An Algorithm for Removing Artifacts in Polysomnography Signals

Quyen Thao Ngoc Nguyen, Toan Le, Quan T. T. Vu, Khue D. Bui, and Hoan T. Ngo

Abstract Polysomnography (PSG) is considered the gold standard for sleep disorders diagnosis. However, its signals are difficult to read in the presence of artifacts. This study presents a biosignal processing method that can help to remove artifacts from PSG signals. The method consists of two main parts. Firstly, sleep diary and feature extraction using Fourier transform and Wavelet transforms were used to detect different artifacts in PSG signals including physiologic artifacts such as cardiac artifact, muscle artifact, movement artifact, ocular artifact...and non-physiologic artifacts. Secondly, ICA (Independent Component Analysis) and Wavelet transform were used to remove the detected artifacts and reconstruct the signal. The results indicate that our method could adequately remove ECG and EOG artifacts in 70%–80% of the cases and wandering baseline and 50 Hz artifacts in 100% of the cases. We hope this algorithm will become a useful tool in removing artifacts in PSG signals, thus helping to make PSG signal reading more straightforward.

Keywords Polysomnography · Signal processing

1 Introduction

In sleep study, PSG collects brain activity, heart activity, respiratory activity, oxygen saturation in blood, body position, and eye and leg movements during sleep [1]. An example of biosignal data recorded by PSG is shown in Fig. 1. The collected data can be used for determining patient's sleep stages, arousals, apneas, hypopneas, and possible leg movement disorder, etc. In addition, apnea index (number of apneas per hour), apnea–hypopnea index (AHI), snoring time, number of rapid eye movement (REM) sleep, sleep latency…can also be calculated [2]. PSG provides

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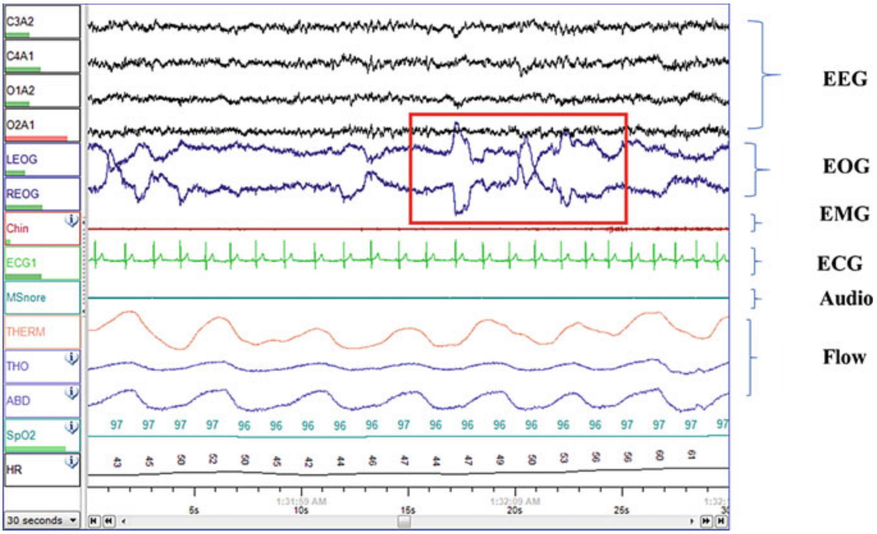


Fig. 1 Polysomnographic record of sleep

a large amount of information for diagnosing sleep disorders. And it is quite time-consuming for evaluators to read PSG signals due to the existence of different artifacts in PSG signals. In this paper, we propose an algorithm for removing artifacts in PSG signals.

2 Background

2.1 Characteristics of PSG Signals

In general, two main applications of PSG are sleep stages quantification and sleep disorders identification. There are various biosignals recorded by PSG: EEG, EOG, EMG, Respiratory events, SpO_2, etc. Below is a brief review of some biosignals which are often present in sleep reports:

Electroencephalogram (EEG) measures and records brain waves to determine sleep stages and detect seizure. Frequency of **EEG** signals ranges from 0.01 Hz to around 100 Hz with main EEG bands and their corresponding frequencies shown in Table 1 [3].

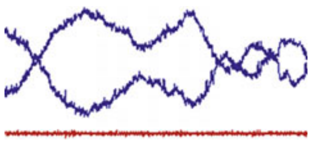
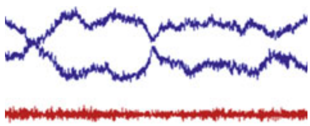
Electrooculogram (EOG) measures eye movement. These information are important for determining sleep stages, especially the REM stage [4].

Electromyogram (EMG) records muscle activity (e.g., teeth grinding, face twitching, limb movements). Chin EMG is important to differentiating REM from

Table 1 The frequency range of Sleep EEG bands and events

Freq. Band	Freq. range (Hz)
Alpha	8 –13
Beta	13–30
Delta	0.5–4
Theta	4–8
Sleep Spindles	12–14
K-Complex	0.5–1.5

Table 2 Characteristic of EOG and EMG in REM and Wake stage

EOG Chin EMG	REM	WAKE
		

wakefulness (chin EMG tone remains low in REM). Limb EMG can detect periodic limb movement disorder (PLMD) [5].

Table 2 shows EOG and EMG signals during the REM and Wake stages, respectively. It illustrates that tone of EOG and EMG in Wake are higher than in REM due to higher muscle activities.

Electrocardiogram (ECG) records heart rate (HR) and rhythm. During sleep, analysis of HR and heart rhythm from ECG are useful for detecting apnea and phenotyping sleep sections besides respiratory patterns [6].

Pulse oximetry monitors oxygen saturation in blood (SpO_2). It can be used to detect hypopnea and respiratory disorders in human sleep (hypopnea is defined as reduced airflow for at least 10 s and a fall in SpO_2 of at least 4%) [7].

Respiratory monitor measures respiratory effort (thoracic and abdominal) during sleep interval. There are several types of sensor for monitoring respiratory effort including impedance sensor, inductance sensor, strain gauges sensor, etc. [8].

2.2 *Types of Artifacts*

Artifacts are extraneous signals interfering with the desired signals and can significantly affect quality of the desired signals. In general, a holistic knowledge about type or source of the artifact is needed to efficiently eliminate the artifact. Artifacts can be classified into physiologic artifacts (cardiac, muscle, movement, ocular, sweat, respirations…) and non-physiologic artifacts (including equipment artifacts: electrode impedance/50 Hz/60 Hz, electrode pop, overamplification, loose respiratory belt, etc. and environmental artifacts: nearby equipment, phones…) [9]. Main physiologic artifacts during sleep recording including ocular artifact, muscle artifact, cardiac artifact as well as non-physiologic artifacts will be explained below:

Ocular Artifacts are caused by eye movements and blinks which can propagate over the scalp and typically affects EEG signals (Fig. 2).

Muscle Artifacts is caused by increased muscle activity, subject talking, etc. (Fig. 3).

Cardiac artifacts exist when ECG signal is present in other channels such as EEG channels (Fig. 4).

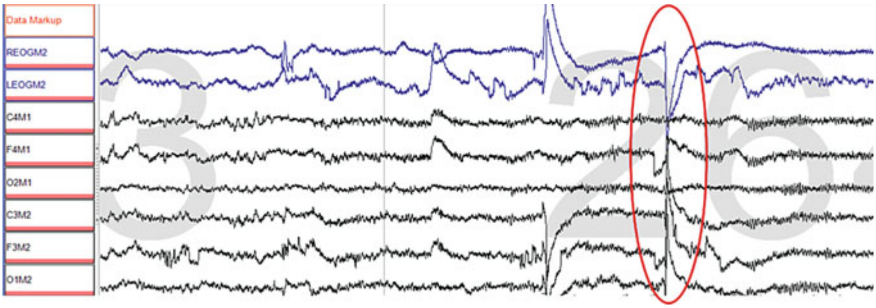


Fig. 2 Example of Ocular artifacts in EEG channels

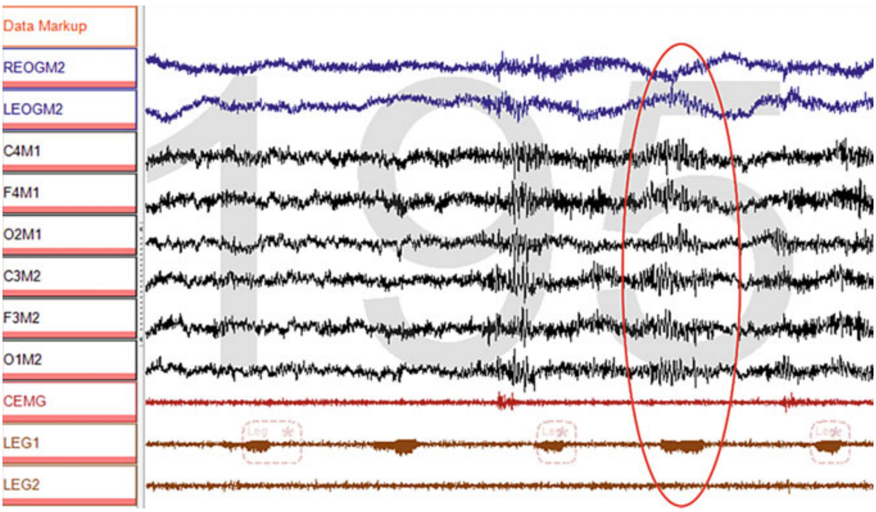


Fig. 3 Example of muscle artifacts in EOG and EEG channels

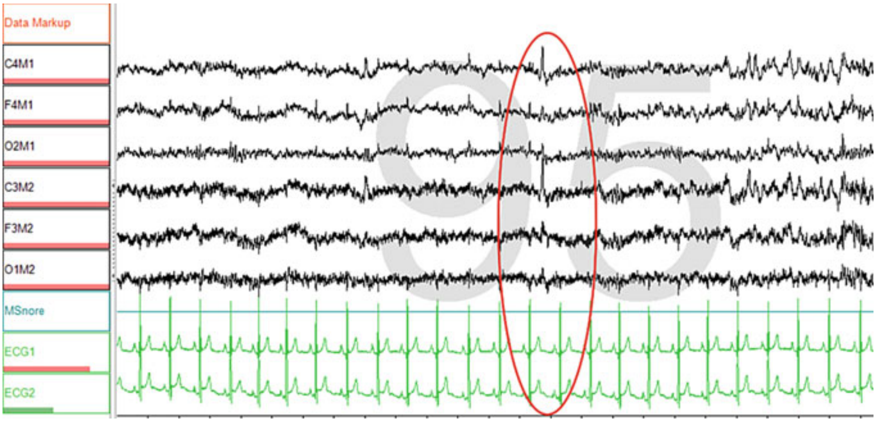


Fig. 4 Example of cardiac artifacts in EEG channels

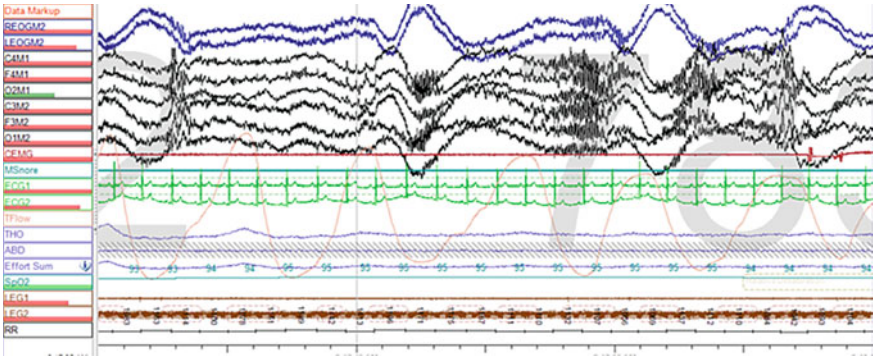


Fig. 5 Example of non-physiologic artifacts caused by poor electrode contact

Non-physiologic artifacts can be caused by poor electrode contact which results in variations in electrode impedance and can be seen in different channels such as EEG, ECG, EOG, EMG (Fig. 5).

3 PSG Database

In this study, we built a PSG database. Total 48 anonymous PSG recordings from 48 subjects were retrieved from a sleep laboratory of the University Medical Center Clinic 1 in Ho Chi Minh City, Vietnam. Alice 6 PSG system was used for PSG recordings. The study was approved by a institutional review board. Figure 6 shows distribution of age of the subjects and Fig. 7 shows diagnosis of the subjects after sleep measuring.

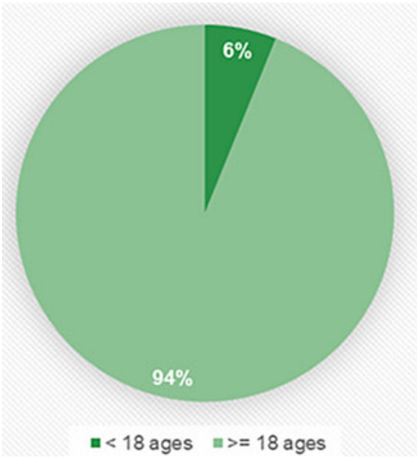


Fig. 6 Age distribution of the subjects

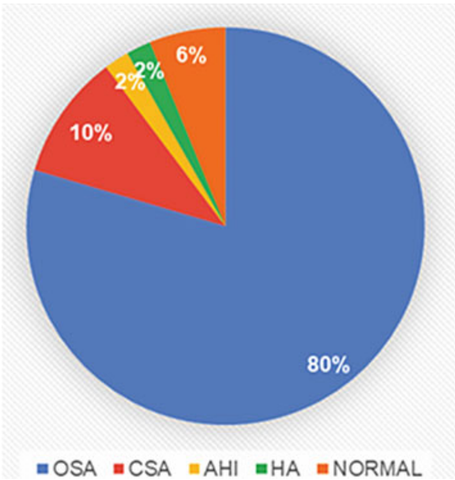


Fig. 7 Diagnosis of the subjects includes OSA (objective sleep apnea), CSA (Central sleep apnea), AHI (abnormal apnea–hypopnea index), HA (Hypopnea), and Normal

4 Methodology

As mentioned above, there are various PSG artifacts. We propose a framework for removing PSG artifacts as shown in Fig. 8.

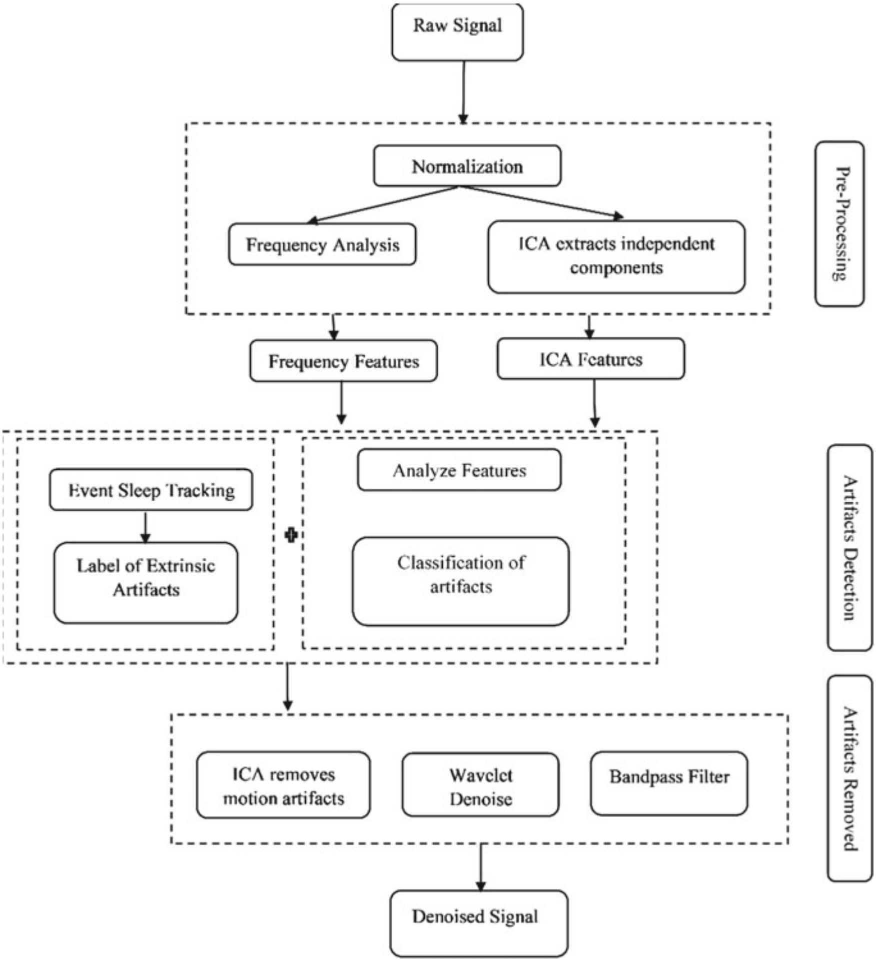


Fig. 8 Artifacts removal diagrams

4.1 Fourier Transform

Spectrum frequency is found by applying fast Fourier transform to detect extrinsic artifacts (50 Hz and 60 Hz impedances, white noise, etc.). Besides, the concept of Short Time Fourier Transform (STFT) is the localization of motion artifacts and sleep events (EEG signal) [10]. Figures 9 and 10 show the mixing of various un-known signal in EEG while the pure EEG which used to detect sleep stages has range from 0.5 to 30 Hz.

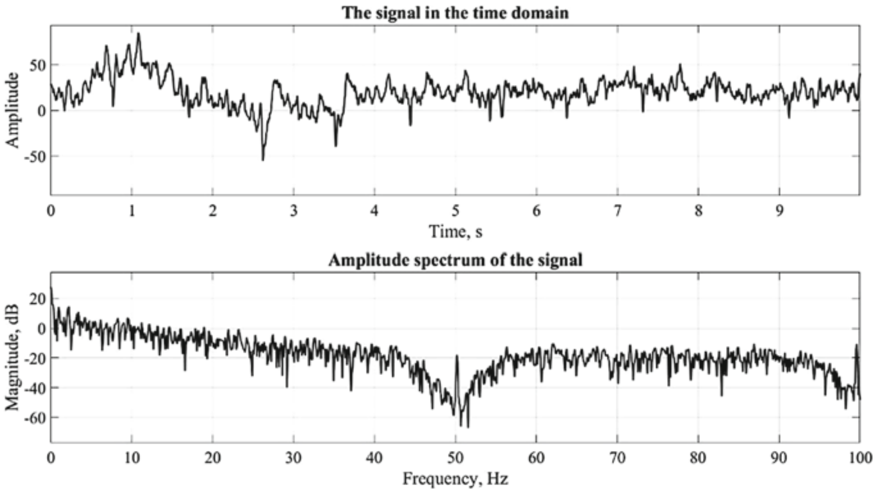


Fig. 9 Analyzing raw clinical EEG signal in frequency domain

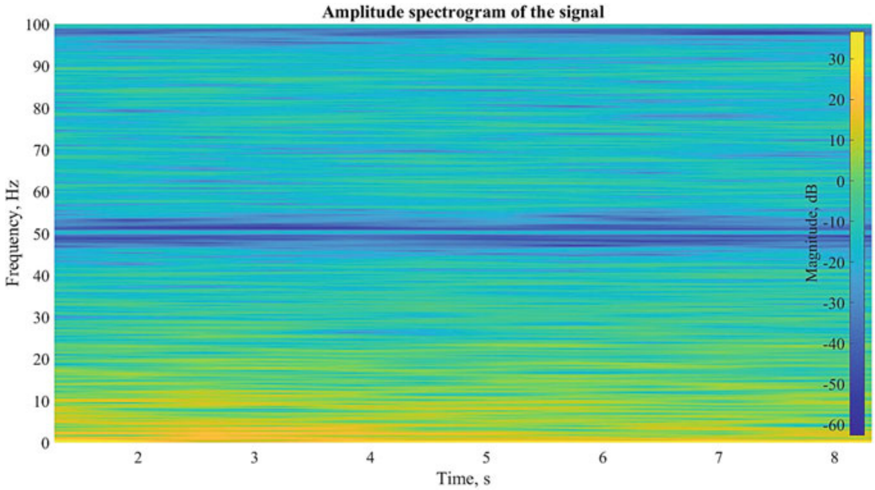


Fig. 10 Analyzing raw clinical EEG signal in time and frequency domain by using STFT

4.2 Discrete Wavelet Transform:

Discrete Wavelet Transform (DWT) is characterized by the main concept that includes two filters: low pass filter and high pass filter which are considered as a quadrature mirror filter. When the signal passed through DWT; then the output of the first filter are the approximation coefficients and the output of the second filter are the detail coefficients [11]. In summary, DWT (db4) (Fig. 11) is a potential method which can be used to remove EOG and ECG artifacts in EEG channels (Figs. 12 and 13).

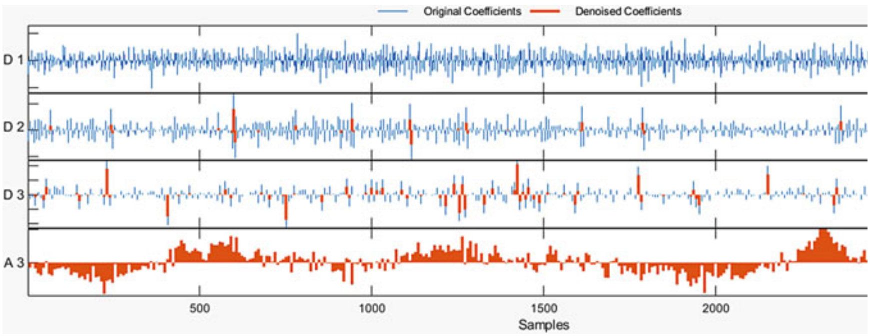


Fig. 11 Discrete wavelet transform multilevel denoise algorithm

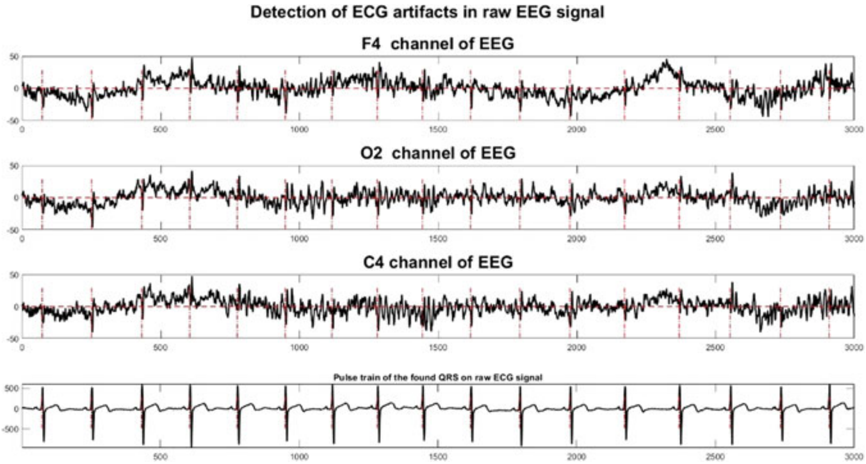


Fig. 12 Detection of ECG artifacts in clinical EEG signal

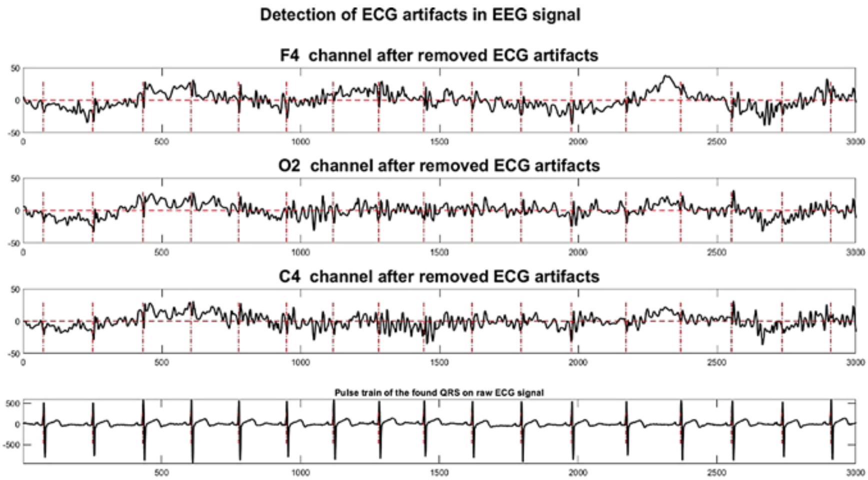


Fig. 13 Remove ECG artifact from clinical EEG signal using DWT

4.3 Independent Component Analysis (ICA)

ICA is a method for separating a multivariate signal into their independent components by exploiting their independence. This independence is found by focusing on finding sources that are the most non-Gaussian. The joint density of Gaussian sources is completely symmetric, making it impossible to estimate the individual independent sources [12]. By using the ICA, the list of artifacts is determined and inverse ICA which is used to remove those artifacts out of original signals. Figures 14, 15 and 16 presents the features extraction to detect the ocular artifact in EEG signal by using Fast-ICA and max-kurtosis algorithms [13, 14]. Fast-ICA find an orthogonal rotation of mixing matrix to maximizes a measure of non-Gaussianity by recursively maximizing both the kurtosis and negentropy of the signals. Kurtosis is the fourth order cumulant of a signal and is zero for a random Gaussian source. The kurtosis of a signal provided by Fast-ICA is defined as

$$kurt(y) = E\left\{y^4\right\} - 3. \tag{1}$$

Negentropy has been shown with statistical theory to be good measure of non-Gaussianity. Fast-ICA algorithm proposed an approximated function to estimate Negentropy (J)

$$J(y) = [E\{G(y) - E\{G(v)\}]^2 \tag{2}$$

where J is the negentropy approximation for any non-quadratic function G.

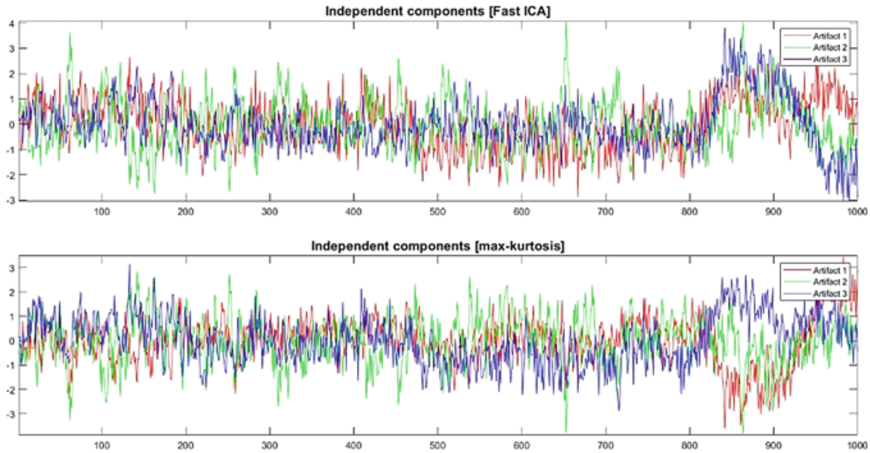


Fig. 14 Feature Extraction of the independent components from EOG signal in EEG signal

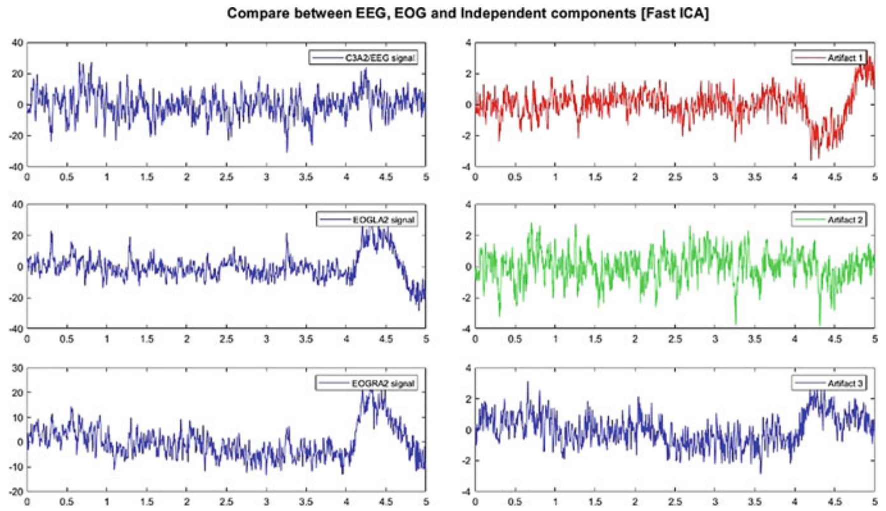


Fig. 15 Comparison between the independent components from Fast-ICA with EOG and EEG to detect ocular artifacts

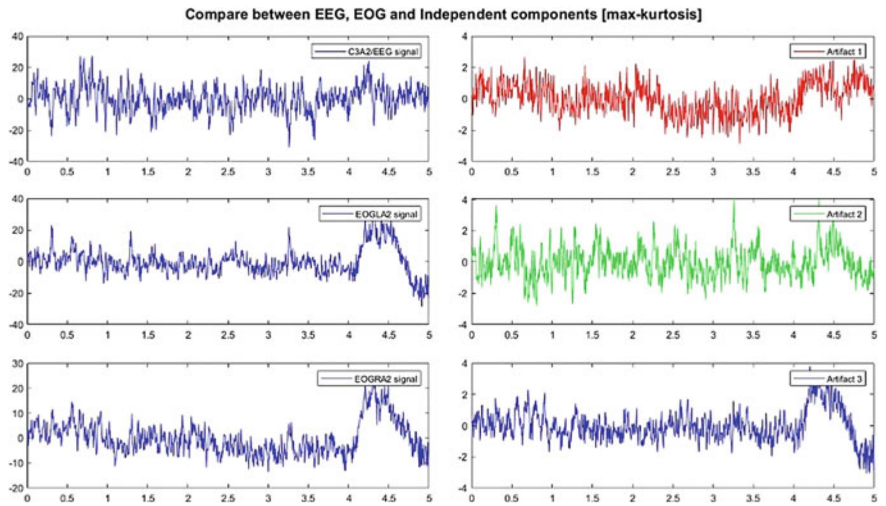


Fig. 16 Comparison between the independent component from max-kurtosis with EOG and EEG to detect ocular artifacts

5 Results

In this research, we aim to develop a method to remove artifacts out of EEG, EOG, EMG, ECG PSG signals since these signals are important in scoring sleep stage. According to this study protocol, clinical coordinators and physician were provided sleep diaries to record different events that occurs during sleep recording sessions. From this sleep diaries, artifacts in PSG signals were labeled. In addition, the PSG signals were also analyzed by our algorithm to automatically detect artifacts which could not be labeled using sleep diary. Artifacts existing in EOG, ECG, EEG, LEG EMG channels are shown in Fig. 17.

According to Fig. 17, EEG channels typically have numerous noise which affects the morphology of EEG waves such as alpha, sleep spindle. Muscle and Extrinsic artifacts are common reasons that change waveform of EOG signal because EOG originates from movement of the eye muscle so movement of other muscles could affect quality of EOG signal. Finally, in sleep measurement, ECG and LEG EMG channels usually have better quality compared to EOG and EEG channels because ECG and LEG EMG channels are usually only influenced by extrinsic/non-physiologic artifacts which are easier to eliminate than intrinsic/physiologic artifacts.

To evaluate the effectiveness of our proposed algorithm in removing artifacts in PSG signals, first, every epoch of sleep data was divided into 5–6 small windows based on R peak of ECG in each epoch. Second, labels of artifacts were generated for each window and denoise algorithm was applied. Number of windows that could be adequately denoised from each of wandering baseline, EOG, ECG, 50 Hz artifacts was counted. Finally, percentage of windows that could be adequately denoised from each of the aforementioned artifacts was calculated. Figure 18 shows that wandering baseline and 50 Hz artifacts caused by muscle and extrinsic artifacts could be adequately removed 100% of the cases because they have specific frequencies and space transition compared to other artifacts. On the other hand, EOG and ECG artifacts could be adequately removed 80.07% and 73.91% of the cases respectively. To compare performance of ICA and Wavelet transform in removing artifacts

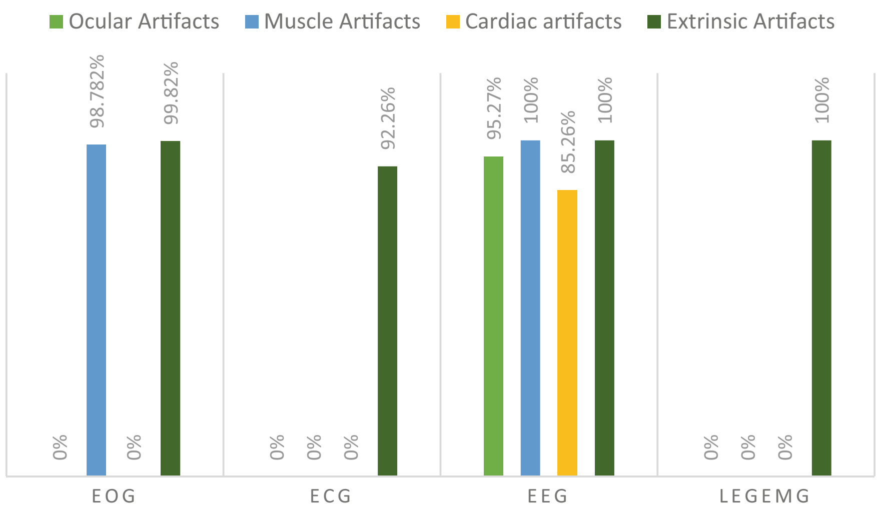


Fig. 17 Frequency of four artifacts including ocular artifact, muscle artifact, cardiac artifact, and extrinsic artifacts that exist in EOG, ECG, EEG, LEG EMG channels of PSG data

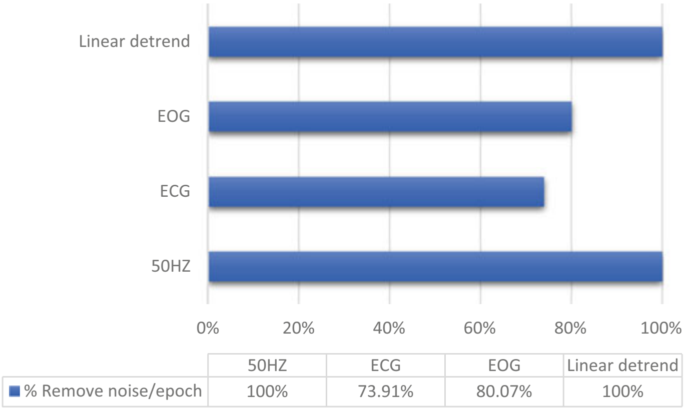


Fig. 18 Wandering baseline (linear detrend) and 50 Hz artifacts could be adequately removed 100% of the cases while EOG and ECG artifacts 80.07% and 73.91% of the cases respectively

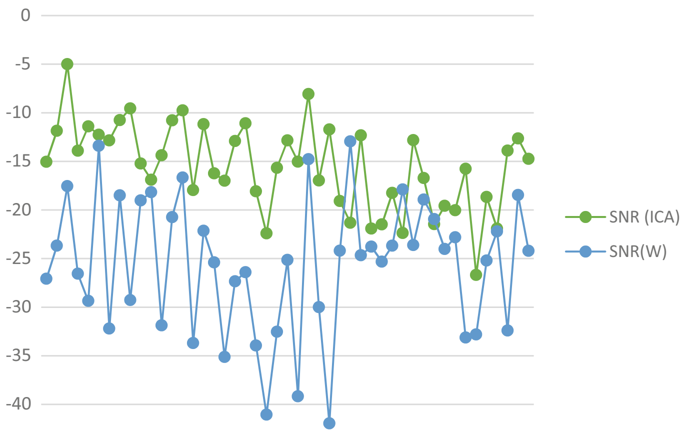


Fig. 19 SNR (in dB) of EEG signal after denoised by ICA and Wavelet transform algorithms

from EEG channel, signal to noise (SNR) ratio of EEG signal after artifact removal by the two methods was calculated (in dB unit) and shown in Fig. 19. The results show that ICA is better than Wavelet transform in removing artifacts existing in EEG channel. This can be explained by the existence of independent components, in this case independent artifacts, in EEG channel and ICA is better in recognizing these independent components.

6 Conclusion

There are different physiologic and non-physiological artifacts that affect quality of PSG signals. These artifacts make PSG signals reading more difficult, and removing them is challenging. In this study, we propose an algorithm that can effectively detect and remove artifacts such as EOG, ECG, 50 Hz from PSG signals. In addition, usage of sleep diary during sleep recording is useful for labeling artifacts in PSG signals. The proposed method has some limitations because it is not very stable and requires manual tuning to achieve the best performance. In future work, automatic tuning could be added, and we hope this algorithm would become a useful tool for PSG signal pre-processing.

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Conflicts of Interest The authors have no conflict of interest to declare.

References

1. Collura TF (1993) History and evolution of electroencephalographic instruments and techniques. J Clin Neurophysiol 10(4):476–504
2. Aserinsky E, Kleitman N (1953) Regularly occurring periods of eye motility, and concomitant phenomena, during sleep. Science 118(3062):273–274
3. Campbell IG (2009) EEG recording and analysis for sleep research. Curr Protocols Neurosci 49(1):10.2.1–10.2.19
4. Berry RB, Wagner MH (2014) Sleep medicine pearls E-Book. Elsevier Health Sciences
5. Butkov N, Lee-Chiong TL (2007) Fundamentals of sleep technology. Lippincott Williams & Wilkins
6. Clifford GD (2002) Signal processing methods for heart rate variability. Oxford University, UK
7. Morillo DS et al (2009) Poincaré analysis of an overnight arterial oxygen saturation signal applied to the diagnosis of sleep apnea hypopnea syndrome. Physiol Meas 30(4):405
8. Nakajima K, Matsumoto Y, Tamura T (2001) Development of real-time image sequence analysis for evaluating posture change and respiratory rate of a subject in bed. Physiol Meas 22(3):N21
9. Carney PR, Berry RB, Geyer JD (2005) Clinical sleep disorders. Lippincott Williams & Wilkins
10. Van Hoey G, Philips W, Lemahieu I (1997) Time-frequency analysis of eeg signals. In: Proceedings of the ProRISC workshop on circuits, systems and signal processing
11. Akansu AN et al (2001) Multiresolution signal decomposition: transforms, subbands, and wavelets. Academic Press
12. Comon P (1994) Independent component analysis, a new concept? Signal Process 36(3):287–314
13. Stone JV (2004) Independent component analysis: a tutorial introduction. MIT Press
14. Ungureanu M et al (2004) Independent component analysis applied in biomedical signal processing. Meas Sci Rev 4(2):18