Comparison of Adaptive Cancellation and Laplacian Operation in Removing Eye Blinking Artifacts in EEG

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Abstract

The long-term goal of our project is to develop a brain computer interface for locked-in patients. In this study, we designed a controlled experiment and compared the efficacy of real-time adaptive cancellation and Laplacian operation in removing eye blinking artifacts in EEG. Scalp EEG was recorded while the subject performed thumb movements in three different states of eye blinking, i.e., persisted eye opening, persisted eye closure and natural blinking. The collected data were preprocessed with one of three preprocessing algorithms, namely, adaptive cancellation, Laplacian operation and null and, then, passed through windowed Fourier transform to calculate the change of wave power. Templates of wave power were derived by averaging the whole set. Correlation coefficients of templates and single-pass experimental results were calculated and a threshold value of coefficient was chosen to define the detection of thumb movements. The validity of detection was tested by EMG of thumb extensor. The efficacy of preprocessing algorithms was evaluated by ANOVA and chi-square tests. The results showed that, compared with the control group, both adaptive cancellation and Laplacian operation enhanced the wave suppression percentage. There is no difference between the group results of two preprocessing methods, while the individual difference is prominent. The implication of the effect of preprocessing on enhancing event detection rate is discussed.

Keywords: EEG, Adaptive cancellation, Eye blinking, Laplacian operation

Introduction

Electrical activities (electroencephalogram, EEG), which reflect the state of brain activations, can be recorded on the scalp by electrodes. μ rhythm is the 8-12 Hz waveform recorded at the Rolandic area of cortex (C3 and C4 of the standard international 10-20 electrode system) while the subject is wakeful and relaxed. Since μ rhythm is suppressed by the voluntary movements and sensory stimuli of contralateral upper limbs [1], it is a potential candidate for the control source in brain-computer-interface (BCI) technology [1-5].

Eye movements are common source of artifacts in EEG recording [7]. Though eye movements may not change the topographical asymmetry of alpha and beta wave, they exert substantial general effects on the whole EEG spectrum [8]. It is not well studied how significant eye movements can affect μ waves. Different eye movements have different topographies and have to be treated individually [9]. Most of the past studies about μ rhythm discarded the experimental data interfered by the eye blinking by naked eye inspection. Yet, if EEG is to be used as a real-time control source in BCI, the interference due to eye blinking has to be eliminated by signal processing procedures in real time. For removing artifacts due to eye movements, many techniques have been developed in the past, ranging from simple thresholding [10] and linear regression [11-13] to more sophisticated methods, such as aligned-artifact average [14], independent component analysis [15], discrete cosine transform [16] and adaptive linear processing [17]. Simple methods were unsatisfactory in performance while more sophisticated methods have better performance at the cost of more extensive calculation. For BCI applications, the algorithm has to be effective and, at the same time, simple in order to be implemented in real time.

The main purpose of this study was to develop an algorithm to process EEG for identifying the attempts of thumb movements in real time under the natural eye blinking condition. The algorithm consisted of two parts. The first preprocessing part was to remove the influence of eye blinking. The second part, the template correlation, was to identify the movement attempt. In contrast to most of the previous studies, we considered not only the true positive results, but also false positive and negative cases.

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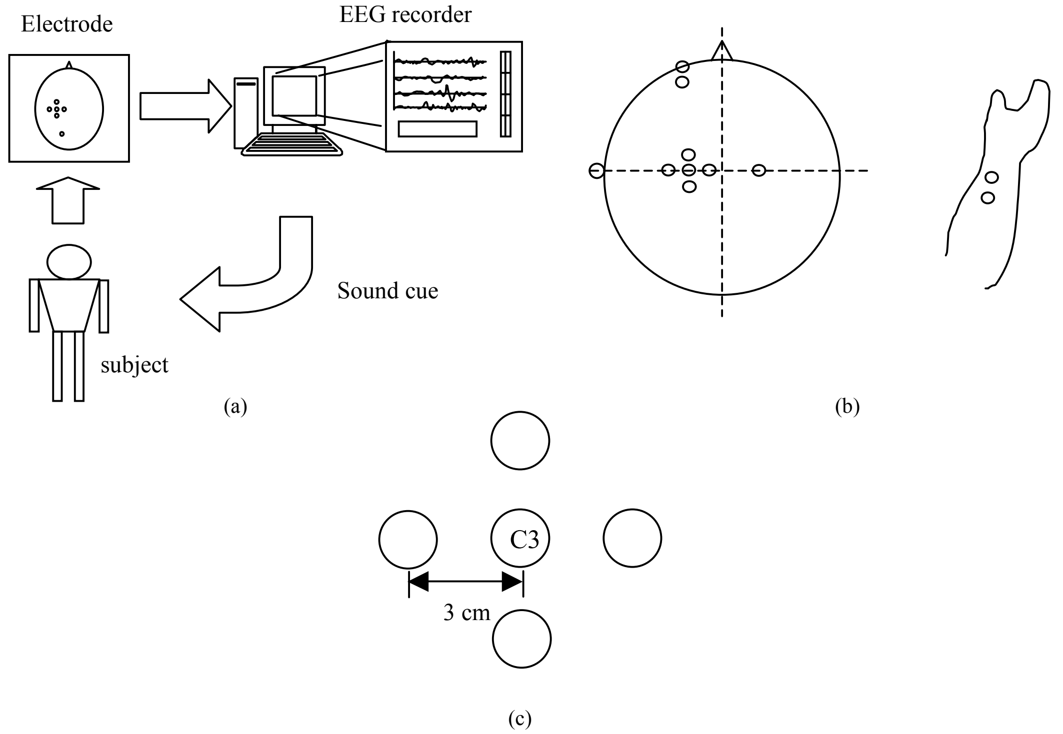

Figure 1. Schematic drawing of the experimental setup. (a) The whole scheme, (b) electrode location, and (c) the electrode configuration around C3 electrode.

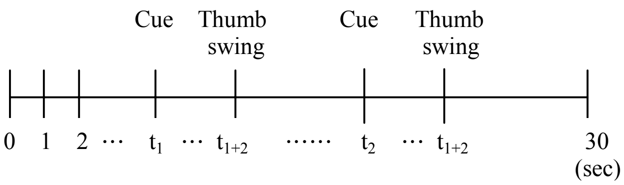

Figure 2. Experimental procedure of one trial.

Methods

Experimental setup (Fig. 1a)

EEG was recorded by using a commercial digital EEG recorder (Profile, Medelec, Oxford Instrument, www.oxford-instruments.com) and all experiments were performed in a shielded room. Eight channels of signals, including six channels of scalp EEG and two channels of surface EMG from the right thumb extensor and the forehead were recorded, respectively (Fig. 1b). All EEG electrodes were referenced to the left earlobe (A1). The four electrodes, each 3 cm from C3 and forming a cross (Fig. 1c), were used for spatial filtering at the software level. EMG of the forehead was recorded to monitor the eyelid movements, and EMG of thumb extensor was used to define the onset time of thumb movements. EEG signals were filtered by a 0.5~100 Hz analog bandpass filter, amplified by 10000x and sampled at a rate of 256 Hz per channel. EMG was also amplified, filtered and sampled at an identical rate by the same EEG machine.

Experimental procedures

The study protocol was approved by the human experiment and ethics committee of National Cheng Kung University Hospital. Before the experiment, the whole experimental procedure and the potential hazards were explained clearly to the subject. The subject lay on a deck chair in a supine position with the right upper limb well supported. The forearm was in the neutral position with the fingers in the naturally flexed posture. Before the trials, the subject was asked to be calm and relaxed for twenty minutes. The procedure of one trial was shown in Fig. 2. The duration of one trial was 30 seconds and within it there were two movements separated by approximately 10 seconds. When the subject heard the auditory cue produced by the experimenter, he/she was asked to make a fast and brief thumb extension and natural falling back to the original position. The experiment was designed to test the capability of the preprocessing algorithms to deal with eye movements. The subject was asked to perform the trials under three states: (1) natural state, i.e., blinking eyes naturally, (2) persisted eye opening and (3) persisted eye closure. In each state, the trial was repeated 18 times. There was sufficient time for rest between consecutive trials in order to prevent interaction of trials.

Six young male subjects were recruited in this study. The subjects were healthy and right-handed and had no known neurological deficits.

Data processing

Two methods were respectively employed for preprocessing the EEG data, namely, adaptive cancellation (ANC) and Laplacian operation (LAP). The emphasis was on adaptive cancellation method, and Laplacian operation was employed for comparison. Then, the preprocessed EEG segments, after windowed FFT, were aligned according to the

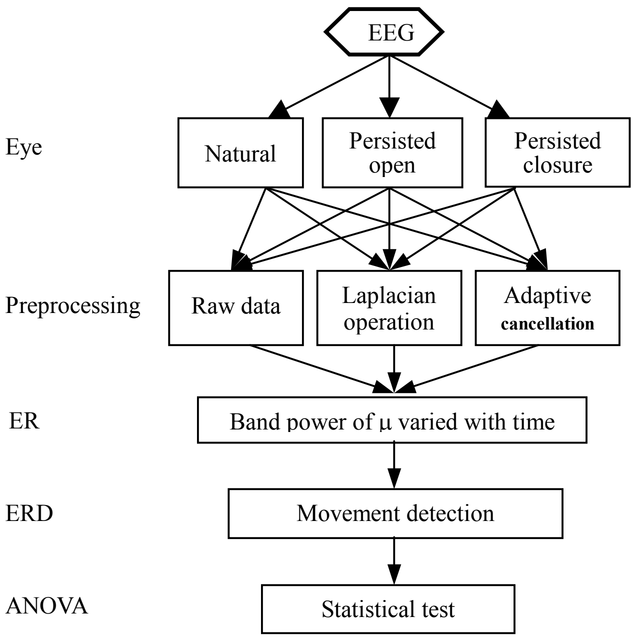

Figure 3. Block diagram of adaptive cancellation.

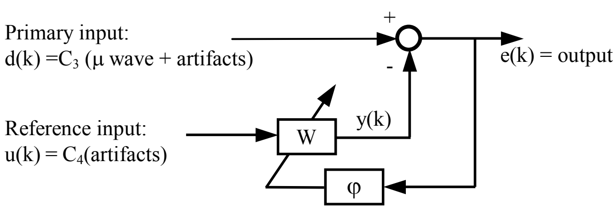

Figure 4. Flow chart of data processing.

peak of EMG envelope and the μ wave bands were averaged to obtain a template. Cross-correlation coefficients between the template and trials were calculated as the indicators of thumb movements. Each step was depicted in Fig. 3 and described in more details in the following.

Adaptive cancellation

A block diagram of the adaptive filtering was shown in Fig. 4 [18]. The output y(k) of the adaptive filter could be expressed as a difference function of reference input, u(k):

$$y(k) = w_1(k)u(k-n+1) + w_2(k)u(k-n+2) + \ldots + w_n(k)u(k) \quad (1)$$

where k indexed the number of samples, $w_i(k)$ (i = 1 … n) were the filter coefficients and n was the order of the filter. The error signal e(k) was defined as

$$e(k) = d(k) - y(k) \quad (2)$$

where d(k) was the primary input. The coefficients $w_i(k)$ were updated by using least mean square method [19]:

$$w_i(k+1) = w_i(k) + \varphi * u(k) * e(k) \quad (3)$$

where φ was a constant.

In this study, EEG from C3 electrode was regarded as d(k) and C4 as u(k). It was assumed that the changes in μ wave power due to right thumb movements were greater in C3 than in C4, so that the adaptive filter would remove the background part and preserve the difference between C3 and C4.

Laplacian operation

EEG of the 4 electrodes surrounding the C3 electrode were used to perform the Laplacian operation as a spatial filtering:

$$E_{C3}' = E_{C3} - \frac{(E_1 + E_2 + E_3 + E_4)}{4} \quad (4)$$

where E_{C3}' was the filtered EEG at C3, E_{C3} was the original EEG at C3, and E_1, E_2, E_3 and E_4 were the EEG of the 4 electrodes surrounding the C3 electrode.

Template formation and cross-correlation

After preprocessing, EEG data were then aligned by the maximum of EMG, representing the start of movement (T_m), and cut into segments of 9 seconds with T_m at the center of the segment. The segments were passed through a windowed FFT with a Hamming window of 1-second width and shifting per 1/8 second. The absolute values of Fourier coefficients of 8~12 Hz were summed as the power of μ rhythm. ERD were defined as [20]:

$$(\mu \text{ power - mean power})/(\text{mean power}) \times 100\% \quad (5)$$

where mean power was the power per second over the first and the last 2 seconds. The ERD trajectories of all the training segments were averaged to obtain a template (T_{C3}).

In the next step, ERD of the original data (R_{C3}) spanning 1 second and shifting per 1/8 second were calculated. Then, the cross-correlation coefficients (C_c) between R_{C3} and T_{C3} were calculated. Empirically, we selected three different thresholds, namely, 0.35, 0.4 and 0.45, to compare the detection rates. A detection was defined as a true positive result if the time that C_c exceeded the threshold was within ±1 second of T_m. Consecutive detections in less than 1 second were regarded as a single detection. A false positive result was defined as when a detection was claimed outside ±1 second of T_m and a false negative result was defined as no detection was claimed inside ±1 second of T_m. By this definition, it was possible to have more false negative results than the number of true movements.

Statistical analysis

The results of classification had four possibilities: (1) thumb movement was detected correctly (true positive), (2) thumb movement was not detected (false negative), (3) there was no thumb movement but a detection was claimed (false positive) and (4) no detection was filed when there was no thumb movement (true negative).

There were three control variables in this study, i.e., (1) preprocessing methods: Laplacian operation, adaptive filtering and null control (ORI), (2) experimental states of subjects: persisted eye opening, persisted eye closure, and blinking naturally and (3) thresholds of cross-correlation coefficients: 0.35, 0.4 and 0.45. Hit rate was defined as the ratio of the number of true positives to the sum of positive calls. Analysis of variance (ANOVA) was utilized to investigate the significance of differences among all groups. Finally, chi-square test (preprocessing in column and state of eye blinking in row) was used to compare which combination of these three parameters would yield better classification results [21].

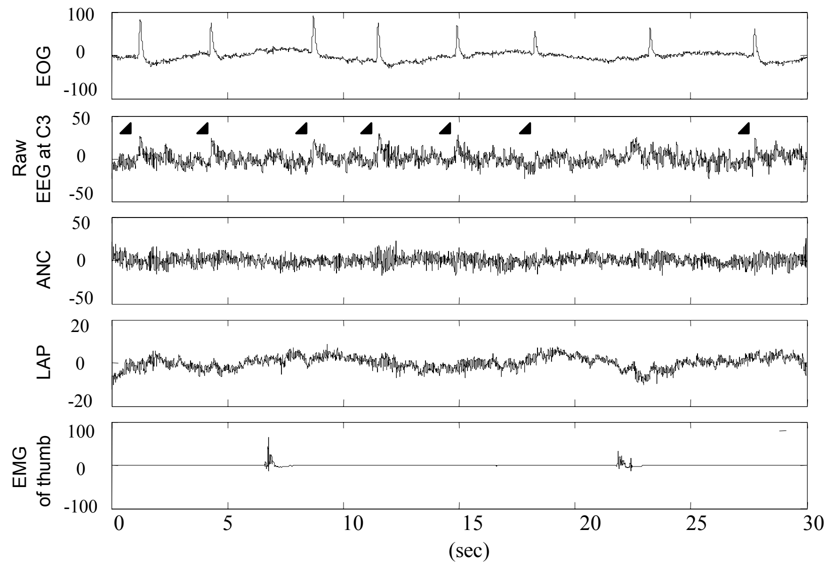

Figure 5. An example trial in naturally blinking state. EOG stands for electrical signals recorded from forehead leads and other abbreviations are described in the text. Arrowheads show the artifacts in raw EEG due to blinking.

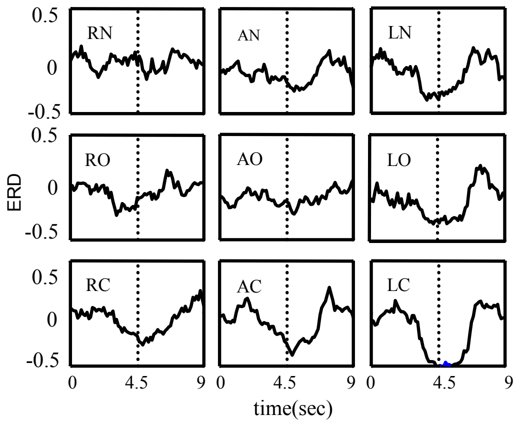

Figure 6. ERD templates. The dashed line marks the start of a thumb movement. 'R', 'L' and 'A' denotes raw data (un-preprocessed), Laplacian operation and adaptive filtering, respectively. 'N', 'O' and 'C' denotes blinking naturally, persisted eye opening and persisted eye closure, respectively.

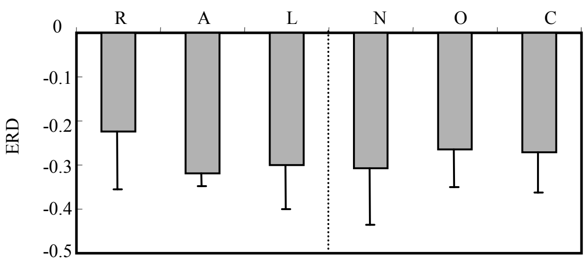

Figure 7. Means and standard deviations of largest suppression percentages of all trials in all subjects. The notations are identical with those in Figure 5.

Results

An example trial in naturally blinking state is shown in Fig. 5. Before preprocessing, the EEG recorded at C3 leads were plagued with blinking artifacts. Both ANC and LAP preprocessing procedures removed the artifacts. As described

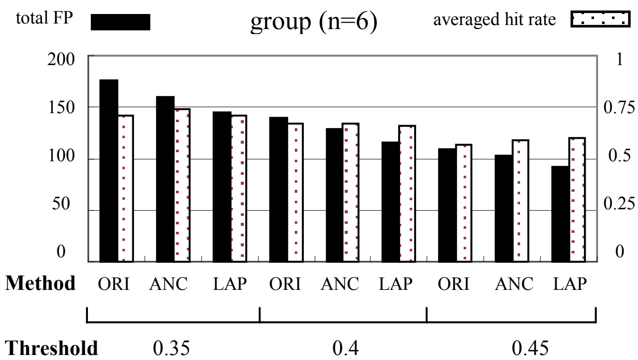

Figure 8. The influences of preprocessing algorithm and threshold value on group mean hit rates and mean total numbers of false positive detection. The abbreviations are described in the text.

before, there was one ERD template associated with one combination of preprocessing methods (raw, Laplacian operation, adaptive filtering) and experimental states (eyes opened, closed, natural). Nine ERD templates in total were derived. A set of example templates of one subject is shown in Fig. 6. In this example, the suppression of μ wave power is more evident in the state of eye closure and in the groups of preprocessing with LAP. The means and standard deviations of largest suppression percentages of all trials in all subjects are shown in Fig. 7. By one-way ANOVA, the difference of results among different preprocessing methods is marginally significant ($F_{2,51} = 2.93$ and $p = 0.06$). In other words, preprocessing with ANC or LAP marginally enlarged the suppression percentage of μ wave power. There is no difference among the results of different states of eye blinking.

Fig. 8 shows the influence of preprocessing methods on the hit rates and the numbers false positives of all the subjects. It can be seen that both the averaged hit rates and the averaged total FP decrease as the threshold increases from 0.35 to 0.45. At a fixed threshold level, the averaged hit rates are about the

Table 1. χ^2 of thresholds versus preprocessing methods and states of eye blinking.

Threshold	Method	State
0.35	2.005	0.015
0.40	1.036	0.277
0.45	1.384	0.787

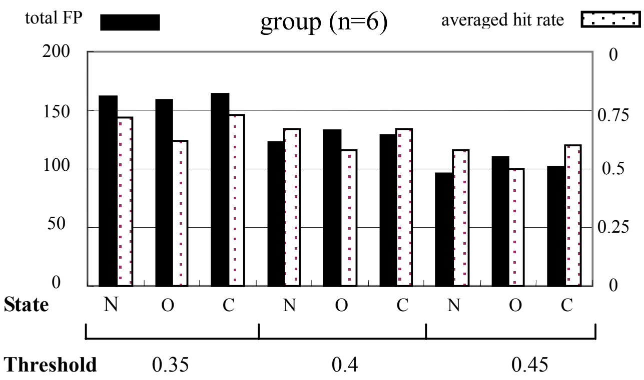

Figure 9. The influences of state and threshold value on group mean hit rates and mean total numbers of false positive detection.

same for different preprocessing methods. The averaged total FP decreases from ORI group to ANC and LAP groups, though the differences tested by two-way ANOVA with interaction are insignificant statistically ($F_{2,2,45}$ = [1.37, 0.04] and p = [0.264, 0.961], $F_{2,2,45}$ =[1.63, 0.08] and p = [0.208, 0.920] and $F_{2,2,45}$ = [0.82, 0.47] and p = [0.449, 0.631] for threshold = 0.30, 0.40 and 0.45, respectively). Fig. 9 shows the influence of states of eye blinking on the hit rates and the numbers false positives of all the subjects. As in Fig. 8, both the averaged hit rates and the averaged total FP decrease as the threshold increases from 0.35 to 0.45. At a fixed threshold level, the averaged hit rate is smaller for the group of persisted eye opening, while the results of averaged total FP are about the same. Tested with two-way ANOVA, the differences are insignificant.

Table 1 summarizes the results of chi-square tests on the influence of preprocessing and state of eye blinking, respectively. The results indicated that there is no significance among different preprocessing groups or among different states of eye blinking. The influence of threshold values is also tested. The results indicated that the threshold (χ^2 = 7.607 and $p < 0.05$) has a significant influence on the results.

Discussion

Both preprocessing algorithms (ANC and LAP) enhanced the suppression of μ wave power, while neither improved the hit rates. There are many possible explanations. First, the sample size or the number of trials is not large enough. This was a pilot study and only six subjects were recruited. Second, the magnitude of μ wave suppression and correlation coefficient might not be related. The magnitude of μ wave suppression is a single time point evaluation, while correlation coefficient is a property of a time period evaluation.

Though there was no difference between the group results of ANC and LAP, the performances of the two algorithms in some subjects differed greatly. The relative location of electrode to the center and size of μ wave suppression may be more dominant factors. When the actual center of μ wave suppression is closer to the midline, then, adaptive filtering may be ineffective. On the other hand, when the side of μ wave suppression is greater than the range of Laplacian operation, then, LAP is ineffective. It implies that, in practical applications, one algorithm may be more suitable for one group of subjects and the other algorithm more suitable for the other group. In other words, we can choose one algorithm for a particular subject to improve the detection rates. It also implies that brain mapping of μ wave suppression in thumb movements by multiple electrodes may help to select the preprocessing method by estimating the center and size of μ wave suppression.

There was a tendency for the preprocessing algorithms to reduce the false positive rates, though the differences to the control results were not significant. This raised a possibility that the, if we used a higher threshold value for the control group, the false positive rates of the three groups would be similar and the difference in hit rates would be enhanced. Because both false positive rate and hit rate were influenced by the threshold value, in contrast to most of the past studies that only compared true positive rates but neglected false positive rates, we used chi-square test for comparison. Chi-square test did not support that the preprocessing methods and experimental states had a significant influence on hit rates and false positive. The statistical results do not affirm that the preprocessing algorithms are useless, because the probable problems include the sample size and the main detection algorithm. In our and other researchers' past experience, enhancing μ wave suppression is the prerequisite for a better detection rate. We did not probe further into other processing methods because the emphasis of the current study is on preprocessing for removing the eye blinking artifacts.

It was unanticipated that the states of eye blinking had no significant influence on the detection results. Again, the small sample size might be the cause. On the other hand, it is also possible that, using the current combination of preprocessing algorithm and template correlation, the effect of eye blinking was removed. We are recruiting more subjects for solving this problem.

Conclusion

In this study, we designed a controlled experiment and tested the efficacy of real-time adaptive cancellation in removing eye blinking artifacts in EEG. The results showed that both adaptive cancellation and Laplacian operation, enhanced the μ wave suppression but did not improve the detection rates. There is no difference between the group results of two preprocessing methods, while the individual difference is prominent.

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