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Brain Tumor Detection using Scalp EEG with Modified Wavelet-ICA and Multi Layer Feed Forward Neural Network

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Abstract– Use of scalp EEG for the diagnosis of various cerebral disorders is progressively increasing. Though the advanced neuroimaging techniques such as MRI and CT-SCAN still stay as principal confirmative methods for detecting and localizing brain tumors, the development of automated systems for the detection of brain tumors using the scalp EEG has started attracting the researchers all over the world notably since 2000. This is because of two important facts: (i) cheapness and easiness of methods of recording and analyzing the scalp EEG and (ii) lower risk and possible early detection. This paper presents a method of detecting the brain tumor using the first, second and third order statistics of the scalp EEG with a Modified Wavelet-Independent Component Analysis (MwICA) technique and a multi-layer feed-forward neural network.

I. Introduction

DIAGNOSIS and following (early) treatment are either missed or delayed in 69% of the brain tumor cases due to the fact that the most of the brain tumor symptoms are highly misleading according to the survey [12]. The advanced neuroimaging techniques such as MRI and CT or biopsy are not immediately suggested due to the following facts: they are either costly or invasive or do involve risks like hazardous radiation, especially in case of children, pregnant women and patients with implant devices [15]. The delay in diagnosis worsens the outcome [14]. Hence a better method that does not involve much cost, risks or complexity is required to detect the presence of a brain tumor (structural pathology) at an early stage [14].

II. EEG in Brain Tumor

Generally it is accepted that brain tumors on superficially accessible portions of cerebral hemispheres involve some localized loss of electrical activity causing some localized slow waves on the scalp EEG [1]-[9] [16]. The general findings on the brain tumor symptoms on EEG are [2] [6] [9]: Polymorphic delta activity (PDA), Intermittent rhythmic delta activity (IRDA), Diffuse or localized theta activity, Localized loss of activity over the area of the tumor, Asymmetric beta activity, Disturbance of the alpha rhythm and Spikes, sharp waves, or spike-wave discharges. Reactivity and persistence of these abnormalities often are the best indicators of the degree of damage: continuous slow activity (e.g., persistent PDA) indicates severe structural pathology such as large, deep hemispheric lesions whereas intermittent slow activity (e.g., frontal IRDA) generally indicates small lesions [16].

III. Earlier Works on Brain Tumor Detection using EEG

Noteworthy earlier works on the detection of brain tumor using scalp EEG are [1] [2] [3] [4] and [5]. In [4] it has been shown how the one- and two- dimensional minimum orders of non-linear Markov models, which approximate the structure of the hidden dynamics in the EEG time-series of the pair of channels F3 and F4, vary with respect to the age and the structural pathologies (the tumors). In [2] it has been shown that a multilayer Self-Organizing Map (SOM) trained with the wavelet and frequency features can be used to classify the scalp EEG traces of normal, Glioma and Meningioma patients. In [3] it has been discussed how the graphs of the scalp EEG patterns of healthy subjects from those of subjects with brain tumors can be classified using Multi Layer Feed Forward (MLFF) network. In [1] it has been studied to separate EEG signals from tumor patients into spatially independent source signals using a probabilistic ICA algorithm modified by kernel-based source density estimation. In [5] the authors have presented their work in classifying the tumor EEG using Support Vector Machine (SVM) with FFT-based spectral features.

In this paper, a successful proposal on the use of a combination of time-domain and frequency-domain features of the independent components of the scalp EEG obtained using a Modified Wavelet-ICA (MwICA) in training a Multi Layer Feed Forward (MLFF) Neural Network, popularly known as Back Propagation Network (BPN), to classify a brain tumor EEG segment from a normal one has been presented. Two first order statistical features, namely the Mean Square Amplitude (MSA) and the Mean Slope Rate

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(MSR) that track the time-domain (morphological) variations in the EEG signal, one second order statistical feature, namely the Mean-to-Maximum Ratio of Power Spectrum (mmrPS) and one third order statistical feature, namely the Peak Bispectrum (pBS) that track the frequency-domain (spectral) variations in the EEG signal have been chosen. The literatures, [18] & [19] present the efficiency in the use of these four statistical features in classifying various characteristic waves (alpha, delta, spindle and K-complex) of sleep EEG.

IV. Materials and Methods

A. Materials

Nineteen Common Average Referenced (CAR) EEG Channels in the standard 10-20 electrode system, were obtained in digital format from 3 healthy subjects and 6 subjects with brain tumor (any type of brain structural pathology was considered) in the age group of 8 to 60 years for 20-25 minutes in the awake state with their eyes closed at a sampling rate of 256 Hz. All EEG records were bandpass-filtered to 1-70 Hz, 50-Hz-notch-filtered and EMG-filtered using the software accompanied with the EEG recorder. However some artifacts such as eye blinks, eye movements, forehead and head movements, transient noises and muscle noise resulting from facial muscle movements were still present. Eliminating the epochs containing these artifacts by visual inspection, only the artifacts-free 1000 seconds (256000 data points) of all the EEG records were retained for the analysis.

B. Methods

Fig. 1 shows the block diagram representation of the entire proposed method. The proposed method comprises the following steps: the preprocessing of the EEG signal, a new Independent Component Analysis (ICA) approach, namely the Modified Wavelet-ICA (MwICA) for the separation of EEG components, the extraction of features that track the morphological and spectral variations of the signal and the process of detection by a Multi Layer Feed Forward (MLFF) neural network popularly known as the Back Propagation Network (BPN).

C. Preprocessing

All the 19-channel, 1000-second (normal and brain tumor) EEG records were split into 2-second (512 data points) EEG epochs for further analysis in order to account for the quasi-stationarity of the EEG signal. The issue of stationarity is not a problem for the wavelet transform [25] and the ICA [26]. However this is required for the features to be extracted. The quasi-stationarity of the EEG signals varies from 1 second to several minutes [25] [29]. However a quasi-stationarity period of 1-2 seconds is typical for most of the EEG signal analysis [28]. All these 19-channel, 2-second EEG epochs were then lowpass-filtered to 40 Hz using a 128-tap FIR filter as the EEG components of interest were only below this frequency.

D. Modified Wavelet Transform based ICA (MWT-ICA)

The wavelet transform of a time-series is its multiband, multiresolution decomposition using orthogonal (lowpass and highpass) filters. The concept of wavelet transform and its practical implementation version known as the discrete wavelet transform (DWT) are very well discussed in [40] [41] [42] and [43]. The Independent Component Analysis (ICA) is a blind source separation technique that separates statistically independent (rather uncorrelated) sources or components from their linear mixtures [30]. The concept and algorithms of the ICA techniques are discussed in [30] and [44]. The application of the ICA to biomedical signals, especially EEG is discussed in [21], [22], [23], [24], [45] and [46].

The noteworthy earlier works on the efficient combination of the wavelet transform and ICA are [35]-[38]. The Modified Wavelet-ICA (MwICA) is a modified version of the Wavelet-ICA (wICA) techniques discussed in [36] & [38]. However this proposal was a direct consequence of the article in the literature [27]. According to [26], the number of data points required to separate n sources is preferably some multiples (at least equal to) n^2. But the wavelet decomposition not only decorrelates the data but also reduces the data size thereby increasing the speed of convergence by ICA in the blind source separation process.

Fig. 2 (a) to (d) depict the entire process of MwICA. First each of the 4500 19-channel, 2-second EEG epochs was decomposed to a depth of level 3 using the Symlets wavelet, 'sym5' on a channel-by-channel basis. The choice of decomposition level and the wavelet type was made based on trial and error. The wavelets, Daubechies (db1 to db9), Coiflets (coif1 to coif5) and Symlets (sym2 to sym8) were tried for 1 to 10 decomposition levels. After the wavelet decomposition, the ICA of the 3^{rd} level approximate coefficients was performed using the SOBI-RO algorithm. The resulting demixing (separating) matrix was used to demix the detail coefficients of third, second and first levels. The demixed wavelet coefficients were then reconstructed on a channel-by-channel basis to obtain the final set of independent components (ICs). However the result showed that the ICs obtained from the 3^{rd} level approximate coefficients alone were very much sufficient. This was evident from the MwICA of the simulated data.

E. Feature extraction

The following features were then extracted from all the 4500 19-component 2-second independent components sets on a component-by-component basis.

1) First Order Statistics: The Mean Square Amplitude (MSA_{ci}) of an ith component, $x_{ci}(n)$ of a 19-component, 2-second (512 data points) IC set was calculated as the mean of the squares of the samples of the component [18] [19] i.e.,

$MSA_{ci}=\{\Sigma_n[x_{ci}^2(n)]/length(x_{ci}(n))\}$. The Mean Slope Rate ($MSR_{ci}$) for an ith component, $x_{ci}(n)$ of a 19-component, 2-second (512 data points) IC set was calculated as described in [18] and [19] i.e., $MSR_{ci}=mean\{\Sigma_k[x_{ci}(k)-x_{ci}(k+1)]/[t_k-t_{k+1}]\}$.

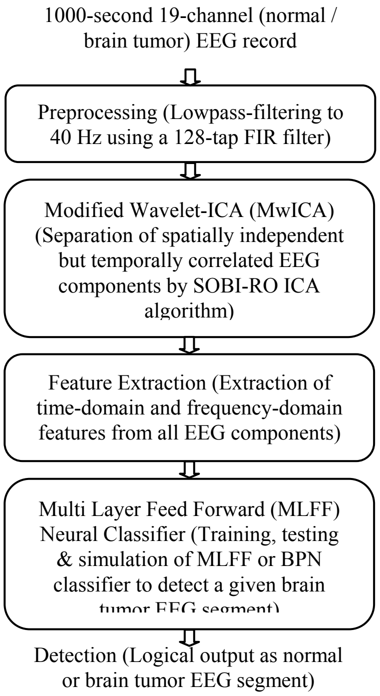

Fig. 1 The block diagram representation of the proposed method is shown.

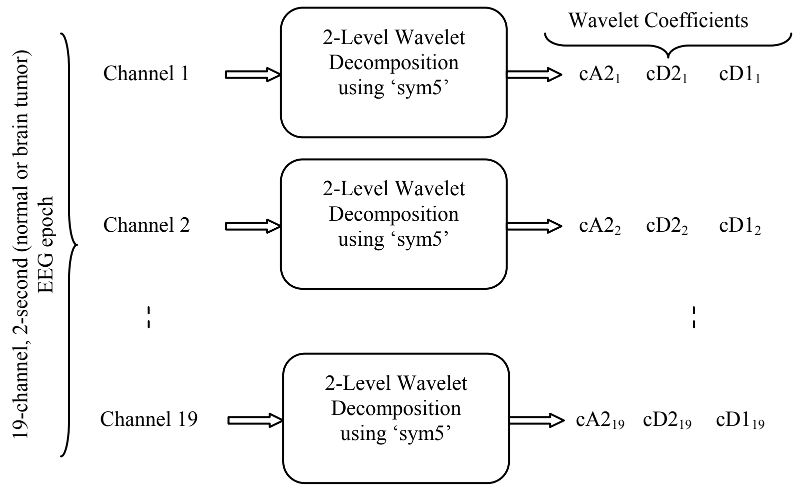

Fig. 2 (a) A 2-level wavelet decomposition of a 19-channel, 2-second (normal or brain tumor) EEG epoch using the Symlets wavelet, 'sym5' on a channel-by-channel basis is shown.

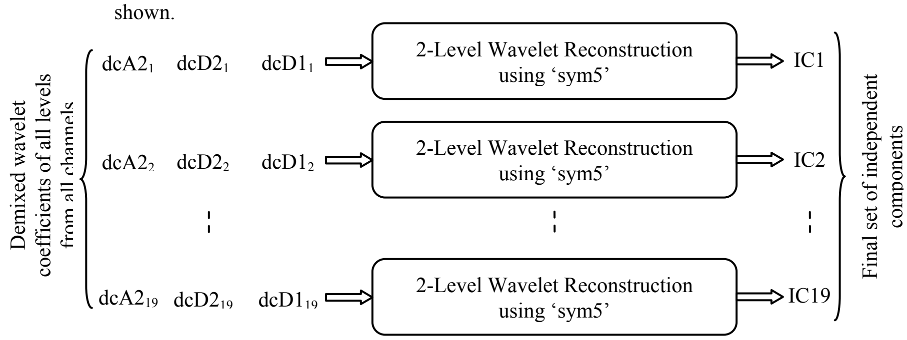

Fig. 2 (d) Reconstruction of the demixed wavelet coefficients of all channels using the Symlets wavelet 'sym5' on a channel-by-channel basis is shown. The output of this step was the final set of independent components.

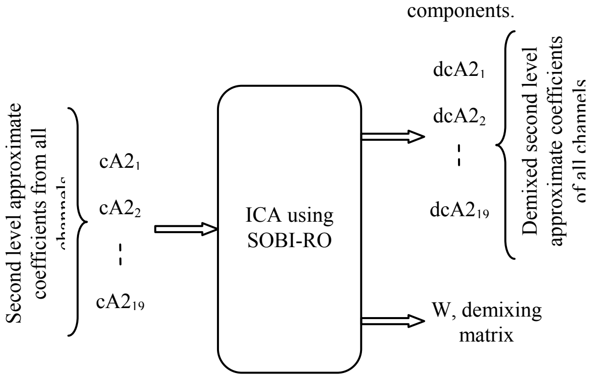

Fig. 2 (b) The ICA of the 3rd level approximate coefficients from all channels using the SOBI-RO algorithm is shown. The resulting demixing matrix, W was used to demix the detail coefficients from all channels.

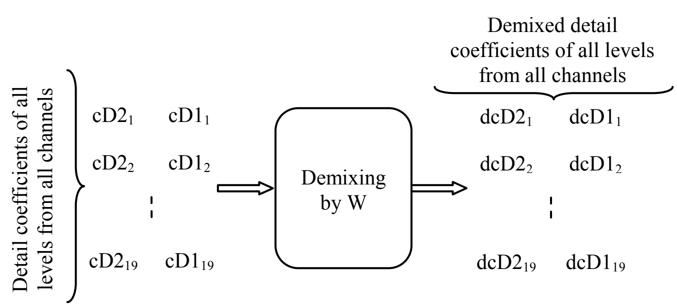

Fig. 2 (c) The demixing of the detail coefficients of all levels from all channels using the demixing matrix, W obtained from the step shown in Fig. 2 (b) is shown.

2) Higher Order Statistics: The Power Spectral Density (PSD) or simply the Power Spectra (PS) of a stationary time-series is defined by the Wiener-Khintchine theorem as the Fourier transform of the autocorrelation sequence of the time-series [32] and in this work, the Welch method was used to estimate the PSD of the given short-time series. The Maximum-to-Mean Ratio of Power Spectrum ($mmrPS_{ci}$) of an ith component, $x_{ci}(n)$ of a 19-component, 2-second (512 data points) IC set was computed as the ratio of the maximum value of the power spectrum, $P_{ci}(f)$ computed to its mean value [18] [19] i.e., $mmrPS_{ci}=max\{P_{ci}(f)\}/mean\{P_{ci}(f)\}$. Here two values of *mmrPS*, one being measured below the frequency 6.5 Hz, named as $mmrPSslw_{ci}$ (*Max-to-Mean Ratio of Slow Power Spectrum*), and another above it, named as $mmrPSfst_{ci}$ (*Max-to-Mean Ratio of Fast Power Spectrum*), were considered.

The bispectrum of a stationary time series, $x(n)$ is defined as the Fourier transform of its third order cumulant [33] i.e., $B(f_1,f_2)=FFT[R_{xx}(m_1,m_2)]$ where $R_{xx}(.)$ is the third-order cumulant of x(n) defined as the expected value of the triple product i.e., $R_{xx}(m_1,m_2)=E\{x(n)x(n+m_1)x(n+m_2)\}$.

The bispectrum can be shown [33] to be $B(f_1,f_2)=X(f_1)X(f_2)X^*(f_1+f_2)$ where $X(f)$ is the discrete Fourier transform of the sequence, $x(n)$.

The minimum variance estimation of bispectrum requires a large number of data points. However it has been shown in [39] that 512 data points (2 seconds) sampled at a rate of 256 Hz are sufficient to make a reasonable estimate of bispectrum. The Peak Bispectrum (*pBS*) of an ith component, $x_{ci}(n)$ of a 19-component, 2-second (512 data points) IC set was computed as the maximum value of the bispectrum, $B_{ci}(f_1,f_2)$ of $x_{ci}(n)$ computed using the Fast Fourier Transform (FFT) as explained in [31]. Here again two values of *pBS*, one being measured below 6.5 Hz, named as *pBSslw* (*Slow Peak Bispectrum*), and another above it, named as *pBSfst* (*Fast Peak Bispectrum*), were considered.

At the end of this step there were 4500 feature vectors, each of length 114 (6 features per component for each 19-component, 2-second (512 data points) IC set), of which 1500 belonged to normal EEG and 3000 to brain tumor EEG. Of these 4500 feature vectors, 3000 (1000 from normal set and 2000 from brain tumor set) feature vectors were chosen as the training set for the network to be discussed in section F and the remaining for testing the trained network.

TABLE I
FOUR POSSIBILITIES OF NETWORK OUTCOMES IN DETECTION PROCESS

		Actual case	
		P	**N**
Network decision	**P′**	True Positive	False Positive
	N′	False Negative	True Negative

TABLE II
VALUES OF FOUR POSSIBILITIES OF NETWORK OUTCOMES LISTED IN TABLE I

		Actual case		
		P	**N**	**Total**
Network decision	**P′**	930	53	983
	N′	70	447	517
	Total	1000	500	**1500**

P-Actual brain tumor cases; N-Actual normal cases; P′-Brain tumor cases as per network; N′-Normal cases as per network

TABLE III
VALUES OF PARAMETERS GIVEN BY EQUATIONS (9) TO (12)

Sensitivity or TPR	0.930
FPR	0.106
Accuracy	0.918
Specificity or TNR	0.894

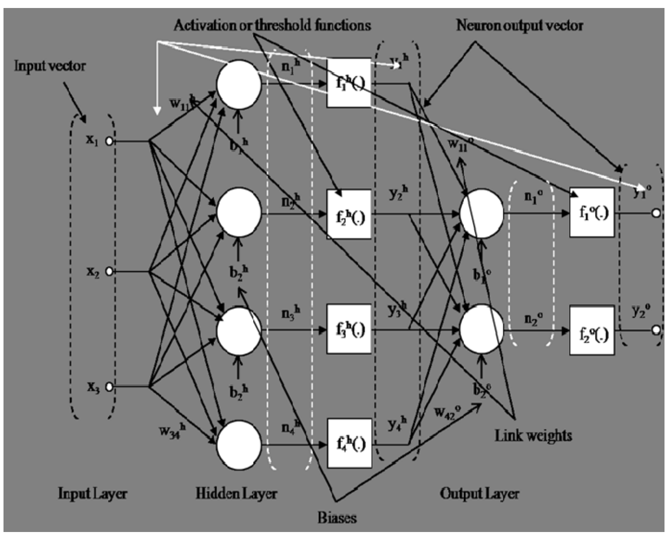

Fig. 3 A 3-layer Multi Layer Feed Forward (MLFF) neural network is shown.

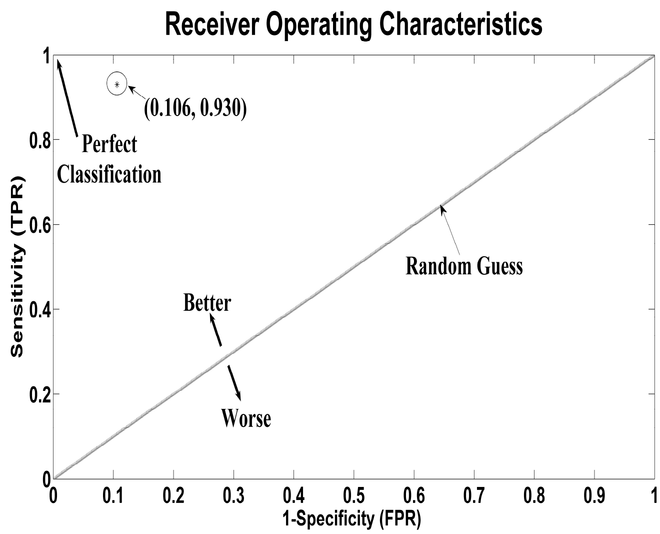

Fig. 4 Receiver Operating Characteristics: The proposed method has the point encouragingly at (0.106, 0.930).

F. Detection by Multi Layer Feed Forward (MLFF) neural network

The choice of multi layer network, which is a non-linear classifier [17], is based mainly on the fact that the scatter plots of features within and between the classes (normal and brain tumor cases) exhibit non-linearity. The other reasons are the generalization of network, the ease of implementation, the lesser computation overhead and the availability of large options of network architectures with simple addition or deletion of layers and/or neurons, efficient learning and training algorithms etc. The factor for the success of the training process and the generalization of the network are discussed in [17] and [47] respectively. The formulation of this aspect has been presented in [19].

A 3-layer MLFF network such as the one shown in Fig. 3 was chosen for the proposed work. The number of input layer neurons was made equal to the dimension of the input vector, i.e., 114. As there were two possible outcomes whether the feature vector that was input to the network belonged to normal EEG or brain tumor EEG, the logical outputs that correspond to these two outcomes were chosen to be the target vectors. The number of the output layer neurons was chosen to be the size of the target vector. For this proposed work the number of hidden layer neurons was randomly chosen to be one-thirtieth of the number of training vectors available i.e., 100.

V. Result and Discussion

The result of the testing phase has been shown in Table II. The testing phase included the remaining 1500 cases, of which 500 belonged to normal case and 1000 to brain tumor case. The status that the chosen EEG epoch belonged to a brain tumor case was considered as 'positive' and that it belonged to a normal case as 'negative'. Then the four possibilities of the network outcomes were [48]: True Positive (TP) if the network decided that a chosen EEG belonged to a brain tumor case when it actually did, True Negative (TN) if the network decided that a chosen EEG belonged to a normal case when it actually did, False Positive (FP) if the network decided that a chosen EEG belonged to a brain tumor case when it actually belonged to a normal case and False Negative (FN) if the network decided that a chosen EEG belonged to a normal case when it actually belonged to a brain tumor case. This is depicted in Table I. From Table II the following parameters were calculated to estimate the performance of the proposed method [48] [49]: *Sensitivity* or *True Positive Rate* (*TPR*) as *[TP/(TP+FN)]*, *Accuracy* (*ACC*) as *[(TP+TN/(P+N)]* and *Specificity* or *True Negative Rate* (*TNR*), which is one minus *False Positive Rate* (*FPR*), as *[TN/(FP+TN)]* where P stands for the total number of positive (brain tumor) cases considered and N for that of negative (normal) cases considered. The values of these parameters have been listed in Table III. The ROC (Receiver Operating Characteristics) was obtained from the values listed in Table III. Fig. 4 shows the ROC. From the ROC it is clear that the performance of the proposed method in detecting the brain tumor using the scalp EEG is very much encouraging.

VI. Future Development

To improve the detection (or classification) rate, not only the features, such as the ones (except, possibly, the bispectrum [34]) discussed in this paper, which track the linear dynamics of the EEG signal but also the features which track the nonlinear dynamics of the EEG signal can be considered since the EEG exhibit both the linear and nonlinear properties [50].

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