Epileptic Seizure Detection Using Artifact Reduction and HOS Features of WPD

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***Abstract*—The use of computer aided diagnosis systems for disease identifiscation, based on signal processing, image processing and video processing terminologies is common due to emerging technologies in medical field. The detection of epilepsy seizures using EEG recordings is done by different signal processing techniques. To reduce the disability caused by the uncertainty of the occurrence of seizures, a recording system which shall result accurate and early detection of seizure with quick warning is greatly desired. To optimize the performance of EEG based epilepsy seizures detection, in this work we are presenting a method based on two key algorithms. Here, we propose unique algorithm based on SWT (Stationary Wavelet Transform), for easier seizure analysis process, along with improved performance of the application of seizure detection algorithms. Then, we propose the algorithm for feature extraction that makes use of Higher Order Statistics of the coefficients that are calculated using Wavelet Packet Decomposition (WPD).This helps in improving the epilepsy seizures detection performance. The proposed methods helps to improve the overall efficiency and robustness of EEG based epilepsy seizures detection system.**

***Index Terms*—Artifacts, EEG, Feature Extraction, Higher Order Statistics, Stationary Wavelet Transform, Seizure, Wavelet Packet Decomposition.**

I. Introduction

Epilepsy characterize a disorder of brain, which can occur to people with any age. One of the main symptoms of epilepsy is the occurrence of the epileptic seizure. Reason for occurrence of seizure may be hereditary or due to some brain injury. Epilepsy can show symptoms through any neurological part of the body, but the mostly affected organ is the brain. Due to this, the diagnostic equipment which can help in the detection and further help in the treatment of the epilepsy is the Electroencephalogram (EEG). The main issue while detecting the epilepsy with the help of EEG is that, the artifacts mix with the seizure signals and can appear as seizure which can result in the misdiagnosis in the level of the disease. These artifacts can be system generated as well as can be generated by the human body due to various factors such as blinking of eye, body movement,etc[1]. So, the purpose of this work is to remove artifacts effectively so as enhance the seizure detection due to epilepsy.

There are many acknowledged systems working for this purpose[3]-[13], but there are some or the other drawbacks or issues related to it like some systems can detect only particuar type of artifacts, some algorithms are complex affecting the effectiveness and the usefulness of the system. There are also some feature extraction methods mentioned in the literature[14]-[15], but resuts in less efficient output.In this work, we try to overcome the issues by using the methods which can perform well and will give effective results in terms of accuracy and also in terms of number of false positive. Here, we use SWT for the process of seizure analysis, and for better detection of epilepsy seizure, we propose a feature extraction method that makes use of Higher Order Statistics (HOS) of WPD coefficients.

II. Proposed Classification System

SWT in addition with denoising process helps us to abolish the artifacts. The bandwidth of the EEG signal is 0.05Hz to 128Hz, whereas the seizure activities occur in the range of 0.5 Hz to 29 Hz. Depending on this frequency band, the level of decomposition of the EEG can be decided. The decomposition of the EEG using SWT results in the approximate and the detailed coefficients. These coefficients are denoised to discard the artifacts that are incorporated in the EEG signal. Figure 1 imitate the layout for the proposed system. Non-negative garrote shrinkage function is availed to discard the artifacts as it is less sensitive to the change in the input[10]. For denoising the coefficients, we make use of the universal threshold which is given by[8] :

$$T_H = T_P \mu_{j,l} \sqrt{2lnL} \qquad (1)$$

Here, L denote the epoch duration and $\mu_{j,l}$ denote noise variance and is represented as $\delta_{j,l}$ which can be calculated by the formula give below:

$$\mu_{j,l} = \frac{median(|\delta_{j,l}|)}{0.6745} \qquad (2)$$

$\delta_{j,l}$ is the coefficient of the wavelet for l th level of decomposition. A new parameter T_P is observed for thresholding the coefficients. $(T_P)_A$ is used for thresholding the approximate coefficients and $(T_P)_D$ is used for thresholding the detailed coefficients.

The features represent the nature of the EEG signal. So here we make use of the feature extraction methods for the effective seizure detection. Feature extraction method includes calculation of the HOS of the WPD Coefficients.

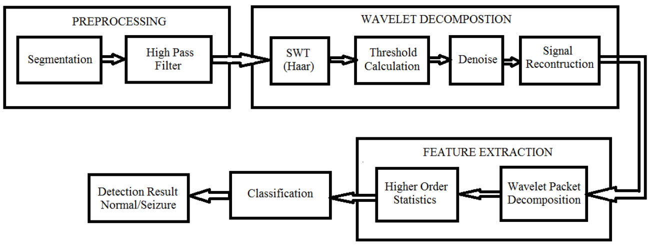

Fig. 1. Block Diagram

A. *Wavelet Packet Decomposition*

WPD is a Wavelet Transform which decomposes signal as low pass approximation coefficients and high pass detailed coefficients[19]. These coefficients are further decomposed into respective approximate and detailed coefficients creating a full binary tree as shown in the figure 2. The main advantage of WPD over Discrete Wavelet Transform (DWT) is that, DWT only break down the low frequency approximate coefficients which can result in the loss of data from the detailed coefficients. WPD decomposes both approximate as well as the detailed coefficients, helping us to extract more features further increasing the accuracy in seizure detection.

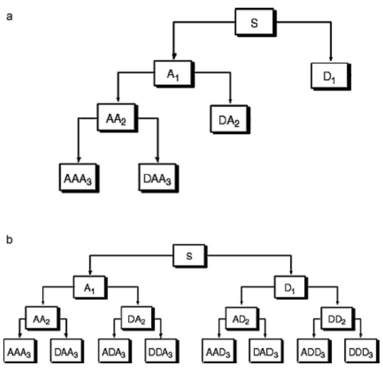

Fig. 2. (a) DWT and (b) WPD[19]

B. *Higher Order Statistics*

Higher Order Statistics (HOS) is used when we deal with nonlinear signals, and most of the applications are based on nonlinear signals. And in our work, we work on EEG which is a nonlinear signal. The initial two order statistics consists of the mean as well as the variance whereas, HOS consists of the cumulants and moments. The 2nd, 3rd and 4th order cumulants are determined considering a lag 0. These cumulants are given paarticular names, viz, variance for the second order cumulants, and Skewness and Kurtosis for third and fourth order cumulants repectively. Higher Order Statistics generate 30 sub-bands for 4 level. From each sub-band, 3 features are extracted which results in total of 90 features for all the levels of Wavelet Packet Decomposition as shown in figure 3. Although, the lower order statistics consists and works on variance and mean; HOS focuses on cummulants and moments[19].

$$\varphi(t) = E[exp(ktx)] \qquad (3)$$

For digitalized signal with zero cummulants, moments and mean, can be shown as:

$$m_2(p) = E[X(L), X(l+p)]$$

$$m_3(p,q) = E[X(L), X(l+p).X(l+q)]$$

$$m_4(p,q,r) = E[X(L), X(l+p).X(l+q).X(l+r)]$$

Here $E[\cdot]$ denotes operation of Expectation where as $X(\cdot)$ represents a random process. Also $X(l)$, which is the second characteristic function is given as:

$$X(t)ln\varphi(t) = E[exp(ktx)] \qquad (4)$$

and this is also called as cummulant generating function

$$c_2(p) = m_2(p)$$

$$c_3(p,q) = m_3(p,q)$$

$$c_4(p,q,r) = m_4(p,q,r) - m_2(p)m_2(q-r) - m_2(q)m_2(r-p) - m_2(r)m_2(p-q)$$

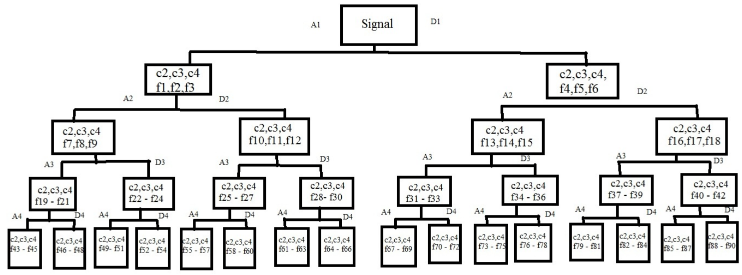

Fig. 3. Extraction of 90 HOS features from the fourth level of WPD[19]

Hence, the HOS methods are used for the extraction of new and less features from WPD coefficients. Cumulants for decomposition level are calculated using HOS methods. As mentioned previously, there are 30 subbands for the 4 levels. 3 features are derived for each decomposition level by using HOS. 90 features are acquired as shown in fig (fig 3) for all levels of WPD.

C. *Data Normalization*

Data normalization is used to reduce data redundancy and which results in the improvement of the data integrity. It converts the data in the range of -1 to 1.

$$Y(n) = 2[\frac{X(n)-X(n)_{min}}{X(n)_{max}-X(n)_{min}}] - 1 \qquad (5)$$

The above expression gives normalized matrix,
Here $X(n)$ represents the n^{th} sample vector.

III. Performance Evaluation and Simulation Results

To evaluate the performance of the above method, here we calculate the metrics so as to verify and quantify the efficiency of the work.

A. *Performance Metrics and Evaluation*

1)η: Artifact Reduction is given by:

$$\eta = 100(1 - \frac{C_R - C_{RC}}{C_R - C_A}) \qquad (6)$$

Where,
C_R : Coefficient of autocorrelation of the reference signal for a time lag 1
C_A : crosscorrelation coefficients among reference and artifactual signal.
C_{RC} : crosscorrelation coefficients among reference and reconstructed signals

2) $\triangle SNR$: Considering that the signals posses zero mean, then $\triangle SNR$ is calculated as the difference in SNR prior and after artifact removal:

$$\triangle SNR = 10log_{10}(\frac{\sigma^2_{X_R}}{\sigma^2_{e_{br}}}) - 10log_{10}(\frac{\sigma^2_{X_R}}{\sigma^2_{e_{ar}}}) \qquad (7)$$

where
$\sigma^2_{X_R}$: reference signal variance
$\sigma^2_{e_{br}}$: error signal prior artifact removal
$\sigma^2_{e_{ar}}$ error signal after artifact removal

3) Spectral Distortion P_{sd}:

Let
$P_{ref}(f)$: PSD for Reference Signal
$P_{art}(f)$: PSD for artifactual signal, and
$P_{rec}(f)$:PSD for reconstructed signal, PSD- Power Spectral Density then P_{sd} is calculated as follows:

$$P_{sd} = \frac{\sum_{f=1}^{\frac{F_s}{2}}[(P_{rec}(f))^2}{\sum_{f=1}^{\frac{F_s}{2}}[(P_{ref}(f))^2} \qquad (8)$$

4) $\triangle Cor$: Correlation helps in determining the similarity between two signals in time domain. The improvement in correlation $\triangle Cor$ caused due to the removal of artifact can be given by :

$$\triangle Cor(\%) = \frac{C_{RC} - C_A}{C_A} 100 \qquad (9)$$

where
C_A:cross correlation coefficients among ref and artifact consisting signal and
C_{RC} : cross correlation coefficient among reference and reconstructed signals

5) $\triangle Coh$: Coherence helps in determining the analogy among signals in frequency domain. It is characterized among two signals $p(t)$ and $q(t)$ as

$$\triangle Coh = \frac{|SD_{pq}|^2}{SD_{pp}G_{qq}} \qquad (10)$$

where $|SD_{xy}|$: cross-spectral density , and
SD_{xx} and $SD_{yy}$are the autospectral density.
$\triangle Coh$ is calculated by:

$$\triangle Coh = \frac{Coh_{aft} - Coh_{bef}}{Coh_{bef}} \qquad (11)$$

6) SNR_{art}: For calculating SNR Artifact, Let, artifact be the signal and reference neural signal be noise, hence,

$$SNR_{art} = 10log_{10}\frac{{\sigma^2}_{e_{br}}}{{\sigma^2}_{x_{ref}}} \qquad (12)$$

7)$\triangle T_{art}$: It represents the percentage of the duration of the artifact out of the total length of the signal.

$$\triangle T_{art}(\%) = \frac{T_{art}}{T_{total}} * 100 \qquad (13)$$

TABLE I
Results for Artifact Removal Based on Different Artifact SNR (SNR_{Art})

SNR_{Art}	η	$\triangle$ SNR	$\triangle$ PDS_{dis}	$\triangle$ $Corr(\%)$	$\triangle$ $Coher(\%)$
3.50	51.59	0.05	98.00	90.47	40.98
14.60	44.22	0.27	98.00	42.26	44.99
16.85	39.26	0.18	97.00	39.00	34.99

TABLE II
Results for Artifact Removal Based on Different Artifact Durations ($\triangle$ T_{Art})

$\triangle$ T_{Art}	η	$\triangle$ SNR	$\triangle$ PDS_{dis}	$\triangle$ $Corr(\%)$	$\triangle$ $Coher(\%)$
31.00	37.88	4.77	98.00	37.60	42.00
32.00	46.37	6.46	96.00	46.82	44.00

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B. Simulation Results

The images below show the signals prior and after abolishing the artifacts from the signal, the artifact signal in the EEG, and the coefficients for the four level decomposition

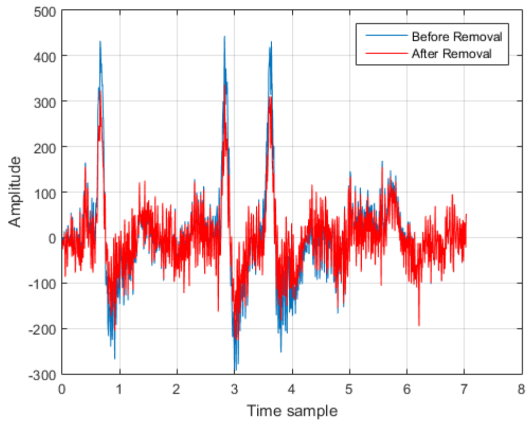

Fig. 4. Artifactual Data and Reconstructed Data

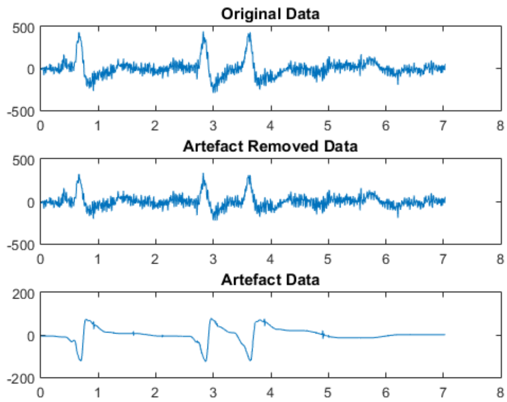

Fig. 5. Original Data, Artifact Removed Data and Artifact Data

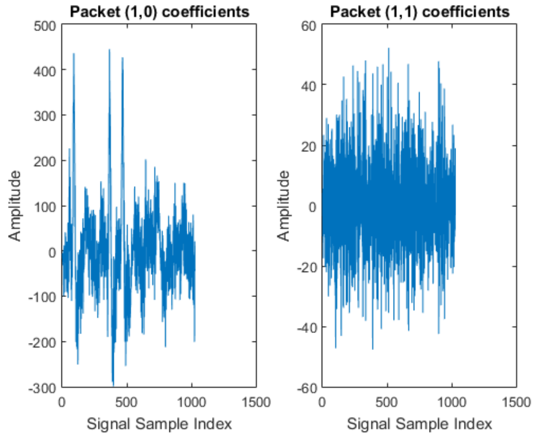

Fig. 6. 1st level decomposition coefficients

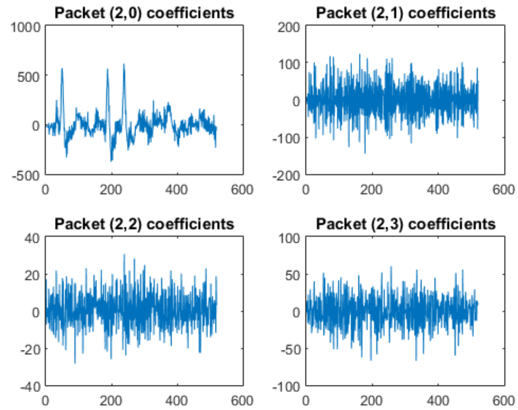

Fig. 7. 2nd level decomposition coefficients

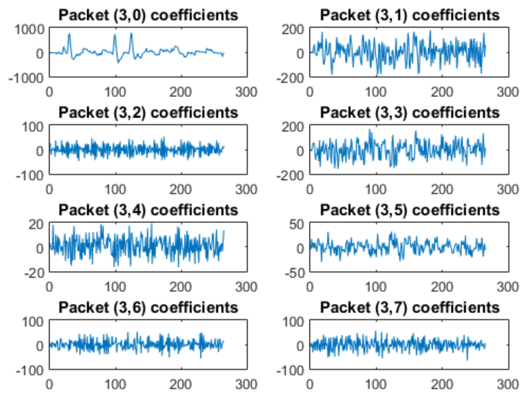

Fig. 8. 3rd level decomposition coefficients

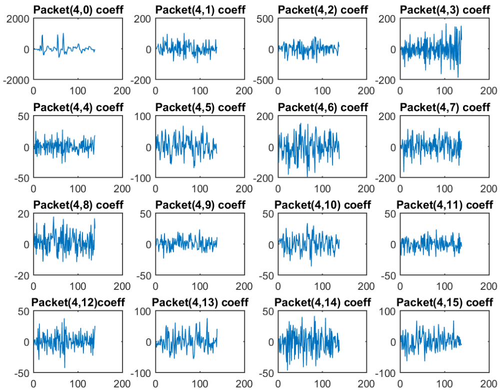

Fig. 9. 4th level decomposition coefficients

TABLE III
CLASSIFICATION PERFORMANCE MEASURES

Performance Measures	**Using Sample Entropy(%)**	**Using WPD and HOS(%)**
Detection Accuracy	83.26	90.44
Improvement in Seizure Detetction	69.78	84.04

IV. CONCLUSION

In this work, EEG artifact removal is analyzed and used to enhance the seizure detection process. Sationary Wavelet transform is used for artifact removal which also retaines the signal of interest or the events that represented a seizure activity. In the proposed work, seizure detection performance is enhanced using the Wavelet Packet Decomposition and Higher Order Statistics of it. The proposed method based on WPD and its HOS features excels as compared to the methods available in the literature in terms of detection accuracy and the improvement seizure detection as shown in the table 3.

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