31st Annual International Conference of the IEEE EMBS
Minneapolis, Minnesota, USA, September 2-6, 2009

A New Improved Model-based Seizure Detection using Statistically Optimal Null Filter

Rajeev Yadav, *Student Member, IEEE*, R. Agarwal, *Member, IEEE*, and M.N.S. Swamy, *Fellow, IEEE*

Abstract— **A patient-specific model-based seizure detection method using statistically optimal null filters (SONF) has been recently proposed to aid the review of long-term EEG [1, 2]. The method relies on the model of *a priori* known seizure (template pattern) for subsequent detection of similar seizures. Artifacts, non-epileptic EEG rhythms, and at times modeling errors lead to increased false or missed detections. In this paper, we present a new improved model-based seizure detection that introduces a pre-processing block for artifact rejection, an adaptive technique of modeling the template patterns, and a new evolution-based classifier. The proposed classifier tracks the temporal evolution of seizure to improve the classification accuracy. With the help of simulated EEG, we illustrate the significance and need for these modifications. Further, performance of the complete algorithm is tested on single channel depth EEG of seven patients, and compared with the previous approaches. In terms of sensitivity and specificity, the proposed method resulted in 84% and 100%, method of [1] 65% and 84%, and method of [2], 84% and 90% respectively. An overall performance improvement is seen as enhanced detection sensitivity and reduced false positives. This is preliminary result on seven patient data.**

Keywords- Automatic seizure detection, EEG, SONF

I. Introduction

Epilepsy is a common neurological disorder characterized by unprovoked recurring epileptic seizures. Epileptic seizures result in an abnormal synchronization of electrical neuronal activity that can be observed as rhythmic discharges on the electroencephalogram (EEG) [3]. These electrographic events are monitored and identified by performing long-term monitoring (LTM) of the EEG. Later, these recordings are reviewed by electroencephalographer (EEGer) to identify the occurrence of all electrographic seizures during the monitoring session. The task of continuous visual examination of long-term digital EEG is challenging as well as tiresome. A robust and easy to use method for automatic seizure detection is needed to assist in the review of the digital EEG.

Complexity in seizure detection arises due to highly variable seizure morphology and unknown time of occurrence. However, in most patients, one or two and sometimes more types of seizure repeat themselves [4]. Seizures within each type are similar to one another, but never identical. Therefore, if a seizure has been previously detected or visually identified, it is possible to develop a technique to detect future occurrences of similar seizures.Patient-specific seizure detection methods rely on this concept for development of a seizure detection system. Difficulties in patient-specific approach (PSA) are in: (a) selection of background EEG, (b) selection of template seizure (template pattern), and (c) complex training of the classifier. Recently, a new model-based seizure detection algorithm using statistically optimal null filters (SONF) has been proposed that addresses some of the challenges in the PSA [1]. The method derives a model for the template pattern provided by the EEGer where the template pattern is segmented into stationary disjoint segments (epochs). Dominant rhythms of the disjoint epochs are extracted in the wavelet domain that serve to build the model or the basis functions required in the SONF. The training consists of computing the detection threshold by using the model on the template pattern itself. Later, the trained classifier detects seizures in the long-term EEG.

The method of [1] relies on visual segmentation of the template pattern into three disjoint stationary segments (epochs) of fixed duration. The task of visually segmenting and extracting three disjoint stationary epochs of fixed length is very challenging, and was recently addressed using short-time Fourier transform (STFT)-based automatic segmentation algorithm [2] . Artifacts and non-stationarity of seizures cause poor selection of stationary epochs in automatic segmentation, and is problematic.

Non-ictal EEG rhythms, such as alpha rhythms, mu rhythms, lambda waves, sleep spindles, and sub-clinical rhythmic discharges (SREDA) are commonly observed at different time intervals during the EEG monitoring. These normal EEG rhythms vary in duration from a few seconds to as long as 30 to 40 seconds [3]. The intrinsic characteristics of these non-ictal EEG rhythms may sometimes match one or more of the template epochs, resulting in false detections by the trained classifier. Electrographic seizures evolve with sustained dominant rhythm (for a few seconds to several seconds) before evolving to a new rhythm. In contrast to seizures, normal EEG rhythms do not evolve. Therefore, quantification of seizure evolution can be exploited in the model-based seizure detection to reduce false detections due to non-ictal rhythms.

In different clinical settings, EEG is recorded with different sampling frequency. Dependence of automatic seizure detection system on the recording sampling frequency may lead to inconsistent performance, and thereby reducing its wide-spread applicability. One such dependence present in the method of [1, 2] is due to wavelet decomposition for modeling the template pattern.

This paper addresses the challenges in model-based seizure detection using statistically optimal null filter. We propose a new algorithm for artifact rejection, an adaptive

The authors are with Center for Signal Processing and Communications (CENSIPCOM), Department of Electrical and Computer Engineering, Concordia University, 1455 de Maisonneuve Blvd. West, Montreal, QC, H3G1M8, Canada. Email:-r_yadav@ece.concordia.ca, ragarwal@stellate.com and swamy@ece.concordia.ca.

method of modeling the template pattern, and a modified classifier that captures the temporal evolution of seizure for its classification. It is observed that high amplitude artifacts cause perturbations in the tracking of the signal by the SONF. Pre-processing and artifact rejection block reduce the impact of high amplitude artifacts on the SONF. A new adaptive modeling technique is proposed that rejects non-valid epochs *prior* to derivation of the model which is not dependent on the sampling frequency. Further, to reduce false detection due to non-ictal EEG rhythms, the characteristic property of seizure, *i.e.,* evolution of seizure is utilized to modify the existing model-based classifier. The performance of the proposed method is evaluated on simulated data as well as on 140 hours of single channel EEG obtained from seven patients and compared with the original approach of [1, 2]. A significant improvement is observed in terms of sensitivity and the specificity.

In Section II, the principle of model-based seizure detection using SONF is described. In Section III, the proposed artifact rejection algorithm, adaptive modeling of the template pattern and temporal evolution-based classifier are illustrated. Section IV, compares the results of the proposed with those of the original method (visual segmentation and STFT-based segmentation). Conclusion and future work are provided in Section V.

II. Model-based Seizure Detection

In SONF-based estimation of a signal with known shape, we assume that the desired signal $\mathrm{s}(n)$ can be modeled as $\mathrm{s}(n)=\sum_{i=1}^{N}\mathrm{v}_i\Phi_i(n)$, where $\Phi_i(n)$ are known basis functions and v_i are unknown scaling variables. The output of the instantaneous marched filter $v_i(n)$ are scaled by $\lambda_i(n)$'s to produce the estimate of the desired seizure signal $\widehat{\mathrm{s}}(n)=\sum_{i=1}^{N}\lambda_i(n)v_i(n)$ [5]. If the observed EEG contains the same type of seizure as described by the model, the output of the SONF will represent the estimate of seizure. In this case the energy ratio (γ') between the seizure estimate and the observed EEG should be large; conversely, if the observation contains only background EEG, the output will be nearly zero. Spurious peaks in $\gamma'$are removed by applying a moving average operation. The smooth energy ratio (γ) is compared with a threshold value, and persistence of γ for sufficient duration is used to decide whether a seizure is present or not [1, 2]. The complete recursive algorithm for implementing SONF is summarized in the following equations [5]:

$$v(n)=v(n-1)+\mathrm{x}(n)\Phi(n) \tag{1}$$

$$\mathrm{P}(n)=\mathrm{P}(n-1)-\frac{\mathrm{P}(n-1)\Phi(n)\Phi^T(n)\mathrm{P}(n-1)}{1+\Phi^T(n))\mathrm{P}(n-1))\Phi(n)} \tag{2}$$

$$\lambda(n)=\mathrm{P}(n)\Phi(n) \tag{3}$$

$$\widehat{\mathrm{s}}(n)=v^T(n)\lambda(n) \tag{4}$$

The gain matrix $\mathrm{P}(n)$ is initially chosen to be positive definite. As a general rule, $\mathrm{P}(0)=SNR\cdot I$, where I is the identity matrix and $v(0)=\mathrm{x}(0)\Phi(0)$.

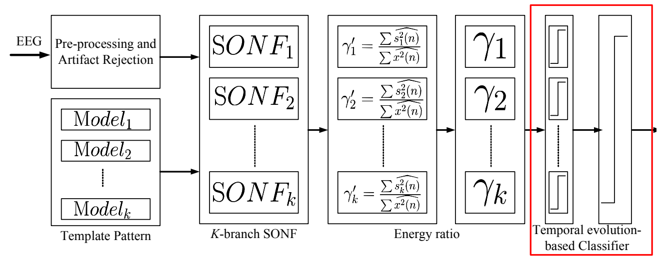

Figure 1. Proposed model-based seizure detection scheme.

III. Method

The proposed method consists of *'k'* parallel implementations (one for each extracted epoch of the template) of the original method as shown in Fig. 1. In addition to this modification, it includes a pre-processing and artifact rejection block. To address the problem of false detections that are sometimes due to non-ictal EEG rhythms, the concept of evolution-based classifier is introduced. Evolution-based classifier tracks the occurrence of seizure signature (the sequence of template epochs) through *k*-parallel blocks. Each of these processing blocks of the proposed method is described in the following sub-sections.

A. Pre-processing and Artifact Rejection

Depth EEG or stereoencephalogram (SEEG) are relatively free from artifacts in comparison to the scalp EEG, but consist of a wide frequency spectrum, highly variable seizure morphology and a variety of sharp transients, ranging from needle-like fast activity to much slower discharges [3]. SEEG is low-pass filtered using a 5^{th} order Butterworth IIR digital filter (cut-off frequency $\mathrm{f}_c=30\mathrm{Hz}$) to remove unwanted high frequency interferences. The amplitude in depth EEG is relatively higher than scalp EEG that spans $\pm 2500\ \mu V$. Therefore, an epoch in which the EEG amplitude is above $\pm 2500\ \mu V$ is not considered and the seizure detection is suspended for next 60 seconds. Presence of a few sharp transients relatively higher in amplitude than the observed EEG cause deviations in the tracking ability of the special instantaneous matched filter (IMF) of the SONF. Thus, it becomes important to reduce the effect of such transients in the data. We define the signal $\mathrm{n}(n)$ to be a mixture of background EEG $\mathrm{n}_b(n)$ and high amplitude artifacts $\mathrm{n}_a(n)$, *i.e.* $\mathrm{n}(n)=\mathrm{n}_b(n)+\mathrm{n}_a(n)$. The output of the IMF reveals step discontinuities in the output signal-to-noise ratio (SNR_o) in the presence of any high amplitude artifacts as shown in Fig. 2c. The output of the IMF $v(n)$ is analyzed to remove high amplitude artifacts. Histogram of $\dot{v}(n)=v(n)-v(n-1)$ is computed to locate high amplitude artifacts (outliers). The distribution of $\dot{v}(n)$ is unknown, therefore, we have used Chebyshev inequality to detect outliers. The sample points that is 3σ (three standard deviation) away from the mean were considered to be due to sharp transients, and the amplitude of the neighboring seven samples in the original signals was scaled by 0.25. An example of this nonlinear filtering is shown in Fig. 2.

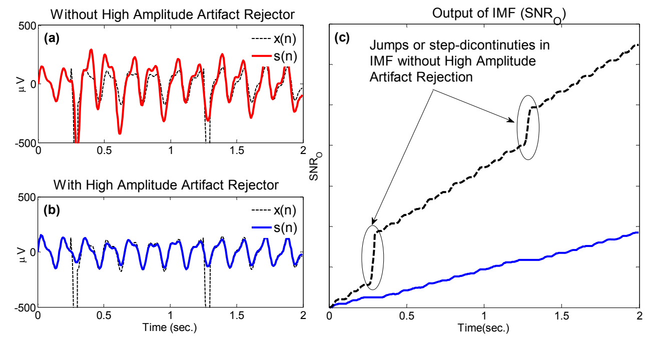

Figure 2. Effect of high amplitude artifacts in the SONF. (a): The input signal $\mathrm{x}(n)$ shown in 'black dashed' line that contains two high amplitude artifacts. Estimate $\mathrm{s}(n)$ of $\mathrm{x}(n)$ using the SONF is represented by 'red solid' line. (b): The effect of high amplitude artifact is removed with the proposed algorithm, and represented by 'blue solid' line. (c): IMF output without artifact rejection is shown in 'black dashed' line whereas after artifact rejection by 'blue solid' line. Jumps or step discontinuities in the IMF output are encircled.

B. Adaptive Modeling and Evolution-based Classifications

The template pattern is segmented into stationary disjoint epochs (segments) using STFT-based segmentation method [2] to derive the necessary model. These short duration epochs occur in ordered sequences that are unique and specific to the template seizure pattern. The set of disjoint stationary epochs (E_k) make up the $\mathrm{T_{PAT}}$ for the template seizure pattern, $\mathrm{T_{PAT}} = [\mathrm{E}_1, \mathrm{E}_2, ..., \mathrm{E}_k]$ as shown in Fig. 3. In other words, the seizure signal $\mathrm{s}(n)$ is an ordered collection of short duration signals, *i.e.*, $\mathrm{s}(n) = \{\mathrm{s}_1(n), \mathrm{s}_2(n), ..., \mathrm{s}_k(n)\}$ where each $\mathrm{s}_k(n)$ can be represented as $\mathrm{s}_k(n) = \sum_{i=1}^{N} \mathrm{v}_{ki}\phi_{ki}(n)$. Therefore, the model for the $\mathrm{T_{PAT}}$ is a collection of models $\Psi_i = \{\phi_{i1}, \phi_{i2}, ..., \phi_{iN}\}$, $i = 1, 2, ..., k$, and constitutes the foundation for *k*-parallel implementation of the SONF. The problem is to detect occurrence of each of these short-duration epochs by the SONF. Non-ictal EEG rhythms that sometimes match one of the models and detected by the SONF, are not expected to occur in the specific order of the template pattern. Thus, an evolution-based classifier identifies a seizure by an ordered detection of each of the signal models $\mathrm{s}_k(n)$, that make up the $\mathrm{T_{PAT}}$ within a specific time duration (60 seconds).

In model-based seizure detection using SONF, the estimate of $\widehat{\mathrm{s}}_k(n)$ is as good as the basis function used to model the k^{th} template epoch. Therefore, errors in modeling can increase false or missed detections. This can occur when the template pattern consists of some background EEG. Stationary epochs obtained from automatic segmentation algorithm in this situation will include the epochs representing background EEG. An example is presented in Fig. 3 where the template pattern is segmented into stationary epochs that include an epoch (E6) of background EEG, and can occur in the beginning or at the end of template seizure. Using the SONF, model for individual epochs are compared with one another. Background EEG does not have any consistent dominant rhythm. This causes

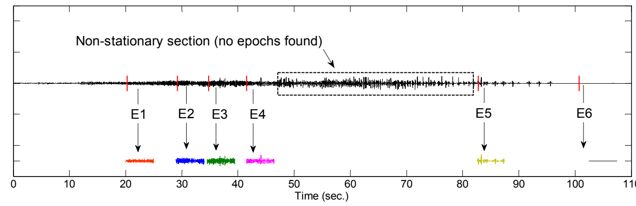

Figure 3. Adaptive segmentation of the template pattern. The dashed rectangular box represents the non-stationary section in the template pattern.

poor modeling of the background epoch, and results in a very low detection threshold (during classifier training). Therefore, when a background model is applied to measure similarity among other epochs, all template epochs will be detected. On the contrary, seizure epoch consists of a dominant rhythm, and the model derived results in a higher detection threshold. A model for seizure epoch either detects such an epoch, or any similar epoch but not all. Using this idea, models that detected all epochs were considered to be due to the background EEG. All epochs that were either background EEG or similar to other epochs (redundant) are removed from the $\mathrm{T_{PAT}}$. Further, a reference background EEG section reduces the possibility of errors in selection of the template pattern or in the modeling by removing common spectral components. The reference background is automatically selected in contrast to other PSA's in the literature. The reference background is 30 s of EEG section preceding the template seizure pattern. Usually, the spectra of the background EEG and template epochs do not overlap. The ratio of power spectral density of the template epochs and the reference background EEG ensure the selection of only seizure epochs [6]. Each template epoch is bandpass filtered into three different frequency bands using 5th order IIR Butterworth bandpass filters: 3-6 Hz, 6-12 Hz and 12- 25 Hz similar to the wavelet scales in the method of [1, 2]. Frequency bands that contributed more than 20% to the total energy were selected. From each of the selected band, frequencies that contributed more than 75% to the total spectral power were selected and modeled using sinusoids and their Hilbert transforms.

The data is processed using a sliding window of fixed duration with a step size of 0.25 seconds. The energy ratio (γ') between the estimate seizure $\widehat{\mathrm{s}}(n)$ and the observed EEG $\mathrm{x}(n)$ is calculated at 0.25 seconds interval. Spurious peaks in γ' are removed by applying a moving average filter (length of moving average filter is proportional to length of the sliding window). The detection threshold for the model is obtained using the template pattern and the SONF, and is set to 1/3rd of maximum γ. In the previous method of [1] (*Method A*), three disjoint epochs of 6 s each were selected from the template seizure pattern. Therefore, the duration threshold for the classifier was set to 18 seconds. In the method of [2] (*Method B*), the duration threshold was set proportional to the length of epoch multiplied by the total number of epochs. As mentioned earlier, a fixed duration threshold in the previous approach is problematic. Therefore, in our approach, we considered evolution-based detection. Evolution-based classifier consists of *k*-classifiers one for

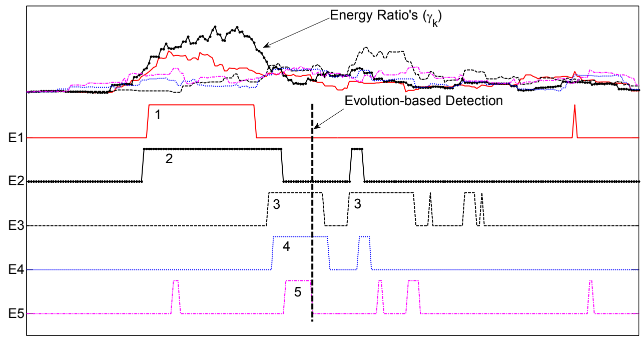

Figure 4. Evolution-based Classifier. The energy ratios of the k-models are shown as γ_k, and detection by individual models are numbered for the evolution-based classification. Vertical 'dashed 'line denotes the final detection of an event similar to the template pattern.

each template epoch E_k in the T_{PAT}, and a cascaded classifier that analyzes the sequential detection by these k-classifiers within a time-frame of 60 seconds. Detection threshold for each classifier is computed as described above. The sequence of occurrence of E_k's is stored during adaptive modeling of the template pattern. The duration threshold in the k-classifier is set equal to length of the template epoch. An event is detected by one of the k-classifiers when the observed energy ratio γ is persistently above the detection threshold for at least a minimum duration (length of template epoch). Upon detection by all k-classifiers, the sequential classifier performs final decision by analyzing the signature or sequential occurrence of the detected events. A seizure is detected when the occurrence of events matches to the signature of the template pattern, and all events are within a time span of 60 seconds. An example to illustrate the evolution-based classification is demonstrated in Fig. 4. The energy ratio from k-SONF and detections from each of the k-classifiers are shown. The sequential detection by k-classifiers is numbered. The sequential detection is compared with the template pattern for final classification, and is represented by vertical 'dashed' line in Fig. 4.

IV. RESULTS / DISCUSSION

We have used *sensitivity, specificity* and *false detection rate* (FDR) to evaluate the performance of the algorithm. Sensitivity is defined as the percentage of the manually marked seizures detected by the algorithm. Specificity is defined as percentage of detected seizure events that are true positives, and FDR is defined as the number of false detections per hour. An event is identified as true positive if it occurs within 60 seconds of a manually marked seizure event, otherwise it is a false detection.

Due to unknown time of occurrence and unknown duration of the ictal EEG, we have used simulated EEG to demonstrate the effectiveness of the proposed modifications. An approach similar to the method of [7] is used to generate the simulated EEG. The four-hour long simulated EEG consists of background EEG (non-repeating) with high amplitude artifacts, rhythmic spikes, and normal EEG rhythms. The template pattern was generated by cascading three disjoint stationary segments with consistent dominant

Table I: Summary of Improvements on Simulated EEG

Method	Sensitivity (%)	Specificity (%)
Method A	46.7	87.5
Method B	73.5	64.7
Method B + Artifact Rejection	100	83.3
Method B + Artifact Rejection + Evolution-based Classifier	100	100
Proposed System (Adaptive modeling + Artifact Rejection + Evolution-based classifier)	100	100

rhythm. The template pattern was segmented to extract the stationary epochs using STFT-based segmentation algorithm. The template epochs were modeled using a 4th order autoregressive (AR) model.

Fourteen similar seizures were obtained in a similar manner by cascading stationary epochs generated by the AR models. The simulated seizures were of three different lengths (> 60 s, <30 s and < 10 s). Out of these fourteen seizures, two seizures included additional non-stationary epoch in between the template epochs, and was not a part of the T_{PAT} to reflect non-stationarity in the seizures. Background EEG preceeding the seizure had a different seizure-to-background ratio (10 dB, 0 dB and -5 dB) as well as embedded sharp transients and spikes. Three different types of EEG rhythms were part of the background EEG. One of the rhythms considered was SREDA rhythms, and contained dominant rhythm similar to one of the template epoch. The simulated template seizure pattern was visually segmented for evaluating the performance of *Method A*, and automatically segmented using STFT-based segmentation for evaluating the performance of *Method B,* and the proposed evolution-based classifier.

The model for the template pattern was derived as proposed in the *Method A*. The duration threshold was set to 18 seconds for *Method A*, 6 seconds (3 epochs of 2 seconds) for *Method B*, and 2 seconds for the proposed evolution-based classifier. *Method A* missed all seizures that were less than 18 seconds in duration resulting in 47% sensitivity and 87% specificity, whereas *Method B* improved the sensitivity by 26%, but at the cost of 22% loss in the specificity. Most of the false detections were due to artifacts and non-ictal rhythms. With the help of pre-processing and artifact rejection block, *Method B* improved the sensitivity by 27% and specificity by 17%. Non-ictal rhythms detected were removed by the introducing evolution-based classifier in the *Method B* with pre-processing and artifact rejection block, which resulted in 100% sensitivity and 100% specificity. The proposed evolution-based classifier rejected all non-ictal rhythms which improved the overall specificity. Finally, the proposed method that included a non-wavelet-based adaptive modeling technique of the template seizure pattern, including the pre-processing block and evolution-based classifier provided 100% sensitivity and 100% specificity similar to the wavelet-based technique with the proposed modifications. The wavelet-based method is dependent on the sampling rate of EEG recording, and limits wide-spread applicability of the algorithm. This issue is resolved with the proposed new approach of modeling (without wavelet) along with other improvements in model-based seizure detection. Summary of the overall results for each approach is tabulated in Table I.

The SEEG data from seven patients is used to evaluate the performance of the proposed method on real data. Each patient had five 4-hour long recordings that included three recordings with at least one seizure, one recording during wake period and one recording during sleep. For each patient, the seizures belong to the same type as classified by the EEG expert. First seizure occurring in each patient was used as the template pattern. Models are constructed using the above described approach. For each patient, the complete 20 hours of SEEG data for a single channel is processed. Further, the proposed method is compared with *Method A* and *Method B* and results are presented in Table II.

For our analysis, we categorized the data into three groups based on duration and characteristics of the seizures. Group A contained four patients (P1, P2, P3, P4) with slowly evolving and long duration seizures (> 30 s). Group B had one patients (P5) with short duration rhythmic seizures (< 30 s). Group C contained two patients (P6, P7) with short duration and mixed type of seizures. In Group A, the template seizure pattern of patient P1 had non-stationarity at the beginning of the seizure which later evolved into a rhythmic seizure. Segmentation algorithm ignored non-rhythmic section in generating the models.

Upon manual review of detections in P1, it is observed that, majority of missed seizures did not fully develop into rhythmic components represented by the template pattern. For this patient, *Method A* resulted in poor performance with slightly improved results by *Method B* and the proposed method. In Group B and C, due to short length of seizure, it was difficult to visually segment the template pattern in three disjoint stationary epochs, and this resulted in poor model for the template pattern. Automatic segmentation algorithm extracted template epochs that represented a better model over the *Method A* which improved the sensitivity in P5 and P6. Some false detection for patient P5 and P6 were due to sharp wave complex discharges, and were rejected by the pre-processing block of the proposed method. The proposed method missed a seizure in Group A. The missed seizure was of relatively short length compared to the template seizure pattern. This caused detection in only 2 of the 6 models, and therefore, was considered as an artifact by the evolution-based classifier. Similarly, in Group C, a seizure was missed due to short duration (8 s) and rejected by the proposed classifier. Overall, the proposed method shows similar detection sensitivity to *Method B*, and a greatly improved sensitivity (84% vs 64%) compared to the *Method A*. In terms of specificity, the proposed method improved specificity by 10% when compared to *Method B*.

Table II: Summary of results for depth EEG

PID #	Manually Detected Events	Method A		Method B		Proposed Method	
		SN (%)	SP (%)	SN (%)	SP (%)	SN (%)	SP (%)
1	13	7.7	100	30.8	100	30.8	100
2	4	100	100	100	100	75	100
3	6	100	100	100	100	100	100
4	3	100	100	100	100	100	100
5	6	16.7	100	100	66.7	100	100
6	9	33.3	100	77.8	63.6	100	100
7	6	100	100	83.3	100	83.3	100
Total	**47**	**65.4**	**100**	**84.6**	**90**	**84.2**	**100**

PID: Patient Number, SN = Sensitivity, SP = Specificity

V. Conclusions

The performance in model-based seizure detection using SONF is dependent on the model. However, the presence of artifacts and non-ictal EEG rhythms cause false detections. The evolution in the amplitude and the frequency are intrinsic characteristics observed only in seizures. We have reduced the possibility of false detections due to artifacts or non-epileptic rhythms by introducing adaptive modeling of the template pattern and evolution-based classifier. Improvement in terms of sensitivity, specificity and FDR was observed as compared to the previously presented approaches. This is preliminary result on seven patient data and manuscript for journal publication is under preparation on a larger patient data set.

Acknowledgment

The authors would like to thank Stellate Systems, Montreal, Canada for providing the SEEG data used in the present study.

References

[1] L. Shi, R. Agarwal, and M. N. S. Swamy, "Model-based seizure detection method using statistically optimal filters," *Conf Proc IEEE Eng Med Biol Soc,* vol. 1, pp. 45-8, 2004.

[2] R. Yadav, R. Agarwal, and M. N. S. Swamy, "STFT-Based Segmentation in Model-Based Seizure Detection," in *Proc. Canadian Conference on Electrical and Computer Engineering CCECE 2007*, 2007, pp. 729-732.

[3] E. Niedermeyer and F. H. Lopes da Silva, *Electroencephalography : basic principles, clinical applications, and related fields*, 5th ed. Philadelphia: Lippincott Williams & Wilkins, 2005.

[4] H. Qu and J. Gotman, "A patient-specific algorithm for the detection of seizure onset in long-term EEG monitoring: possible use as a warning device," *IEEE Trans Biomed Eng,* vol. 44, pp. 115-22, Feb 1997.

[5] R. Agarwal, E. I. Plotkin, and M. N. S. Swamy, "Statistically optimal null filter based on instantaneous matched processing," *Circuits, Systems, and Signal Processing,* vol. 20, pp. 37-61, 2001.

[6] S. M. Haas, M. G. Frei, and I. Osorio, "Strategies for adapting automated seizure detection algorithms," *Med Eng Phys,* vol. 29, pp. 895-909, Oct 2007.

[7] N. Yeung, R. Bogacz, C. B. Holroyd, and J. D. Cohen, "Detection of synchronized oscillations in the electroencephalogram: an evaluation of methods," *Psychophysiology,* vol. 41, pp. 822-32, Nov 2004.