DETECTION OF EPILEPTIC SPIKES BY MEANS OF SMOOTHED PSEUDO-WIGNER DISTRIBUTION

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ABSTRACT

Electroencephalographical (EEG) signal is an especially important clinical tool for the evaluation of epilepsy. Common electrophysiological manifestation of this disease during interictal period (i.e. between seizures) is presence of spikes and sharp waves. Reliable detection of these transient patterns is persistent problem in EEG analysis. In this work is developed spike-detection algorithm based on smoothed pseudo Wigner distribution.

1 INTRODUCTION

Automatic analysis of the human EEG for assisting in the diagnosis of epilepsy progressed in two main directions: seizure detection, and interictal event detection [1]. Interictal spikes and sharp waves in human EEG are characteristic signatures of epilepsy. The reliable detection of such potentials has been the long-standing problem in EEG analysis, especially after long-term monitoring became common in investigation of epileptic patients [2]. The traditional detection of a spike based on its amplitude, duration, sharpness, and emergence from its background are not reliable due to the presence of numerous transients and artefacts. Another detection methods include linear and nonlinear prediction, nonlinear energy operators, correlation, and neural networks applied on raw signal or its features. Automatic EEG analysis is a formidable task because of the lack of features that reflect the relevant information. Another difficulty is the nonstationary nature of the spikes and the background in which they are embedded. Time-frequency representation (TFR) techniques are developed for the treatment of such nonstationary time series. Short-time Fourier transform, wavelet transform, the matching pursuit decomposition, Wigner and Cohen class of distributions have been used most frequently in this area.

Based on state of the art one can conclude that wavelet transform and signal approximation by matching pursuit are preferably used for transient signal (such as spikes, K-complexes) detection. Cohen class TFRs have been used to analyze seizure EEG, ECoG and K-complex detection. However, interictal spikes still have not been analysed by means of Cohen-type distributions (according to author’s knowledge). In next sections, detection methods based on smoothed pseudo-Wigner distribution will be presented.

2 METHOD

Several Cohen class time-frequency representations were applied to the spikes analysis. The smoothed pseudo Wigner distribution (SPWD) of signal $x(t)$, defined as

$$SPWD_{x(x)}(t, f) = \int_{-\infty}^{\infty} g(t - t') x(t' + \frac{\tau}{2}) x^*(t' - \frac{\tau}{2}) dt' h(\tau) e^{-i2\pi f \tau} d\tau$$  \hspace{1cm} (1)$$

where $g(t)$ and $h(t)$ are time and frequency smoothing windows, was used to represent the epileptic events in the time frequency plane. Candidates for classification were selected by means of local maxima of the SPWD.
Decision parameters were extracted from the time and frequency sections of the smoothed pseudo Wigner distribution images. Four variants of detection procedure (denoted as ThrS, Bay1, Bay2, BayT), that incorporate parameters thresholding and/or Bayesian decision, were realized and tested on EEG data.

2.1 EEG signal pre-processing
Since the most important part of useful signal (the epileptic spike events) energies is concentrated to the frequency band of 5 to 50 Hz, the appropriate band pass filter was used. Complex-valued analytic signal was associated with filtered EEG to reduce interference term in SPWD image.

2.2 Decision parameters
Parameters used in decision (see Tab. 1) were derived from time section SPWD(t,f₀) and frequency section SPWD(t₀,f) provided that SPWD(t₀,f₀) is local maximum representing spike candidate in classification process; see Fig. 1.

![Fig. 1 Parameters extracted from (a) the time, (b) frequency sections](image)

<table>
<thead>
<tr>
<th>Par.</th>
<th>Description</th>
<th>Definition</th>
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<tbody>
<tr>
<td>P₀</td>
<td>Tₐₜₜ, : Duration of the time section, read from 50% level of SPWD calculated with &quot;short&quot; h(t) window (39 samples), see fig. 1 a</td>
<td>P₀ = Tₐₜₜ</td>
</tr>
<tr>
<td>P₁</td>
<td>Amplitude estimation from quadratic TFR Amplitude of a spike (expressed in µV) estimated from energy local maximum (SPWD with &quot;short&quot; window)</td>
<td>P₁ = const √ ( \frac{A}{Tₐₜₜ} )</td>
</tr>
<tr>
<td>P₂</td>
<td>SPWD amplitude ratio Ratio of two SPWD amplitudes, calculated using &quot;short&quot; window (39 samples) and &quot;long&quot; h(t) window (139 samples)</td>
<td>P₂ = ( \frac{A}{A_{139}} )</td>
</tr>
<tr>
<td>P₃</td>
<td>Frequency bandwidth ratio Ratio of absolute bandwidths read from 50% level of SPWD frequency sections, calculated using &quot;short&quot; window and &quot;long&quot; window</td>
<td>P₃ = ( \frac{B_{39}}{B_{139}} )</td>
</tr>
<tr>
<td>P₄</td>
<td>Time section duration (&quot;short&quot; window SPWD) – center frequency product</td>
<td>P₄ = Tₐₜₜ • f₀</td>
</tr>
<tr>
<td>P₅</td>
<td>Relative frequency bandwidth Ratio of absolute bandwidth read from 50% level of &quot;long&quot; window and center frequency</td>
<td>P₅ = ( \frac{B_{139}}{f₀} )</td>
</tr>
<tr>
<td>P₆</td>
<td>Relative undershoot measured in time section using &quot;short&quot; window SPWD</td>
<td>P₆ = ( \frac{A_{\text{min}}}{A} )</td>
</tr>
<tr>
<td>P₇</td>
<td>Shape measure parameter in time section use 10%, 50%, and 90% level durations read from &quot;short&quot; window SPWD</td>
<td>P₇ = Tₐₜₜ • ( \frac{T_{\text{low}} + T_{\text{high}}}{2} )</td>
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</tbody>
</table>
2.3 Decision rules

Algorithm ThrS (Simple Thresholding)
The candidate is classified as spike, if the following conditions are fulfilled:
\[ P_0 < T h 0; \quad P_1 > T h 1; \quad P_2 > T h 2; \quad P_3 < T h 3; \]
\[ T h 4 L < P_4 < T h 4 H; \quad T h 5 L < P_5 < T h 5 H; \quad T h 6 L < P_6 < T h 6 H; \quad T h 7 L < P_7 < T h 7 H. \]

Algorithm Bay1 (Bayesian decision)
This algorithm uses Bayes classification method simplified for Gaussian parameter distribution and uniform prior probabilities. Classification software computes \( M \) discriminate functions \( d_i \) (one for each class), and chooses the class yielding the largest discriminate:
\[ d_i(\beta) = -\frac{1}{2} \ln |C_i| - \frac{1}{2}(\beta - m_i)^T C_i^{-1}(\beta - m_i) + \ln(P(w_i)) \quad (2) \]
where \( i = 1, 2, \ldots, M \), \( M \) is the number of classes, we assume \( M = 2 \) (\( i = 1 \) represents spike, \( i = 2 \) represents non-spike)
\[ m_i = E(\beta | w_i) \] is the expectation of the \( i^{th} \) class parameters,
\[ C_i = E(\beta - m_i)(\beta - m_i)^T \] is the covariance matrix of the \( i^{th} \) class parameters.
The expectations and the covariance matrices can be estimated from available vectors of parameters (training set) as
\[ \hat{m}_i = \frac{1}{L_i} \sum_{j=1}^{L_i} \beta_{j,i} \quad (3) \]
\[ \hat{C}_i = \frac{1}{L_i} \sum_{j=1}^{L_i} (\beta_{j,i} - \hat{m}_i)(\beta_{j,i} - \hat{m}_i)^T \quad (4) \]
where \( L_i \) is the number of vectors in each class and \( \beta \) is vector of parameters.

Algorithm Bay2 (Bayesian decision)
The Bay2 algorithm is similar to the Bay1, but amplitude parameter \( P_1 \) was replaced by \( B_{39} \) (the bandwidth of the frequency section obtained by using a 39-window length), see Fig.1b). The reason of ignoring \( P_1 \) is making the decision of the algorithm to be independent of the amplitude value that may be useful when detecting spikes in EEG with non-specific amplitude information.

Algorithm BayT (Bayesian & Thresholding)
The fourth algorithm mixes both concepts. It is an extended version of the Bay2 algorithm, by adding a threshold value for the parameter \( P_1 \) before applying the Bay2 algorithm. The threshold value of \( P_1 \) can be changed by user to handle sensitivity/specificity trade-off.

3 RESULTS

Digital recordings sampled at 240 Hz obtained from epileptic patients according to the international 10-20 standard with the reference average electrode have been used to evaluate proposed method. The data contains two types of EEG signals. The first type are tracings with spikes or sharp waves, second type contains artefacts and portions of EEG tracings without spikes or sharp waves. An example of SPWD showing six spikes is given in Fig. 2. The whole data were divided into training group, and testing group. The training group will take part in the process of constructing the detection algorithm, which will be applied later to the testing group. Algorithm evaluation in terms of sensitivity and specificity for testing group is summarized in tab. 2. The threshold value of \( P_1 \) (BayT) was changed from 10 \( \mu \)V to 50 \( \mu \)V that result in sensitivity decreasing and specificity increasing.
Fig. 2 Pseudo-colour map of SPWD showing epileptic spikes

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>ThrS</th>
<th>Bay1</th>
<th>Bay2</th>
<th>BayT (10μV)</th>
<th>BayT (30μV)</th>
<th>BayT (50μV)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensitivity</td>
<td>98.63%</td>
<td>91.78%</td>
<td>86.30%</td>
<td>86.30%</td>
<td>86.30%</td>
<td>79.45%</td>
</tr>
<tr>
<td>Specificity</td>
<td>82.81%</td>
<td>83.59%</td>
<td>82.81%</td>
<td>85.16%</td>
<td>90.63%</td>
<td>96.10%</td>
</tr>
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</table>

4 CONCLUSION

We have developed new algorithm that is successful in distinguishing real spike EEG events from real non-spikes EEG events. Despite the fact that Cohen class TFRs are nowadays only rarely used for detection of transient signal patterns, proper pre-processing method and parameter selection make this TFR class highly effective in detection. This fact may be documented by comparison performance measures published in different works. Detection method developed in [3] by using the wavelet transform implemented sensitivity of 70%, and specificity of 67%. Detection of epileptic spikes by means of matching pursuit published by [4] yielded also very promising results in terms of sensitivity/ selectivity (92% /84%). However, when comparing these results to other detectors quoted in [3] we must remember that the performance presented in [4] and in our study was evaluated on a limited example dataset [5].

REFERENCES


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