A Wavelet Based Approach for K-complexes Identification for Automated EEG Sleep Staging

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Abstract – **In this paper we present an approach for k-complexes identification in human EEG. This algorithm is intended to be a key part in a new automatic system for assessment of sleep staging. The features extraction is based on discrete wavelet decomposition and reconstruction, amplitude and time parameters and histogram analysis as well. The classifier is properly trained ANN. The experimental results show satisfactory results considering the single channel processing.**

Keywords – **EEG, K-complex, Sleep staging.**

I. Introduction

According to [1] the sleep process can be divided into several relatively distinctive stages grouped into two main types: Rapid Eye Movement (REM) and Non-Rapid Eye Movement (NREM). NREM sleep itself consists of three or four stages, during which the muscles are not paralyzed and the dreaming occurs rarely. Determination of duration of such stages and their consequence in time is crucial for sleep quality assessment. The sleep stages more or less impact some characteristics of the well known physiological signals such as encephalogram (EEG), electromyogram (EMG), electrooculogram (EOG), electrocardiogram (ECG), etc. [2]. Taking into account the publications covering this area the EEG and EOG are considered as the most significant physiological signals for automatic sleep staging.

The normal human EEG consists of background and transient activity (k-complexes, sleep spindles, vertex sharp waves, etc.). These activities both depend on sleep process, but this paper is concentrated on development of algorithms for identification of k-complexes. The presence of k-complexes and sleep spindles in EEG is the most reliable feature to distinguish stage 2 in NREM sleep [3].

A complete system for automated sleep staging should rely on the following EEG features: spectral characteristics of the signal over time; spatial origin of signal components; presence of certain kinds of transient activity. Some results of the researches in EEG analysis for sleep staging can be found in [4], [5]. Despite of these successful works, the necessity of development of new effective and fast algorithms for EEG transient activity recognition and classification is undoubted.

The remainder of the paper is organized as follows: in section II we describe the used methodology for k-complexes identification; in section III some experimental results and a brief discussion on them are given; section IV concludes the work and some aspects for future investigations and possible improvements of the approach are mentioned.

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II. Methodology

A. The Complete Procedure

A simplified diagram of the complete approach is shown in Fig. 1.

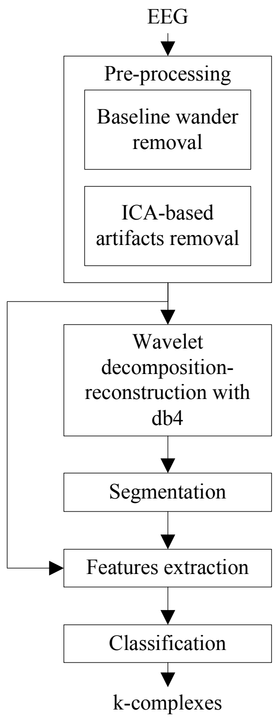

Fig. 1. The complete procedure for k-complexes identification

We realized the classification stage in two ways: a simple thresholding over the set of features or using an Artificial Neural Network (ANN).

B. EEG Signal Pre-processing

The first procedure of the EEG pre-processing is to remove the baseline wander. We implemented it as wavelet decomposition and reconstruction from all levels excepting approximation coefficients, thus reducing all frequency contents below 0.5Hz. The second procedure is to exploit the well known Independent Component Analysis (ICA) in order to select an independent component which is free of interference with EOG origin.

C. Features Extraction

We use the discrete wavelet decomposition and reconstruction from A5 level in order to suppress the unwanted frequency components in the processed EEG signal. We consider that the k-complexes occupy the frequency region from 0.5Hz to 4Hz. The decomposition-reconstruction procedure can be seen in Fig 2. The input signal is re-sampled at 128Hz sample rate. The used wavelet function is Daubechies 4.

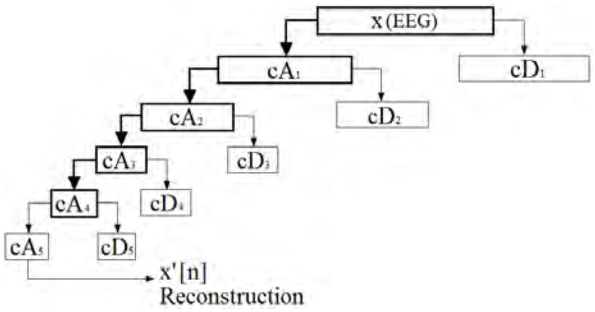

Fig. 2. The wavelet decomposition-reconstruction procedure for k-complexes identification

The typical k-complex is described as a relatively large usually biphasic wave with duration of more than 0.5s (Fig. 3). It has a relatively steep negative deflection followed immediately by a slower decaying positive component. In our segmentation stage we use the zero crossing criteria of $x'[n]$ for onset and offset detection of the k-complex candidate and the border between its negative and positive component as well.

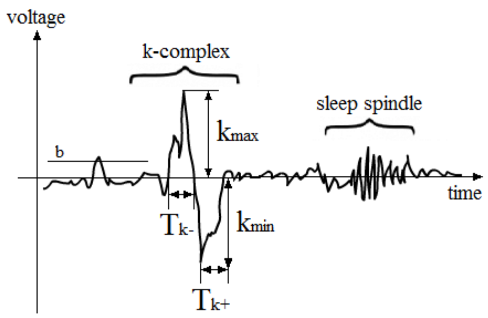

Fig. 3. A typical k-complex waveform and used features for its identification

The used features can be seen also in Fig. 3. They are closely based on characteristics of the k-complexes suggested in [1]. The amplitude features are related to the background activity preceding the potential k-complex. The background activity b is expressed as:

$$b = w \max_i (h_i), i = 1,...,N, \quad (1)$$

where h_i is an element of the vector $\mathbf{h} = [h_1, h_2, ..., h_N]$ representing the histogram of the local maxima of the $x'[n]$ and w is the histogram bin width. The histogram analysis is performed on the subset from $x'[n]$ taken 10s before every k-complex candidate.

When using an ANN as classifier for k-complexes identification the input feature vector for training and testing is composed as follows:

$$\mathbf{f} = [T_{k-}, T_{k+}, k_{\max}, k_{\min}, b]^T. \quad (2)$$

As an alternative a much simple approach for k-complexes identification is to apply some thresholds over the set of used features. For rejection a signal subset candidate as k-complex one of the following criteria must be satisfied:

$$T_{k-} + T_{k+} < 0.5s \quad (3)$$

or

$$T_{k-} > T_{k+} \quad (4)$$

or

$$|k_{\max}| < |2k_{\min}| \quad (5)$$

or

$$|k_{\min}| < |2k_{\max}| \quad (6)$$

or

$$|k_{\max}| + |k_{\min}| < 2b. \quad (7)$$

D. Classification

The used classifier is a neural network of type Multilayer Perceptron (MLP) with sigmoidal activation function and two hidden layers [6]. The number of layers is chosen experimentally by finding the minimum number of hidden layers at which the achieved Mean Squared Error (MSE) in the training process remains relatively unchanged.

III. Experimental Results and Discussion

The suggested approaches were tested and evaluated with the “The Sleep-EDF Database” provided by PhysioNet [8], [9]. In Fig. 4 can be seen an example of successfully identified k-complex in the file st7052j0.rec taken from the mentioned database.

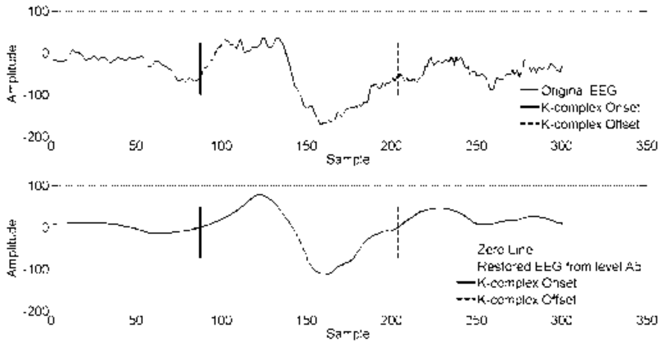

Fig. 4. A sample of EEG containing one successfully identified k-complex and its boundaries. Original EEG (above) and restored EEG from level A5 (below)

According to the attached hypnograms we selected train and test subsets taken only from stage 2 in NREM sleep. In the used databases there are no available annotations for presence of k-complexes and its onsets and offsets, so the selected signals were manually annotated by an expert. For evaluation of the approach we use the sensitivity *Se* and specificity *Sp* as criteria for binary classification quality. The achieved *Se* and *Sp* for k-complexes identification are summarized in Table I.

TABLE I
SENSITIVITY AND SPECIFICITY OF K-COMPLEXES IDENTIFICATION

Classification method	*Se* , %	*Sp* , %
Thresholding	82.4	76.6
ANN-MLP	84.7	79.1

Additionally we performed a limited test of the proposed approach with EEG signals representing different sleep stages. Carrying out the experimental investigations the following imperfections have been observed: there is a significant prone for misclassification between k-complexes and some artefacts in EEG; the k-complexes are extremely hard to be distinguished from dominant delta waves in EEG.

For future improvement of the approach for k-complexes identification it is desirable to add some other features. These features have to describe more accurately the morphology of the different kinds of k-complexes. The k-complexes should be identified in the context of surrounding background wave patterns of EEG.

IV. CONCLUSION

In this paper we presented an approach for identification of k-complexes in EEG. The experimental results prove the correct work of the algorithm and give the possibility to implement it as a part in new sophisticated systems for automatic sleep staging. Apparently there is an evidence of significant correlation between the occurrence of k-complexes and sleep spindles in sleep stage 2. This dependency has to be exploited in our future work for increasing the robustness of the detection.

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