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Automated drowsiness detection through wavelet packet analysis of a single EEG channel

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ABSTRACT

Advances in materials engineering, electronic circuits, sensors, signal processing and classification techniques have allowed computational systems to interpret biological quantities, recognizing physiological conditions. The next scientific challenge is to turn those technologies portable, wearable or even implantable, above all, being energy efficient. A prospective application for the next generation of portable electroencephalogram (EEG) signal processing systems is hazard prevention in attention-demanding activities. EEG keeps closest connection to the preoptic area where sleep is originated. In this paper, a methodology for assessing alertness level based on a single EEG channel (Pz–Oz) is proposed, allowing the reduction of the required hardware and the computational time of the algorithms, besides being more portable than multi-channel based ones. Two new spectral power-based indices (i) γ/δ and (ii) $(\gamma+\beta)/(\delta+\alpha)$ are computed from EEG rhythms through the normalized Haar discrete wavelet packet transform (WPT). The Haar WPT allows precisely resolving the brain rhythms into packets whilst demanding a relatively low computational cost. The effectiveness of the proposed indices in drowsiness detection is evaluated by comparison with five indices originally proposed for multi-channel processing. Statistical Wilcoxon signed rank test is applied to evaluate the performance of the entire set of indices, evidencing the significant changes in the alert-drowsy transitions of 20 subjects of a public database. The proposed indices (ii) and (i) presented the most and second more significant p-Values ($p < 0.001$ and $p = 0.001$), respectively.

1. Introduction

The way electronic systems interact with living organisms has evolved into a higher level, turning bio-data gathering less invasive, while promoting the development of new portable, wearable or even implantable technologies. Recent researches are employing them to enhance learning (Breteler, Arns, Peters, Giepmans, & Verhoeven, 2010), to explore brain-to-brain communication (Rao et al., 2014), to build brain-controlled prostheses (Raspopovic, Capogrosso, Petrini, Rigosa, Di Pino, et al., 2014) and health monitoring systems (Chi et al., 2010; Lara, PéRez, Labrador, & Posada, 2012), just to mention a few. One of the prospective brain-computer interface (BCI) application is warning systems for preventing fatigue caused accidents (Lin et al., 2010). Making implantable and wearable BCIs feasible requires energy efficient circuits and algorithms. This paper aims contributing to enhance the performance of drowsiness identification on a single-channel EEG as part of a more ambitious goal of designing low-power integrated circuit blocks for wearable and implantable BCIs.

The drowsy state is characterized by the decrease of the subject's information processing speed and memory capacities (Eoh, Chung, & Kim, 2005), occurring when one is about to fall asleep. The drowsy state may rise when a person is submitted to monotonous but attention-demanding activities (Jun, Makeig, Stensmo, & Sejnowski, 1997), which impairs his/her efficiency and performance in carrying out such tasks (Jap, Lal, Fischer, & Bekiaris, 2009). As argued in Lin et al. (2010), the drowsiness largely contributes for increasing the number of accidents. Examples of professionals under high risk include, but not restrict to, flight pilots (Hunn, 1993), air traffic controllers (Subasi, 2005) and lorry and regular drivers (Eoh et al., 2005; Subasi, 2005). Therefore procedures to avoid or prevent the drowsy state-in particular situations–are highly desirable.

Several methods to detect the drowsy state can be found in literature. They may consider a wide range of inputs, as facial

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movements (Aoi, Kamijo, & Yoshida, 2011; Gu, Ji, & Zhu, 2002), eyes closures (Tsuchida, Bhuiyan, & Oguri, 2009; Wierwille, Wreggit, Kirn, Ellsworth, & Fairbanks, 1994) and physiological signals as electromyogram (EMG) (Aoi et al., 2011), electrocardiogram (ECG) (Zhang & Liu, 2012), electrooculogram (EOG) (Chieh, Mustafa, Hussain, Hendi, & Majlis, 2005) and electroencephalogram (EEG) (Eoh et al., 2005; Jap et al., 2009; Subasi, 2005). However, as argued in Artaud et al. (1995) and mentioned in Jap et al. (2009), EEG signals contain the most reliable indicators of drowsiness and thus, by analyzing them, promising techniques can be developed.

It is well established in literature the existence of special frequency ranges of EEG signals (called rhythms) (Bear, Connors, & Paradiso, 2007). When measured on the scalp, those rhythms are faded expressions of the characteristic synchrony between populations of neurons that appear more or less intensely in each phase of the circadian cycle. Through analysis of short time intervals of the raw signal, labeled as epochs, it is possible to recognize the subjects' brain activities, described by the different rhythms. For example, the delta rhythm increases during high sleep (Jap et al., 2009) and also can indicate the need for sleep (Subasi, 2005). The theta activity gradually increases whilst the alpha rhythm decreases from the wakefulness to resting conditions (Kiymik, Akin, & Subasi, 2004). High and low activities in beta band are related to the alert and drowsy states, respectively (Eoh et al., 2005). Finally, the low-gamma is associated to the attention and working memory (Jia & Kohn, 2011) at the alert state.

Eoh et al. (2005) and Jap et al. (2009) employed these knowledge, proposing and analyzing indices based only on the power spectrum of brain activities. They have included the theta, alpha and beta rhythms in their studies, analyzing these rhythms' behavior and the relationship between them. Respectively, in their studies, 8 and 30 EEG channels were used to perform the experiments in driving simulation tasks. Albeit not stating explicitly, as Eoh et al. (2005) averaged all channels to compute rhythm energies and Jap et al. (2009) employed Analysis of Variance (ANOVA) to choose the electrodes containing significant variations, their results suggest drowsiness is detectable with fewer EEG inputs. Furthermore, the demand for methodologies based on fewer channels (Yu et al., 2013) has increased in the present decade because of the blooming of portable devices. Thanks to the increasing power and popularity of portable electronic systems, those like the one proposed in Lin et al. (2010) became an attractive option to process EEG and other physiological signals. According to Zhu, Li, and Wen (2014), multi-channel equipment limits the subjects' movements and are harder to use than single-channel devices. In this context, contrasting to the literature on the sleep stages scoring problem (Ebrahimi, Mikaeili, Estrada, & Nazaren, 2008; Fraiwan, Lweesy, Khasawneh, Wenz, & Dickhaus, 2012; Zhu et al., 2014), few studies have regarded this relevant requirement for drowsiness detection systems and methods (Lin et al., 2010; da Silveira, Kozakevicius, & Rodrigues, 2015).

Therefore the current study investigates a set of spectral power ratio indices initially designed for multi-channel EEG's, proposed in Eoh et al. (2005) and Jap et al. (2009), to be applied over the single-channel EEG context. Additionally, as main contributions, the designed simulations strongly indicate that the two new proposed ratio indices, based in low-gamma and delta rhythms (frequently discarded in related studies), can outperform results from previously proposed indices in the single-channel EEG context. When compared with multi-channel approaches, the proposed methodology also provides computational gains in terms of CPU time, as presented in Section 3.2.

Aiming to extract informations of the specific rhythms' frequency ranges, it is employed the normalized Haar wavelet packet (Daubechies, 1992). Wavelet transforms can efficiently analyze non-stationary signals evidencing their statistical properties (Subasi, 2005) while keeping temporal markings. Haar wavelet is chosen since there is no need to treat signal boundaries, which avoids possible distortions in transformed data. Moreover, the wavelet packet formulation provides a finer frequency decomposition than the cascade algorithm (Daubechies, 1992), allowing a better matching to brain rhythms.

As figure of merit, the significance of the proposed indices is compared to those in (Eoh et al., 2005; Jap et al., 2009) at the transitions between alert to drowsy states through the Wilcoxon signed-rank test (McDonald, 2014). This statistical tool allows the comparison of observations pairs from several subjects, aiming to discover if a significant change occurred between those two measurements (Walpole, Myers, Myers, & Ye, 2012). The choice of the Wilcoxon test, regarding to Student's *t*-test or ANOVA, is due to its acceptance of non-normal distribution of data (McDonald, 2014). Since the EEG signals are non-stationary (Subasi, 2005), it is not possible to guarantee their main behavior and, thus, Wilcoxon test is preferred for providing more accurate results.

The remainder of this paper unfolds as follows. Section 2 presents the description of considered data, explains the Haar wavelet packet transform and introduces two novel power ratio indices. Statistical and computational results as well as the respective discussions are addressed in Section 3. Finally, some remarks are exposed in Section 4.

2. Methodology

Relevant aspects of the employed data are introduced in the following subsection. Afterwards, the drowsiness detection algorithm is carefully described in the upcoming sections.

2.1. Data description

The experimental data used in this study were obtained from the public Sleep EDF [Expanded] database (Kemp, Zwinderman, Tuk, Kamphuisen, & Oberye, 2000), which is part of the Physionet Bank (Goldberger et al., 2000). The main advantage of using information from a public database is the possibility of testing, verifying and extending the proposed methodology by any research group interested in this subject. This database provides two night recordings from 20 healthy subjects.

The first night recording of all available[1] subjects, who stated not having any sleep-related medication while participating to the experiments, were used. The second night recordings, also available in the database, were discarded in this study in order to avoid possible subject-dependent patterns, which could interfere in the statistical analysis. These available recordings from the Physionet Bank refer to ten males and ten females subjects with ages between 25 and 34 years. They contain for each subject's recording two EEG channels, Fpz–Cz and Pz–Oz, sampled at 100 Hz besides EOG and EMG signals.

In the current study, the Pz–Oz channel is adopted, after Berthomier et al. (2007); Ronzhina, Janoušek, Kolářová, Honzik, and Provaznik (2012); Zhu et al. (2014) concluded this channel to be more accurate for scoring sleep stages. Furthermore, Pal et al. (2008) found that Oz location can provide discriminating power and have high correlation with the drowsiness state. Maglione et al. (2014) have found similar results, but considering EEGs from the parietal region.

In addition to being open accessible, which allows any researcher to repeat or compare results, the Physionet also provides hypnogram annotations in accordance to the Rechtschaffen and Kales (1969) (R&K) recommendations. They are written by sleep

[1] Available recordings in Physionet (2013) until April 9th 2015.