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A Kalman filter based methodology for EEG spike enhancement

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ABSTRACT

In this work, we present a methodology for spike enhancement in electroencephalographic (EEG) recordings. Our approach takes advantage of the non-stationarity nature of the EEG signal using a time-varying autoregressive model. The time-varying coefficients of autoregressive model are estimated using the Kalman filter. The results show considerable improvement in signal-to-noise ratio and significant reduction of the number of false positives.

1. Introduction

Electroencephalography (EEG) is one of the clinical tools used in diagnosis, monitoring and management of neurophysiological disorders related to epilepsy. Epilepsy is characterized by sudden recurrent and transient disturbances of mental function and/or movements of body due to excessive discharge of brain. The presence of epileptiform activity in the EEG confirms the diagnosis of epilepsy which sometimes can be confused with other disorders producing similar seizure-like activity [1].

During the seizures (ictal activity) the scalp EEG of patients who suffer from epilepsy is usually characterized by high amplitude synchronized periodic waveforms reflecting abnormal discharge of a large group of neurons. Between, before or after seizures (interictal activity), the EEG might contain occasional epileptiform transient waveforms. As a result relatively short recordings can still be useful in the diagnosis of epilepsy [2]. These transient waveforms, isolated spikes, sharp waves and spike-and-wave complexes are clearly distinguished from background activity. More specifically, spikes are defined as having duration from 20 to 70 ms, while sharp waves have duration from 70 to 200 ms. On the other hand, spike-and-wave complexes are defined as spikes followed by slow waves and have duration from 150 to 350 ms [3,4]. Throughout this paper, no distinction is made among spike, sharp waves and spike-and-wave complexes and therefore they are collectively termed spikes. In general, the detection of epilepsy includes visual scanning of EEG recordings for spike by an experienced EEGer. This process, however, is time consuming, especially

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in the case of long recordings [3,5]. In addition, the detection of epileptiform activity in the EEG is far from straightforward due to the variety of morphology of spikes and their similarities to waves which are part of the background activity and to artefacts (i.e. muscle activity, eye blinking activity, etc.) [6].

Several methods for spike detection have been proposed based on single and multichannel approaches. Those methods can be classified into six categories: (a) methods based on traditional recognition techniques, known as mimetic techniques [7–9], (b) methods using template matching algorithms [10], (c) methods based on parametric approaches [11], (d) methods based on artificial neural networks (ANNs) [2–5,12–19], (e) methods employed data mining techniques [20–22] and (f) methods utilizing knowledge-based rules [5,23–26]. The methods belonging to the first category imitate the visual analysis followed by an expert. In particular, the features of EEG waveforms, such as duration, slope, sharpness and amplitude, are compared with values which are provided by the experts. In the second category, template matching is used for a priori known spike waveforms. The user selects manually spikes from a set of test data, which are averaged to create a template. Recent approaches use wavelets. The EEG signal is filtered using wavelets to obtain features of the signal energy which are used in the detection of spikes. The methods belonging to the third category assume local stationarity of the background activity and use single-channel or multichannel predictive filtering. Spikes are detected as deviation from stationarity. Implicit in these approaches is that non-stationarity behaviour comes only from spikes. In the fourth category ANNs are used to recognize patterns, which are learnt by the network during the training phase. Supervised and unsupervised ANNs have been used in the diagnosis of epilepsy, either to study sleep behaviour, to detect seizures, to predict seizures or to classify and analyze waveforms in the EEG recordings. Methods belonging to the fifth category have the advantage of interpreting their decisions. The majority of the methods, mainly those belonging to the first two categories treat single channel data only. In the sixth category, knowledge-based reasoning in addition to the above-mentioned methods is widely used. This arises from the need to incorporate knowledge of the experts which takes the form of rules including temporal rules.

Essentially, the spike detection problem can be simply transferred to the detection of the presence of spikes in the multichannel EEG recording with high sensitivity and selectivity. That is, a high proportion of true events must be detected with a minimum number of false detections. Thus, a balance must be obtained between having high sensitivity and high selectivity. It is relatively easy to adjust system parameters to obtain performance where all spikes are found in a given patient but this would usually be accompanied by an unacceptably large number of false detections. On the other hand, it is also relatively easy to have a system with very low false detection rate but then this would usually be accompanied by an unacceptably large number of missed events. Many researchers argue that it is better to have a high sensitivity, minimize missed events and suffer more false detections which can be checked by the EEGer rather than missing events altogether. If we look at the system from the point of view of minimizing the number of false detections then the number of missed events will increase. However, if possible spikes can be enhanced prior to the use of a spike detector it should be possible to increase the sensitivity minimizing missed events, while maintaining the selectivity at a satisfactory level.

Thereby, a spike enhancer would not be a detector but would simply aim to enhance anything vaguely spike like. This means that real spikes, as well as spike like artefacts and background will be enhanced, i.e. a large number of unwanted waveforms will be enhanced along with real spikes. This is quite acceptable as long as the spike detection system has high selectivity. To our knowledge, there exist only a few methods that perform spike enhancement. James et al. [27] make use of multireference adaptive noise cancelling (MRANC) in which the background EEG on adjacent channels in the multichannel EEG recording is used to adaptively cancel the background EEG on the channel under investigation. In addition, adaptive noise cancelling has been applied to enhance somatosensory evoked potentials [28] and in cancelling the presence of electrooculogram (EOG) in the EEG [29]. The above methods assumed that EEG signal is a stationary one. However, it is well known that EEG contains non-stationarities [30]. In this work, we propose a novel method for EEG spike enhancement. The method is based on a time-varying autoregressive (AR) model in order to take advantage of the non-stationarities of EEG signal. The AR coefficients are estimated with the use of Kalman filter (KF).

2. Methods

2.1. Time-varying autoregressive model

Let the vector $\mathbf{y}$ be the one channel EEG signal. We suppose that the EEG can be described by an autoregressive model (AR). The AR model has found many applications in EEG analysis [30–32], although EEG is a non-stationary signal. The AR model is given as:

$$y(t) = \sum_{i=1}^{p} s(i)y(t-i) + \upsilon(t), \tag{1}$$

where p is the order of the model, $s(i)$ the AR parameters, $y(t)$ the observations and $\upsilon(t)$ the Gaussian noise with zero mean and variance σ^2. Because the EEG is non-stationary signal we let the AR parameters to vary with time:

$$y(t) = \sum_{i=1}^{p} s_t(i)y(t-i) + \upsilon(t), \tag{2}$$

or in vector notation:

$$y(t) = C(t)^{\mathrm{T}}\mathbf{s}(t) + \upsilon(t), \tag{3}$$

where $C(t) = [y(t-1), y(t-2), \ldots, y(t-p)]^{\mathrm{T}}$ is a $p \times 1$ vector and $\mathbf{s}(t) = [s_t(1), \ldots, s_t(p)]^{\mathrm{T}}$. The vector $\mathbf{s}(t)$ contains the AR parameters and varies in time:

$$\mathbf{s}(t) = A\mathbf{s}(t-1) + \mathbf{w}(t), \tag{4}$$