AUTOMATIC EEG ARTIFACT REMOVAL BASED ON ICA AND HIERARICAL CLUSTERING

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***Abstract*— Electroencephalography (EEG) is the recording of electrical activity along the scalp produced by the firing of neurons within the brain. These activities can be decoded by signal processing techniques, however, they are typically influenced by extraneous interference, like muscle movements, eye blinks, eye movements, background noise, etc. Therefore, a preprocessing step to remove artifacts is extremely important. This paper presents an effective artifact removal algorithm, based on Independent Component Analysis (ICA) and Hierarchical Clustering. Our technique utilizes general temporal and spectral features and particular information about target Event-Related Potentials (ERPs) (e.g. the timing of N200 and P300 on inhibition task or the specific electrodes contributing to the ERPs) to separate ERPs and artifact activities. Our method considers templates for desired ERPs to select event-related components for signal reconstruction. In our experimental study, we show that our proposed method can effectively enhance the ERPs for all fifteen subjects in the study, even for those that barely display ERPs in the raw recordings.**

***Index Terms*—** *EEG, ICA, Hierarchical Clustering*

1. INTRODUCTION

THE electroencephalogram (EEG) systems capture brain activities from the scalp. Several types of cognitive functions and underlying brain states have been associated with EEG signals: language tasks, information coding, and response inhibition. EEG signal analysis provides researchers with a better understanding of brain activities that can potentially be used for diagnosis and treatment. EEG signals are recorded by a set of electrodes placed over the scalp. These electrodes are capable of capturing action potentials, which are electrical impulses used to communicate information between neurons and from neurons to muscle fibers. Since EEG signals are highly susceptible to noise and artifacts, it is almost impossible to see any Event-Related Potentials (ERPs), the stereotyped electrophysiological responses to an internal or external stimulus, on the raw EEG signals. However, neuroscientists are often interested to visualize the signals and their time domain ERPs such as N200 (a negative peak around 200 ms after the excitation of the stimuli that is mainly observed on *Fz* channel electrodes) or P300 (a positive peak around 300 ms after the excitation of the stimuli that is mainly observed on *Fz*) [1]. Researchers often rely on manual cleaning of the signals with assistance from Independent Component Analysis (ICA) [2, 3]. However, that process is lengthy, time consuming, subjective and unpruned to human errors. Currently, there exist a few automatic artifacts removal methods. However, some of these techniques only focus on removing particular artifacts such as EOG [4] and BCG [5]. Other investigations only use general features, such as lagged auto-mutual information [6], pair-wise mutual information [7, 8], temporal information and spectral information (e.g. power density distribution on various frequency bands) [9]. They do not consider features that would highlight target ERPs (e.g. the timing or the specific electrodes contributing to the ERPs) in the artifacts removal framework. Therefore, the prior techniques cannot effectively enhance the visibility of ERPs in the reconstructed signal. However, in our proposed technique, utilization of features that contribute to the target ERPs will create relevant clusters and signals of higher quality.

In this paper, we introduce a novel method for automatic artifact removal which can significantly enhance prominence of ERPs in the clean signal. This method is based on separation of the raw multichannel EEG recordings into Independent Components (ICs) and subsequent clustering these component based on general features (e.g. temporal and spectral information) and also with special event-related features (e.g. the timing of N200 and P300 and their corresponding electrodes for inhibition task). Finally, we use templates of the desired ERPs to identify and remove components with artifacts, while retaining the relevant components that will be used to reconstruct the clean signal. The novelty of the proposed algorithm lies on the use of event-related features in the clustering procedure, and the use of event-related template in the cluster-selection procedure to objectively identify event-related components.

2. RELATED WORKS

Unfiltered EEG signals are usually associated with artifacts

such as eye blinks, eye movements, muscle movements, background noise, and heart beat signals. All these non-event related components affect the fidelity of EEG signals. They create challenges for extracting useful ERPs and for the analysis and the visualization of the EEG signals. Therefore, a large body of prior work has been investigating artifact removal techniques. Among them, the most popular approach is the ICA. The ICA method has been shown to effectively separate artifacts, event-related activities, and non-event-related activities into different components [10].

Manual IC selection in ICA require expert and well trained staff. Therefore, automatic IC selection has become an attractive alternative. Researchers have investigated automatic clustering techniques to group similar ICs after application of the ICA, based on specific features extracted from each IC. Several features and clustering methods have been presented. H, Qi *et al* presented a K-means clustering based on the similarity between every two components in multi-trial EEG analysis [11]. Another commonly used clustering method is fuzzy C-means clustering [9, 12]. Both K-means and fuzzy C-means clustering are iterative methods. They both require the target number of clusters *a priori* to terminate the clustering iterations. Clustering methods like hierarchical clustering have been used because the target number of clusters often is unknown for artifact removal. N. Nicolaou *et al* propose an artifact removal algorithm via hierarchical clustering based on auto-mutual information [6]. M. Milanesi *et al* utilize the pair-wise mutual information as hierarchical clustering feature for EEG late potential selection [7, 8]. However, using mutual information or temporal and spectral information is not always enough to highlight ERPs. For this reason, we propose a clustering method that uses relevant features to the target ERPs and use a template matching technique to select relevant ICs and clusters.

3. METHODS

3.1 Independent Component Analysis (ICA)

The first step in our proposed algorithm is the ICA transform. ICA is a computational method for separating a multi-channel signal into additive subcomponents supposing the mutual statistical independence of the non-Gaussian source signals [13]. Assume that we observe an array of electrodes that provide a vector of N channel signals $\boldsymbol{v}(t)=[v_1(t), v_2(t), \ldots, v_N(t)]^T$ that are linear combinations of N unknown and statistic independent sources $\boldsymbol{s}(t)=[s_1(t), s_2(t), \ldots, s_N(t)]^T$. The objective of the ICA algorithm is to find a separating matrix W, such that

$$s(t) = W * v(t) \quad (1)$$

When applying the ICA to the EEG signals, the resulting independent components represent the event-related potentials and non-event-related sources (including artifacts) [10]. This makes the ICA to be an effective method for removing the artifacts. The inverse matrix W^{-1} gives the relative projection strengths of the respective components to each of the scalp electrodes, which will be used as features for further clustering. These inverse weights define the scalp topography of each component, and provide the evidence for the components' physiological origin [2].

Several ICA algorithms have been implemented and are publicly available. In this paper, we use the FastICA algorithm in the EEGLAB [14] to transform the original multi-channel EEG signals into ICs.

3.2 Features Extraction and Clustering

To group independent components (ICs), a hierarchical clustering approach is chosen for two reasons. Firstly, the dendrogram in clustering not only encapsulates the grouping for clusters, but also provides information on the closeness of the elements in each cluster that corresponds to the height of the node. Secondly, the entire clustering procedure can be accomplished without determining the number of clusters *a priori*. In particular, four kinds of features are extracted for clustering.

1) Spectral features: The main power of EEG signals are in delta band (0-4 Hz), theta band (4-8 Hz), alpha band (8-13 Hz), beta band (13-30 Hz), and gamma band (30-80 Hz). Additionally, the artifacts show dissimilar power distribution compared to event-related components. These differences can be represented by the *ratios of spectral power* (50/30 Hz, 50/20 Hz, 50/10 Hz, 40/20 Hz, 20/10 Hz, and 10/5 Hz).

2) Topographical features: The artifacts and the event-related potentials are projected on different groups of electrodes. For instance, the Go/NoGo-related potentials are concentrated on the frontal and central electrodes (around *Fz* channel), while the eye blinks project most strongly to the far frontal site on the scalp [1]. Topographical features can be presented by the median of the component's weight.

3) Similarity over trials: The artifacts are random, unexpected, and usually only occur in parts of the trials. Thus, the trials that contain artifacts have no common pattern and exhibit very low similarity with other trails. On the other hand, the trials with event-related components exhibit higher similarity with other trials. The average normalized cross correlation value is adopted to measure the similarity among trials. Several trials are concatenated to compose $\boldsymbol{v}(t)$.

4) Temporal features: The kurtosis for each component was employed.

Overall, a 10-dimension feature vector (6 spectral features, 1 topographical feature, 2 similarity features and 1 temporal feature) is used for hierarchical clustering.

3.3 Event-related Cluster Selection

Since the artifacts can randomly occur and are unexpected, they are difficult to identify. Thus, instead of detecting and removing artifacts, our approach is to extract the event-related components based on a global pattern that

encapsulates models for signals of interest (e.g. N200, P300). In this investigation, we use the inhibition task with Go and NoGo stimulus. Neuroscientists have found that, for the inhibition task, most event-related components project strongly around *Fz* channel and have two fixed significant ERP patterns: N200 and P300 [1]. N200 is a negative deflection occurred after 200 ms, constrained to the frontal scalp locations. P300 is a large positive deflection occurred after 300 ms in the frontal, central, and the parietal regions. In addition, the difference of amplitude between N200 and P300 for NoGo signals is larger than Go signals [15]. Hence, we build a template based on this *a priori* knowledge to guide the cluster selection procedure. We then calculate the contribution of each cluster to the desired ERPs (N200 and P300) for the cluster selection. The contribution value ϕ_j (Eq. 3 & 4) for each cluster is presented by the average back-projection value p_i (Eq. 2) in a specified time range.

$$p_i = W^{-1}(i) * cp(i) \quad (2)$$

p_i is the back projection value of component i, W^{-1} is the inverse weight matrix, cp is the component matrix.

$$\phi_j^{p_3}(t) = \frac{1}{t_{p_3}^+ - t_{p_3}^-}[\sum_{t=t_{p_3}^-}^{t_{p_3}^+}(\frac{1}{m}\sum_{i=1}^{m} p_i(t))] \quad (3)$$

$$\phi_j^{n_2}(t) = \frac{1}{t_{n_2}^+ - t_{n_2}^-}[\sum_{t=t_{n_2}^-}^{t_{n_2}^+}(\frac{1}{m}\sum_{i=1}^{m} p_i(t))] \quad (4)$$

$\phi_j^{p_3}$ is the contribution value for desire ERP (P300) of cluster j, $\phi_j^{n_2}$ is the contribution value for N200, m is the total number of components included in the cluster j and t is the specified time range. In our study, we define $t_{n_2}^-$ =200 ms, $t_{n_2}^+$ =300 ms, $t_{p_3}^-$ =300 ms, $t_{p_3}^+$ =500 ms.

Finally, the cluster j which maximizes the difference between $\phi_j^{p_3}$ and $\phi_j^{n_2}$ is chosen, the all its components are used to reconstruct the clean signal.

4. EXPERIMENTAL SETUP

We collected EEG data from 15 participants. All subjects were asked to complete the standard Go/NoGo tasks, in which, the subject is instructed to push a button if green up-arrow (Go) is shown on a display, and do nothing if red octagon (NoGo) is presented. Go/NoGo stimuli are presented for 300 ms followed by 1700 ms of blank screen. For each subject, we collected 80 trials of Go and 20 trials of NoGo. Continuous EEG signals were recorded from 64 electrodes sensor cap placed according to the modified international 10-20 system. The EEG signals were sampled at 1000 Hz, and filtered by a band pass filter with a cutoff frequency of 0.5-100 Hz.

5. RESULTS

Among all 15 subjects, only 6 had visible desired ERPs (N200-P300) in the original Go/NoGo signals, which are averaged over all trails. After our proposed ICA-clustering based automatic artifact removal algorithm, all 15 subjects had enhanced view of N200-P300 complex in the refined Go/NoGo signals.

The signal before and after our artifact removal techniques are shown in Fig. 1 and 2 for two selected subjects. Figure 1 shows the results of one subject which obtains the visible view of ERPs (N200-P300) in the original Go/NoGo signals. The average Go/NoGo signals for all trials before artifact removal are shown in the left diagram of (a). The average signals after the automatic artifact removal is shown in the right diagram of (a). As indicated in Fig.1 (a), after ICA-clustering procedure, the N200-P300 complex is more prominent. Furthermore, we introduce the following measures to assess the effectiveness of our proposed approach highlighting N200 and P300, which we call the Negative-to-Positive Ratio (NPR). The NPR measure is the difference in amplitude between N200-P300 peaks for Go/NoGo (Eq. 5).

$$NPR = \frac{Pn_{P3} - Pn_{N2}}{Pg_{P3} - Pg_{N2}} \quad (5)$$

NPR is the ratio value, Pn_{P3} and Pn_{N2} are the peak amplitude values of P300 and N200 for NoGo signals, respectively, and Pg_{P3} and Pg_{N2} are the peak amplitude values of P300 and N200 for Go signals, respectively. We expect to observe larger peak-to-peak amplitude for NoGo over Go [15]. Therefore, the *NPR* is expected to be larger than one. The result shows the *NPR* for before and after processing are 0.8 and 1.2 respectively, proving a clear improvement in visualization of desired ERPs. The slope of N200-P300 complex for Go/NoGo signal is another measure that we use to assess if N200 and P300 are well pronounced. We observe that the slope increases from 1.2 to 1.8 after the application of our method. Fig. 1(b) represents the single-trial ERP image for the original and refined Go/NoGo signals. These plots illustrate the effectiveness of the proposed technique enhancing individual ERPs in single trial, especially for the NoGo signals.

Figure 2 depicts the signals for another subject. N200-P300 complex is not visible in the left diagram which depicts the average of trials before artifact removal. As shown in the right diagram, after artifact removal, a view of N200-P300 is clearly recognizable. It demonstrates that the proposed algorithm can effectively extract the ERP from even when there are no clearly visible ERPs in the original signals.

Overall, for the 6 subjects, with visible N200-P300 complex in the original signals, the average *NPR* is increased from 1.1 to 1.6 and the average slope of N200-

P300 complex is increased from 1.3 to 2.1, after our artifact removal procedure. These results illustrate the effectiveness of the proposed algorithm removing the artifacts and other non-event-related sources, and highlighting N200-P300 complex on all subjects. Researchers and clinicians may use the refined signals, the timing and the relative amplitude of N200 and P300 for better investigation and clinical diagnosis.

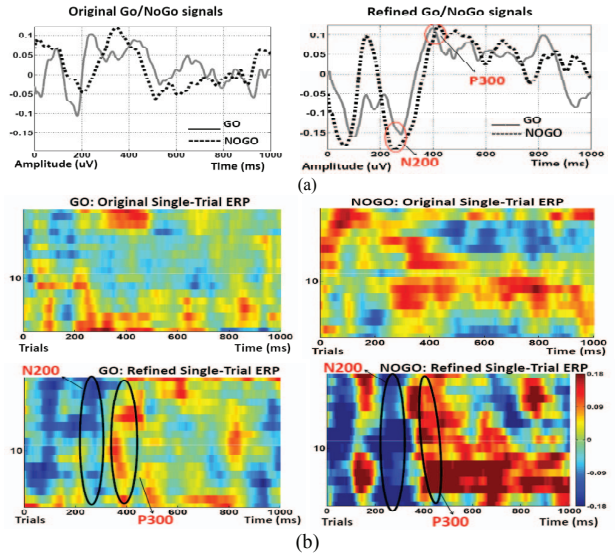

Fig. 1 EEG signals for subject with visible N200-P300 in the original signals
(a) Left: Average of original Go/NoGo signals. Right: Average of refined signals. Both exhibit N200-P300 complex, but the complex becomes more prominent after application of our proposed technique
(b) Top: Single-trial ERP of original Go signals (left) and original NoGo signals (right) Bottom: Single-trial ERP of refined Go signals (left) and refined NoGo signals (right), they both show the enhanced view of N200-P300 ERPs.

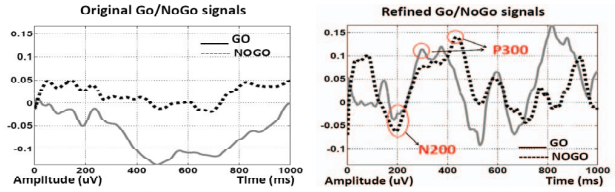

Fig. 2 EEG signals for subject with no visible N200-P300 in the original signals (Left) Average of original Go/NoGo signals. (Right) Average of refined signals. The original Go/NoGo averages do not exhibit N200-P300 complex, and the refined Go/NoGo averages clearly show N200-P300 complex

6. CONCLUSION

In this paper, we described an ICA based clustering algorithm to automatically extract event-related components and refine raw EEG signals. We first obtained independent components from multi channel raw EEG signals using ICA transform. Subsequently, for each independent component, we extracted a 10-dimensional feature vector that contained spectral, temporal and topographical features, along with features based on similarity measures. We used a hierarchical clustering technique to group all independent components into several hierarchical clusters, and selected a suitable cluster based on pre-determined template constructed for desired target ERPs (in our study, we used N200 and P300 in the inhibition task). Finally, we reconstructed the refined EEG signals using ICs in the selected cluster through the inverse ICA transform. Using our proposed artifact removal technique, the visibility of event-related components (N200-P300 complex) was clearly increased. The NoGo signals have larger amplitude and sharper slope than Go signals in the refined signals.

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