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Convex optimisation-based methods for K-complex detection

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ABSTRACT

K-complex is a special type of electroencephalogram (EEG, brain activity) waveform that is used in sleep stage scoring. An automated detection of K-complexes is a desirable component of sleep stage monitoring. This automation is difficult due to the ambiguity of the scoring rules, complexity and extreme size of data. We develop three convex optimisation models that extract key features of EEG signals. These features are essential for detecting K-complexes. Our models are based on approximation of the original signals by sine functions with piecewise polynomial amplitudes. Then, the parameters of the corresponding approximations (rather than raw data) are used to detect the presence of K-complexes. The proposed approach significantly reduces the dimension of the classification problem (by extracting essential features) and the computational time while the classification accuracy is improved in most cases. Numerical results show that these models are efficient for detecting K-complexes.

1. Introduction

Currently in the world there is an alarming number of people suffering from sleep disorders. The diagnosis of such disorders is performed in a test called polysomnogram (PSG). PSG studies a series of biomedical signals such as brain activity (EEG), muscle movements (EMG), heart beat (ECG) and eye movement (EOG) for diagnosis of sleep disorders. The analysis of an EEG, in particular, the sleep stages identification (scoring), is an active research area in biomedical signal processing.

In manual scoring, medical doctors look for specific patterns (sleep events) based on specially developed scoring rules [1]. Then, one of the sleep stages (awake, sleep stage 1, 2, 3 or REM) is assigned to each signal segment of an EEG (called epoch, normally lasts 30 seconds). This is a time consuming task. Therefore, an accurate method for automation of manual scoring is desirable. We are focusing on an automatic detection of K-complexes that are essential waveforms for distinguishing between sleep stage 1 and sleep stage 2 of an EEG signal.

There have been several attempts to address this issue. Most approaches are based on artificial neural network [2], wavelet transforms [3] and an electronic system using filters and threshold detectors [4]. However, medical practitioners still report that the accuracy of K-complex detection is not satisfactory [1,5]. Therefore, an accurate method for automatic detection of K-complexes is very desirable. This automation would reduce the number of manual tasks significantly, thereby making the process more reliable and cost efficient.

We develop and test three convex optimisation-based models for automatic detection of K-complexes. In these models, we approximate the original signal (EEG) by a sinusoidal curve with the amplitude approximated by a piecewise polynomial

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function. Then, the parameters (key features) of the approximations (rather than original signals) are used to detect the segments with K-complexes.

This paper is organised as follows. An overview of sleep stage scoring approaches and their automation is given in Section 2. Section 3 presents our newly developed models for K-complex detection based on the convex optimisation to extract key features of a signal. The results of the numerical experiments are presented in Section 4. Section 5 provides the conclusions and identifies our further research directions.

2. Sleep scoring and possible automations for K-complexes detection

The usual method for sleep stage identification is visual (manual) inspection of an EEG signal by a medical doctor. The sleep stage scoring is based on the standardized scoring Rechtschafen and Kales (R&K) rules [6]. One of the major deficiencies of these rules is arbitrarily defined thresholds for sleep stage identification. This can lead to unreliable results and poor agreement between scorers.

Recently, the American Academy of Sleep Medicine (AASM) [1] developed an updated set of rules to identify sleep stages. There are two main purposes for these changes. First of all, the new rules are simpler and easier to apply; and therefore, a higher level of agreement between different manual scorers can be achieved. Second, the updated rules are more straightforward to automate.

Human (adult) sleep consists of two main parts: Rapid Eye Movement (REM) sleep and Non-REM (NREM) sleep. Typically, patients begin the sleep cycle with a period of NREM sleep followed by a very short period of REM sleep. The AASM divides NREM into three further stages [1].

- NREM stage 1 is the transition from waking to sleep.
- NREM stage 2 is signaled by K-complexes in the EEG.
- NREM stage 3 is called Slow-Wave-Sleep (SWS), deep sleep or delta sleep.

After NREM stage 3, the patient returns to NREM stage 2 and then enters REM stage.

Reliable detection of K-complexes in an EEG signal is essential for sleep stage scoring since they constitute one of the main markers of the transition from NREM stage 1 to NREM stage 2. K-complexes consist of an initial small negative, somewhat sharp wave, followed by a large positive wave. This definition has been established by medical practitioners in [6]. Informally, this means that the amplitude increases abruptly and then, returns back to the original value. Since EEG signals are non-linear, non-stationary and not repeatable, K-complexes have a wide variety of shapes and are difficult to distinguish from other EEG waves. There have been two studies that are also based on approximation.

First, in [7] the authors suggested to extract essential signal features via signal approximation by a sine wave with a piecewise polynomial (polynomial spline) amplitude. The variables of the corresponding optimisation problems were the spline (amplitude) parameters, frequency and phase. This approach enables the doctors to enhance the classification accuracy, however the computational time was not satisfactory due to the complexity of the model.

Second, in [8] the authors proposed a slightly different approach. The signal is approximated by a sine wave with a piecewise polynomial amplitude, but the corresponding frequency and shift were constants and they formed a fine grid. For each combination of frequency and shift values, the only function they needed to optimise was the amplitude. The authors were solving a sequence of convex (linear least squares) optimisation problems. It appeared that this approach is much faster than the one in [7] and the corresponding classification accuracy is high.

We propose three new convex optimisation-based models for the automatic detection of K-complexes and then, compare them with each other and with the one developed in [8]. Our procedure consists of two major steps.

- First, we extract key features of an EEG signal and reduce the dimension of the data. This procedure is based on optimisation.
- Second, we apply classification algorithms to evaluate the classification accuracy of an EEG signal in presence of K-complex.

There are two main contributions of this work.

1. The development of approximation models that are
   - simple and computationally inexpensive;
   - accurate enough to achieve a high level of classification accuracy.
2. The implementation and comparison of the proposed models, in particular, their classification accuracy and the corresponding computational time.

3. Extracting key features through approximation and convex optimisation

3.1. Feature extraction through optimisation

Many signals can be modelled as sine waves $A(t)\sin(\omega(t)\,t+\tau(t))$, where $A(t)$ is the amplitude, $\omega(t)$ is the frequency and $\tau(t)$ is the shift (phase). Consider the following problem:

$$\min_{A,\omega,\tau}\sum_{i=1}^{N}\{y_i-A(t_i)\sin[\omega(t_i)\,t_i+\tau(t_i)]\}^2, \tag{1}$$