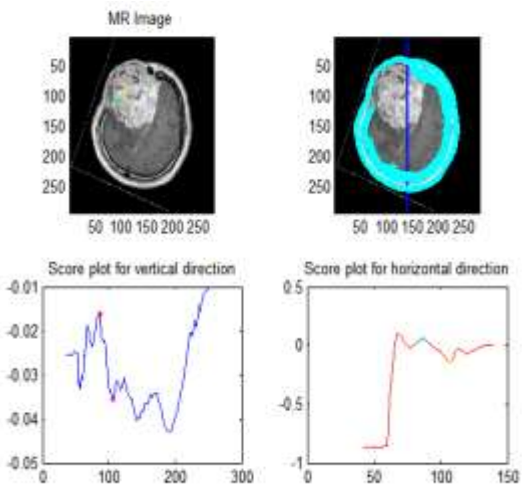
IM1 IM2

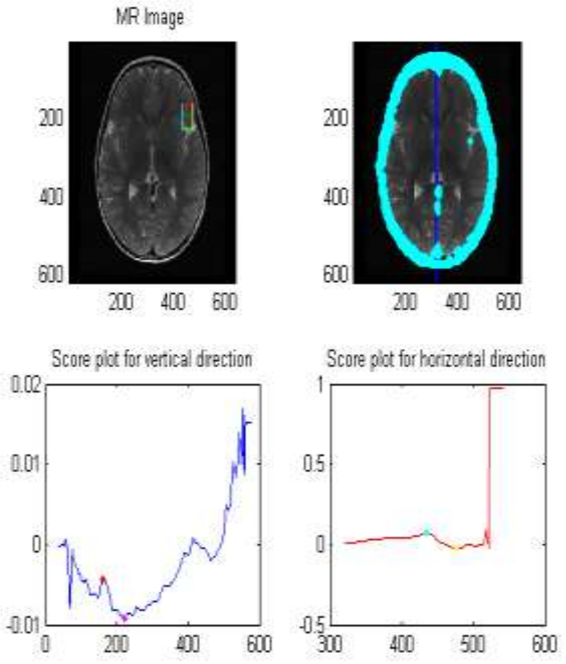


IM3 IM4



IM5 IM6





IM7 IM8

Fig.2 Bounding Boxes on 2D MR slices (Dataset from www.cancerboard.ab.ca)

3.1 Anisotropic Diffusion Filter

Brain Tumor is a fatal disease which cannot be confidently detected without MRI. In the project, it is tried to detect whether patient's brain has tumor or not from MRI image using MATLAB simulation.

To pave the way for morphological operation on MRI image, the image was first filtered using **Anisotropic Diffusion Filter** to reduce contrast between consecutive pixels. After that the image was resized and utilizing a threshold value image was converted to a black and white image manually. This primary filters the plausible locations for tumor presence. On this semi processed image morphological operations have been applied and information on solidity and areas of the plausible locations was obtained. A minimum value of both of these characters has been determined from statistical average of different MRI images containing tumor. Then it was used to deliver final detection result.

Formal definition

Formally, let $\boldsymbol{\Omega} \subset \boldsymbol{R^2}$ denote a subset of the plane and $I(;t): \Omega \rightarrow R$ be a family of gray scale images, then anisotropic diffusion is defined as

$$\frac{\partial I}{\partial t} = div(c(x,y,t)\nabla c.\nabla I + c(x,y,t)\Delta I$$

whereΔ denotes the Laplacian,∇ denotes the gradient, div(….)s the divergence operator and $c(x,y,t)$ is the diffusion coefficient c(x,y,t) ontrols the rate of diffusion and is usually chosen as a function of the image gradient so as to preserve edges in the image. proposed two functions for the diffusion coefficient:

$$c(\nabla I\| = e^{-(\|\nabla I\|/K)^2}$$

and

$$c(\nabla I\| = \frac{1}{1+\left(\frac{\|\nabla I\|}{K}\right)^2}$$

the constant K controls the sensitivity to edges and is usually chosen experimentally or as a function of the noise in the image.

Motivation

The diffusion equations presented above can be interpreted as the ___ equations for the minimization of the energy functional $\boldsymbol{E}: \boldsymbol{M} \leftrightarrow \boldsymbol{R}$ defined by

$$\boldsymbol{E[I] = \frac{1}{2}\int_{\Omega} g(\|\nabla I(x)\|^2)dx}$$

where $g: R \rightarrow R$ is a real-valued function

$$\boldsymbol{\frac{d}{dt}/_{t=0}E[I+th] = \frac{d}{dt}/_{t=0}\frac{1}{2}\int_{\Omega} g9\|\nabla(I+th)(x)\|^2\,dx}$$

$$\boldsymbol{= \int_{\Omega} g'(\|\nabla I(x)\|^2)\nabla I.\nabla h\,dx}$$

$$\boldsymbol{-\int_{\Omega} div\,(g'(\|\nabla I(x)\|^2\nabla I)h\,dx}$$

where the last line follows from multidimensional integration by parts. Letting $\boldsymbol{\nabla E_1}$ denote the gradient of E with respect to the $L^2(\Omega,R)$ inner product evaluated at I, this gives

$$\nabla E_1 = -div(g'(\|\nabla I(x)\|^2)\nabla I)$$

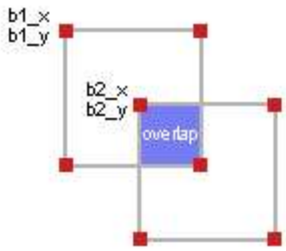
Therefore, the gradient descent equations on the functional E are given by

$$\frac{\partial I}{\partial t} = -\nabla E_1 = div\,(g'(\|\nabla I(x)\|^2\nabla I)$$

Thus by letting c = g' we obtain the anisotropic diffusion equations

3.2 Bounding Box Method & SVM

While not the fastest method of collision detection, Bounding Box (BB) is often a favourite among many developers. Put simply, this technique involves checking whether an object has intercepted (overlapped) an invisible square boundary that is usually placed over, and often remains relative to, a game object.



An illustration of a Bounding Box -> Bounding Box collision check

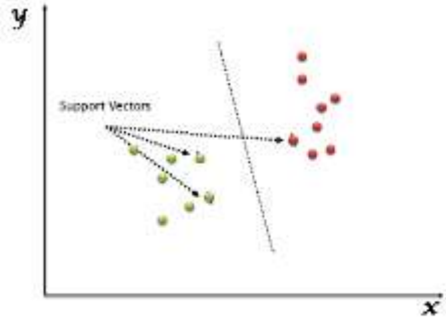
As a BB consists of four sides (making a square), a BB collision routine needs four values for each BB involved: a location vector (the x and y position of the BB object), as well as the BB's height (h) and width (w). Using these four values we can calculate:

- The location of the top-left corner of the BB (x, y)
- The location of the top-right corner of the BB (x + w, y)
- The location of the bottom-left corner of the BB (x, y + h)
- The location of the bottom-right corner of the BB (x + w, y + h)

The Bounding Box method is fairly simple. As such, there are very few issues or complications with its usage.

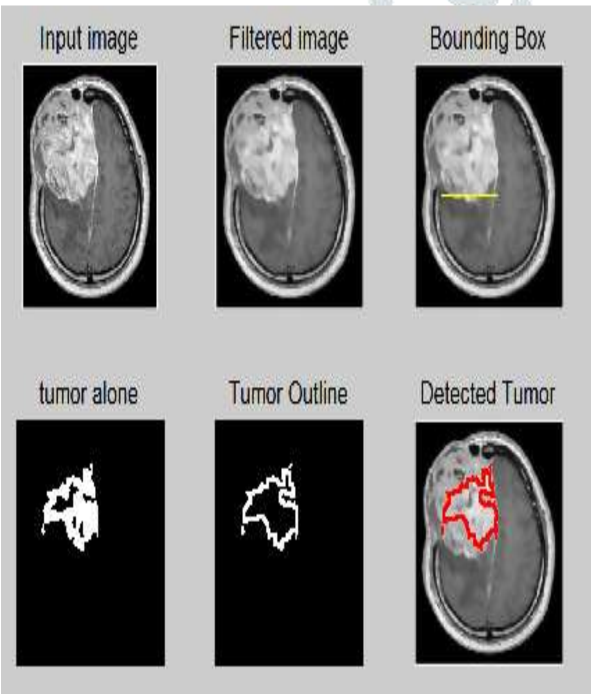
- Bounding Boxes do exactly what they say on the tin. The problem here is, if you are trying to check collisions against a particularly complex object (one that has an obscure shape), BB may not be the method for you. Notice the diagram to the right. Now, if you consider that BB's are typically invisible to the end-user, it is possible that some objects within your game will appear to detect collisions with other objects seemingly before they occur! One solution to this problem is to simply reduce the size of the bounding box so that it fits within your object.

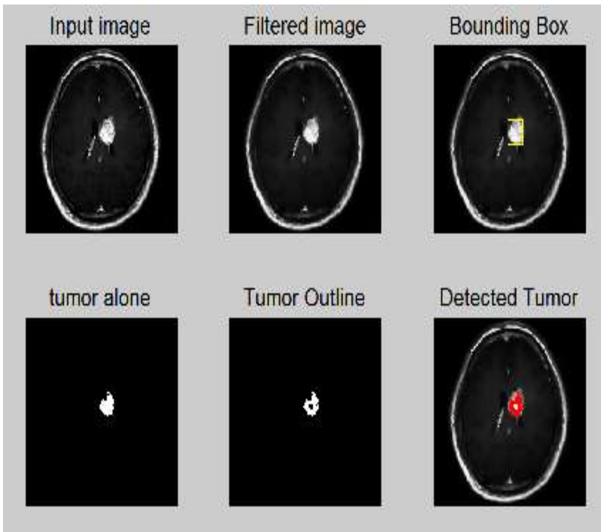
SVM is a supervised machine learning algorithm which can be used for both classification or regression challenges. However, it is mostly used in classification problems. In this algorithm, we plot each data item as a point in n-dimensional space (where n is number of features you have) with the value of each feature being the value of a particular coordinate. Then, we perform classification by finding the hyper-plane that differentiate the two classes very well (look at the below snapshot).



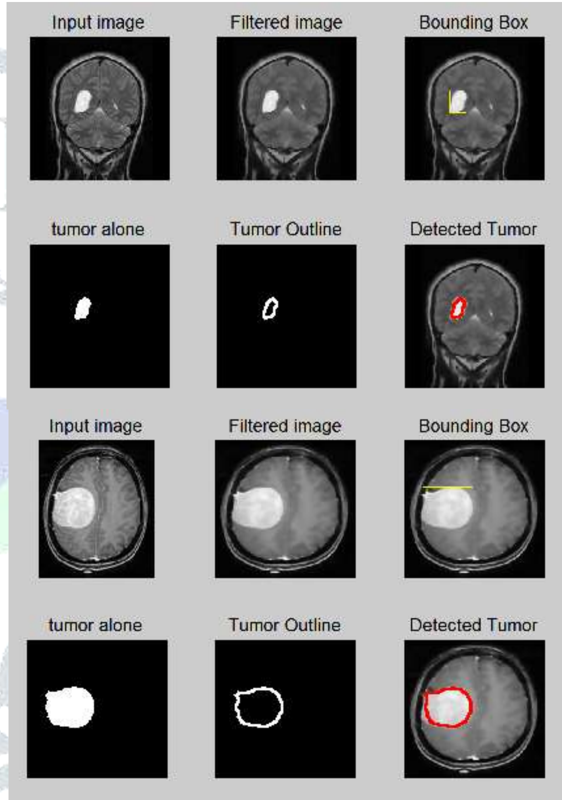
4. ALGORITHMS

1. Take Tumor Data from Data file
2. Select different samples as an input for Bounding Box method
3. Apply Bounding Box method
4. Compare Similarity from Axis of Symmetry (XY axis) using energy function graph
5. Save results
6. Again take input samples from Data file
7. Apply Diffusion Filter to remove Noise
8. Take filtered image for Bounding Box Input
9. Apply Bounding Box on Filtered image
10. Take result and compare with results of unfiltered bounding box results and Previous tumor detection methods

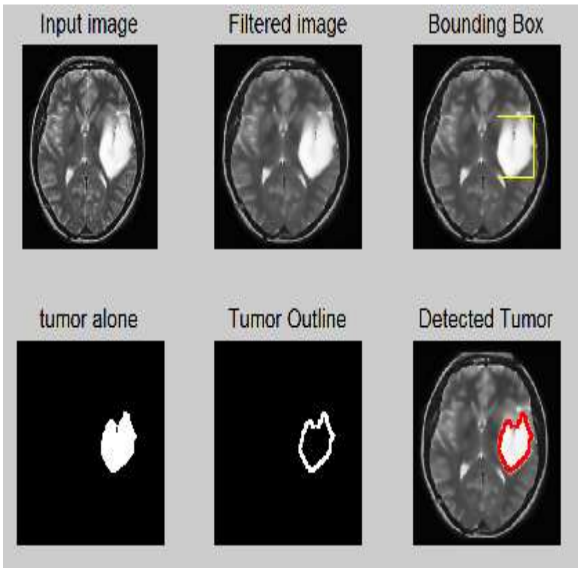




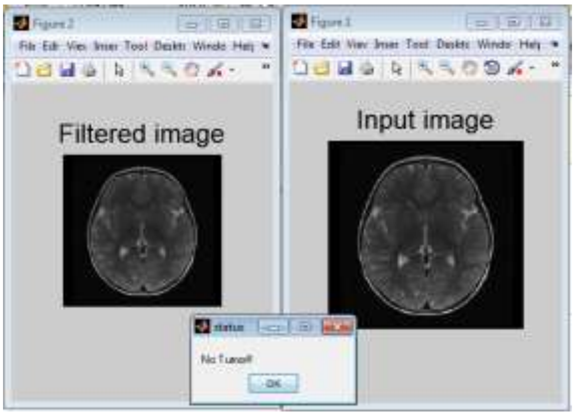
IM7 AND IM1



IM5 AND IM6



IM4 AND IM3



IM8

Fig.3

Table 1 Comparison of brain tumor detection techniques

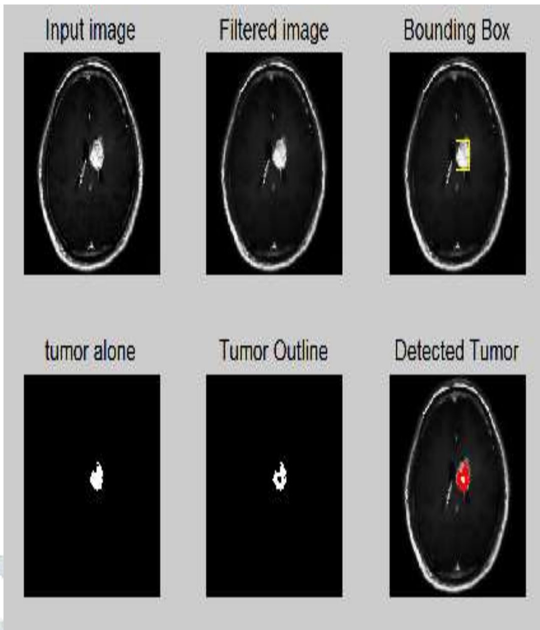
S.NO	TECHNIQUES	SEGMENTATION ACCURACY AND GROUND TRUTH OF BRAIN TUMOR
1.	Bounding Boxes	80% - 73.2%
2.	Anisotropic Diffusion Filter	97.2% - 98.1%

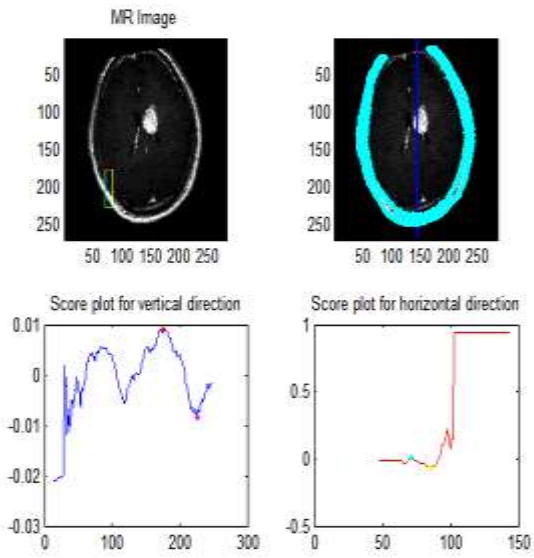
S.NO	TECHNIQUES	ADVANTAGES	DISADVANTAGES
1.	Bounding Boxes	This method detects tumor to around real value Least execution time	Efficiency needs to be augmented .more modification is needed
2.	Anisotropic Diffusion Filter	It is simple and intuitive process	Need to add more accurate filter

S.NO	IMAGE	BOUNDING BOX DETECTION Accuracy and ground Truth	ANISOTROPIC DIFFUSION FILTER Accuracy and ground truth
1	IM1	87%-80%	96%-95.2%
2	IM2	90%-87%	99%-98.3%
3	IM3	60%-51%	80%.-77.6%
4	IM4	85%-81%	96%-94.8%
5	IM5	88%-83%	97%-97.3%
6	IM6	70%-56%	93%-91.2%
7	IM7	7%-2%	55%-51.9%
8	IM8	2%-0%	No tumor detected

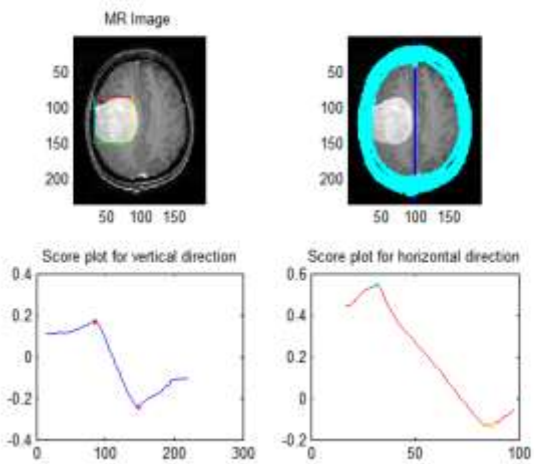
5. RESULT DISCUSSION

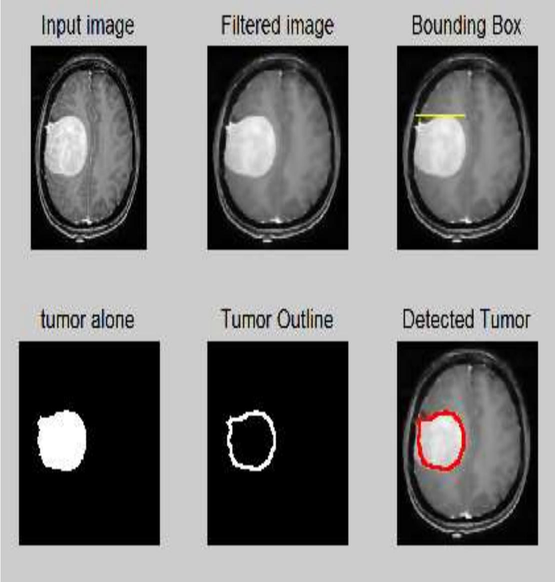
The goal of our approach is to justify bounding box algorithm separately and with which is based on Anisotropic Diffusion Filter .Dataset have been tested with bounding box approach in two different manner exiting bounding box and modified bounding box based on Anisotropic Diffusion Filter approach. Difference can be seen in results where modified bounding box method can locate tumor accurately than old one while old bounding box approach give best result for different type of Dataset .we can use both of them as per the requirement of sample and dataset.New bounding box approach have been developed to solve problems related to tumor detection for certain cases





CASE 1 In this Anisotropic Diffusion Filter based bounding is better than old bounding box approach which is unable to locate tumor





CASE 2 In this Anisotropic Diffusion Filter based bounding box is not better than old bounding box approach some part left undetected while old approach gives 98 % good result

6. CONCLUSION

This compares various techniques for segmenting the brain tumor disease. Technique is Anisotropic Diffusion Filter based on bounding box used for capturing the diseased MRI images through plotting and comparing them with their nearest neighbors. Filtering technique is used for filtering the tumor images out of good ones using pixels.

In bounding box we compared similarity from Axis of Symmetry (XY axis) using energy function graph where a region of change (*D*) is detected on a test image (*I*), when compared with a reference image (*R*).

Bounding box is based upon change detection principle which has its drawbacks in small tumor detection that can be understood by Case 1 and Case 2 respectively.

7. FUTURE SCOPE

Thresholding is one of the techniques utilized for image segmentation for future work. In bi-level thresholding techniques, a given image is separated into two classes while in multilevel image segmentation; the image is divided into several classes depending on the requirement of the problem.

This technique performs the multilevel thresholding on the dataset. By applying the multilevel thresholding we find the optimal threshold values within the range [0, L-1] which in turn , maximizes the fitness criterion.

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