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AN EMG-BASED BRAIN-COMPUTER INTERFACE FOR COMMUNICATION-IMPAIRED PATIENTS: A CASE STUDY

P. Raggam[1,2], M. Eder[1], A.-T. Popa[1], P. Fugger[1], M. Grosse-Wentrup[1,3,4]

[1]Research Group Neuroinformatics, Faculty of Computer Science, University of Vienna, Vienna, Austria
[2]Doctoral School Computer Science, Faculty of Computer Science, University of Vienna, Vienna, Austria
[3]Research Network Data Science, University of Vienna, Vienna, Austria
[4]Vienna Cognitive Science Hub, University of Vienna, Vienna, Austria

E-mail: philipp.raggam@univie.ac.at

ABSTRACT: Electromyography (EMG)–based brain-computer interface (BCI) systems primarily rely on electrical signals generated by muscle activity instead of the typically used brain activity measured via electroencephalography (EEG). Such EMG-BCIs are promising systems that enhance communication and control. This study introduces a simple EMG-BCI communication system developed as a football game for a communication-impaired participant. The football in the game can be moved to a left-side or a right-side goal, representing answers to two-state queries, i.e., yes-or-no-questions. By using restricted game controls, correctly following verbal instructions, and showing movement-related brain activity preceding muscle contractions, our participant can deliberately control the directions of the ball movements and, thus, successfully use our game for communication.

INTRODUCTION

BCI technology has witnessed significant advancements by integrating a diversity of neurophysiological signals besides the traditionally used EEG signals [1, 2]. EMG-based BCI systems have emerged as a promising approach among these neurophysiological signals. Making use of the electrical activity generated by skeleton muscle contraction, the integration of EMG enhances the scope and precision of BCI applications, unlocking new possibilities for communication and control [3, 4]. Initially used for prosthetic control and rehabilitation, EMG-BCI systems have expanded their scope to include assistive technology, gaming, and communication [5, 6]. Zhang et al. introduced an EMG-based wearable multifunctional eye-control glass to control home appliances and communicate by voluntary blinks [7], Chai et al. and Rashid et al. combined steady-state visually evoked potentials (SSVEPs) and EMG to control communication interfaces [8, 9].

This study introduces an EMG-BCI communication system designed as a simple football game developed for a communication-impaired participant. The idea behind developing this communication system was twofold: 1. test whether our participant was intellectually and physically capable of communicating with others, and 2. if so, provide a very simple yet engaging game as a communication basis. The following sections introduce our participant, the game design and controls, the recording modalities, and the implemented signal processing procedures. Furthermore, we demonstrate with our results that our participant understood verbal instructions and intentionally controlled arm muscle activity to move the ball to the left or to the right.

MATERIALS AND METHODS

Participant: The study was designed for one participant (seven years old, male) who suffered through an accident from a severe hypoxic-ischemic encephalopathy (especially in the basal ganglia), dysphagia, dysarthrophonia, and a severe bilateral spastic and dystonic cerebral movement disorder. Based on our interactions, we learned that our participant communicates by looking and smiling at someone to show joy or contentment or by looking displeased if otherwise. During the whole study, our participant's parents were present, and the comfort and safety of our participant were our highest priorities. The study was approved by the University of Vienna's ethics committee.

Game design: We designed our communication system to resemble a football game since it was one of our participant's biggest interests before the accident. With that, we wanted to ensure that the game was engaging enough to be played over a longer period of time. The game was designed in Python[1] using the PsychoPy[2] library. Fig. 1 shows the interface of the football game. The game's aim is to move the football to the left-side or the right-side goal and can be played in two modes: practice or playing. During practice, the distances to the goals are shortened to learn how the game is controlled

[1]https://www.python.org/
[2]https://www.psychopy.org/

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more easily. At the beginning of each round, the ball is placed at the center of the field.

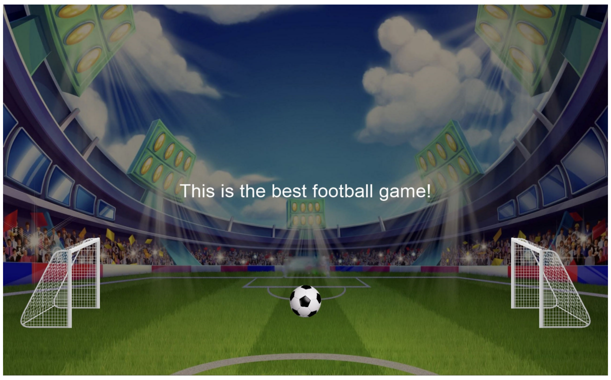

Figure 1: The interface of the football game.

Game controls: The football's movement is controlled by the EMG. To move the ball to the left or the right, the left-arm or the right-arm muscles must be activated, causing an increase in the EMG signal amplitude. The ball can move in single steps or continuously, depending on the duration of the muscle contraction. Two restrictions were introduced to avoid random, unintended movements: a signal threshold window and one-sided contraction. The signal threshold window ensures a controlled movement of the ball by only moving the ball if the signal amplitude is within a lower and an upper limit. Furthermore, the ball only moves if the arm muscles are contracted only on one side and stops if the muscles are contracted at both arms simultaneously. As feedback for the user, the ball turns red if a restriction is applied, i.e., if the signal amplitude is above the upper limit of the threshold window or if both arms are contracted simultaneously.

Recording sessions: Fig. 2 shows the recording setup. Our participant was sitting in a wheelchair, looking at a monitor to play the football game. The game was played over four sessions. The first two sessions were used to accustom our participant to the game and its controls. In the beginning, a squeeze bulb was used to move the ball. After establishing that the principles of the game were understood, the game controls were switched to the EMG since it did not require the coordinated muscle activation necessary to squeeze a bulb and, hence, was easier to use. The third session was split into practice runs and a playing run. During the playing run, our participant was instructed verbally to move the ball to the left or the right goal. In session four, we recorded both the EMG and the EEG. The session was divided into a resting-state run and two playing runs. Playing run one (run P1) was further split into six trials, where our participant was asked again to move the ball to the left or the right goal (three trials for each side).

Recording modalites: EMG and EEG signals were recorded with the Bittium NeurOne™ Tesla EEG system[3], with a sampling frequency of 1 kHz. The EMG was

[3]https://www.bittium.com/medical/bittium-neurone

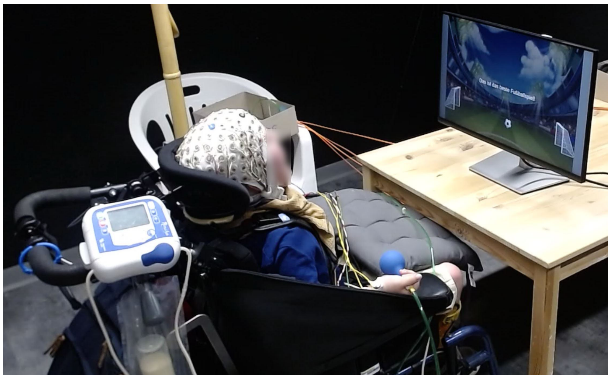

Figure 2: Setup for our participant playing the football game.

recorded with bipolar electrode channels at the following arm muscles (for each side): flexor digitorum profundus (FDP), extensor digitorum (ED), and abductor pollicis longus (APL). For the EEG, passive, gel-based electrodes were used at the following channels: F1, Fz, F2, FC3, FC4, C3, C1, Cz, C2, C4, CP3, CP4, and Pz. In addition to the physiological signals, event markers were recorded to put time stamps on certain events or phases of the game, e.g., when a new trial started or a goal was scored.

Online signal processing: To access the recorded signals in (near-)real-time, the lab streaming layer (LSL)[4] and its Python interface pylsl[5] were used. With the pylsl library, the EMG signals could be streamed into the PsychoPy game framework for further processing. The EMG signals were processed in three steps: 1. applying a 4^{th}-order Butterworth bandpass filter between 20 and 40 Hz, 2. calculating the envelope via Hilbert transform, and 3. smoothing the signal with a Savitzky-Golay filter [10]. Since our participant suffered from a spastic and dystonic movement disorder, we decided to define a personalized EMG signal band. The EMG bandwidth was chosen by maximizing the cross-correlation coefficients between the squeeze bulb signal and the EMG signals. After processing the EMG signals and checking the movement restrictions, the position or color of the ball on the screen was updated, giving feedback to the user on whether the movement attempt was successful.

Offline data analysis: The offline data analysis was also implemented in Python. Similar to the EMG signal processing, we also personalized the EEG frequency bands. After inspecting the power spectral density (PSD) function of the resting-state EEG, the following frequency bands were chosen for further investigation: 5–7 Hz for the mu band and 15–25 Hz for the beta band. The EMG was again filtered between 20 and 40 Hz. The band power was calculated for each frequency band (mu, beta, and EMG) by squaring the amplitude values. All applied filters were 4^{th}-order Butterworth filters.

Due to our participant's involuntary repeated head movements during the recording session, the EEG cap was pressed and shifted against the headrest, which led to a

[4]https://github.com/sccn/labstreaminglayer
[5]https://github.com/chkothe/pylsl

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low signal-to-noise ratio (SNR) and gel bridges between channels. Artifact correction with independent component analysis (ICA) proved to be ineffective. However, a simple bipolar derivation, i.e., subtracting channels from one another, led to clean EEG signals of a few channel pairs.

After cleaning the EEG, we investigated the mu and beta rhythms. First, the cross-correlation functions (CCFs) of mu and beta band power vs. right-hand and left-hand EMG were calculated. After inspecting the results, we decided to continue with the mu band only since the CCFs of the beta band were inconclusive. Next, the continuous signals of run P1 were split into left-goal and right-goal trials for calculating the cross-correlation functions of mu band power vs. right-hand and left-hand EMG. A permutation test with cyclical shifts and n = 1000 permutations was applied to generate p-values for the CCFs, i.e., finding significance in our results. The p-values were corrected using the false discovery rate (FDR) correction with the Benjamini-Hochberg procedure [11].

RESULTS

All results in this section were generated from EMG and EEG signals recorded in session four's resting-state run and run P1 since this was the only session with EEG recordings, and only run P1 included verbal instructions.

Resting-state EEG: The resting-state EEG signals were used to find personalized frequency bands for our participant's mu and beta rhythms. Fig. 3 shows the power spectral density (PSD) function of the resting-state EEG at channel pair Cz-C4. We can clearly see the alpha/mu peak between 5 and 7 Hz and the beta bump between 15 and 25 Hz. The alpha/mu rhythm is slower than an average adult's (8–13 Hz [12]). However, this is not a pathological indicator since the alpha rhythm increases with age during childhood and adolescence [13].

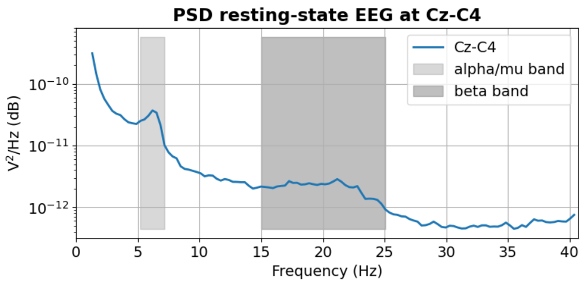

Figure 3: PSD of resting-state EEG at channel pair Cz-C4.

Run-level analysis: We first looked at run P1 as a whole. In Fig. 4, we see the power of the right-hand (blue lines) and left-hand (orange lines) EMG. Individual EMG channels (FDP, ED, and APL) were averaged on each side. The left-hand EMG power is much lower than the right-hand EMG power, possibly due to a Botox treatment on our participant's left arm before the recording session.

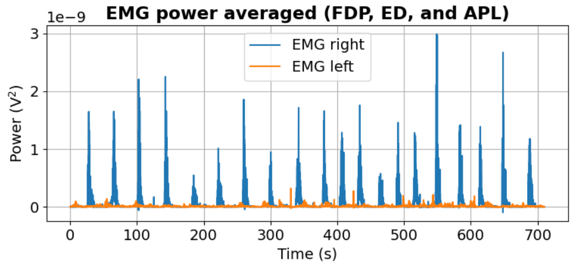

Figure 4: Right-hand (blue) and left-hand (orange) EMG power of run P1. Individual EMG channels (FDP, ED, and APL) were averaged on each side.

Fig. 5 shows the CCFs of EEG mu band power (subfigure A) and beta band power (subfigure B) at channel pair Cz-C4 vs. right-hand (blue lines) and left-hand (orange lines) EMG power. In the mu band, we can observe a negative correlation between EEG power and both left-hand and right-hand EMG at time lag = 0. A negative correlation means that the mu rhythms desynchronize (decrease in EEG mu power) when the arm muscles are activated (increase in EMG power), which displays typical, non-pathological event-related desynchronization (ERD) [14]. Also, having mu rhythm ERD on the right hemisphere (Cz-C4) for both left-hand and right-hand EMG indicates bilateral cortical activation for one-sided movements. Even though bilateral mu rhythm ERD is uncommon, it can occur during one-sided hand movements, especially in the context of motor planning and execution [15].

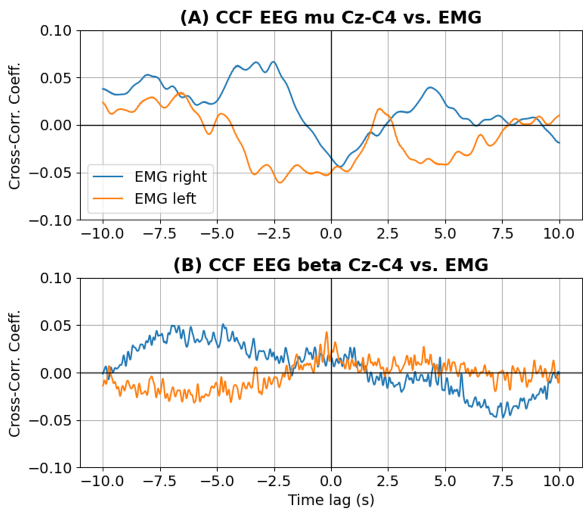

Figure 5: CCFs of EEG mu band power (A) and beta band power (B) at channel pair Cz-C4 vs. right-hand (blue) and left-hand (orange) EMG power.

When we look at the time course of the CCFs, however, we can observe very unusual behavior: For the right hand, the desynchronization process starts roughly 2.5

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seconds before the muscles are activated, whereas for the left hand, it starts about five seconds before muscle activation. The mu rhythm desynchronization is very slow compared to healthy people [15]. This means that our participant can react quickly to instructions, but it takes very long to activate the motor system to cause a muscle contraction. The initially stated damage in the basal ganglia could be a possible reason for that. The Botox treatment on the left arm again may have caused the difference between right-hand and left-hand ERD time.

The CCFs of EEG beta band power with EMG power didn't show any conclusive results, and hence, only the mu band was used for further investigations.

Trial-level analysis (left-goal/right-goal split): Next, EMG and EEG signals were split into trials. Our participant successfully moved the football to the correct goal in all six trials of run P1 (three left-goal trials and three right-goal trials). Therefore, we used the left-goal and right-goal trials for ball movements to the left and the right, respectively.

In Fig. 6, we can see the CCFs of EEG mu band power at channel pair Cz-C4 vs. right-hand (blue lines) and left-hand (orange lines) EMG power at left-goal trials (subfigure A) and right-goal trials (subfigure B). The cross-correlation coefficients are rather small, but the CCFs are highly significant ($p < 0.05$) around time lag = 0, as shown in Fig. 7 by the corresponding FDR-corrected p-values.

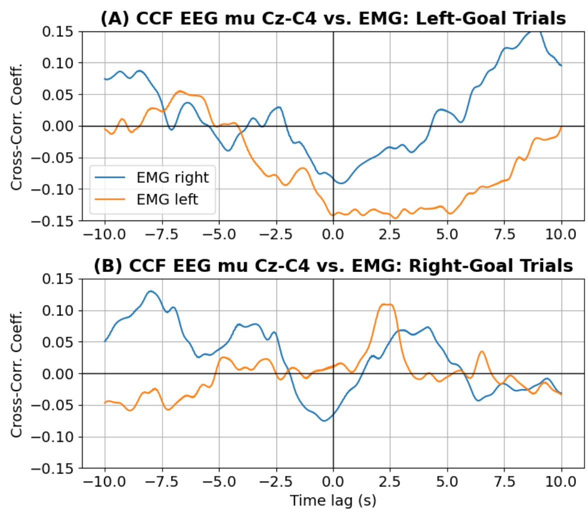

Figure 6: CCFs of EEG mu power at channel pair Cz-C4 vs. right-hand (blue) and left-hand (orange) EMG power at left-goal trials (A) and right-goal trials (B).

Looking at the right-goal trials, we can observe a negative correlation between EEG mu band power and right-hand EMG power but no correlation between mu power and left-hand EMG. These results suggest that there is only a clear mu rhythm ERD for right arm muscle activity, meaning only the right hand was intentionally used for moving the ball to the right goal, which is expected behavior.

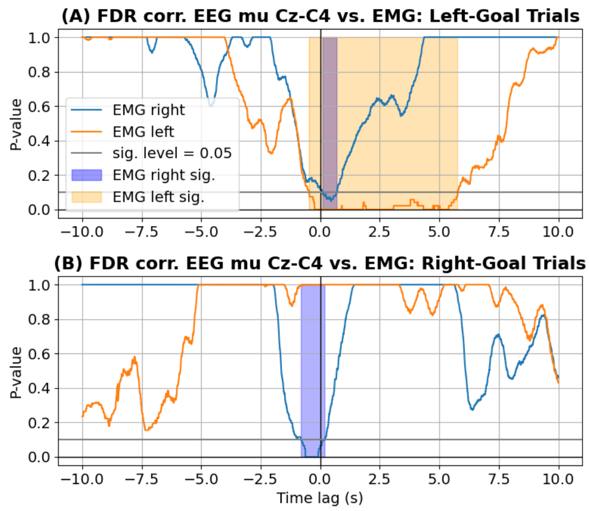

Figure 7: FDR-corrected p-values of CCFs of EEG mu band power (A) and beta band power (B) at channel pair Cz-C4 vs. right-hand (blue) and left-hand (orange) EMG power. The p-values were calculated by a permutation test with a cyclical shift and n = 1000 permutations, including an FDR correction with the Benjamini-Hochberg procedure.

For the left-goal trials, however, we see something very interesting: There is a negative correlation between EEG mu band power and both left-hand and right-hand EMG. This indicates clear mu rhythm ERD for left and right arm muscle activity, meaning both hands were intentionally used for moving the ball to the left goal. This could mean that our participant used the right-hand activity to trigger a left-hand activity, which we could actually observe during the recording sessions. A reason for that could be again the Botox treatment on the left arm, which is also manifested in the slow and long-lasting (~ 5 s) mu rhythm ERD, compared to the faster ($\sim$2.5 s) desynchronization for right-hand muscle activity.

DISCUSSION

In the first two recording sessions, we tested whether our participant could use the game controls. Both the squeeze bulb and the EMG were successfully used to move the ball to the left or right. We decided to continue controlling the game with the EMG because it does not require coordinated muscle activations necessary to squeeze a bulb and, hence, was easier to use. In the third session, our participant could follow our verbal instructions to go to the left or the right goal. In run P1 of the fourth session, our participant again successfully followed verbal instructions, this time split into six trials, with three left-goal and three right-goal trials in random order.

Overall, we found three indicators that demonstrated that the ball movements did not occur randomly but were the results of deliberate control of our participant:

1. Game control restrictions: Every ball movement resulted from precise muscle activity since a lower and an upper threshold defined an EMG amplitude/power window. Furthermore, only one-sided EMG activity led to a

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ball movement.
2. *Successful task completion:* In session four, run P1, all six trials were completed successfully. That means our participant could understand the verbal instructions and generate the appropriate response to suit the game controls.
3. *Mu rhythm ERD preceding muscle contraction:* By simultaneously recording EMG and EEG signals in the fourth session, we could further demonstrate that the muscle activity to move the ball did not occur through random or spastic contractions but followed movement-related brain activity. Fig. 6 and Fig. 7 show a clear decrease in mu band power that precedes muscle contraction for ball movements on both sides. The slow mu rhythm desynchronization could be due to the damaged basal ganglia, which could cause a delay in activating the motor system. The left arm was also treated with Botox, which would explain the even slower and long-lasting left-hand mu rhythm ERD. It is also noteworthy that our participant developed a strategy to overcome the increased difficulty of activating the left arm muscles by involving the right arm, which eventually triggered the left-hand muscle contraction.

CONCLUSION

This study demonstrated that our participant could deliberately control a football game and follow verbal instructions despite the severe impairments. Furthermore, the combination of EEG and EMG revealed normal reaction times to instructions but a slow motor system activation. This provided important information about our participant's mental abilities for the family.
Currently, the game can be used for simple two-state queries, e.g., answering yes-or-no-questions by moving the ball to the left or the right. Future game adaptations could facilitate the controls or increase the number of goals, i.e., the number of answers to select. Combining EMG and EEG signal features could further improve our communication system's precision and robustness.
Finally, we also want to emphasize that even simple systems can be very effective. Straightforwardness and convenience are key features for people with mobility and/or communication impairments.

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