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An application of the Empirical mode decomposition to Brain Magnetic Resonance images classification

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Abstract: *A new approach to distinguish normal from abnormal brain magnetic resonance (MR) images is presented. First, the empirical mode decomposition (EMD) is applied to brain MR images to obtain high frequency intrinsic mode functions (IMF) from which features are extracted. Then, an entropy-based selection process is used to identify the most informative and non-redundant features from each IMF before classification by support vector machines (SVM). The validation of the approach with a MR image database consisting of Alzheimer's disease, glioma, herpes encephalitis, metastatic bronchogenic carcinoma, multiple sclerosis, and normal condition shows its effectiveness as well as slightly better classification efficiency in comparison to using discrete wavelet transform-based alternatives. However, the EMD approach is substantially more time consuming.*

Keywords: *Empirical mode decomposition (EMD), support vector machine (SVM), intrinsic mode functions (IMF), magnetic resonance images (MRI).*

1. INTRODUCTION

The Brain magnetic resonance imaging has become the primary imaging modality for early diagnosing and monitoring of brain pathologies. However, the existing MR imaging systems cannot yet perform automatic diagnosis and help offload the physicians in their diagnostic and treatment work. As a result, several studies have been conducted to automate the classification of two-dimensional brain MR images. The typical approach starts by filtering the image to remove unwanted components. Then, textural information is extracted from the filtered image to form a feature vector. Finally, the latter is processed by a classifier algorithm to class the MR image. Currently, there appears to be a convergence of the various techniques that have been reported in the literature to use the discrete wavelet transform (DWT) as the first step, prior to feature extraction. For instance used wavelets as input to support vector machine (SVM) to classify brain magnetic resonance (MR) images as either normal or abnormal, the discrete wavelet transform was applied to each MR image to obtain level-2 Daub4 wavelet approximation coefficients and feed them to the SVM classifier. The approach was validated on with a dataset consisting of fifty-two brain MR images, of which six normal and forty-six of brains affected by Alzheimer's disease, four normal images and six abnormal. Curing cancer has been a major goal of medical researchers for decades, but development of new treatments takes time and money. Science may yet find the root causes of all cancers and develop safer methods for shutting them down brain tumors are benign and can be before they have a chance to grow or spread. Approximately 40 percent of all primary successfully treated with surgery and, in some cases, radiation. The number of malignant brain tumors appears to be increasing but for no clear reason. Magnetic Resonance Imaging (MRI) has become a widely used method of high quality medical imaging, especially in brain imaging where MRI's soft tissue contrast and non-invasiveness is a clear advantage. MRI provides an unparalleled view inside the human body. The level of detail we can see is extraordinary compared with any other imaging modality. Reliable and fast detection and classification of brain cancer is of major technical and economical importance for the doctors. Common practices based on specialized technicians are slow, have low responsibility and possess a degree of subjectivity which is hard to quantify. MR imaging is unique among diagnostic imaging modalities because it employs several independent parameters which determine the image scale. The image intensity permits the detailed visualization of the internal anatomical structures in living human subjects. MR image parameters include tissue relaxation times: the spin-lattice relaxation time (T1) and the spin-spin relaxation time (T2), and the proton density (PD). The goal of MR image segmentation is to accurately identify the principal tissue structures in these image volumes. The BP algorithm, however, has a very slow convergence rate and requires a priori learning parameters. These drawbacks have significantly limited the application of neural networks in this area, especially since the MR images training sets required are very large. Recently, several improved training algorithms have been reported in the literature. One of these methods, the least square back propagation (LSB), operates by looking at the structure of neural networks, separates the neural networks into linear and non-linear parts, and then optimizes the linear part of each layer from the output layer to the input layer using the least square method. The main advantage of the LSB algorithm is that it can converge within less than 10 iterations. It therefore makes possible the application of neural networks for medical image processing where large training sets are required. The system also finds sufficient usage under cancer

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detection in the area of medical sciences such as Computer Aided Diagnosis and Mammography etc. Brain cancer is a complex disease, classified into 120 different types. So called non malignant (Benign) brain tumors can be just as life-threatening as malignant tumors, as they squeeze out normal brain tissue and disrupt function. The glioma family of tumors comprises 44.4 % of all brain tumors. Glioblastoma type of astrocytoma is the most common glioma which comprises 51.9 %, followed by other types of astrocytoma at 21.6 % of all brain tumors. Brain tumors are the leading cause cancer death in children under the age of 20. They are the second leading cause of cancer death among 20-29 year old males. Metastatic brain tumors result from cancer that spreads from other parts of the body into the brain.

2. LITERATURE REVIEW

Chaplot et al. [1] used wavelets as input to support vector machine (SVM) to classify brain magnetic resonance (MR) images as either normal or abnormal. The discrete wavelet transform was applied to each MR image to obtain level-2 Daub4 wavelet approximation coefficients and feed them to the SVM classifier. The approach was validated on with a dataset consisting of fifty-two brain MR images, of which six normal and forty-six of brains affected by Alzheimer's disease. Four normal images and six abnormal images were randomly chosen for training the SVM and forty-two images were used for testing. The obtained correct classification rate was 98% when using a polynomial or Gaussian kernel for the SVM. **El-Dahshan et al.**, [2] used the Haar wavelet to extract third level approximation and details coefficients from MR brain images. Then, principal component analysis (PCA) was employed to reduce the number of features to seven and feed the ensuing vector to the classifier. The approach was validated on dataset included ten normal images and sixty abnormal images of various brain diseases. The learning and test set size were not indicated. The experimental results showed 97% classification accuracy when using the back propagation artificial neural network (BPNN) classifier trained with the Levenberg-Marquardt numerical algorithm and 98% when using the *k* nearest neighbour algorithm. **Zhang et al.** [3] also applied Haar wavelets and third-level decomposition to extract the low frequency coefficients from the MR images. Then, PCA was used to reduce the dimension of the feature space to 19 principal components. The reduced feature set was then fed to a feed-forward neural network whose parameters were optimized using adaptive chaotic particle swarm optimization; the validation procedure consisted of *k*-fold stratified cross validation. The proposed system achieved 98.75% correct classification rate. More recently, **Zhang et al.,** [4] employed a feed-forward back-propagation artificial neural network trained with the scaled conjugate gradient algorithm to classify MR brain images as normal or abnormal. The PCA analysis was the same, leading again to a 19 component feature vector, the validation dataset consisted of 18 normal and 48 abnormal images of several brain pathologies. The data were randomly divided into two equalized learning and test sets and the obtained correct classification rates on both training and test images were 100%, but an attempt to reproduce these results independently yielded à lower accuracy; in [5], Lahmiri and Boukadoum presented a methodology based on edge extraction and subsequent analysis by means of fractal dimension and spectral energy distribution high order statistics. Using leave-one-out cross validation on the same data used by [4], the obtained classification accuracy by support vector machines with a quadratic kernel was 91.78 % ± 0.01. In comparison, applying the feature extraction technique based on the DWT and PCA yielded 82.69%±0.08 accuracy. Although useful for image decomposition, the DWT has also drawbacks [6-7].

3. METHODOLOGY

The overall methodology is described in more details next:

3.1 THE EMPIRICAL MODE DECOMPOSITION

The EMD is to decompose Sum of functions such that the following two conditions are satisfied for each one of them: 1) It has the same numbers of zero crossings and extreme; 2) it is symmetric with respect to its local mean. The two conditions allow computing the so called Intrinsic Mode Functions or IMF. The IMFs are found at scales that range from fine to course by an iterative procedure referred to as the sifting algorithm. For signals (t), the EMD decomposition is performed as follows.

(a) Find all the local maxima, Mi ,i = 1,2,..., and minima, mk , k = 1,2,..., in s(t).

(b) Compute by interpolation -for instance a cubic Spline- the upper and lower envelopes of the signal: $M(t) = fM(Mi, t)$ and $m(t) = fm(mi, t)$.

(c) Compute the envelope mean e (t) as the average of the upper and lower envelopes: $e(t) = (M(t) + m(t))$ 2.

(d) Compute the details as $d(t) = s(t) - e(t)$.

(e) Check the properties of d (t): If d (t) meets the conditions on the number of extrema and symmetry stated previously, compute the ith IMF as $IMF(t) = d(t)$ and replace s (t) with the residual $r(t) = s(t) - IMF(t)$. If d (t) is not an IMF, then replace s (t) with the detail: $s(t) = d(t)$.

(f) Itterate steps (a) to (e) until the residual r (t) satisfy a given stopping criterion.

In the end s (t) expressed as follows:

$$s(t) = \sum_{j=1}^{N} IMF_j(t) + r_N(t) \quad \text{……. (1)}$$

Where N is the number of IMF which is nearly orthogonal to each other and all have nearly zero

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means; and *rn* (*t*) is the final residue which is the low frequency trend of the signal *s* (*t*). Usually, the standard deviation (SD) computed from two consecutive sifting results is used as the criterion to stop the sifting process by limiting the SD size such that:

$$SD(k)=\frac{\sum_{t=0}^{T}\left|d_{k-1}(t)-d_k(t)\right|^2}{\sum_{t=0}^{T}d_{k-1}^2(t)}<\varepsilon \qquad \text{……(2)}$$

3.2 FEATURES EXTRACTION AND SELECTION

Five statistical textural features are extracted from the first four intrinsic mode functions which account for most of the high frequency elemental signals in comparison with the remaining IMFs make the hypothesis that the high frequency elemental signals capture sudden changes in the biological tissue that may serve to characterize it. The statistical features computed for each of the four IMFs are the mean, standard deviation (std.dev), smoothness, third moment, and uniformity. In order to select the relevant features to be fed to the classifiers, the computed statistics are ranked based on their respective class conditional entropies. The latter measure the level of uncertainty of each feature as a class descriptor the smaller it is, the more discriminatory the related feature is.

3.3 CLASSIFICATION AND PERFOMANCE MASUREMENT

The support vector machine (SVM) with the quadratic kernel function was adopted for classification. The leave-one outcross validation method (LOOM) was used to enhance the generalization capability of the proposed approach, and the average and standard deviation of the correct classification rate were computed.

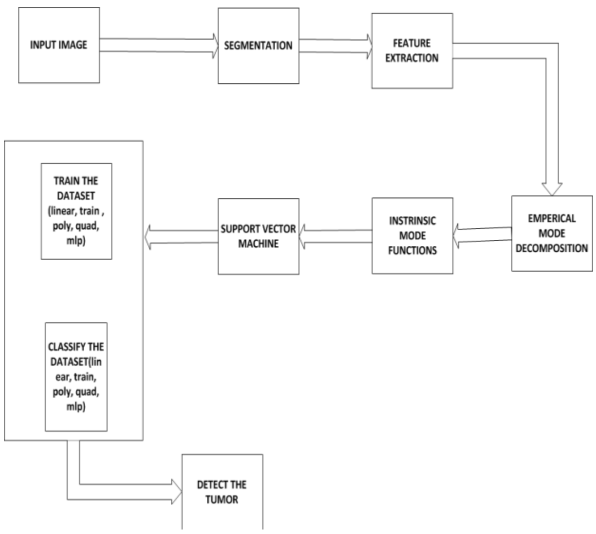

Figure 1: Empirical mode decomposition

4. RESULT

Magnetic resonance images classification by empirical mode decomposition process by using support vector machine.

Feature extraction to classify MR images by support vector machine first load the image after that segment the image then the statistical and texture features are extracted.

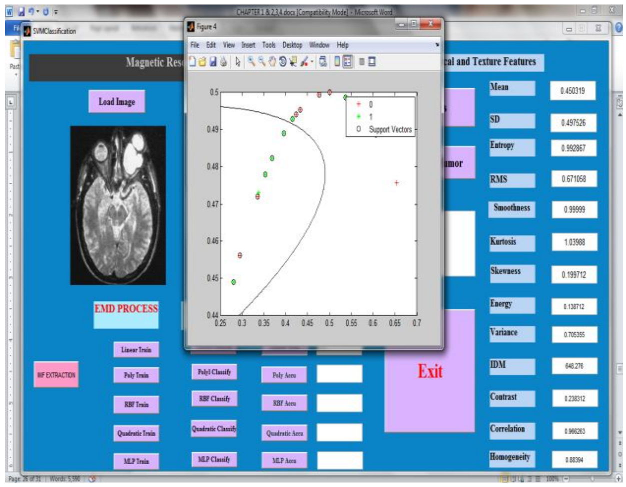

Figure 2: Extract IMF functions to train the images and classify them

Extract IMF functions to train the images and classify them as shown in fig 4, intrinsic mode functions are extracted for linear, poly, RBF, quadratic and MLP train of images after training the images classify those images to get the accurate result.

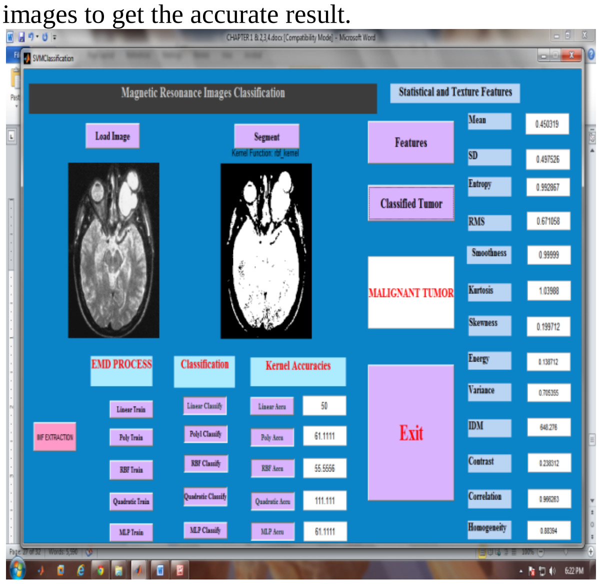

Figure 3: Classify tumor either malignant or denign

As shown in fig 5 Accuracy has been got for different types of classification after that it will classify the tumor either malignant or denign.

5. ANALYSIS

The performance of the empirical mode decomposition (EMD) features with those obtained with discrete wavelet transform (DWT) in the problem of the

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classification of normal retina digital images versus abnormal retina photographs. The generic detection system contains four basic steps; namely image acquisition using appropriate ophthalmology equipment, gray scale conversion, pixels equalization, EMD or DWT processing, features extraction, principal component analysis (PCA) (optional), and classification. In our study, three detection systems (approach) are designed: the EMD, DWT, and EMD-PCA system. The latter approach is considered to check whether principal component analysis reduced (selected) features helps improving the accuracy of the EMD-based features.

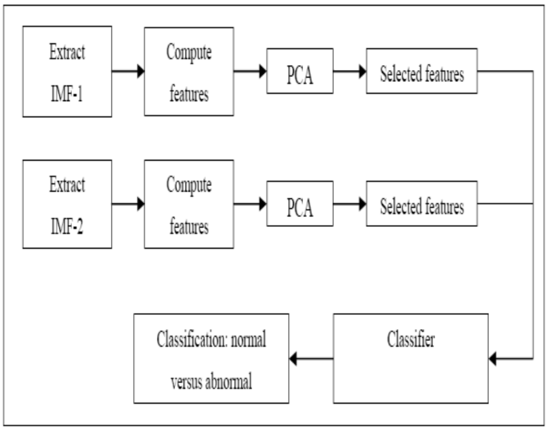

Figure 4: EMD Method

6. CONCLUSION

The potential of the empirical mode decomposition as a basis of feature extraction to classify normal versus abnormal brain magnetic resonance images, The ensuing computer aided diagnosis system uses the EMD mode to decompose the process the brain image into components, an entropy statistic to select the most significant features in them, and support vector machines to perform classification. The experiments on a database of 10 images of normal brains, and 52 of abnormal brains indicate that the EMD-based features are effective to characterize brain images and lead to slightly better performance by a SVM classifier than their DWT-based counterparts. Overall, the proposed method can make an accurate and robust classification system.

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