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Combining CEEMDAN with PCA for Effective Cardiac Artefact Suppression from Single-Channel EEG

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The large signal due to cardiac activity can easily distort the signals originating from the relatively weak electrical activity of the brain, commonly measured as an Electroencephalogram (EEG). The artifact due to cardiac activity in EEG is called cardiac artifact, which contaminates the EEG data and makes interpretation of the EEG difficult for clinicians. Hence it is crucial to remove the cardiac artifact from EEG data. To suppress the cardiac artifact, we propose a novel approach to effectively extract cardiac artifacts from single-channel contaminated EEG data without using reference Electrocardiogram (EKG) data. The proposed methodology uses Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) to decompose EEG data contaminated by cardiac activity into the Intrinsic Mode Functions (IMFs). Principal Component Analysis (PCA) is performed on these IMFs to obtain the principal components arranged in the order of decreasing variance. Effective cardiac artifact extraction is achieved by optimizing the signal reconstruction process so that only those principal components that capture the cardiac activity are retained with the constraint that distortion introduced in EEG data should be minimum. The comparison clearly shows that the proposed method outperforms conventionally employed methods like wavelet-based approach.

Keywords: CEEMDAN, ECG, EEG, PCA, Wavelet

Introduction

In a clinical setting, EEG recordings are commonly used to detect functional abnormalities in the brain. EEG signals are often contaminated by different types of artifacts[1] and make interpretation of the EEG data difficult. Hence it is crucial to suppress the artifact from the contaminated EEG data to obtain clean EEG data. The artifacts originated from biological activities are inevitable in nature and can be classified into two types:

1) Type-I: These artifact signals such as eye-blink and subject's movement originate at a particular instant of time. EEG data segments contaminated by type-I artifacts can be discarded in long-duration of recorded EEG data. Several different techniques[2–8] have been implemented to remove the artifact in relatively shorter EEG recording.
2) Type-II: In this category of artifact (those originating from cardiac activity), the whole EEG recording is contaminated as the artifact is continuously present. There are a few approaches[9–11] available in the literature for the effective extraction of the cardiac artifact. Moreover, most of these approaches require additional information. These additional information are obtained either using an additional reference Electrocardiogram (EKG) channel or based on multichannel EEG data. From Fig. 1 the cardiac contamination in multi-channel EEG recording could be observed.

The wavelet-based approach is one of the popular techniques for suppressing cardiac artifacts from single-channel EEG data. In the wavelet-based approach, a predefined mother wavelet function is utilized to decompose the EEG data using a fixed set of filters or basis functions. The efficacy of wavelet-based artifact suppression depends upon the selection of a particular mother wavelet function. This limitation is addressed by data adaptive techniques, where the analytic functions are derived adaptively directly from the input signal.[12] However, these data adaptive approaches, Empirical Mode Decomposition (EMD), and Ensemble Empirical Mode Decomposition (EEMD) techniques suffer from the generation of different modes, leading to different realizations of the reconstructed signal.

A new ensemble approach is recently proposed called Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) to

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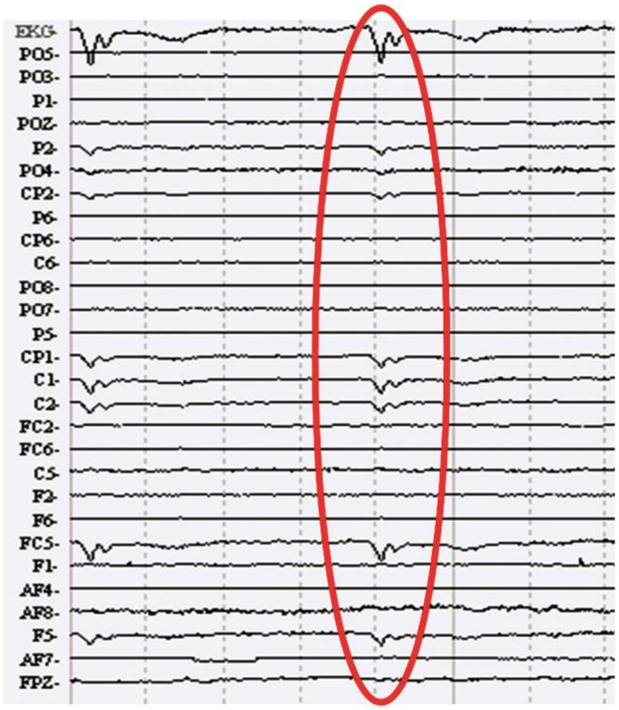

Fig. 1 — Cardiac artefact contamination in multi-channel EEG data

overcome this draw backs. CEEMDAN estimates the local means, whereas EEMD estimates modes from the resultant signal (signal plus added white noise). Modes overlapping avoided in the CEEMDAN approach by adding EMD mode of noise instead of white noise for generating all the IMFs, resulting in less residual noise in the modes and, hence, a better-reconstructed signal. Details of the CEEMDAN approach could be found in the literature.[13,14]

In the present work, CEEMDAN is combined with Principal Component Analysis (PCA) to effectively extract cardiac artifacts from single-channel contaminated EEG data. The CEEMDAN technique is implemented on the contaminated EEG data to decompose into IMFs. The cardiac artifact extraction is achieved by implementing PCA on IMFs and selecting those principal components, which extract the signal associated with the cardiac activity from the IMFs.

Materials and Methods

Data Acquisition

A total of 20 subjects (age: 25 to 35 years) took part in the EEG experiments and written informed consent for participation was taken from all the subjects. All EEG recordings were done using a 64 channel Neuro-Scan system for acquiring brain signals with a sampling rate of 1 kHz, and bandwidth was selected from 0 to 200 Hz. In each experiment, EEG data was recorded for approximately 10 minutes of duration. The EEG data was found to be significantly contaminated by cardiac artifacts for five subjects (subject_1, subject_2, subject_3, subject_4, subject_5), making it imperative to adopt a suitable strategy for cardiac artifact suppression.

Artifact Detection Measures and its Removal Evaluation

Kurtosis and the absolute skewness value were used to identify the cardiac artifact in each epoched data segment of one-second duration.

i) Skewness: The presence of cardiac artifact in a contaminated EEG data segment may result in a higher absolute value of skewness.[15,16]

$$\text{Skewness} = E[(\frac{x-\mu}{\sigma})^3] \quad \ldots (1)$$

where, E is the expectation operator, μ is the mean and σ is the standard deviation.

ii) Kurtosis: It indicates the degree of peakedness of a distribution. A higher value of kurtosis in the EEG data segment contaminated by cardiac activity is expected due to the presence of R-peak in the cardiac cycle.[15,16]

$$\text{Kurtosis} = (\frac{\mu_4}{\sigma^4}) \quad \ldots (2)$$

In the present work, we have used the correlation coefficient (between the extracted cardiac artifact and reference channel EKG) and changes in the grand Power Spectral Density (PSD) in the frequency range of brain rhythms (delta: 0.5–3 Hz, theta: 4–7 Hz, alpha: 8–12 Hz and beta: 13–30 Hz) as metrics to compare the performance of the proposed artifact extraction methodology with that of the conventional wavelet-based technique. The correlation coefficient shows a linear correlation between two variables, and its values range from +1 to −1, where +1 represents complete similarity, and 0 indicates no similarity. The correlation coefficient is computed between the reference channel EKG data and the cardiac artifact extracted from the contaminated EEG data to measure the extent of the similarity.

The criteria used for selecting a superior approach for the cardiac artifact suppression among the different approaches are based on the higher value of the correlation coefficient and the lower value of distortion introduced into the brain signal after the suppression of the cardiac artifact.

Data Analysis

Contaminated EEG channels CP2, CP1, C1, and C2 clearly showed the characteristic pattern of the cardiac signal for five subjects. In the present study, the first ten segments of these contaminated channels were selected from each subject. Hence, 200 segments were available from five subjects for analyzing the EEG data contaminated by cardiac artifacts. The contaminated data segment recorded at the CP2 electrode and the corresponding reference channel EKG data from subject_1 is shown in Fig. 2.

The present work subtracted the mean from all the EEG channels before processing the EEG data. EEG data were segmented into one-second duration using a moving window approach, ultimately capturing a cardiac cycle. In a moving window of 1-second duration, R peak occurrence is checked in the contaminated EEG data. Python-based software was used for analyzing the EEG data.[17,18] All 200 contaminated EEG segments were taken to validate the artifact's detection based on numerical values of kurtosis and absolute skewness. The applied approach is summarized as follows:

i) In the present work, it was possible to detect all the EEG data segments contaminated due to the cardiac activity by setting suitable thresholds for the absolute skewness > 2.45 and kurtosis > 8.95.

ii) CEEMDAN was performed on a contaminated EEG data segment recorded at the CP2 electrode resulting in IMFs as shown in Fig. 3.

iii) After obtaining IMFs, PCA was used to capture the features corresponding to the cardiac activity from the IMFs. All these IMFs were given as input for PCA to obtain principal components. The optimum number of principal components retained for the reconstruction of the cleaned EEG data is based on the maximum extraction of cardiac artifact with lesser distortion introduced in the brain signal.

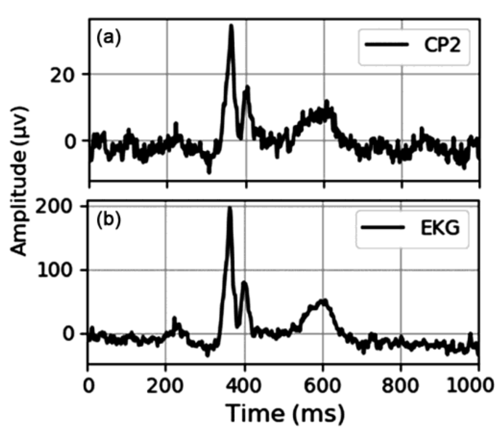

Fig. 2 — A section of contaminated EEG data: (a) recorded at CP2 electrode from subject_1, (b) the corresponding section of the reference EKG electrode

The amplitude of the extracted cardiac artifact is shown in Table 1, after reconstructing the clean EEG data by varying the principal components from 1 to 4 during reconstruction for a contaminated CP2 segment. The change in the grand PSD of the EEG data using Welch's method after suppression of cardiac artifact using the proposed method could be observed from Table 1.

Results and Discussion

In the present work, retention of only a few principal components for a reconstruction of the clean EEG signal (up to four principal components were retained for the reconstruction of the clean EEG signal) was found to be optimum to extract the cardiac artifact from the contaminated EEG segment effectively. The extracted cardiac artifact from the

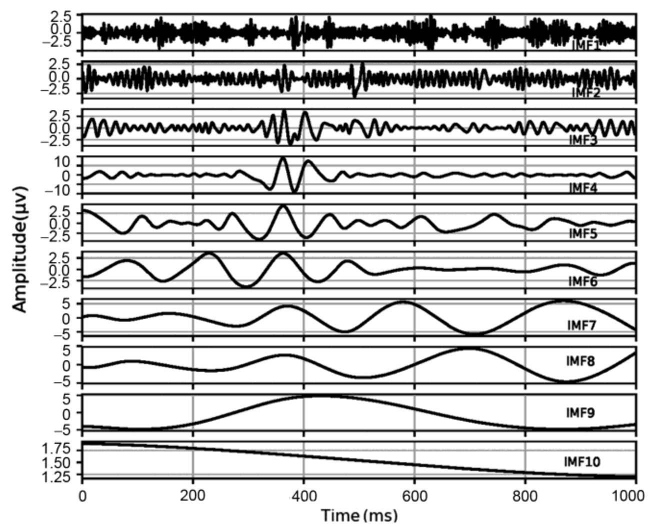

Fig. 3 — Decomposition of the contaminated EEG data recorded at the CP2 electrode (IMF1 to IMF10) using CEEMDAN

Table 1 — Amplitude of the cardiac artifact extracted from the contaminated EEG data (CP2 electrode from subject_1) and change in the grand ΔPSD of the EEG data when the clean EEG signal is reconstructed by varying the number of principal components retained

Amplitude of the extracted cardiac artifact (μV)	Grand ΔPSD $(\mu V)^2/Hz$	Number of Principal Components retained
3.18	6.78	1
18.91	2.83	2
29.75	2.54	3
30.11	2.43	4
30.71	3.71	5

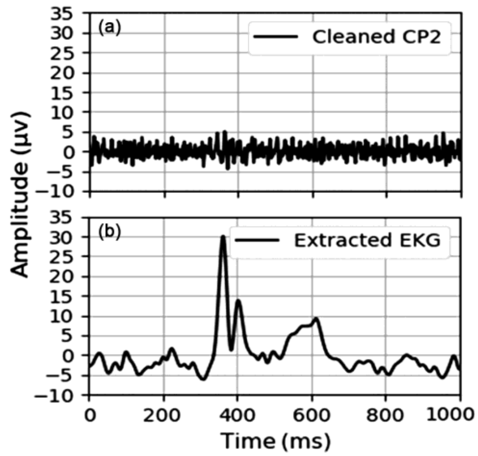

Fig. 4 — (a) Cleaned EEG data after suppression of cardiac artifact using the proposed method; (b) *m*:EKG artifact extracted from the contaminated EEG data

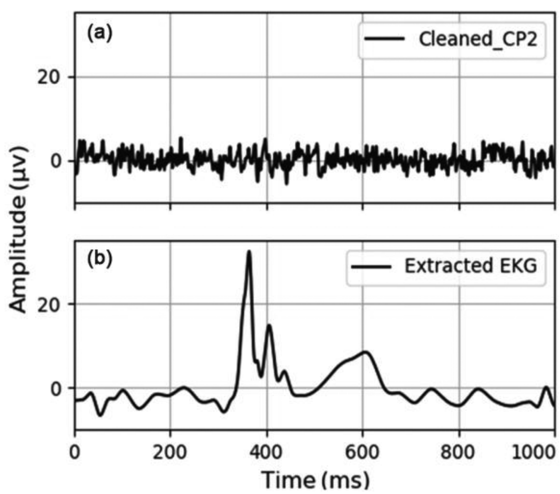

Fig. 5 — (a) Cleaned EEG data after suppression of cardiac artifact using the wavelet based, (b) EKG artifact extracted from contaminated EEG

contaminated EEG data segment using the proposed approach is shown in Fig. 4. The wavelet-based method's results are depicted in Fig. 5; a Symlet (sym8) function was used as the mother wavelet.[19] The cleaned EEG data were reconstructed by setting the coefficients of noisy components of the wavelet decomposed data to zero.

A quantitative comparison of the performance obtained by using wavelet and proposed approach is shown in the Table 2. The comparison metrics are based upon the correlation coefficient between the extracted cardiac artifact and the EKG reference electrode data, as well as the distortion introduced in the brain signal by the method used for the suppression of the cardiac artifact (change in grand power spectral density of the EEG data in frequency

Table 2 — Comparison of performance of the proposed method with other conventional approaches based on correlation coefficient and change in the grand ΔPSD in the EEG data (CP2 electrode from subject_1) using one EEG segment

Technique	Correlation coefficient	Grand ΔPSD $(\mu V)^2/Hz$
Wavelet approach	0.90	3.12
Proposed approach	0.96	2.43

Table 3 — Comparison of performance of the proposed method with other conventional approaches for cardiac artifact suppression using 200 contaminated EEG segments

Technique	Correlation coefficient (mean ± std)	Grand ΔPSD $(\mu V)2/Hz$ (mean ± std)
Wavelet	0.81 ± 0.14	9.66 ± 6.21
Proposed	0.89 ± 0.09	7.16 ± 4.17

bands corresponding to the brain activity when the cardiac artifact is suppressed) using one contaminated EEG segment CP2 recorded from subject_1. Higher correlation with the artifact reference channel shows better artifact extraction, and lower change in grand PSD values correspond to lower distortion introduced in the EEG data. Overall comparison based on 200 contaminated EEG segments is tabulated in Table 3. It is evident from Table 2 and Table 3 that the proposed technique yields a high value of correlation coefficient with the lowest distortion introduced in the actual brain signal compared to other conventional approaches. Furthermore, one-way ANOVA and Tukey HSD post-hoc test is performed on correlation coefficient and grand Δ PSD based on Table 3, which indicates that the proposed technique results are significant ($p < 0.05$).

Conclusions

The proposed method is capable of suppressing the cardiac artifact effectively and minimally distorts the EEG data. In the present work, effective suppression of cardiac artifacts can be achieved after proper detection, and hence optimal adjustment of the detection parameters may be required for different EEG setups. The most significant advantage of the present approach is that it does not require any reference channel. The proposed method is more accessible and overcomes the limitations of selecting the optimal basis functions in the wavelet-based technique. In future studies, the feasibility of the proposed approach can be investigated for cardiac artifact suppression in the advanced functional neuro imaging technique called Magneto encephalography.

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Ethical approval

This study was carried out on volunteers, with informed consent obtained from them prior to commencing the collaborative work between the Jawaharlal Institute of Postgraduate Medical Education and Research (JIPMER), Pondicherry and the Indira Gandhi Centre for Atomic Research (IGCAR), Kalpakkam.

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