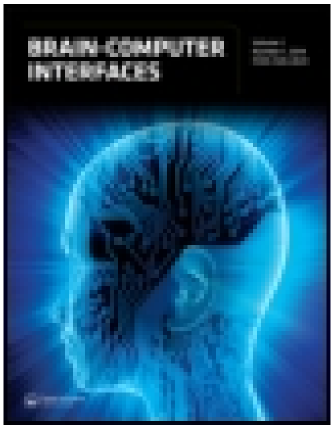

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The feedback mechanism used in a brain-computer interface (BCI) forms an integral part of the closed-loop learning process required for successful operation of a BCI. However, ultimate success of the BCI may be dependent upon the modality of the feedback used. This study explores the use of music tempo as a feedback mechanism in BCI and compares it to the more commonly used visual feedback mechanism. Three different feedback modalities are compared for a kinaesthetic motor imagery BCI: visual, auditory via music tempo, and a combined visual and auditory feedback modality. Visual feedback is provided via the position, on the *y*-axis, of a moving ball. In the music feedback condition, the tempo of a piece of continuously generated music is dynamically adjusted via a novel music-generation method. All the feedback mechanisms allowed users to learn to control the BCI. However, users were not able to maintain as stable control with the music tempo feedback condition as they could in the visual feedback and combined conditions. Additionally, the combined condition exhibited significantly less inter-user variability, suggesting that multi-modal feedback may lead to more robust results. Finally, common spatial patterns are used to identify participant-specific spatial filters for each of the feedback modalities. The mean optimal spatial filter obtained for the music feedback condition is observed to be more diffuse and weaker than the mean spatial filters obtained for the visual and combined feedback conditions.

Keywords: brain-computer interfaces (BCI); music feedback; visual feedback; music tempo; electroencephalogram (EEG); motor imagery

1. Introduction

Brain-computer interfaces (BCIs) seek to provide a mechanism for individuals to communicate and interact with their environment via brain activity alone, without activation of the efferent nervous system. Therefore, BCIs provide a potential method of communication for individuals with severe movement and/or communication difficulties (for example, people with spinal cord injury or amyotrophic lateral sclerosis).[1]

Of all the operation stages of a typical BCI (data acquisition, pre-processing, feature extraction, classification, and application control/feedback [2]), feedback is arguably the least explored in BCI research.[3] More often, large efforts are placed in the development of new processing and classification methods to produce improvements in performance.[4] However, feedback is an integral part of the closed-loop control (in which the output of the BCI system is fed back to the user) that is a key component of BCI operation.[1]

Indeed, the increasing use of BCI for applications such as neurorehabilitation,[5] motor learning,[6] and neurofeedback [6] means that the use of BCI-driven closed-loop control is increasingly coming into the spotlight.[4] This includes applications such as stroke rehabilitation,[7,8] proposed treatments for emotional disorders,[9] and proposed treatments for conditions such as attention deficit hyperactivity disorder.[10] In each of these applications the feedback mechanism by which BCI control actions are reported to the user forms an integral part of the treatment. For example, BCI-based closed-loop motor control may be used to attempt to induce changes in neuroplasticity that result in beneficial motor cortex changes for BCI users who have had a stroke.[11]

There is strong evidence that the feedback mechanism plays an important role in determining how well a user can learn to control a BCI. For example, it has been shown in stroke patients that providing proprioceptive feedback during motor imagery significantly improves BCI control performance.[12] Additionally, feedback is known to strongly affect the BCI learning process.[3] Despite this only a small number of studies have looked into how feedback mechanisms affect BCI learning.[4]

Finally, the feedback modality is also known to have a significant effect on which user groups are able to make use of a BCI. For example, visual feedback may only be used by individuals without severe visual impairment, while tactile feedback requires users to have functioning afferent nerves, and audio feedback requires users to not have severe hearing impairments.

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Additionally, some BCIs require further active control over some functions. For example, some visual feedback-based BCIs also require users to maintain control over their eye gaze direction.[13]

Of the three main feedback modalities that may be considered for BCI control (visual, haptic, or auditory), auditory feedback has good potential for user groups where visual or tactile feedback may not be suitable. These include individuals with spinal cord injury for whom a loss of haptic perceptual abilities makes haptic feedback unsuitable,[14] or people with stroke who may experience some loss of haptic perception while maintaining hearing and vision.[15] Additionally, even when the user has vision and active control over their gaze, auditory feedback can provide advantages since, in contrast to vision-based BCIs, it does not require the user to be visually engaged in the BCI control and can thus enable the user to use their eyes for other activities such as making eye contact with their communication partners.[16]

There are a number of different options available to auditory BCI users regarding the type of feedback. In [17] auditory BCI control is achieved via the use of auditory steady-state potentials (ASSRs). Amplitude-modulated tones at different frequencies are played into each ear of the BCI user and, by attending to one of the tones, the user is able to indicate which option they would like to select. This type of BCI is able to produce high control accuracies, but has been reported to be very annoying for participants.[18]

A different feedback mechanism is presented in [19], in which recordings of tones at different frequencies are played to BCI users through different speakers. By attending to one of the tones the user is able to generate an event-related potential (ERP) upon hearing the target tone. Hence, they are able to indicate their preferred option. Although this type of BCI may be less annoying than the ASSR BCI, the unnatural nature of the stimuli may also be somewhat unpleasant to users.

An alternative feedback mechanism that has been proposed for use in BCI is music-based feedback. This may be done via playing different music pieces for different control actions or, in the case of analogue BCI control, modifying some aspect of the music in response to the user's attempts to control the BCI.[20]

However, currently there is very little evidence available to inform us about the efficacy of music as a feedback mechanism for BCI control. In some studies, music has been used as a discrete feedback mechanism but not investigated as a continuous feedback signal. For example, in [22] a user was instructed to select music scores from a discrete set of options via SSVEP. After selection of the musical score a musician played the selected piece and the user began selecting the next score. Although the music playing was continuous, the timing delay and variability of this delay introduced by such an approach make it very difficult to judge the efficacy of this feedback mechanism.

In contrast, Nijboer et al. did investigate music for continuous feedback.[23] They mapped the volume of two musical instruments, a harp and a bongo, to the synchronization and desynchronization strength of the sensorimotor rhythm (SMR). Their results showed that visual feedback led to significantly higher accuracies than the music volume-based feedback at the start of training, but that after three training sessions performance was the same in both groups. The authors conclude that the development of auditory BCIs is worthy of further investigation. In particular, we note that there may be other parameters that would be more effective for a BCI feedback mechanism. We therefore propose that it is worthwhile studying other musical properties that can be changed continuously by the user.

Additionally, the music used in the study described in [23] was two very short pre-generated excerpts of harp music and bongo music. Both these pieces of music were played to participants multiple times, negating the well-known effects of surprise and anticipation associated with music-induced emotion [24] and leading to over-familiarization of the participants with the music. Additionally, music volume is known to affect listeners' perceptions of note duration, time, and arousal [25] and, therefore, there may be other music features which act as more effective BCI feedback mechanisms. In particular we note that perception of different volumes is not uniform across different age groups and that differences in volume can be annoying (too loud) or too difficult to clearly hear.

Therefore, we attempt to explore the use of music tempo as the continuous feedback mechanism. Music tempo is chosen as the modulated signal due to the immediacy of our perception of tempo changes in music when compared to other acoustic attributes such as timbre, as well as the relative universality of this musical property and the wide range of values it can take. Additionally, tempo may be argued to be more directly musical than volume changes. The aim of the study presented here is to characterize how participants can use music tempo feedback in comparison with the more commonly used visual feedback mechanism. Participants are asked to control a BCI via a kinesthetic motor imagery task under three feedback conditions: visual, auditory via music tempo, and a combined visual and auditory modality. We make no a priori hypothesis as to which feedback modality will allow users to learn to control the BCI more quickly or to higher levels of accuracy. Instead, we present each user with a randomly selected feedback modality and explore how quickly they are able to learn to control the BCI and to what degree of final accuracy.

An additional contribution of this work is that we develop a novel music-generation engine able to produce piano music on a continuous basis according to defined parameters. This enables us to continuously change the music feedback provided by the BCI, meaning that listeners are not subject to a high number of repetitions of the same music clip, as was the case in [24]. As discussed in [24], sustained performance with a BCI requires persistent motivation, and having new music to listen to over a large number of trials could potentially influence performance.

2. Methods

2.1. Participants

Eighteen individuals participated in our experiment. Four of the participants were female. The median age of the participants was 21 (range 18–26). All participants were right-handed.

The participants were recruited from the student population of the University of Reading via emails and posters placed around the department. Each person received £10.00 (GBP) for their participation. Ethical approval for the experiments was granted as per the University of Reading ethics guidelines for experimentation. All participants provided informed consent before participating in the study.

2.2. EEG recording

EEG was recorded from 19 channels positioned according to the international 10/20 system for electrode placement at FP1, FP2, F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1, and O2. The reference was placed at FCz and the ground electrode was placed at AFz.

The EEG was sampled at a rate of 1000 Hz and recorded from a BrainAmp amplifier (Brain Products, Germany). All impedances were kept below 5 kΩ.

2.3. BCI paradigms

The BCI was constructed to allow control over each of the three different feedback modalities via kinesthetic motor imagery. Each paradigm was tested over nine runs, the first of which was a calibration run designed to train the internal parameters of the BCI. Each run was split into multiple trials, with the calibration run containing 30 trials and each subsequent run containing 18 trials. The timing of each trial was as follows.

From $t = -4$s to $t = 0$s a fixation cross was displayed in the center of the screen (note, all times are reported relative to the beginning of the period when the user was meant to be controlling the BCI). From $t = 0$s through to $t = 12$s the user was cued to control the BCI and was able to use kinesthetic motor imagery to perform one of two tasks, which depended upon the feedback modality. From $t = 12$s to $t = 12.5$s, after the end of the BCI control period, a visual reward was displayed on the screen in the form of a smiling cartoon face if the user had managed to achieve the cued task or a sad face if they had not. An inter-trial interval between the disappearance of the face and the next fixation cross was imposed with a duration uniformly drawn from the range 1–3 s.

The tasks differed for each of the feedback modalities. The timing of each of the paradigms is illustrated in (Figure 1).

2.3.1. *Visual feedback*

For the visual feedback modality a blue ball (visual angle ≈ 5°) was displayed in the middle of the left edge of the screen. From this position it moved across the screen at a constant speed such that it reached the right hand side of the screen at $t = 12$s. On the right-hand side of the screen two targets were displayed in the form of two vertical bars occupying, respectively, the upper and lower halves of the screen. One of the bars was indicated to be the target and colored solid green. The other bar was the non-target and colored with horizontal stripes of two different shades of red.

The user was instructed to attempt to adjust the position of the ball on the vertical axis as it moved across the screen. The ball could be moved up via kinesthetic motor imagery of the right hand and moved down via relaxation (that is, not performing kinesthetic motor imagery). The task was to attempt to adjust the vertical position of the ball such that, when it reached the right-hand side of the screen, it hit the green target bar. The configuration of this paradigm is illustrated in (Figure 1).

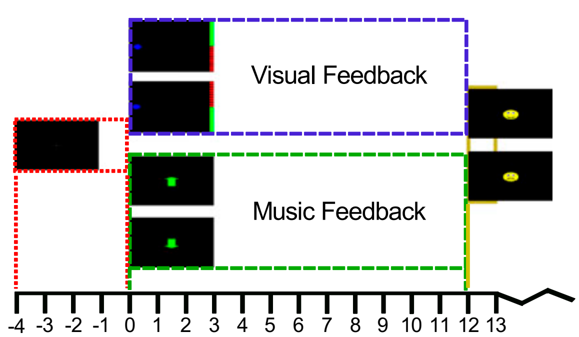

Figure 1. (Color online) BCI paradigm timing. From $t = -4$s to $t = 0$s a fixation cross was displayed. From $t = 0$s to $t = 12$s visual feedback, music feedback, or combined music and visual feedback was provided as a feedback modality by the BCI. From $t = 12$s a visual reward was displayed for 0.5s.

2.3.2. *Music feedback*

In the music feedback task music was dynamically generated at a base tempo of 148 bpm (beats per minute) and played to the user from the appearance of the fixation cross at $t = -4$s until the end of the control period of the trial at $t = 12$s. From the disappearance of the fixation cross at $t = 0$s the user was able to dynamically change the tempo of the music in the range of 99 bpm to 288 bpm. The user was cued to either increase or decrease the tempo of the music via an arrow placed in the center of the screen (visual angle ≈ 7.5°). Thus, the aim was for the user to have the music played either faster or slower at $t = 12$s than at $t \leq 0$s.

Music tempo could be increased via performing kinesthetic motor imagery or decreased via relaxing. The tempo was updated every 100 ms and the music was generated dynamically via a novel generative algorithm, as described below. Thus, the music played to the participants was novel in every trial.

The generative algorithm allowed the BCI-user to specify three parameters from which it created sequences of tone rows (strings of pitch classes with no repeated notes) and a pool of rhythm data. In our system the generated row was used to supply the selection of notes from which the musical sequences were derived.

Our system used six pitch values arranged in a tone row to create musical sequences, by combining notes from the tone row with rhythms. Rhythms were generated by sequencing selections from a series of duration values (with up to eight quavers in a sequence). Variations in the duration values were introduced according to the starting parameters. To create a finished musical sequence, duration values were selected aleatorically and assigned to pitches from the tone row, creating a large variation of possible musical sequences from a small amount of seed data (a tone row and a series of duration values). The starting note of the sequence was selected randomly for each participant. This allowed the system to create continuously varying musical stimuli without excessive repetition or reliance on existing musical stimuli which might risk complications on the basis of existing listener familiarity.

2.3.3. *Combined feedback*

A combined feedback paradigm was also explored using both visual and music tempo feedback to allow control of the BCI. In this paradigm both the music feedback and the visual feedback were presented to the user simultaneously; i.e. the user was able to control the position of the ball on the vertical axis and the tempo of the music. Increasing the tempo of the music and the height of the ball was performed via kinesthetic motor imagery of the right hand, while decreasing the height of the ball and the tempo of the music was performed via relaxation. Both the red/green target bars and the up/down arrows were used in this paradigm to convey the target to the user.

2.3.4. *User groupings*

The 18 users were randomly allocated into three different groups, one for each of the BCI paradigms. Six users were allocated the visual feedback paradigm, seven were allocated the music feedback paradigm, and five were allocated the combined-modality feedback paradigm.

For each paradigm users were provided with written instructions on how to operate the BCI. These took the form of an explanatory document detailing the objectives of the experiment, a more general slideshow describing an overview of each of the BCIs, and a detailed powerpoint presentation describing the specifics of the BCI type they had been randomly assigned. Users were asked to read through each set of instructions at their own speed and given an opportunity to ask questions.

2.4. ***BCI control***

The BCI was controlled via kinesthetic motor imagery or relaxation. To obtain a measure of kinesthetic motor imagery strength the event-related desynchronization (ERD) was used. ERD was measured via the alpha band power strength (8–13 Hz) of the EEG recorded over the left motor cortex (contralateral to the right hand, which was used for motor imagery). Thus, the mean EEG band power in the range 8–13 Hz recorded on channels F3, T3, C3, Cz, and P3 was inverted, scaled by a constant scaling term k, and mapped to the height of the ball in the visual and combined tasks and the tempo of the music in the music and combined tasks. Therefore, performing kinesthetic motor imagery of the right hand created an ERD, decreasing alpha band power, and relaxing increased alpha band power.

Inter-user differences mean that it is necessary to train the BCI to respond accurately to each user's control attempts. This was performed via a staircase training algorithm in the calibration run (the first run of the paradigm).

Therefore, the scaling term k was trained as follows. The calibration run was split into pairs of trials. Each pair of trials contained one trial with a cue to increase the music tempo and/or move the ball up (depending on the feedback modality), which was denoted the 'up-trial', and one trial with a cue to decrease the music tempo and/or move the ball down, denoted the 'down-trial'.

After each pair of trials the results were evaluated. If, for both trials, the user had increased the music tempo and/or moved the ball up the value of k was increased by an adjustment term α; $k = k + \alpha$. If, for both trials, the user had decreased the music tempo and/or moved the ball down the value of k was decreased; $k = k - \alpha$. If the user was able to increase the tempo and/or move the ball up for one trial and decrease the tempo and/or move the ball down for the other trial in the pair k was not adjusted and instead α was halved; $\alpha = \frac{\alpha}{2}$. The scaling terms k and α were both restricted to positive values.

2.5. *Artifact removal*

The EEG was visually inspected for artifacts via an experimenter who was blinded to the contents of each of the trials, the BCI paradigm, and the results achieved by the users. Portions of the EEG containing blinks, electromyographic artifacts, movement, failing electrodes, electrocardiographic artifacts, and/or eye movements were marked on the contaminated channels and time points.

Trials were rejected from the dataset and not included in subsequent analysis steps if they were observed to contain artifacts on the channels used for control of the BCI (F3, T3, C3, Cz, and P3) during the BCI control period ($t = 0 - 12$s).

2.6. *Analysis*

User performance at each of the BCI paradigms was analyzed in terms of accuracy and learning rates. Additionally, the strength of the ERD generated by each of the users during each of the attempts to increase the music tempo and/or move the ball up was measured and used as a criterion to assess the ability of users to learn to control each BCI feedback modality.

2.6.1 Performance

Performance was measured in terms of control accuracy of the BCI using each of the three feedback modality paradigms. Additionally, performance was also measured via learning rates, the rate at which users were able to learn to control each of the BCI paradigms.

Accuracy was measured via the balanced accuracy measure (the sum of the sensitivity and specificity of the classification result, divided by two). This provides a measure of accuracy which is not biased by differences in numbers of trials in each class.[26] This was necessary because the artifact-removal stage may have resulted in the removal of more trials recorded during one cued task (e.g. increase music tempo and/or move the ball up) than the other cued task.

Learning rate was measured as the steepness of the curve of accuracies over runs between the first run after the calibration run (run 1) and the run in which the peak accuracy was observed. Learning curve steepness was measured as the change in accuracy over the number of runs taken to reach the peak accuracy. Additionally, the number of runs required before peak accuracy was reached was also used as a measure of BCI learning rate.

Additionally, performance was measured over time by looking at the variance of the BCI control action (either the height of the ball or the tempo of the music) over the length of the trial. For example, it may be the case that users are able to accurately control the BCI for the first few seconds of the trial, but are unable to strongly maintain the necessary ERD strength for the entire 12 s trial and, therefore, exhibit greater variance towards the end of the trial. Therefore, BCI control action variance was explored over the length of the trial in a 1 s window slid by 0.5 s across the trial.

Finally, it has been reported elsewhere that there is a relationship between the variance of musical tempo and ERD strength in participants passively listening to music.[27] Therefore, to determine whether this effect produces any change in our BCI control accuracy we will look for correlations between music tempo variance (as controlled by the BCI) and the final outcome of the BCI control. For example, if there is a positive correlation between music tempo variance during the trial and the users more frequently increasing the final tempo of the music at the end of the trial this could indicate an interference effect between music tempo variance and the ERD strength.

2.6.2. Neurological activity

Neural correlates of kinesthetic motor imagery may be used to provide some measure of the user's success in attempting the correct mental strategy to control the BCI. Thus, the strength of the ERD was used as a measure of the strength of each user's mental imagery. Differences in ERD strength between different paradigms may indicate differences in a user's ability to utilize each feedback modality in the control of a closed-loop BCI.

ERD strength was measured as the mean relative band power strength in the alpha frequency band (8–13 Hz) over channels F3, T3, C3, Cz, and P3 from $t = 0$s through to $t = 12$s. This mean band power was measured relative to the baseline period (the period in which the fixation cross is on screen but the user is not yet able to control the BCI; $t = -4$s through to $t = 0$s).

Additionally, common spatial patterns (CSP) were used to attempt to identify optimal spatial filters for each participant that differentiate the ERD and non-ERD conditions. This was used to determine whether there is any difference in the spatial topography of ERD maps between the different feedback modalities. This analysis was performed offline. The spatial maps were also used to compare the differences in neurophysiological processes involved in operating a BCI with visual feedback compared to operating a BCI with music tempo feedback.

Finally, the CSP filters were trained and used in conjunction with a linear discriminant analysis (LDA) classifier to attempt to classify the EEG offline during each feedback modality. This was done in order to investigate the effect of using optimal spatial filters on classification accuracy. To do this a 10×10 cross-fold train and validation scheme was used to train and test the CSP filters and LDA classifier.

3. Results

Participants were able to control the BCI at statistically significant rates of accuracy when using the tempo feedback. However, performance was significantly worse when compared with the other two conditions.

Users were randomly allocated a feedback paradigm. The number of users in each group is listed in Table 1. Note that the balance of males to females is approximately similar across feedback modalities.

A mean of 18.55 (±21.74) artifacts were removed from the EEG dataset recorded from each participant. This left a mean of 125.44 (±21.74) trials for use in the analysis.

3.1. Performance

Users were observed to control each of the BCI paradigms with statistically significant levels of accuracy ($p < 0.05$). Table 2 shows the accuracies achieved by each user for each session for the visual feedback paradigm.

Table 3 shows the accuracies achieved by each of the users when using the combined visual feedback and music feedback paradigm. Note that significant accuracies ($p < 0.05$) were achieved in one or more runs for all users with this BCI feedback mechanism.

Finally, Table 4 shows the balanced accuracies achieved by each of the users who used the music tempo feedback modality for BCI control. While significant accuracies ($p < 0.05$) were achieved in some runs by six out of the seven users, the accuracies were considerably lower than those achieved in either the visual feedback or the combined visual and music tempo feedback conditions. Additionally, one user (user 17) withdrew from the study after six runs.

Table 1. Number of participants in each group and male/female split.

	Males	Females
Visual feedback	4	1
Combined feedback	4	2
Music feedback	6	1

Accuracies over sessions for each of the feedback conditions are illustrated in Figure 2. For each condition there was an increase in balanced accuracy over sessions as the users learned to control each of the feedback paradigms. There was also a decrease in accuracy after a peak point. This is discussed further below.

Accuracies were compared between groups via a 1×3 ANOVA with factor 'paradigm' (including 'Visual', 'Combined', and 'Music'). A significant effect of 'paradigm' was found ($F(2, 138) = 3.75, p = 0.026$). Post-hoc testing was performed via t-tests and a significantly lower accuracy was found for the music vs. visual feedback and music vs. combined feedback conditions ($p < 0.01$). No significant difference was found between the visual and combined feedback conditions.

Learning rates (as measured both by the accuracy curve steepness and by the number of runs taken to reach the peak accuracy) were compared between the different paradigms via a 1×3 ANOVA with factor 'paradigm' ('Visual', 'Combined', and 'Music'). No significant differences were observed between any of the paradigms in terms of learning rate ($p = 0.891$). Thus, although BCI users were able to control the visual and combined feedback paradigms more accurately, they did not learn how to do so more quickly.

It is also interesting to note that there is a visually apparent difference in IQR between the different conditions, with the combined modality condition apparently exhibiting lower IQR than the other modalities. This is statistically verified by a 1×3 ANOVA with factor 'Feedback' and levels 'Visual only', 'Combined', and 'Music only'. A significant effect is found, ($F(2, 23) = 4.75, p = 0.0199$). Post-hoc pair-wise t-tests between each pair of groups reveal the combined condition to have the lowest IQR and that it is significantly lower than the music-only IQR ($p = 0.012$). This is illustrated in Figure 3.

We also look at the variance of the BCI control action over the course of the trial. Linear regression is used to determine whether there is a significant trend in the observed variance of the BCI control action over time for each of the feedback modalities. For the visual feedback and combined feedback modalities no trend is found ($p = 0.274$ and $p = 0.168$ respectively). However, for the music feedback modality a significant trend of increasing variance in the BCI control action is found over the length of the trial ($R^2 = 0.054, p = 0.015$). Therefore, in the music feedback modality the BCI control becomes less stable over time.

Finally, to explore whether there is any relationship between this tempo variance and the final control action taken by the BCI (either increase/ decrease the tempo over baseline or move the ball up or down), we explore correlations between the variance of the BCI control action (the tempo in the case of the music feedback and

Table 2. Balanced accuracies achieved by users of the visual feedback BCI paradigm, median accuracies over all users per session and inter-quartile range (IQR). Significant accuracies ($p < 0.05$) are indicated in bold.

		Runs (18 trials per run)							
User	Paradigm	1	2	3	4	5	6	7	8
1	Visual	0.51	0.62	0.50	0.48	0.44	0.44	0.59	0.38
2	Visual	0.50	0.50	0.47	0.49	**0.75**	0.49	**0.75**	0.56
3	Visual	0.57	**0.66**	0.36	**0.71**	0.57	0.49	**0.67**	-
4	Visual	0.65	**0.72**	**0.87**	**0.90**	**0.88**	**0.78**	**0.72**	**0.81**
5	Visual	0.59	0.51	**0.79**	**0.89**	**0.87**	0.59	0.48	0.57
6	Visual	**0.83**	**0.83**	**0.94**	**0.83**	**1.00**	**1.00**	**0.87**	**0.82**
Median		0.58	0.64	0.64	0.77	0.81	0.54	0.69	0.57
IQR		0.14	0.21	0.40	0.40	0.31	0.29	0.16	0.25

Table 3. Balanced accuracies achieved by users of the combined visual and music tempo feedback paradigm for BCI control, median accuracies, and inter-quartile range (IQR). Significant accuracies ($p < 0.05$) are indicated in bold.

		Runs (18 trials per run)							
User	Paradigm	1	2	3	4	5	6	7	8
7	Combined	0.44	0.50	**0.75**	**0.78**	0.61	**0.67**	**0.69**	**0.78**
8	Combined	0.50	0.35	0.54	**0.81**	**0.66**	0.57	0.56	0.48
9	Combined	0.61	0.54	0.56	0.55	0.36	**0.76**	0.58	**0.67**
10	Combined	**0.74**	**0.83**	**0.88**	**0.87**	0.60	**0.79**	**0.78**	**0.75**
11	Combined	**0.85**	**0.72**	**0.81**	**0.94**	**0.82**	**0.90**	**0.76**	**0.69**
Median		0.61	0.54	0.75	0.81	0.61	0.76	0.69	0.69
IQR		0.24	0.22	0.25	0.09	0.06	0.12	0.18	0.08

Table 4. Balanced accuracies achieved by users of the musical tempo feedback modality for BCI control, median accuracies, and inter-quartile range (IQR). Significant accuracies ($p < 0.05$) are indicated in bold.

		Runs (18 trials per run)							
User	Paradigm	1	2	3	4	5	6	7	8
12	Music	0.44	0.45	0.44	0.50	0.56	0.50	0.55	0.50
13	Music	0.36	0.53	0.52	0.30	0.55	0.34	**0.73**	0.57
14	Music	**0.71**	**0.76**	**0.75**	**0.69**	0.62	0.56	0.50	0.37
15	Music	**0.80**	**0.80**	**0.87**	**0.80**	**0.89**	**0.69**	**0.70**	**0.89**
16	Music	0.50	0.50	0.50	0.51	**0.67**	**0.72**	0.56	0.59
17	Music	**0.92**	**0.81**	**0.72**	0.63	0.61	**0.69**	-	-
18	Music	0.30	0.30	0.31	0.62	**0.83**	**0.75**	0.42	0.33
Median		0.50	0.53	0.52	0.63	0.63	0.69	0.55	0.54
IQR		0.44	0.35	0.31	0.19	0.27	0.22	0.20	0.22

combined modalities) and the final control action. We find a significant correlation between tempo variance and the final BCI control outcome in the music feedback modality ($r = 0.078$, $p = 0.024$), indicating that as the variance in the tempo increases the user is more likely to increase the final tempo over its baseline value.

3.2. Neurological activity

Neurological activity was compared between the different feedback paradigms to determine whether there was a significant difference between paradigms in terms of neural correlates of motor imagery (the action performed by the users to attempt to control the BCI). The event-related desynchronization (ERD) was used as a neural correlate of motor imagery.

ERD strength was measured in the alpha (8–13 Hz) frequency band for each trial included in the analysis (that is, trials without artifacts). A 1×3 ANOVA was performed with factor 'paradigm' ('Visual', 'Combined', and 'Music') and a significant effect of 'paradigm' was found ($F(2, 339) = 5.75, p = 0.0035$). Post-hoc t-tests revealed

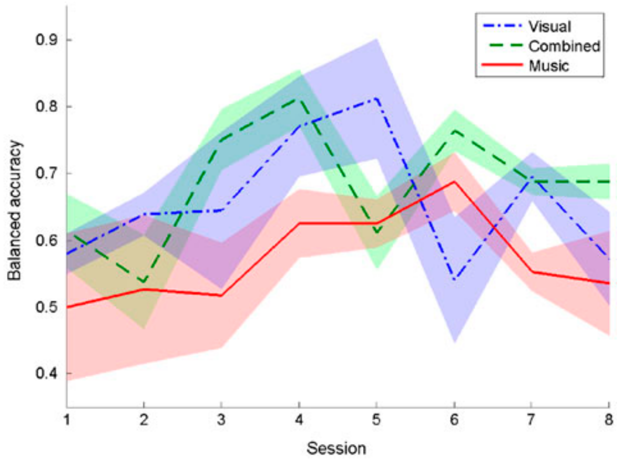

Figure 2. (Color online) Median accuracies over sessions for each of the BCI feedback conditions. The lines represent median accuracy and the shaded areas $\pm 2 \times Var$, where Var denotes the variance of the balanced accuracies over users.

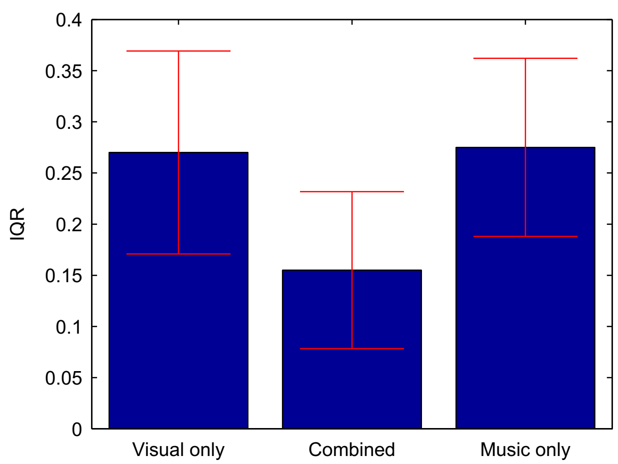

Figure 3. (Color online) Mean and standard deviation of IQR values across participants and sessions for each of the feedback modalities.

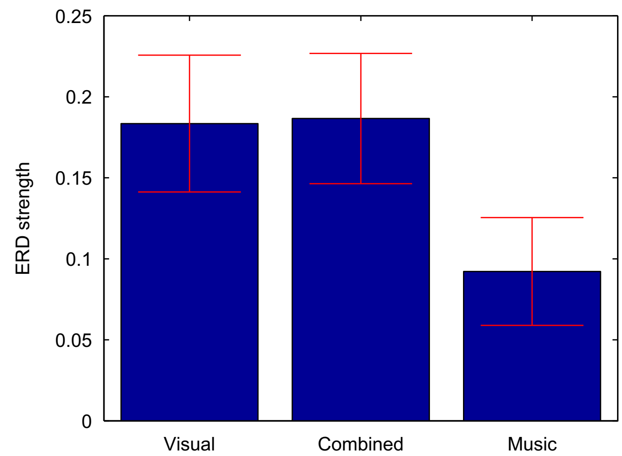

Figure 4. (Color online) Mean across all trials of ERD strength (measured as absolute difference in band-power from baseline) recorded on a single trial basis from each feedback paradigm. The bars indicate ±1 standard deviation.

a significantly lower ERD strength in the music paradigm than the other two paradigms ($p < 0.01$) and no significant difference in ERD strength between the visual and the combined paradigms. This is illustrated in Figure 4.

Common spatial pattern filters are calculated offline for each of the three feedback conditions within a 10×10 cross-fold train and validation scheme. The mean spatial filters across sessions and participants in each group are illustrated in Figure 5. It is interesting to note that for both the visual and combined feedback modalities CSP identifies a spatial filter centered over the left motor area with a strong, and almost equal, weighting on channels C3 and P3, while for the music feedback condition the CSP filter is more diffuse.

CSP was also used to filter the data prior to classification via a linear discriminant analysis (LDA) classifier in a 10×10 cross-fold train and validation scheme. The mean and standard deviation of the classification accuracies across participants for each condition are reported in Table 5.

Pairwise t-tests were used to compare the accuracies between different feedback conditions. No significant difference in accuracy was found between the visual feedback and the combined feedback condition ($p = 0.871$). However, significant differences were found between the visual feedback and music feedback conditions ($p = 0.042$), and between the combined feedback and music feedback conditions ($p = 0.049$).

4. Discussion

Our study aimed to explore the use of music tempo as a feedback mechanism for BCI control and compare it to the more commonly used visual feedback mechanism and a combined visual and musical feedback mechanism. We used a novel music-generation system to do this.

The results indicate that each of the feedback paradigms, including music-tempo-based feedback, can be integrated into closed-loop BCI control. Users of a BCI using each of the feedback mechanisms can learn to manipulate the feedback provided and the majority of users can control each of the BCIs at statistically significant rates of accuracy ($p < 0.05$).

However, the accuracy at which users can control a BCI via the music-tempo-based feedback mechanism is significantly lower than that observed for the visual and combined visual-music feedback mechanisms. This suggests that users are not able to utilize music-tempo-based

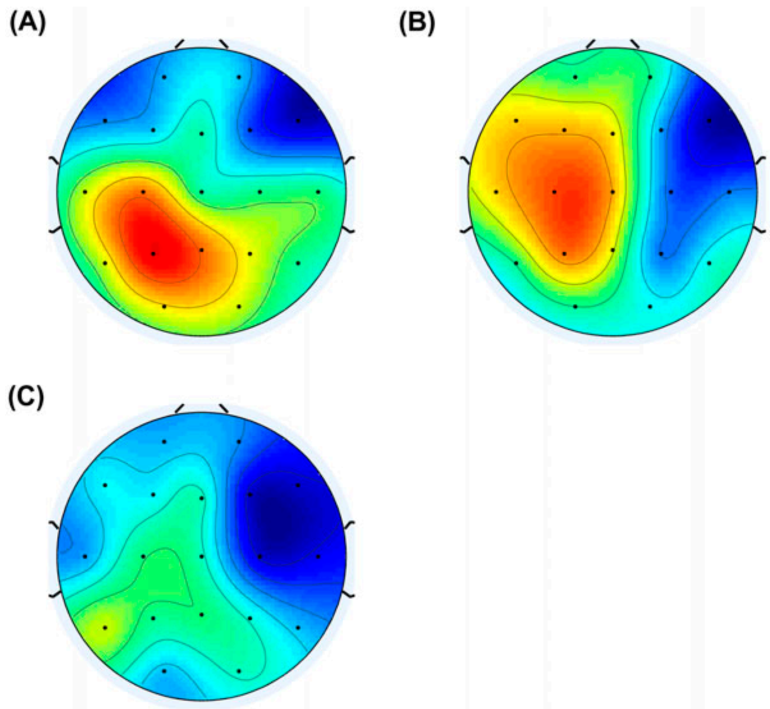

Figure 5. (Color online) Mean common spatial pattern (CSP) filters for the three feedback conditions, (A) visual feedback, (B) combined feedback, and (C) music tempo feedback.

Table 5. Mean and standard deviation (Std.) of accuracies achieved by LDA classification of the CSP-filtered EEG recorded during each feedback paradigm.

	Accuracy	
Condition	Mean	Std.
Visual feedback	0.687	0.128
Combined feedback	0.699	0.065
Music feedback	0.639	0.077

feedback as well as visual feedback in the control of a BCI.

Within BCI research the threshold of 70% accuracy is widely cited as the level of accuracy required to achieve useful communication.[28] Both the visual feedback and the combined feedback modalities allow users to achieve accuracies above this threshold; music tempo feedback does not. However, this threshold is based upon work with only two individuals with amyotrophic lateral sclerosis [29] and is only intended to serve as an approximate rule-of-thumb test to indicate a BCI is ready for use for communication purposes. We suggest that any BCI control accuracy that is statistically significant indicates that it is worth further investigation.

The number of participants in each group differs. This is due to a small number of participants not turning up to their assigned time slot without warning near the end of the study. Nonetheless, the statistical tests used to compare the groups are robust to imbalanced group sizes and, therefore, our results remain valid.

These results reinforce the understanding that, when developing new BCI applications, it is important to consider the feedback modalities that will be used. The music-tempo-based feedback represents a novel type of feedback mechanism. Specifically, the use of music as a feedback mechanism classifies this type of BCI as a brain-computer music interface (BCMI).[22] Currently, only a few types of BCMI have been developed. The majority have allowed control over music via selection from a discrete set of options. For example, in [22] discrete sets of musical scores are available to users who may select the score they wish to use via focusing on a steady-state visual evoked potential (SSVEP), while in [23] short music clips are repeatedly played at BCI-controlled volumes to BCI users. Thus, the analogue control of tempo in continuously generated, non-repeating, music via a BCI user represents a unique advance in the field of BCMI and has some potentially interesting applications in areas such as entertainment and music therapy.

Specifically, allowing users of a BCI to interact with some properties of music, such as tempo, provides a means of creative output. Such creative output has been demonstrated to be very important for some BCI user groups, such as individuals with amyotrophic lateral sclerosis (ALS), who would otherwise have difficulty creatively expressing themselves. For example, in [21] a BCI application is provided to allow individuals with ALS to paint and is demonstrated to allow them to be productive, creative, and interact with society in new and beneficial ways.

Music-based feedback also has an advantage over other auditory feedback mechanisms by providing a mechanism which may be considerably less annoying to users than either ASSRs or human voice feedback (as used in [19]). Additionally, the ability of music to induce different affective states in the BCI user opens up interesting possibilities in the use of BCI for treating patients suffering from depression (for example), via dynamic modulation of properties of the music known to induce particular emotional responses.[21]

Additionally, the ability of music to induce different affective states opens up interesting possibilities in the use of BCI for treating emotional problems such as depression via dynamic modulation of properties of the music known to induce particular emotional responses.[30] Finally, music-based feedback in BCI may also open up possibility for the use of BCI in mainstream user groups. For example, BCI use for entertainment is a significant possibility for a music feedback mechanism.[31]

However, visual feedback is observed to be significantly easier to control than music-tempo-based feedback. Nonetheless, visual feedback is not suitable for all users and it is important to consider the context in which the BCI will be used. For example, visually impaired users would be unable to use this type of feedback mechanism and, for this user group, it is important to develop BCIs that are able to make effective use of alternative feedback mechanisms.[13]

Lower ERD strengths were observed during the music-tempo feedback paradigm. This reinforces results reported elsewhere (see, for example, [3]) that the feedback mechanism is important in the correct production of ERD activations. There are a number of possibilities that may explain why music feedback does not result in ERD activations as large as observed in the visual and combined feedback conditions. It is possible that the users are distracted by the tempo of the music in a way that they are not by the visual stimuli. For example, high-tempo music has been reported elsewhere to correlate with inducing feelings of excitement in the listener.[32] Thus, when the tempo was increased the BCI user may have become less focused on the motor imagery task. However, we may consider this to be unlikely as no such effect was observed during the combined feedback paradigm, when the music would also potentially be distracting the users.

The common spatial patterns (CSP) algorithm was used to identify optimal spatial filters for separating the EEG via control conditions for each of the feedback modalities. The resulting CSP filters reveal both visual feedback and combined feedback modalities to have a corresponding filter concentrated over the left motor cortex, while the spatial filter for the music feedback paradigm is more diffuse and distributed over a wider area. This reinforces the view that the participants were not able to produce clear well-defined ERDs during music feedback.

Alternatively, it is possible that the music was inducing brain activation patterns which were interfering with the users' attempt to control the tempo of the music via motor imagery. It was reported in [27] that changes in the tempo of music clips taken from film scores induced changes in ERD activation strengths in listeners' motor cortices while listeners sat passively and did not attempt any movement or motor imagery. Specifically, the variance in tempo of music over time was observed to significantly correlate with ERD strength in the left motor cortex in right-handed participants. The greater the variance in tempo observed over a 12 s long musical clip, the greater the ERD strength. Thus, changes in tempo of our music-based feedback mechanism could be interfering with ERD responses related to our users' attempts to control the BCI.

For example, if the user of our BCI with music tempo feedback is able to initially relax and reduce their ERD strength at the start of the trial this will reduce the tempo of the music. However, if they then momentarily disengage from the task and the tempo increases again this variation in tempo may result in an ERD, which in turn will further increase the tempo of the music. This is confirmed by inspecting the correlation between tempo variance over the trial and the final outcome of the BCI control (either an increase or a decrease in the tempo). When looking at the first half of the trial (0–6 s) there is a significant correlation between tempo variance and final outcome (r = 0.078, p = 0.024), indicating that as the variance in the tempo increases the user is more likely to increase the final tempo over its initial baseline. This effect is not seen in the visual condition (r = 0.026, p = 0.466) or the combined condition (r = 0.035, p = 0.357).

The accuracy of the BCI control over time improves until runs 5 or 6, at which point it begins to decline. This may be caused by fatigue in the users, as all the runs were performed sequentially on the same day in a 1 hour session, which can be tiring. It is also interesting to note that the combined feedback condition exhibits lower IQR than the other two conditions. Thus, when multimodal feedback is provided cross-participant performance variance is reduced. There may be a number of reasons for this: for example, the provision of multimodal feedback may allow users of the BCI to more accurately judge their current performance than a single feedback modality alone. This suggests that more consistent BCI performance could, potentially, be achieved with a multi-modal feedback mechanism.

An additional consideration is the short-term memory requirements of the musical feedback modality. Throughout the visual feedback modality the users were able to judge where the central line on the vertical axis was and how the current position of the ball related to this line. In the music feedback condition it was not possible to simultaneously present music at the baseline and at the adjusted tempo. Therefore, the user had to rely on their memory of the baseline tempo to judge whether the current tempo of the music was greater or less than this. Thus, the additional short-term memory requirements of this feedback modality may place additional restrictions on the users' ability to control it effectively.

These results have a number of interesting implications for BCI research. This is one of the first explorations of the efficacy of the tempo of continuously generated novel music as a feedback mechanism and suggests that, although the performance is low, it could be useful for some user groups in future. However, the significantly lower performance observed for users of the music tempo feedback task compared to the visual task suggests that, where suitable, visual feedback or combined-modality feedback should be used when the aim is the development of a fast and accurate communication device.

For BCMI development it is important to pair the feedback mechanism with the correct cognitive task which is to be used as a control strategy. For example, strategies should be complementary to each other and non-interfering. Thus, music tempo may not be best suited to BCI control via motor imagery, but may be better suited to control via other cognitive strategies. For example, the use of affective state imagery, as proposed in [30], may be useful for control of BCMIs.

Additionally, the ability of music to induce particular affective states suggests it may be suitable for use in a BCI intended to modulate and/or regulate users' emotions. For example, neural correlates of music-induced emotion may be detected (for example, see [33]) and used to adjust some properties of dynamically generated music.

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