

Brain Tumor Texture Analysis – Using Wavelets and Fractals

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Abstract: Brain tumor segmentation is quite popular area of research but detection of its surface texture is challenging for researchers. Normally, MRI datasets have very low resolution. This paper utilizes image enhancement technique based on wavelet. It is used to scale the low resolution image to a suitable resolution without loss. Secondly the proposed method is focused on implementation of a trained classifier using features: fractal dimension, fractal area, and wavelet average to classify type of texture present in brain tumor.

Keywords: Wavelet Transform, Fractal Analysis, Image Classification, Feature Extraction, Texture Analysis, Image Processing

1. Introduction

Automatic image analysis has a lot of scope for implementation, from image classification to image retrieval. Semantic gap problem [1, 2], which corresponds to the alteration between the user image perception and automatic extracted features. An important aspect of feature extraction task is to obtain a set of features (i.e. a feature vector) for representing the visual content of an image. In many applications texture features are used for maintaining orthogonal nature among different classes. On the other hand, it can be effectively implemented to address the semantic gap problem. As a result, research on texture classification is focused on improving the distinguish-ability of the algorithm.

In the paper the problem of identifying the type of texture in tumor of brain from MRI is addressed. Segmentation technique is utilized to visually extract the position and size of the tumor. Wavelet transform is established as a very efficient tool for analyzing an image's frequency components in a localized manner. The popular SFTA algorithm, is used along with the features extracted from wavelet transform.

The input MR Image is first subdivided in small blocks of pixel. Next, texture of each sub block is obtained in order to

identify the texture of the tumor. Multi resolution wavelet transform is implemented to get the details of input image including energy and frequency details. The feature vector thus obtained is easily achievable in terms of complexity. The feature vector is 1x26 array consisting of multi resolution wavelet detail of different wavelet families.

2. Related Works

In image processing textural information plays a key role to identify the type of object present in the images. It dominates in the field of remote sensing, quality control & medical imaging due to its close relation to the underlying semantics.

Texture features captures the granularity and the repetitive pattern in the image. From statistical point of view texture information can be termed as fractal whose Area, Mean, Dimension can be accepted as Fractals features. Fractals [3] are small pictorial patterns those tend to repeat in a textured surface.

Another widely accepted approach is to use grayscale co-occurrence matrices (GLCM) by counting the number of occurrences of the gray levels at a given displacement and

angle. Statistical quantities such as contrast, energy, entropy are computed from the GLCM to obtain the texture features as proposed by Haralick et al.

Filter Bank [4, 5] approach is a widely accepted method for texture classification and segmentation. Gabor filters is among the popular filter banks known for its invariance with respect to scale, rotation and displacement. Where θ is the filter orientation, σ the standard deviation and λ the wavelength of the sinusoid,

Equation shows the formal representation of the Gabor filter,

$$g(x,y) = (1/2\pi\sigma_x\sigma_y) \left(-\frac{1}{2}A + \frac{2\pi i R_1}{\lambda} \right)$$

$$A = \left(\frac{R_1^2}{\sigma_x^2} + \frac{R_2^2}{\sigma_y^2} \right) \& \begin{bmatrix} R_1 \\ R_2 \end{bmatrix} = \begin{bmatrix} \cos \theta & \sin \theta \\ -\sin \theta & \cos \theta \end{bmatrix}$$

The pixel position is given by x, y .

Fractal dimension measurements can be used to estimate and quantify the complexity of the shape or texture of objects. The most common is the Hausdorff’s dimension. An object with a Euclidean Dimension E , Hausdorff’s fractal dimension D_0 computed by the following equation:

$$D_0 = \lim_{e \rightarrow 0} \frac{\log N(e)}{\log e^{-1}}$$

where $N(E)$ is the counting of hyper-cubes of dimension E and length that fill the object.

Hausdorff’s dimension [7, 8] is an important feature describing the fractal structure. The algorithm for obtaining the dimension value can be described as follows, if an object is described using a binary image I_b , then an approximate Dimension value can be calculated using box counting algorithm. The image is divide into small sub matrix of size $e \times e$. By varying the size, it is possible to generate an approximated straight line curve using $\frac{\log N(e)}{\log e^{-1}}$. The slope of the line gives Hausdorff dimension.

Another prior art is FFS [9] (Fast Fractal Stack) in which the fractal dimension is computed from a set of binary images obtained from the input grayscale image using the binary stack decomposition algorithm. The image is

decomposed by applying successive operation using threshold value. Depending on the number of threshold value, image forms a binary image stack. The main disadvantage of this method since threshold intensities are chosen at an equal interval hence a lot of information gets lost during the operation.

The above algorithm proves to have an efficiency of 76% when implemented with a Knn classifier [10, 11] and 80% when trained with a discriminant based classifier. It is time consuming algorithm. For achieving higher classifier efficiency number of operation needs to be increased, hence there is a tradeoff between the classifier efficiency and the speed of the algorithm.

The thresholding using multilevel Otsu algorithm improves the intra class variance between the binary stack images is least.

3. Proposed Method

Wavelet Decomposition technique to the input image is firstly applying for obtaining the feature based on the decomposition. Secondly applying multilevel Otsu algorithm for finding threshold of the input image and then implementing box counting algorithm to obtain the features from it. The features obtained from both algorithms will serve as the feature set for the classifier. The trained classifier will then utilize it to predict texture of the new image.

Wavelet proves to be a very suitable and efficient method to obtain the localized frequency information of any signal. Previously frequency details were retrieved using Fast Fourier Transform. On the other hand, Wavelet based transform gives the localized information about the frequency content as feature.

Wavelet transform over the image generates two kind of features:

- (i) Approximated image (A_i , where i denotes the level of transform)
- (ii) Frequency Detail (*also termed as detail in the rest of the paper*) of the input image. Depending on the level of transform the features that are obtained increases in a tree form. (D_i , where i denotes the level of transform)

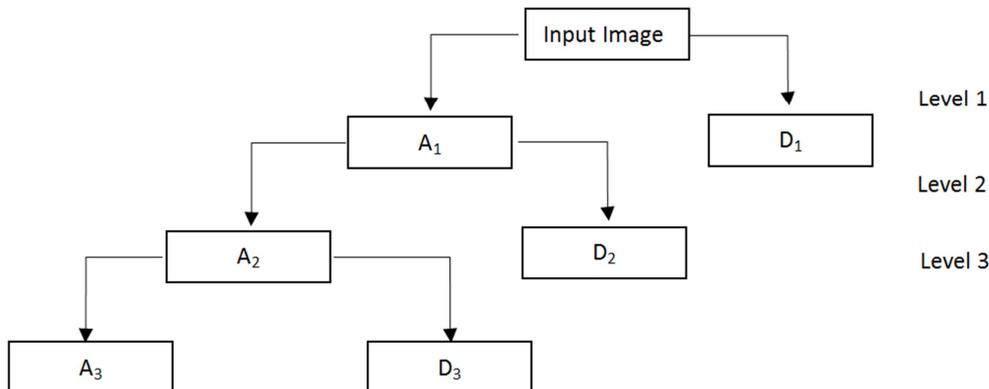


Fig. 1. Frequency guided level wise decomposing of image.

Input image = $A_3 + D_3 + D_2 + D_1$

When the images are decomposed into further levels then approximate image (A_i) gets smoother and holds the information about low pass filter applied over the initial image. On the other hand, frequency domain details of the image (D_i) preserves the high pass filter information.

These values use as a set for classifying texture. The decomposition Algorithm finds the Energy values and Detail values calculated using different types of wavelet packets. The Wavelet families are used for feature extraction (i) Haar (ii) Daubechious (iii) Bior (iv) Coiflet.

The following algorithm is used to find out feature vector using wavelet transform:

- I. Load the image
- II. Convert it into gray scale image
- III. For the converted image for each wavelet 5 levels of detail are obtained (details need to be specified)
- IV. Store all the 20 detail values and 4 Energy values corresponding to the 4 wavelet families
- V. First set of feature vectors are stored.

Energy and Detail of the input image are obtained using these equations.

$$E_{\text{detail}} = \sqrt{d_j^H + d_j^V + d_j^D}$$

$$E_{\text{approx}} = \sqrt{(a_j)^2}$$

$$E_{\text{ratio}} = E_{\text{detail}} / E_{\text{approx}}$$

After the first set of features are obtained, second set of features are extracted from the fractal analysis. This Algorithm incorporates two basic algorithm (i) Multilevel Otsu Algorithm [12] (ii) Bounding box technique to obtain the fractal dimension [3]

- a) Multilevel Otsu Algorithm

The Otsu algorithm takes a grayscale image $I(x, y)$ as an input and calculate the user defined number of threshold points such that the intra class variance becomes minimum. It incorporates the gray level distribution function to generate the threshold levels. When the threshold points (T) are obtained the next task is to generate the binary images using two threshold segmentation levels from the equation.

$$I_b(x, y) = \begin{cases} 1 & \text{if } t_l < I(x, y) \leq t_u \\ 0, & \text{otherwise} \end{cases}$$

where t_l and t_u denote, respectively, lower and upper threshold values. The set of binary images is obtained by applying the two threshold segmentation to the input image using all pairs of contiguous thresholds from $T \cup \{nl\}$ and all pairs of thresholds $\{t, nl\}$, $t \in T$, where n_l corresponds to the maximum possible gray level in $I(x, y)$.

- b) Box Counting Algorithm to compute the Fractal

Dimension, Area, Mean

After applying the Multilevel Otsu Algorithm to the input gray level image, the feature vector is constructed as the resulting binary images' size, mean gray level and boundaries' fractal dimension. The regions' boundaries of a binary image $I_b(x, y)$ denoted by border image $\Delta(x, y)$ and computed as follows:

$$\Delta(x, y) = \begin{cases} 1 & \text{if } \exists(x', y') \in N_8[(x, y)] : \\ & I_b(x', y') = 0 \wedge \\ & I_b(x, y) = 1 \\ 0, & \text{otherwise.} \end{cases}$$

where $N_8[(x, y)]$ denotes the set of pixels that are 8-connected to (x, y) . $\Delta(x, y)$ has value 1 if the pixel at position (x, y) in the corresponding binary image $I_b(x, y)$ has the value 1 and having at least one neighboring pixel with value 0. Otherwise, $\Delta(x, y)$ takes the value 0. Hence, one can realize that the resulting borders are one-pixel wide. Fractal Dimension are extracted using Box Counting algorithm in which the binary image is divided in to small grid and for each sub grid part the fractal dimension is stored given by the number of instance a border is found. Mean and Area of the fractals are computed without much computational power.

Having described the basic processing tools used in the algorithm, the complete explanation of the algorithm goes in the following way.

Algorithm can be decomposed in two stages:

- A. Training a Discriminant classifier using some known datasets whose texture is known by the user.
- B. Using the Discriminant classifier on the segmented tumor image for detecting the texture type.

3.1. Training Phase Algorithm

- I. Input Image.
- II. Feed the input image from the training datasets used.
- III. Find level 1 detail of the Haar, Daubechies, BiOrthogonal, Coiflet wavelet transform.
- IV. Using Multilevel Otsu algorithm to find two level threshold values.
- V. Obtained Threshold values are used to generate two binary images.
- VI. Fractal Dimensions are calculated using hausdorff method [7, 8].
- VII. Using Fractal Dimension, Level 1 detail of the wavelets as features to identify the texture detail [3].
- VIII. Repeat the previous steps until the features are stored for the whole dataset.
- IX. Use the Feature matrix to train a Discriminant classifier with the labels as indicated in the following table.

Table 1. Materials specifying texture classes.

Type	Class
Floor	Slight Smooth
Marble	Very Smooth
Knit	Moderately Rough
Corduroy	Moderately Rough
Fur	Moderately Rough
Bark	Very Rough
Glass	Very Smooth
Brick	Slight Rough
Wall	Slight Rough
Upholstery	Slight Rough
Plaid	Slight Rough
Pebbles	Very Rough
Wallpaper	Slight Rough
Wood	Very Rough
Water	Slight Smooth
Granite	Moderately Smooth
Carpet	Moderately Rough

Table 2. Level 1 texture details obtained using OTSU Algorithm.

Class	Feature values		
	Mean Level 1	Area Level 1	Dimension Level 1
Very Smooth (0% Rough 100% Smooth)	1.726699823	79.36368951	82103
Moderately Smooth (20% Rough 80% Smooth)	1.7088903	83.24563	56231
Slight Smooth (40% Rough 60% Smooth)	1.677946534	114.1885945	59445
Slight Rough (60% Rough 40% Smooth)	1.347586482	87.13088195	10987
Moderately Rough (80% Rough 20% Smooth)	1.712092195	75.91502644	68080
Very Rough (100% Rough 0% Smooth)	1.711876879	110.1846481	77710

Table 3. Level 2 texture details obtained using OTSU Algorithm.

Class	Feature values		
	Mean Level 2	Area Level 2	Dimension Level 2
Very Smooth (0% Rough 100% Smooth)	1.726953297	104.7969757	81010
Moderately Smooth (20% Rough 80% Smooth)	1.79839231	102.23231	75092
Slight Smooth (40% Rough 60% Smooth)	1.479879362	104.3540146	19180
Slight Rough (60% Rough 40% Smooth)	1.79390182	52.06027164	129215
Moderately Rough (80% Rough 20% Smooth)	1.721312591	77.54282501	72014
Very Rough (100% Rough 0% Smooth)	1.622193522	98.09344798	45940

Table 4. Level 1 texture details obtained using Haar Wavelet.

Class	Feature values	
	Haar Average Level 1	Haar Detail Level 1
Very Smooth (0% Rough 100% Smooth)	97.31444573	2.685554273
Moderately Smooth (20% Rough 80% Smooth)	98.33424367	0.56234244
Slight Smooth (40% Rough 60% Smooth)	99.62078049	0.379219514
Slight Rough (60% Rough 40% Smooth)	92.6145109	7.385489097
Moderately Rough (80% Rough 20% Smooth)	97.75745902	2.242540978
Very Rough (100% Rough 0% Smooth)	99.11477746	0.88522254

Table 5. Level 1 texture details obtained using Daubechies Wavelet.

Class	Feature values	
	Daubechies Average Level 1	Daubechies Detail Level 1
Very Smooth (0% Rough 100% Smooth)	98.73633881	1.263661195
Moderately Smooth (20% Rough 80% Smooth)	97.23242342	1.05243233
Slight Smooth (40% Rough 60% Smooth)	99.8322521	0.167747905
Slight Rough (60% Rough 40% Smooth)	94.91961194	5.080388064
Moderately Rough (80% Rough 20% Smooth)	98.73764835	1.262351652
Very Rough (100% Rough 0% Smooth)	99.44868289	0.551317111

Table 6. Level 1 texture details obtained using Bi-Orthogonal Wavelet.

Class	Feature values	
	Bi-Orthogonal Average Level 1	Bi-Orthogonal Detail Level 1
Very Smooth (0% Rough 100% Smooth)	97.18699987	2.81300013
Moderately Smooth (20% Rough 80% Smooth)	98.33423424	0.890334242
Slight Smooth (40% Rough 60% Smooth)	99.58879022	0.411209782
Slight Rough (60% Rough 40% Smooth)	92.51087882	7.489121185
Moderately Rough (80% Rough 20% Smooth)	97.67231902	2.327680976
Very Rough (100% Rough 0% Smooth)	99.04748648	0.952513519

Table 7. Level 1 texture details obtained using Coiflet Wavelet.

Class	Feature values	
	Coiflet Average Level 1	Coiflet Detail Level 1
Very Smooth (0% Rough 100% Smooth)	98.36831315	1.631686849
Moderately Smooth (20% Rough 80% Smooth)	97.4934932	1.152352324
Slight Smooth (40% Rough 60% Smooth)	99.78445554	0.215544459
Slight Rough (60% Rough 40% Smooth)	94.2230022	5.776997803
Moderately Rough (80% Rough 20% Smooth)	98.57000487	1.429995132
Very Rough (100% Rough 0% Smooth)	99.36600026	0.633999745

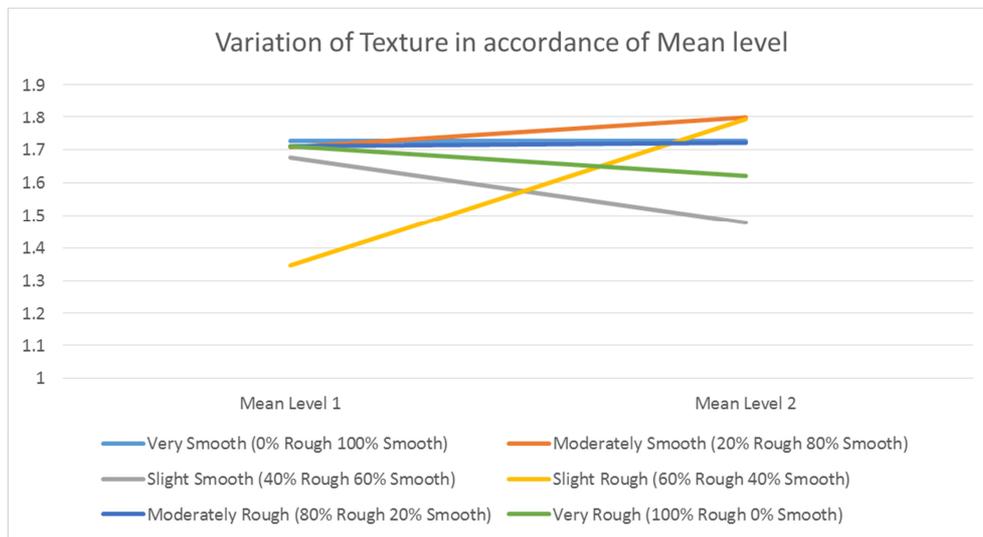


Fig. 2. Variation in Texture from Mean level 1 to level 2.

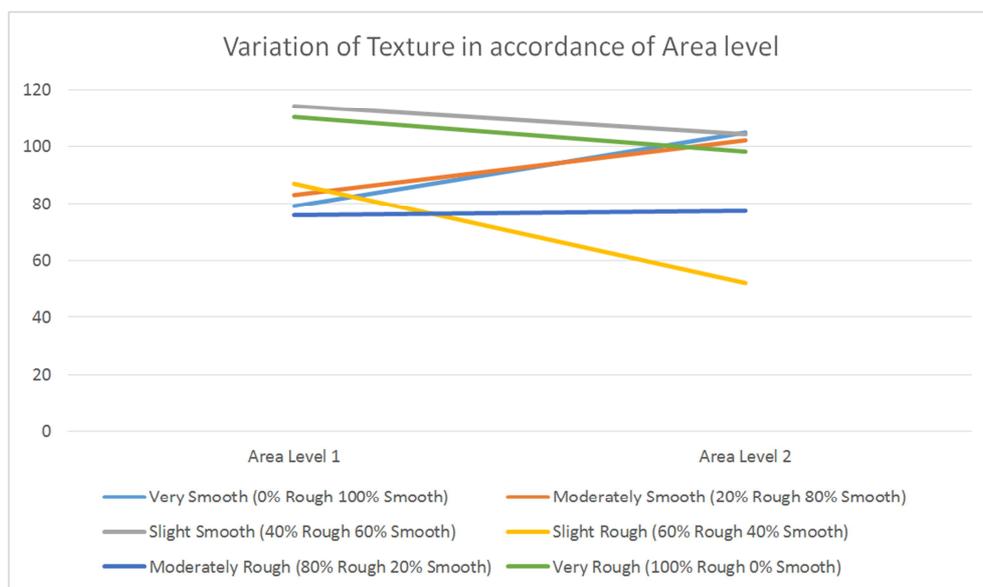


Fig. 3. Variation in Texture from Area level 1 to level 2.

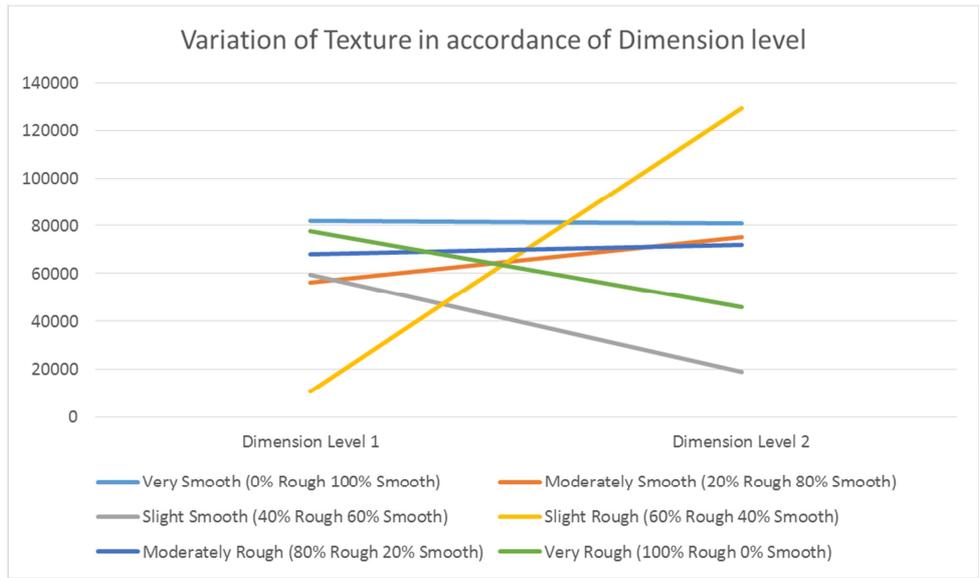


Fig. 4. Variation in Texture from Dimension level 1 to level 2.

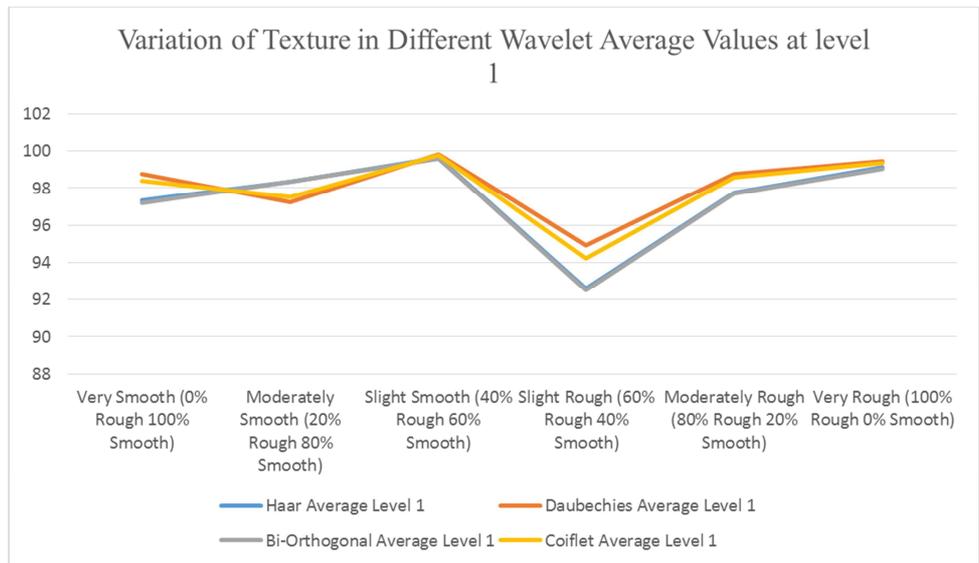


Fig. 5. Variation of Wavelet Average Values for Texture Classes.

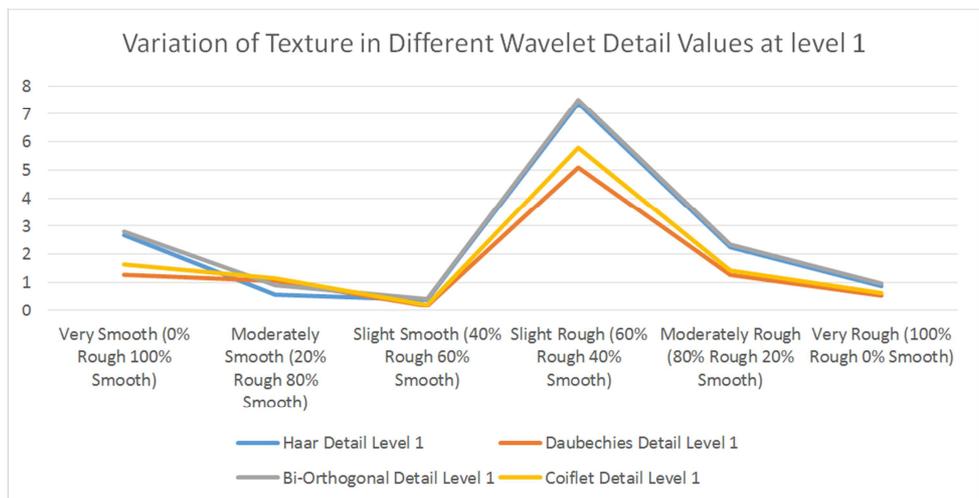


Fig. 6. Variation of Wavelet Detail Values for Texture Classes.

As the experiments reveal the wavelet energy and details efficiently describe a texture pattern and forms a highly uncorrelated feature sets. More over the Fractal analysis algorithm not on describe the texture completely but also forms an orthogonal set of feature. As mentioned in the prior work [3] SFTA Algorithm was implemented which gave an amazing texture classification but with 4 threshold level. In our algorithm we reduced the number of threshold, but reducing the threshold points decreases the strength of the feature sets. So along with reduction in the threshold points we introduced the wavelet based features which not only improve the classification efficiency but also reduced the classification time.

3.2. Deployment Phase Algorithm

- I. Input MR Image.
- II. Equalize Histogram of the Image.
- III. Separate out the Skull for Segmenting the Tumor from the brain.
 - a) Thresholding is implemented such that the binary image obtained so has least intra class variance.
 - b) Subtract the thresholded image to get the Skull less brain.
 - c) Divide the image in 64*64 blocks
 - For each block among 4096 divided blocks, Daubechies wavelet transform is implemented to segment out the tumor.
 - Tumor is segmented using thresholding based on the wavelet based features and the coordinates are stored for further processing.
 - Morphological Operations are performed so as to display the actual positions of the tumor as an image.
 - a) Finding the texture information for the blocks which have a part of the tumor is our area of interest, hence it reduces a ton of computational complexity.
 - b) For each block having a part of Tumor
 - The size of the blocks is too small to find textures features so Wavelet based resolution enhancement is implemented.
 - The image so obtained from each block is decomposed using Haar wavelet transform to generate Average Image, Horizontal Detail Image, Vertical Detail Image, Diagonal Detail Image.
 - Each Image is resized 10 folds.
 - All the new images so obtained are fed to inverse Haar wavelet transform to get the new resolution enhanced image.
 - For each enhanced block
 - Find level 1 detail of the Haar, Daubechies, BiOrthogonal, Coiflet wavelet transform.
 - Using Multilevel Otsu algorithm to find two level threshold values.
 - Obtained Threshold values are used to generate two binary images.
 - Fractal Dimensions are calculated using hausdorff

method.

- Using Fractal Dimension, Level 1 detail of the wavelets as features to identify the texture detail.
- The Features so obtained are fed to earlier trained Discriminant classifier and the output class is registered for each block having the tumor part.
- With the knowledge of the registered class for each block, a grayscale image is generated showing the texture details with the different grayscale levels.

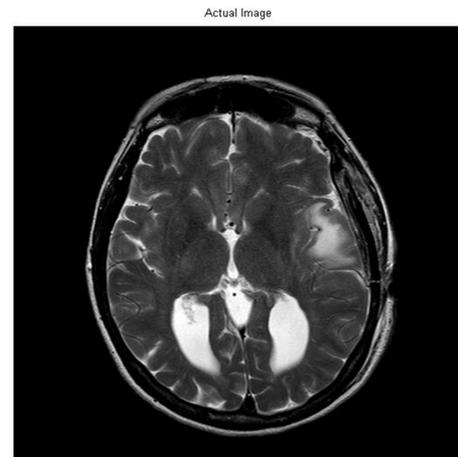


Fig. 7. Actual Image.

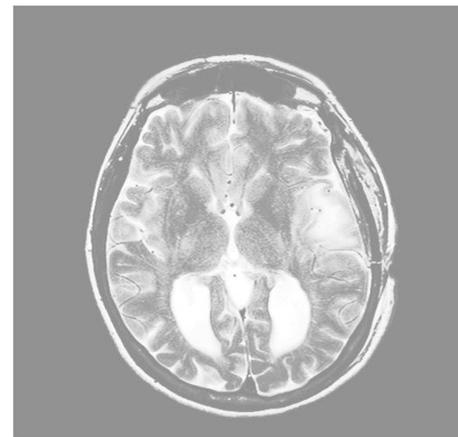


Fig. 8. Histogram Equalized.

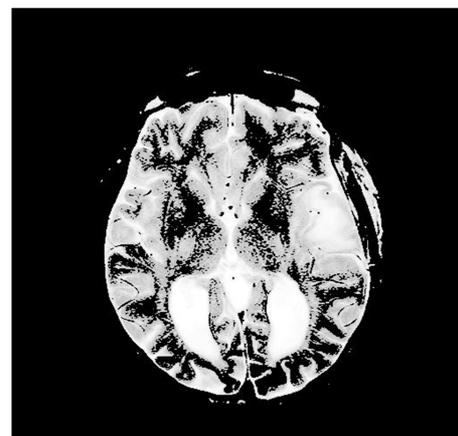


Fig. 9. Skull Removed.

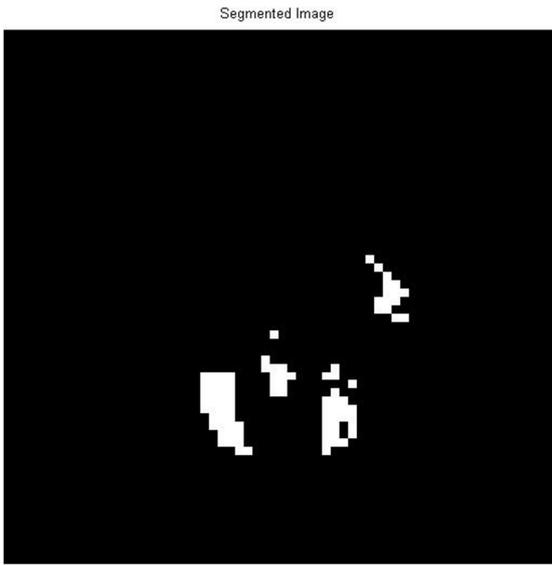


Fig. 10. Segmented Image.

After Morphological Operation

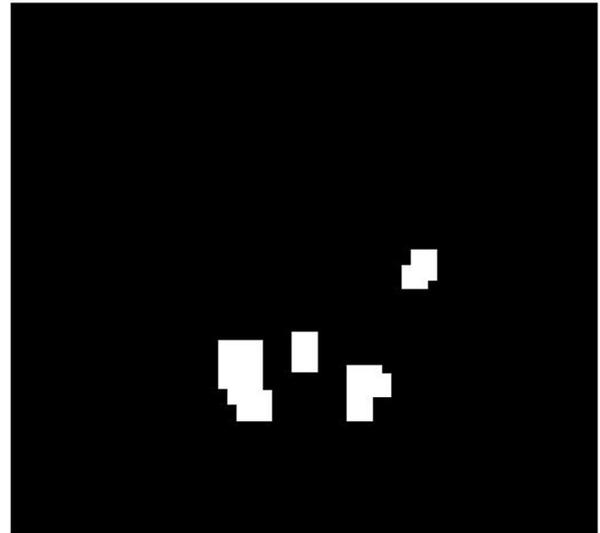


Fig. 11. Tumor.

Texture Information



Fig. 12. Texture Detail.

Table 8. Obtained Texture Values for the Tumor.

Smooth Texture of Brain Tumor Surface with 100% Smoothness and 0% Roughness		Rough Texture of Brain Tumor Edge with 60% Smoothness and 40% Roughness	
Feature values	Values	Feature values	Values
Mean Level 1	1.45772585	Mean Level 1	1.34633022
Area Level 1	239.1263369	Area Level 1	235.9642857
Dimension Level 1	1496	Dimension Level 1	392
Mean Level 2	1.498535377	Mean Level 2	1.761117175
Area Level 2	238.7133867	Area Level 2	233.3372549
Dimension Level 2	1748	Dimension Level 2	25532
Haar Average Level 1	99.99902423	Haar Average Level 1	92.99393589
Haar Detail Level 1	2.459757713	Haar Detail Level 1	6.064112307
Daubechies Average Level 1	98.74385556	Daubechies Average Level 1	95.99413996
Daubechies Detail Level 1	0.095614444	Daubechies Detail Level 1	5.006003782
Bi-Orthogonal Average Level 1	99.99901163	Bi-Orthogonal Average Level 1	92.99392059
Bi-Orthogonal Detail Level 1	2.698836768	Bi-Orthogonal Detail Level 1	6.079409778
Coiflet Average Level 1	98.45903827	Coiflet Average Level 1	96.99443848

Coiflet Detail Level 1	1.639617285	Coiflet Detail Level 1	5.561519573
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So from the Texture detail image [Fig. 12] it can be seen that the tumor boundaries are slight rough whereas the center and rest portion are having very smooth textures.

Gray Scale Values corresponding to different classes:

Table 9. Gray Level Indicating Different Classes.

Class	Gray Scale Value (Black -> 0 & White->255)
Very Smooth (0% Rough 100% Smooth)	42.5
Moderately Smooth (20% Rough 80% Smooth)	85
Slight Smooth (40% Rough 60% Smooth)	127.5
Slight Rough (60% Rough 40% Smooth)	170
Moderately Rough (80% Rough 20% Smooth)	212.5
Very Rough (100% Rough 0% Smooth)	255

4. Conclusion

The proposed technology is useful to doctors as well as to the diagnostic center as it portrays the texture that tumor is having. Our algorithm defines the texture of tumor in reference to our daily known textures. The proposed state-of-the-art algorithm utilizes both fractal analysis along with wavelet features to make the prediction much more firm in terms of accuracy. Generally, tumor appears as very smooth type and near the sides it becomes slight rough. The texture detail image will let medical practitioner know the type of texture of the tumor. This will help in diagnostics of the Brain tumor by correlating with other clinical tests and findings.

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