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Multichannel sleep spindle detection using sparse low-rank optimization

Ankit Parekh[a,*,1], Ivan W. Selesnick[b], Ricardo S. Osorio[c], Andrew W. Varga[d], David M. Rapoport[d], Indu Ayappa[d]

[a] Dept. of Electrical and Computer Engineering, College of Engineering, University of Iowa, United States
[b] Dept. of Electrical and Computer Engineering, Tandon School of Engineering, New York University, United States
[c] Center for Brain Health, Department of Psychiatry, School of Medicine, New York University, United States
[d] Division of Pulmonary, Critical Care and Sleep Medicine, Icahn School of Medicine at Mount Sinai, United States

HIGHLIGHTS

- Proposed method aims to detects global and local spindle activity in human sleep EEG.
- Sparsity-aware convex optimization is used to separate transients from oscillations.
- Performance of proposed method is illustrated on 2 publicly available datasets.
- Global spindle detection across 6 channels of overnight sleep EEG takes about 4 min.

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ABSTRACT

Background: Automated single-channel spindle detectors, for human sleep EEG, are blind to the presence of spindles in other recorded channels unlike visual annotation by a human expert.
New method: We propose a multichannel spindle detection method that aims to detect global and local spindle activity in human sleep EEG. Using a non-linear signal model, which assumes the input EEG to be the sum of a transient and an oscillatory component, we propose a multichannel transient separation algorithm. Consecutive overlapping blocks of the multichannel oscillatory component are assumed to be low-rank whereas the transient component is assumed to be piecewise constant with a zero baseline. The estimated oscillatory component is used in conjunction with a bandpass filter and the Teager operator for detecting sleep spindles.
Results and comparison with other methods: The proposed method is applied to two publicly available databases and compared with 7 existing single-channel automated detectors. F_1 scores for the proposed spindle detection method averaged 0.66 (0.02) and 0.62 (0.06) for the two databases, respectively. For an overnight 6 channel EEG signal, the proposed algorithm takes about 4 min to detect sleep spindles simultaneously across all channels with a single setting of corresponding algorithmic parameters.
Conclusions: The proposed method attempts to mimic and utilize, for better spindle detection, a particular human expert behavior where the decision to mark a spindle event may be subconsciously influenced by the presence of a spindle in EEG channels other than the central channel visible on a digital screen.

1. Introduction

Sleep spindles are short rhythmic oscillations visible on an electroencephalograph (EEG) during non-rapid eye movement (NREM) sleep. The center frequency of sleep spindles is between 11 and 16 Hz (Silber et al., 2007). The duration of sleep spindles is defined to be at least 0.5 s, with some studies imposing an upper limit on their duration to 3 s (Warby et al., 2014). Sleep spindles reflect a heritable set of traits which is implicated in both sleep regulation and normal cognitive functioning (Manoach et al., 2016). Recent studies have linked spindle density (number of spindles per minute), duration, amplitude and peak frequency of spindles to memory consolidation during sleep (Fogel and Smith, 2011; Clawson et al., 2016), cognition in schizophrenia patients (Manoach et al., 2016; Wamsley et al., 2012), brain dysfunction in obstructive sleep apnea (Carvalho et al., 2014) and biomarkers for Alzheimer's disease (Wohlleber et al.,

* Corresponding author.
E-mail address: ankit-parekh@uiowa.edu (A. Parekh).
[1] Source Code available at https://github.com/aparek/mcsleep.git.

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0165-0270/

2016). As a result, understanding the characteristics of sleep spindles is key in studying their relation to several neuropsychiatric diseases.

Traditionally, sleep spindles are annotated in clinics using visual heuristics: number of peaks or bumps of the EEG signal are counted within a specified time window. Not only is this process subjective and time-consuming, but it is also prone to errors. Moreover, visual inspection underscores the fine details of putated spindles (Purcell et al., 2016). In order to reduce the subjectivity of visual detection, it is not uncommon for studies to utilize more than one expert for detecting spindles. However, in several cases this leads to a high variability in inter-scorer agreement. The Cohen's κ coefficient for inter-rater agreement in manual scoring usually ranges between 0.46 and 0.89 (Stepnowsky et al., 2013; Nonclercq et al., 2013). As such, the presence of reliable automated spindle detectors may not only reduce the scoring variability (Younes et al., 2016; Younes, 2017) but may also aid in complex longitudinal studies that involve studying global or local sleep spindle dynamics (Purcell et al., 2016; De Souza et al., 2016; O'Reilly and Nielsen, 2014).

Broadly categorized, there exist two-types of automated sleep spindle detectors for single channel EEG: filtering based and non-linear signal decomposition based. Filtering based approaches vary from basic methods, which utilize a bandpass filter with constant or adaptive thresholds, to advanced methods that use time-frequency information along with bandpass filtering. Most of the filtering based methods involve pre-processing of the desired channel of the EEG (usually a central channel) for artifact removal (Jaleel et al., 2014). One of the first automated detectors to be proposed used a bandpass filter in conjunction with an amplitude threshold (Schimicek et al., 1994). This idea is still the basis of a majority of the bandpass filtering-based automated detectors (Wendt et al., 2012; Devuyst et al., 2006; Martin et al., 2013; Ferrarelli et al., 2007; Clemens et al., 2007; Gais et al., 2002). Advanced methods utilizing time-frequency information either use a wavelet transform (Lajnef et al., 2015; Adamczyk et al., 2015; Andrillon and Yuv, 2011; Erdamar et al., 2012; Tsanas and Clifford, 2015; Ahmed et al., 2009) or a short-time Fourier transform (STFT) (Costa et al., 2012; O'Reilly et al., 2015; Devuyst et al., 2011) with adaptive thresholding to detect spindles. Several machine-learning based spindle detectors and sleep staging algorithms have also been proposed for single channel EEG (Acir, 2005; Gorur et al., 2002).

Non-linear signal decomposition based methods (Parekh et al., 2014, 2015; Lajnef et al., 2015; Durka and Blinowska, 1996) attempt to separate the non-rhythmic transients or artifacts from sinusoidal spindle-like oscillations in the single channel sleep EEG. These methods make use of the differing morphological aspects (Starck et al., 2005) of the transients and spindles to overcome the drawbacks of filtering and Fast Fourier Transform (FFT) based techniques (Ray et al., 2015). As an another example, Gilles et al. considered the removal of ballistocardiogram (BCG) artifacts from EEG using low-rank and sparse decomposition (Gilles et al., 2014). In addition to these morphological component analysis (MCA) based methods, independent component analysis (ICA) and principal component analysis (PCA) have also been used to detect spindles for single channel EEG (Babadi et al., 2012). However, note that ICA assumes linearity and stability of the mixing process along with statistical independence of input sources (Durka et al., 2005).

1.1. Motivation

Automated spindle detectors that consider only a single channel are blind to the presence of spindles in other recorded channels. Such a spindle detection mechanism may not be in concordance with the way spindles are annotated visually. The American Academy of Sleep Medicine (AASM) manual recommends using F4, C4 and O2 channels (or alternatively Fz, Cz and C4) of the recorded EEG with F3, C3 and O1 as backup channels (Silber et al., 2007) for scoring of sleep and associated events. As such, while annotating sleep events, such as spindles, rarely does an expert view a single channel of the EEG in isolation to the other channels. This is certainly the case for studies either looking to characterize individual global sleep spindle density (Bódizs et al., 2017) or tracking the propagation of spindles overnight (Purcell et al., 2016; Coppieters et al., 2016). As a result, it may be possible that the presence of spindles in channels other than the channel of interest subliminally influences the experts' decision of marking an event as a spindle.

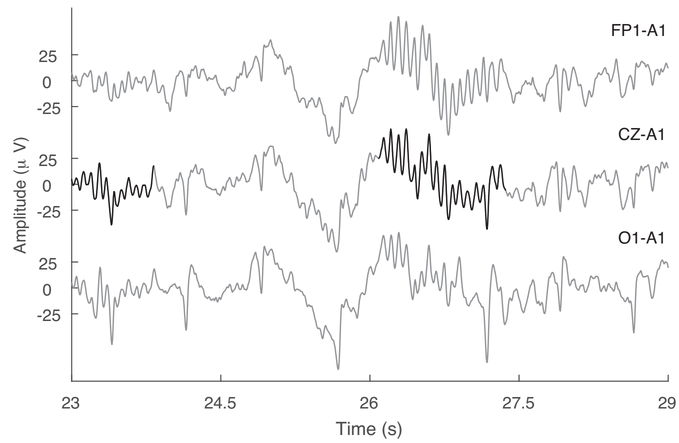

Fig. 1. An example of a 3 channel scalp EEG from DREAMS (Devuyst et al., 2010) database. Experts annotated two spindles (shown in bold) in the 6 s excerpt using the central channel. The annotated spindle at 26 s has different amplitude in different channels.

As an example, consider the 3-channel EEG shown in Fig. 1. The experts visually annotated the presence of a spindle at approx. 26 s. While it is suggested that only the central channel was used for annotating spindles (Devuyst et al., 2006), it can be seen that the spindle at approx. 26 s is also present in the frontal and the occipital channels, though with different amplitudes. As such it is highly likely that the decision by a human to mark the presence of a spindle at approx. 26 s in the central channel is reinforced by its presence in other channels if they are viewed together on a digital screen. Similar behavior can be seen in the case of the EEG excerpt in Fig. 2 where the experts annotated a spindle at approx. 29.5 s. While the degree to which the decision of marking a spindle was influenced by its presence in other channels (if it occurred simultaneously in more than one channel) is an open question out of the scope of this paper, utilizing it can certainly aid in a better design of the automated spindle detectors.

Another motivation for considering multichannel EEG for studying spindle activity comes from the fact that while single channel detectors may be used to study global spindle activity, their usage comes at a price. Since the amplitude of spindles vary in each channel (see for example Fig. 1), amplitude-based thresholds used by automated detectors need to be tuned separately for each channel, adding to the overall computational complexity. Additionally, the CPU time is multiplied by the number of channels recorded. While this additional computing time may not be significant for the case of basic filtering-with-thresholding methods, it is certainly significant for advanced methods that utilize either time-frequency information or non-linear signal decomposition.

Classifying spindles as either global (occurring across all channels) or local (occurring across a single or group of channels) (Clawson et al., 2016; Brunton et al., 2016) is difficult using single channel based methods. Spindles that appear on the right channels (F4, C4, and O2 channels in Fig. 2) may be entirely missed by detectors using the left channels (F3, C3 and O1) or vice-versa, which is the case with most detectors (Warby et al., 2014). In fact, most