2014 IEEE International Conference on Acoustic, Speech and Signal Processing (ICASSP)

AUTOMATIC REMOVAL OF EEG ARTIFACTS USING ELECTRODE-SCALP IMPEDANCE

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ABSTRACT

Due to the low signal-to-noise ratio of electroencephalographic (EEG) recordings, the quality of the electrode-scalp contact is an important factor in EEG-based brain-computer interfaces (BCIs). For this reason, the impedance between each individual electrode and the scalp is measured prior to each EEG recording session. In order to obtain high quality EEG signals and accurate performance, the impedance has to be low (below 5K Ohms). Typically, researchers have reduced the electrode-scalp impedance by performing time-consuming electrode adjustments prior to the data acquisition stage. In this paper, we utilize the electrode-scalp impedance information to remove the EEG artifacts caused by high impedance electrodes in order to enhance the signal quality during the signal processing stage. Our proposed method is based on the independent component analysis (ICA) algorithm, which is used to decompose the EEG signals into independent components. The electrode-scalp impedance is employed to automatically distinguish irrelevant components from event-related components. The experimental results show that our method can effectively remove artifacts and enhance the BCI performance compared to the scenario where no artifacts were removed, and the scenario in which irrelevant independent components were removed manually based on prior knowledge.

Index Terms— EEG, ICA, Electrode-scalp impedance

1. INTRODUCTION

Event-related potentials (ERPs) are voltage fluctuations, recorded at the scalp, that are evoked by a physical or mental action in human brain. These scalp potentials are extracted and averaged over several time-locked Electroencephalographic (EEG) signals. However, the amplitude of the EEG signals is generally less than 100 µV and the signal-to-noise ratio is very low, making them very sensitive to noise. The impedance between the recording electrodes and the subject's scalp is one of the significant sources of noise in the EEG signals [1]. High electrode-scalp impedance can lead to distortions that are difficult to separate from the actual EEG signal. Therefore in many existing EEG systems, electrode-scalp impedance is measured prior to data acquisition. In order to prevent signal distortions, the impedance at each electrode in contact with the scalp should be below 5K Ohms [2]. When the impedance is above 5K Ohms, it is an indication that there is poor connectivity between the electrode and the scalp. Currently, researchers reduce the impedance of the electrodes by injecting more gel in wet-electrode systems, for instance, or providing more pressure and adjusting the location of the electrodes in dry-contact systems. These adjustments are typically made prior to (or during) the data acquisition stage, and can be very time-consuming. The goal of our study is to investigate if the noise caused by high impedance can be removed from the EEG signals without the time-consuming adjustments.

Previous studies [3, 4] have demonstrated a correlation between the electrode-scalp impedance and EEG signal quality. In [3], Ferree et al. showed that lower impedance between the electrodes and the scalp improves the quality of EEG signals and mitigates the noise. In another study, Kappenman et al. showed that the electrode-scalp impedance measure enables the characterization of the ERP signal quality. They found that the low-frequency noise in the ERP signal increases at electrodes with a higher impedance compared to those with low impedance [4]. Inspired by the aforementioned works, our study is focused on leveraging the impedance information to remove the noisy signals in the signal enhancement stage without considering the time-consuming adjustments prior to data acquisition.

Signal enhancement is a crucial step in EEG signal processing because EEG signals are always contaminated by artifacts such as, eye movements, eye blinks, and muscle movement. During the past 30 years, researchers have proposed several methods to remove these artifacts. In the earlier works, regression methods were implemented for artifact removal in the time domain [5] or frequency domain [6]. However the performance of the regression methods depended on having a good regressing channel (e.g., Electrooculography (EOG) channel). Principal component analysis (PCA) was also employed to remove the artifacts from multichannel EEG [7]. However, PCA may not effectively separate artifacts from the brain signals, especially when they have comparable amplitudes [8]. More recently, independent component analysis (ICA) has been shown as one of the most effective methods for artifact removal [9] [10]. The existing versions of the ICA method decompose the raw EEG signals into several independent components and require the user to select the event-related components. The selection process can be done manually based on researcher's prior knowledge of topographic patterns [11] and time domain patterns [12]. It can also be done automatically based on mutual information [13], temporal and spectral information [14], and ERP related features after hierarchical clustering [15]. All these signal enhancement technologies can generally be used to remove the artifacts such as eye movements and muscle movements. However the EEG artifacts that are specifically caused by high impedance between electrodes and the scalp have not yet been studied in the traditional artifact removal methods mentioned above.

In this paper, we propose a novel artifact removal algorithm incorporating the electrode-scalp impedance in the ICA decomposition process. Our method utilizes this impedance information to automatically distinguish the event-related components from irrelevant ones. The electrode-scalp impedance is measured in the data acquisition stage and no extra computation is needed. Due to the computational efficiency property, our method is appropriate for a wearable real-time EEG device. To the best of our knowledge, no previous work has been done for artifact removal using electrode-scalp impedance in EEG signal processing thus far. Our investigations show the effectiveness of using this electrode-scalp impedance measure for signal enhancement.

The paper is organized as follows: Section 2 describes the experimental setup and Section 3 proposes the EEG artifact removal method based on ICA using electrode-scalp impedance. The experimental results are presented in Section 4. Finally, some conclusions are given in Section 5.

2. EXPERIMENT SETUP

2.1. Data Acquisition System

The data acquisition system is a custom built platform designed and developed by our lab, shown in Figure 1a. It comprises two daisy-chained TI ADS1299 analog front ends for EEG, a TI MSP430 microcontroller and a BlueRadios dual mode Bluetooth radio for wireless communication of the data to a PC or any mobile device [16].

In order to measure the electrode-scalp impedance for each individual electrode, we use the "lead-off detection" feature of the TI ADS1299. A 24nA sinusoidal AC current at a known frequency of 30.5Hz is injected for each electrode (the lead-off detection technique is described in more detail in Section 3.1).

Our data acquisition system is capable of recording 16 electrodes simultaneously and is approximately 3x1.5 inches in size. The EEG signals were filtered between 0.5 Hz and 30 Hz with a sampling frequency of 250 Hz.

2.2. P300-based BCI Task

The BCI application implemented in our study is the P300 speller introduced in [17]. This application enables users to spell a character from a 6x6 matrix that includes all the letters of the alphabet as well as other useful symbols (Fig. 1 b). Every 100ms a new row or column flashes randomly. To spell a character, the user is instructed to concentrate on the character they wish to communicate by counting how often it flashes. In response to this counting, a P300 evoked potential is elicited in the brain (i.e. a positive deflection in the EEG after 300ms) [17].

Five healthy subjects participated in the experiment. They had no previous experience with the P300 speller task. EEG data was acquired using our own data acquisition system described in Section 2.1 and the P300 speller paradigm was implemented using C# and displayed on a laptop. Eight dry electrodes were placed at Fz, Cz, P3, Pz, P4, Oz, PO7 and PO8 using the international 10-20 system and the right mastoid was used as the reference. Each subject recorded 5 sessions with 5 characters in each session. Before each P300 session, a 10-second electrode-scalp impedance measurement was recorded. In order to simulate all the scenarios of impedance between electrodes and the scalp, no extra efforts were made to adjust the locations and connectivity of the cap and electrodes.

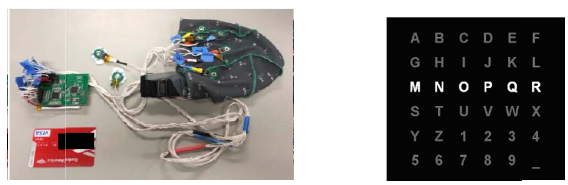

Figure 1 a) EEG data acquisition system b) P300 speller matrix with one row intensified

3. METHOD

3.1. Electrode-Scalp Impedance Measurement

Detecting the connectivity of an electrode to the scalp is essential in any EEG implementation. Accurate measurement of the EEG signal relies heavily on a low-impedance conductive path from the subject's scalp to the data acquisition device. If there is any disruption between an electrode and the scalp, the reported results may not be accurate. For this reason, the impedance of each electrode is usually measured prior to a normal EEG recording. One method to measure the electrode-scalp impedance would be to inject a current at the signal electrode shown as I_a in Figure 2. This technique is called "Lead-off detection", and is provided on the TI ADS1299. When the applied current is a sinusoid at a known frequency f_o then we have,

$$V_{out,f_0} = I_{a,f_0} \times Z_{overall} \quad (1)$$

The frequency response of V_{out} at f_o is dominated by the voltage drop across the overall impedance of the circuit due to the injected current, I_a. The overall impedance $Z_{overall}$ is the combination of $Z_{elec,sig}$ (the impedance faced by the signal electrodes), Z_L (the impedance of the length of the scalp between two electrodes), and $Z_{elec,ref}$ (the impedance faced by the reference electrode). The power spectrum of the signal V_{out} at f_o is directly proportional to the impedance faced by the constant current I_a.

If the electrodes are properly connected, the injected signal has minimal impact on V_{out}. However when the contact becomes weak, the impedance $Z_{elec,sig}$ increases. Since the impedances Z_L and $Z_{elec,ref}$ remain constant, the overall impedance $Z_{overall}$ increases and the injected signal begins to dominate V_{out} at the frequency f_o.

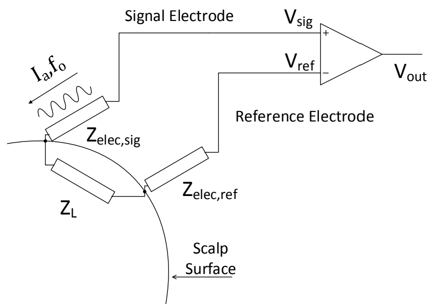

Figure 2 Injecting current into the signal electrode for impedance measurement

3.2. Independent Component Analysis (ICA)

ICA is a statistical technique that aims at finding linear projections of the data that maximize their mutual independence [18]. It is assumed that we observe an array of electrodes that provide a vector of N electrode signals $\boldsymbol{v}=[v_1, v_2, \ldots, v_N]^T$ that are linear combinations of N unknown and statistically independent sources $\boldsymbol{s}=[s_1, s_2, \ldots, s_N]^T$. The objective of the ICA algorithm is to find a separating matrix W, such that

$$\boldsymbol{s} = W \times \boldsymbol{v} \tag{2}$$

3.3. Automatic EEG artifacts Removal Based on Electrode-Scalp Impedance

In our study, we inject a sinusoidal signal with f_o=30.5Hz as the constant current I_a and compute the power of the output signals at 30.5Hz as a measure of the impedance between the electrode and the scalp. A higher magnitude of voltage at 30.5 Hz, measured at one output channel, implies higher impedance faced by that electrode and therefore poorer contact between that electrode and the scalp. Figure 3 shows the magnitude of the power spectra between 25 Hz and 35 Hz for the signal coming from each of the eight electrodes for subject #1. Among all the electrodes, electrodes #4 (Pz) and #7 (PO7) obtain extremely high magnitude at 30.5 Hz.

In order to separate electrodes #4 and #7 from the others, a Euclidean-distance-based hierarchical clustering procedure is employed on the magnitude values at 30.5 Hz. Figure 4 shows the dendrogram plot after the clustering process where electrodes #4 and #7 are grouped together.

We then apply the FastICA algorithm to decompose EEG signals and the resulting 8 independent components (ICs) represent the event-related potentials as well as irrelevant artifacts. In our study, the BCI task is P300 speller in which, the event-related potentials should contain two patterns: N200 and P300 [19]. N200 is a negative deflection that occurs around 200 ms after the stimulus (letter flash) and the P300 is a large positive deflection that occurs around 300 ms after the stimulus. Following these two patterns, component #3 in Figure 5 can be seen as an ERP component and components #1 and #2 represent artifacts.

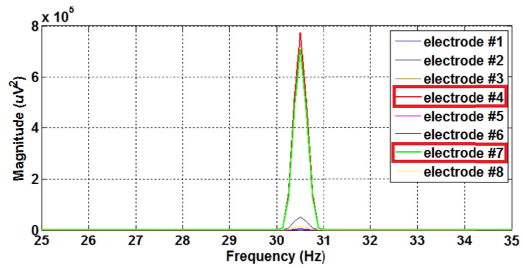

Figure 3 Electrode-scalp impedance for all electrodes on subject #1

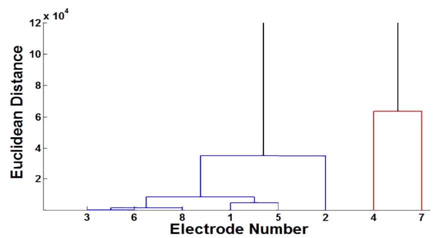

Figure 4 Dendrogram plot for 8 electrodes' impedance on subject #1

As a linear transformation, we can transform equation (2) in a linear combination way:

$$s_i = \sum_{j=1}^{N} w_{ij} \times v_j \tag{3}$$

where i is the independent component number and j is the electrode number. w_{ij} is the ij^{th} element of the separating matrix W. Each component s_i consists of all the electrodes, and each electrode has its own contribution w_{ij}. The contribution of each electrode to the ICs is shown in Figure 6. For the artifact components (IC #1 and IC #2), electrodes #4 and #7 provide the maximal contributions. However, for the ERP component (IC#3) electrodes #4 and #7 have minimal contributions.

Based on the relationship between the impedance and the contribution of each individual electrode to the ICs, we propose the following automatic EEG artifact removal method.

Step 1: Calculate the electrode-scalp impedance for each individual electrode. Employ the clustering technique to find the worst electrode set. For example, 2 electrodes (#4 and #7) are treated as the worst electrode set for subject #1 described above.

Step 2: Apply an ICA to generate the ICs. Compare the contributions of all the electrodes for each IC. The ICs that represents the impedance noise should satisfy the following condition: the electrode in the worst electrode set provides the maximal contributions. If this condition is satisfied, the corresponding ICs are removed.

Step 3: Reconstruct the refined EEG signal from the remaining ICs.

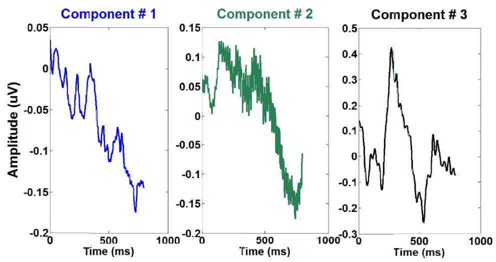

Figure 5 Three ICs generated from Subject #1's data: Component #1 and #2 are the irrelevant artifacts and component #3 is the event-related potential

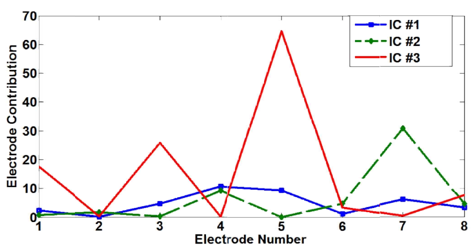

Figure 6 Contribution of the electrodes in the ICs for Subject #1

4. RESULTS

To assess the performance of our automatic EEG artifact removal algorithm, we compare the classification accuracies achieved by the system with no artifact removal vs. using our proposed method reported in Table 1. The classification accuracies are obtained by Stepwise Linear Discriminant Analysis (SLDA). The classification accuracies obtained by our proposed method lead to significant improvements for all the subjects as well as the average accuracy over the five subjects. Note that we aimed to simulate all the scenarios in the presence of impedance between the electrodes and the scalp. For this reason, no extra efforts were made to adjust the location or connectivity of the cap or electrodes in the experiment setup procedure. Instead, we solely rely on our proposed method to remove the noise automatically in the signal enhancement stage. The fingers of the dry contact electrodes may not fully contact the scalp and some electrodes may be placed at non-optimal locations, which can hurt the accuracy of the system with no artifact removal capability. Nevertheless, Table 1 shows that our proposed method is effective to employ the electrode-scalp impedance to automatically distinguish irrelevant artifacts from event-related information for the P300 speller task.

Table 1 Classification accuracy (in %) achieved without EEG artifact removal vs. our proposed method

	without artifacts removal	our proposed method
Subject #1	70.5	83.2
Subject #2	68.4	73.9
Subject #3	66.9	81.5
Subject #4	65.7	75.3
Subject #5	68.9	77.2
Average	**68.1**	**78.22**

Next, we evaluate the effectiveness of the automatic artifact removal procedure in our proposed method. The manual removal of artifacts using ICs is one of the most effective and accurate methods [12], since it implements based on researcher's prior knowledge of artifacts. Therefore, the classification accuracy of our automatic method is compared to the manual IC removal method in [12] to evaluate the effectiveness of our method. Table 2 shows the classification accuracy comparison for the five participating subjects. The accuracies achieved by our method outperform the manual selection for most of the subjects, individually. We also conducted the statistical t-test and achieved the p-value < 0.04 which indicates that the improvement in accuracy is significant.

Table 2 Classification accuracy (in %) achieved by manual IC selection vs. our proposed automatic IC selection

	manual IC selection	our automatic IC selection
Subject #1	76.2	83.2
Subject #2	72.1	73.9
Subject #3	75.9	81.5
Subject #4	68.9	75.3
Subject #5	75.6	77.2
Average	**73.74**	**78.22**

5. CONCLUSION

In this paper, we proposed an automated signal quality enhancement method based on the electrode-scalp impedance instead of relying on manual, time-consuming adjustments in the traditional EEG experiments. In the proposed method, electrode-scalp impedance was employed to distinguish the worst electrode set. After implementing the ICA decomposition, we compared the contribution of each individual electrode to the ICs. If an electrode from the worst electrode set provided the maximal contribution, the corresponding IC was removed. The experimental results showed that significant performance improvements were achieved using our proposed method compared to the case of no EEG artifact removal method as well as the manual removal of noisy ICs.

6. ACKNOWLEDGMENT

This work was supported by the Semiconductor Research Corporation, task # 1836.103 through the Texas Analog Center of Excellence (TxACE).

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