Brain Dynamics Based Automated Epileptic Seizure Detection

V. Venkataraman, I. Vlachos, A. Faith, B. Krishnan, K. Tsakalis, D. Treiman and L. Iasemidis

***Abstract*— We developed and tested a seizure detection algorithm based on two measures of nonlinear and linear dynamics, that is, the adaptive short-term maximum Lyapunov exponent ($ASTL_{max}$) and the adaptive Teager energy (ATE). The algorithm was tested on long-term ($0.5-11.7$ days) continuous EEG recordings from five patients (3 with intracranial and 2 with scalp EEG) with a total of 56 seizures, producing a mean sensitivity of 91% and mean specificity of 0.14 false positives per hour. The developed seizure detection algorithm is data-adaptive, training-free, and patient-independent.**

I. INTRODUCTION

Continuous long-term EEG monitoring is the gold standard for recording epileptic seizures and assisting in the diagnosis and treatment of patients with epilepsy. However, this process still requires that seizures are visually marked by experienced and trained electroencephalographers, which is an extremely time consuming and costly task.

The task of automating the detection of epochs of EEG having seizure (ictal) activity is non-trivial due to several factors, including the differences in seizure morphologies within and across patients, and the presence of movement and other recording artifacts. An initial automated seizure detection algorithm was designed by Gotman [1] and produced a sensitivity of $70-80\%$. Gotman's algorithm was later updated and after extensive evaluation has now been integrated into several commercial medical devices for clinical use [2]. Despite improvements, the algorithm still suffers a major drawback of a large number of false positives ($1-3$ per hour).

Seizure detection approaches based on artificial neural networks improved the detection performance by training the algorithm on EEG epochs of seizure and non-seizure epochs [3], [4]. A seizure detection algorithm, developed by Osorio *et al.* [5] to primarily run on intracranial EEG, claimed an ideal sensitivity of 100% with no false detections. However, this algorithm was evaluated on 125 ictal and 205 inter-ictal EEG epochs, but not on continuous EEG. A wavelet-based approach for seizure detection in intracranial EEG developed by Khan *et al.* [6] has claimed a reduction in false detections of seizures to 0.3 per hour.

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In approaches based on neural networks, the length of training datasets is usually larger than the one of testing datasets, which in itself should be considered a disadvantage for development of automated seizure detection algorithms. Additionally, the large variability of seizures across patients makes it harder to obtain good results by training a network on a set of single patient's EEG recordings and testing it on another.

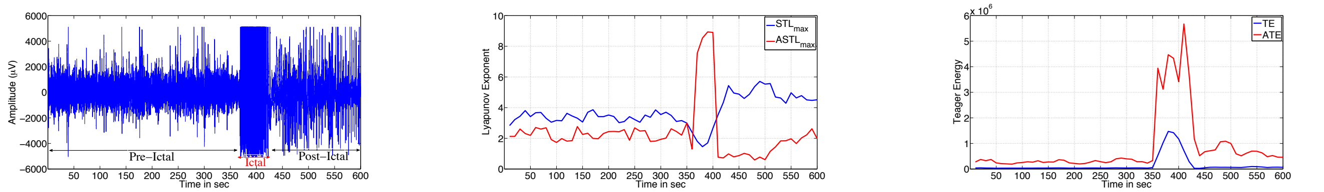
Recently, attempts have been made towards applications of nonlinear techniques to seizure detection. The findings in [7] suggested that best results could be achieved by using a combination of linear and nonlinear measures as features for seizure detection. A novel wavelet-chaos-neural network method for EEG segment classification into ictal, and inter-ictal using correlation dimension and largest Lyapunov exponent was attempted by Adeli *et al.* [8]. It was shown that largest Lyapunov exponent can be effectively used to classify ictal versus inter-ictal EEG.

The aforementioned approaches with artificial neural networks have improved seizure detection at the cost of algorithm's training. The attempts made towards development of algorithms for classification of epochs of EEG into ictal and inter-ictal cannot be used for online prospective seizure detection. Approaches based on user-defined thresholds prevent the use of such algorithms across patients without input by a trained person. Therefore, in this study, we focused towards development of a seizure detection algorithm that eliminates the need for training or user-defined thresholds. We intended to develop a patient-independent and data-adaptive algorithm, eliminating the need for any changes in the algorithm when used across patients.

II. METHODS AND TOOLS

A. Short-Term Maximum Lyapunov Exponent - A Measure of Nonlinear Chaotic Dynamics

A positive maximum Lyapunov exponent is a signature of chaos in nonlinear dynamical systems and indicates divergence of the orbits of a system in its state space. Wolf *et al.* [9] described the first practical algorithm for estimating the largest Lyapunov exponent (L_{max}) from stationary real data by following the divergence/convergence rate of nearby trajectories in the state space. An improved method for estimating this dynamical measure from experimental EEG data was proposed by Iasemidis *et al.* [10]. This method estimates an approximation of L_{max} from non-stationary data, called STL_{max} (Short-Term Maximum Lyapunov exponent). STL_{max} is estimated from the signal $x(n)$ through the formation of time-delayed state space vectors $\mathbf{x}(n) =$



(a) Raw EEG Time Series Data (b) Lyapunov Exponent Profiles (c) Teager Energy Profiles

Fig. 1: (a) A sample EEG including a 2min seizure that starts about 350sec into the recording, (b) STL_{max} (blue line) and $ASTL_{max}$ (red line) profiles, (c) TE (blue line) and ATE (red line) profiles.

$\left[x_n, x_{n-\tau}, ..., x_{n-(m-1)\tau}\right]$, where m is the embedding dimension and τ the embedding delay (time lag). Details of the algorithm are described in [10].

B. Teager Energy (TE)

Teager energy operators [11] have proved to be a useful tool for analyzing signals from an energy point of view. This energy function is a local property of the signal depending only on the signal amplitude and its first two derivatives. It is a popular algorithm having wide applications in the field of signal processing due to its simplicity in implementation. In the discrete time domain, TE is defined by the formula,

$$\psi(x[n]) = x_n^2 - x_{n-1}x_{n+1} \tag{1}$$

The average Teager energy of a segment of N data points is then estimated as:

$$TE = \frac{1}{N-2}\sum_{n=2}^{N-1}\psi(x[n]) \tag{2}$$

The performance of TE was found to be good for high signal-to-noise ratio (SNR) but degraded for low SNR. An improved TE, called multi-resolution TE, was proposed and outperformed the traditional TE [12]. The new measure, k-TEO is given by

$$\psi_k(x[n]) = x_n^2 - x_{n-k}x_{n+k} \tag{3}$$

The factor k should be optimized which requires prior knowledge of the signal. In a real-time setting, this optimal value for k varies; having a single fixed value for k will reduce the algorithm's performance, which is a major drawback of this approach.

C. Adaptive Lyapunov Exponents $(ASTL_{max})$ and Adaptive Teager Energy (ATE)

Unlike the traditional STL_{max} estimation, where the embedding delay τ was kept constant over time and equal to a value that only seizure states were well embedded, we here estimate the optimal value of τ for every ictal or inter-ictal EEG data segment we analyze over time. The result is an adaptive estimation of STL_{max}, which we call $ASTL_{max}$. The idea behind the use of the traditional STL_{max} was to capture the dynamics of the transitions of the epileptic brain from normal (inter-ictal) to abnormal (ictal) states, with the ictal states being embedded in a well-characterized (constant embedding parameters) state space. This process facilitated the prediction of ictal states (seizures). However, in the present study, our goal was to detect rather than predict seizures. Hence, a changing value for the time delay τ to characterize the state space of the ongoing dynamics over time was recommended for seizure detection. In order to make the estimation of the Lyapunov exponent data adaptive, we select the embedding delay τ as the first zero-crossing of the sample autocorrelation function [13]. Fig. 1 (b) shows that $ASTL_{max}$ values can be more different than pre-ictal or post-ictal ones when compared to the respective STL_{max} values.

Similar to the estimation of $ASTL_{max}$, we propose the use of the data-adaptive embedding delay τ derived from sample autocorrelation function as the lag index k for TE, thus making it also data-adaptive. The reasoning for the use of the adaptive TE is the same as in [12], so that ATE is sensitive to the frequency content of the signal. ATE can be estimated from Eq. 2 and Eq. 3, where the factor k is set equal to the τ value estimated above, and its comparative advantage for seizure detection versus TE is shown in Fig. 1 (c).

III. Experiments

A. EEG Data Acquisition

For our study, data from intracranial EEG (3 patients) and scalp EEG (2 patients) recordings were collected. Intracranial EEG recordings were obtained from epilepsy patients with bilaterally, surgically implanted intracranial electrodes in the hippocampus, temporal and frontal lobe cortices. The multichannel $(28-32)$ intracranial EEG signals were obtained from long-term $(6-11.7$ days) continuous recordings in three patients.

Scalp EEG recordings with 22 recording electrodes, placed according to the International $10-20$ system, were obtained from 2 epilepsy patients . The recordings were approximately 12 hours in duration for each patient.

B. Seizure Detection Algorithm

The automated seizure detection algorithm with data-adaptive threshold and capability to select the "optimal electrode" over time is presented below.

1) Preprocessing of EEG: The analog EEG was either sampled at 200 Hz or down-sampled to 200 Hz. The digital EEG was subsequently bandpass filtered between $0.1-30$ Hz. This digitally filtered EEG signal was then segmented into overlapping 30 sec epochs (20 sec overlap between epochs).

2) Embedding Dimension m: We selected $m = 7$ for reconstruction of state space as per the findings reported by Iasemidis *et al.* [14].

3) Time Lag τ: For every 30sec EEG epoch, the time lag τ was estimated as the first zero-crossing of the sample autocorrelation function.

4) Algorithm: The features, $ASTL_{max}$ and ATE measures are used in cascade for seizure detection. The following steps are employed towards this goal:

(i) 360 values of $ASTL_{max}$ and ATE (corresponding to approximately 1 hour of EEG) per electrode are fed into the electrode selector routine. The value 360 was selected so that we have enough data for a statistically sound selection of an electrode in step (ii) and of the outliers described in step (iii) below.

(ii) The electrode selector selects one "optimal electrode" based on the range of the $ASTL_{max}$ values. The electrode that exhibits maximum range (difference between the maximum and the minimum) in $ASTL_{max}$ values was selected for further analysis.

(iii) For the $ASTL_{max}$ values from the electrode selected in (ii) above, a statistical threshold is calculated as:

$$Th_1 = mean(ASTL_{max}) + 5 * std(ASTL_{max}) \quad (4)$$

which typically corresponds to a statistical significance value of $\alpha = 0.00001$. $ASTL_{max}$ values above Th_1 are then identified as outliers and their respective 10 sec EEG epochs S_i are stored as possible epochs within seizures.

(iv) The ATE values for the 1 hour EEG segment under consideration, and only for the electrode selected in step (ii) above, are employed to define a second threshold Th_2 to determine outliers such that

$$Th_2 = mean(ATE) + 3 * std(ATE) \quad (5)$$

which typically (Gaussian distribution) corresponds to a statistical significance value of $\alpha = 0.001$. Around every i^{th} candidate EEG epoch S_i identified in step (iii) above, $m_1 = 21$ consecutive ATE values (ten values before and after the i^{th} value and the i^{th} value itself; time span of approximately 2 minutes) are considered. S_i is declared to be within a seizure if at least $m_2 = 2$ consecutive out of the 21 ATE values were found to be above Th_2. The maximum (21) and minimum (2) values for m_1 and m_2 respectively were selected to ensure that detection spans the range of duration of clinical (typically as long as 2 minute) and subclinical (typically as short as 40 sec) seizures in our patients with temporal lobe epilepsy.

The above procedure is repeated for every S_i epoch within the 1 hour EEG window. The window is then moved by 10sec to the next available 1 hour of EEG, and the steps (i)-(iv) are repeated for the 360 $ASTL_{max}$ and ATE values within the window.

5) Example: In Fig. 2 (a)-(d), we present the results of each step of our seizure detection algorithm from 1 hour EEG data segment that includes one seizure from Patient D3 (Table I). Initially, the $ASTL_{max}$ values from all electrodes are given to the electrode selector routine (for clarity of presentation, the $ASTL_{max}$ values from only four electrodes are shown in Fig. 2(a)). The selector routine picks electrode-2 as the optimal electrode for seizure detection. Fig. 2(b) shows the $ASTL_{max}$ profile of electrode-2 along with the threshold Th_1 derived from the data. Out of the identified 3 outliers at this stage, only the first one corresponded to a seizure occurrence (verified by two physicians / EEGers) and is marked in green color (true seizure detection), while the other two outliers were deemed false positives (marked in red color). In the next stage of analysis, the ATE profile, threshold Th_2 and the respective outliers are estimated for electrode-2 and shown in Fig. 2(c). We see that only the first outlier is common in both $ASTL_{max}$ and ATE profiles. The results from the last stage of the analysis (step (iv)) are shown in Fig. 2(d), where the first outlier passes the set criteria and is declared occurring at a seizure.

IV. Results

Sensitivity and specificity results on seizure detection from all the available continuous EEG recordings per patient and across all five patients are shown in Table I. The sensitivity ranged from 85.71% to 100%, while the false positives per hour ranged from 0 to 1 every 6.5 hours. The average sensitivity across all five patients was 91.81% with an average specificity of 0.14 false positives per hour. Our algorithm is patient-independent, training-free and data-adaptive and performs at least in par with algorithms that are training and patient dependent. This is substantiated by its high sensitivity and very low false positive rate from intracranial and scalp EEG across five patients. We would like to also note here that two of the missed seizures in intracranial recordings (in patients D1 and D3) were subclinical events of smaller duration ($<$ 10sec) than the pre-determined algorithm's resolution. The three seizures missed in patient D2 were localized to a specific region of the brain and also lasted less than 10sec.

V. Conclusion

We developed and tested a novel seizure detection approach based on measures from nonlinear and linear dynamics, that is, the adaptive short-term maximum Lyapunov exponent ($ASTL_{max}$) and the adaptive Teager energy (ATE) respectively. It is expected that this algorithm will assist physicians in reducing the time spent on detecting seizures from long-term EEG recordings, lead to faster and more accurate diagnosis, evaluation of treatment, and possibly online real-time neuromodulation therapies for epilepsy.

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TABLE I: Seizure detection results on long-term EEG monitoring dataset collected from intracranial EEG (3 patients) and scalp EEG (2 patients).

Patient Number	Type	Duration (hrs)	Seizures	True Positives	False Positives	Sensitivity (%)	False Positives /hr	Mean Sensitivity (%)	Mean False Positives /hr
D1	Intracranial	281	7	6	32	85.71	0.11		
D2	Intracranial	217	24	20	36	83.33	0.17	**86.35**	**0.13**
D3	Intracranial	145	20	18	14	90.00	0.10		
S1	Scalp	11	2	2	2	100.00	0.18	**100.00**	**0.17**
S2	Scalp	12	3	3	2	100.00	0.17		
Total	**5**	**666**	**56**	**49**	**86**	**91.81**	**0.14**		

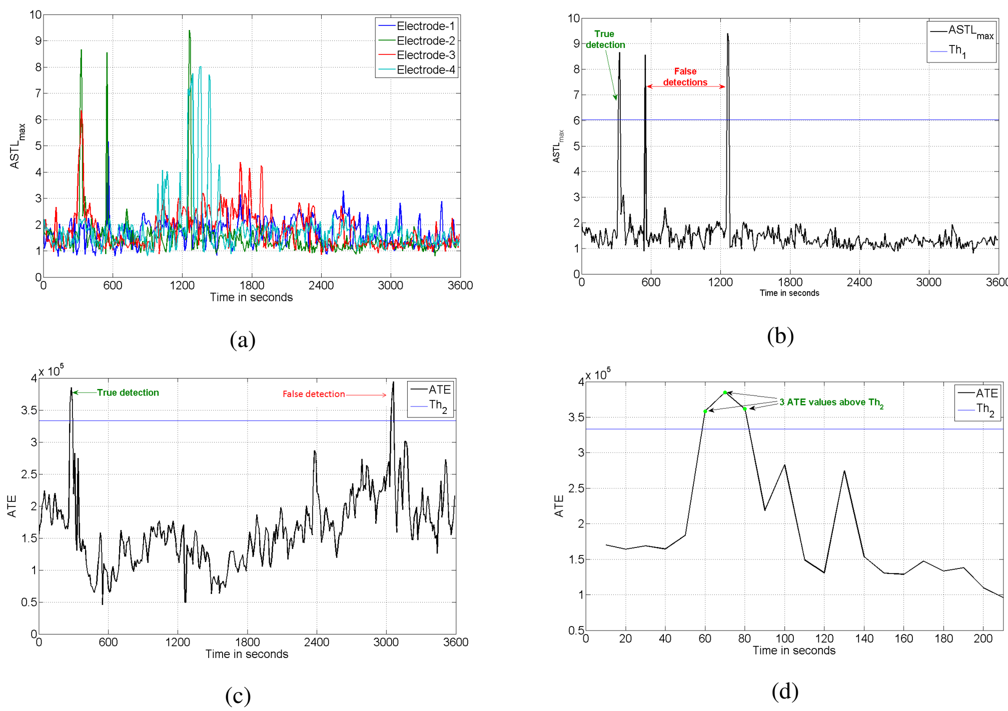

Fig. 2: Results from each step of the seizure detection algorithm applied to 1 hour segment of EEG recorded from patient D3 and including only 1 seizure (true positives are denoted by green and false positives by red color): (a) $ASTL_{max}$ values from 4 electrodes. (b) $ASTL_{max}$ values of the selected optimal electrode (electrode-2) and threshold Th_1. (c) ATE values of electrode-2 and threshold Th_2. (d) Combination of $ASTL_{max}$ and ATE gives only one positive seizure detection (around 70sec). 21 ATE values of electrode-2 around the common outlier of (b) and (c) show a duration of 30sec above Th_2, thus implying a seizure occurrence.

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