A Novel Few-Channel Strategy for Removing Muscle Artifacts from Multichannel EEG Data

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Abstract—Electroencephalography (EEG) recordings are often contaminated by muscle artifacts. Various methods have been proposed to suppress muscle artifacts from multichannel EEG recordings. However, the existing multichannel approaches have their own limitations. Instead of using multichannel techniques, in this paper, we propose an effective few-channel technique that combines multivariate empirical mode decomposition (MEMD) with canonical correlation analysis (CCA), termed as MEMD-CCA, to remove muscle artifacts from multichannel EEG recordings. The proposed method consists of two steps. First, the proposed method partitions multichannel EEG into several few-channel EEG groups and deals with each group individually. Next, MEMD is utilized to decompose every few-channel EEG groups into intrinsic mode functions (IMFs) and then CCA is applied on the IMFs to separate sources related to muscle activity. We compare the denoising performance between multichannel and few-channel approaches through simulated and real-life EEG data contaminated by muscle artifacts. The results demonstrate the advantage of few-channel approaches over multichannel ones for rejecting muscle artifacts without altering the desired EEG information.

I. INTRODUCTION

Electroencephalography (EEG) is a noninvasive and portable technique to record physiological signals associated with the brain function. Due to its high temporal resolution and cost-effective, EEG recordings have been widely used for the clinical diagnosis of brain diseases and studying brain functions [1]. However, scalp EEG recordings can be highly susceptible to noncerebral artifacts, which obscure the EEG recordings and make the subsequent analysis difficult. Among those artifacts, the artifacts induced by muscular activity, possessing high amplitude, broad spectral and variable topographical distribution, are particularly difficult to remove [2]–[4].

In recent years, using the blind source separation (BSS) technique, independent component analysis (ICA) and canonical correlation analysis (CCA) have been proposed to suppress muscle artifacts from EEG recordings. ICA utilizes higher order statistics (HOS) to decompose the EEG recordings into statistically independent components (ICs). During the process of reconstruction, removing the artifact-related ICs from the raw EEG signals can reach the aim of signals denoising. However, in [5], [6], due to crosstalk of brain and muscle activities, muscle artifacts seriously contaminate most ICs. To address this issue, CCA based on the second order statistics (SOS) has been explored for muscle artifact elimination recently [7]. CCA aims to find the sources mutually uncorrelated and simultaneously maximally autocorrelated [8]. Since electromyogram (EMG) artifacts, compared to EEG signals, approach a temporal structure of noise and have lower autocorrelation, CCA can separate EMG sources from the raw EEG into a few components. In previous studies (e.g., [9]–[12]), CCA has been shown to outperform ICA through different kinds of EEG data. Hence, CCA has been recommended as a superior multichannel method [13].

One basic requirement of multichannel methods based on BSS algorithms is that the number of electrodes (channels) is larger than or equal to the number of underlying sources [14]. However, in reality, the real number of muscle sources with complex topographic and spectral characteristics can be much larger than that of the electrodes (channels). Additionally, when the signal-to-noise ratio (SNR) of EEG recordings is low and the contamination is complex, the denoising performance of CCA is unsatisfactory and the same is true of other existing multichannel methods. Considering the unique characteristics of muscle artifacts, the increase in EEG channels may lead to the increase of source complexity. In this case, multichannel approaches may lose their inherit advantages [8].

In this study, we propose to isolate muscle artifacts from multichannel EEG datasets in a few-channel approach based on Multivariate empirical mode decomposition (MEMD) and CCA, termed as MEMD-CCA. First, the contaminated multichannel EEG signals are respectively divided according to a set of three channels relatively close on the topographic map. Later, MEMD-CCA is applied on these sets respectively. MEMD is able to simultaneously make the decomposition by considering inter-channel time-frequency information [15]. Then, by putting all the MIMFs together into one matrix, CCA can further explore inter-channel SOS information in a linear mixing model. We first validate the proposed method on realistic simulated data. We then apply it to a challenging real-life EEG recording.

II. METHODS

In the BSS problem, the multichannel EEG is expressed by a time course $\mathbf{X}(t) = [x_1(t), x_2(t), ..., x_Q(t)]^T$ ($t = 1, 2, ..., T$).
with $Q$ the number of channels and $T$ the number of samples. The time course $X(t)$ is the linear mixture of a batch of unknown source signals $S(t) = [s_1(t), s_2(t), ..., s_Q(t)]^T$. The matrix multiplication can be expressed as

$$X(t) = AS(t), \quad (1)$$

where $A$ is the mixing matrix. It can also be transformed as

$$Z(t) = WX(t), \quad (2)$$

where $Z(t)$ is the unknown source matrix and $W$ is the inverse of the mixing matrix.

A. Canonical Correlation Analysis

CCA solves the problem using the EEG recording and its time-delayed version by maximizing the correlation coefficient (SOS) between the corresponding sources from the two data sets [7]. In this case, the sources extracted from the EEG recordings are forced to be maximally autocorrelated and mutually uncorrelated. In other words, the sources are sorted in terms of their autocorrelation. Due to the relatively lower autocorrelation, muscle artifacts could be isolated into the last several sources using CCA. For more details, one may refer to the related works [7], [8].

B. Multivariate Empirical Mode Decomposition

MEMD, introduced by Rehanm et al. in [16], is a multivariate extension of Empirical Mode Decomposition (EMD) for dealing with the multidimensional signal. In EMD algorithm, it is a key step to calculate the mean of input signal. However, the local extreme of multidimensional signal can not be defined directly. To address this issue, MEMD generates the multiple-dimensional envelopes by projecting the multivariate signals along different directions in variate spaces. The mean then can be obtained by averaging those envelopes. MEMD calculates all the IMFs in a similar manner to EMD. The major steps of MEMD for multivariate IMF (MIMF) calculation are summarized in [15]. Later in [17], Rehman et al. proposed nosie-assisted MEMD. It takes advantage of the quasi-dyadic filter bank properties on white Gaussian noise (WGN) as a novel decomposition method for multivariate signals. Noisi-assisted MEMD can further alleviate the mode mixing problem by adding noise channels. After the composite signal is processed via noisi-assisted MEMD, only the IMFs corresponding to the recordings are retained by rejecting the IMFs associated with multidimensional WGN [15]. It is introduced in more details in [17].

C. MEMD-CCA

MEMD-CCA is a combination of MEMD and CCA and is based on a two-step strategy. First, MEMD decomposes $(n+b)$-dimensional composite signals, comprising $n$-channel EEG recordings and $b$-channel independent WGNs, into $(n+b)$ sets of IMFs. The matrix $X$ is generated by rejecting the IMFs associated with the $b$-channel independent WGNs and only contains IMFs corresponding to the $n$-channel EEG recordings. It should be noted that the MIMFs of different EEG channels are stored in the matrix $X$ according to the order of channel indexes. Second, the matrix $X$ is employed as the input to the CCA algorithm and the underlying sources $S$ are extracted with the mixing matrix $A$. The last several sources sorted by autocorrelation correspond to muscle artifacts. By setting artifact-related sources to zero, the cleaned multichannel signal $\tilde{X}$ can be reconstructed by multiplying source matrix with the mixing matrix $A$. The denoised EEG signal in each channel can be eventually obtained by summing the cleaned IMFs corresponding to the channel in $\tilde{X}$.

III. DATA GENERATION AND ACQUISITION

In this study, two types of data were utilized to illustrate the performance of the proposed method in comparison to CCA in the multichannel situation. The EEG and EMG signals of the first type of data were generated by real pure brain and muscle signals. Since the ground truth of the first type of data is known, Relative root mean-squared error (RRMSE) and correlation coefficient (CC) will be utilized to compare the performance of the methods. The definition of RRMSE and CC is described in detail in our previous study [8]. The second type of data is a real-life background EEG signal contaminated by muscle and ocular artifacts. Since the ground truth of this data is unknown, power spectral density (PSD) is opt to evaluate the performance of the above mentioned methods in removing muscle artifact from the data set. The details of these two types of data are introduced below.

A. Simulated Data

The EEG data contaminated by muscle artifacts is simulated by mixing pure EEG with EMG in an artificial approach. The ethics board of Hefei University of Technology has approved this study. An EEG Quick-Cap with a NuAmps amplifier (Compumedics Neuroscan, El Paso, TX) and a Delsys Trigno Wireless EMG system (Delsys Inc., Boston, MA) were used. The pure EEG data was recorded from eleven healthy subjects (6 males and 5 females with the mean age 22) using 19 scalp electrodes. The sampling rate was 1000 Hz and the EEG recording was 10 s. In the process of signal acquisition, the subjects were instructed to sit in a comfortable way and keep their eyes close to avoid eye blink/movement and muscle artifact. According to the visual inspection of an experienced neurophysiologist, eleven EEG epochs without muscle artifacts were selected from the recordings. The pure EEG was then stored in a $19 \times 10000$ dimensional matrix $X_{EEG}(t)$. To obtain the pure and varied EMG data, we chose to place 2 electrodes on two sides of the left and right forearms to record three types of muscle activities, respectively. The three types of EMG were obtained by fistig one second, five seconds and ten seconds in the recording time of 10 s respectively. EMG sources were randomly chose from the EMG recordings of 23 experimental subjects and each EMG source was selected from different experimental subject to ensure the sources were mutual independent. An 19-channel EMG source matrix $S_{EMG}(t)$ was produced to match with EEG data $X_{EEG}(t)$. 

977
Fig. 1. The simulated signal: (a) the clean 19-channel EEG signals; (b) the 19-channel EMG source signals; (c) the 19-channel EMG mixed signals (d) the simulated EEG signals contaminated by muscle activity with SNR = 1.5. The horizontal axis represents time with unit second and the vertical axis represents channel index.

The simulated muscle mixed signal $X_{EMG}(t)$ can be calculated by the following equation:

$$X_{EMG}(t) = PS_{EMG}(t),$$

with $P$ representing the field distribution of EMG sources of $X_{EMG}(t)$. To introduce sufficient spatial structure, each column of the mixing matrix was set to have 5 to 8 non-zero entries, indicating that every independent muscular source simultaneously exists in 5 to 8 channels [8]. Additionally, we adjust the signal-to-noise ratio (SNR) to set the different muscle artifacts contamination levels. The definition of SNR is described in detail in [8]. The simulated EEG, EMG sources, mixed EMG and contaminated $X_{Simulated}(t)$ with SNR = 1.5 are shown in Fig. 1.

B. Real Data

To illustrate the performance of the proposed method on real-life application, we used one real-life EEG data set. The data set, which consists of a 21-channel ictal EEG signal, utilized in the study derives from an online database established by Sabine Van Huffel and is shown in Fig. 2. The ictal EEG was recorded from a patient with mesial temporal lobe epilepsy (MTLE) and contained ictal activity contaminated with eye blinks and muscle activity. The sampling rate was 250 Hz and the time duration was 10 s.

IV. RESULTS

A. Results From Simulated Data

In this section, we applied CCA and MEMD-CCA on the simulated EEG data and performed a performance comparison in rejecting muscle artifacts at different SNR values. The last several components decomposed by the two methods are judged as muscle-related sources due to their low autocorrelation values. Since the ground truth is known, the computer program will automatically present the best performance at each SNR value for all the methods by selecting and removing the optimal number of components in the process of reconstruction. The optimal number means that by removing this number of the last components the corresponding RRMSE value is minimum in comparison to the other numbers.

Fig. 3 shows the performance of the methods outlined in Section II. It can be observed that the MEMD-CCA algorithm outperforms than MEMD-CCA according to the performance metrics both RRMSE and ACC. Excluding the artifact-related sources from $X_{Simulated}(t)$ described in Fig. 1(d) results in the outputs shown in Fig. 4. There exist muscle activities in all the reconstructed signals of CCA. Both the waveform and amplitude of the reconstructed EEG signal were almost perfectly recovered using MEMD-CCA and the reconstructed EEG signal was closest to the ground truth, contrary to CCA, where the waveform and amplitude of the reconstructed signals were severely changed.

B. Results From Real Data

we recommend setting a proper threshold value for the autocorrelation to remove the muscle artifacts automatically. The components with the value below the threshold are regarded as muscle artifacts. We suggest the threshold should
be set to 0.9. The components marked as muscle artifacts were rejected and EEG data was reconstructed by the two approaches. Fig. 5 illustrate the impact of the two methods on the 21 channels in the frequency domain by comparing their PSDs of reconstructed signals. Fig. 5 suggests CCA has little effect on the muscle artifact in the high frequency range of the EEG channels. The PSDs of MEMD-CCA are relatively close to the original ictal signals at the low frequency range. Additionally, the PSDs of MEMD-CCA are relatively lower than the PSDs of CCA at the high frequency range. Since muscle artifacts primarily alter the EEG recordings at the higher frequency range, the PSDs of the 21 channels demonstrate that MEMD-CCA have a better performance in reducing muscle artifacts and retaining the useful information.

V. DISCUSSION

The basic requirement of multichannel methods based on BSS algorithms is that the number of channels is not less than the number of underlying sources. However, in reality, the real number of muscular sources with complex topographic and spectral characteristics is often much larger than the channels. Hence, the multichannel methods don’t function well in this situation.

Different from integrating all channels and processing them jointly, the few-channel MEMD-CCA method divides the multichannel EEG recordings into several groups according to a set of three channels relatively close on the topographic map and then deals with each group individually. Each group of channels are decomposed by MEMD into a multidimensional IMF matrix. In a certain extent, part of myogenic sources has been separated from brain sources into a portion of IMFs. In a group, the number of all the IMFs is also significantly increased. Then CCA is utilized to process all the IMFs of each group. This procedure satisfies the basic requirement of multichannel methods and takes into account the local inter-channel relationship.

Additionally, in reality, there exist quite a few similar myogenic and brain sources in the spatially close channels. MEMD has the mode alignment property to make use of similar scales in different data sources, which helps to align the corresponding intrinsic mode functions from multiple channels. The MEMD algorithm, using the cross-channel information, yields a more accurate estimation of IMFs and increases robustness to muscle artifacts.

VI. CONCLUSION

This study suggests a seemingly contradictory, yet promising tool for dealing with muscle artifacts in multichannel EEG data. The few-channel method MEMD-CCA was compared to one available denoising method CCA through both simulated EEG and ictal EEG data. The performance of the two methods was evaluated from two different aspects: the ability to remove muscle activity and the ability to retain sufficient structural information of neural data. The results have demonstrated that the few-channel method outperforms the multichannel method for multichannel EEG artifact removal.

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