EEG Sleep Spindles Identification Using Empirical Mode Decomposition and Morphological Operations

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Abstract – **In this paper we present an approach for sleep spindles identification in human EEG. This approach is planned to be involved in a new automatic system for assessment of sleep staging. The sleep spindles are extracted from the EEG background using EMD and their envelope is found with morphological filtering. The main decision stage is based on adaptive thresholding. The proposed approach is validated and evaluated with real EEG signals.**

Keywords – **EEG, Sleep spindle, Empirical Mode Decomposition, Sleep staging.**

I. Introduction

The sleep spindles are specific transient activities in the human electroencephalogram (EEG) which occur mainly in sleep stage 2 in Non-Rapid Eye Movement (NREM) sleep [1]. Their presence in the signal is one of very few features used for recognition of sleep stage 2 [2]. The sleep spindles occupy the frequency region from 12 to 15Hz. In most cases they appear in consequence with k-complexes as a single burst (Fig. 1) or as a burst train. Their positive and negative envelopes are relatively symmetrical, but there is a large variety of possible morphologies. Nevertheless, most of the researchers consider waxing and waning trends in the oscillations [1].

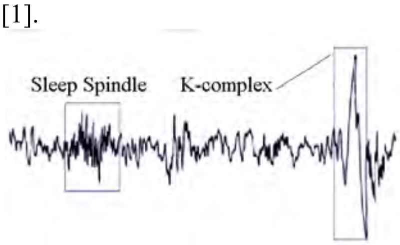

Fig. 1. A typical sleep spindle and a k-complex seen in sleep stage 2

The most common approach for sleep spindles identification is preprocessing with band-pass filter [3]. Some authors use the wavelet decomposition-reconstruction as a key stage for uncovering the sleep spindles from background activity [4]. The suggested approach is simple and probably fast, but we believe that the frequency band from 8-16Hz is too wide for this purpose.

In this paper we describe a new approach combining the Empirical Mode Decomposition (EMD) for sleep spindles uncovering and morphological filtering for envelope detection. The potential of this approach is the possibility for precise detection of onsets and offsets of the wanted transients. Also the simplified envelope is very convenient for extraction of some other kind of features for achieving a better recognition rate.

In section II is described the used methodology. In section III is summarized the achieved experimental results. Section IV concludes the work and some directions for future researches are given.

II. Methodology

A. The Complete Procedure

A simplified diagram of the complete approach is shown in Fig. 2.

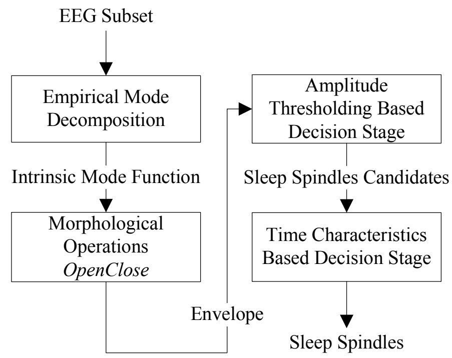

Fig. 2. The complete procedure for sleep spindles identification

The procedure utilizes EMD for background filtering, morphological operations for envelope detection and two cascaded decision stages. In the following sections each step is described in detail.

B. Empirical Mode Decomposition

The EMD is a powerful tool for analysis of non-stationary and nonlinear time series [5]. It overcomes the inefficiency of the Short-Time Fourier Transform (STFT) or wavelet transform in terms of combined time-frequency resolution and non-adaptive levels of time/frequency scales respectively. The EMD decomposes the signal into superposition of components called Intrinsic Mode Functions (IMF) with well defined

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instantaneous frequency. An IMF has two properties: the number of extrema and the number of zero crossing are equal or differ by one in the whole data set; at any point the mean of envelopes defined by the local minima and maxima is zero. The procedure of finding an IMF is iterative. It consists of: identifying the extrema of the signal $x(t)$; generating the envelopes with a cubic spline [6]; determination of the local mean μ_1. The process repeats (1) until the first IMF candidate h_1 satisfies the mentioned above properties.

$$x(t)-\mu_1 = h_1 . \tag{1}$$

After k iterations the first component $c_1 = h_{1k}$ represents the finest oscillations in the signal. The complete set of the residues r_n are calculated according to:

$$r_n = c_n - r_{n-1}, ..., r_2 = c_2 - r_1 , \tag{2}$$

where $r_1 = x(t) - c_1$. Finally the signal is decomposed as follows:

$$x(t) = \sum_{i=1}^{n} c_i + r_n . \tag{3}$$

In this paper we use h_1 as a component containing mostly the wanted sleep spindles.

C. Morphological Operations

The basic idea behind the mathematical morphology is an interaction of the signal with another simple pre-defined shape called structuring element. For extracting the sleep spindles we use the following morphological operations [7]:

$$OpenClose(h_1) = Open(Close(h_1, g), g), \tag{4}$$

where g is a flat structuring element of type disk with radius of 7. The type and the parameters of g are chosen experimentally considering signals sampled at 128Hz rate.

D. Decision Stages

In the first decision stage we perform an amplitude thresholding for finding the sleep spindles candidates. For each signal subset with 20s duration a proper threshold is selected using the triangle method over the histogram. Although not optimal, the method performs well in this application. The second decision stage discards or merges the input candidates according to time parameters of a single sleep spindle or sleep spindles train [1].

III. Experimental results and discussion

The proposed approach has been tested and evaluated with the “The Sleep-EDF Database” provided by PhysioNet [8], [9]. In Fig. 3 is shown an example of successfully identified sleep spindles. In the same figure the result of the proposed approach is compared with band-pass filtered EEG with zero-phase filter. Also the Hilbert envelope is given and its detected extrema. It can be seen that the EMD assures better sleep spindles discrimination from the background level.

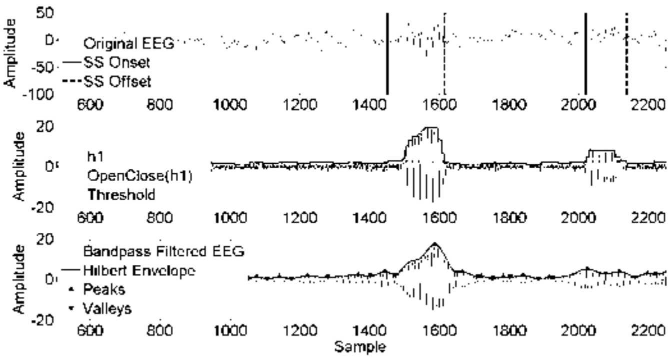

Fig. 3. A sample of EEG containing two successfully identified sleep spindles and its boundaries (first graph) according to proposed approach (second graph). A comparison with high pass filtering and Hilbert envelope is also given (third graph)

From the database we selected EEG signals from four subjects. After that we extracted the subsets marked as sleep stage 2. The sleep spindles onsets and offsets were manually annotated by an expert. For evaluation of the approach we use the standard criteria for binary classification performance: sensitivity Se and specificity Sp. Also we investigated the relative errors of the detected onsets and offsets of the sleep spindles according to:

$$e_{on,i} = \frac{\hat{s}_{on,i} - s_{on,i}}{s_{on,i} - s_{off,i}} \times 100\%, s_{on,i} > s_{off,i} \tag{5}$$

and

$$e_{off,i} = \frac{\hat{s}_{off,i} - s_{off,i}}{s_{on,i} - s_{off,i}} \times 100\%, s_{on,i} > s_{off,i} , \tag{6}$$

where $s_{on,i}$ is the expert annotated onset, $s_{off,i}$ is the expert annotated offset, $\hat{s}_{on,i}$ is the detected onset, $\hat{s}_{off,i}$ is the detected offset by the algorithm and i is the number of the detected sleep spindle. We achieved Se of 84.7% and Sp of 79.3 %. The mean value of the relative onset errors $\mu(\mathbf{e}_{on})$ is 7.8 % with standard deviation $\sigma(\mathbf{e}_{on})$= 10.2%. The mean value of the relative offset errors $\mu(\mathbf{e}_{off})$ is 9.4 % with standard deviation $\sigma(\mathbf{e}_{off})$=14.4%.

We performed a limited test of the proposed approach with EEG signals with dominant alpha waves. The experiments showed the necessity of some future improvements in order to use the type of the background activity as additional input of the algorithm.

IV. Conclusion

In this paper we presented an approach for sleep spindles identification in EEG. Its purpose is to be a key part into a multimodal system for automated sleep staging. The approach performs well in binary classification test and gives satisfactory results in terms of achieved errors of the sleep spindles boundaries detection. The future work will be concentrated on development of better classification stage with probabilistic output in order to exploit the statistical dependency between occurrence of sleep spindles and k-complexes in sleep stage 2.

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