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RESEARCH ARTICLE

Comparison of Epileptic Seizure Detection using Auto-Regressive Model and Linear Prediction Model

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Abstract— Artifacts causes the incorrect reading of Electroencephalography (EEG) Signal. Specific filtering technique is to be followed to remove the artifacts. In this paper, combination of Adaptive Filtering (AF) and Stationary Wavelet Transform (SWT) is proposed to remove artifacts from the EEG signal. EEG Signals from a healthy subject and from an Epileptic subject are compared using the Autoregressive Model and Linear Prediction Model. These models does not account for the presence of noise. The dominant pole (closest to the unit circle in the z-plane) of Linear Prediction Model shows better result as compared to the dominant pole of Autoregressive Model.

Keywords— EEG; Artifacts; Electrical Activity; SWT; Adaptive Filtering; Pre-Ictal; Ictal

I. INTRODUCTION

The nervous system is one of the most complex systems in the world. Disease or defects in a biological system cause alterations in its normal physiological processes that lead to pathological processes affecting the health and general well-being of the system [17]. Electroencephalography (EEG) is a non-invasive process that reads scalp electrical activity generated by the brain structures. These signals often contain unwanted signals which may bias the analysis of the signals, and may lead to wrong conclusions. Several modern approaches to reduce such artifacts have been reviewed; each of those approaches has its own pros and cons. In this paper, combination of Adaptive Filtering (AF) and Stationary Wavelet Transform (SWT) is proposed to remove artifacts from EEG signal. Once noise is removed from the EEG signal, Normal (healthy), Pre-Ictal (Prior to seizure) and Ictal (during the seizure) state has been compared using the Autoregressive Model and Linear Prediction Model in order to track the poles for the early detection of the epilepsy seizure.

II. METHODOLOGY

The datasets used in this research are taken from the Epilepsy centre, Bonn University, Germany acquired by Ralph Andrzejak [18]. Each set contains 100 single channel EEG segments in ASCII code of 23.6 sec duration, and each segment is sampled at 173.61 Hz (4096 data points). Amplitudes of surface EEG recordings are typically in the order of some µV. For intracranial EEG recordings, amplitudes range around some 100 µV. For seizure activity these voltages can exceed 1000 µV.

This data is usually not clean so some pre-processing steps are needed. EEG signals are complex, making it very hard to extract information out of them using only the naked eye. In today's world of computers, we can apply complex processing algorithms that allow us to extract hidden information from EEG signals. The application tested here is noise cancellation of 50 Hz line noise from the EEG raw data using adaptive least mean square (LMS) algorithm. To remove other artifacts, Stationary wavelet transform has been used. The first step is to feed raw EEG signal to adaptive LMS filter to remove 50 Hz line noise as shown in the figure below.

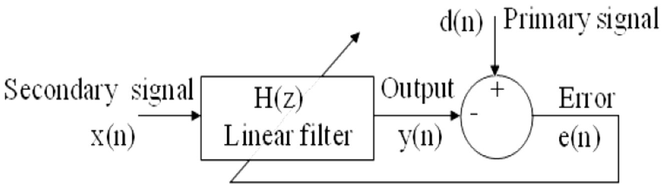

Figure 2.1: *Structure of Adaptive filter*

The LMS algorithm can be defined as a function:

$$y(n) = w^T(n)x(n) \quad (2.1)$$

$$e(n) = d(n) - y(n) \quad (2.2)$$

$$w(n+1) = w(n) + 2\mu\, e(n)x(n) \quad (2.3)$$

where *n* is the time index;
y(n) is the output from the adaptive filter;
e(n) is the output error;
μ is the adaptation of the step size;
w(n) is the vector of filter weight, and
d(n) is the desired signal.

$$w(n)=[w_0(n)\ w_1(n)\ ...\ w_{M-1}(n)]^T \quad (2.4)$$

$$x(n)=[x(n)\ x(n-1)\ x(n-2)\ ...\ x(n-M+1)]^T \quad (2.5)$$

where *w(n)* is the filter weight and
x(n) is the input signal.

In the second step, the output of adaptive filter is decomposed into five levels using SWT. SWT technique is an improved technique from wavelet transform. SWT is used to analyse the signal without losing the time invariance of the signal.

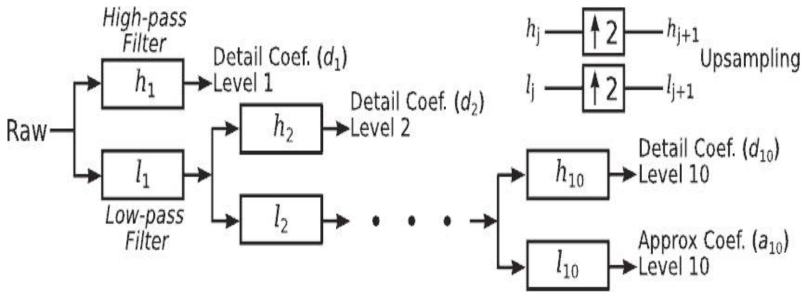

Figure 2.2: *The SWT decomposition*

EEG Signal analysis has been widely used in the treatment of patients with epilepsy by providing a quantitative means to detect an oncoming seizure. The early warning of an epileptic seizure is essential given that the behavioural treatment of epileptic patients by conditioning or stimulation requires information regarding the exact occurrence of the seizure. When this information is unavailable, patients may be randomly administered with therapy that is laced with side effects. Thus, to diagnose patients suffering from epilepsy, there are several algorithms that can be used as predictors. In the proposed work AR model and linear prediction model is used to estimate the model parameters from which the roots corresponding to the poles are presented.

Using autoregressive model and linear prediction model, the 7 prediction coefficients were calculated using a window of 296 samples in length. The locations of the poles of the predictor in the z-plane were derived from the predictor coefficient, each pole plotted in Z-plane. The window was then moved to next 296 samples in length ahead, the poles of a predictor recalculated and plotted in same Z-plane. The total length of 4096 samples scanned according to this procedure.

For each sample, the prediction coefficients $a_k[n]$ are extracted from the adaptive AR model. The poles of the AR model are calculated. The roots are considered as poles, and are shown in the z- plane. Fluctuations in the poles of the AR model are used to track any change in the statistics of the EEG signals.

$$A(z) = \frac{E(z)}{X(z)} \tag{2.6}$$

$$A(z) = 1 - \sum_{k=0}^{M-1} a_k(n) z^{-k} \tag{2.7}$$

Linear prediction model determines the coefficients of a forward linear predictor by minimizing the prediction error in the least square sense. It finds the coefficients of a p^{th}-order linear predictor (FIR filter) that predicts the current value of the real-valued time series 'x' based on past samples.

$$\hat{x}(n) = -a(2)x(n-1) - a(3)x(n-2) - ... - a(p+1)x(n-p) \tag{2.8}$$

where p is the order of the prediction filter polynomial, a = [1 a(2) ... a(p+1)]. The length of p must be less than or equal to the length of the input signal.

III. Results

The first step is to feed raw EEG signal to adaptive LMS filter to remove 50 Hz line noise which is shown in figure 3.1.

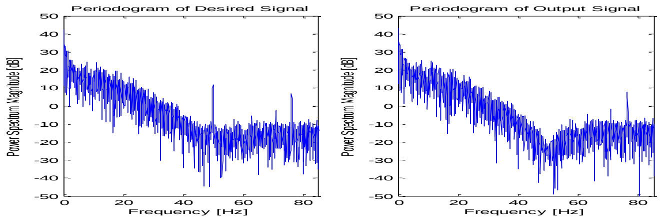

Figure 3.1: *Removal of 50 Hz line noise from EEG Signal*

The output of adaptive filter is decomposed into five levels using SWT, and the clean EEG signal is shown in figure 3.2.

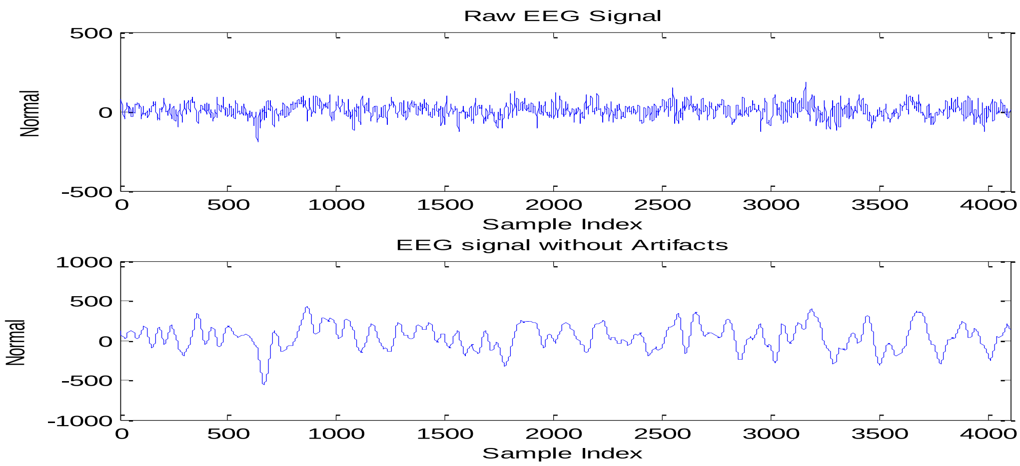

Figure 3.2: *(a) EEG Signal with artifacts (b) EEG Signal without artifacts*

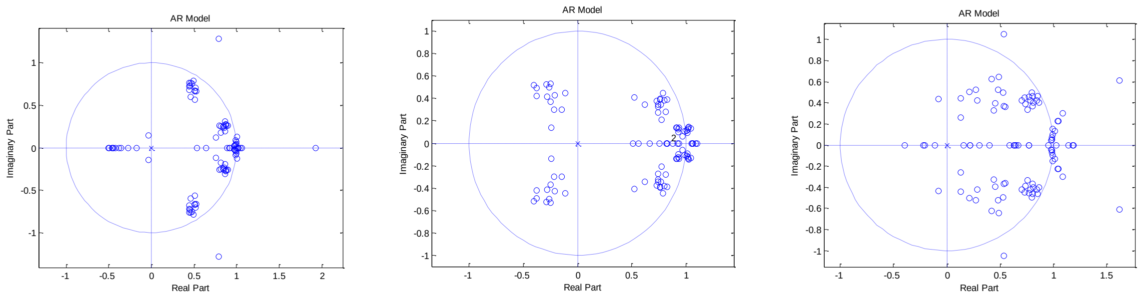

Figure 3.3: *AR model Z -plane plot (a) Normal (b) Pre-Ictal (c) Ictal State*

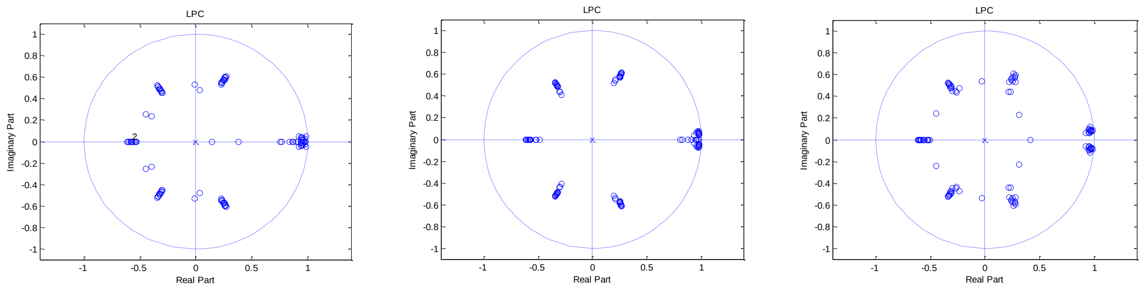

Figure 3.4: *Linear prediction model Z -plane plot (a) Normal (b) Pre-Ictal (c) Ictal State*

IV. CONCLUSIONS AND FUTURE SCOPE

Combined filtering method is investigated in this paper. Fig.3.1 shows the removal of 50Hz line noise from the EEG signal. The advanced filtering technique is able to remove noise and retain the frequency information of the signal.

The dominant poles moves from inside the unit circle at the time of normal state and then the same dominant poles are very close to the unit circle at the time of the seizure (Pre-Ictal State), and at the time of Ictal state, these dominant poles are moving outside the unit circle in case of Autoregressive model. This shows that patient becomes unstable from Normal to Ictal state. This moving pole can be utilized to predict the start of seizure. In case of linear prediction model, when the dominant poles leave the real axis may be utilized in predicting the time of a seizure. The dominant pole (closest to the unit circle in the z-plane) of Linear Prediction Model shows better result as compared to the dominant pole Autoregressive Model.

In the proposed work, data was taken from single channel, as a part of future work multichannel data could be used, as averaging measurements from multiple sensors will reduce the standard deviation of the measurements variability or noise by the square-root of the number of averages. For this reason, it is common to make multiple measurements whenever possible. Non-linear seizure prediction can be carried out, which results in estimation of Attractor dissimilarity, Lyapunov exponent, correlation dimension, complexity loss.

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