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Advanced daytime polysomnographic preprocessing: A versatile approach for stream-wise estimation

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ABSTRACT

The enhancement of monitoring biosignals plays a crucial role to thrive successfully computer-assisted diagnosis, ergo the deployment of outstanding approaches is an ongoing field of research demand. In the present article, a computational prototype for preprocessing short daytime polysomnographic (sdPSG) recordings based on advanced estimation techniques is introduced. The postulated model is capable of performing data segmentation, baseline correction, whitening, embedding artefacts removal and noise cancellation upon multivariate sdPSG data sets. The methodological framework includes Karhunen–Loève Transformation (KLT), Blind Source Separation with Second Order Statistics (BSS-SOS) and Wavelet Packet Transform (WPT) to attain low-order, time-to-diagnosis efficiency and modular autonomy. The data collected from 10 voluntary subjects were preprocessed by the model, in order to evaluate the withdrawal of noisy and artefactual activity from electroencephalographic (EEG) and electrooculographic (EOG) channels. The performance metrics are distinguished in qualitative (visual inspection) and quantitative manner, such as: Signal-to-Interference Ratio (SIR), Root Mean Square Error (RMSE) and Signal-to-Noise Ratio (SNR). The computational model demonstrated a complete artefact rejection in 80% of the preprocessed epochs, 4 to 8 dB for residual error and 12 to 30 dB in signal-to-noise gain after denoising trial. In comparison to previous approaches, N-way ANOVA tests were conducted to attest the prowess of the system in the improvement of electrophysiological signals to forthcoming processing and classification stages.

1. Introduction

In neuroscience, one of the most relevant fields of research concerns sleep as a pivotal state of consciousness. The regularisation of healthy sleeping patterns ensures physical and psychological recovery to cope with demanding tasks on a daily-based routine [1]. Although, sleep process is an intricate matter consisting of converging processes of different nature; the interpretation of their bioelectrical activity offers a valuable framework to decipher the structure and bodily relationships [2]. Thus, the polysomnogram (PSG) stands out as a technique for electrophysiological monitoring of sleep-related dynamics. Based on temporal and spatial capabilities, the PSG is a unique assisting tool for staging of sleep macrostructure and microstructure [3], as well as, diagnosis of sleep disorders [4]. Each PSG recording collects a set of biological signals from different sources; such as neuronal, ocular, muscular, cardiac, respiratory, body movement, etc. [5]. Those signals wait upon posterior application of feature extraction and classification mechanisms to deploy computer-aided systems to support clinical assessments.

Certainly, inspiring approaches have been formulated to improve the biosignals resolution, either to diminish artefactual effect or to shrink down noise disruption attending to the hectic variations. Hereafter, some meritorious models are elicited. The amalgamation of coloured noise and non-stationarity processes within the neuronal sources becomes distinguishable by signal extraction methods in [6]. However, the exclusive usage of simulated data in the evaluation of the algorithms restrains the possibility to assess the impact on actual clinical data. In correspondence, [7] suggests EEGLAB, a multi-purpose toolbox for processing electroencephalographic (EEG) recordings; including artefact rejection, filtering, epoch selection, etc. Although, the robustness of the estimation core is not debatable, the complexity of the related algorithms questions its efficiency with limited number of channels, samples or computational resources. On this direction, solutions founded on second-order-statistics (SOS) demonstrate sustainable error reduction over EEGLAB utilities. In one study [8], the artefact correction is applied to datasets with event-related potentials

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(ERP). Therefore, the adaptation of the methods to polysomnographic data could convey new findings with dissimilar electrical responses. An alternative approach is proposed by [9] making use of wavelet-based decomposition to remove artefacts of semi-simulated data with 7.5 seconds of time duration. These two aspects motivate the enquire about the suitability of sleep-related data to be tested through such a multi-resolution analysis. Respectively, [10,11] describe comparable methodologies to weaken electrocardiographic (ECG) artefacts and additive noise from EEG channels. The manifested exclusion of electrooculographic (EOG) and electromyographic (EMG) activity as potential artefacts generators keeps an open discussion when multivariate PSG data is deconstructed. Recently in [12], a novel tandem arrangement to cope with preprocessing and classification tasks sets out remarkable conclusions in terms of consecutive separation-denoising function blocks. In this sense, the present work deploys a model to improve integration, time-to-diagnosis and algorithmic versatility; subject to hundreds of PSG epochs.

Here, we introduce a short daytime PSG (sdPSG) preprocessing model as part of an ongoing initiative to provide computer-assisted resources related to sleep studies. Therefore, its development bears a well-structured roadmap, starting on preprocessing middleware towards supporting systems in sleep staging and diagnosis of disorders. The system tracks and suppresses external and embedding interferences that tantalise the achievement of performant scores in self-guided recognition and diagnosis. The usage of a statistical-oriented middleware instead of event-specific allocation incorporates a software-based package with purpose-specific. Besides, pseudo-online preprocessing, here denoted as streaming operation mode, pursues the avoidance of iterative and time-extended computational effort by streaming the bodily activity, as soon as it is sensed and digitally converted. In order to remove additive Gaussian noise and artefact-embedded activity, whilst neither reduction nor expansion transformation on the original data is addressed [13]. Furthermore, the computational methods aim to deal adequately with the highly complex characteristics of EEG waveforms; since non-stationarity and non-linearity assets make a major difference in contrast to its counterparts. Hereafter, the preprocessing middleware makes use of sophisticated techniques to refine EEG features over 1) subgaussian and slow time-varying EOG signals; 2) supergaussian, spiky and periodic ECG leads; and 3) high frequency EMG distributions. Once, the denoising and artefact rejection tasks are fully accomplished, sdPSG channels are sufficiently spanned to provide valuable information about sleep composition or associated abnormalities [14]. This condition is meant to be applied in subsequent processing and classification routines, expecting gainful aftermaths in comparison to current approaches [15]. According to this, the present paper attempts to reveal the intrinsic constituents of the preprocessing model under low-order and time-to-diagnosis efficiency constraints, which convey to a plausible streaming orientation with operational outcomes. In order to attest the performance degree, a complete experimental framework was prepared, regarding a testing cohort and measurable metrics from qualitative and quantitative perspectives, such as signal ratio and residual error.

The paper is organised as follows: Section 2 makes a detailed description of the active modules within the preprocessing approach; including conditions of experiments, test subjects and employed transformation/decomposition techniques. Then, Section 3 portrays the final arrangement of modules and parameters for experimental proceedings. Section 4 discusses the product of performance metrics applied to actual clinical data. Afterwards, Section 5 realises a critical analysis about the obtained results, stressing strengths and downsides of the adopted methods. Finally, Section 6 argues additional insights and remarks about future challenges and opportunities of improvement.

2. Methods

In the present manuscript, we introduce a sdPSG preprocessing computational model conceived to fulfil operational and performing requirements over simultaneous electrophysiological recordings. The performing drivers are specifically oriented to surmount the most common tributaries of distortion upon biological signals, i.e. sdPSG self-embedded artefacts and additive noise.

According to this, the preprocessing system delegates to three independent modules the whitening of recorded channels, followed by artefact removal, and latest the noise mitigation. Furthermore, the operational conception engages time-to-diagnosis efficiency and modularity principles towards streaming preprocessing mode. The former exploits the native epoch-based analysis for sleep staging, whilst the non-stationarity constraint of biological signals is attended. Hence, the temporal gap between data acquisition and channels preprocessing is conveyed in a streaming basis for faster output retrieval. In turn, modularity stresses the differentiation of functionalities into autonomous modules, such that, outcomes respond to a customisable interaction amongst them, rather than ever-fixed sequential rules. Hereafter, a performant preprocessing system is attained, in order to support improved time-to-diagnosis frames and diversified paths of convergence. These conditions are highly sought upon multivariate sdPSG data representation, transformation and rendering; inasmuch as subsequent processing and classification stages are expected.

The forthcoming sections offer a more-detailed description about the constitutive modules of the system, as well as, determined metrics for the performance assessment with self-evaluation and comparative intentions.

2.1. Subjects

The short daytime polysomnographic recordings correspond to 10 male healthy subjects ($M = 28.3$, $SD = \pm 6.75$), identified as S01, S02, S03, S04, S05, S06, S07, S08, S09 and S10. Generally, sdPSG recordings include a minimum of 3 EEG, 2 EOG, 1 EMG, 1 ECG and 1 respiratory channel with pulse oximetry [16]. Although, this present paper is restricted to an arrangement of 6 channels full-complaint with international 10–20 electrode montage designated as: EEG-O2, EEG-C3, Right EOG (REOG), Left EOG (LEOG), ECG and EMG submental, since at least one representative biophysical source is required for the adequate model deployment. Correspondingly, each signal has 20 minutes duration with sampling frequency equivalent to 256 Hz. Besides, no filtering or previous preparation was applied. RMIT Ethics Committee approved the sdPSG recording for Dr. Cvetkovic's biofeedback study.

2.2. Notation

The polysomnographic recording is modelled as a multivariate system with the same number of inputs and outputs, since neither reduction nor expansion upon data length is pursued at the preprocessing stage. Then, a suitable representation of multidimensional sdPSG datasets resides in state-space realisations [17]. By the generalisation of the electrophysiological compound into the two model expressions, we obtain

$$\mathbf{x}[k] = \mathbf{x}[k-1]\mathbf{A}^{\mathrm{H}} + \eta[k]\mathbf{B}^{\mathrm{H}}; \quad \eta \sim \mathcal{N}(0, \Sigma_{\eta\eta}) \tag{1}$$

$$\mathbf{y}[k] = \mathbf{x}[k]\mathbf{C}^{\mathrm{H}} + \nu[k]; \quad \nu \sim \mathcal{N}(0, \Sigma_{\nu\nu}) \tag{2}$$

where Eq. (1) and Eq. (2) represent the system and observation model equations, respectively. Momentarily, the computational proceedings are exclusively focused on an observational characterisation of sdPSG data channels, therefore Eq. (1) is neglected from the modelling exercise [17]. In consequence, $\mathbf{y}[k]$ denotes