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# Epileptic Spike Detection Using a Kalman Filter Based Approach

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***Abstract*—The electroencephalogram (EEG) consists of an underlying background process with superimposed transient nonstationarities such as epileptic spikes (ESs). The detection of ESs in the EEG is of particular importance in the diagnosis of epilepsy. In this paper a new approach for detecting ESs in EEG recordings is presented. It is based on a time-varying autoregressive model (TVAR) that makes use of the nonstationarities of the EEG signal. The autoregressive (AR) parameters are estimated via kalman filtering (KF). In our method, the EEG signal is first preprocessed to accentuate ESs and attenuate background activity, and then passed through a thresholding function to determine ES locations. The proposed method is evaluated using simulated signals as well as real inter-ictal EEGs.**

## I. Introduction

The electroencephalogram (EEG) is the reflection upon the scalp of the summed postsynaptic potentials of millions of neurons. It is an important clinical tool for the diagnosis of epilepsy since the EEG of patients with epilepsy can reveal typical epileptiform activity, during seizures (ictal EEG) and between seizures (inter-ictal EEG). The most prominent example of inter-ictal epileptiform activity is the epileptic spike (ES). The shape and size of ESs vary among patients. Thus, they appear in the EEG as isolated spikes, sharp waves, as well as quasi periodic oscillations of spikes-and-waves [1]. In signal processing techniques, spikes are nonstationary short-time broadband events with high instantaneous energy [2].

Generally, the detection of epileptiform events can be achieved by visual scanning for ESs, of inter-ictal EEG recordings by an experienced EEGer. However, visual review of the vast amount of EEG data has serious drawbacks. It is prohibitively time consuming and difficult since normal brain activity, non pathological events that resemble pathological ones, noise and instrumental artefacts can be misinterpreted as ESs. In addition, disagreement among the EEGers regarding the same recording is possible due to the subjective nature of the analysis. For this reason computer-assisted analysis becomes necessary in practice [3].

Research in automated ES detection began as early as the 1970s and has produced a variety of different algorithms to address this problem [4,5]. All methods employed belong to one of the following approaches: mimetic [6], template matching [7], predictive filtering [8], artificial neural network [9] and rule-based [10]. Each method has some unique advantages, but none of them alone can fulfil the requirement of ES detection. Thus, it is widely recognised that a promising way to solve such a complicated problem is to combine these methods and let them supplement each other. On the other hand, the majority of the above methods are supervised and the quality of the classification depends on the quality of the dataset. Hence, it is necessary to develop unsupervised techniques for EEG analysis.

From the signal processing point of view, the detection of spikes is an important problem in many biomedical applications [11]. Usually, a spike detection scheme can be thought as a two-step process; enhancement and detection. The purpose of the enhancement step is to make the spike samples stand out from the rest of the data, thereby simplifying the subsequent task of detection. Depending on the nature of the enhancement strategy, the overall schemes can be categerorized into three broad classes: (i) time domain techniques [12,13], (ii) signal modelling approaches [14,15,16] and (iii) transform-domain methods [17,18].

In this paper, a signal modelling approach is used to detect ESs in EEG recordings. Our method is unsupervised and can be divided into two steps. The first step is a preprocessing step whose main goal is to pre-emphasize the ESs. For this reason, the EEG signal is first modelled as an output of time-varying autoregressive model (TVAR). The TVAR parameters are estimated with a Kalman Filter (KF) algorithm. In the second step, ESs are identified by the output of the filter, compared to a threshold. More specifically, a thresholding function is applied in the estimated EEG to detect the ESs. To our knowledge, several spike detection algorithms rely on a simple voltage threshold with little or without preprocessing. Simple thresholding has proved to be attractive for real-time implementations because of its computational simplicity.

## II. Methods

The proposed method for detection of ESs involves a two-step process: 1) ESs pre-emphasis using a Kalman Filter (KF) based approach, and 2) ESs detection using a thresholding procedure.

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### A. Pre-emphasis step: Kalman Filter approach

The formulation of the Kalman Filter equations is based on *state-space formulation.* In this paper, the EEG dynamics are estimated using a TVAR model of order $p$ given by:

$$x_t = -\sum_{j=1}^{p} a_t^{(j)} x_{t-j} + e_t, \qquad (1)$$

where $a_t^{(j)}$ is the value of the $j^{th}$ AR parameter at time $t$ and $e_t$ is the observation error. By denoting:

$$H_t = (x_{t-1}, ..., x_{t-p}), \qquad (2)$$

$$\theta_t = (-a_t^{(1)}, ..., -a_t^{(p)})^T, \qquad (3)$$

the TVAR model can be written in the form:

$$x_t = H_t \theta_t + e_t, \qquad (4)$$

which is a linear observation model. The evolution of the state (i.e. the AR parameters) $\theta_t$ when no prior information is available is typically described as:

$$\theta_{t+1} = A\theta_t + w_t, \qquad (5)$$

where $w_t$ is the state noise term and $A$ is a *pxp* matrix.

Equations (4) and (5) form the state-space signal model for the TVAR process $x_t$ and the evolution of the AR parameters can now be estimated using the KF algorithm.

The KF is a real time processing algorithm in which the state estimate is updated when a new observation is available. KF computes the linear square estimator $\hat{\theta}_t$ for state $\theta_t$ given the observations $x_1$, $x_2$,…,$x_t$. Both the observation and the state noises $e_t$ and $w_t$ are assumed to be zero-mean random processes with variances $R$ and covariance $C_{w_t}$, respectively. The derivation of the KF equations can be found in [19].

For the TVAR model, these equations can be written in the form:

$$C_{\hat{\theta}_{t|t-1}} = C_{\hat{\theta}_{t-1}} + C_{w_{t-1}}, \qquad (6)$$

$$K_t = C_{\hat{\theta}_{t|t-1}} H_t^T (H_t C_{\hat{\theta}_{t|t-1}} H_t^T + R)^{-1}, \qquad (7)$$

$$\hat{\theta}_t = \hat{\theta}_{t-1} + K_t (x_t - H_t \hat{\theta}_{t-1}), \qquad (8)$$

$$C_{\hat{\theta}_t} = (I - K_t H_t) C_{\hat{\theta}_{t|t-1}}, \qquad (9)$$

where $\hat{\theta}_t$ is the state estimation error, $\hat{\theta}_t = \theta_t - \hat{\theta}_t$, $\hat{\theta}_{t|t-1}$ is the state prediction error $\hat{\theta}_{t|t-1} = \theta_t - \hat{\theta}_{t-1}$, $K_t$ is the Kalman gain vector and $I$ is the identity matrix.

#### A.1. Initialization of the algorithm

Particular care must be paid in the choice of parameters entering our approach. Those parameters are: the variance of the observation noise, the variance of the state noise and the matrix $A$. The form of matrix $A$ reflects the correlations between them and different time instants. We assume by construction of our model that there is no correlation between the coefficients in time instant $t$, with those in time instant $t$-1. In the case where this hypothesis does not hold, the matrix $A$ should not be diagonal, adding in this way complexity in our model. Moreover, we assume a low degree of correlation between AR coefficients in adjusted time instants. Thus, the diagonal elements of $A$ must have values <<1. We choose matrix $A$ as:

$$A = \begin{pmatrix} 0.1 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 0.1 \end{pmatrix}.$$

The final order ($p$=5) of the AR model was determined heuristically, after several experiments. The variance of the observation noise $R$, is:

$$R = 0.5x \ (\textit{mean absolute value of the EEG signal}).$$

The covariance matrix $C_{w_t}$, of the state noise is chosen as:

$$C_{w_t} = \begin{pmatrix} 0.1 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 0.1 \end{pmatrix}.$$

We initialize $C_{w_t}$ matrix as diagonal in order to reduce the complexity of the model. The value 0.1 was determined heuristically, after several experiments.

### B. Detection step: Thresholding procedure

After the pre-emphasis step, peaks from the output of the filter which are higher than a predefined threshold are considered as an indication of the existence of an ES at that location in the time series. More specifically, the absolute value of the estimated EEG is used. In any spike detection algorithm the threshold is optimized to minimize missing of true peaks, while keeping the number of falsely detected peaks within a reasonable limit. For the proposed method the threshold is taken as scaled version of the mean of the absolute value of the estimated data in the whole signal duration. This modification makes the detection algorithm robust. Therefore, the threshold value for the KF-based approach is chosen as:

$$T = \lambda \frac{1}{N} \sum_{t=1}^{N} z(x_t), \qquad (10)$$

where $N$ is the number of samples, $\lambda$ is a scaling factor and $z(x_t)$ is the absolute value of the estimated data.

We compare the proposed approach with a smoothed nonlinear operator (SNEO) approach which has been employed in [2] to detect ES in EEG signals. SNEO is a smoothed version of the nonlinear operator. The nonlinear operator is applied to the time series $x_t$ and is defined as:

$$\psi(x_t) = x_t^2 - x_{t+1} x_{t-1}. \qquad (11)$$

Smoothing is achieved by convolving $\psi(x_t)$ with a time domain window and is expressed as:

$$\psi_s(x_t) = \psi(x_t) \otimes w_t, \qquad (12)$$

where ⊗ denotes the convolution operator and $w_t$ represents the window (3-point Barlett window).

SNEO is also a two-step process with involves ES accentuation and thresholding to detect ESs. Mukhopadhyay and Ray [2], defined the threshold of SNEO as the mean energy multiplied by a scaling factor $\lambda$ as follows:

$$T = \lambda \frac{1}{N} \sum_{t=1}^{N} \psi_s(x_t), \tag{13}$$

where $N$ is the number of samples.

## III. Results

The performance of the proposed approach was evaluated using both simulated signals and real inter-ictal EEGs.

### A. Simulated signal

For the purpose of evaluating the performance of the proposed method we use the following simulated signal [2].

$$x_t = b_t + s_t, \tag{14}$$

where $b_t$ and $s_t$ are the background signal and the spike train, respectively. The background is chosen as follows:

$$b_t = \sin(\omega t) - \sin(2\omega t + \phi) + \sin(4\omega t) + n_t, \tag{15}$$

where $\omega = 2\pi/75$, $\phi = \pi/2$ and $n_t$ is white Gaussian noise. The position, the amplitude and the sign of the spikes are generated by a random number generator and properly scaled to distribute it throughout the range of the signal. The spike amplitude has distribution $U$ [2.5, 7.5].

The signal is sampled at a rate of 128 Hz (Fs=128 Hz). The signal in Fig. 1(a) shows 8 spikes represented with a randomly varying duration of 3 to 9 samples since the duration of real ES ranges from 20 to 70 msec. Fig. 1(b) shows 640 samples of $x_t = b_t + s_t$, with SNR=5 dB.

In order to assess the noise sensitivity of the proposed method, we used simulated signals with signal to noise ratio (SNR) of, -5dB, 0dB, 5dB, 10dB with 50 realizations for each selected SNR. The scaling factor for thresholding of SNEO and KF output is adjusted to be 1.75 as proposed in [2]. Lower bound for thresholding of KF output is not chosen. For a given spike detector, let the false-negative ratio be FNr= (Number of spikes missed)/(Actual number of spikes), and the false-positive ratio be FPr=(Number of spikes detected)/(Actual number of spikes).

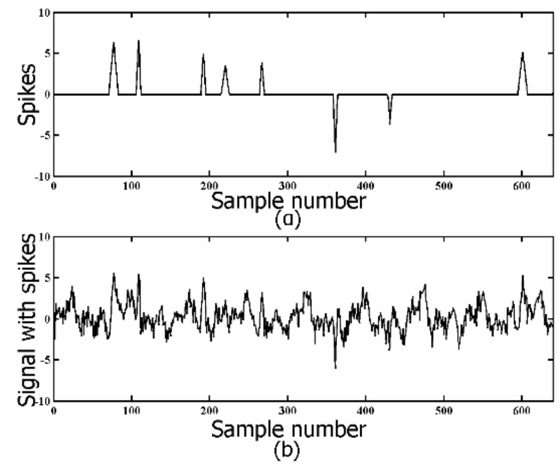


Fig.1: (a) Spike train, (b) Signal with spikes, $x_t$ with SNR= 5dB..

Table I reports FNr and FPr, together with the standard deviation of the results obtained by applying the SNEO and KF-based approaches to 50 simulated signals with 10dB, 50 simulated signals with 5 dB, 50 simulated signals with 0 dB and 50 simulated signals with 5dB SNR.

The KF-based approach is found to be superior to the SNEO approach as it is shown in Table I. The FP ratio (FPr) using KF is lower than that of SNEO, for the signal at high SNR as well as at low SNR. It should be mentioned that by adjusting the threshold level, either the FN ratio (FNr) or the FP ratio (FPr) can be improved. In that respect the true integrity of measure should be a linear combination of both ratios.

TABLE I
COMPARISONS OF PERFORMANCE OF TWO APPROACHES FOR THE SIMULATED SIGNAL WITH SPIKE EMBEDDED IN NOISE

| Approach | KF (μ± σ) | | | | SNEO (μ± σ) | | | |
|---|---|---|---|---|---|---|---|---|
| SNR | 10dB | 5dB | 0dB | -5dB | 10dB | 5dB | 0dB | -5dB |
| FNr | 0.08± 0.07 | 0.22± 0.09 | 0.19± 0.13 | 0.09± 0.10 | 0.12± 0.11 | 0.09±0.09 | 0.10± 0.12 | 0.08± 0.08 |
| FPr | 1.89± 0.36 | 3.88± 0.37 | 4.56± 0.50 | 5.71± 0.57 | 7.44± 1.22 | 9.24± 2.87 | 8.02± 1.30 | 7.17± 0.55 |

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*B. Real EEG signal*

To evaluate the performance of the proposed KF–based approach on real signals, the inter-ictal EEG of an adult patient has been used. The data has been sampled at Fs=256 Hz. Both SNEO and KF-based approaches are applied to a 5 seconds EEG signal and the results are shown in Fig.3. The scaling factor for thresholding of both approaches is chosen to be 1.75 [2]. The threshold is shown in Figs.3(b)-(c).

All the ESs have been successfully detected using both the SNEO and the KF based approach as depicted in Figs.3 (b)-(c). However, Fig. 3(c) shows that the SNEO technique has more false detections than the KF-based approach.

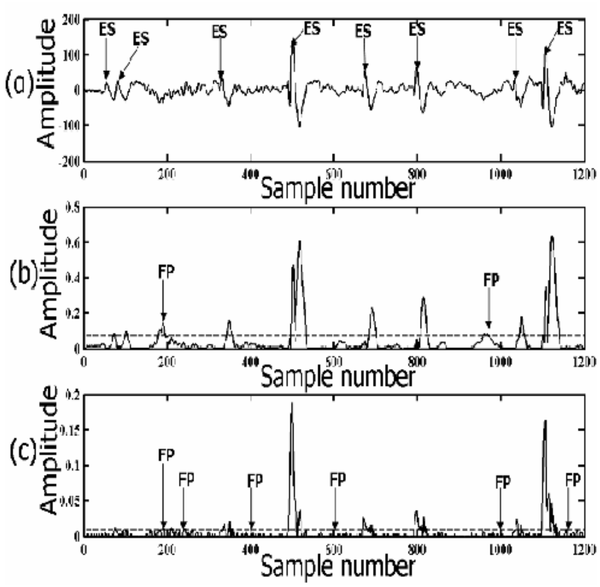


Fig.1: (a) A real EEG, (b) the output of the KF-approach, (c) the output of the SNEO approach. The dashed line is the mean-based threshold. False detected ESs are depicted by arrows.

## IV. Discussion

In this paper we have presented an approach for ESs detection in EEG recordings. It is based on the assumption that EEG consists of an underlying background activity and superimposed transient nonstationarities. The method uses a TVAR model for the accentuation of spikes. The parameters of the model are estimated by KF. Then, a thresholding function is used to distinguish between the ESs and the rest of the data.

There are several ES detection approaches in the literature [2,8,13,15,17,18]. Most of these approaches are based on the assumption that the background signal is stationary. In fact these methods pre-process the signal to highlight the nonstationary ESs in a stationary background. These methods have limited success in the detection of ESs in EEGs, where the background is nonstationary [8,13]. In contrast, our approach uses the temporal information and the time varying nature of EEG components to detect the ESs.

The detection of ESs in the EEG signal is difficult because of the wide variation of ESs characteristics. This difficulty is compounded in presence of noise. KF-based approach performed well in all the simulated and real signals. The extremely low computation complexity is a major attraction of the KF-based approach.

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