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A Single-trial Toolbox for Advanced Sleep Polysomnographic Preprocessing

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***Abstract*— The application of polysomnographic (PSG) studies for monitoring sleep activity is a multi-parametric practice that involves a diverse group of biological signals. A suitable preprocessing of such signals assures a more profitable feature extraction and classification operations. Therefore, the proposed preprocessing toolbox performs segmentation, filtering, denoising, whitening and artefact removal tasks upon multi-channel PSG recordings. In order to assess toolbox's efficiency, clinical experiments are conducted, as well as, quantitative and qualitative metrics are discussed. Our findings reveal outperforming efficiency by artefacts and noise rejection after single-trial and multi-stage preprocessing.**

I. INTRODUCTION

The polysomnogram (PSG) is a monitoring technique for sleep structure assessment and detection of related anomalies or disorders. Due to the gathering of multi-parametric biological signals, such as neuronal, ocular, muscular, cardiac and respiratory; the encounter of accurate diagnosis can be promptly conveyed by specialists [4]. By convention, PSG recordings include a minimum of 3 electroencephalographic (EEG), 2 electrooculographic (EOG), 1 electromyographic (EMG), 1 electrocardiographic (ECG) and 1 respiratory channel. Though, the present work considers an arrangement of 6 channels as follows: EEG O2, EEG C3, Right EOG, Left EOG, ECG and EMG submental, whereas at least one biophysical source is required for toolbox deployment.

The development of computer-assisted or manual visualisation systems for sleep staging or disorders detection are commonly distinguished by feature extraction and classification stages [6]. Nevertheless, the presence of bodily endogenous and exogenous interferences, frequently denoted as noise and artefacts, tantalises the achievement of performant scores in autonomous recognition and diagnosis processes. For this reason, the introduction of a prior preprocessing stage is proposed to enhance the original signal properties by embedded artefacts correction and noise removal, whilst neither reduction nor expansion transformations are invoked [10]. In addition, the introduced toolbox intends to deal properly with the highly complex characteristics of EEG waveforms, since non-stationarity and non-linearity assets ground a major difference with its counterparts. Hereafter, the preprocessing settlement makes use of sophisticated techniques to ameliorate EEG attributes over platykurtic and slow time-varying EOG signals, peaky and periodic ECG leads, and leptokurtic and fast time-varying EMG datastream [5]. Once, the denoising and artefact rejection tasks are fully accomplished by the preprocessing toolbox, EEG/EOG channels are sufficiently spanned to provide valuable information about distinctive sleep construction [11]. This condition is expected to be applied in subsequent processing and clustering courses with more gainful aftermaths, in comparison to current approaches. In order to assess the toolbox's performance degree, a complete experimental framework was prepared, regarding a clinical cohort and measurable metrics from qualitative and quantitative perspectives [14]. Likewise, configuration guidelines are suggested to rendezvous outperforming preprocessing models, given the presented toolbox's modules.

The present paper is organised as follows: Section II makes a detailed description of the active modules within the preprocessing toolbox, including employed transformation and decomposition techniques. Section III summarises the experiment's conditions, test subjects, constraints and metrics; also the obtained results are discussed. Finally, Section IV argues additional insights and remarks about the generated results and overall preprocessing toolbox development.

II. METHODS

The proposed PSG preprocessing toolbox strives to fulfill two major concerns: modularity and time-efficiency. The former stresses the distinction of system functionalities on disjoint modules, such that, biosignal outputs correspond to a dynamic interaction rather than fixed-sequential rules. Thus, the attainment of partial outcomes (i.e. segmentation, noise removal, whitening or artefacts removal) turns into a feasible option by the overall system configuration under the operator's discretion. Furthermore, the preprocessing stage is intended to be a preparation phase with restrained complexity compared to subsequent signal proceedings. Therefore, computational efficiency and optimal resolution times are highly sought upon data representation, transformation and rendering.

Straightforward, a detailed description of the deployed modules is addressed. Also, some remarks about the core algorithms are introduced, in order to discuss the prowess and eventual downsides of toolbox's backbone.

A. Data segmentation module

Usually, polysomnographic recordings collect the biophysical activity related to an overnight period, that means 6-8 hours timeframe. From this point patient's dataset requires to

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be segmented into fixed-size epochs, whereas the scoring system of sleep stages is based on successive EEG/EOG-epochs evaluation. On regard of this, the initial toolbox module aims to fragment each PSG channel into shorter chunks of samples, considering temporal alignment, sampling frequency and adjustable epoch length criteria. The module's output consists of a tridimensional array denoting data samples, time epochs and PSG channels. Such a disruption lightens the computational burden managed by the additional preprocessing modules, as well as, facilitates EEG/EOG sleep-data matching according to standard manuals [11].

B. Filtering module

Either rejection or enhancement of spectral components over PSG channels can be achieved by the filtering module application. Essentially, the module's logic performs a cancellation of interference frequencies from power lines (50 and 60 Hz), i.e. notch filter. Along with bandpass filtering to preserve the frequency ranges of particular significance for the detection of sleep abnormalities. In general, the module generates a quite similar data output, like that conveyed by the segmentation module, but undesired spectrum bands are effectively removed.

C. Whitening module

Basically, the module engages a Karhunen-Loève transformation (KLT)—a.k.a. Principal Component Analysis—characterised by the observation of correlated PSG channels and followed by a decomposition into uncorrelated components [10]. Accordingly, KLT arranges principal components in function of a maximised variance basis by selecting a subset of channels (e.g. EEG/EOG channels), which indexes the largest contributions from the original data block [8]. The KLT-based preprocessing reaches improved spatial resolution, baseline correction and decorrelated observations; whilst maximum power density and signals integrity are attained. The latter is strongly chased in the preservation of the original features of biological datasets. Additionally, baseline correction takes place to subtract minor deviations of time points from the reference level that might lead to misinterpretations in actual signals' amplitudes.

D. Artefacts removal module

Assuming an adequate whitening process, the correction of embedded artefacts is supported on the well-known Blind Source Separation (BSS) technique [12], and specifically by Independent Component Analysis (ICA) [1]. Recalling the biophysical nature of EEG/EOG observations, the presence of coloured noise and non-stationary sources is foreseen. Henceforth, ICA decomposition becomes a suitable approximation for a linear demixing of the channels, whilst differential time delays are neglected [4]. Besides, the implementation of second-order-statistics (SOS) methods stands out as a reasonable approach for the separation of multichannel PSG into statistically independent components [3] [5]. Taking advantage of the whitening and temporally decorrelation processes carried out by the previous module; AMUSE [13] and SOBIRO [14] algorithms are adopted as BSS-SOS-based representatives for EEG/EOG sources detachment from neighbouring ECG and EMG activity. Attending to the toolbox's low complexity principle, both algorithms guarantee closed form solution for the separation, disregarding iterative and time-extended computational effort [13].

E. Noise removal module

The denoising process can be tentatively applied to the raw epochs generated by the segmentation module or onto the outputs generated by the aforementioned units. Anyway, the module's elements converge in the attenuation of frequency components that reside either in the spectrum's bottommost till high-regime zones, as long as slow- or fast-varying signal properties are followed. The module's machinery is sustained by the Wavelet Packet Transform (WPT) [9] [7], which defines a group of filters to produce a collection of PSG frequency subbands at different resolution levels. The transformation forges a shrinkage process on each PSG epoch/channel, through the computation of approximation and detail coefficients. Given that spectral power of non-neuronal or non-ocular activity might likely drown EEG/EOG significant information, the WPT-based module outperforms as an alternative filtering choice [6].

III. EXPERIMENTAL FRAMEWORK

The PSG datasets used to conduct the experiments correspond to 10 male healthy subjects within (25-43) age interval, identified as S18, S19, S20, S21, S22, S23, S25, S27, S29 and S30. Each datastream contains 6 channels denoted as: EEG O2, EEG C3, right EOG, left EOG, ECG and EMG simultaneously recorded with 256 Hz as sampling rate and 20 minutes time duration. The electrode montage is 10-20 system-compliant.

The performance of PSG Preprocessing Toolbox is determined by one qualitative assessment and two quantitative metrics. A visual inspection of contaminated PSG-epochs constitutes the qualitative evaluation, i.e. noisy and artefact-affected epochs from 10 different patients are manually picked. Neither random nor statistical procedures are employed for the selection of testing epochs, since strongly distorted data samples are desired to challenge the actual toolbox's preprocessing capability. The two remaining metrics are Signal-to-Noise Ratio (SNR) [1] [3] and Root Mean Square Error (RMSE) [6]; both of them examine artefacts-free module's aftermaths and question denoising module's behaviour. Hereafter, a specific number of epochs per channel are drawn based on the sample size estimation method explained in [2]. So, SNR and RMSE metrics are computed with a confident PSG-epochs pool out of the entire dataset population.

A. Preprocessing model

The modularity in the toolbox design leads to a limited cluster of possible models, obtaining the full-equipped package for data transformation or at least a custom combination of it. For the experimental work, the toolbox modules are

aligned as Figure 1 depicts, subject to the following constraints.

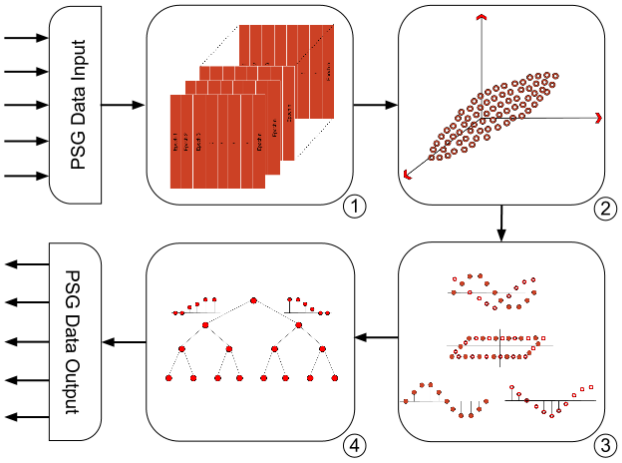

Fig. 1. Adopted model for PSG Preprocessing Toolbox.

The data segmentation module ① yields fixed-length and aligned 10-second epochs for all 6 channels. The chosen epoch length is short enough to allow the visual tagging of artefacts and noise-affected data fragments; and long enough to assure single-trial removal of embedded artefacts by the BSS-SOS-based algorithms [13]. The whitening module ② is not deeply intervened, since temporal decorrelation and baseline correction functions are addressed straightforward. However, the artefacts removal module ③ is set up to execute SOBIRO over AMUSE as blind separation method, whereas it has previously shown to be the most performant option for highly distorted EEG/EOG signals [14]. Additionally, the module is particularly conceived to get rid of ECG and EMG activity expressed as a pulse artefact over EEG and EOG channels. Similarly, the noise removal module ④ requires a more extensive tuning process, due to the constellation of drivers for WPT-based decomposition. Then, Table I summarises the adopted criteria. Finally, filtering module is overpassed from the final experimental model to avoid the appearance of spurious spectrum components in any of the PSG channels.

B. Results

From the 10 collected PSG recordings, 6 of them are profoundly contaminated by colour/white Gaussian noise and invasive artefacts, whilst 4 of them are only affected by high-frequency noise. After applying the assembled model

TABLE I
NOISE REMOVAL MODULE SETTINGS

Criterion	Argument
Levels	7
Wavelet family	db4
Thresholding	Soft
Threshold value	SURE

to noisy and artefact-related epochs from 10 different PSG-datasets, the following results were encountered: 6 datasets were successfully denoised and artefact-free processed, i.e. EEG/EOG channels were ostensibly disassociated from cardiac or muscular activity; 4 datasets were properly denoised, but not artefact-free processed. Nonetheless, the latter group of preprocessed recordings requires a distinction to explain its failure by removing the artefacts. A total of 2 datasets are originally artefact-free from the data acquisition stage, so only 2 recordings were slightly disjoint or failed to be released from ECG/EMG-artefacts. The Figure 2a portrays step-by-step a well-preprocessed EEG O2-epoch. Likewise, Figure 2b illustrates a denoised EEG O2-epoch with remnant presence of ECG artefacts.

With respect to the quantitative analysis, the results obtained by the testing cohort are shown in Table II. The RMSE metric exhibits a significant performance in EEG channels, as well as, EOG measurements. Hence, average 6 dB and 5 dB residual error are generally maintained by both group of channels, correspondingly . Such a condition allows to infer a substantial reduction of the error component upon biosignals by internal and external sources during data acquisition stage. Correspondingly, the lower part of Table II sets out the signal-to-noise ratios for both EEG and EOG signals. Thus, SNR driver outperforms with significant values for EEG channels, and even better quotients are obtained in EOG channels. Accordingly, the signal-to-noise ratios cover $9-13$ dB in O2 and C3 leads, whilst right and left EOG surpass with $17-29$ dB interval. Then, SOBIRO algorithm and WPT denoising perform a sophisticated data estimation to guarantee appealing ratios amongst EEG/EOG signals against distorted versions.

IV. DISCUSSION

Considering the obtained qualitative results, the proposed preprocessing toolbox demonstrates a formidable behaviour in noise removal task, since 10 out of 10 datasets were successfully decontaminated from coloured and high-frequency noise. In regard to artefacts rejection function, the toolbox displays a moderate efficiency with 6 satisfactory artefact-free recordings and only 2 failing datasets (the missing 2 datasets are originally artefacts dismissed). A plausible explanation for the separation failure might correspond to the violation of independence condition during acquisition stage. For an appropriate sources separation, each PSG channel must be strictly independent from the others, then a misplaced reference electrode or loose leads might point to this anomaly. Alternatively, the dimensional relation between number of channels and sources is a pulling assumption for BSS methods success. Therefore, a larger number of channels is always a highly pursued scenario. Taking into account the quantitative outcomes, SNR and RMSE metrics support the topmost toolbox's motivation by attaining remarkable figures in error components rejection and signal-to-noise ratio enhancement.

Summing up, qualitative and quantitative metrics prove the convenience of the presented preprocessing toolbox to

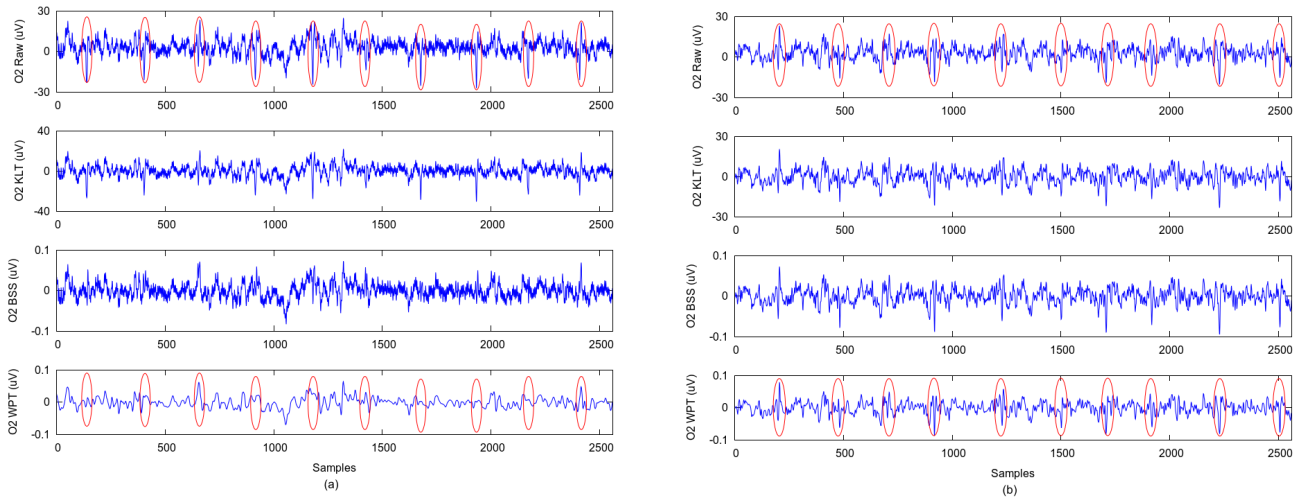

Fig. 2. (a) The enclosed transients represent the successfully removed ECG artefacts in EEG O2 for S18 and (b) unsatisfactory removal of artefacts in EEG O2 for S30.

TABLE II
RMSE AND SNR RESULTS UPON EEG/EOG CHANNELS

RMSE (dB)	S18	S19	S20	S21	S22	S23	S25	S27	S29	S30
EEG O2	7.5768	8.2038	7.6409	6.6084	6.0480	4.6745	7.2099	5.7904	5.3815	5.0329
EEG C3	7.1015	7.8408	7.4977	6.5809	5.8055	5.0593	7.0251	6.9191	5.8069	5.0527
REOG	7.1116	8.2896	5.2002	4.9131	6.2430	5.1415	5.5477	7.5475	5.3013	5.9435
LEOG	7.3253	8.6010	4.6650	4.9851	5.7716	4.9524	6.5611	4.0941	5.4662	4.2674
SNR (dB)	**S18**	**S19**	**S20**	**S21**	**S22**	**S23**	**S25**	**S27**	**S29**	**S30**
EEG O2	12.2688	7.9056	13.0977	8.3617	9.6807	11.8758	6.0281	10.6271	11.3378	8.9539
EEG C3	9.8238	8.4913	12.1245	9.3631	13.2425	13.7029	11.1958	9.0833	10.3479	9.0739
REOG	29.4871	14.2168	24.2674	20.9610	21.6794	16.8947	17.9017	23.4313	21.0104	25.6235
LEOG	27.8947	18.1229	24.7089	18.2550	20.6428	16.9675	19.9162	26.3425	20.6135	24.6627

engage elimination of embedded artefacts and substantial noise removal, respectively. Thereafter, feature extraction and classification proceedings can be more confidently conducted.

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