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Detection of Alzheimer’s Disease in Brain MRI Using Fractal Analysis

Srinivasan Aruchamy[1], Partha Bhattacharjee[1], Nanditha N.[2] and Goutam Sanyal[3]

Abstract: Alzheimer’s disease (AD) is the common neurodegenerative and irreversible disease in the population. Early detection and treatment to this disease will control the disease progression. Mostly classification of this disease is performed manually in the clinical studies. It is time consuming as well as manual classification is difficult and it is purely based on clinician’s ability. Multimodality MR Imaging techniques are used to study the Alzheimer’s disease. Brain volume study helps to find the Alzheimer’s disease precisely. Changes in the brain internal structure shows the abnormalities present in the brain. In the proposed work brain MR images are studied for detection of Alzheimer’s disease. The proposed method consist of two stages: in the first stage the MR images are pre-processed, segmented and skull stripped. In the Second stage Fractal based analysis like box counting method, differential box counting method and fractal Brownian motion analysis are performed and compared. This analysis aids to find the micro level structural changes in the brain structure which helps to identify the neurological disorder in the brain.

Keywords: Brownian motion; Fractals, Thresholding, MR images, Skull stripping, Box counting method, Differential Box counting method.

I. INTRODUCTION

Alzheimer s Disease[AD] is a neuro-degenerative disease which gradually damages the normal functioning of the brain [1]. This disease is incurable, but the progression rate can be limited by early identification of the disease. In great extend the classification of these disease is performed manually and is a time consuming process. Manual classification is difficult and it is purely based on the clinician s ability. According to statistics, about 35 million persons are suffering with Alzheimer s disease and the number is expected to increase in future [2]. Therefore, it is high time to develop a computer aided diagnostics which will make the system faster as well as accurate. Archana et.al [3] applied phase-based level set method for extracting brain tissues. Normal and AD images are differentiated by structural features like orientation, energy, anisotropy index, and GLCM parameters. SVM, adaboost, naive bayes and random forest classifiers are compared and they achieved the up to 88% accuracy in classifying normal and AD. Wenlu Yang et.al [4] classified the MR image into three categories which are AD, Mild Cognitive Impairment (MCI) and healthy. In their study they found brain tissue loss in both AD and MCI subjects. Different white matter, gray matter features were extracted and feature selection has been done using independent component Analysis finally SVM is used for classification. Jie Zhu et.al [5] proposed semi-supervised learning classifier for AD classification. In their study they found that co-training method classification performs better in both MRI and Positron Emission Tomography (PET) images. Finally they compared co-training method with other supervised and semi-supervised classifiers for AD classification. The above studies focused on binary classification but in work presented in [6] aims to provide multiple scores. They calculated multiple outcomes jointly by performing a sparse multi response tensor regression considered continuous clinical studies performed in different time intervals. The same way the modeled multiple voxel images jointly. Chaddad

[1] Robotics and Automation Group, CSIR-CMERI, Durgapur, India, *E-mail: srinivaspsg@gmail.com*

[2] Department of ECE, NMAM Institute of Technology, Udupi, *E-mail: nanditha.267@gmail.com*

[3] Department of Computer science and Engineering, National Institute of Technology, Durgapur, *E-mail: nitgsanyal@gmail.com*

et.al [7] done features analysis and classification on T1-weighted MR images where they have applied 3D GLCM and 3D discrete wavelet transform for feature extraction. Random forest transform is used as a classifier and they perform experiments in publicly available database OASIS achieved more than 70% accuracy rate.

This paper is organized as follows. In the section 2.a image pre-processing and segmentation are introduced and different fractal analysis techniques namely classical box counting method differential box counting method and

fractal Brownian motion analysis procedures are explained. In Section 3, Normal and abnormal brain MR images are used to evaluate the proposed methods. Concluding remarks are given in the section 4.

II. PROPOSED ALGORITHM

The figure 1 shows the Schematic view of proposed Method where the input image is in DICOM [8] format. From the input image single slice is extracted and the following steps are performed.

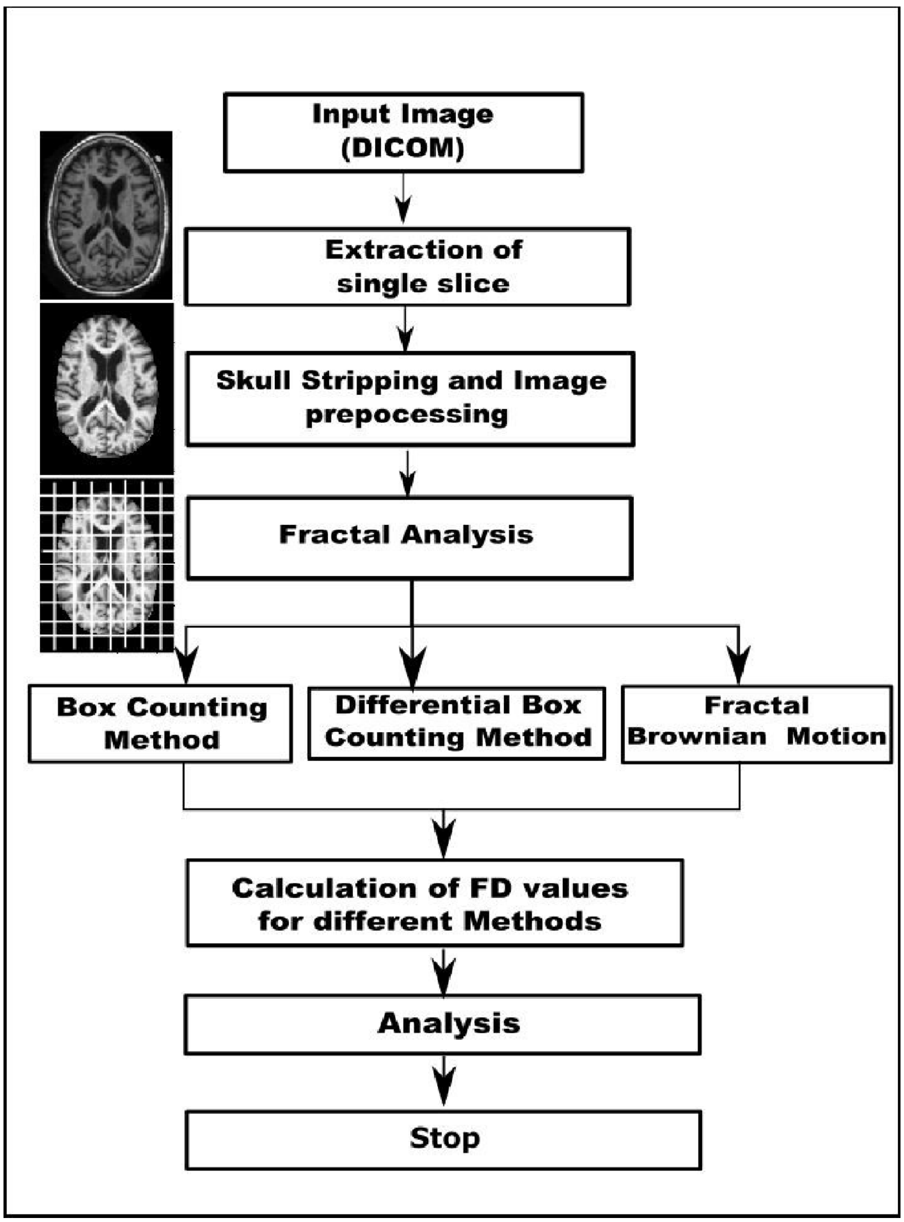


Figure 1: Schematic view of proposed Method

2.1. Image Pre-Processing

The image quality is enhanced by increasing the contrast of the input image. Contrast Limited Adaptive Histogram (CLAHE) [9] technique is used, which is one of most suitable method for medical image analysis. Where the input image is divided into non-overlapping equal size windows then conventional histogram equalization techniques is performed separately in the individual windows. The figure 2 shows the input image and the pixel intensity values of the input image.

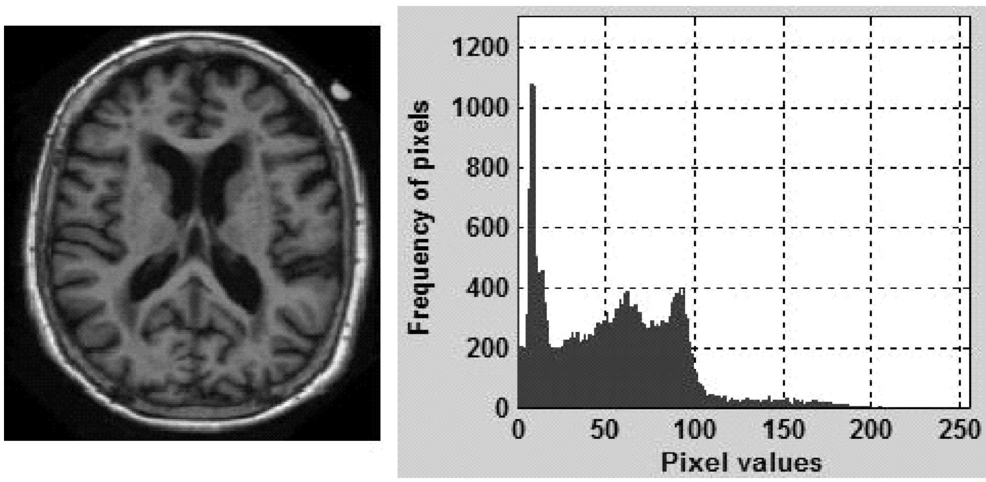


Figure 2: (a) Original Image (b) Histogram of the original image

Once the image is enhanced skull stripping is performed [10]. As shown in the figure 3 Skull stripping is the process in which brain tissues is segmented from non-brain tissues. Skull stripping reduces the computation complexity and increase in identification of disease symptoms.

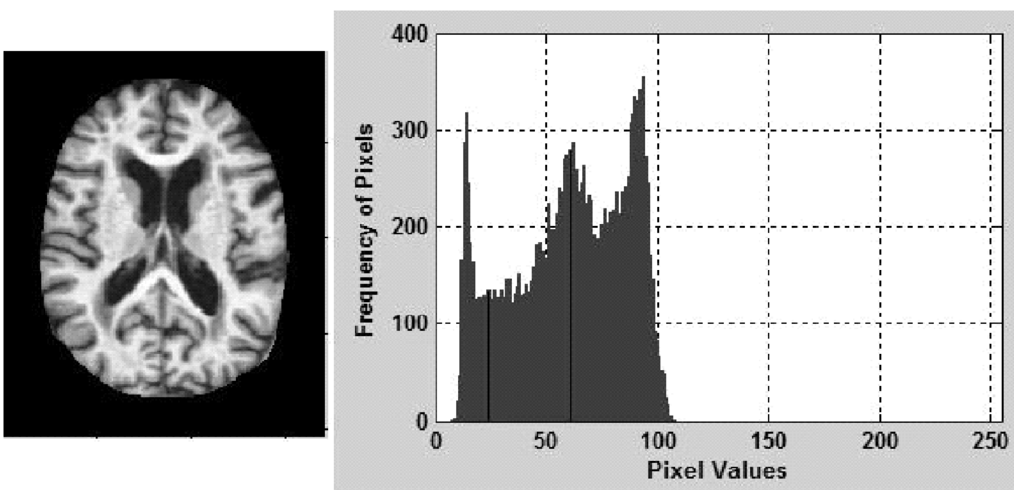


Figure 3: (a) Pre-Processed Image (b) Histogram of the pre-processed image

2.2. Fractal Analysis

Fractals are self similar structures in nature and the fractal theory is developed by Mandelbrot [11]. Euclidean geometry may not able to describe the morphology and structural behavior of complex objects that are established in nature. Theses shapes are described in topological dimension. Fractal analysis is performed with Brain MRI images to discriminate between normal and abnormal (pathological). Fractal dimension is calculated using box counting method in the resultant image of otsu thresholding [12]. Box counting methods work in the principle of covering the boxes over the image in non overlapping fashion shown in the figure

4(a) and 4(b). This will be repeated with different scale and the fractal dimension is calculated using the equation 1.

$$FD = \lim_{r \to 0} \frac{\log(n)}{\log\left(\frac{1}{r}\right)} \tag{1}$$

Where, FD is the fractal dimension and n is number of boxes needed to cover the entire image and r is the scaling factor. The scaling factor r will be changes with different values and covers the entire image. The slope of the logarithmic function between n and 1/r called the box dimension. Figure 5 shows the logarithmic plot of scaling factor r versus number of boxes n.

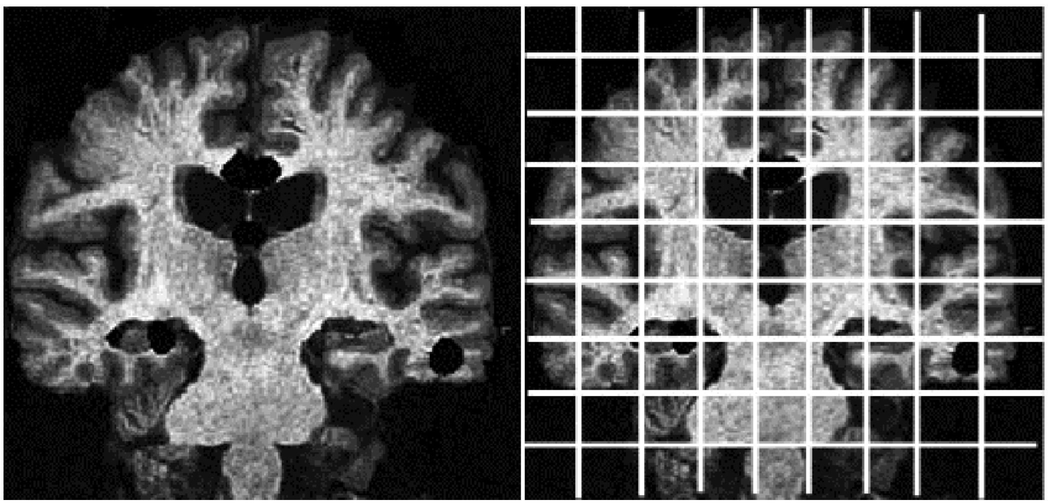


Figure 4: (a) MRI Image (b) MRI Image covered with boxes

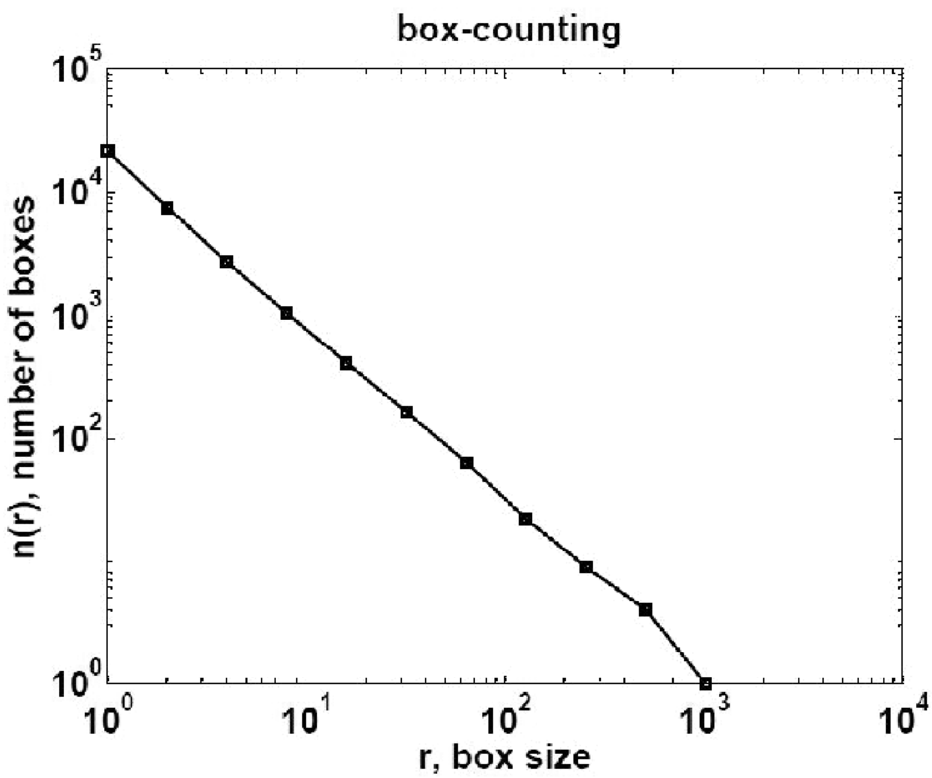


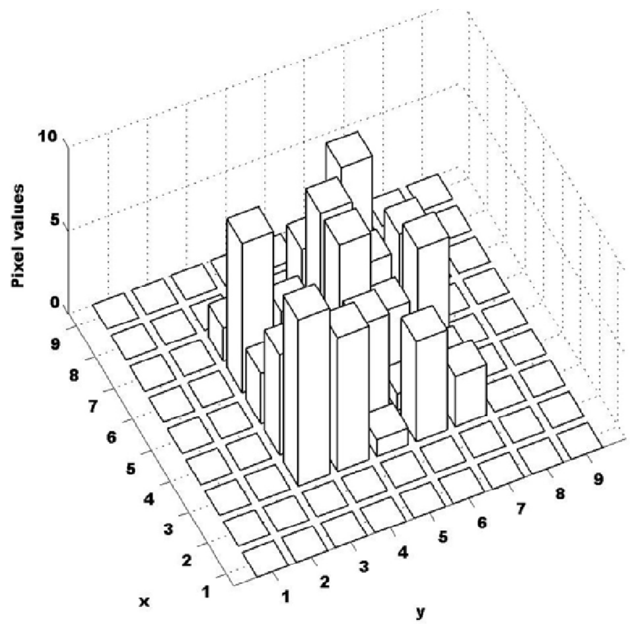
Figure 5: Box counting Fractal dimension of the skull stripped brain MR image

2.3. Differential Box Counting Method (DBC)[13]

Box counting method works binary images where as differential box counting works with grayscale images. Consider an image of size N X N shown in figure 6 (a) the differential box counting method is performed in the image by dividing the image into grid of cubes for different scaling factor *s*. where *1 > s <=N/2*. This image can be represented as 3 dimensional spatial surface were the pixel positions are denoted as x, y plane and the intensity values will be denoted as z plane. (The z plane of first *s x s* shown in the figure 6 (b)). Figure 7 depicts the DBC based logarithmic plot of scaling factor r versus number of boxes n.

2	4	7	1	9	5	3	8	4
7	9	4	7	5	8	3	1	2
6	11	7	8	3	6	1	4	7
4	5	10	6	3	9	2	8	1
3	9	8	4	2	4	1	2	7
5	5	1	6	9	9	5	4	8
4	8	6	1	4	5	9	3	1
4	6	2	3	7	6	2	1	4
7	2	1	5	4	8	9	1	2
1	8	4	2	7	9	6	3	2

(a)



(b)

Figure 6: (a) Sample 9x9 Gray image for DBC calculation (b) 3D representation of image pixels

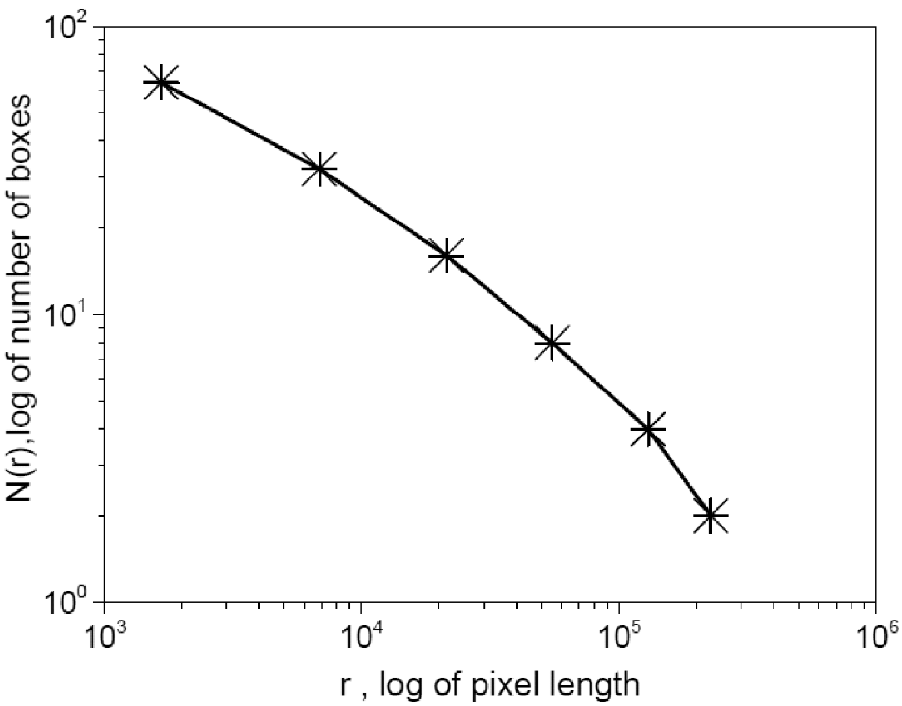


Figure 7: DBC Fractal dimension of the skull stripped brain MR image

2.4. Fractal Brownian Motion

Fractal Brownian motion [14] is an self similar random fractal [15] which is Gaussian consider an image M X M the absolute pixel intensity difference is calculated by the difference between row wise pairs and column wise pairs using the equations (2)

$$P_{id} = \Sigma_{x1=1}^{M}\Sigma_{x2=1}^{M}\Sigma_{y1=1}^{M}\Sigma_{y2=1}^{M}\left|f(x_1,y_1)-f(x_2,y_2)\right| \tag{2}$$

where P_{id} is the sum of pixel intensity differences and (x1,y1) , (x2,y2) are the pixel pair indices in the image matrix. The Absolute pixel pair indices will be calculated using equation (3). The figure 8 depicts the Fractal Brownian motion based logarithmic plot of scaling factor r versus number of boxes n.

$$P_{Aid} = \frac{P_{id}}{No.of\ \ pixel\ pairs\ with\ scaling\ \ factor\ r} \tag{3}$$

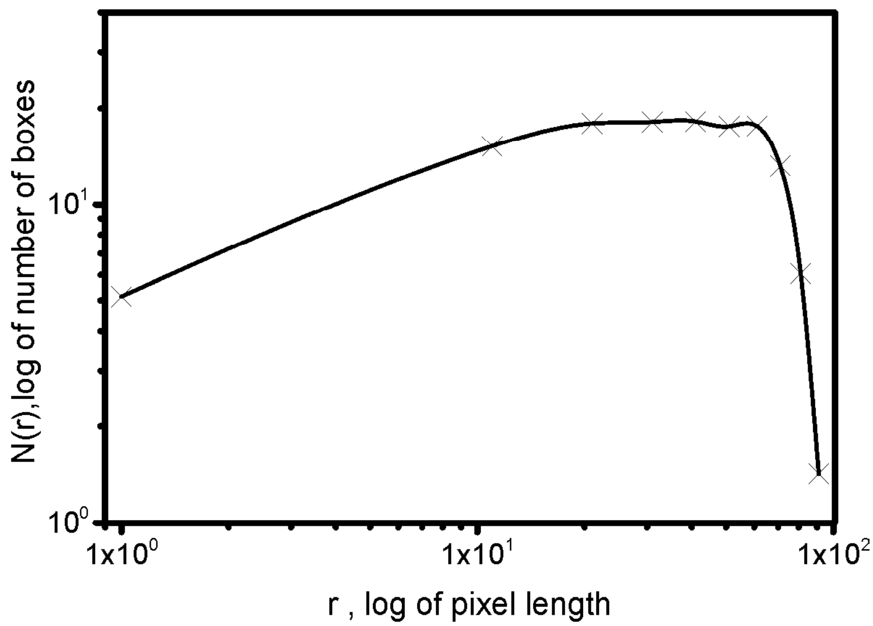


Figure 8: Fractal Brownian Motion dimension of the skull stripped brain MR image

III. RESULT AND ANALYSIS

To check the accuracy of the implemented algorithms the standard list of fractals [16] were used and analyzed.

Table 1
Fractal dimension estimation using box counting method for some standard fractals

S No	*Name of the image*	*Fractal dimension obtained*	*Standard value of Fractal dimension*	*Absolute error in the result*	*Percentage of error*
1	Juliaset	0.9749	1.0812	0.1063	9.83%
2	Triflake	1.1699	1.262	0.0921	7.29%
3	Apollonian gasket	1.4987	1.3057	0.193	14.78%
4	Spierpinski hexagon	1.4336	1.6309	0.1973	12.09%
5	Pentaflake	1.5850	1.8617	0.2767	14.863%

Table 2
Fractal dimension estimation using Differential box counting method for some standard fractals

S No	*Name of the image*	*Fractal dimension obtained*	*Standard value of Fractal dimension*	*Absolute error in the result*	*Percentage of error*
1	Juliaset	1.0040	1.4649	0.4609	31.463%
2	Triflake	1.048	1.26	0.212	16.825%
3	Apollonian gasket	1.4064	1.7	0.2936	17.271%
4	Spierpinski hexagon	1.8588	1.6309	0.2279	13.974%
5	Pentaflake	2.114	1.8617	0.2523	13.568%

Table 3
Fractal dimension estimation using Fractal Brownian motion method for some standard fractals

S No	*Name of the image*	*Fractal dimension obtained*	*Standard value of Fractal dimension*	*Absolute error in the result*	*Percentage of error*
1	Juliaset	1.2204	1.0812	0.1392	12.87%
2	Triflake	1.1805	1.262	0.0815	6.46%
3	Apollonian gasket	1.1805	1.3057	0.1252	9.59%
4	Spierpinski hexagon	1.4109	1.6309	0.22	13.499%
5	Pentaflake	2.1169	1.8617	0.2552	13.707%

Table 4
Fractal dimension estimation using all the proposed methods for brain MR images

Image. No	*BC*	*DBC*	*FBM*	*Image. No*	*BC*	*DBC*	*FBM*
1	0.8763	0.7157	1.0805	22	0.8120	0.7086	1.0774
2	0.7865	0.6899	1.4797	23	0.8181	0.7283	1.0846
3	0.7769	0.7245	1.0873	24	0.6987	0.7034	1.2491
4	0.7123	0.6973	1.0854	25	0.7337	0.7021	1.0515
5	0.7760	0.7011	1.1020	26	0.8006	0.7000	1.0499
6	0.7965	0.7063	1.9043	27	0.7034	0.6983	1.0288
7	0.7106	0.6890	1.1940	28	0.7743	0.7295	1.0505
8	0.6598	0.6960	1.8037	29	0.7998	0.6932	1.2138
9	0.7865	0.6983	1.0118	30	0.6878	0.6909	1.2999
10	0.7671	0.7370	1.1156	31	0.7211	0.6808	1.0375
11	0.6987	0.6915	1.1099	32	0.8021	0.7455	1.2508
12	0.7337	0.7173	1.2038	33	0.7760	0.7412	1.1256
13	0.8006	0.7074	1.9740	34	0.7965	0.7450	1.0146
14	0.7034	0.7223	1.2724	35	0.7106	0.7400	1.2385
15	0.7743	0.6877	1.1742	36	0.6598	0.7416	1.2926
16	0.7998	0.7377	1.2245	37	0.7991	0.7638	1.6981
17	0.6878	0.7069	1.0686	38	0.8221	0.7343	1.0767
18	0.7211	0.6977	1.0786	39	0.7791	0.7505	1.0140
19	0.8021	0.7414	1.0396	40	0.8162	0.7367	1.1663
20	0.6916	0.7330	1.0109	41	0.7852	0.7428	1.1611
21	0.6611	0.6892	1.0277				

The table 1, 2 and 3 depicts the standard list of fractals their actual fractal dimension and fractal dimension obtained by implemented algorithms. For classical box counting method the average absolute error value is 0.173, for differential box counting method the value is 0.2893 and for fractal Brownian motion method the value is 0.1642. Fractal dimension values have been observed for the images which have a pre-defined standard value. There were slight variations in the result obtained and accordingly percentage error and efficiency have been calculated. The efficiency of classical box counting method is 85.287%which shows the slightly better than the Differential box counting method efficiency which is 76.725% .The fractal Brownian motion efficiency 88.774 % which is outperformed the former two methods. Then, 41 Brain MR Images were taken from publicly available database (OASIS) [17] out of which 20 images were healthy brain images, 10 were having mild cognitive impairment and remaining 11 images are having Alzheimer's diseases cases. Two classes have been predefined. The healthy and slightly defective have been put in class 1 and the significantly defective have been put in class 2. All 41 images were examined using proposed fractal analysis techniques and their corresponding fractal dimension is shown in the table 4.

IV. CONCLUSION

In this work, a fractal analysis based method is developed for the Alzheimer's disease detection. The proposed algorithm first performs the image pre-processing and skull stripping. Gary matter and white matter segmentation is performed with the skull stripped image using ostu thresholding algorithm. Three different fractal analysis were proposed and implemented. The implemented fractal techniques accuracy has been calculated using standard fractal data set and reported. In the proposed techniques, the Fractal Brownian motion performance shows better than the other two methods. Publicly available brain MR image data set OASIS has been used for validating the implemented methods and the results has been reported.

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