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Robust removal of ocular artifacts by combining Independent Component Analysis and system identification

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ABSTRACT

Eye activity is one of the main sources of artifacts in electroencephalogram (EEG) recordings, however, the ocular artifact can seriously distort the EEG recordings. It is an open issue to remove the ocular artifact as completely as possible without losing the useful EEG information. Independent Component Analysis (ICA) has been one of the correction approaches to correct the ocular artifact in practice. However, ICA based approach may overly or less remove the artifacts when the EEG sources and ocular sources cannot be represented in different independent components (ICs). In this paper, a new approach combining ICA and Auto-Regressive eXogenous (ARX) (ICA-ARX) is proposed for a more robust removal of ocular artifact. In the proposed approach, to lower the negative effect induced by ICA, ARX is used to build the multi-models based on the ICA corrected signals and the reference EEG selected before contamination period for each channel, and then the optimal model will be selected for further artifact removal. The results applied to both the simulated signals and actual EEG recordings demonstrate the effectiveness of the proposed approach for ocular artifact removal, and its potential to be used in the EEG related studies.

1. Introduction

Among the possible sources of artifacts in electroencephalography (EEG), eye-activity is one of the major contamination sources. Eye-activity usually causes an obvious change in the electric field especially surrounding the eyes, and the electric field over the scalp of actual brain activities [1] will be seriously distorted by eye-activity. The ocular artifact induced by eye-activity is not only a theoretical concern of research, but also an essential issue of EEG application clinically. With regard to a reliable EEG analysis, the effect of ocular activities on EEG must be taken into account, which needs to correct the ocular artifacts. As of current, various methods have been introduced to remove ocular artifacts [2–8], and the fundamental requirement of an ocular artifact removal approach is to remove artifacts as completely as possible without distorting the underlying interesting EEG recordings [1,8].

In the early effort, ocular artifacts are reduced by restricting eye movements and blinking during data acquisition or simply excluding artifact contaminated trials from further analysis by setting a threshold criterion [2]. In practice, it is very difficult for subjects to control the eye movements and blinking, and the ocular artifacts still exist even in the well controlled experiments. As for the threshold criterion based approach, except for the challenge for threshold setting, another main problem is that those trials not satisfied with the criterion will be rejected for further analysis, which may lead to the loss of trials [1]. One scheme for keeping those artifact contaminated trials is to design a classifier that takes into account the influence of the artifact [9]. Another feasible idea is to estimate the artifact or the useful EEG signal from the contaminated recordings, and this kind of approach includes Electrooculogram (EOG) subtraction [4], Principal Component Analysis (PCA) [5,6,8] and Independent Component Analysis (ICA) [1,3,10], and have attracted much attention in recent EEG related studies. As for the EOG subtraction approach, after the proportion of ocular contamination is estimated using a simultaneously recorded EOG for each channel, the EOG signals are subtracted from the original EEG based on the estimated proportion of ocular contamination. However, EOG subtraction can lead to a considerable distortion of the subsequent EEG responses if the proportion is not accurately estimated. Based on the different assumptions of EEG components, PCA and ICA are two widely used approaches for ocular artifact removal. Based on decomposing the signals into uncorrelated components, PCA treats the first component with the largest variance as

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the ocular artifact component. PCA may easily isolate an ocular artifact of large amplitude, but PCA cannot well separate eye artifacts from brain signals when they have comparable amplitudes [11]. ICA decomposes the signals into mutually independent components (ICs), and has also been successfully applied to correct ocular artifacts, as well as other varieties of artifacts from EEG recordings. Compared to PCA, ICA forces components to be mutually independent rather than simply uncorrelated. However, it still has some problems such as how to separate source signals completely or how to remove the artifacts automatically due to the lack of the important order information of the variances of the components, to be solved.

In general, ICA can eliminate the artifact components which are mixed in the brain activity effectively [1]. One limitation of using ICA for ocular correction is that a straightforward removal of the ICs containing artifacts most likely results in some loss of EEG data, because those ICs rarely consist of only blink-related EOG activity. One limitation of using ICA for ocular correction is that a straightforward removal of the ICs containing artifacts likely results in the loss of useful EEG information, because those ICs may not only consist of blink-related EOG activity, but also EEG information. That is to say, eye-blink activity and useful EEG data are usually mixed in the same IC components, and it is inevitable to cause the distortion of EEG information [8,12–15]. Whether the PCA or ICA based approach, the performance to remove artifact is largely dependent on whether the artifact and signal can be represented in different components. When the artifact and signals are represented in the same component, it is very difficult to remove the artifact without distorting the useful signal.

System identification is the science of building mathematical models of dynamic systems from observed input–output data [16–18]. It can be seen as the interface between the real world of applications and the mathematical world of control theory and model abstractions. System identification is essentially realized by adjusting parameters within a given model until its output coincides as well as possible with the measured output. Various studies have proved that system identification technique can effectively mine the dynamics underling between the input and output, and it has been widely used in the control and signal processing communities. Auto-Regressive eXogenous (ARX) is one model of system identification realizations [18,19].

To remedy the bias introduced by ICA, in this paper, ARX [18,19] model was proposed to recover the actual EEG information from the ICA filtered EEG. In the correction procedure, a short period of 'clean' EEG before the contamination was used as reference for EEG correction. With the reference EEG as output and the corresponding ICA purified EEG as input, multiple ARX models were estimated for each EEG channel and the optimal model was selected from those models for each channel. Based on the selected optimal model, the corresponding EEG filtered by ICA was fed into the selected model to correct the possible bias induced by ICA for each channel. ARX identification with lower computational complexity and human supervision has been fully developed for several decades. Because ARX uses the temporal structure provided by background signal and object signal to robustly estimate the model parameters under various conditions, it has been widely and successfully applied in processing of neurophysiological signal for various purposes such as signal extraction of evoked potentials [20] and artifact removal [21,22].

The structure of this paper is as: Section 2 depicts the detailed introduction for the correction procedure, and the corresponding information about the used datasets is also given in this section; Section 3 shows the results for the simulated and actual datasets; the discussion of this paper is mentioned in Section 4.

2. Materials and methods

2.1. Materials

In this paper, we used both the simulated EEG and the experimental EEG to test the performance of the ICA-ARX based correction.

2.1.1. Simulated EEG data

The simulated EEG data were used to quantitatively evaluate the performances of both ICA and ICA-ARX artifact correction approaches. In this simulation, the Electrocorticogram (ECoG) recorded with a sampling rate of 250 Hz on the cortex was regarded as the EEG source waveforms and a 3-shell head model was used to project those source waveforms to the international 10-20 system defined 128 scalp sensors, which can be treated as the pure EEG without ocular artifacts. In practice, a 2000-point long (8 s) ECoG waveforms were selected for forward calculation [23]. The scalp EOG recorded at one EOG channel of an experimental subject was used to generate the ocular artifacts by the forward calculation. To be consistent with the simulated EEG, a 2000-point long (8 s) segment of EOG containing the ocular artifacts was adopted for the simulation. Due to the volume conductivity of scalp, due to the volume conductivity of scalp, the EEGs will be also mixed in the EOG channel. Considering that EOG is of narrow frequency band compared to EEG, we used a band-pass filter (FIR, 50 orders, 2–8 Hz) to exclude EEG to refine a relatively clean EOG, with which to construct the simulated dataset. The filtered EOG waveforms were regarded as the waveforms of EOG source, and the same 3-shell sphere model still performed the forward calculation to generate the scalp EOG by seeding EOG source in the frontal eye fields of cortex [23]. The recorded EEG was simulated by mixing the pure EEG and pure EOG. To evaluate the performances of correction approaches when EEG was contaminated by ocular artifacts with different powers, the ratio of the maximal amplitude of the pure EOG to that of the pure EEG was varied in the simulated study. In the evaluation study, we used the data in the interval from 3.4 s to 7.6 s (1050 points long) containing the artifacts for evaluation.

2.1.2. Experimental EEG data

The used EEG was recorded in the visual stimulation discern experiment of the Inhibition of Return (IOR) experiment [24] using a Geodesic Sensor Net (GSN) of 128-scalp electrodes consistent with the International 10-20 system. The vertex was used as the reference. The EEG recordings from each electrode site were digitized online at 250 Hz and filtered with a band-pass of 0.5–45 Hz. The impedances of all GSN electrodes were kept below 40 kΩ during recording. The averaged value across all electrodes was used as a re-reference when the data were analyzed.

Fifteen subjects attended the experiment, and the recordings of 7 subjects with obvious ocular artifacts were manually selected for further analysis, where the ocular artifacts are defined as the EEGs with amplitude exceeding ±60 μV threshold. The ages of the 7 subjects range from 20 to 31 years, with a mean of 25. This study was approved by the Institution Research Ethics Board at the University of Electronic Science & Technology of China, and each participant provided written consent prior to the study. After experiment, participants received a monetary compensation for their time and efforts.

2.1.3. Evaluation index

In this paper, we used relative error (RE) to evaluate the performances of artifacts removal approaches, where RE is defined as,

$$\mathrm{RE} = \frac{|X - Y|}{|X|} \tag{1}$$