Epileptic Seizure Detection - An AR Model Based Algorithm for Implantable Device

Hyunchul Kim*, Jacob. Rosen**
Dept. of Electrical Engineering (*), Dept. of Computer Engineering (**)
University of California Santa Cruz, 1156 High Street, Santa Cruz, CA 95064-1099
e-mail: hyunchul@soe.ucsc.edu, rosen@ucsc.edu; URL: http://bionics.soe.ucsc.edu/

Abstract— **The algorithm of epileptic seizure is at the core of any implantable device aimed to treat the symptoms of this disorder. A training free (on line) epileptic seizure detection algorithm for implantable device utilizing Autoregressive (AR) model parameters is developed and studied. Pre-recorded (off line) epileptic seizure data are used to estimate the internal parameters of an AR model prior and following the seizure Principle Component Analysis (PCA) is used for reducing the dimension of the problem while allowing only the salient features representing the seizure onset to be saved into the implantable device. The implantable device estimates the AR model parameter in real time and compares the saved features of seizure onset with feature from the incoming signals using cosine similarity. In order to guarantee an efficient on line signal processing, Weighted Least Square Estimation (WLSE) model is utilized. Simulation result shows that the proposed method has average 96.6% detection accuracy and 1.2ms latency for the data sets under study. The proposed approach can be extended to multi channel approach using Multi-Variant Autoregressive (MVAR) model which enables seizure foci localization and the sophisticated seizure prediction.**

I. Introduction

THE Epilepsy is a chronic and complex neurological disorder, which affects approximately 1% of the world population. Pharmacotherapy is a standard treatment offered to epileptic patients. However, for more than 25% of patients pharmacotherapy does not provide seizure control or generate side effect as a response to medication [1]. Although surgical intervention may be considered as an alternative treatment for this group of patients, many individuals are excluded since the epileptogenic region may contain brain areas that lead to sensory or motor deficits. As a result, several new therapeutic techniques are investigated including but not limited to closed-loop stimulation [2] which directly stimulate affected region of brain electrically or chemically. This treatment highly depends on robust seizure detection algorithms and technical complexity of an integrated system that can be implanted on the brain [3].

It is known that epilepsy can be detected based on the electroencephalogram (EEG) signal analysis. EEG signal of epilepsy patients during a seizure shows patterns which are significantly different compared to the normal state of the brain with respect to space, time and frequency patterns. In recent years, many research efforts demonstrated the feasibility of using intracranial or scalp EEG signal to predict and detect seizures. Short-time mean Teager energy detection based on Nonlinear Energy Operator (NEO) was used to detect abrupt energy variation during the seizure [4]. For improving the detection, three different energy operators were previously used including mean curve length, mean energy, and Teager energy as features and Support Vector Machine (SVM) for a classifier [5]. In this scheme, seizure detection is declared when the parameters change significantly from their nominal values while representing normal brain activity. Frequency-based and time-based methods were previously developed for seizure detection for example Fourier Transformation (FFT) with sliding window [6], along with discrete wavelet transform and Artificial Neural Network (ANN) [7]. In addition, Auto Regression (AR) model is widely used to convey the spectral information [8]. The AR parameters suppress the noise effect and emphasize the characteristics of the signal while FFT process the signal and noise equally.

To some extent all the existing algorithms are subject to one or more of the following limitations: (1) detection latency, (2) computational complexity, (3) patient-specific tuning and (4) long training period. These limitations narrow down the list of algorithms that can be considered as potential candidates for implantable system. In this paper, a novel AR model-based algorithm is developed and tested for Epileptic seizure detection that is suitable for an implantable device. The proposed model does not require complex training procedure while minimizing the requirements for patient specific parameter tuning.

II. Methods

A. EEG data recording

Three different datasets were used in the current study including: healthy group (Set B), Interictal group (Set C) and Ictal group (Set E). The datasets were made available online by Dr. Ralph Andrzejak of the Epilepsy Center at the University of Bonn, Germany [9]. EEGs are gathered from five different patients whose epileptogenic focus is correctly diagnosed as one of the hippocampal formations. A total of 300 EEG datasets are available and they are sampled at 173.61 Hz for 23.6 sec (4097 data points). The spectral bandwidth ranged from 0.5 Hz to 85 Hz and low-pass filter of 40 Hz was applied.

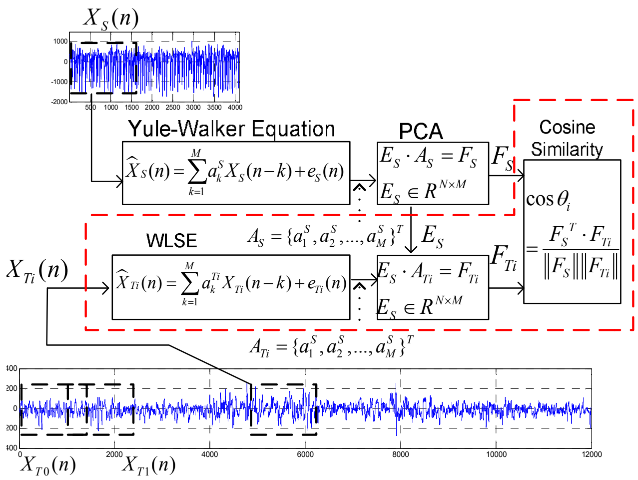

Fig. 1: System overview of Epileptic seizure detection. Signal processing blocks included in the dotted region are embedded in the implantable device.

B. System overview

Fig. 1 depicts an overview of the system architecture for the Epileptic seizure detection algorithm. The AR model estimation for extracting features from the signal was selected since temporal changes of EEG signal, which plays an important role in an epileptic seizure evolution, affect the AR model parameters. For the training-free detection, features from the single EEG segment $X_S(n)$ containing the early stage of the seizure onset duration were first extracted. PCA was then used to reduce the dimension of the features of AR parameters in addition to the selection of the salient elements F_S among the entire feature set. The similar procedure was continuously applied to the EEG signal as described inside the red box in Fig. 1. According to this, continuously received EEG signal was captured by the window and fed into the system inside red box. Note that here $X_{Ti}(n)$ is defined as an EEG signal segment captured at any discrete time T_i having the same window size as $X_S(n)$ and F_{Ti} represent N dimensional feature vector extracted from $X_{Ti}(n)$ based on AR model estimation and PCA. Unlike the AR model estimation technique used for $X_S(n)$, WLSE based AR model estimation technique is taken into account considering the computational complexity. The similarity between two features F_{Ti} and F_S was calculated according to the cosine similarity function defined by Eq. 1 and identify the similarity in the range of [0 1] where a value of 1 indicates similar features (parallel identical vectors) and 0 indicates non-similar features (orthogonal vectors) in the feature space.

$$\cos\theta_i = \frac{F_S^{\ T} \cdot F_{Ti}}{\|F_S\|\|F_{Ti}\|} \tag{1}$$

Given a selected threshold for the similarity factor, seizure onset is detected by constantly calculating Eq. (1) with fixed

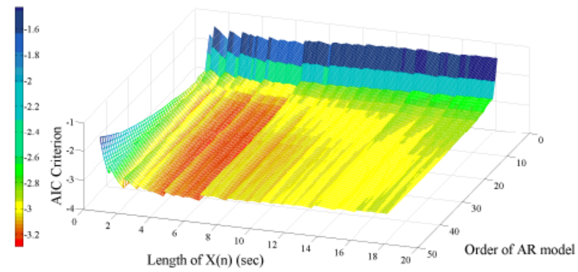

Fig. 2: AR model order estimation based on AIC criterion. When the model order and length of x(n) is set to 30 and 5 sec, AIC criterion reaches its minimal value

features of the EEG signal obtained during the epileptic seizure and features of EEG signal received in real-time.

C. Autoregressive model for EEG

Assuming that EEG signal $x(n)$ has a zero mean and may be considered as a stationary signal in a finite time window ($n = mT+1,\ mT+2\ ...,\ mT+N$), it is possible to represent the current observation $x(n)$ as a linear combination of past values and white noise as formulated in Eq. (2) [10]

$$x(n) = \sum_{k=1}^{M} a_k x(n-k) + e(n) \tag{2}$$

,where $a_1, a_2 ..., a_M$ are AR parameters and $e(n)$ is white noise with zero mean. In Eq. (2) the linear prediction of the current sample vector is given by

$$\hat{x}(n) = \sum_{k=1}^{M} a_k x(n-k) \tag{3}$$

The estimation error or residue of this estimated value is given by

$$x(n) - \hat{x}(n) = e(n) \tag{4}$$

The computational task is to determine the coefficients of the filter such that a function of the prediction error is minimized. In current study the AR parameters are estimate based on the Yule-Walker equation utilizing the Least Mean Squared (LMS) method criterion [10]. The model order of Eq. (2) is determined by the AIC criterion [11] and given by

$$AIC = \frac{2M}{N} + \ln\left(\frac{1}{N}\sum_{i=1}^{N} e^2(n)\right) \tag{5}$$

,where M and N represent model order and number of samples in $x(n)$ respectively. The optimal order for the AR model is achieved by minimizing Eq. (5) and it represents a trade-off between the estimation error and the size of the model order.

Fig. 2 depicts AIC as a function of the AR model order and number of samples used to estimate AR parameters The results depicted in Fig. 2 indicated that the Eq. (5) reaches its minimal value when the order of the for AR model is 30 for the data set under study.

D. WLSE for implantable device

Yule-Walker equation was first used to compute A_S, however this method involves complex matrix inversions and correlation computations that are not suitable for the hardware implementation. Given this implementation constraint, the WLSE algorithm was used to estimate AR model parameters which minimize the weighted sum of error between the predicted values and actual values of the EEG signals defined as

$$\beta(\mathbf{a}) = \frac{1}{2}\sum_{i=1}^{k} \alpha_i [\mathbf{a}_M^T \mathbf{u}(i) - x(i)]^2 \qquad (6)$$

, where $\alpha_i = \alpha^{i-1} (\alpha < 1)$ are the weights and $\mathbf{u}(k)$ is the input to the filter at time $t = k$.

$$\mathbf{u}(k) = [x(k-1)\ x(k-2)\ \ldots\ x(k-M)]^T \qquad (7)$$

Also

$$\hat{x}(k) = \mathbf{a}_M^T (k-1)\mathbf{u}(k) \qquad (8)$$

In Eq. (6) α_i ($\alpha^{k-1} \ll 1$), which is referred to as the forgetting factor, will be neglected after sufficient time by deemphasizing the old data points. Thus by properly selecting the weights, it is possible to overcome storage limitation problem in the practical implementation. The optimum value of α depends on the property of the input process. Usually $\alpha = 0.99$ [12] is chosen.

The filter coefficients $\mathbf{a}_M^T$ were adaptively computed to meet the minimum WLSE criterion in Eq (6). An outline of the WLSE is listed below (for detailed explanation of the WLSE see [12]).

For k = 2 to ∞

1. Calculate the current predicted output

$$\hat{x}(k) = \mathbf{a}_M^T (k-1)\mathbf{u}(k)$$

2. Updata the coefficient vector

$$\mathbf{a}_M(k) = \mathbf{a}_M(k-1) + \frac{\mathbf{P}(k-1)\mathbf{u}(k)}{\alpha + \mathbf{u}^T(k)\mathbf{P}(k-1)\mathbf{u}(k)}[x(k) - \hat{x}(k)]$$

3. Update the $\mathbf{P}$ matrix

$$\mathbf{P}(k) = \frac{1}{\alpha}\left\{\mathbf{P}(k-1) - \frac{\mathbf{P}(k-1)\mathbf{u}(k)\mathbf{u}^T(k)\mathbf{P}(k-1)}{\alpha + \mathbf{u}^T(k)\mathbf{P}(k-1)\mathbf{u}(k)}\right\}$$

, where it starts from $\mathbf{a}_M(1) = \{1, 0, \ldots, 0\}^T$ and $P(1) = I \in R^{M \times M}$ Identity Matrix. Hence, one can adaptively estimate the next sample of the input process and a new set of filter coefficients at time instant $t = k+1$ using the values at the previous instant of time $t = k$. This method provides the relatively fast convergence rate and enables real time implementation of a Linear Predictor which does not require computation of autocorrelation function of the input process.

E. PCA for dimensionality reduction

PCA is a simple and effective method of reducing dimension of the complex data sets such that only the most relevant information underlying the complex data sets can be revealed. Let $A_S = \{a_1^S, a_2^S, \ldots, a_M^S\}^T \in R^M$ whose elements are AR model parameters with order M estimated from $X_S(n)$ in Fig. 1. Then by projecting feature vector A_S and A_{Ti} on $E_S = \{e_1^S, e_2^S, \ldots, e_N^S\}^T \in R^{N \times M}$, only the most salient N principal components can be selected as follows. Note that $e_j^S \in R^M$ in E_S is the eigen vector of covariance matrix of A_S.

$$\begin{aligned} F_S &= \{f_1^S, f_2^S, \ldots, f_N^S\} = E_S \cdot A_S \in R^{N \times M} \\ F_{Ti} &= \{f_1^{Ti}, f_2^{Ti}, \ldots, f_N^{Ti}\} = E_S \cdot A_{Ti} \in R^{N \times M} \end{aligned} \qquad 9)$$

Thus when A_S and A_{Ti} have the similar structure, cosine similarity of F_S and F_{Ti} will be close to one. Finally threshold value will be determined for a desired detection rate based on the Receiver Operating Characteristic (ROC) result.

F. Similarity test

Let $D = [D_E, D_B, D_C]$ is the collection of Ictal group (Set E), Healthy group (Set B) and Interictal group (Set C). Each element of set D is composed of 100 independent EEG segments of which data points are 4097. F_S is extracted from the first two second time segment of EEG data set E. As D is sequentially fed into the detector, F_{Ti} is computed in real time according to the proposed method. Here F_{Ti} is estimated with data in 1 second duration window which slides every 0.5 second. As shown in Fig. 3, cosine similarity is close to one when data duration is within D_E.

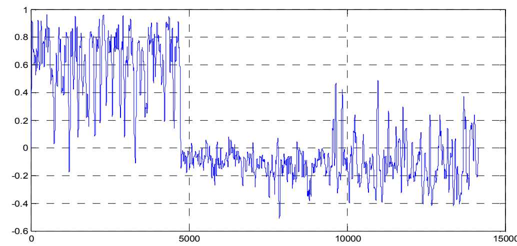

Fig. 3: Cosine similarity test result for a data set E, B and C.

III. RESULT

In order to assess the detector performance, the ROC curve is computed and depicted in Fig. 4 for the proposed method and a line length detection method [3] which is defined as

$$LL(n) = \frac{1}{K}\sum_{k=n-N}^{n} abs[x(k-1) - x(k)] = \frac{L(n)}{K} \qquad (10)$$

$LL(n)$ is the running sum of distance between successive points within the sliding window of size N, $x(k)$ is the k th sample data and K is the normalization constant. Since the line length grows as the signal power or frequency increases, it can act as an amplitude and frequency demodulator.

In the simulation, both features are extracted using a block processing approach where data are windowed for feature extraction and the window slides by overlapping windows.

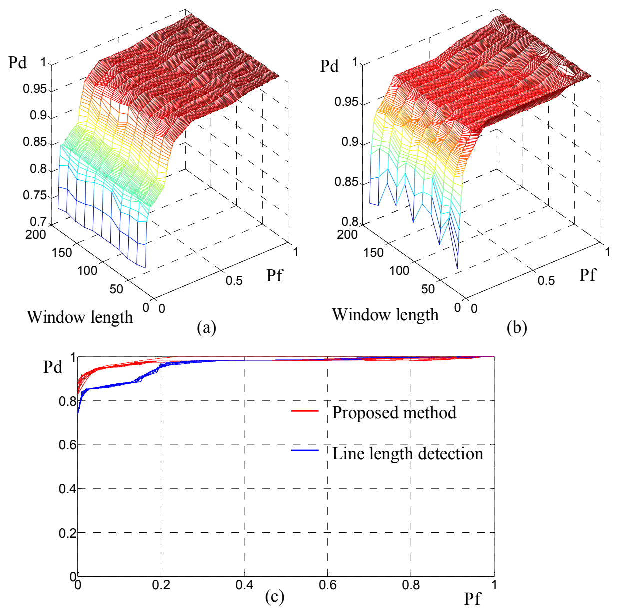

Fig. 4: Upper left and right figures are ROC curve for line length detector and proposed method respectively. Lower one shows the comparison of ROC curve projected on to Pd-Pf plane. Note that Pf, Pd and Window length in Fig 4 represent the probability of false detection, probability of correct detection and window length for feature extraction respectively.

Window size typically ranges between 0.25 and 5 seconds in EEG signal analysis. We use 1 second window duration as a default with 0.5 second overlap. Window duration for feature extraction changes from 1 to 2 second by 0.1 second step resolution [13]. In each case, ROC curves were estimated for both detection algorithms as shown in Fig 4. According to the simulation result in Fig 4 (a) and (b), it is demonstrated that window length does not significantly affect detection performance for our simulation condition. Thus we projected both ROC curves on to Pd-Pf plane for the easier comparison of detector performance as shown in Fig 4 (c). Result shows that the proposed method outperforms line length detector with higher accuracy when the false detection probability is ranged from 0 to 0.3. In addition, the average detection latency is simulated in Fig 5 for different window durations. The result indicates that proposed method detect epileptic seizure activity earlier than line length detection method for all window durations. By averaging detection delay over all window size, it is easily found out that average delay of proposed method is 400ms less than one of the line length detection.

IV. Conclusion

The research demonstrated a training-free Epileptic seizure detection algorithm based on AR model parameters detection which may offer a potential solution of implantable device. The simulation result indicated that AR model parameters robustly capture the abnormal brain activity and the proposed method improves the accuracy of the seizure detection compared to the line length based seizure detection algorithm.

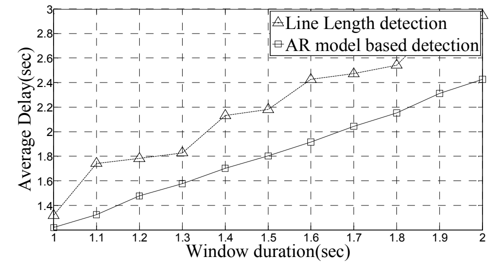

Fig. 5: Detection latency for Line Length detection and AR model based detection algorithms.

The proposed method is not based on any prior knowledge for the patient condition and requires minimal patient-specific parameter tuning with reasonable computational complexity. The proposed approach can be extended to multi channel approach using Multi-Variant Autoregressive (MVAR) model which enables seizure foci localization and the sophisticated seizure prediction. .

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