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Detection and Segmentation of Brain Tumors using AdaBoost SVM

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ABSTRACT— Segmentation plays a vital role in determining the tumor in brain MR Images. The analysis is done using multifractional Brownian motion (mBm) to devise the tumor in brain MR images. The spatially varying feature is extracted using mBm and corresponding algorithm. Then segmentation is carried out based on multifractal features. An algorithm for segmentation is proposed by modifying the well-known AdaBoost algorithm. The modification of AdaBoost algorithm is known as Adaboost Support Vector Machine (SVM). In SVM, the weights are assigned to component classifiers based on their ability to classify difficult samples.

KEYWORDS— AdaBoost Classifier, Brain Tumor Detection and Segmentation, Fractal, MRI, Multi-Fractal Analysis, Multiresolution wavelet, Texture Modeling

I. INTRODUCTION

Brain is one of the most complicated structures. A tumor is an abnormal tissue that grows by uncontrolled cell division. Tumor segmentation from MRI data is an important process. The main task is to detect the presence of tumors in MR images of the brain, and segment the abnormal pixels from the normal pixels. In automatic segmentation, tumor is perceived using varying intensity of tumors in brain MR images. Brain tumor segmentation depends on two major techniques, they are feature based [1] [2] [3] [4] [5] [6] [7] [8] and atlas based. [9] [10] [11]. In [10], Warfield et al. proposed elastic atlas registration with statistical classification to mask brain tissue from surrounding structures. Digital anatomic atlas and MR image intensity is used for brain tumor segmentation in Kaus et al.[11]. In [9], Prastawa et al. developed tumor segmentation and statistical classification of brain MR images using an atlas prior. There are few challenges associated with atlas-based segmentation. Atlas based segmentation requires manual labeling of template MRI. In [13], Davatizikos et al. used systematic deformations due to tumor growth to match preoperative images of the patient with that of the postoperative. In [14], Menze et al. proposed a generative probabilistic model for segmentation by augmenting atlas of healthy tissue priors with a latent atlas of tumor.

Among feature based techniques, Lee et al. [2] proposed brain tumor segmentation using Discriminative Random Field (DRF) method. In this a set of multi-scale image-based and alignment-based features are used for segmentation. Corso et al. [3] discussed Conditional Random Field (CRF) based hybrid discriminative generative model for segmentation and labeling of brain tumor tissues in MRI. Reference [5] uses intensity, intensity gradient and Haar-like features in a Markov Random Field (MRF) method that combines probabilistic boosting trees and graph cuts for tumor segmentation.

Cobzas et al. [4] studied textons [15] and level set features with atlas-based priors to build statistical models for tissues. Such level set techniques are very sensitive to initialization and known to suffer from boundary leaking artifacts. In [8], the authors proposed a parametric active contour model that facilitates brain tumor detection in MRI. The proposed model makes rather simplistic assumption that there is a single continuous region associated with tumor. Reference [16] exploits patient-specific initial probabilities with non-local features to capture context information. The authors use a standard classification forest (CF) as a discriminative multi-class classification model. The techniques in [16] combined

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random forest (RF) classification with hierarchical CRF regularization as an energy minimization scheme for tumor segmentation.

Fractal analysis [1] [6] [7] is one of the successful method in image segmentation. It is a part of texture feature extraction techniques. The complex texture pattern of brain tumor in MRI may be more flexible to multifractional Brownian motion (mBm) analysis [6] [7] [21]. In [21], the adequacy of different feature selection and tumor segmentation techniques using multiple features including mBm for brain tumor segmentation. The mBm feature effectively models spatially-varying heterogeneous tumor texture.

Consequently, in this work, we propose formal stochastic models to estimate multi-fractal dimension (MultiFD) for brain tumor texture extraction in pediatric brain MRI. We further propose Adaptive Boosting (AdaBoost) algorithm for classifier fusion. Our modifications help the component classifiers to concentrate more on difficult-to-classify patterns during detection and training steps.

II. BACKGROUND REVIEW

This section provides brief discussions on several topics that are relevant to this work.
Fractal and Fractional Brownian Motion (fBm) for tumor segmentation

Brownian motion is a mathematical model used to describe random movement of a particles. In Probability theory, a normalized fractional Brownian motion (fBm), also called a fractal Brownian motion, is a generalization of Brownian motion without independent increments. A fractal is an irregular geometric object with an infinite nesting of structure at all scales. Fractal texture can be quantified with the non-integer fractal dimension (FD). In (1), continuous-time Gaussian process $B_H(t)$ on [0, T] is estimated which starts at zero for all t in [0, T], and has the following Covariance function:

$$E[B_H(t)B_H(s)] = \frac{1}{2}(|t|^{2H} + |s|^{2H} - |t-s|^{2H}), \qquad (1)$$

Where H is a scalar parameter $0 < H < 1$ known as Hurst index (Holder exponent). The value of H determines the fBm process such that the curve $B_H(t)$ is very rough if H=0.01, while for H=0.99, the curve is very smooth. Figure 1 shows an example of simulated $B_H(t)$ vs. time plots for different H values. The Figure confirms variation of surface roughness with variation of H values.

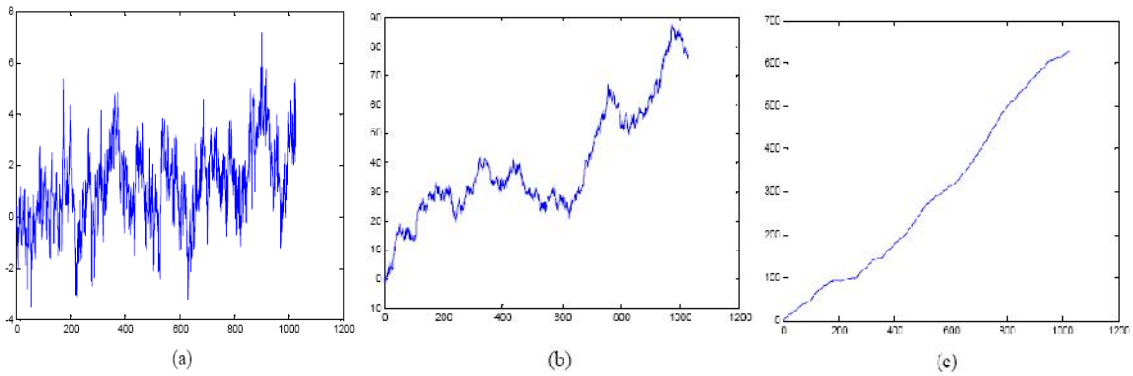

Figure 1. Simulation of fBm process with different H values; (a) H = 0.01; (b) H = 0.5; (c) H = 0.99

The FD is related to the Hurst parameter, H, as follows,

$$FD = E + 1 - H \qquad (2)$$

The parameter E is Euclidean dimension (2 for 2D, 3 for 3D and so on) of the space.

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Multifractal Process

A multifractal system is a generalization of a Fractals system in which a single exponent (the Fractal dimension) is not enough to describe its dynamics; instead, a continuous spectrum of exponents (the so-called Singularity spectrum) is needed. Initially mBm is used to analyse MR images by classifying into texture in multifractal dimension i.e, it is used to analyse the courseness of object or texture. It is used to estimate roughness of the sample path that varies with location (Spatial variation).

Even though fBm is applicable for brain tumor texture analysis [20], considering the rough heterogeneous appearance of tumor texture in brain MRI, fBm appears homogeneous, or monofractal. In fBm process, the local degree of *H* is considered the same at all spatial/time variations. However, like many other real world signals, tumor texture in MRI may exhibit multifractal structure, with *H* varying in space and/or time. Takahashi et al. [27] exploit multifractal to characterize micro structural changes of white matter in T2-weighted MRIs. Consequently, this work proposes a model to estimate multifractal dimension of tumor and nontumor regions in MRI based on mBm analyses. In general, mBm is generalization of fBm with a zero mean Gaussian process. The major difference between the mBm and fBm is that, contrary to fBm, the *H* of mBm is allowed to vary along spatial/time trajectory.

Classifier Boosting

To make the classification method efficient a novel boosting method is proposed. Such boosting method yields a highly accurate classifier by combining many moderately accurate component classifiers. In this method, each component classifier is successively added and trained on a subset of the training data. Among different variations of boosting methods, adaptive boosting such as AdaBoost [22] is the most common.

Many studies report AdaBoost with Decision Trees [30], Neural Networks [31] or Support Vector Machine (SVM) [32] as component classifiers are used. A Diverse AdaBoostSVM algorithm is proposed in our work. The diverse AdaBoostSVM offers superior performance over its counterparts for unbalanced dataset.

III. ALGORITHMS FOR SEGMENTATION

When applying Boosting method to strong component classifiers, these component classifiers must be appropriately weakened in order to benefit from Boosting. Hence, if RBFSVM is used as component classifier in AdaBoost, a relatively large value, which corresponds to a RBFSVM with relatively weak learning ability, is preferred. In the proposed AdaBoostSVM, without loss of generality, the re-weighting technique is used to update the weights of training samples. AdaBoostSVM can be described using algorithm: Initially, a large value is set to s, corresponding to a RBFSVM classifier with very weak learning ability. Then, RBFSVM with this s is trained as many cycles as possible as long as more than half accuracy can be obtained. Otherwise, this s value is decreased slightly to increase the learning capability of RBFSVM to help it achieve more than half accuracy. By decreasing the s value slightly, this prevents the new RBFSVM from being too strong for the current weighted training samples, and thus moderately accurate RBFSVM component classifiers are obtained. The reason why moderately accurate RBFSVM component classifiers are favored lies in the fact that these classifiers often have larger diversity than those component classifiers which are very accurate. These larger diversities may lead to a better generalization performance of AdaBoost.

SVM is added to the AdaBoost in an unconstrained manner, the performance may degrade since each additional SVM may be actually a "weak learner". However, in our framework, we never add any new SVM unless the total diversity, as defined in (20), goes up. That is how the overall classification performance is expected to increase.

Algorithm: AdaBoostSVM

1.Input: a set of training samples with labels $\{(x_1, y_1), \ldots, (x_N, y_N)\}$; the initial σ, σ_{ini}, the minimal σ, σ_{min}.

2.Initialize: the weights of training samples: $W_I^1 = \frac{1}{N}$, for all i = 1, . . . , N.

3.Do While ($\sigma > \sigma_{min}$)

(a) Train a RBFSVM component classifier, h_t, on the weighted training set.

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(b) Calculate the training error of h_t : $\varepsilon_t=\sum_{i=1}^{N} W_i^t$, $y_i \neq h_t(x_i)$.

(c) If $\varepsilon_t > 0.5$ goto step1.

(d) Set the weight of component classifier h_t: $\alpha_t=\frac{1}{2}\ln\left(\frac{1-\varepsilon_t}{\varepsilon_t}\right)$

(e) Update the weights of training samples : $W_I^{t+1} = \frac{w_i^t \exp\{-\alpha_t y_i h_t(x_i)\}}{c_t}$

where c_t is constant, and $\sum_{i=1}^{N} W_i^t = 1$.

4.Output: f(x) = sign $(\sum_{t=1}^{T} \alpha_t h_t(x))$

IV. PROCESS OF TUMOR DETECTION AND SEGMENTATION

The overall flow diagram is shown in Fig. 2. Following standard preprocessing steps for brain MRI, the corresponding fractal, texton and intensity features are extracted. In the next step, different combinations of feature sets are exploited for tumor segmentation and classification. Feature values are then directly fed to the AdaBoost classifier for classification of tumor and non-tumor regions. Manual labeling to tumor regions is performed for supervised classifier training. The trained classifiers are then used to detect the tumor or nontumor segments in unknown brain MRI.

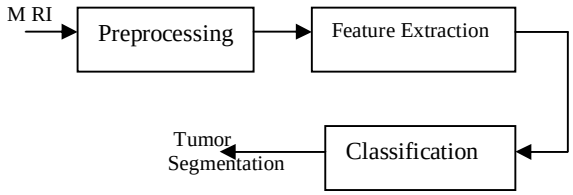

Figure 2 Simplified overall flow diagram

MRI Preprocessing

Preprocessing images commonly involves removing low frequency, background noise, normalizing the intensity of individual practical images, removing reflections and masking portion of images. Image processing is the technique of enhancing data images prior to computational processing. The following preprocessing steps involves realignment and unwarp slices within a volume, separately for every modality

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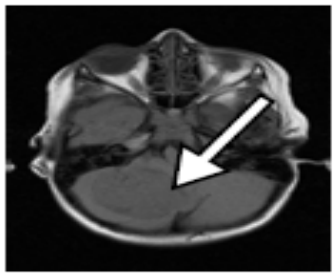
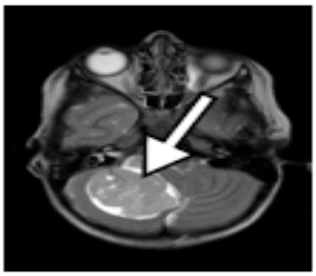
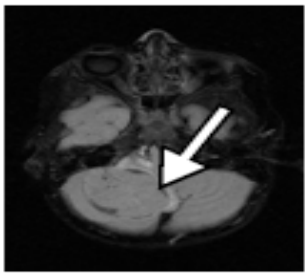


(a) Original T1



(b) Original T2



(c) Original Flair

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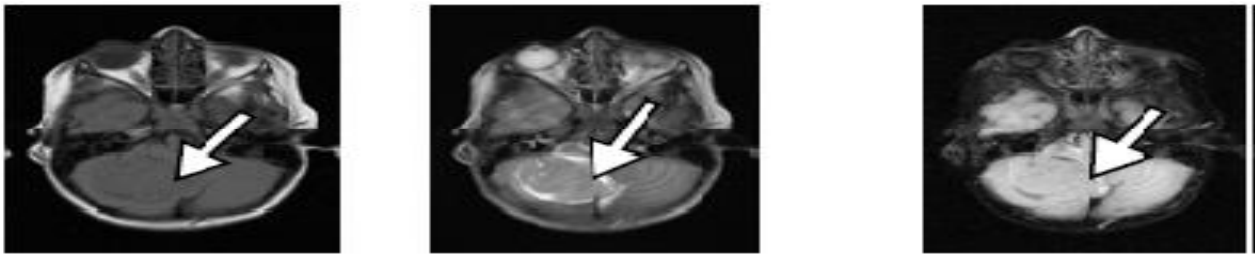


(d)T1 after realign,unwrap (e)T2 after realign,unwrap (f)Flair realign

Figure 3 Multimodality MRI slices showing different preprocessing steps

Feature Extraction

Feature extraction is a special form of Dimensionality reduction. When the input data to an Algorithm is too large to be processed and it is suspected to be notoriously redundant (e.g. the same measurement in both feet and meters) then the input data will be transformed into a reduced representation set of features (also named features vector). Transforming the input data into the set of features is called *feature extraction.* If the features extracted are carefully chosen it is expected that the features set will extract the relevant information from the input data in order to perform the desired task using this reduced representation instead of the full size input.

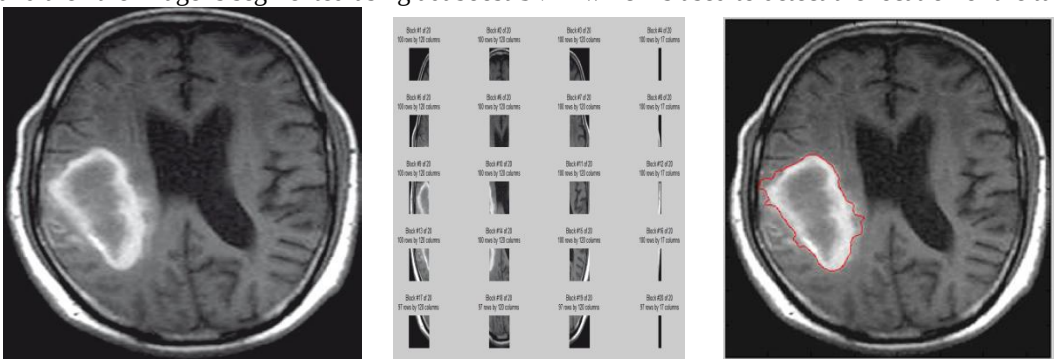
Brain tumor segmentation and classification from non-tumor tissue

A support vector machine searchs an optimal separating hyper-plane between members and non-members of a given class in a high dimension feature space . The inputs to the SVM algorithm are the feature subset selected during data pre-processing step and extraction step. In SVM kernels functions are used such as graph kernel, polynomial kernel, RBF kernel etc. Among these kernel functions, a Radial Basis Function(RBF) proves to be useful, due to the fact the vectors are nonlinearly mapped to a very high dimension feature space.

For tumor/non-tumor tissue segmentation and classification, MRI pixels are considered as samples. These samples are represented by a set of feature values extracted from different MRI modalities. Features from all modalities are fused for tumor segmentation and classification. A modified supervised AdaBoost ensemble of classifier is trained to differentiate tumor from the non-tumor tissues.

V. RESULTS AND DISCUSSION

The figure shows that the MR images of brain are analysed to detect and segment tumor. The MR image is initially classified into sub images or blocks and each block is analysed using multifractional Brownian motion to obtain its features and then the image is segmented using adaboost SVM which is used to detect the location of the tumor.



(a) (b) (c)

Figure 4 (a) original MRI (b) sub blocks of MRI (c) segmented tumor using SVM

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VI. CONCLUSION

In this work, novel multi-fractal (MultiFD) feature extraction and supervised Classification techniques for improved brain tumor detection and segmentation are proposed. The MultiFD feature characterizes intricate tumor tissue texture in brain MRI as a spatially varying multifractal process in brain MRI. On the other hand, the proposed modified AdaBoost algorithm considers wide variability in texture features across hundreds of multiple patient MRI slices for improved tumor and non-tumor tissue classification. As a future direction, incorporating information from registered atlas may prove useful for segmentation of more subtle and complex tumors. In addition, it may be interesting to investigate the proposed modified AdaBoost classification.

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