Optimization of Electrode Configuration for the Removal of Eye Artifacts with Adaptive Noise Cancellation

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***Abstract*— Scalp electroencephalography (EEG) is a neural source signal that is extensively used in neuroengineering due to its non-invasive nature and ease of collection. However, a drawback to the use of EEG is the prevalence of physiological artifacts generated by eye movements and eye blinks that contaminate the brain signals. Previously, we have proposed and validated an H^{∞}-based Adaptive Noise Cancellation (ANC) technique for the real-time identification, learning and removal of eye blinks, eye motions, amplitude drifts and recording biases from EEG simultaneously. However, the standard electrooculography (EOG) electrode configuration requires four electrodes for EOG measurement, which limits its applicability for reduced-channel mobile applications, such as brain-computer interfaces (BCI). Here, we assess multiple configurations with varying number of EOG electrodes and compare the ANC effectiveness of these configurations to the ideal four-electrode configuration. From an analysis of the root mean squared error (RMSE) and differences in signal to noise ratios (SNR) between the ideal four-electrode case and the alternative configurations, it is reported that several three-electrode alternative configurations were effective in essentially replicating the ability to remove EOG artifacts in an experimental cohort of ten healthy subjects. For nine subjects, it was shown that only two to three EOG electrodes were needed to achieve similar performance as compared to the four-electrode case. This study demonstrates that the typical four-electrode configuration for EOG recordings for adaptive noise cancellation of ocular artifacts may not be necessary; by using the proposed new EOG configurations it is possible to improve electrode allocation efficiency for EOG measurements in mobile EEG applications.**

I. INTRODUCTION

Scalp electroencephalography (EEG), a non-invasive measurement of electrical signals produced by the brain and collected at the scalp, is the most heavily researched source signal for BCI and other neuroengineering applications due to its ease of collection, accessibility and lower cost [1]. However, EEG analysis requires significant pre-processing due to the high incidence of physiological and non-physiological artifacts, which contaminate the EEG measurements. One of the most common and challenging artifacts are the ocular artifacts [2], which is the contamination of EEG with electrical signals produced when blinking or during eye movement. Ocular artifacts are especially difficult because the contamination is not restricted to certain electrodes with a predictable effect, but, instead, contaminates all electrodes with a varying effect due to volume conduction [3]. Many methods have been suggested to remove ocular artifacts from EEG, including Independent Component Analysis (ICA), Principle Component Analysis (PCA), and neural network -based methods [4], but these methods are typically not real-time applicable. This makes their deployment into real-time BCI systems infeasible. Artifact Subspace Reconstruction (ASR) has been proposed as alternative that can be implemented for online eye artifacts removal [5]. However, ASR can suppress high amplitude EEG and in particular low-frequency components [6], therefore distorting delta band activity. H-infinity-based Adaptive Noise Cancellation (ANC) has been proposed as a robust real-time applicable control framework to remove eye blinks, eye motions, amplitude drifts and recording biases from EEG without any *a priori* knowledge of the noise statistical characteristics [7], [6]. ANC frameworks use a reference source to estimate the true noise over all input channels with the goal of removing that estimate from the contaminated signal, in order to calculate an output that closely estimates the true underlying uncontaminated signal. For the removal of artifacts from EEG, this framework requires a representation of the noise signal, which is typically accomplished with the addition of four electrooculographic (EOG) electrodes around the eyes. [8]

A drawback of current mobile EEG approaches, including BCI systems, is that they typically require four additional electrodes in order to collect the EOG noise references. This necessarily means that electrodes that could have been used for additional EEG locations must be reserved for EOG collection. While this is not a problem for high-count EEG electrode applications, applications that are limited in the number of total electrodes may not be able to use the ANC framework. Furthermore, from a computer science standpoint, a higher channel count is associated to a higher computational complexity [9], which directly impacts in longer processing times and more energy consumption. [10]. Consequently, this aspect assumes particular significance in the context of embedded applications, which has been addressed by various approaches in the existing literature

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The rest of the paper is as follows: Section II presents a brief background of adaptive noise cancellation and the methods for this research; Section III will detail the results of this analysis; and Section IV will discuss the conclusions and future work for this type of algorithm on EEG/BCI applications.

II. Methods

A. Data Acquisition

The dataset was collected at the University of Houston under a protocol approved by the Institutional Review Board (IRB G0501521). Ten able-bodied adult subjects (5 males and 5 females) gave their written informed consent prior to performing a single session of an eye movement task. During the task, the participants were seated comfortably in a room with the lights on and performed a series of randomized eye movements, as instructed by a display placed directly in front of them at eye level. The eye movements included blinks, and slow and fast eye movements in four directions. EEG data was measured with a 32-channel (1000 Hz sampling frequency) active-electrode EEG system (actiCap system, Brain Products GmbH). Twenty-six channels were reserved for EEG collection while six were relocated to positions around the eyes.

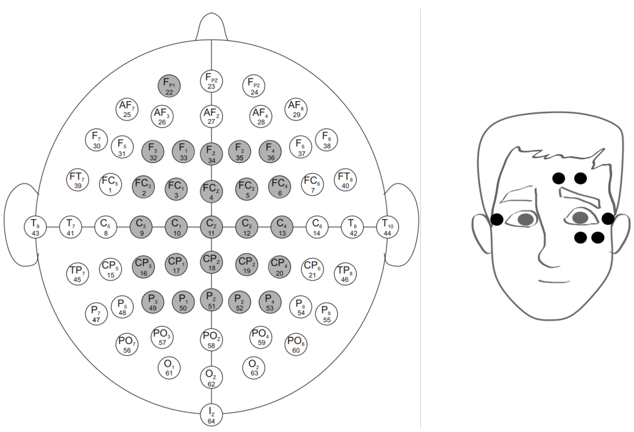

Fig. 1. EEG and EOG sensor placement

B. Alternative EOG Configurations

Thirty-four alternative EOG configurations were created from the six EOG electrode placements. These are presented in Figure 2. Three-electrode configurations (configurations A through L) include sensor combinations with at least one horizontal and at least one vertical electrode. A concern that one may have when selecting appropriate EOG electrodes is how to specifically create the noise references. For each set of three electrodes, two different methods for creating the horizontal noise reference are created for comparison. For example, configurations A and B employ the same electrodes, but differ in how the horizontal noise reference is created. Generally, these selections did not include electrodes from approximately the same area, such as a configuration that included both of the sensors underneath the right eye, since the EOG signal collected from these areas would be very similar.

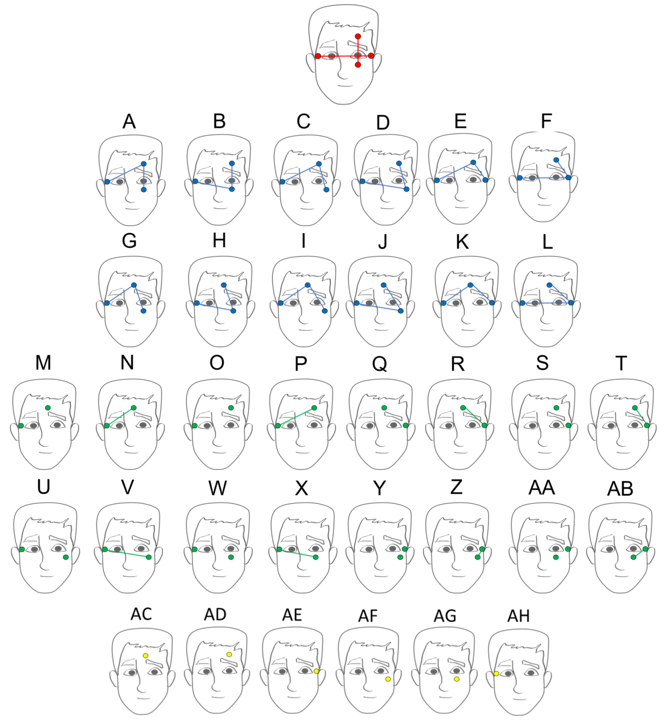

Fig. 2. EOG sensor combinations for the creation of alternative noise representations. First row: four electrodes. Second and third rows: three electrodes. Fourth and fifth rows: two electrodes. Sixth row: one electrode.

Two-electrode configurations (configurations M through AB) were designed to consider combinations of electrodes that were not close to each other and also investigate how to create the noise references. Here, we compare the differences between two electrodes taken independently as two noise references versus creating a single noise reference. For example, configurations M and N use the same electrodes but differ in that configuration M uses the electrodes independently whereas configuration N creates a single reference between the two electrodes.

Single electrode configurations are composed of the individual references input as the sole noise reference into the denoising framework.

C. Pre-Processing Methods

The collected EEG signals are first high pass filtered (fourth order Butterworth filter) above 0.1 Hz. While this is not entirely necessary as past research provides support that H-infinity adaptive noise cancellation can approximate a high pass filter [13], it would be more difficult to compare Root-Mean-Square Error (RMSE) and Signal to Noise Ratio (SNR) values if this preprocessing step is not identical across different configurations. Following the high pass filter, the signals were cleaned with the ANC framework and the resulting clean signals were compared.

a) Adaptive Noise Cancellation: Figure 3 presents an overview for the adaptive noise cancellation framework. Here, a single- or multi-channel contaminated signal s acts as the primary input to the system. This signal is made up of the uncontaminated signal and uncorrelated noise. A second input to the system is a representation of the noise that is correlated, in some way, to the true noise signal. This secondary signal is sent through a filter, the output of which is a transformed representation of the noise based on how it contaminates the single- or multi-channel primary signal. If the reason for how the noise affected the signal directly was known, a fixed filter could be used to remove the noise. However, the assumption with this framework is that the statistical characteristics of the noise are unknown, which is why an adaptive filter is necessary. Once the filter learns how the noise signal propagates through the signal source, the transformed noise representation is subtracted from the contaminated signal. The objective here is to produce a signal output that is the best least mean squares (LMS) estimate of the signal.

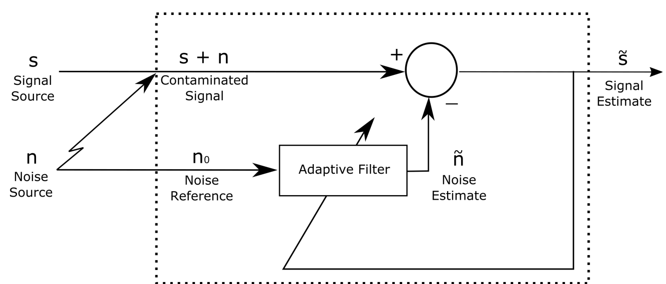

Fig. 3. General adaptive noise cancellation system diagram

One assumption for this LMS ANC framework was that the primary signal and noise signal were statistically stationary and that the system model was known. However, in the application of this method to EEG analysis, ocular artifacts are stochastic and time-varying and the underlying neural model is unknown, meaning that the prior assumption induces a susceptibility to estimation errors. H^∞ estimation is an attempt to address this problem in that the basic idea is to minimize the maximum energy gain from disturbances due to estimation errors, regardless of the nature of the disturbances.

H^∞ control methods are a branch of optimal control theory that attempts to synthesize controllers with reliable performance. The term H^∞ comes from the mathematical space over which this optimization takes place: the Hardy space, or spaces of holomorphic functions that are locally differential and bounded in the right half of the complex plane. The norm of this space, the H^∞ norm, can be considered the maximum energy gain, which we attempt to minimize.

There are a wide variety of H^∞ algorithms that could potentially be used for this application. Here, the specific H-infinity control method used for this ANC framework assumes that the filter weights are time-varying, which best matches the time-varying assumption of the EOG noise input [6].

b) H^∞ Parameter Selection: There are three parameters that must be selected prior to employing H-infinity ANC frameworks: γ (the optimality parameter), p_0 (the initialization value for the noise covariance matrix), and q_0 (the parameter that affects how quickly the framework learns the noise representations). In [14], the authors performed extensive parameter optimization for the 4-electrode ideal case. The analysis was based on energy comparisons between sections with and without eye movement artifacts while accounting for different sampling frequencies. For the 100 Hz sampling frequency case, the authors found the following parameter ranges:

TABLE I
PARAMETER RANGES FOR THE 100 HZ 4-ELECTRODE IDEAL CASE [14]

Parameter	Value
γ	1.15 - 1.2
p_0	5
q_0	$10e^{-10}$ - $20e^{-10}$

The mean value for each parameter range was selected as the intent of this research was on assessing the effectiveness of different EOG configurations rather than parameter optimization. The resulting cleaned signal from the 4-electrode case is then compared against the cleaned signals from all other configurations by calculating the average Root Mean Square Error (RMSE) and Signal to Noise Ratio (SNR) values.

III. RESULTS

The performance differences in terms of RMSE and SNR between the ideal 4-electrode case and the alternative configurations are represented in figures 4, 5, and 6. For the most restrictive of cases, where only 1 electrode can be allocated to EOG collection, the best selection in terms of the difference in RMSE and SNR values compared to the ideal 4-electrode case was the electrode on the participant's right temple (i.e., configuration AH in Figure 4).

Figure 5 presents the cases where two electrodes can be allocated for EOG collection. For two-electrode configurations, configurations are split between using the EOG sensors independently or combining the electrodes as a single noise reference. For RMSE comparisons, the majority of subjects did not see much difference when comparing how the electrodes are used in the noise reference calculations. For a single subject, Subject 2, who had more noisy signals generally, the difference in noise reference calculation methods was significant, with the combined noise references leading to drastically smaller RMSE differences. In terms of SNR values, the most consistent setups for all subjects were when employing the electrode at the left temple and either the electrode above the right eye or at the nasion.

The authors recommend that, for two-electrode EOG configurations, researchers select the electrode positions at the left temple and directly above the right eye (e.g., configuration P in Figure 5), and that these electrodes be combined to

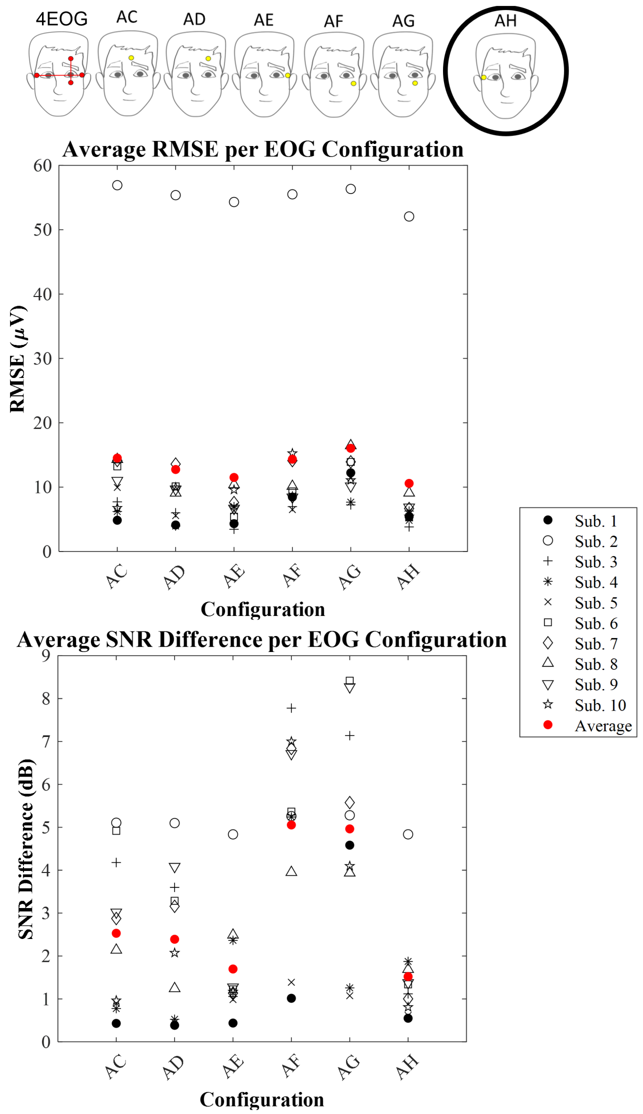

Fig. 4. Average RMSE and SNR differences between the one-electrode alternative configurations and the ideal four-electrode case.

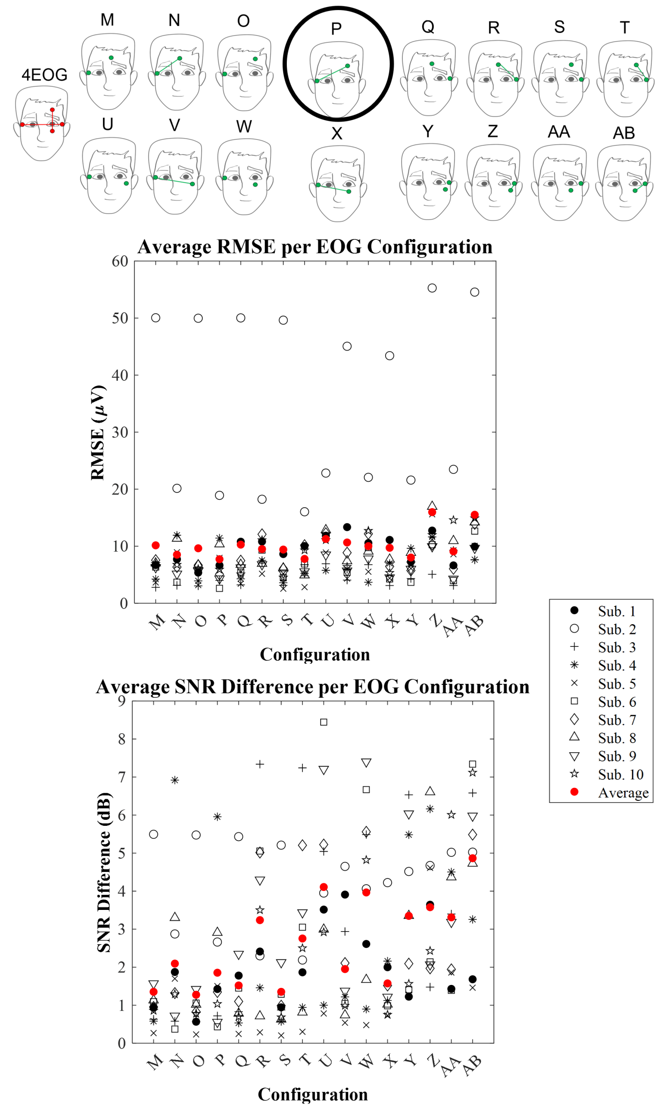

Fig. 5. Average RMSE and SNR differences between the two-electrode alternative configurations and the ideal four-electrode case.

form a single reference. While it is always recommended to emphasize good collection practices, this selection will help to prevent poor performance of the de-noising framework for particularly noisy data or when collecting with non-research grade equipment.

For 3-electrode configurations, there was not significant difference in de-noising performance when comparing configurations with the same electrodes but different noise representation creation methods, except for one case of interest. The best performing configuration over all configurations was configuration F. Configuration F was composed of the electrodes at the left temple, directly above the right eye, and the right temple, with the temple electrodes forming the horizontal noise reference and the left temple/ right eye electrodes forming the vertical reference. The comparison between configuration E and F, both of which were composed of the same electrodes, showed the most significant difference between performance and the method for noise representation creation. Overall, 3-electrode configurations generally performed significantly better than the 1- or 2-electrode configurations, particularly when comparing SNR to the ideal case. This is confirmed when comparing the cleaning performance between the selected configurations with Figure 7. In Figure 7, the ability of the selected configurations to clean an eye blink from participant 3 are presented next to each other. While the selected one- and two-electrode configurations are able to reduce the amplitude of the eye blink, the three-electrode configuration performs significantly better, with that configuration barely deviating from the ideal four-electrode case.

IV. Discussion and Conclusions

The contamination of EEG with physiological artifacts is a recognized challenge to address in EEG/BCI applications. This challenge arises from the stochastic and time-varying

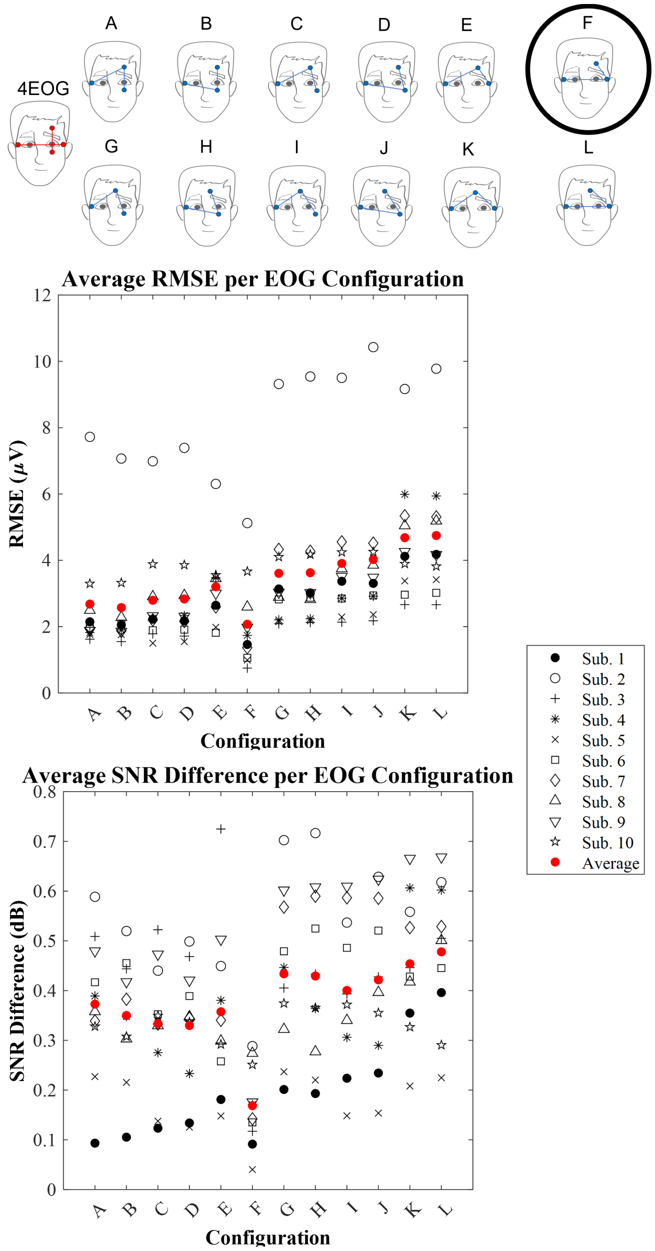

Fig. 6. Average RMSE and SNR differences between the three-electrode alternative configurations and the ideal four-electrode case. Three-electrode EOG configuration depicted in case F showed the best de-noising performance for ocular artifacts.

nature of these artifacts, the influence of volume conduction on their diverse propagation patterns across different electrode locations, and the inherent uncertainty in both the EEG signal model and the noise model.

In this article, H^{∞} weight optimization ANC-variation scheme was employed for the removal of ocular artifacts using reference provided by EOG electrodes. The choice of this technique was motivated by its ability to handle model uncertainties and adapt to the time-varying characteristics of ocular artifacts.

While the industry standard for this framework required the use of four EOG electrodes to extract noise references

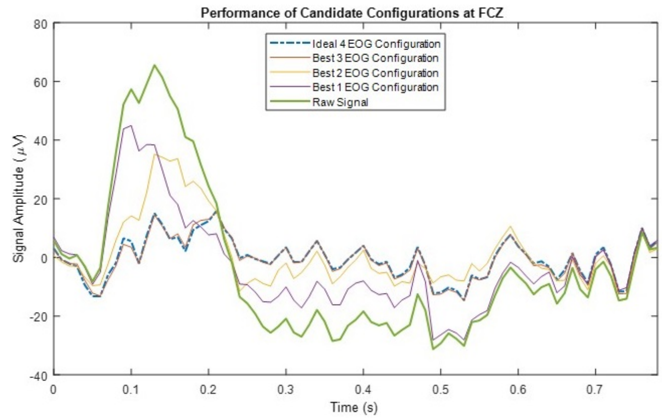

Fig. 7. Differences in cleaning of an eye blink for subject 3 at channel FCz when comparing the selected configurations for the one, two, and three channel restrictive cases against the ideal four-electrode case and the raw data.

for artifact removal, in this research was presented support that effective removal of ocular artifacts from EEG can be achieved using only two or three EOG electrodes. This finding expands the applicability of the framework to scenarios with limited available channels or in applications that require lower computational complexity, thereby enhancing its usefulness in practical applications.

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