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Improving the Performance of Dry Based Electrodes for P300 brain-computer interfaces

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Abstract

We present a performance comparison of gel and dry based electrode caps for use with the P300 speller system, and investigate the potential for a data-driven dynamic data collection algorithm to compensate for the lower signal-to-noise ratio of P300 responses recorded via dry electrode systems. In static data collection, performance with a dry electrode system resulted in a substantial loss in performance. Using dynamic data collection, this loss in performance was reduced; however, dynamic data collection did not fully compensate for the lower SNR. Additional work is likely needed to further improve the performance of dry electrode systems.

1 Introduction

Despite encouraging improvements over the last decade, the P300 Speller remains primarily a research device rather than a home-based communication aid. One limitation that inhibits its widespread use outside the research lab is the complexity of setting up the system. Standard P300 systems employ gel based electroencephalographic (EEG) electrode caps to record electrical activity along the scalp. These caps require a conductive gel to be applied to each electrode in order to ensure electrical contact with the users scalp, and the caregiver must check each electrode to ensure that low impedances levels have been achieved. The process can require thirty minutes or more for an experienced lab technician. For people with locked-in syndrome who need to use the system on a daily basis, minimizing this set up time is highly desirable.

In an effort to improve the set-up time of the system, the use of dry electrode caps for P300 Spellers has been proposed. Dry electrode caps are much faster and easier to apply since they do not require any gel to be applied to the users scalp. However, despite sophisticated pre-amplification, recording EEG with dry electrodes tends to introduce a greater amount of noise into the system. The lower signal-to-noise ratio (SNR) can decrease the detectability of the P300 potential which may negatively impact both the spelling speed and accuracy of the P300 Speller. To compensate for the lower SNR, we propose using a data-driven dynamic stopping algorithm that relies on a Bayesian update process to determine the amount of data collection needed based on a probabilistic level of confidence that a character is the target [1].

In this study, we first compare the differences in performance of gel and dry based electrode caps in the standard static data collection environment for online testing. We then present the preliminary data performance results of each cap using a dynamic stopping algorithm.

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2 Methods

Data collection for this study took part in two separate experiments. EEG responses using the standard static stopping criterion were collected from seventeen healthy participants at East Tennessee State University (ETSU), while the results from the dynamic stopping criterion were collected from ten healthy participants at Duke University. Participants in both experiments completed two P300 Speller sessions; one with a gel based electrode cap and one with a dry based electrode cap.

EEG responses were measured using electrodes positioned on standard 32-channel caps according to the International 10-20 system and connected to a computer via a 16-channel GugerTec g.USBAMP Biosignal Amplifier. The dry electrode cap utilized the GugerTec g.SAHARA active dry electrode system, which is comprised of 8-pin golden alloy electrodes. The gel electrode cap was purchased from Electo-Cap International, Inc. Eight electrodes (Fz, Cz, P3, Pz, P4, P07, P08, and Oz) were used for data collection and classification. These electrodes have been demonstrated to provide adequate information for P300 Speller communication [2]. The EEG responses were sampled at a rate of 256 Hz.

Participants were presented with a 9x8 grid of characters, which was flashed based on the checkerboard paradigm [3]. Each target character was flashed twice in a sequence of 24 flashes. The flash duration was set at 62.5 ms followed by an inter-stimulus interval of 62.5 ms, with an inter-target interval of 3.5 s. The number of sequence responses collected per target character differ between experiments and are detailed in Sections 2.1 and 2.2.

2.1 Static Data Collection

For the static data collection experiment, both the gel and dry based electrode cap sessions consisted of three calibration runs and three online test runs. At the start of each calibration session, the participant was asked to copy-spell three six-character words randomly drawn from a subset of words from the English language (18 characters total). For each character presented, EEG responses to five flash sequences, or 120 flashes (5 sequences x 24 flashes/sequence = 120 flashes), were collected. These data were preprocessed and features were extracted according to a method described by Krusienski *et al.* [4]. Stepwise linear discriminate analysis (SWLDA) was used to classify the extracted features. Responses to five flash sequences per target of three six-character words were collected for the three online test runs.

2.2 Dynamic Data Collection

The calibration runs for both sessions in the dynamic data collection experiment were gathered in a similar manner to the static data. However, due to the performance results of the static data (Section 3), we chose to collect more data to improve the weights of the classifier. Each participant in this experiment was asked to copy-spell five six-character words randomly drawn from a subset of words from the English language (30 characters total). For each character presented, EEG responses to seven flash sequences, or 168 flashes (7 sequences x 24 flashes/sequence = 168 flashes), were collected. Preprocessing techniques, feature extraction, and classification methods were identical to the static data collection experiment.

Five online test runs were collected in each session using the dynamic stopping criterion presented in Section 1. Instead of having a pre-set number of sequences for data collection, the dynamic stopping algorithm automatically determined the necessary amount of data to collect for each target character. The amount of collected data was controlled by a threshold of 90% on the probabilities that each character in the matrix was the target character. The character

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probabilities were updated after each response to a flash was collected and data collection stopped once one of the character probabilities increased above 90%.

3 Results

The results from the static data collection experiment illustrate the impact of the lower SNR resulting from the dry electrode caps. In Figure 1, accuracy and bit rate are plotted for both the dry and gel cap sessions of both experiments. Assuming a binomial distribution on the probability of correctly selecting a set of characters, chance level accuracy was 11.1% for the static data collection experiment and 10.0% for the dynamic data collection experiment [5] [6]. Bit rate is a measure of communication systems that incorporates accuracy, speed, and the number of selectable characters presented [7].

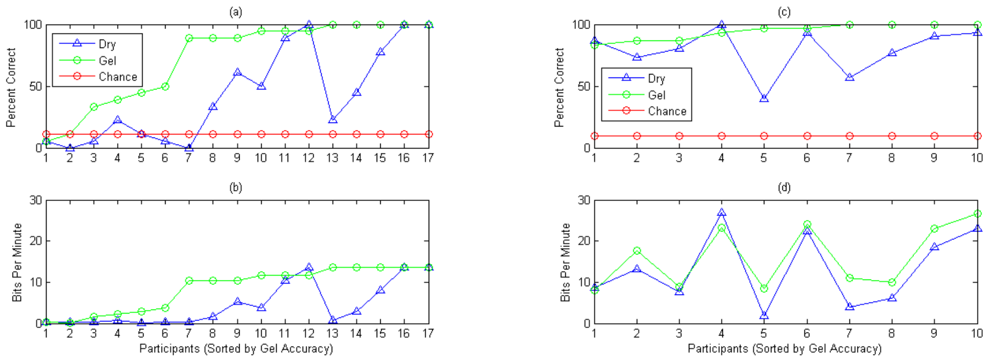

Figure 1: Comparison of dry and gel electrode caps in terms of (a) static data collection accuracy, (b) static data collection bit rate, (c) dynamic data collection accuracy, and (d) dynamic data collection bit rate. Participants are sorted by gel cap accuracy.

Figure 1(a) and Figure 1(b) display the accuracy and bit rate performance for the results of the static data collection experiment. Thirteen out of the seventeen participants performed worse when wearing the dry electrode cap than when wearing the gel electrode cap. An average decrease of 30% in accuracy and 4.1 (bits/min) in bit rate was observed from the dry electrode session of this experiment.

The results of the dynamic data collection experiment are shown in Figure 1(c) and Figure 1(d). These results suggest that the dynamic stopping algorithm may improve the performance of the dry electrode cap by collecting additional data in the online test runs to help compensate for the added noise. Although the performance of the dry electrode cap remains lower when compared to the results of the gel electrode cap, the difference between gel and dry electrode accuracy and bit rate decreased with an average decrease of 15% in accuracy and 3.5 (bits/min) in the bit rate. The increase in data collection for the dry electrodes can be observed in Figure 2. For comparison, the number of flashes that would have been collected for a static data collection of 5 sequences per target character is included. Dynamic data collection increased the amount of data collected across all participants for the dry electrode system, indicating that the data-driven dynamic data collection algorithm can detect and respond to the need for increased data collection in low SNR scenarios. However, the increased data collection was not able to fully compensate for the low SNR responses measured using dry electrodes.

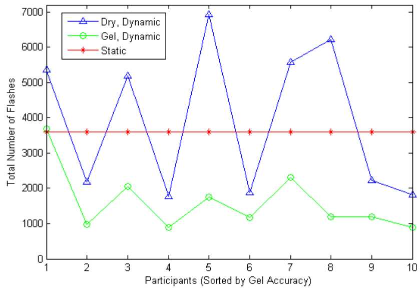

Figure 2: Amount of data collected for each participant in the dynamic data collection experiment. A simulated static data collection was included (5 sequences per target character).

4 Conclusion

Using a dry electrode cap with the P300 Speller would greatly reduce the complexity and time it takes to set up the system. However, dry electrodes can reduce the SNR of the recorded responses, reducing their potential utility for a home-based communication aid. Preliminary results using a data-driven dynamic stopping algorithm compensates for the additional noise by collecting more data, but performance is still lost when compared to the gel electrode cap and the time to complete the task is increased. Additional work is needed to further improve the performance of dry electrode caps in P300 Speller systems.

Acknowledgments

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