Real-time cardiac artifact removal from EEG using a hybrid approach

Aysa Jafarifarmand
Faculty of Electrical and Computer Engineering
University of Tabriz
Tabriz, Iran
a.jafari@tabrizu.ac.ir

Mohammad Ali Badamchizadeh
Faculty of Electrical and Computer Engineering
University of Tabriz
Tabriz, Iran
mbadamchi@tabrizu.ac.ir

***Abstract*—BACKGROUND: Electroencephalogram (EEG) signals are sometimes contaminated by cardiac artifacts (CAs). The artifacts resulted by electrical activities of heart, named electrocardiogram (ECG), appear in EEG recordings as spiky potentials that may obscure the information in EEG data and reduce their interpretability. OBJECTIVE: Real-time removal of CAs is of great importance in several applications of EEG, and particularly brain-computer interface (BCI). The process is, however, often neglected due to the time-consuming computations. METHODS: This paper applies a new real-time hybrid approach to remove ECG artifacts from EEG signals. The method is based on the combination of independent component analysis (ICA) and adaptive noise cancellation (ANC), referred to as ICA-ANC. ICA is applied to a few EEG signals in order to extract the reference signal for ANC. The method so utilizes a few EEG channels without synchronous ECG channel, and thus is suited to portable BCI applications. RESULTS: ICA-ANC is evaluated for datasets of five different subjects. CAs are efficiently removed while preserving the cerebral information. The approach is shown to outperform a state of the art method. CONCLUSION: The proposed new algorithm is capable of real-time cardiac artifacts removal using a few EEG channels.**

Keywords—electroencephalogram, cardiac artifacts, real-time artifact removal, adaptive noise cancellation, independent component analysis

I. Introduction

Electroencephalography (EEG) is an essential tool in clinical monitoring, diagnosis, and management of neurological disorders, as well as brain computer interface (BCI) systems [1]. Considering the fact that it is impossible to avoid some vital activities during EEG recordings, the signals are always contaminated to biological artifacts, mostly generated by ocular, muscular, and cardiac activities [2]. These inevitable artifacts impose unwanted potentials on EEG signals and obscure their useful information content. Removal of artifacts is thus an essential level prior to any analysis of EEG signals. The level is however mostly neglected in real-time applications due to the time-consuming operations and the need to the additional electrodes in most cases.

Cardiac artifacts (CAs) are originated by electrical activities of heart, namely electrocardiogram (ECG), which are generally present in EEG recordings as spiky potentials. The severity of the appearance of the spikes varies dependent mainly on the body physique of the subjects. The amplitude of the spikes may be so large that results in misreading the EEG information.

Various approaches have been proposed to remove CAs from EEG signals [3–11]. In average subtraction based methods, artifacts are reduced by subtracting the averaged signals around spikes in consecutive epochs [11]. The algorithms might consequently cause distortion in the underlying cerebral information. Separate ECG recording is also usually required to identify the cardiac spikes. Independent component analysis (ICA) [3, 4, 9] and adaptive noise cancellation (ANC) [6, 7] are the most considered algorithms. Nevertheless, ICA requires large number of EEG channels in order to achieve precise decomposition. The combination of the artifactual and cerebral sources is assumed linear in all distances from the signals origin. The other concern is the need for accurate detection of artifactual ICs. ANC also needs additional artifact source ECG electrodes.

Hamaneh *et al.* [3] used ICA to remove CAs. Continuous wavelet transforms (CWT) has been applied to detect artifact related ICs. In [12], also ICA has been applied to 19-channel EEG and CA related ICs were detected based on stockwell transform. In [4], an ICA-based algorithm has been proposed for real-time removal of cardiac artifact in magneto-encephalography. The algorithm applied additional ECG electrodes to optimize the cost function in ICA. Navarro et al. [5] applied empirical mode decomposition (EMD) to decompose the EEG to CA affected and non-affected components. Adaptive filtering based on recursive list square (RLS) has then been applied to remove ECG artifacts from affected components. In [6], a neural networks-based adaptive filter was utilized to remove CAs by directly measuring the ECG signal. Patel et al. [13] applied ensemble empirical mode decomposition (EEMD) to extract clean CA reference signal from simultaneously measured ECG, and regression has been considered to filter the cardiac noise from EEGs.

In our previous work [14], a hybrid algorithm based on ICA and ANC has been proposed to remove ocular artifacts from EEG signals. Here a modified ICA-ANC based algorithm is introduced for real-time removal of ECG artifacts in EEG. The algorithm utilizes just a few EEG electrodes and bypasses the linearity assumption of ICA for all the electrodes throughout the scalp. The problem of detecting the artifactual ICs is also handled by taking only a small number of highly affected channels into account. The algorithm doesn't need additional ECG recording.

II. Materials and methods

A. EEG Data Acquisition

EEG datasets are recorded using a Mitsar amplifier and WinEEG software. Sampling rate is 250 Hz and electrodes impedance is maintained below 10 kΩ. The datasets are collected from five healthy participants. The subjects are selected of relatively short and stout physique with short neck in order to have prominent contribution of cardiac artifacts. A 19 channels EEG cap based on the international 10-20 system (Fp1, Fpz, Fp2, F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1, Oz, O2 and earlobe A1 and A2 channels) is utilized. Recordings are monopolar with the

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link of earlobes served as reference, and AFz as ground electrode. All EEG data are band-pass filtered between 0.5 Hz and 45 Hz using the FIR filter embedded in WinEEG, prior to the real-time analysis, to remove mains interference.

In order to avoid accidental results, each dataset consists of two EEG data recorded from the same subject in two separate sessions. Each session is comprised of approximately two minutes of relaxing mode with eyes closed at the beginning, to be utilized for initial training of the algorithm, followed by a BCI-based paradigm. The paradigm is designed based on the cue-based BCI according to BCI Competition IV composed of four different motor imagery tasks (right/left hand, foots and tongue) [1, 15].

B. *Artifact Source Electrodes*

In pursuance of making the algorithm suited to convenience and also portable applications, a tradeoff between the number of the EEG electrodes and ICA decomposition accuracy is considered. The electrodes with more cardiac and less cerebral activities contribution would increase the ICA ability in separation of purer ECG artifactual components. Considering the motor area located immediately anterior to the central lobe, and the fact that CAs affect maximally over the left temporal and occipital area [16], various groups of left-occipital channels have been investigated. The group of four channels: O1, O2, T3, and T5 are empirically reported as the suited channels group for extraction of the CA source IC.

C. *ICA-ANC Algorithm for Cardiac Artifacts Removal*

The block-diagram of the proposed algorithm for ECG artifacts removal is presented in Fig. 1. The involved steps are detailed below.

1) Independent component analysis

ICA [17], here, is just applied to extract CA related IC that would be utilized as reference input in ANC. ICA decomposition is performed over CA source signals.

$$\hat{S} = W \times X, \quad (1)$$

where $X = \left(x_1, x_2, \ldots, x_n\right)^T$ is matrix of raw artifact source EEG signals, and $\hat{S} = \left(\hat{s}_1, \hat{s}_2, \ldots, \hat{s}_n\right)^T$ is the matrix of the estimated ICs. the natural-gradient version of Infomax ICA algorithm has been applied [18].

The linear combination assumption of cardiac potentials is consequently considered just for the highly affected EEG channels, not the farther located ones.

2) Automatic detection of cardiac component

Normal ECG potentials contaminate the EEG signals within a wide frequency range up to 100 Hz [16]. The power spectrum of the QRS complexes as the main responsible of contaminating in EEG is, however, mostly concentrated in frequencies more than about 5 to 10 Hz [19]. In order to achieve more accurate detection of CA related component, the IC signals are first high-pass filtered with cut-off frequency of 8 Hz. First-order Butterworth filter is preferred aiming at reducing the unwanted bandwidth while retaining the signals waveforms as possible.

Regarding the quasi-periodic spiky waveform of the normal heart activity, appearance of the specific number of the quasi-periodic peaks, during the specific time interval can be the marker. The detection algorithm is therefore divided into two stages of first pre-emphasizing the spikes in order to stronger recognition and then periodicity test of the recognized spikes. In stage 1, emphasizing is conducted using the Teager-Kaiser energy operator [20] that is an efficient tool for spike detection because of its sensitivity to instantaneous changes. Teager-Kaiser energy $\Psi(t)$ of a sample of a filtered IC signal on time t, denoted by $\hat{s}'(t)$, is calculated as follows:

$$\Psi(t) = \hat{s}'^2(t) - \hat{s}'(t+1)\hat{s}'(t-1). \quad (2)$$

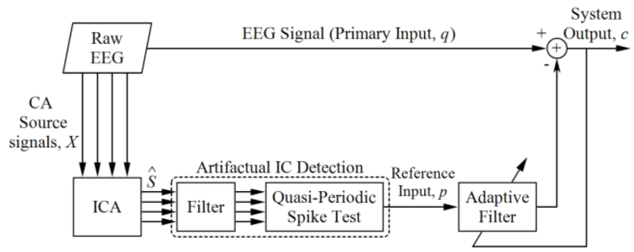

Fig. 1. Block-diagram of the proposed ICA-ANC method for cardiac artifacts removal from EEG

Considering the rapid change of the signal amplitude during the QRS spikes, the energy operator will enhance the peaks, while the remnant samples with small amplitude variation will have the energy close to 0. A peak detection algorithm is then conducted considering the peaks that are more than 100 ms apart and higher than a threshold, Ψ_{thr}. The threshold value is chosen to be the upper-quartile energy added to the inter-quartile multiplied by a scaling factor C as follows:

$$\Psi_{thr} = C.IQR(\psi) + UQR(\psi). \quad (3)$$

The constant, C, is heuristically determined to be 5.8. Defining the threshold in this way guarantees that the detected peaks are outliers. An example of spikes detection in a CA relevant IC is illustrated in Fig. 2.

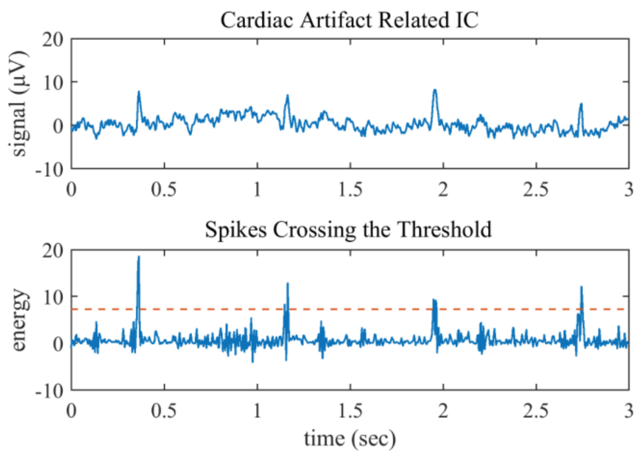

Fig. 2. CA related IC detection

In stage 2, the periodicity of the detected peaks is determined based on the periodicity test proposed in [3]. Measuring the elapsed time between any two consecutive detected peaks $t_{peak\text{-}peak}$ the frequency $f = 1/t_{peak\text{-}peak}$ is calculated for each $t_{peak\text{-}peak}$. For an IC signal with n_p detected

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peaks, $n_p - 1$ frequencies are thus obtained. Median of the resulted frequencies is computed as F. An IC is considered related to ECG, if F is in the range of normal heart rate for a healthy adult. For adults 18 and older, a normal resting heart rate is between 60 bpm (equal to 1 Hz) and 100 bpm (equal to 5/3 Hz) typically. Here, by considering the ±1/3 Hz permissible error, the IC with resulted F between 2/3Hz and 2Hz is taken as cardiac artifact related component, $\hat{s}_{CA}$.

3) Adaptive noise cancellation

Feeding the raw EEG signal and extracted CA source IC as primary and reference inputs respectively, ANC is applied to remove ECG artifacts from EEG. Given $q(t)$ as primary and $\hat{s}_{CA}(t)$ as reference input at time t, adaptive filtering is utilized to model the dynamic function, g, between the artifact reference and interference contribution. Corrected EEG is thus achieved as:

$$c(t) = q(t) - g\left(\hat{s}_{CA}(t)\right). \tag{4}$$

The FLN-RBFN based filter, proposed in our previous work [14] is applied for adaptive filtering. The filter is an expansion of radial-basis function neural networks (RBFN) by increasing the input space dimension in the consequent part, applying Chebyshev polynomials-based functional-link networks (FLN). The network has been proven to be well capable of approximating nonlinear functions [6, 14].

Real-time artifact removal is conducted by performing two system training and artifact correcting processes in parallel based on sliding windows. Considering adequate overlap, parameters of ICA decomposition matrix, W_i, and adaptive filter, AF_i, for the current segment, i, are calculated by using the parameters of previous segment, W_{i-1} and AF_{i-1}, serving as initial values. Correcting is performed applying the latest calculated parameters at each required instance considering the need of real-time operation. With accordance to the similarity in dynamics of ICs, in pursuit to the proper overlap of segments, artifactual IC detection is enough to be conducted just once during the initial training of the system. Owing to the low amplitude fluctuation of EEG potentials in relaxing mode, detecting the CA relevant IC is straight forward during initial training. The resulted index will then be utilized during real-time process. Real-time CA removal procedure consequently concludes just two levels of applying ICA decomposition and performing ANC.

D. Performance Evaluation

In order to evaluate the artifact removal success rate resulted by the proposed ICA-ANC based algorithm, several metrics are used in time and frequency domains [21]. The performance in time domain can be expressed in terms of relative root mean square error (RRMSE) between the measured and corrected EEG signals. RRMSE for contaminated EEG signal, q, and corrected signal, c, is given by:

$$RRMSE = \frac{\sqrt{\sum_{t=1}^{N}\left(q(t) - c(t)\right)^2}}{\sqrt{\sum_{t=1}^{N}\left(q(t)\right)^2}}, \tag{5}$$

where N is the length of the segment of the EEG signal. The RRMSE value of 0 can be interpreted as complete preserving of the measured EEG that would be desirable during the non-artifact affected segments. In high artifact contaminated parts, larger RRMSE values are expected that indicates the successful removal of the artifact.

The other metric is applied in order to evaluate the removal performance in frequency domain. The metric measures the correlation in frequency domain. Correlation between the raw and artifact corrected EEG signals, in frequency domain, can be interpreted equivalent to the correlation of the raw and frequency filtered signals, in time domain [22]. The frequency correlation between the raw and corrected EEG signals is defined as:

$$f_c = 0.5 \times \sum_{\omega_1}^{\omega_2}\left(c^*\tilde{q} + \tilde{c}q^*\right) / \sqrt{\sum_{\omega_1}^{\omega_2} c^*\tilde{q} \times \sum_{\omega_1}^{\omega_2} \tilde{c}q^*}, \tag{6}$$

where ω_1 and ω_2 are limits of the interested frequency window (0.5–45 Hz, here). $\tilde{c}$ and $\tilde{q}$ indicate the Fourier coefficients of c and q, and c^* and q^* are the complex conjugations of $\tilde{c}$ and $\tilde{q}$ respectively. The correlation takes a value between 0 and 1. For the complete loss of the frequency content, f_c gets 0, and it is 1, if the frequency content is completely unaffected.

In frequency domain, additionally, the difference between the power spectral density (ΔPSD) of the contaminated and corrected EEG signals is also used to represent the changes in frequency content. The criterion is computed using Welch's method over the three main rhythms, containing: theta (4–8 Hz), alpha (8–13 Hz), and beta (13–30 Hz).

III. Results

Data segment of 12 sec is considered for training of ICA-ANC system. Sliding windows are conducted by 50% overlapping according to [4]. Real-time removal of CAs is performed every 2 sec according to the BCI competition IV requirement [15].

An example of performance of the system is illustrated in Fig. 3. Raw affected EEG signal, the extracted CA related IC, and the corrected EEG signal are displayed. It can be seen that the cardiac spikes have been successfully removed, and the underlying cerebral signal has been remained highly intact.

In order to evaluate the performance of the ICA-ANC algorithms quantitatively, in time-domain, RRMSE is calculated for data intervals of R-peaks of cardiac activities, and the intervals between sequential spikes as artifact-free cerebral parts. The averaged results over two recordings of each subject and the total mean values are reported in Table I. High percent of removal during the artifact occurrence, versus the low percent for artifact-free parts indicates the well removal of CA spikes while preserving the underlying neural information.

The correlation between the raw and corrected EEG signals in frequency domain is also computed for artifactual and non-artifactual data intervals. The average values are presented in Table I. Low correlation for the QRS intervals and high value of the unaffected parts also reflects that the CA is well suppressed and the frequency content of the signal of interest is kept intact.

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TABLE I. RESULTS OF FREQUENCY-DOMAIN AND TIME-DOMAIN ANALYSIS

		ICA-ANC						CARTA [4]
		S1	S2	S3	S4	S5	Mean	
f_c	mean around R-peaks of CAs (%)	43.76	36.03	34.76	47.23	43.31	41.02±5.37	62.13±6.31
	mean around artifact-free EEG (%)	97.65	97.10	96.93	97.85	97.09	97.32±0.40	97.33±1.89
RRMSE	mean around R-peaks of CAs (%)	94.41	96.86	94.26	95.82	97.23	95.72±1.36	92.40±4.88
	mean around artifact-free EEG (%)	21.48	23.62	23.88	23.89	23.61	23.30±1.02	23.07±5.10

The obtained results are also compared to the average of the percentages reported for the state-of-the-art CARTA (cardiac artifact rejection for real-time analysis) approach in [4]. It is seen that the ICA-ANC algorithm has almost the same performance as CARTA in preserving desired information in time domain (RRMSE: 23.30 vs. 23.07) and outperforms the approach in CA removal (RRMSE: 95.72 vs. 92.40). The equal mean value of frequency correlation around CA-free intervals also proves the comparable capability of the methods in keeping frequency content of underlying EEG intact (f_c: 97.32). More success of the proposed ICA-ANC in ECG artifacts removal can be realized in frequency domain (fc: 41.02 vs. 62.13).

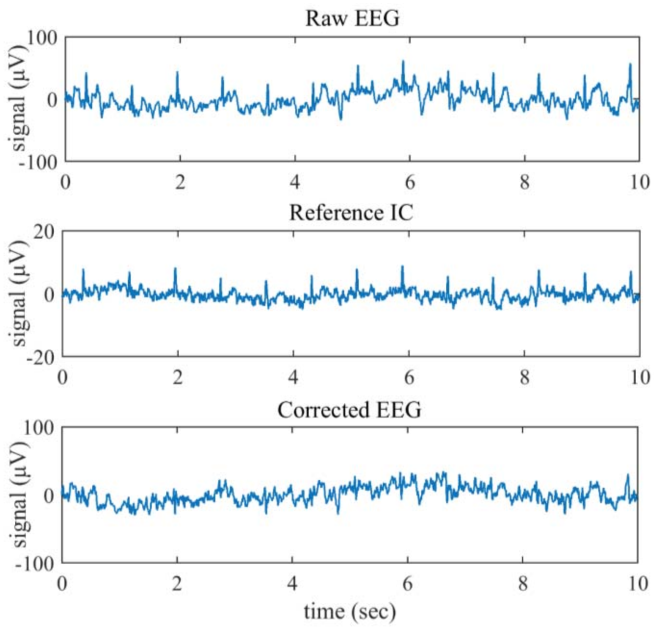

Fig. 3. The CA contaminated EEG in time domain. CA related reference IC, and time series of the corrected EEG by ICA-ANC based algorithm.

The proposed ICA-ANC is consequently superior to CARTA using very fewer number of EEG electrodes, and without applying direct ECG recording.

Moreover, ΔPSDs are also calculated over several randomly selected CA-free intervals of existing ten datasets. Representing as mean and standard deviation values, the results are obtained as $\Delta PSD_\theta = 1.69 \pm 1.20$, $\Delta PSD_\alpha = 0.40 \pm 0.32$ and $\Delta PSD_\beta = 0.09 \pm 0.05$. Comparing with the results reported in the other state-of-the-art regression based method in [13] as $\Delta PSD_\theta = 4.65 \pm 1.78$, $\Delta PSD_\alpha = 0.53 \pm 0.02$ and $\Delta PSD_\beta = 0.41 \pm 0.32$, superiority of the proposed ICA-ANC algorithm in preserving the cerebral information is seen in this case too.

IV. CONCLUSION

This paper proposes a real-time algorithm for cardiac artifacts removal from EEG data, without simultaneous recording of ECG signal. By decomposing four of highly contaminated EEG signals via ICA, CA related independent component is extracted that is well accepted to be correlated to directly measured ECG source signal. The component is then applied as reference input to remove the artifact from EEG through ANC. The artifactual IC is detected based on quasi-periodic spiky feature of cardiac activities. Adaptive filtering is also performed utilizing a powerful hybrid neural network based on RBFN and FLN. Real-time removal of CAs is conducted by applying the correction procedure in parallel to the training process based on overlapping sliding windows. The algorithm has been evaluated using real EEG signals recorded as ten datasets from five different subjects in a cue-based motor imagery BCI paradigm. The results showed that the algorithm is sufficiently capable of CA removal while preserving the cerebral information in real-time. The analysis in time and frequency domains showed that the algorithm outperforms a state-of-the-art approach based on ICA in removing CA, by achieving 21.11% less mean f_c, and 3.32% more mean RRMSE around CA-affected intervals, and has almost the same performance in retaining the desired EEG. The superiority of the algorithm to another state-of-the-art approach based on regression, in preserving the desired information, has also been presented by obtaining less mean PSD change around CA-free intervals.

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