# Brain-computer music interfacing for continuous control of musical tempo

Ian Daly<sup>1</sup>, Duncan Williams<sup>2</sup>, Faustina Hwang<sup>1</sup>, Alexis Kirke<sup>2</sup>, Asad Malik<sup>1</sup>, Etienne Roesch<sup>1</sup>, James Weaver<sup>1</sup>, Eduardo Miranda<sup>2</sup> and Slawomir J. Nasuto<sup>1</sup>

<sup>1</sup> Brain Embodiment Lab, School of Systems Engineering, University of Reading, RG6 6AY, UK i.daly@reading.ac.uk

<sup>2</sup> Interdisciplinary Centre for Computer Music Research, University of Plymouth, PL4 8AA, UK

#### Abstract

A Brain-computer music interface (BCMI) is developed to allow for continuous modification of the tempo of dynamically generated music. Six out of seven participants are able to control the BCMI at significant accuracies and their performance is observed to increase over time.

Keywords Brain-computer music interface, Music generation, EEG, Online continuous control

## 1 Introduction

Brain-computer music interfaces (BCMIs) are devices that allow control over, or interaction with, music via brain activity and without activation of the efferent nervous system [6]. BCMIs therefore allow individuals to interact with, create, or modify music in situations where this would not otherwise be possible. For example, individuals with severe movement restrictions may benefit from use of a BCMI for recreation or as a therapeutic device.

Previous studies have presented BCMIs for passive modification of musical properties, such as beat and loudness, via measurements of complexity of different frequency bands in the electroencephalogram (EEG) [5]. They have also demonstrated selection from a discrete set of two-tone bass frequency drone sounds via emotional imagery [3] and selection from a discrete set of musical scores via steady-state visual evoked potentials (SSVEPs) [4].

Thus, BCMIs have been shown to allow active control of music generation via selection from a discrete set of instructions or passive interaction with music. However, there is an opportunity to further investigate whether BCMI users can wilfully modify musical properties on a continuous scale during a period of online music control.

Therefore, a BCMI is constructed to allow users to modulate the tempo of a piece of music dynamically via intentional control. Specifically, users are able to increase the tempo of the music via kinaesthetic motor imagery (MI) [7] and decrease the tempo via relaxation. Music tempo is mapped to the strength of the users motor imagery allowing them to move the tempo continuously across a specified range.

## 2 Methods

#### 2.1 Participants

Seven healthy right-handed individuals (median age=23; SD=2.9; 6 males) voluntarily participated in the experiment. All participants gave informed consent, and the study was approved as per the University of Reading guidelines for ethics.

### 2.2 Measurements

EEG was recorded from 19 channels positioned via the international 10/20 system, referenced to a central electrode at FCz, and a ground electrode at AFz.

EEG was sampled at a rate of 1,000 Hz via a Brain Products BrainAmp EEG amplifier (Brain Products, Germany). Impedances were kept below 5 k $\Omega$  for all participants.

### 2.3 Music generation

To sustain novelty and avoid complications caused by user familiarity, a generative algorithm was implemented to produce monophonic piano music, with real-time control over tempo.

The generative algorithm allows the user to specify three parameters from which it creates sequences of tone rows (string of pitch classes with no repeated notes) and a pool of rhythm data. In our system the generated row is used to supply the selection of notes from which the musical sequences are derived.

Our BCMI uses 6 notes in a tone row. The rhythm pool is generated according to a list of default values (eight quavers per sequence), with a number of variations introduced according to the starting parameters. The rhythm pool is used to select notes from the generated tone rows randomly, creating a large variation of possible musical sequences (musical streams created by combining notes from the tone row with rhythms from the pool) from a small amount of seed data. The starting note was randomly selected for each participant, and tempo was scaled between the range of 99 beats per minute (bpm) to 288 bpm.

#### 2.4 Brain-computer interface

Musical tempo was mapped to the mean alpha (8-13 Hz) band-power recorded over electrodes F3, T3, C3, Cz, and P3 centred over the left motor cortex. Participants were instructed to increase the tempo of the music via kinaesthetically imagining squeezing a ball in their right hand or decrease the tempo by relaxing. Mean alpha band-power was inverted, scaled by a constant k, and mapped to music tempo. Thus, relaxing increases alpha and decreases tempo.

A single trial of the BCMI control paradigm first presented a fixation cross from -4 s to 0 s. Music playing began at a fixed tempo of 148 bpm with the appearance of the cross. An arrow cue (either up; increase tempo, or down; decrease tempo) was presented in the centre of the screen (visual angle  $\approx 7.5^{\circ}$ ) at second 0. The cue remained on screen for 12 seconds, while the tempo was mapped to the alpha band power recorded over the left motor cortex and updated every 100 ms. Upon disappearance of the cue the music generation ceased and a visual feedback stimuli was presented for 500 ms. This took the form of either a happy face or a sad face.

The paradigm was split into 9 runs. The first was a calibration run to train the parameter k. This run contained 30 trials in pairs of increase and decrease tempo trials. After each pair k was either increased by  $\alpha$  ( $\alpha = 10$  at the start of the run) if tempo was reduced in both trials, decreased if tempo increased in both trials, or held constant. If k was held  $\alpha$  was halved.

For all subsequent runs the term k was held constant at the value arrived at after the calibration run. Each run contained 18 trials and participants were given breaks between runs.

The BCMI was constructed using open standards developed in the TOBI framework [1].

#### 2.5 Analysis

EEG was visually inspected for artefacts via a scorer blinded to the contents of the trials and results. Trials were rejected if they contained artefacts on channels F3, T3, C3, or P3.

Session									
Participant	1	2	3	4	5	6	7	8	Avg.
1	0.444	0.450	0.444	0.500	0.556	0.500	0.550	0.500	0.50(0.04)
2	0.357	0.527	0.518	0.300	0.548	0.341	0.732	0.571	0.52(0.14)
3	0.708	0.764	0.750	0.687	0.625	0.556	0.500	0.375	0.66(0.13)
4	0.800	0.800	0.875	0.800	0.889	0.687	0.700	0.889	0.80(0.07)
5	0.500	0.500	0.500	0.512	0.667	0.722	0.556	0.587	0.53(0.08)
6		0.812							0.71(0.12)
7								0.333	0.38 (0.22)
Avg.	0.50	0.53	0.52	0.63	0.63	0.69	0.55	0.54	-
	(0.23)	(0.19)	(0.19)	(0.13)	(0.13)	(0.14)	(0.12)	(0.19)	

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Table 1: Balanced accuracies over sessions for each participant. Statistically significant accuracies (p < 0.05) are in bold. Bonferroni correction is applied on a per participant basis.

Event related (de)synchronisation (ERD/S) was identified in the EEG recorded over the left motor cortex by extracting band-power measures of alpha (8-13 Hz) frequency band activity relative to a baseline period, defined as the fixation cross presentation period (-4 to 0 s).

Balanced accuracy was used to evaluate each user's ability to control the BCMI [2].

## 3 Results

A total of 154 trials were excluded due to artefact contamination (the presence of blinks, movement, and other sources of noise). Additionally, one participant (participant 6) did not complete the last two runs of the experiment. Thus, a total of 818 (84.16%) of the trials were artefact free and may be used to evaluate user performance.

Table 1 reports accuracies achieved by each participant over the sessions. Figure 1 illustrates the median and standard deviation of accuracies over sessions achieved by participants.



Figure 1: Balanced accuracy over sessions. The solid line indicates median accuracy and the shaded area  $\pm 1$  standard deviation.



Figure 2: Relative mean alpha bandpower on C3, participant 4, all sessions. Dotted line, bandpower during the increase condition.

Figure 2 illustrates the median change in alpha band-power over the left motor cortex (channel C3) relative to the pre-cue baseline period. Note, for the reduce tempo (motor imagery) condition the user was able to produce a sustained event-related desynchronisation (ERD).

## 4 Discussion

Music can be actively controlled via 6 out of our 7 BCMI users with significant accuracy in one or more sessions. It may be argued that multiple comparison correction is needed. However, sessions are not independent, thus Bonferroni correction on a per session basis is not appropriate. Instead, Bonferroni correction is applied to mean accuracies per participant, revealing 3 participants to be able to control the BCMI at significant accuracies.

There is considerable variability and for some sessions participants were not able to control the BCMI at significant accuracies. Nonetheless, our results demonstrate that music tempo can be understood and utilised as a feedback mechanism by the majority of BCMI users.

These results open up the possibility of allowing users a greater level of control of music than previously explored [4, 3]. The performance increase over sessions visible in figure 1 is also encouraging as it suggests that users can, through increased experience, improve their ability to control tempo. We also note, however, that in the final sessions our users displayed a performance reduction. This may be due to fatigue, but further exploration is required.

Future work will seek to compare users' ability to learn to control properties of a piece of music with feedback modalities more traditionally used in BCI control (for example, visual feedback). We will also explore the effects of more advanced computational methods on the performance of the BCI. Additionally, the interaction of music and emotion is an interesting research angle and it would be very interesting to extend the work presented in [3] to allow continuous emotional imagery based control of musical features such as tempo, mode, or timbre. Therefore, future work will also look at extending our BCMI to continuously detect emotions.

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