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A Novel Method to Model Brain Tumor using Wavelet Transform and Fractal Parameters

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ABSTRACT

Background: In recent years, brain tumor has been known to be a leading preventable ailment affecting the survival of human beings. The uncontrollable growth of brain cells forming abnormal tissue mass cause brain tumor which impedes usual brain activities. In this paper the algorithms proposed by various researchers for detection and segmentation of brain tumors in MRI images are reviewed. The algorithms were implemented for the images reported by the respective researchers; several computational models of brain tumor are also reviewed.Objective: We propose a simple method to model brain tumors which can be used as a standard test model.Results:Themodeled brain tumor is used to implement KLD-EM algorithm and HFS – SOM algorithm. Conclusion: This model can be used for validating algorithms under development.

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INTRODUCTION

Long-term dependencies are implicated in maximum physical phenomena, and 1/f-type spectral behaviors are detected over wide range of frequencies (Keshar, 1982). Fast Fourier Transform (FFT), a classic tool cannot be used for analyzing signals if the spectral characteristics are not expressed as rational fractions. AR (Autoregressive model) or ARMA (Autoregressive Moving Average model), the familiar models with constant parameters are not suitable. Such broad range of signals is known as 1/f noise. Mandelbrot and van Ness (Mandelbrot B.B., 1983) explained the complex geometry of the objects in nature by fractal concept. The statistically self-similar Fractional Brownian motion (fBm) can be observed (from statistical point of view) as a scaled version of a larger part of the process. The biomedical study on images is significant with respect to the scale-invariance and self-similarity, central to fractal models (Lundhal*et al*., 1986;Pesquet-Popescu, 2002). In general, tumor growth gives structures that have some fractal features. These are evident in brain vasculature in which tree structure of arteries visualizes a fractal like pattern (Risser, 2007;Heinzer, 2006). This concept is used for simulating the tumor model.

II. Background Study:

The two segmentation algorithms Mean shift algorithm and normalized cut (Ncut) algorithm are combined in an algorithm proposed by (Vishal B.Padole*et al*., 2012). Over segmentation phenomenon is the drawback observed in Mean shift algorithm. As the number of pixels in the image increases, the need for generation of graph nodes are more which add to the complexity of the Ncut algorithm. Preprocessing the image by mean shift algorithm reduces the computational time. The exact tumor area in the MRI images are calculated by applying Ncut algorithm followed by connect component extraction analysis. Such combination of algorithm showed improvements in the detection of tumor.

Fast volume segmentation (HFS – SOM) algorithm and Entropy – Gradient segmentation – SOM (EGS – SOM) algorithm were proposed by (Ortiz *et al.,* 2013). In HFS – SOM algorithm, image is preprocessed using histogram computation followed by histogram modeling using SOM and SOM clustering to obtain segmented image. HFS – SOM algorithm works for the whole volume whereas EGS – SOM algorithm works slice – by - slice. In EGS –SOM algorithm feature extraction is done after image preprocessing followed by genetic algorithm (GA) based feature selection and EGS –SOM based

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clustering resulted in segmented image. In EGS – SOM algorithm, image preprocessing followed by genetic algorithm (GA) based feature selection for feature extraction and EG –SOM clustering resulted in segmented image. EGS – SOM algorithm works slice – by – slice. Parametric or supervised methods are inferior to HFS – SOM, a faster segmentation algorithm.

The effectiveness of four different feature selection techniques, namely, Kullback – Leibler divergence (KLD), Principal Component Analysis (PCA), boosting and entropy were investigated by (Shaheen Ahmed *et al.*,2011). Among these algorithms KLD gives better results. In addition, Shaheen investigated three different feature fusion and segmentation techniques, namely, top down and bottom approach, Expectation Maximization algorithm (EM), and graph cut. Among these EM is found to be an efficient feature fusion and segmentation algorithm. Shaheen Ahmed also proposed the combined framework of KLD and EM and concluded that it gives the best performance among the techniques investigated.

Fractal dimension (FD) has been proved to be a statistically a major indicator for tumor identification by (JustinM.Hook and Khan M.Iftekharuddin, 2005). Justin Hook proposed two conclusions about the use of fractal dimension for tumor location. Firstly, the tumor tissue images have an FD lower than the average FD of non - tumor tissue. Secondly, a negative FD difference between a sub image in one half and its corresponding sub image in the other half of an image locates tumor.

The innovative methodology for wavelet – fractal extraction, automated segmentation and classification of brain tumor in T1 MR image was proposed by (Iftekharuddin*et al.*, 2005). The technique proposed by K.M.Iftekharuddin in which fractal dimension and pixel intensity parameters were calculated for the input MR image and incorporated in feature vector. Segmentation of SOM algorithm utilizes feature vector. Feed Forward (FF) neural network is used for tumor classification. Mean values of fractal dimension and intensity were computed. The computed data is used as descriptors for the corresponding segmented regions. The classifier was not tested with hard to detect tumors. It is evident that feature vectors are not adequate to distinguish different types of brain tissues.

A computer based procedure was developed by (Arati Kothari, 2012) to detect tumor blocks or lesions and classify the type of tumor using Artificial Neural Network in MRI images of different patients with Astrocytoma type of brain tumors. The extraction of texture features in the detected tumor has been achieved by using Gray Level Co-occurrence Matrix (GLCM). The Neuro Fuzzy Classifier has been developed to recognize different types of brain cancers. The whole system has been tested in two phases firstly Learning/Training Phase and secondly Recognition/Testing Phase. The system was found efficient in classification of these samples and responds to any abnormality.

The modeling objectives and challenges in developing in silico brain tumor models were reviewed byZhihui Wang and Thomas S.Deisboeck, 2008 and also highlighted their significance in treating brain tumor. The discrete and continuum modeling were discussed in detail and opportunities for the future hybrid multi scale multi resolution modeling were discussed. The paper explains the significance of integrative computational neuro oncology filed in brain tumor treatment.

In hybrid models, utilizing Finite element or other models define tumor boundary definition or the degree of diffuse invasion of tumor cells into the surrounding brain tissue. These 'ROI' regions of interest remain difficult to analyze in conventional medical imaging or to understand the co - ordinate system models.

Finite element and numerical techniques will provide a place to provide advancement in silico oncology to provide clinical level quantitative insights into dynamic cross scale relationships moving brain tumor treatment into personalized systems.

The ordinary Brownian motion can be extended naturally as Fractional Brownian motion (fBm)(Mandelbrotand Van Ness1968).It is a Gaussian zero – mean non-stationary stochastic process$B_H(t)$, indexed by a single scalar parameter $0 < H < 1$, the usual Brownian motion being recovered from the specification H = ½.

Mandelbrot and Van Ness (1968) had carried out the ground-breaking work, which defines fBm by its stochastic representation

$$B_H(t) = \frac{1}{\Gamma\left(H+\frac{1}{2}\right)}\left(\int_{-\infty}^{0}\left[(t-s)^{H-\frac{1}{2}}-(-s)^{H-\frac{1}{2}}\right]dB(s)+\int_{0}^{t}(t-s)^{H-\frac{1}{2}}dB(s)\right) \quad (1)$$

Where Γ represents the Gaussian function

$$\Gamma(\alpha) = \int_{0}^{\infty} x^{\alpha-1} exp(-x)dx \quad (2)$$

The non-stationary property of fBm is evidenced by its covariance structure (Yaglom, 1986):

$$E[B_H(t)B_H(s)] = \frac{\sigma^2}{2}\left(|t|^{2H}+|s|^{2H}-|t-s|^{2H}\right) \quad (3)$$

Where $H \in (0,1)$called the Hurst parameter or fractal parameter. The fractal parameter is related to the dynamic behavior of the fBm and when H = ½, fBm is the well-known classical Brownian motion. The variance of the fBm is of the type (Patrick Flandrin, 1992)

$$var(B_H(t)) = \sigma^2|t|^{2H} \quad (4)$$

The fractal dimension is given by (Mandelbrot, 1983; Falconer, 1990)

$D = 2 – H$ (5)

According to the possible values of H, it follows that $1 < D < 2$, the scalar fBm parameter H being related to the roughness of fBm samples.

A normalized fractional Brownian motion $B_H = \{B_H(t): 0 \leq t < \infty\}$ with $0 < H < 1$ is uniquely characterized by the following properties (Ton Dieker, 2004)

1. $B_H(t)$ has stationary process with proper increments
2. $B_H(0) = 0$ & $EB_H(t) = 0$; $for t \geq 0$
3. $EB^2{}_H(t) = t^{2H}$; $for t \geq 0$
4. $B_H(t)$ has a Gaussian distribution for $t > 0$.

The wavelet representation of fBm(Sellan and Meyer,1996)

$$B_H(t) - b_0 = \sum_k b_h(k)\phi_{0,k}^{(s)}(t) + \sum_{j\leq 0,k} \gamma_j(k) 4^{-s} 2^{-js} \psi_{j,k}^{(s)}(t) \quad (6)$$

Where $s = H + \frac{1}{2}$, b_0 is an arbitrary constant, γ_j are independent identically distributed Gaussian random variables, $b_h(k)$ is a fractional $ARIMA(0, s, 0)$ process, and $\phi_{0,k}^{(s)}$ and $\psi_{j,k}^{(s)}$ are suitably defined fractional scaling function and wavelet.

III.Proposed Methodology:

A. Tumor Modeling:

Researchers propose their algorithms based on the MR images acquired from hospitals in their localities. This gives rise to difficulties in comparing different algorithms as algorithms are image dependent. In this paper, a method for generating standard tumor model is presented.

As the tumor growth is non-linear, two dimensional random samples with zero mean and non –zero variance is generated and due to self – similarity property the fractal parameters like fractal dimension D and Hurst exponent H are initialized and used to find the time and frequency components of two dimensional samples using discrete wavelet transform.

Generate random two dimensional zero mean, non - zero variance samples denoted by $u = u_{(x,y)}$. The samples are used to simulate fBm which is denoted by B (u) with initial fractal dimension D and Hurst parameter. Incremental of B(u) is denoted as $\Delta B(u)$ and determined by

$\Delta B(u) = B(u+ \Delta u) - B(u)$ (7)

Expectation of $\Delta B(u)$

$E[\Delta B(u)] = 2C_2 \Delta u^H$ (8)

where C_2 a function of H

The above equation is function of Hurst exponent of fBm.

Perform Wavelet Transform to estimate D & H and find final wavelets coefficients.

2-D CWT function of B (u) is given by(ConorHenegan*et al.*,1996)

$CWT_\Psi^B(a,b,\theta) = 1/a \int_u \Psi^*(R^\theta [(u-b)/a)])B(u)du$ (9)

where Ψ^* - 2 – Dimensional spatial wavelet, a – Scaling factor, θ - Angle,
b – 2- Dimensional translation vector, R^Θ - A Rotation by the angle θ in 2- D plane.

Considering isotropic wavelet 2 – Dimensional CWT of B (u) has no functional dependence on θ and expectation of CWT calculated as,

$E[| CWT_\Psi^B(a,b) |^2] = 1/a^2 \int_u\int_v \Psi^*((u-b)/a)\Psi((v-b)/a)E[B(u)B(v)] du dv$ (10)

The substitutions p = (u-b)/a leads to

$E[| CWT_\Psi^B(a,b) |^2] = C_2 a^{2H+2}\int_p CWT_\Psi^\Psi(1, p) | p |^{2H}dp$ (11)

Difference between Expectation of initial $\Delta B(u)$ and Expectation of final $CWT_\Psi^B(a,b)$

$E[\Delta B(u)] - E[| CWT_\Psi^B(a,b) |^2] = 2C_2\Delta u^H - C_2 a^{2H+2}\int_p CWT_\Psi^\Psi(1, p) | p |^{2H}dp$ (12)

The low level features can be calculated accurately when the number of wavelet decomposition levels are high. The difference between feature values is inversely proportional to the wavelet decomposition levels. Generally decomposition gives the time dependent features. Whenever the highest decomposition levels are reached the difference in successive low level features become almost constant. Over all minimum difference and maximum scale gives the final model of the features. The above Maximum Time Scale Dependent condition is verified by convergence of low level features by the condition

$E[\Delta B(u)] - E[| CWT_\Psi^B(a,b) |^2] = 0$ (13)

The above process creates a model for tumor and further morphological operations are applied to the model to get the image version of the model.

B.Flow chart of the proposed method:

The flow chart representation of the proposed method is shown in Fig. 1.

IV. Experimental Results and Discussion:

This section explains the results of the proposed method implemented in MATLAB. The curves of convergence process are shown in Fig.2.Once the curves get converged then the morphological operations are performed to get the tumor model. The samples of modeled tumor are shown in Fig. 3.The images show the growth of the brain tumor. The modeled tumor and its distribution is shown in Fig. 4.The modeled tumor embedded in different locations in MRI brain image are shown in Fig, 5. The parameters like energy, entropy, contrast and fractal dimension are calculated for the samples of modeled tumor and shown in the Table 1.

The combined framework of KLD and EM algorithm (Shaheen Ahmed *et al*., 2011) is implemented and the segmented image is shown in Fig. 6(a) and 6(b).The combined Fast volume segmentation (HFS – SOM) algorithm (A.Ortiz*et al*., 2012) is shown in Fig. 6(c) and 6(d).The results show that the modeled tumor embedded in normal brain can be used as an input image for segmentation algorithms.

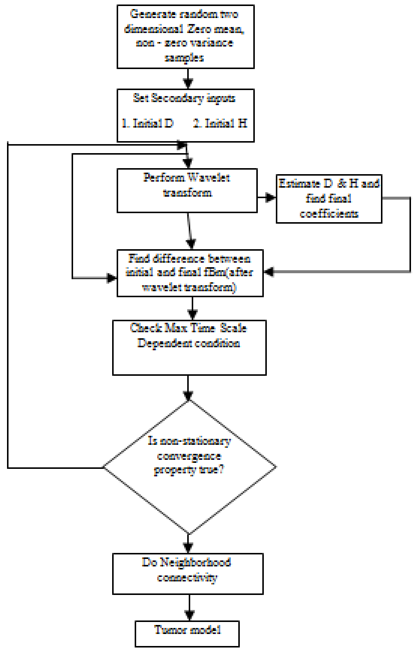


Fig. 1: The proposed method.

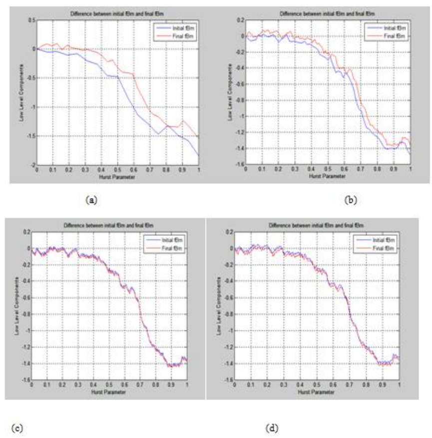


Fig. 2: Convergence Process.

Fig. 3: The modeled tumor.

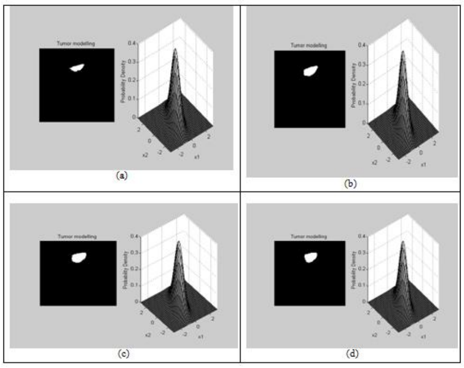


Fig. 4 : Modeled tumors and the corresponding distributions.

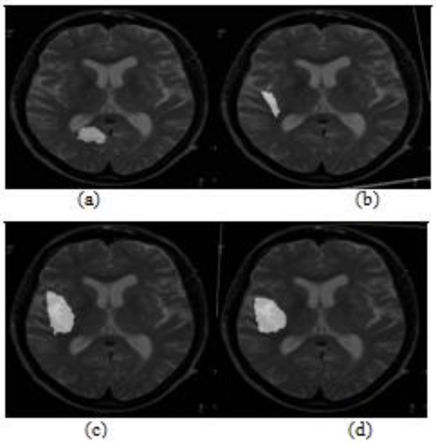
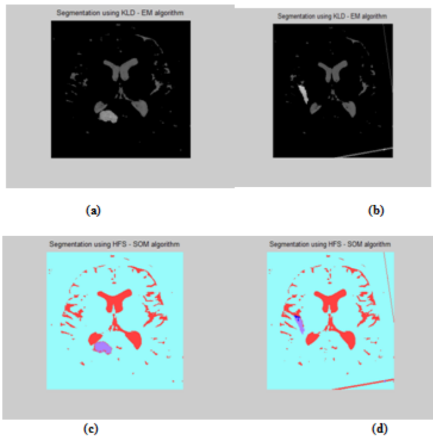


Fig. 5: Tumor Embedded in MRI.

Table 1: Parameters calculated for the modeled tumor.

S.No.S S.No.	Parameters	Figure 5 (a)	Figure 5(b)	Figure 5(c)	Figure 5(d)
1	Energy	0.9916	0.8808	0.9262	0.90815
2	Entropy	0.0303	0.2932	0.1932	0.23595
3	Contrast	0.2075	2.7275	1.7825	2.1075
4	Fractal Dimension	1.87	1.8664	1.8678	1.8670



Fig, 6: Segmentation Results.

V. Conclusion:

In this paper wavelet based method for modeling the tumor has been presented. The modeled tumor is embedded in the MRI brain image and results for the KLD –EM algorithm and HFS-SOM algorithm combined with ANN are obtained. It is suggested that this method can be used for modeling the tumor.The KLD – EM algorithm and HFS – SOM algorithm works well for the image in which the modeled tumor has been embedded.

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