Implicit Brain-Computer Interaction Applied to a Novel Adaptive Musical Interface

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ABSTRACT
We present a novel brain-computer interface (BCI) integrated with a musical instrument that adapts passively to users' changing cognitive state during musical improvisation. Traditionally, musical BCIs have been divided into camps: those that use some mapping of brainwaves to create audio signals; and those that use explicit brain signals to control some aspect of the music. Neither of these systems take advantage of higher level semantically meaningful brain data or implicit brain data which could be used in adaptive systems. We present a new type of real-time BCI that assists users in musical improvisation by adapting to users' measured cognitive workload. 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 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; passive BCI

ACM Classification Keywords
H.5.m. Information Interfaces and Presentation (e.g. HCI): Miscellaneous

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 [2, 37]. 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. It can then use it as an additional input channel that modifies the music at appropriate times, almost acting as a user's third hand.

Traditionally, many musical BCIs have been based on different variations of mapping brainwaves to soundwaves. For example, the magnitude spectrum of the brain signals are used to shape the spectrum of musical frequency [22, 23, 27] or certain features are mapped to certain musical features [25, 43]. More recently, the power spectrum of EEG signals have been used to map algorithm selection to create music [25]. However we seek the ability to go beyond the lower level signal and to extract meaningful information from the brain data about cognitive activity [23, 26, 33, 34].

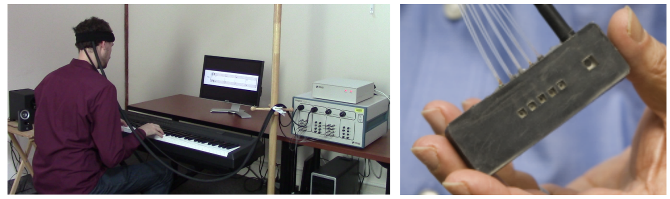
Recent events in the field of brain sensing point to such a way of measuring and using higher level meaningful cognitive data. Cognitive workload has been measured by fMRI [7, 20], EEG [9, 18] as well as fNIRS [4, 5, 29]. Solovey et al. [37] demonstrated the first real-time BCI that adapted to users' cognitive state with fNIRS. Ayaz et al. [4] and Afergan et al. [1] used cognitive workload to assist user load in unmanned aerial vehicle (UAV) simulations with fNIRS.

BCI technology has now reached the point where this is an opportune time to introduce a musical system that 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 adapt to users in the creative task of musical improvisation. BRAAHMS adapts to the users 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.

In order to develop such a system, we first demonstrated that high and low cognitive workload could be automatically classified when users were playing the piano. Our next challenge was to create appropriate ways in which a novel musical instrument might respond in real-time to pianists' cognitive workload/brain activity. This required several design iterations and pilot studies to investigate how and when the musical adaptations would occur. Finally, we ran a second experiment to evaluate our resulting system and found that 15 out of 20 users preferred our brain-controlled musical instrument over other conditions because it helped them feel more creative.

Thus, the contributions of the paper are as follows:

1. Discovery and demonstration that high and low cognitive workload can be measured using fNIRS when users play the piano.
2. Iterative design and demonstration of a novel musical instrument system that uses cognitive workload in real-time to passively adapt to pianists.
3. Experimental evidence from interviews and subjective rankings show that users prefer this novel musical instrument to other conditions because they felt more creative and that the system was responsive to them.



(a) (b)

Figure 1: FNIRS equipment and experiment setup. a)Subject is playing the piano keyboard while wearing the fNIRS sensor. Imagent is visible on the right. b)An fNIRS sensor with light sources (left) and one detector (right).

RELATED WORK

Music and BCI

Traditionally, most musical BCI systems have been based on a mapping of brainwaves to audio signals. In 1965, the first musical piece was performed with a BCI by directly mapping the players alpha brainwaves over loudspeakers to resonate onto percussion instruments [19]. In their biosignal musical interface, Knapp et al. used EEG alpha waves in the occipital cortex to change the MIDI program [15]. In their demonstration they gave they example of changing from a violin to a glockenspiel sound [15]. More recently, Miranda et al. built a BCI-Piano that responded to certain frequencies of EEG activity with assigned musical passages [23, 24]. Arslan et al. used a combination of eyeblinks based on EEG alpha-bands and motor imagery stimulation from the motor cortex to apply a mapping to note triggers and diffusion of sound over loudspeakers [3]. Mealla et al. used the magnitude spectrum of EEG to shape the spectrum of white noise in their musical table-top interface [22].

There have also been examples of BCIs where direct brain signals are used to control a grid of options to select icons as a replacement for a keyboard and mouse in order to compose music using the P300 signal [6] and steady-state visually evoked potentials [17]. While such systems are excellent designs for users with motor disabilities, they are slower to operate than a mouse and keyboard for able-bodied users.

A clear need for higher level semantically meaningful brain data has been highlighted in the field of musical BCIs [23, 26]. Rosenboom [33] discussed the possibility of using Event-Related Potentials with EEG. Miranda et al. [26] ran a pilot study on a EEG-based BCI that detected active versus passive listening. Active listening is when a user would imagine the riff continuing for 2 bars after it finished whereas passive listening involved no extra effort. However, they reported difficulty in reliably detecting listening behavior [25]. They also discussed building another musical BCI that would direct the tonality of the music based on auditory cortex stimulation. However they reported that only the generative music system had been built so far which is based on hypothetical brain data [25]. Girouard et al. used fNIRS to classify between two non-music related tasks and changed the background music according to the predicted task [10]. They found no effects of background music on the tasks but their main goal was to produce a proof-of-concept passive adaptive BCI rather than a musical BCI [10]. Grierson et al. [13] 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.

Brain Sensing in the Prefrontal Cortex 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 prefrontal cortex, 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 [8] and a decrease in deoxy-Hb. This hemodynamic response can be measured by emitting frequencies of near-infrared light around 3 cm deep into the brain tissue [41] 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 prefrontal cortex is the seat of higher cognitive functioning such as complex problem solving and multitasking [16]. In this paper, we measure activation in the anterior prefrontal cortex with fNIRS to analyze and respond to differences in cognitive activity when users are faced with a musical task that varies in difficulty level.

The fNIRS signal has been found to be resilient to respiration, heartbeat, eye movement, minor head motion, and mouse and keyboard clicks [35]. It is generally more tolerant of motion than EEG and has a higher spatial resolution. However it does have a slower temporal resolution than EEG with a delay of 5-7 seconds due to the hemodynamic response of blood flow to the brain. 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 the HCI community [1, 2, 4, 29, 36, 37].

Passive Brain Computer Interfaces

Many musical BCIs have used brain signals as a direct input to an application, such as using the P300 signal to directly control a synthesiser [12] or select harmonies [40]. Icons from a grid have been selected to compose music instead of the standard keyboard and mouse using the P300 signal [6] or steady-state visually evoked potentials [17].

While such active BCIs can be invaluable to people with motor disabilities, to the general population they are slower and less accurate than their standard mouse and keyboard. Recently, however, fNIRS and other brain-sensing technologies have been used for passive brain computer interfaces, where the user performs a task normally, but the user's brain signals act as an *additional* communication channel that are used to assess cognitive state and adapt the interface accordingly. Passive BCIs are characterized by implicitly state measuring user cognitive state without any additional effort from the user [45] and without the purpose of voluntary control [44], thus resulting in a more natural interaction between the human and system [46].

One of the most promising signals to control real-time BCIs is cognitive workload, which has been used since the first fully adaptive loops [31, 42], and has been shown to successfully adapt an interface using fNIRS [1, 10]. In addition, fNIRS has also been used to control passive BCIs using preference [28] and multitasking signals [2, 37]. In this paper, we build and evaluate a passive BCI that analyzes and responds to users' cognitive workload in a musical task.

RESEARCH GOALS

Our primary research goal was to use semantically meaningful brain data to develop and evaluate a passive, 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:

- Experiment 1 was a feasibility study carried out on 15 participants to determine whether differences in brain data corresponded with high and low difficulty levels when users played the piano.
- Through a iterative design process and pilot studies we built BRAAHMS, a passive real-time BCI that adapts to the brain signal established in Experiment 1 during musical improvisation by adding or removing musical harmonies.
- Experiment 2 was an evaluation study 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.

EXPERIMENT 1: PIANIST WORKLOAD CLASSIFICATION

In the first study we collected data from 15 individuals with the goal of examining the feasibility of automatic classification of cognitive workload using fNIRS while users played the piano.

Materials

We chose 15 easy pieces and 15 hard pieces for participants to play on the piano for 30 seconds at a time. The criteria for the easy pieces were that a) all notes were in C major

(a) An example of a hard piece, excerpt from Impromptu No.1, Opus 25 by Gabriel Fauré

(b) An example of an easy piece

Figure 2: An example of a a) hard piece and b) easy piece. Both pieces are nine measures long.

(i.e. no sharps (♯) or flats (♭)), b) there were only whole notes (𝅝) (very slow, long notes), c) there were no accidentals (i.e. no additional sharps, flats, or naturals (♮) that are not part of the scale), d) all notes were within the C to G range so that participants did not need to move their hands e) there were no dynamics (i.e. volume of a note or stylistic execution). The hard pieces were chosen by a musicologist and the criteria consisted of pieces that a) had a harder key signature (most pieces had a key signature of at least 3 sharps or flats), b) contained accidentals , c) contained mostly eighth (♪) and sixteenth notes (𝅘𝅥𝅯) (i.e. short, fast notes), d) required some moving of the hands but not too excessively, and e) contained dynamics. Figure 2 shows an example of an easy and hard piece.

Experimental Procedure

Participants were given 15 easy and 15 hard pieces of music in random order to play on the piano. They were given 30 seconds to sight-read each piece (i.e. play a previously unseen piece) followed by a 30 second rest period. A metronome was played at the start of each piece for 4 seconds at a speed of 60 beats per minute. Participants were asked to try to stick to this speed but told they could go slower if they needed to. Figure 1a shows the setup of Experiment 1.

Participants

Fifteen participants took part in the first experiment (7 female, mean age of 21, SD of 2.4) and were compensated $15 for participating. Subjects had been playing piano for a mean of 9 years (SD 5.4).

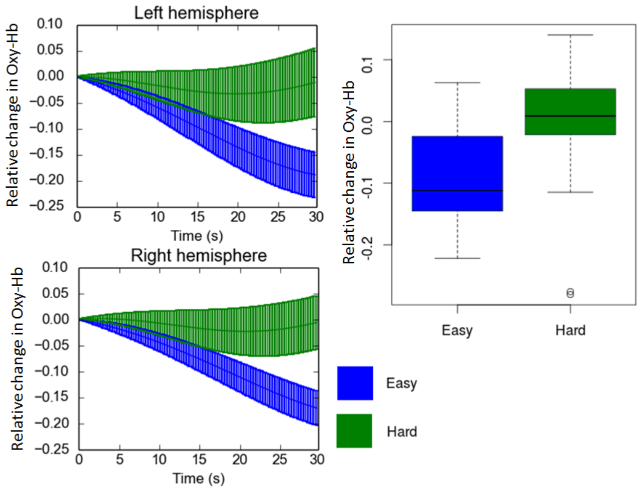


Figure 3: Left: Mean change and standard error in oxy-Hb in Experiment 1 across all participants. Although each participant was modeled individually, the fNIRS signal exhibited a general trend with higher levels of oxy-Hb corresponding with hard pieces. Right: The mean change in oxy-Hb was significantly higher in participants when they played an hard piece than an easy piece ($p < .01$).

fNIRS System

Equipment

We used a multichannel frequency domain Imagent fNIRS device from ISS Inc. (Champaign, IL) for our data acquisition. Two probes were placed on a participant's forehead to measure data from the two hemispheres of the prefrontal cortex. Each probe contains 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 1b). The source-detector distances ranged from 1.5 and 3.5 cm, and the sampling rate was 11.79 Hz. The signals were filtered for heart rate, respiration, and movement artifacts using a third-degree polynomial filter and low-pass elliptical filter.

Training and Modeling Brain Data

The easy and hard musical pieces were used to train the system to learn each individual user's cognitive activity for low and high cognitive workload, respectively. During each musical piece, the system calculated the change in optical intensity compared to a baseline measurement for each of the sixteen channels. Markers sent at the beginning and end of each trial denoted the segments for each piece. 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]. We also carried out 10-fold cross-validation in order to verify that the model was accurate.

Experiment 1 Results and Discussion

Figure 3 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 3 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 3.

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 consumption is less than the volume of oxy-Hb provided, resulting in more oxy-Hb [8].

Although it seems at first glance that the two different musical scores in Figure 2 would cause a great difference in hand motion, participants actually only managed to play one or two measures from the hard pieces very slowly. This is because the hard pieces were purposefully chosen by a musicologist to be complex. Furthermore, sight-reading (playing a piece that you have never seen before) is a challenging task by itself. Therefore the difference in hand motion between the easy and hard pieces was minimal.

The fNIRS signal is resilient to minor hand movement [35] as caused by the simplicity of the easy pieces and the complexity of the hard pieces. This is an advantage of fNIRS over EEG in a musical study such as this. Thus, the significant differences in oxy-Hb reported in Figure 3 can be related to differences in cognitive workload in users when playing easy versus hard pieces on the piano.

BRAAHMS: ITERATIVE AND FINAL DESIGNS

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

Design Iterations and Pilot Studies

Prior to designing the musical adaptation used in Experiment 2, a number of design iterations and pilot studies took place. These iterations explored the space of possible musical additions that an adaptive system could provide, and resulted in a final design that selected the musical enhancements indicated as most helpful or pleasing by users in the pilot studies.

Preliminary Interviews

We discussed the topic of a brain-based adaptive musical interface with one professor of music and engineering, one professor of music and machine learning, and several music graduate students before designing and building the system.

The main outcomes were that 1) expert musicians would not appreciate interference in their creativity, and 2) most people who take piano lessons are classically trained to play musical scores, but are not generally taught how to improvise (this was also later reflected in our participants' improvisational experience in Experiment 2). We therefore decided to focus on building a system designed to aid beginner to intermediate pianists at musical improvisation.

Melodic fragments from all piano pitches

The starting point of the iterative design process was a system that inserted precomposed melodic fragments while the user was playing, making use of any pitches present on a standard piano keyboard. We determined that this form of musical addition did not complement the user input and was instead experienced as contrarian, such as the following report from a participant: "*[The additions] made composing/improvising much more difficult because it distracted my hearing and what I was playing and distracted me*". This starting point had two main drawbacks. First, since the melodic fragments were precomposed, they did not tend to coincide with the users' playing. Second, the unrestricted availability of all pitches on the piano resulted in pitch additions that altered the harmonic content of the users' music in a confusing way.

Layered melodic fragments with harmonic consistency

To address the confusing harmonic alterations, a restriction was added to force all system additions to match the same harmonic center (or "musical ke") as the user input. For example, in the key of C major, only white keys on the piano are available to the system. To further refine the exploration, four layers of musical additions were created and tested. The layers were:

- Simple melodic additions in conjunction with the user input, which used a subset of pitch classes from the major scale (e.g. for a piece in the key of C, using a subset of the white keys only).
- More complex melodic additions, which played more notes faster in conjunction with the user input.
- Harmonic additions to the melodic portion of the user input, using harmony rules derived from Western music theory.
- Harmonic bass additions to accompaniment portion of the user input, using harmony rules derived from Western music theory.

As the user maintained a low level of measured cognitive workload, additional layers were added every ten seconds, starting with simple melodic additions and ending with all four layers combined. If the measured cognitive workload became higher, layers were removed.

User feedback on these musical additions was more positive than the precomposed fragments from earlier. For example, one user wrote: "*I really enjoyed playing the simple melody when each of the other melodies/harmonies came in - it led to some really pretty sounding music that I felt I was controlling with only a few keys!*". However, other users still found the melodic portions intrusive, specifically with respect to their experience of the tempo and rhythm of the composition. Another participant wrote: "*Sometimes the timing of the additions seemed to clash with the speed I was trying to play*". Overall, the aggregated feedback suggested that the melodic additions were experienced as mixed positive and negative by participants, whereas the harmonic bass additions were consistently experienced as pleasing enhancements to the music created by the user without compromising creative control.

This iterative design process made it clear that the best approach for the adaptive system was to use a simple harmonic addition to reinforce the user input while making sure to respect the rhythmic and tempo choices of the user. This formed the basis for the musical system design used in Experiment 2.

Final Design for BRAAHMS

Musical Real-Time Adaptation by the System

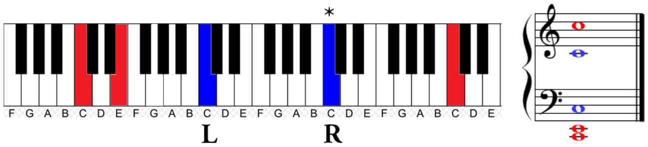
The design iterations and pilot studies made it clear that the most pleasing adaptation is to harmonically supplement the music created by the user while staying true to the melodic and rhythmic choices provided by the user. The musical adaptation system accomplishes this with a simple harmonic addition that re-emphasizes the melodic pitches and reinforces the harmonic center provided by user-selected pitches, matching the user note onset times to maintain the same rhythm as the user. The right-hand user input (higher pitch middle C or above) typically plays the more melodic portion of a piece. For the right-hand input, the system adds the pitch one octave above the user pitch (+7 notes of the major scale). The left-hand user input (lower pitch below middle C) typically plays the accompaniment or bass part in a piece. For the left-hand input, the system adds two pitches: 1) one octave below the user input pitch (-7 notes of the major scale), and 2) the third of the chord between the octave and the user pitch (-5 notes of the major scale). These intervals are shown in Figures 4a and 4b. These musical additions are consistent with typical Western harmonies [30].

The octave additions serve to re-emphasize the pitches chosen by the user. The addition of the second left-hand note provides a harmonic reinforcement of the tonal center specified by the left-hand user input. The added pitch is the third of the chord (e.g. if the user plays a C, then the added note will be an E). [30]. Adding this enriches the harmonic texture of the musical sound. The third of the chord is specific to the harmonic mode of the music overall (e.g. if the user plays a C, the added E implies C major rather than C minor), so adding the third of the chord can help maintain a harmonic consistency across different user inputs. This adds musical depth to the harmonic content chosen by the user.

By providing these simple harmonic additions in this way, the system adds depth and richness to enhance the musical choices made by the user. The user retains a great deal of flexibility to make melodic choices with their right-hand, and retains complete control of the rhythmic aspects of the music creation experience.

Sound Engine

These musical additions were implemented in Pure Data (PD) with a piano soundfont through the software synthesizer FluidSynth. QjackCtl was used to connect all systems on a Linux



(a) (b)

Figure 4: The musical harmonies added by BRAAHMS. a) Blue notes denote the keys the user is pressing. Red notes denote the additions made by the system. The L and R depict the fingers of the left and right hand respectively. The * indicates middle C. b) Music notation showing a sample user input (blue) with the additional pitches provided by the system (red).

Operating System. Subjects played their chosen notes on an electronic piano keyboard, which sent MIDI inputs to PD. The combined harmonic MIDI outputs along with users' original notes were generated in PD and sent to the keyboard via the soundfont on FluidSynth which converted the MIDI outputs into audible piano sounds. PD only added or removed musical additions when it received a marker from the fNIRS system, the real-time classifications of which are discussed below.

Musical Guidance for Participants

As it is challenging even for expert musicians to improvise or perform in a completely open-ended musical context, participants were provided with a simple piece of notated music to use as a basis for their musical creation. Participants were invited to improvise beyond the confines of the simple skeleton provided by the notated music. The notated music is shown in Figure 5. The notation outlines a repeating I-IV-V-I musical chord progression, which is one of most prevalent chord progressions in Western music and is likely familiar and aurally pleasing to participants [14]. In the key of C, the chords are: C-F-G-C. This musical skeleton provides an easy way for participants to approach the musical creation task.

Figure 5: Notated music provided as guidance only to participants during musical improvisation.

fNIRS System

Real Time Classification

To predict user state in real time, we used the same LIBSVM machine learning tool and training procedure as Experiment 1 to build the model. However, while the user was improvising, the machine learning model also 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. Each prediction was sent every 500 ms, and the system averaged 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 while designing BRAAHMS 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 [37, 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. In this way, the thresholds were set at a more accurate and representative level of each user's cognitive workload while improvising. This ensured that the system would only add or remove musical additions when it was confident in the user's cognitive state.

EXPERIMENT 2: EVALUATION OF BRAAHMS

We carried out an evaluation study of BRAAHMS in Experiment 2 over 4 different conditions on a new set of 20 participants. We investigated user preference through subjecting rankings and post-experiment interviews .

Experimental Design

In order to evaluate user preference, 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 when brain signals correspond with low cognitive workload and are removed when brain signals correspond with high cognitive workload.
- *BCI2*: Musical harmonies are added when brain signals correspond with high cognitive workload and are removed when brain signals correspond with low cognitive workload.
- *Constant*: Musical harmonies are always present.
- *Non-adaptive*: There are no musical harmonies.

Users 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 and were simply asked to improvise and that this would be repeated 4 times. Each of the 4 conditions were filmed with the participants' consent.

We also carried out and recorded post-experiment interviews during which participants watched each condition back on

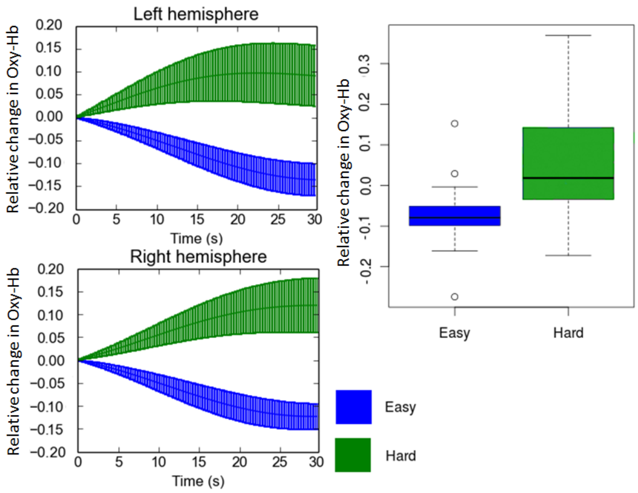


Figure 6: Left: Mean change in oxy-Hb and standard error across all trials and participants. Although each participant was modeled individually, the fNIRS signal exhibited a general trend with higher levels of oxy-Hb corresponding with hard pieces, consistent with the findings of Experiment 1 (Figure 3). Right: he mean change in oxy-Hb was significantly higher in participants when they played an hard piece on the piano versus an easy piece consistent with the findings of Experiment 1 ($p < .001$, also see Figure 3).

video and were asked three questions as they watched each condition: 1) *Do you have any comments about this trial?* 2) *Do you have any comments about the additions in this trial?* 3) *Do you have any other comments?* They were still blind to differences in conditions. At the end of the interview they filled in a short questionnaire where circled their favorite trial out of the 4 options: 'System 1' 'System 2' 'System 3' and 'System 4' and then rank each trial with 1 being their favorite and 4 being their least favorite.

Participants

Twenty participants took part in the second experiment (14 female, mean age of 21, SD of 1.9) and were compensated \$20. We requested beginner to intermediate pianists. Mean length of time participants had played piano was 7 years (SD 5 years) while 10 of them no longer played piano and 4 only played once a year. Seven had never improvised and seven only improvised rarely.

Experiment 2 Results and Discussion

Technical evaluation

The fNIRS data in Experiment 2 was consistent with the findings from Experiment 1 whereby brain signals correlated with high vs. low levels of difficulty when participants played the piano (Figure 6). Similar to our findings in Experiment 1, we performed a t-test on the mean change in oxygenated hemoglobin which revealed a significant difference between when participants were playing an easy piece ($\mu = -0.1, \sigma = 0.1$) versus a hard piece ($\mu = 0.1, \sigma = 0.1$) on the piano ($t(18) = -4.50, p < .001$). The means and standard errors of these conditions are shown in Figure 6.

The increase in oxy-Hb during the hard pieces and decrease in oxy-Hb during the easy pieces are once again consistent with harder tasks resulting in higher levels of oxy-Hb [8].

Participants Prefer 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. Figure 7 shows the favorite conditions of participants.

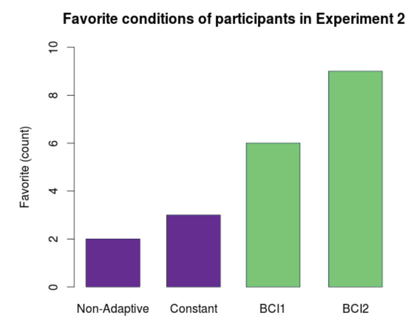


Figure 7: Favorite conditions of 20 participants in Expt 2

To investigate why participants preferred the BCI conditions, we turn to the interview data. Both BCI conditions were preferred by different individuals, and while we discuss this in terms of musical expertise, the discussion of why the BCI conditions were preferred in general over non-BCI conditions can also help shed some light on this.

Participants felt more creative in their favorite BCI condition

Findings from interview data revealed that 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, 1 of which had ranked the constant condition as their favorite. Participants commented that they felt more creative during their favorite BCI condition, such as:

"*[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.*

In addition, we present some quotes on how subjects' favorite BCI condition would help them creatively in contrast with their constant condition. One subject found the additions helpful in their favorite BCI condition:

"*During [BCI2] I thought the additions were pretty helpful. It's hard to say how. Maybe because introducing another note*

leads you in a slightly different direction than you were heading originally, that can be nice."
However the same subject did not like the constant condition:
"*I thought that sometimes the additions were confusing because I thought that the note that I was trying to play wasn't the note that was coming out. For some reason in this last trial I started to notice them [the additions] more.*"

Similarly, another subject commented that their favorite BCI condition helped them develop new ideas:
"*I liked the additions, I felt like they almost made it easier to come up with ideas because I was staying in the same octaves before and I was like 'Oh, it sounds pretty when its outside of that'.*" However the same subject did not feel the same way about the constant condition:
"*I felt like there were a lot of them [additions]. I remember at least in the beginning it felt like every note, it was kind of weird to have every single note [with additions].*

These findings suggest that the favorite BCI conditions helped participants achieve a musical level that they would not achieve by themselves or be taken in new directions that they would not have alone. The high number of participants (12 out of 15) who all made similar unprompted comments on their favorite BCI condition in response to open-ended interview questions suggests that this was an important factor in their preference. The contrast in comments between the favorite BCI condition and the constant condition within subjects suggests that adaptive musical additions in response to cognitive state could take participants to a creative place that simple, constant musical additions could not.

Participants felt their favorite BCI condition was responsive

Out of the remaining 15 participants who stated a BCI condition as their favorite, the other reason that was 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*"

"*[BCI1] was my favorite of all of them. I think because I didn't know if the additions were going to come in and out it was fun and felt very fluid with the combination of just regular piano [and additions]. I felt that in this one it was responsive.*"
However in contrast the same subject felt that the their constant condition was not responsive:
"*In [constant] I remember that the additions took a bit more adjustment, I didn't feel that they were as responsive because, I would be in the middle of a very quiet part and all of a sudden it would be doubled and it would be jarring.*"

Another example from a subject who felt that their favorite BCI condition was responsive to them:
"*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 dont know why.*"
And this same subject felt that the other (non-favorite) BCI condition was not responsive:
"*The additions generally seemed random coming in and out... they didn't seem responsive at all.*"

These comments suggest that responsiveness is an important factor in participants' preference of a condition. This is supported by the fact that there were several comments made about other conditions that were *not* the favorite where responsiveness was lacking. It seems therefore 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.

Years of experience affected preference of conditions

Of 20 participants, 5 did not rank a BCI condition as their favorite, instead picking either the Constant (3 participants) or Non-Adaptive (2 participants) conditions as their preferred adaptation strategy. We noticed an interesting characteristic in this group in that 4 of these 5 participants had more years of experience playing the piano (17, 13, 12, and 10 years) compared to the median of 6.5 years of the total group. To investigate these results statistically, we divided the participants into two groups based on years of experience via a median split (at 6.5 years) and examined their rankings of the conditions.

Analyzing the participant's rankings using a Friedman test, there was a statistically significant difference in both the low experience $\chi^2 = 25.74, p < 0.0001$) and high experience groups ($\chi^2 = 27.96, p < 0.0001$). To investigate relationships between conditions, we perform post hoc comparisons using the Wilcoxon rank-sum tests, and correct for multiple comparisons using the Bonferroni technique, resulting in a significance level set at $p < 0.01$ [11]. Figure 8 shows the resulting rank-sums and significant differences.

For the participants with low (≤ 6.5 years) experience ($n = 10$), post hoc comparisons show that participants significantly preferred both BCI conditions to the Constant and Non-Adaptive conditions ($p < 0.001$). There was no significant difference between the [BCI1] and [BCI2] conditions ($p = 0.18$), nor was there a difference between the Constant and Non-Adaptive conditions ($p = 0.59$).

In contrast, for participants with high (> 6.5 years) experience ($n = 10$), post hoc comparisons revealed that participants significantly preferred the [BCI1] condition to both the Non-Adaptive and Constant conditions ($p < 0.001$). However, the [BCI2] condition was not significantly different than either the [BCI1] ($p = 0.04$) (due to the conservative threshold of the Bonferroni correction) nor the Constant ($p = 0.31$) conditions.

The results of these analyses suggest that participants with more experience of playing the piano show more variability in their preferences for adaptations. In contrast, participants with less experience playing the piano show a clear preference of the BCI conditions over the constant and non-adaptive conditions. This is most likely due to more experienced pianists' ease with musical improvisation due to their greater facility with the unadorned piano. It does suggest that such a system would benefit less experienced users and per-

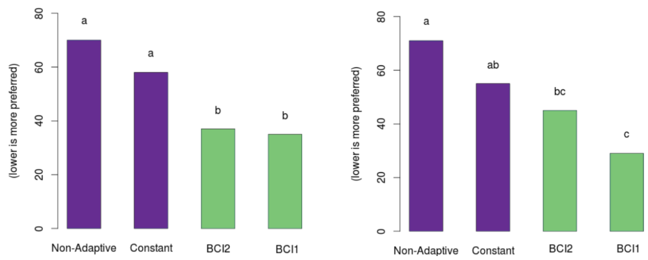


Figure 8: Rank-Sums of the conditions based on a median split (6.5 years) on years of experience playing the piano. Rankings of participants with lower experience (< 6.5 years, $n = 10$) (left) and and higher experience (> 6.5 years, $n = 10$). Lower bars indicate a more preferred condition, and bars with the same letter are not significantly different.

haps would rather interfere more with more experienced players. This is consistent with our original target audience for BRAAHMS, which had been always been less experienced players.

DISCUSSION

We believe this is one of the earliest demonstrations and evaluation of a real-time brain-based musical system that adapts to brain signals that correspond with cognitive workload. This need for semantically meaningful brain data in respect to musical and/or creative tasks has been highlighted as a need by experts in both the fields of Music and BCI [33, 26, 23] and HCI and Creativity[21, 34].

The fact that most users ranked the BCI conditions as their favorite suggests a successful demonstration of our system. The comments ensuing from the open-ended interview questions suggest that one reason for this was that the system helped them achieve a level of musical improvisation that they would not have been able to otherwise, in other words, helped them be more creative. Another reason given was that they felt that their favorite BCI condition felt more responsive which suggests that the timing of the additions are crucial to preference. Adjectives participants used to describe their favorite condition included “responsive”, “fun”, “enjoyed” “dynamic”, “fluid”, and “creative” which suggests that also, simply, the system was enjoyable to use and fun.

One of the important points brought up by musical experts in our pre-design interviews was that experienced musicians would not appreciate interference with their creative process. As noted, BRAAHMS was thus designed for beginner to intermediate pianists. Interestingly, one of our findings was that out of our group of beginner to intermediate players, the relatively more experienced users did show more variance in their preference for adaptations whereas less experienced ones showed a clear preference for the BCI conditions over the constant and non-adaptive conditions. In future musical brain-controlled systems, it would be prudent to consider and incorporate musical expertise and experience into the design process and the adaptation strategy.

While each of the two BCI conditions were preferred over either of the constant and non-adaptive conditions, the choice of which of the two BCI conditions was better varied across subjects. When designing our adaptations, we purposefully had not assumed whether to add musical additions when participants’ cognitive workload was low and remove the additions when cognitive workload was high (BCI1), or vice-versa (BCI2). We thus implemented both possible BCI conditions to explore user preference and to account for individual differences. This is a topic for further investigation to understand which adaptations are best for which users or conditions, or perhaps under what conditions to switch adaptations from one to the other.

FUTURE WORK

This study has focused on music as the creative task in which to aid participants, however, it carries implications for a broader reach in the field of HCI where the user’s goals are also non-specific. In previous BCI work, there is generally a specific goal, where it is assumed that the user knows exactly what they want to do, such as find the most efficient UAV route [1] or direct a robot to its correct location [37]. In many tasks however there are occasions where we do not know exactly what our goal will look like until it is reached, such as in exploratory search or data analysis. In his seminal paper, Tukey [39] spoke of the importance of the non-specificity of goals in scientific fields: “*Science - and engineering... does not begin with a tidy question. Nor does it end with a tidy answer.*” The work in this paper could be viewed as a demonstration of how semantically meaningful brain data can be used in a creative task, where the ultimate goal is non-specific, and the user does not know exactly what the outcome will look like but has a general idea of what they want [38].

Exploratory data analysis in the field of visual analytics is a prime candidate for such work. Analysts are faced with large and complex datasets that they must process, visualise, analyze, and subsequently extract the most critical information out of. In fact, to overcome some of these obstacles, Riche proposes and discusses the use of brain measurements including fNIRS [32]. It is a fertile field in which to explore the use of measuring cognitive state in non-specific goals. We thus view future work in this direction in the broader context of helping users achieve non-specific goals with brain-based automation.

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 then used this semantically meaningful brain data to build a real-time brain-controlled system that adapts musically to the user’s 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 and participant expertise data.

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

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