Hybrid Brain-Computer Interface: Studying Mu Power & Heart Rate Interaction

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Hybrid Brain-Computer Interface: Studying Mu Power & Heart Rate Interaction

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***Abstract*—Brain-Computer Interface (BCI) devices use brain activity to create alternate methods of communication or control. In a BCI system, a user's intent is measured by their neuronal signals, which are translated to a computer program that provides a control mechanism in real-time. This study sought to explore ways in which BCI systems could be expanded and potentially improved, by incorporating other physiological signals in addition to EEG. We examined the relationship between mu power signals and heart rate during motor imagery and relaxation trials.**

Keywords—Brain-Computer Interface; mu rhythm; heart rate; EEG; ECG; motor imagery

I. Introduction

BCI is an exciting and quickly developing field of interdisciplinary research. These devices offer promise for the future as an alternate means of motor control and communication, for those with severe motor impairment. BCIs eliminate the need for voluntary motor output; therefore, they offer an avenue for enhanced quality of life and regaining some forms of autonomy for individuals who are paralyzed or in a "locked-in" state, yet retain their cognitive abilities. BCIs create a neurofeedback loop in which the participant modulates their neural signals in attempt to control a specific paradigm. During signal acquisition, neural data are collected in real-time followed by extraction of significant features from the raw data and signal translation. In this study, the output signal is viewed by the participant as the movement of a feedback bar. Based on the visual output, the participant can modify their neural response through imagined (in)activity, therefore completing the feedback loop. The mu rhythm, a brain signal detected over the sensorimotor cortex that oscillates at frequencies between 8-13 Hz can be controlled through biofeedback training. It is suppressed during motor imagery and has stronger oscillations during rest [1].

Previous research from our lab has focused on how to improve participants' neural signals and overall performance based on instruction type for motor imagery and rest. The three different experimental groups included varying levels of instruction specificity and individualization. Results showed that the non-individualized specific (NIS) and individualized-specific (IS) groups were more successful than the control (vague instructions) at modulating their mu rhythms; however, there was no significant difference between NIS and IS [2].

Even with these results, more work is needed to improve BCI accuracy and control so that it can be used in a real-world setting. The fusion of two inputs, or systems, to create a "hybrid BCI" has been advantageous in this regard. Studies have shown that several physiological changes subconsciously occur in the body during motor imagery just as they do with actual physical activity, including increased heart rate (HR) [3]. This is because of a dynamic communication network in the brain connecting the cortex and the brainstem's cardiovascular control system [3]. Due to integration of HR with various neural signals, some users have demonstrated enhanced performance [4]. This current study aims to examine HR changes during our BCI paradigm. It is expected that HR and mu power will follow similar, yet inverted patterns, with HR increasing and mu power decreasing during motor imagery trials and vice versa during relaxation trials.

II. Methods

A. Participants

The experiment was approved by the Lafayette College Institutional Review Board. This pilot study consisted of 10 undergraduate students (2 male, 8 female) from Lafayette College. Before beginning the experiment, participants provided informed consent and completed a survey about their basic personal information. Upon completion of the experiment, participants filled out a simple questionnaire about their experiences with the BCI system. All participants were given NIS instructions to incorporate specificity and consistency, since it has been demonstrated that this was more effective than vague control directions, but not significantly different than IS instruction type [2].

B. Data Acquisition and Signal Processing

Both EEG and ECG data were simultaneously collected at a sampling rate of 256 Hz using a g.HIamp amplifier system (g.tec, Medical Engineering GmbH, Austria). Using the g.GAMMAcap2 EEG cap, bipolar active electrodes were positioned according to the International 10-20 system over the sensorimotor cortex, at CP3-FC3, CPz-FCz, and CP4-FC4, with ground at Fz, and reference on the earlobe. The EEG data was preprocessed with a fourth order Butterworth bandpass filter from 0.5-30 Hz and an eighth order Butterworth notch filter from 58-62 Hz.

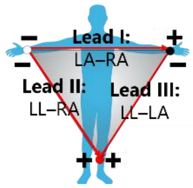

Fig. 1. ECG electrode positions (LL-left leg; LA-left arm; RA-right arm).

The ECG data was not preprocessed. It was collected from adhesive g.LADYbird electrodes (g.tec, Austria) on the left and right wrists and left ankle. These electrode placements form three leads (Fig. 1) which make up Einthoven's triangle, a hypothetical triangle with the heart at the center that produces zero potential when the voltages are summed. EEG (mu power) signals were processed using an adapted Simulink model designed by g.tec, which has been consistently used in our lab for several past studies [5]. ECG signals were processed with a 0.5-40 Hz bandpass filter. The signals were recorded continuously for the entire duration of the paradigm.

HR detection was carried out in three steps: ECG signal processing, peak detection, and peak-to-peak time interval calculation. The ECG signal processing was implemented to obtain the R-slope (R_{sl}) by passing the ECG signal through a bandpass integer filter, a five-point derivative, a square function, and a 38-point moving average filter (corresponding to 150 ms QRS complex time interval at 256 Hz sampling rate) in sequence [6]. A peak of the QRS complex was detected if the following logic is true:

$$R_{sl}>0.5 \text{ AND } R_{sl}(k-1)> R_{sl}(k-16) \text{ AND } R_{sl}(k)> R_{sl}(k-15).$$

This logic reset an integration of time. The output from this integral was the cardiac period, which was then converted to HR. HR update took place when the next peak was detected, unless the difference between the current HR and the previous HR was beyond 50 beats/min. This constraint prevents any sudden HR changes caused by an artifact in the ECG signal.

C. BCI Paradigm

The paradigm used in this pilot study was adopted from previous studies conducted in our lab [2]. Subjects participated in four runs of M/R trials (hand motor imagery vs. relaxation), in which the first run was simply used for calibration purposes. For the remaining three runs, their goal was to follow cues on the screen in order to control the movement of a feedback bar. HR was not integrated into this paradigm; this data was only used for offline analysis.

III. Results

The data presented here are preliminary results in the form of a case study from a single participant. Additional data collection and analyses will be conducted shortly to better understand whether HR can be used to strengthen BCI performance. Fig. 2 demonstrates one subject's mu power and HR during an M/R paradigm. In this one run, the user's average HR was 78.72 bpm. According to our hypothesis, the HR should be above this average and the mu power should be below 0 during M trials, and vice versa in R trials. This was the case in 15 out of 20 M trials (75%), while only in 5 out of 20 R trials (25%). Fig. 2 also suggests that there may be a HR latency period, which should be further analyzed.

IV. Discussion

The work provided here is an initial study, where the goal is to determine the relationship of heart rate patterns with motor imagery and relaxation. We are looking to see if HR is consistently affected in M/R feedback training. No substantial difference between HR during motor imagery and relaxation trials would suggest that HR may not be the best indicator of mu rhythms. If our additional data continues demonstrating the trend described above in the results (poor correlation between HR and mu only during R trials), this may imply that either users are not truly relaxed, or the relationship is confounded by factors we have not yet considered. It is possible that frustration or excitement with the paradigm could result in false positives during M trials. Conversely, inverted patterns between HR and mu in both M and R trials would suggest that incorporating HR into the current algorithm may increase user accuracy. Having two variables, mu power and HR, which may change in correlated and predictable ways in response to motor imagery and relaxation, will hopefully enable users to feel a greater sense of control over the system.

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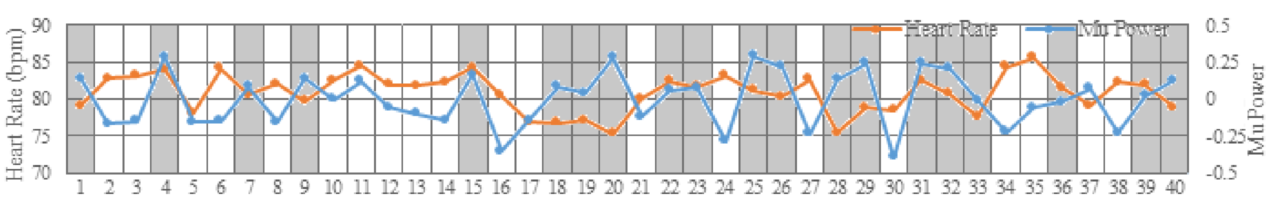

Fig. 2. Mu power & heart rate during one run of the M/R feedback paradigm (Participant A)