BRAAHMS: A Novel Adaptive Musical Interface Based on Users' Cognitive State

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ABSTRACT

We present a novel brain-computer interface (BCI) integrated with a musical instrument that adapts implicitly (with no extra effort from user) to users' changing cognitive state during musical improvisation. Most previous musical BCI systems use either a mapping of brainwaves to create audio signals or use explicit brain signals to control some aspect of the music. Such systems do not take advantage of higher level semantically meaningful brain data which could be used in adaptive systems but still not detract from the attention of the user. We present a new type of real-time BCI that assists users in musical improvisation by adapting to users' measured cognitive workload *implicitly.* Our system advances the state of the art in this area in three ways: 1) We demonstrate that cognitive workload can be classified in real-time while users play the piano using functional near-infrared spectroscopy. 2) We build a real-time, implicit system using this brain signal that musically adapts to what users are playing. 3) We demonstrate that users prefer this novel musical instrument over other conditions and report that they feel more creative.

Author Keywords

brain-computer interface, fNIRS, functional near-infrared spectroscopy, music, adaptive, workload, BCI, piano

ACM Classification

H.5.m [Information Interfaces and Presentation] Miscellaneous; H.5.5 [Information Interfaces and Presentation] Sound and Music Computing

1. INTRODUCTION

Brain-computer interfaces (BCIs) have been used to increase the effective communication bandwidth between the human and the computer by passively obtaining and using extra information about the user [1, 13]. In a musical instrument interface, such as a piano keyboard, the user's communication channels may be limited by the paucity of input devices, body parts, and attention. An adaptive BCI can increase this bandwidth by providing a cognitive communication channel that passively measures user cognitive state without requiring additional effort or attention on the part of the user. This can then be used as an additional input channel that implicitly modifies the music at appropriate times.

Traditionally, most musical BCIs have been based either on different variations of mapping brainwaves to soundwaves [9, 10, 11] or by using brain signals explicitly to modify aspects of the music [4, 6, 14].

Recent events in the field of brain sensing have opened up a new avenue of measuring and using higher level meaningful cognitive data implicitly without any extra attention required from the user. Cognitive workload that has been measured by fNIRS [3] has led to BCIs that can implicitly adapt to user cognitive state in real-time [1, 13].

BCI technology has now reached the point where this is an opportune time to introduce a musical system that implicity adapts in real-time to users' cognitive state. We introduce **BRAAHMS: BRain Automated Adaptive Harmonies in a Musical System**. BRAAHMS is a real-time musical BCI system that calculates cognitive workload to implicitly adapt to users in the creative task of musical improvisation. BRAAHMS adapts to the user's cognitive workload by adding or removing musical harmonies that are related to the notes that the user is currently playing, hence augmenting their music without altering their original general direction.

2. RELATED WORK: MUSICAL BCIS

Semantically meaningful brain data

Traditionally, most musical BCI systems have been based on a mapping of brainwaves to audio signals. Examples include assigning musical passages to certain frequencies of EEG activity [10], applying a mapping to notes [2], or using the magnitude spectrum of EEG to shape the spectrum of white noise [9].

A clear need for higher level semantically meaningful brain data has been highlighted in the field of musical BCIs [10]. Miranda et al. [11] ran a pilot study on a EEG-based BCI that detected active versus passive listening, however, reported difficulty in reliably detecting listening behavior. They also discussed directing the tonality of music based on auditory cortex stimulation, however only the music generation side has been built, which is based on hypothetical brain data [11]. Grierson et al. [7] have used the Neurosky headset's attention and meditation levels to control Brainemin and Brain Controlled Arpeggiator in live performances. However there has been no user evaluation or controlled experiment using these cognitive states.

Implicit brain sensing

Musical BCIs have also used brain signals as direct input to an application, such as using the P300 signal to directly

NIME'15, May 31-June 3, 2015, Louisiana State Univ., Baton Rouge, LA.

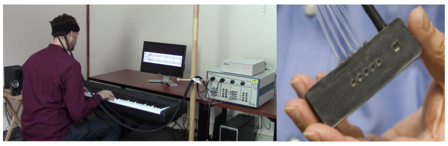

Figure 1: FNIRS equipment and experiment setup.

control a synthesiser [6] or select harmonies [14]. Icons from a grid have been selected to compose music instead of the standard keyboard and mouse using the P300 signal [4] or steady-state visually evoked potentials [8]. While such active BCIs can be invaluable to people with motor disabilities, they are too slow and inaccurate for the general population compared to the standard mouse and keyboard.

Recently, however, advances in brain-sensing technologies have been used for implicitly detecting and responding to users by measuring user cognitive state without any additional effort from the user. In this paper, **we build and evaluate an implicit musical BCI that analyzes and responds to users' cognitive workload.**

2.1 Brain Sensing in the PFC with fNIRS

FNIRS is a non-invasive imaging technique that can be used to measure levels of oxygenated hemoglobin (*oxy-Hb*) and deoxygenated hemoglobin (*deoxy-Hb*) concentrations in brain tissue. When an area of the brain, such as the prefrontal cortex (PFC), is activated, it consumes more oxygen which leads to an increase in blood flow to that area. The increase in oxygen consumption, however, is less than the volume of additional provided oxy-Hb, hence resulting in an increase in oxy-Hb [5]. This hemodynamic response can be measured by emitting frequencies of near-infrared light around 3 cm deep into the brain tissue [15] and measuring light attenuation to determine how much oxy-Hb and deoxy-Hb is flowing in the area.

We can therefore use fNIRS to measure levels of cognitive activation in the anterior prefrontal cortex by placing the sensors on the forehead. The fNIRS signal has been found to be resilient to respiration, heartbeat, eye movement, minor head motion, and mouse and keyboard clicks [12]. Due to its general ease in setting up with users and its relative tolerance of minor motion, fNIRS is an increasingly popular method of brain sensing in HCI [12, 3, 13, 1].

3. RESEARCH GOALS

Our primary research goal was to use semantically meaningful brain data to develop and evaluate an implicit, musical BCI that would measure, analyze and adapt to user cognitive state. In order to do this we conducted three main stages of experimentation and design:

- A feasibility study to determine whether differences in brain data corresponded with high and low difficulty levels while users played the piano (Experiment 1)
- Through an iterative design process and pilot studies we built BRAAHMS, a passive real-time BCI that adapts to the brain signal during musical improvisation by adding or removing musical harmonies.
- An evaluation of BRAAHMS carried out on 20 participants. Two BCI conditions were tested along with a constant and non-adaptive condition.

Experiment 1 was an offline analysis of participants' brain data while Experiment 2 was carried out in in real-time in order to respond to participant's brain signals as they played the piano.

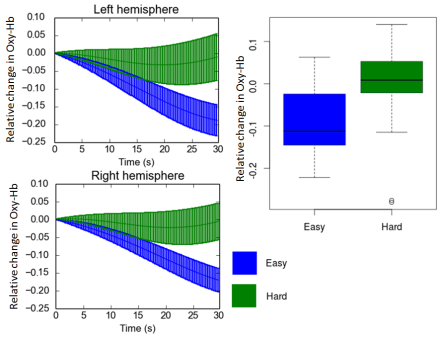

Figure 2: Left: Mean change and standard error in oxy-Hb in Expt 1 across all participants. Right: Mean change in oxy-Hb was significantly higher during hard pieces ($p < .01$).

4. EXPT 1: WORKLOAD CLASSIFICATION

In this section, we examine the feasibility of automatic classification of cognitive workload using fNIRS while users played the piano. Fifteen easy and hard piano pieces were chosen by a musicologist (see [16] for details) for 15 participants (7 female, mean age of 21, SD of 2.4) to play in randomized order for 30 seconds at a time followed by a 30 sec. rest period. Figure 1 shows the setup of Experiment 1.

4.1 fNIRS System

Two probes from an Imagent fNIRS device were placed on a participant's forehead to measure data from the prefrontal cortex. Each probe contained four light sources, each emitting near-infrared light at two wavelengths (690 and 830 nm) and one detector; thus we had sixteen data channels (2 probes x 4 source-detector pairs x 2 wavelengths) (Figure 1). The signals were filtered for heart rate, respiration, and movement artifacts.

Training and Modeling: The easy and hard musical pieces were used to train the system for each individual user's cognitive activity during low and high cognitive workload, respectively. During each piece, the system calculated the change in optical intensity compared to a baseline measurement for each of the sixteen channels. The mean and linear regression slope were calculated by the system for each 30 second trial for each channel resulting in 32 features (16 channels x 2 descriptive features). These features were inputted into LIBSVM, a support vector machine classification tool, with a linear kernel [1].

4.2 Experiment 1 Results and Discussion

Figure 2 shows the mean and standard error in the oxygenated hemoglobin of participants while they played easy (blue) versus hard (green) pieces on the piano. Although we built an individual model for each participant, we present the mean findings across all 15 participants across all 30 trials in Figure 2 to illustrate this general trend.

To investigate differences between hard and easy pieces, we performed a t-test on the mean change in oxygenated hemoglobin. This revealed a significant difference between conditions when participants played an easy piece ($\mu = -0.1, \sigma = 0.1$) versus a hard piece ($\mu = -0.02, \sigma = 0.1$) on the piano ($t(14) = -3.04, p < .01$). Means and standard errors are shown in Figure 2.

The significantly higher levels of oxy-Hb when participants were playing harder pieces on the piano correspond with the hemodynamic literature, whereby, when there is increased cognitive activity in an area of the brain, excess oxygen is provided to that area. The increase in oxygen

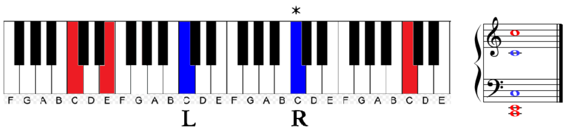

Figure 3: Musical harmonies added by BRAAHMS (red) to user's keys (blue) of the left (L) and right (R) hands (* indicates middle C).

consumption is less than the volume of oxy-Hb provided, resulting in more oxy-Hb [5].

5. BRAAHMS: DESIGN PROCESS

Experiment 1 established that there were differences in the fNIRS signal when participants played easy vs. hard pieces on the piano. We built upon these findings to design a novel musical brain-computer interface BRAAHMS: BRain Automated Adaptive Harmonies in a Musical System.

5.1 Design Iterations and Final Design

The musical adaptations used in Experiment 2 were determined by a number of design iterations and pilot studies. These iterations explored the space of possible musical additions that an adaptive system could provide, and resulted in musical enhancements indicated as most helpful or pleasing by users in the pilot studies.

Please see technical report [16] for full details on iterative designs. Results from this stage of pilot studies showed that participants preferred the simple harmonic additions and experienced them as pleasing enhancements without compromising creative control. This formed the basis for the musical system design used in Experiment 2.

The design iterations and pilot studies showed that participants enjoyed an harmonic supplement to their music which enhanced their playing while staying true to their melodic and rhythmic choices. The musical adaptation system accomplishes this with a simple harmonic addition of one octave above user pitch on the right-hand (middle C or above) and one octave below on the left-hand with the third of the chord between user pitch and octave (Figure 3).

The additions provide harmonic reinforcement of the tonal centers, adding depth and richness, while users retain flexibility for melodic choices and control of rhythmic aspects.

5.2 fNIRS System

Real Time Classification: To predict user state in real time, we used the same LIBSVM machine learning procedure as Experiment 1 to build the model. In addition, while the user was improvising, the machine learning model predicted user cognitive state in real time. The system analyzed the last 30 seconds of real-time fNIRS data to calculate a prediction of user cognitive state (high or low) along with a confidence percentage value. Predictions were sent every 500 ms, with the last 10 seconds of predictions to give a more overall model of cognitive activity.

Confidence Threshold Automation: One of our findings from our pilot studies was that a fixed threshold for confidence average values did not work for all individuals during musical improvisation. In previous adaptive BCIs, the adaptations would occur if confidence averages were above some fixed percentage for low or high cognitive workload levels [13, 1]. In this work, we automated this threshold value for each individual by setting the threshold at the 75th percentile of confidence values for both high and low cognitive workload classifications during the first non-adaptive trial. This ensured that the system would only add or remove musical additions at a more accurate and representative level of each individual user's cognitive workload.

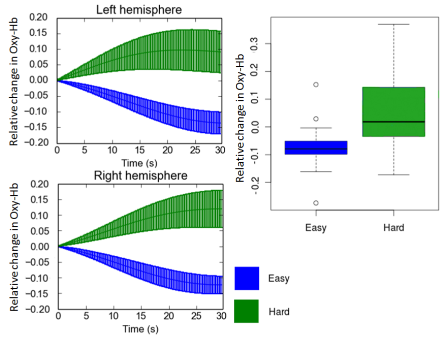

Figure 4: Left: Mean change in oxy-Hb and standard error across all trials and participants. Right: Mean change in oxy-Hb was significantly higher during hard pieces ($p < .001$).

6. EXPT 2: EVALUATION OF BRAAHMS

We tested BRAAHMS over 4 different conditions of musical adaptation. We did not assume whether to add and remove the harmonies when cognitive workload was high or low to account for individual differences and to investigate user preference. We therefore tested 2 different BCI conditions as well as 2 non-BCI conditions:

BCI1: Musical harmonies are added with low cognitive workload and are removed with high cognitive workload.
BCI2: Musical harmonies are added with high cognitive workload and are removed with low cognitive workload.
Constant: Musical harmonies are always present.
Non-adaptive: There are no musical harmonies.

Twenty participants (14 female, mean age of 21, SD of 1.9) first carried out the training task described in Experiment 1 in order to build a model from their brain data. They then carried out the 4 conditions described above in random order except for the non-adaptive condition which had to come first to extract the automated threshold for low and high cognitive workload. Participants had no knowledge that some conditions were brain-controlled or not as they wore the fNIRS sensors throughout the experiment. We also carried out and recorded post-experiment interviews during which participants watched each condition back on video.

6.1 Experiment 2 Results and Discussion

The fNIRS data showed an increase in oxy-Hb during hard pieces that was consistent with the findings from Experiment 1 as well as previous literature [5]. A t-test on the mean change in oxy-Hb revealed a significant difference between easy ($\mu = -0.1, \sigma = 0.1$) versus hard pieces ($\mu = 0.1, \sigma = 0.1$) ($t(18) = -4.50, p < .001$). Means and standard errors of these conditions are shown in Figure 4.

6.1.1 Participants preferred the BCI conditions

Participants were asked to state their favorite trial at the end of the post-experiment interview, after they had watched footage of each trial. They were blind to the conditions of the trials and wore the brain sensors during all trials.

Fifteen out of twenty participants responded that their favorite condition was a brain-controlled condition (Fig. 5). To investigate why participants preferred the BCI conditions, we turn to the interview data.

6.1.2 Participants felt more creative

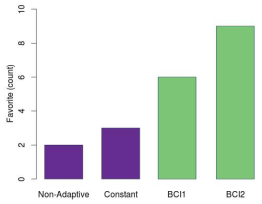

Figure 5: Favorite conditions of 20 participants

Out of the 15 participants who ranked a BCI condition as their favorite, 12 of them commented that the BCI additions helped them to musically perform in a way that they would not have been able to do by themselves. In contrast, only 2 participants made such comments about the constant condition. These are some comments highlighting the general comments about creativity (please see [16] for more detail):

"*[BCI2] was my favorite. I felt I was at my creative peak. Obviously it's clunky because I'm not a real pianist, but I felt like I was playing a real song. I was combining my comfort zone with the additions.*"

"*Being that I am not as experienced and I'm able to get a chord out of just one key, I can do sounds that I probably wouldn't know how to make on my own.*"

6.1.3 Participants felt the BCI was responsive

Out of the 15 participants who stated a BCI condition as their favorite, the other reason given for preference was the responsiveness of the musical additions. Comments on their favorite BCI condition included:

"*[BCI2] was my favorite... I felt like I was responding to the additions and they were responding to me*"

"*In [BCI2] for some reason I felt that the changes were more responsive and I couldn't tell you why... I couldn't quite figure out any pattern of when they were coming and out so I couldn't tell if I was influencing them but for some reason it didn't feel random, I don't know why.*"

It seems that it is not enough for musical additions to be arbitrary, that they must subjectively feel *responsive* to a user, even if the user does not understand why.

7. CONCLUSION

We have demonstrated that it is possible to measure brain signals using fNIRS that correlate with high and low levels of cognitive difficulty while playing the piano. We used this semantically meaningful brain data to build a real-time musical brain-controlled system that adapts implicitly to users' cognitive state. We have carried out pilot studies through an iterative design process to determine which musical additions would add the most pleasing harmonic enhancements to users' playing without compromising control over rhythm or tempo. Finally, we showed in an experiment that 15 out of 20 users preferred a brain-controlled condition, and we have discussed the possible reasons for this through post-experiment interview analysis.

We suggest that BRAAHMS increases the communication bandwidth between human and musical instrument, responding to user cognitive state and providing appropriate musical additions when they are needed, without requiring the user's effort or attention to control them.

8. ACKNOWLEDGMENTS

We thank Kathleen Kuo, Paul Lehrmann, Sergio Fantini, Angelo Sassaroli, Sam Hincks, Tomoki Shibata and Eli Brown. We thank the NSF (grants IIS-1218170 and IIS-1065154) for support of this research.

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