# Improving Participant Performance on Mu Rhythm-Based Brain-Computer Interfaces

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BRAIN computer interfaces (BCIs) bypass normal neural output by translating neural activity into a control command for a computer or other external device. The mu rhythm is an 8-13 Hz sensorimotor rhythm often used to control BCIs because of its potential for voluntary modulation [1]. During normal conditions, the mu rhythm exists in a high power, synchronized state, detectable by EEG over the sensorimotor cortex [1]. When a person undergoes motor behavior, observes motor behavior, or imagines motor behavior, the mu rhythm desynchronizes to a lower power state [2]. Conversely, mu rhythm can be further synchronized from baseline levels via relaxation techniques [3]. Mu rhythm modulation allows two directions of BCI control that can be utilized in various applications, such as computer cursor movement, prosthetics, or gaming. While the mu rhythm offers many opportunities for useful BCI applications, there are several practical issues with mu-rhythm BCIs that need to be addressed. It is not uncommon for training periods up to 60 sessions to be required, with accuracy rates of 70-97% being reported [4]. Although mu-rhythm-based BCI systems allow for greater degrees of freedom in controlling an external device, these issues decrease the widespread usefulness of these applications. Recent studies have demonstrated that machine-learning can improve single session success in BCI-naïve participants [1], however the goal of this study is to determine if bilateral mu-rhythm control can be enhanced by providing participants with specific instructions and visual aids for imagined motor activity (desynchronized activity) and relaxation (synchronized activity). It was hypothesized that specific instruction during the motor imagery condition of the study would produce the greatest mu power with an interaction effect between the type of instruction (general vs. specific), type of imagery (relaxation vs. motor) and the number of sessions (1-3). Data from 36 undergraduate students (20 females, 16 males; 32 BCI-naive) from Lafayette College completed three sessions of an hour in length; all sessions per participant were conducted within a 7 day time span. EEG data was collected at a 256 Hz sampling rate via bipolar derivation from electrodes FC3-CP3, FCZ-CPZ, and FC4-CP4 of the 10-20 International System for electrode placement. The signals were preprocessed with a fourth order Butterworth bandpass filter at 0.5-30 Hz and an eighth order Butterworth notch filter at 58-62 Hz. Signal processing occurred through a Simulink and MATLAB (MathWorks) model modified from a version by Guger Technologies. Raw signals from FC3-CP3 and FC4-CP4 were summed after passing through an 8-13 Hz bandpower calculation, resulting in a composite bilateral mu power value. A 10-based logarithm was applied to this composite mu value, and the resulting value was translated into the length of a feedback bar shown to the participant on a computer screen. The following translation algorithm equation was utilized: $BarLength = (CurrMu\text{-}BaseMu)\cdot W;$ where *BarLength* denotes the position of the end of the bar on a coordinate plane centered in the middle of the screen. *CurrMu* is the composite mu value, *BaseMu* is the participants baseline composite mu value, and *W* is a constant weight value. The baseline mu value was calculated at the beginning of each session for each participant by processing a 3-second data segment. The participant was shown a gray screen with a blue cross hair in the center, denoting the center of a coordinate plane. Each session consisted of 3 runs, and each run contained 20 trials of motor imagery and relaxation, in pseudorandom order. A feedback bar indicated the strength of the desynchronized (motor imagery) or synchronized (relaxation imagery) mu power. *BarLength* values for the duration of the imagination period of each trial was extracted and a 2(instruction type) x 2(type of imagery) x 9 (runs) mixed factors ANOVA was conducted. These data demonstrate that specific instructions increase event-related synchrony (ERS) and desynchrony (ERD) amplitude from baseline across runs [$F(8,208) = 1.8$, $p = 0.08$], with ERS producing the greatest increase from baseline, and the most reliable control, $F(1,26)= 10.8$, $p<0.01$. This study is a first step at examining the effectiveness of goal-directed activity in guiding more reliable control over mu rhythm–based BCI devices within a minimal number of sessions to improve and expand the usefulness of these devices for a broader population. Additionally, the data support the need for further examination of relaxation imagery use to increase the number of degrees of freedom with mu-based BCI devices.

## REFERENCES

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