Tumor Detection and Classification of MRI Brain Image using Different Wavelet Transforms and Support Vector Machines

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***Abstract*— The brain is one of the most complex organs in the human body that works with billions of cells. A cerebral tumor occurs when there is an uncontrolled division of cells that form an abnormal group of cells around or within the brain. This cell group can affect the normal functioning of brain activity and can destroy healthy cells. Brain tumors are classified as benign or low-grade (grade 1 and 2) and malignant tumors or high-grade (grade 3 and 4). The proposed methodology aims to differentiate between normal brain and tumor brain (benign or malign). The study of some types of brain tumors such as metastatic bronchogenic carcinoma tumors, glioblastoma and sarcoma are performed using brain magnetic resonance imaging (MRI). The detection and classification of MRI brain tumors are implemented using different wavelet transforms and support vector machines. Accurate and automated classification of MRI brain images is extremely important for medical analysis and interpretation.**

***Keywords*—brain; classification; denoising; detection; support vector machines; tumor; wavelet transforms**

I. Introduction

MRI is an extensively used technique which facilitates the diagnosis and prognosis of brain tumors in many neurological diseases and conditions. Standard MRI sequences are generally used to differentiate between different types of brain tumors based on visual qualities and contrast texture analysis of the soft tissue. More than 120 classes of brain tumors are known to be classified in four levels according to the level malignancy by the World Health Organization (WHO).

The grading from low to high (1-4) are malignant levels from the least aggressive biological tumor to the most aggressive tumors, as shown by histological criteria, for example, vascularity, invasiveness, and tumor growth rate. Gliomas are the most primary cerebral tumor and a pre-treatment evaluation grade is necessary; however, the exclusive use of standard MRI sequences may be insufficient for a precise diagnosis [1], [2]. As the support vector machines architectures are becoming more mature, they gradually outperform previous state-of-the-art classical machine learning algorithms The literature survey has revealed that some of the techniques are invented to obtain segmentation only; some of the techniques are invented to obtain feature extraction and some of the techniques are invented to obtain classification only.

II. Overview Wavelets and SVMs

A. Wavelet transforms

Wavelets based transform are mathematical tools which are used to extract information from images. These have an important advantage over Fourier transforms, because of their temporal resolution which means that they can capture both frequency and location information in the images, see in Fig.1 [3]. Wavelets are represented both in time and frequency, whereas the standard Fourier transform is represented only in frequency. Wavelet transforms are implemented replacing Fourier transforms for domains as image processing, image watermarking, medical imaging, image compression and many other. They are also used for denoising medical images. Orthogonal wavelets have always played a principal role in biomedical image processing [2], [3].

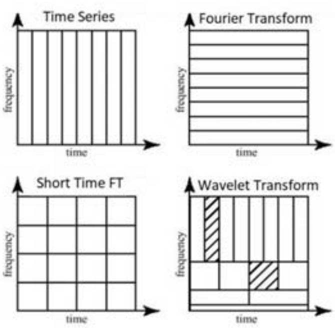

Fig. 1. Wavelet transform [3].

B. Support Vector Machines

Implementing classification is an important responsibility for different applications such as image micro-array gene expression, proteins structure predictions, data classification.

Support Vector Machine (SVM) is an efficient machine method developed from analytical learning. A distinguished property of SVM is to minimize the empirical classification error and maximize the geometric margin synchronously. SVM predominantly classifies the training data into two classes. In this paper training data includes MRI brain tumor images with malign tumor and benign tumor and normal brain image. The training samples have data arranged as vectors such that the number of rows in each vector indicates different observations concerning the medical images and the number of columns represents the set of features. Using training samples the classifier is able to differentiate the tumor in malign and benign, and also the normal brain image can be detected [1], [2] and [16].

III. METHODOLOGY

The proposed technique has three steps:

Step 1. Preprocessing (de-noising using different wavelets with different thresholds and levels, feature extraction and feature reduction);

Step 2. Training the SVMs (linear, kernel);

Step 3. Submit new MRI brains images (training sets) to the trained SVMs and output the obtained prediction.

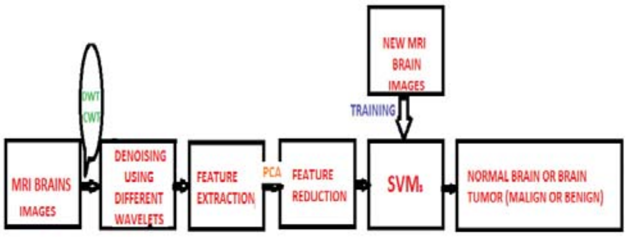

Fig. 2. Detection and classification algorithm

A. *Preprocessing using a different kind of wavelets*

The first step in our processing chain is denoising medical images. We want to show the efficiency of wavelet-based thresholding techniques in noise presence for various wavelet families. We applied Haar, Symlet, Morlet, and Daubechies in denoising MRI brain images. Performance estimation and analysis are accomplished using Signal to Noise Ratio (SNR), Peak Signal to Noise Ratio (PSNR) and Mean Square Error (MSE). We are using wavelets to denoise images. In medical images, edges are places where the image brightness changes fast. Maintaining edges while denoising an image is severely important for intuitive quality. Traditional lowpass filtering removes noise, it often smoothes edges and influences image quality. Wavelets are able to remove noise while maintaining important features [3]. From the obtained results it can be confirmed that the wavelets with higher level tend to give good results. Since the SNR value corresponding to the higher level such as those for Daub level 3 is more as compared to Daub level 1. The same goes for Symlet wavelets. While the best results are obtained using the Haar wavelets, with highest SNR value, least MSE and least Entropy. It can thus be conclude form above results that the wavelets that are higher level show better results.

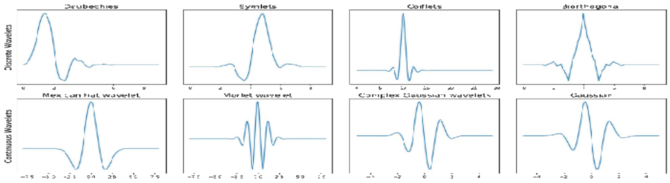

Fig.3. Wavelet families [3].

For finding closely spaced features, it is necessary to choose wavelets with smaller support, such as haar, db2, or sym2.

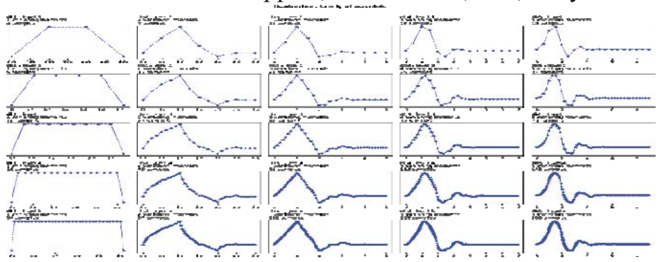

Fig. 4. The Daubechies family of wavelets for several different orders of vanishing moments and several levels of refinement [3].

We have implemented wavelets Daubechies, Haar, Symlet, Morlet level1, level2 and level3 with a threshold for denoising brain tumor images in Matlab. We have obtained for Daubechies the following images Fig.5, Fig.6, Fig.7 and Fig.8 [3].

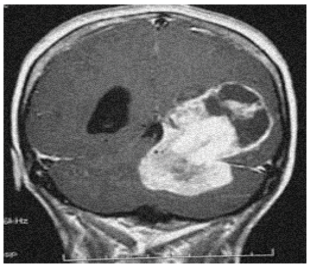

Fig.5. Brain tumor acquisition.

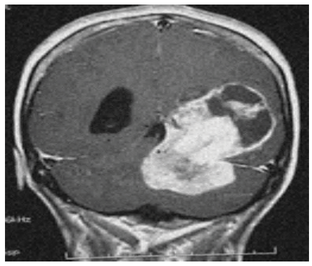

Fig.6. Denoising brain tumor with Daubechies level 1, obtained SNR=0.0319.

Fig.7. Denoising brain tumor with Daubechies level 2, obtained SNR=0.0627.

Fig.8. Denoising brain tumor with Daubechies level 3, obtained SNR=0.1050.

Mother wavelet plays a dominant role in denoising MRI image selection using wavelets. The wavelet transform family has numerous types of wavelets such as Haar, Morlet, Symlet, and Daubechies. Haar transform is the simplest and the oldest transform. It has a discontinuous nature, it behaves just like a step function. Haar is used to analyzing images accurately at various resolutions. Daubechies transform is the most popular transform that leads to the foundation of wavelet-based on multi-dimensional signal processing. Whereas, Morlet and

Symlet transform are both symmetric in shape and has no scaling function [4], [5] and [6]. In conclusion, we can observe that the SNR is getting higher at the same threshold when increasing the level for the wavelet. We have implemented also a Principal Component Analysis (PCA) for obtaining only the necessary features for optimal processing [7]. PCA reduces the dimensionality of the predictor space. Reducing dimensionality can create classification models that prevent overfitting. PCA linearly transforms predictors in order to remove redundant dimensions and generates a new set of variables called principal components [8], [9].

B. Segmentation for feature extraction

- The OTSU [11] method is described using its free parametric character and unsupervised nature of threshold choice and has the following benefits:

  1) This process is very easy; only the zeroth and the first order cumulative moments of the gray-level histogram are used;
  2) We can apply a simple extension to multi-thresholding problems that is possible by the criteria on which the method is based;
  3) We are automatically selecting an optimal threshold or set of thresholds, that are not based on the differentiation (that is - a local property such as valley), but on the integration (that is - a global property) of the histogram.
  4) We can also analyze other aspects for example evaluation of class separability, estimation of class mean levels, etc.
  5) We are able to underline the generality of the method, it covers a large unsupervised decision procedure.

- Otsu's method [11], is used to automatically perform clustering-based image thresholding, or, the reduction of a gray-level image to a binary image in computer vision and image processing. The algorithm presumes that the image contains two classes of pixels following bimodal histogram, it then calculates the optimum threshold separating the two classes so that their mixed expansion is minimal, or uniformly so that their inter-class variance is maximal.

- Creating white and black regions by using global thresholding [12]. Global thresholding is based on the assumption that the image has a bimodal histogram and therefore, the object can be extracted from the background by a simple operation that compares image values with a predefined threshold value T. The histogram is represented in Fig. 9 [12]. The object and background pixels have gray levels grouped into two dominant modes.

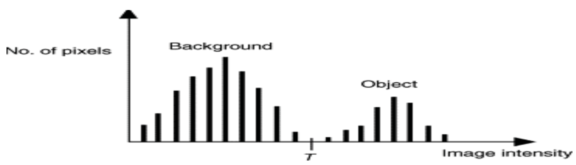

Fig.9. Bimodal histogram with selected threshold *T* [12].

The definition for an image with threshold *g(x, y)* is:

$$g(x,y) = \begin{cases} 1, & if\, f(x,y) > T \\ 0, & if\, f(x,y) \leq T \end{cases} \quad (1)$$

The thresholding result is a binary image, where pixels with an intensity value of 1 correspond to objects, whereas pixels with value 0 corresponding to the background.

Finally, we have applied the segmentation obeying the Otsu algorithm [11]. We have obtained using Matlab following results, represented in: Fig.10, Fig.11, Fig.12 and Fig.13.

Fig.10.Original MRI image after denoising Daubechies level 3.

Fig.11. Otsu binary brain tumor image prepared for segmentation

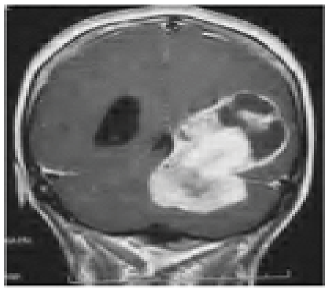

Fig.12.Brain tumor image with white and black features in the group.

Fig.13. Brain tumor segmented image using Otsu segmentation algorithm.

C. Wavelet transforms for detection Discrete Wavelet Transform (DWT) and Continous Wavelet Transform (CWT)

The major difference between the CWT and DWT is how the scale parameters are discretized. The CWT discretizes scales more finely than the DWT. The CWT and DWT transforms differ in how they discretize the scale parameters. We have calculated for both CWT and DWT contrast, correlation, energy, homogeneity, mean, standard deviation, entropy, RMS, variance, smoothness, kurtosis, skewness, image difference-features and accuracy see Table 1. The advantages of wavelets over the more traditional methods are: wavelets recode information in a small number of large value coefficients; SNR of these coefficients is good if the noise is about the same everywhere in the measurement space; a good SNR ensures a good detection rate; finally, wavelets often have the capacity to decrease space dependences enabling the use of simple statistical tests.

D. Classification using SVMs

When our data has specifically two classes we can use a support vector machine (SVM) [13]. We are using a set of new MRI brain images. Finding the best hyperplane that detaches all data points of one class from those of the other class means correct data classification using SVM methods. Establishing the best hyperplane for an SVM means the one with the largest margin between the two classes. The maximal width of the plate parallel to the hyperplane that has no interior data points determines the margin. Complicated binary classification problems do not have a simple hyperplane as a useful separating criterion. There is a variant of the mathematical approach that retains nearly all the simplicity of an SVM separating hyperplane for those problems [13]. We train on big data sets and explore models in our application trained on a subset of our data, then generate the code to train the selected model on a larger data set. In Fig. 14 brain tumor classification detects a malign tumor.

Table 1: SVMs accuracy performance.

[%]	**Support Vector Machines**		
	Binary SVM	***Binary Linear Classification***	***Binary Kernel Classification***
Accuracy	92	91	99

Training with big data an SVM and then validating the classifier is the first step we have to do. We use the trained machine to classify new data, We use various SVM kernel functions to obtain a satisfactory predictive accuracy, and we must adapt the parameters for the kernel functions. We have to do the following actions: to train an SVM classifier, to classify new data with an SVM classifier, finally to adjust an SVM classifier. The Kernel methods are known to be state-of-the-art in classification techniques. However, the training and prediction cost is expensive for big data. In conclusion, linear classifiers can easily scale up but are inferior to kernel classifiers in terms of predictability. SVMs applied in modern research has shown that for some data sets, linear is as good as kernel classifiers. In such cases, the training of a kernel classifier is a waste of time and memory [14], [15], [16].

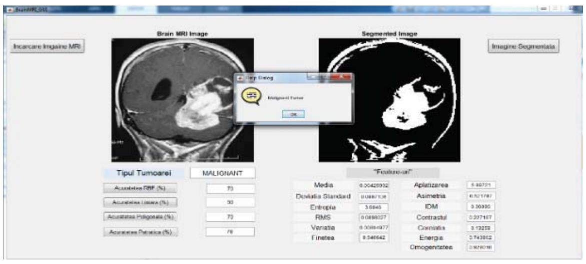

Fig.14. Malign tumor detection (message in dialog box), calculated accuracy and other statistic parameters (left original image, right segmented image).

IV. Conclusion

The brain tumor detection and classification system is implemented using CWT, DWT and SVMs. The proposed method uses different levels for wavelets, the high accuracy part is obtained using CWT. The CWT prevents the loss of edges in segmentation. The result shows that SVMs having the proper sets of training data are able to distinguish between abnormal and normal tumor regions and classify them correctly as a benign tumor, malign tumor or healthy brain. In practice, SVMs have significant computational advantages. Five times improvement in computation speed (22 vs. 110 ms) for our proposed method. This classification is very important for the physician in establishing a precise diagnostic and recommending a correct further treatment. The obtained results show that CWT provides higher computation comparing with DWT. Even if the computation time is longer, if we are mainly interested in visualization, matching and feature detection, it is better to use CWT. If we are interested in de-noising, compression, restoration, then DWT is often more appropriate. A hybrid approach is recommended in solving properly the detection and classification problems in brain tumors.

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