Comparing Performance of Dry and Gel EEG Electrodes in VR using MI Paradigms

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ABSTRACT

Brain–computer interfaces (BCIs) are an emerging technology with numerous applications. Electroencephalogram (EEG) motor imagery (MI) is among the most common BCI paradigms and has been used extensively in healthcare applications such as post-stroke rehabilitation. Using a Virtual Reality (VR) game, Push Me, we conducted a pilot study to compare MI accuracy with Gel or active-dry EEG electrodes. The motivation was to (1) investigate the MI paradigm in a VR environment and (2) compare MI accuracy using active dry and gel electrodes with different Machine Learning (ML) classifications (SVM, KNN and RF). The results indicate that while gel-based electrodes, in combination with SVM, achieved the highest accuracy, dry electrode EEG caps achieved similar outcomes, especially with SVM and KNN models.

CCS CONCEPTS

• **Human-centered computing** → **Human computer interaction (HCI)**; Interaction paradigms; **Virtual reality**;

KEYWORDS

Brain Computer Interface, Virtual Reality, Motor Imagery, Electroencephalogram, Machine Learning

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1 INTRODUCTION

Several applications have employed electroencephalogram-based motor imagery (EEG-MI) paradigms in which a person imagines movement and a machine learning (ML) algorithm decodes their imagined movement based on EEG signals [2]. These EEG-MI paradigms have potential to enable seamless control of agents or objects in Virtual Reality (VR). EEG offers a relatively low-cost, easy to use, portable, non-invasive method to collect high-resolution brain signals. EEG electrodes can be passive/active gel-based or dry. Using EEG electrodes with a conductive gel is cumbersome. Dry sensors are easier to use but have historically provided a slightly degraded signal, although this has improved recently. In this pilot study, we tested if dry electrodes could provide comparable results in a EEG-MI paradigm in VR.

When a person uses motor imagery (MI), imagining movement in their body without physical movement [6], there are changes in multiple frequency bands of EEG signals. Particularly in the mu/alpha (8–12 Hz) and beta (18–26 Hz) band near the sensorimotor cortex, which are associated with preparation for movement [8]. Event-related desynchronization (ERD) and event-related synchronization (ERS) refers to a decrease or increase in oscillatory activity related to internally or externally paced events [8]. ERD reflects a decrease of alpha/beta band power at the sensorimotor cortex during MI, while ERS reflects an increase of power following MI. ERD/ERS with alpha/beta rhythms represent distinct patterns during MI tasks (e.g., right of left hand). Therefore, sensorimotor rhythms (alpha/beta bands) are a great indicator of the MI paradigm [1].

Traditional ML techniques for MI-EEG data classification [1] follow a three-step process: preprocessing, feature extraction, and classification. The preprocessing focuses on the denoising and downsampling of EEG data. Subsequently, feature extraction phase plays a pivotal role in determining the final results, as it involves the identification and selection of critical characteristics that best represent the dataset. These can be broadly classified into three categories: temporal, spectral, and temporal-spectral. The most popular extracted features are power spectral density (PSD) [3], differential entropy (DE) [2], discrete wavelet coefficients [7], and short-time Fourier transform [4]. The final step is employing a classifier to separate extracted features into separate classes. Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Random Forest (RF) are the widely-used functions [1, 2, 5].

2 METHOD OVERVIEW

We designed and used a VR game called “Push Me” in which participants imagine pushing a virtual box while wearing a HP Omnicept head mounted display with dry EEG cap (see Figure 1). Each trial

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began with 3s of baseline rest, followed by 6s of the user trying to mentally push the virtual box to the left or right. We used a random number to move the box to the right and left, but the participant was told that the box would move based on their effort, with the assumption that their perceived control of the box would encourage continued engagement with the task. The study had 120 trials, 60 each for the left and right conditions.

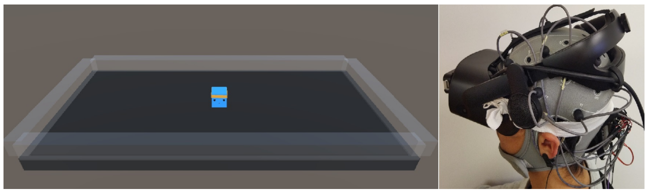

Figure 1: VR EEG Experiment.

EEG data was collected using an OpenBCI gel cap[1] (on 10/20 standard location) and OpenBCI (Think plus)[2] active dry electrodes at FP1, F3, F7, C3, T3, P3, O1, FP2, F4, F8, C4, T4, P4, and O2. The order of the gel and dry electrode tests was counterbalanced across participants. EEG data were sent via the Lab Streaming Layer to Unity3D to add physiological markers at the beginning/end of baseline, and the beginning and end of left or right trials. This data was then stored in csv format for further analysis.

Our pilot study had 4 participants (3 male, 1 female, mean age 26 years old) and took 45 minutes including EEG cap preparation and setting. Participants sat in a chair and were asked not to move to eliminate any artifacts that might affect the EEG data.

Our preprocessing involved a high pass filter (1Hz) and a low pass (49Hz), followed by baseline correction done using the mean and standard deviation of baseline (from 3 second rest [-3000ms 0]) to normalize each individual trial. We extracted 9 features by using the Welch method with 2-second window size on the total size of 6s of each trial which was used to computed power spectral density in each frequency band delta (1-4), theta (4-7), lower alpha (7-10), upper alpha (10-12), alpha (7-12), lower beta (12-18), upper beta (18-28), beta (12-28) and gamma (28-49). Data were split into 80% train and 20% test and separate algorithms were trained for each participants. The model parameters were (C=1, kernel=linear, gamma=auto) for the SVM, (num neighbors=3, weights=uniform, metric=minkowski) for KNN, and (num estimators=100, max depth=5, min samples split=2) for RF.

3 RESULTS, DISCUSSION AND CONCLUSION

Figure 2 illustrates the result of our three classification models (test accuracy and F1). The dry electrodes show similar accuracy as the gel, although gel electrodes may provide slightly better performance on average. The SVM showed the best accuracy and F1 score, indicating a good balance between precision and recall. Of the four participants in this pilot study, two showed identical performance for the gel and dry electrodes in the SVM, one was better for gel and the other for dry electrodes.

[1]https://www.neuroelectrics.com/solutions/enobio/20

[2]https://shop.openbci.com/products/thinkpulse-active-electrode-kit

To measure if there was a difference between gel and dry electrode results we couldn't perform a t-test due to the small sample size and the number of participants as is too small for meaningful statistical analysis. However, we plan to extend this study with more participants for detailed statistic analysis and compare the MI-ML accuracy with functional near-infrared spectroscopy (fNIRS).

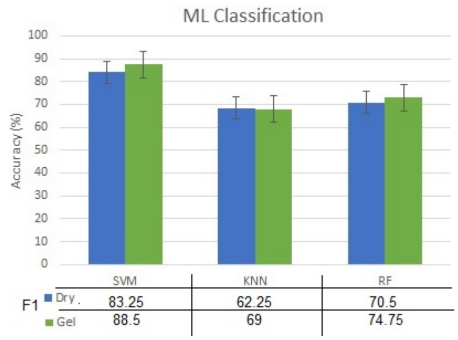

Figure 2: ML Classification.

Despite the slightly higher accuracy and F1 score achieved with the gel electrode, the dry electrode showed remarkable potential. The difference in accuracy and F1 scores between the two types of EEG was not substantial, suggesting that dry electrodes could be a viable alternative for MI classification. If comparably effective, dry electrodes are preferable for integration with a VR HMD, as they have a much shorter set-up time, avoid gel residue in people's hair, and do not drop in effectiveness as the gel dries over time.

In the future, we intend to extend this pilot study to: (1) include a more detailed analysis of the effects of including delta band power in our paradigm with no motor movement, and (2) using functional near-infrared spectroscopy (fNIRS) to contrast EEG with a second mechanism for measuring brain activity during motor imagery.

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