RECOGNITION OF TRANSIENT PHENOMENA IN A BIOSIGNAL

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Abstract

Electrical activity of a human brain measured on the skull (electroencephalogram, EEG) contains in the sleep period many transients (sleep spindles, spike-like structures or vertex waves), i. e. bursts of EEG activity of limited duration, having random occurrence and may be coupled with specific sleep stages. A computer-based detector was designed that detects a transient called K-complex. The detector is based on linear matched filtering and its nonlinear modifications. The linear and nonlinear approaches are compared and evaluated with respect to the detection efficiency.

Keywords

pattern recognition, sleep EEG, nonlinear matched filtering, covariance filtering.

1. Introduction

Sudden physiological changes that are coupled with transients in human sleep EEG can be evaluated by means of event-related averaging, assuming the transient as an event. One of the most important transients is K-complex. It is a specific wave of 0.5 to 2 s duration and occurring every 30 to 100 s during a part of the night. For the purpose of K-complex-related averaging a detector of K-complexes is necessary to detect the pattern in an EEG signal. The detector must take into account very large pattern variability – Fig. 1. This means – in a technical sense- that an exact definition of this pattern cannot be achieved. Therefore it is not surprising that the visual scorers reach only a 50-60% agreement [1]. The recent studies on K-complex detection do not provide us with satisfactory results. In [2] neural network performed well on simulated data but failed on a real EEG signal. It may well be due to the lack of long and consistent set of training vectors. The matching pursuit detection algorithm [3] is computationally inefficient and time-consuming, what together with low sensitivity is unacceptable for the clinical use.

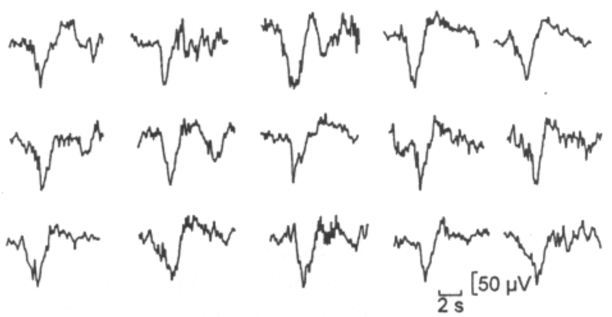

Fig. 1. Many different morphologies of the detected pattern.

For the detection we developed automated detectors that are based on nonlinear modifications of a classical matched filter.

2. Methods

The sleep EEG data (approx. 1000 hours of recording) available for the project were recorded in DLR Institute of Aerospace Medicine, Cologne, Germany. For the processing the data were transferred to an experimental platform MATLAB (The MathWorks, Inc., USA).

The pattern to be detected is described as a biphasic wave that is beginning with a faster negative-voltage wave which is followed by a slower positive wave. The duration of a K-complex is between 0.5 and 2 seconds. The peak-to-peak voltage should exceed 75 μV and should be at least twice as high as the voltage of the activity in 1s interval preceding the K-complex.

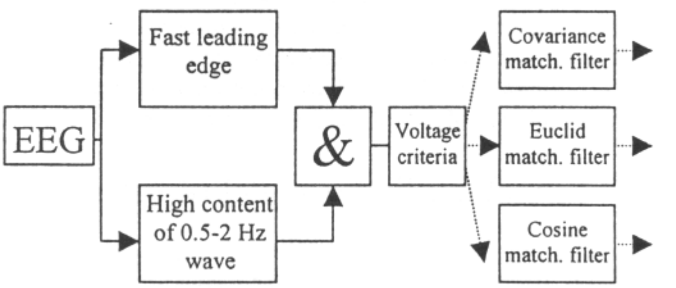

Fig. 2. Architecture of all three detectors. In the EEG signal, parts with fast leading slope and with high voltage in freq. range same as the range of K-complexes, are investigated for sufficient peak-to-peak voltage and then they enter the matched filters.

The matched filters were used as rejecting criteria, i.e. parts of the EEG signal that were equivocal to contain K-complexes were fed into the matched filters. The pre-choice was done by a set of filters and decision logic. As it is stated in the definition, the pattern is biphasic, thus its main spectral component should lie between 0.5 and 2 Hz. At the same time the pattern begins with fast leading edge. A bandpass filter with cut-off frequencies 0.5 and 2 Hz and a differentiator to detect steep leading edge were used in that block. When both conditions are met, the voltage criteria are considered. Then the signal is allowed to propagate to the matched filters – Fig. 2.

2.1 Classical matched filter (covariance filter)

Classical matched filter is used to detect the time instants, when the recorded signal $\mathbf{x}_k$ is similar to the known template $\mathbf{s}$. This is recognised as a maximal output of the matched filter:

$$y_k = \mathbf{x}_k^T \cdot \mathbf{s} \tag{1}$$

where $\mathbf{x}_k = [x_{k-L(s)+1},\ \cdots,\ x_{k-1},\ x_k]^T$ and $\mathbf{s} = [s_0,\ s_1,\ \cdots,\ s_{L(s)-1}]^T$. L(s) is the length of the template. As it was shown in [5], when the local mean value of $\mathbf{x}_k$ is unstable, the detector's peak output is not a reliable indicator of signal similar to $\mathbf{s}$. This can be overwhelmed by subtracting the local mean value both from the $\mathbf{x}_k$ and $\mathbf{s}$ thus obtaining a covariance filter:

$$s_k \rightarrow s_k - \frac{1}{L(s)}\sum_{i=0}^{L(s)-1} s_i\,, \quad x_k \rightarrow x_k - \frac{1}{L(s)}\sum_{i=k}^{k+L(s)} x_i\,.$$

As the pattern's voltage varies from a K-complex to K-complex and it is desirable to detect both low- and high-voltage K-complexes, every possible (equivocal) K-complex is normalised in voltage, before it inputs into the matched filter. The normalisation process is crucial for the proper work of the detector. Many tests were performed including normalisation of signal's energy, amplitude of K-complex's first harmonic component and the best one was chosen. The normalisation yields constant peak-to-peak voltage across all investigated K-complexes. There is no need to subtract the DC shift from the recorded signal, as its mean value is –due to the signal's nature- zero.

2.2 Euclid nonlinear matched filter

The euclid nonlinear filter [5] applies slightly different similarity criteria than the classical covariance filter. The comparison of vectors $\mathbf{x}_k$ and $\mathbf{s}$ is based on minimising of the difference vector

$$\left\|\mathbf{x}_k - \mathbf{s}\right\|^2 = \sum_{i=0}^{L(s)-1}\left(x_{k-L(s)+2} - s_i\right)^2 \tag{2}$$

Simplifying the equation (2) and omitting the constant term $\sum_{i=0}^{L(s)-1} s_i^2$ yields in the output signal

$$y_k = \sum_{i=0}^{L(s)-1} x_{k-L(s)+1+i}\,s_i - \frac{1}{2}\sum_{i=0}^{L(s)-1} x_{k-L(s)+1+i}^2 \tag{3}$$

This so called euclid filter was also applied on the EEG signal with normalised peak-to-peak voltages of each possible K-complex.

It is clearly visible, that the first term of the equation (3) can be computed as a FIR filter with its impulse response identical to the time-reversed vector $\mathbf{s}$. The more the vectors $\mathbf{x}_k$ and $\mathbf{s}$ are similar, the lower output values of y_k is obtained.

2.3 Cosine nonlinear matched filter

The third and the last modification of the classical matched filter, that was tested, was cosine filter. This nonlinear filter evaluates the angle in the signal space (or its cosine) between vector $\mathbf{x}_k$ and the template $\mathbf{s}$:

$$\cos(\varphi) = \frac{\mathbf{x}_k \cdot \mathbf{s}}{\left\|\mathbf{x}_k\right\|\,\left\|\mathbf{s}\right\|} \tag{4}$$

The cosine function is monotonous in the employed interval [5]. Solving the eq. (4) for φ and omitting the factor ||s|| we get

$$y_k = \frac{\sum_{i=0}^{L(s)-1} x_{k-L(s)+i+1}\,s_i}{\sqrt{\sum_{i=0}^{L(s)-1} x_{k-L(s)+i+1}^2}} \tag{5}$$

The templates for the matched filters were chosen from an averaged K-complex - Fig. 3 (average of 200 K-complexes). The template was then resampled in order to get different lengths of templates that could cover the variable length of all the K-complexes to be detected.

All the three matched filters were used in non-continuous operating mode. I.e. a simple pre-selection

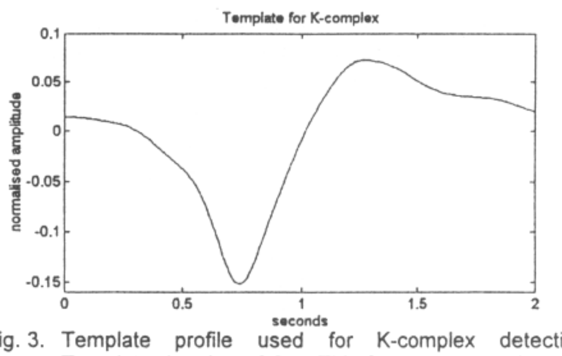

Fig. 3. Template profile used for K-complex detection. Template duration of 2 s. This form corresponds to an approximation of a K-complex profile (bipolar morphology).

algorithm, partly based on the K-complex definition, marked possible K-complexes, and after applying the peak-to-peak voltage criteria, the matched filters were used to reject false detections. The output signal y of the matched filters contained several peaks. Fortunately, the peak corresponding to the detected K-complex has always its stable position within the output vector y. That is why the thresholding logic searched for the peak output only in a certain interval within the output vector y. It enabled us to set lower thresholds values and lead to an increased detection sensitivity.

3. Results

Three computer-based detectors were designed (Fig. 2), capable of detecting the K-complexes in human sleep EEG signal. The detectors are distinct in their fundamental block, i.e. the matched filter. The first filter is based on a classical linear covariance filter, whereas the two others make use of the nonlinear matched filters. The second and the third contain the euclid and the cosine nonlinear matched filter respectively.

The detectors were tested on a sleep EEG taken from different subjects. The signal (ca. 200 minutes, sampling frequency 128 Hz) was visually scored by an expert, who found 304 K-complexes in the recording. That value is taken as true positives (TP). Table 1 shows the number of K-complexes found by each detector, the number of missed patterns in the recording (false negatives, FN) and the number of false detections (false positives, FP).

All three detectors can recognize all clear and unambiguous patterns. The differences among detectors encountered only when detecting more or less unusual shapes. The euclid detector performed well on all patterns except for higher-voltage ones. This can be probably due to smaller similarity of the pattern and the middle-voltage (averaged) template.

Assuming the covariance filter as a standard detector, we can say, that the euclid matched filter produced a twice as high number of both false positive and false negative detections. Primarily due to the number of false positives (approx. 10% of all K-complexes) the detector is inaccurate for being used as a trigger for event-related averaging. Whilst the cosine detector produced a half-number of false positive and false negative detections comparing with the covariance filter. The number of missed patterns (FN) is 28 and the number of false positive detetections is only 4 of 304 K-complexes in the recording. Those results rank the cosine detector to the most reliable that has ever been designed.

Tab. 1. Comparison of the detectors' efficiency.

Detector	Patterns detected by an expert (TP)	Found by detector	Missed by detector (FN)	False detection by detector (FP)
Covariance	304	257	63	16
Euclid	304	216	120	32
Cosine	304	280	28	4

4. Discussion

The detectors are used to mark events for event-related averaging of other biosignals. For that purpose a detector with the lowest number of false positive detections should be used; i.e. the cosine detector can be successfully used, as it gives only negligible number (1.3%) of false positive detections.

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