Affective brain–computer music interfacing

Article

Accepted Version

Published version at: http://dx.doi.org/10.1088/1741-2560/13/4/046022
To link to this article DOI: http://dx.doi.org/10.1088/1741-2560/13/4/046022

Publisher: IOP

Affective Brain-Computer Music Interfacing

Ian Daly[1], Duncan Williams[2], Alexis Kirke[2], James Weaver[1], Asad Malik[1], Faustina Hwang[1], Eduardo Miranda[2], Slawomir J. Nasuto[1]

[1]Brain Embodiment Lab, School of Systems Engineering, University of Reading, Reading, UK

E-mail: i.daly@reading.ac.uk

[2]Interdisciplinary Centre for Music Research, University of Plymouth, Plymouth, UK

Abstract.

Objective

We aim to develop and evaluate an affective Brain-computer music interface (aBCMI) modulating the affective states of its users.

Approach

An aBCMI is constructed to detect a user's current affective state and attempt to modulate it in order to achieve specific objectives (for example, making the user calmer or happier) by playing music which is generated according to a specific affective target by an algorithm music composition system and a case-based reasoning system. The system is trained and tested in a longitudinal study on a population of 8 healthy participants, with each participant returning for multiple sessions.

Main Results

The final online aBCMI is able to detect its users current affective states with classification accuracies of up to 65% (3 class, $p < 0.01$) and modulate its user's affective states significantly above chance level ($p < 0.05$).

Significance

Our system represents one of the first demonstrations of an online affective brain-computer music interface that is able to accurately detect and respond to user's affective states. Possible applications include use in music therapy and entertainment.

Keywords: Brain-computer music interfacing, EEG, Music therapy, Affective computing, Passive Brain-computer interfacing

1. Introduction

Brain-computer interfaces (BCIs) provide a method for their users to interact with or control a computer via brain activity and without needing to move (Wolpaw 2007). They have been researched and developed for a wide range of applications, including allowing their users to communicate (Kübler and Birbaumer 2008), controlling wheelchairs (Leeb et al. 2007), and providing entertainment (Nijholt and Desney 2009). They have also been provided to both healthy individuals and those with a range of different physical disabilities, such as spinal cord injury (Müller-Putz et al. 2014) and cerebral palsy (Daly, Billinger, Laparra-Hernández, Aloise, García, Faller, Scherer and Müller-Putz 2013).

A brain-computer music interface (BCMI) is a specific type of BCI which is designed to allow its' users to interact with or control some properties of music (Miranda 2006). For example, BCMIs have been proposed for use in actively controlling entertainment systems and to provide individuals with disabilities of movement a creative outlet, which lets them actively control music (Miranda et al. 2011).

Music is a powerful method for modulating affect and can make a listener feel a wide range of emotions from joy to melancholy (Juslin and Sloboda 2001). The ability of music to match or influence a listener's emotions has been exploited by, amongst other disciplines, music therapy. Music therapy is a psychological therapy technique which aims to facilitate communication and improve the emotional state of a patient via musical interaction with the therapist. For example, a patient might perform on an instrument in solo or in a duet with the therapist. Music may also be used in order to help individuals to regulate or learn to more beneficially modulate their emotions (Bhattacharya and Lee 2012, McDermott et al. 2013).

A system such as an aBCMI might be useful for such work by facilitating patients who are not musically confident or competent enough to engage in traditional music-making activities as part of the therapeutic process (e.g., performing or improvising new music). Moreover, by enabling the generation of music which matches the emotional state of a patient, an aBCMI might potentially be of use as an expressive tool for patients to express their emotional state to the therapist regardless of physical ability or communicative handicap (for example, patients with autism, Asperger's syndrome, or even locked-in patients with little or no physical mobility).

The theoretical advantage of this approach over conventional music therapy approaches is that the aBCMI is able to directly monitor the user's emotional state via physiological indices of emotion, which have the potential to be more robust and objective measures of emotion than user reports or even the expertise of the music therapist.

Finally, the design and implementation of a successful aBCMI for music therapy might also facilitate modulation of a user's emotion by means of an affective feedback loop. This application would be unique to an aBCMI which might, for example, generate music which gradually improves the mood of the patient in an automatic process without the need for a therapist.

The proposed BCMI system is a form of affective BCI, a BCI intended to interact with the emotions of its user (Nijboer et al. 2009). It is also a form of passive BCI, which seeks to modulate a user's affective state based on specific goals (Zander and Kothe 2011), and is different from previous BCMI systems, which are all active BCIs. We propose a design for this affective BCMI (aBCMI) and conduct a series of experiments in order to train the system and apply it to attempt to modulate the affective states of a group of healthy users.

We seek to explore whether an aBCMI system can be constructed that is able to detect and modulate a user's current affective state. This includes the following sub-questions: (1) Can we detect an individual's current affective state during online aBCMI use? (2) Can we identify a case-based reasoning approach that may be used to identify methods for modulating an individual's affective state? (3) Can synthetically generated music modulated by the aBCMI system dynamically influence an aBCMI user's affective state in order to meet a set of goals (e.g. making the user happier)?

We first describe the proposed system. We then go on to describe the experiments used to evaluate its efficacy at modulating its user's affective states. We then present results to demonstrate the performance of the system and discuss their implications. We investigate whether the proposed aBCMI design is able to modulate user's affective states.

2. Methods

2.1. System design

2.1.1. Overview The proposed aBCMI system is illustrated in Figure 1. It consists of five key elements: (1) the user of the system, (2) the physiological signals recorded from the user (these include the electroencephalogram (EEG), electrocardiogram (ECG), and respiration rate), (3) an affective state detection system to attempt to identify the current affective state the user is experiencing, (4) a case-based reasoning system to determine how to move the user from their current affective state to a new target affective state, and (5) a music generator to play music to the user in order to move them to the target affective state via a best-fit affective trajectory identified by a case-based reasoning system.

2.1.2. Signal acquisition The signal acquisition component of the system attempts to record physiological indices from the user in order to capture aspects of their current cognitive and physiological processes that are related to their current affective state. The specific signals that are recorded are the electroencephalogram (EEG), the electrocardiogram (ECG), galvanic skin response (GSR), pulse oximeter (BPS), and the respiration rate of the participant.

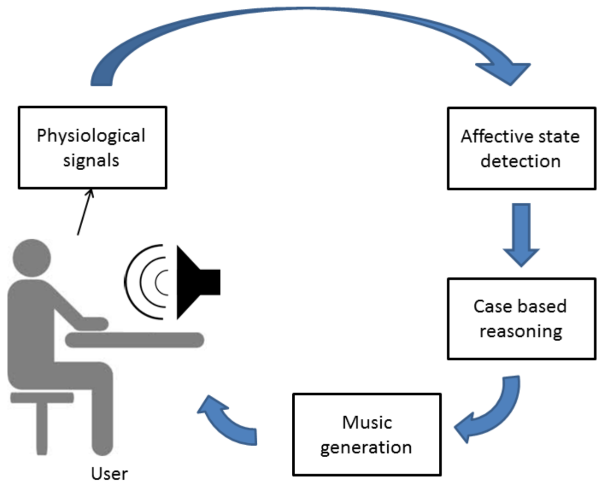

Figure 1. The proposed affective brain-computer music interface (aBCMI).

2.1.3. Affective state detection Affective state detection from the electroencephalogram (EEG) is an ongoing area of research with several approaches previously proposed. These include efforts by Wu et al. (Wu et al. 2010) to identify arousal from the EEG for a proposed use in music therapy and efforts by Schmidt and Trainor to identify music-induced valence and intensity from the EEG (Schmidt and Trainor 2001).

The affective state detection component of the aBCMI is based on these efforts and aims to first extract features from the physiological signals that are most likely to correspond to changes in the user's affective state. These features are then classified to identify the user's current affective state, via the use of a support vector machine.

Specifically, a set of band-power based EEG features are used to identify the user's affective state. These band-power based features were chosen based upon observations and methods reported in (Stikic et al. 2014) that they may be used to identify affective states from the EEG during offline signal processing and the relative ease with which such features can be rapidly estimated during online BCI use. They were augmented by a set of physiological features taken from the ECG, GSR, BPS, and respiration rate measures, which aimed to capture the properties of these signals known to relate to affective state changes.

The affective state detection method was then completed via the use of a support vector machine (SVM). This allowed fast and accurate classification of affective states during online aBCMI use.

2.1.4. Case-based reasoning In order to meet the objectives of the system, moving the user to a final targeted affective state, it may be necessary to modulate the affective state of the user through a number of intermediate steps. Specifically, it has been reported that in order to regulate a listener's mood different strategies are needed depending on the listener's current affective state (Larsen 2000). Thus, music could more effectively modulate a listener's affective state if it is slowly modulated over time in order to gradually move the user to the final target affective state.

In order to allow for the possibility that these complex affective state transitions are a necessary component of an effective aBCMI system, a case-based reasoning system is used. This system aims to identify 'affective trajectories' that can be used to determine which regions of the affective space to target with the music generator in order to move a user from any given starting affective state to any targeted affective state.

2.1.5. Music generator A music generator is used to produce music in real-time during use of the aBCMI. This would allow the aBCMI to generate a theoretically infinite amount of different music pieces, ensuring users of the aBCMI system do not become overly familiar with the music being played. This is necessary because familiarity and repetition influence listener affective states (Livingstone et al. 2012). The generator also aims to produce music which can target any region of the affective space, allowing the aBCMI system to move the user to a specified region via an affective trajectory.

The music generator used in our aBCMI design is an affectively-driven algorithmic composition (AAC) system. It has previously been described in (Williams et al. 2015) and has been evaluated for its ability to move participants to the targeted affective state in (Daly et al. 2015*b*).

2.2. Experiments

2.2.1. Overview In order to evaluate the efficacy of the proposed aBCMI system, a series of experiments were conducted with a group of healthy participants. Each participant was requested to return for multiple sessions of the experiment. This allowed sufficient data to be gathered from each participant to train individual affective state detectors for each participant. The sessions were split into three parts, a calibration session, three training sessions, and a final online testing session.

The calibration session recorded physiological signals from each of the participants as they listened to a series of short 20s excerpts of pre-generated music while reporting their current felt affective states. This session consisted of five runs, each of which contained eighteen trials. A single trial in the calibration session is illustrated in Figure 2. The participants first viewed a fixation cross for a short duration of time uniformly drawn from between 1-2 s. This was followed by 20 s of music (generated via the same music generation system used throughout the experiments) with a 1 s fade-out (21 s total). Listeners were simultaneously presented with FEELTRACE a 2-dimensional on-screen tool for reporting affective states on a moment by moment basis, in which participants use a mouse to position a cursor within the arousal-valence circumplex space (Russell 1980) that best matches how they currently feel (Cowie et al. 2000).

This was then followed by a beep counting task, which acted as a distraction task

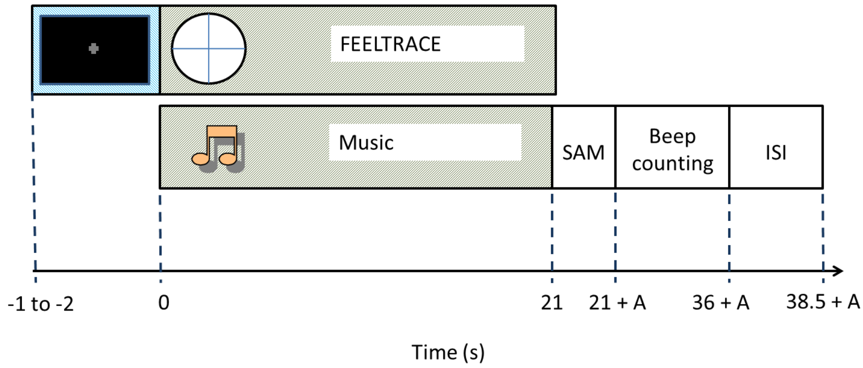

Figure 2. Calibration session trial timing.

to minimise serial effects in the experiment. Specifically, emotionally evocative stimuli, such as music, have effects that last longer than the exposure to the stimulus. Thus, in order to reduce this serial effect of trials contaminating subsequent trials we used a distraction task between trials. This took the form of an auditory oddball paradigm, which is both cognitively engaging enough to distract participants, while being of the same modality as the music, i.e. audio.

Two beeps were played at different tones, a high pitched tone (350 Hz, target) was played 20 % of the time and a lower pitched tone (300 Hz, non-target) was played 80 % of the time. The tones were played in a random sequence with a 400 ms inter-stimulus interval between them. Participants were instructed to count the target occurrences during the 15 s playback.

Finally, an inter-stimulus interval of 2.5 s was imposed before the beginning of the next trial.

After the participants completed the calibration session they were invited back to attend a series of training sessions. The training session was repeated three times (chosen to maximise the amount of training, while allowing as many participants as possible to complete the experiment) over three different, non-consecutive, days and was used to provide data about participant's responses to music for training the case-based reasoning system. Each session was composed of four runs, each of which contained eighteen trials. Music was generated and played to the participants that targeted two different regions of the affective space within each trial. Specifically, the pre-generated music was played for a total of 40 s, with the first 20 s targeting one affective state and the second 20 s targeting a different affective state. In all other aspects the structure of the trial was identical to the calibration session.

It is widely known that music can produce two different effects when listened to. The music can be both perceived and/or felt, wherein perceived emotion may be described as the emotion the listener judges the music to be trying to convey, and felt emotion is the emotion the listener actually experiences (Gabrielsson 2001). An example might be music with a "sad" flavour which, when played to a listener in a negative emotional state may actually make the listener feel happier (Vuoskoski et al. 2012). Participants in our experiments were carefully instructed, via written and oral explanations, to report their felt emotions as they completed the experiment.

The participant's reports of their felt affective states as they listened to this music, provided via FEELTRACE, were used to inform the case-based reasoning system as to how easy or difficult particular affective state transitions were for each participant. For example, it was anticipated that participants may be able to move more easily between affective states that are similar to one another.

The emotional response space is represented via the two dimensional circumplex model of valence and arousal (Russell 1980). This model is divided into discrete regions of uniform size representing high, neutral and low valence and arousal. In order to develop a robust case-based reasoning system to move between any two of the discrete regions, musical excerpts were generated to move between each of the 9 discrete affective states in the valence-arousal space. This resulted in a set of 72 pieces of music, each of which elicits a unique trajectory in the valence-arousal space. Each training session contained 72 trials, one for each of these trajectories. Thus, over the three training sessions music following each trajectory was played 3 times to each participant.

Physiological data recorded during the calibration and training sessions were used to train the affective state detection system to identify the participant's affective states during the final online testing session. This online testing session was used to evaluate the performance of the aBCMI. The session was split into six runs, with ten trials per run. Each trial had a similar structure to the calibration and testing runs. However, the music was played for 60 s. During the first 20 s the participants were played music, via the music generator, in order to move them into a starting affective state. The affective state detection system was then used to attempt to identify the participant's current felt affective state. This measure of the participant's current affective state was then provided to the case-based reasoning system, along with the final targeted affective sate for the current trial.

The case-based reasoning system used the user's detected current felt affective state and the final targeted affective state to identify a trajectory of affective state transitions to move the participant from their current affective state to the target state. This affective state trajectory was then translated into a set of musical features, which were provided to the music generator in order to control the music that was played to the participant over the remaining 40 s of the trial.

2.2.2. Participants Twenty-two healthy individuals were recruited to participate in our experiments via a combination of email and notice board based advertisements. In order to ensure some homogeneity in the participants in terms of their musical preferences, each participant was asked to complete a short test of musical preferences (STOMP) questionnaire (Rentfrow and Gosling 2003). Participants who reported a strong dislike of two or more music genres or a strong dislike of classical music (motivated by the use of classical generated music in the experiments) were excluded. At this stage two

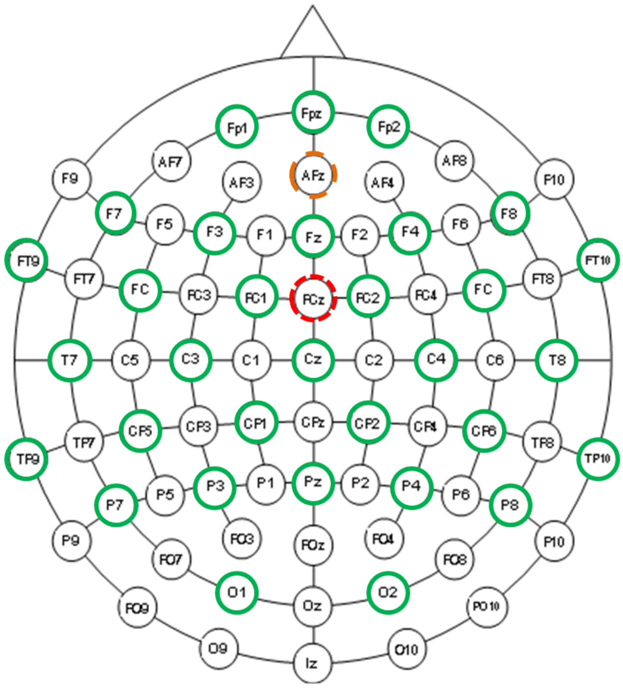

Figure 3. EEG recording montage. The reference electrode (FCz) is denoted by a dotted line and the ground electrode (AFz) by a dashed line.

participants were excluded.

Thus, a total of twenty individuals participated in the study. They had a mean age of 22 (range 19-30, standard deviation 1.45). Nine participants were female and all were right handed. Each participant received £10.00 GBP for each of the sessions they attended. Ethical permission was obtained via the University of Reading, School of Systems Engineering ethics approval guidelines.

2.2.3. Signal acquisition The electroencephalogram (EEG) was recorded from 32 passive Ag/AgCl electrodes positioned according to a slightly modified version of the international 10/20 system. The reference electrode was placed at FCz and the ground electrode was positioned at AFz. This is illustrated in Figure 3.

The EEG was recorded via a BrainAmp EEG amplifier (BrainProducts, Germany) at a sampling rate of 1,000 Hz. All impedances were kept below 10 kΩ for every participant and session.

Galvanic skin response (GSR) was recorded from the ventral medial phalanx positions of the index and middle fingers of the participant's left hand. The electrocardiogram (ECG) was recorded from the ventral position on the participant's left and right wrists. Respiration was recorded via a respiration belt placed around the base of the participant's rib cage. Blood pulse oximeter signals (BPS) were also recorded from the participants left thumb via a pulse oximeter. Finally, the participant's head movements were recorded via a 3D accelerometer placed at position CPz. All these extraneous physiological signals were recorded via a BrainAmp GSR module (BrainProducts, Germany) at 1,000 Hz sampling rate.

2.2.4. Pre-processing Artefacts were removed from the calibration and training sessions during offline processing of the data performed before the final online testing session. The automated artefact removal method "Fully automated and online artefact removal for Brain-computer interfacing" (FORCe), was used to remove artefacts from this offline data by decomposing the signal via, first, wavelets and then independent component analysis, before applying a combination of pre-trained soft and hard thresholds (Daly, Scherer, Billinger and Muller-Putz 2014). The accelerometer signal was also used to inform the application of the FORCe method as detailed in (Daly, Billinger, Scherer and Mueller-Putz 2013). Band-pass filtering was then applied in the range 4-45 Hz (2'nd order Butterworth filter) and trials were discounted from use if their amplitude exceeded ±100 uV. Finally, visual spot checking was used to confirm the absence of artefacts from the remaining dataset.

2.2.5. Feature extraction Features were extracted from the EEG following the method first described in (Stikic et al. 2014) and applied in (Daly et al. 2015*a*). Ten frequency bands and ten scalp regions were identified. The root mean squared band-powers (motivated by previous success with this measure in BCI applications (Verma et al. 2014) and emotion identification from EEG (Bajaj and Pachori 2014)) within each band and region were extracted as features to describe the EEG. The frequency bands and scalp regions are listed in Table 1.

Frequency band	Scalp region
Delta (1-4 Hz)	All channels
Slow theta (4-5.5 Hz)	Frontal channels
Fast theta (5.5-7 Hz)	Central channels
Total theta (4-7 Hz)	Parietal channels
Slow alpha (8-10 Hz)	Occipital channels
Fast alpha (10-12 Hz)	Left temporal channels
Total alpha (8-12 Hz)	Right temporal channels
Sigma (12-14 Hz)	Midline channels
Beta (14-30 Hz)	Left hemisphere channels
Gamma (30-45 Hz)	Right hemisphere channels

Table 1. Band-power features extracted from the EEG. Each band-power feature is extracted from each spatial region. Thus, Delta band-power features were extracted from 'All channels', and 'Frontal channels', and 'Central channels' etc., resulting in 100 candidate features (10 band-powers × 10 scalp regions).

In addition, features were extracted from the other physiological signals. The mean peak to peak intervals of the ECG were extracted as a measure of heart rate during the music listening task. A similar feature was also extracted from the BPS signal set. Specifically, the mean peak to peak intervals of the pulse oximeter readings were also extracted as a secondary measure of heart rate.

The dominant frequency of the respiration rate was estimated from the respiration signal via the Fourier transform and extracted as a descriptive feature. Finally, the mean amplitude of the GSR signals relative to the baseline period (-1 s to 0 s relative to the current time interval) was taken as the GSR descriptive feature.

This feature extraction method produced a candidate feature set containing 100 EEG features from the 32 EEG channels and another 4 features from the other 4 physiological measurements. Thus, 104 candidate features were available to attempt to identify a user's affective state.

2.2.6. Feature selection In order to reduce the dimensionality of the feature set and subsequently avoid overfitting of the classifier, an automated supervised feature selection approach was applied. Stepwise linear regression was used to select a subset of features. For each classification problem the class labels were considered as the dependent variable in the regression and a sub-set of candidate features were considered as the independent variables. Candidate features were iteratively added or removed from the regression model until changing the number of features did not significantly ($p < 0.05$) improve the fit of the regression model any further. This training was done on a per participant basis.

2.2.7. Classification Support vector machines (SVMs) were used to attempt to solve a set of binary classification problems in order to identify a user's current affective state. Features were extracted from 2 s long non-overlapping windows of EEG and physiological signals along with the users current mean reported affective states, which were coarse grained into 1 of 9 discrete regions of the valence-arousal circumplex space.

A 10x10 cross-fold training and validation scheme was then used to select features and train 8 SVMs. Each SVM attempted to solve one of the following binary classification problems: neutral vs. not neutral valence, neutral vs. not neutral arousal, high vs. low valence, high vs. low arousal, neutral vs. high valence, neutral vs. low valence, neutral vs. high arousal, and neutral vs. low arousal. These classifier outputs were then combined into a majority voting scheme to identify the user's current felt affective state. The trained feature sets and classifiers for each user were saved and used during that user's online testing session.

2.2.8. Case-based reasoning The case-based reasoning system was used to estimate the affective state trajectory to move participants from their current affective state to the objective affective state. The affective measures and musical parameters from the experiments were normalized, and a k-nearest neighbour's regression was performed. Predictions were based on the 5 nearest neighbours with distance weighting and a uniform kernel. The model thus provides, given values of valence and arousal, estimated values for all of the musical parameters in the generative model to induce the desired affective state.

2.2.9. Objectives The aBCMI was tested during the online testing session with a set of objectives. These objectives comprise a set affective state trajectories that are potentially of benefit to users of an aBCMI-driven music therapy system. The objectives evaluated during the testing session are listed in Table 2.

Objective	Initial affective state	Target affective state
Make the user happy	Low Valence, Neutral Arousal	High Valence, Neutral Arousal
Calm the user	Neutral Valence, High Arousal	Neutral Valence, Low Arousal
Reduce stress levels	Low Valence, High Arousal	Neutral Valence, Neutral Arousal
Excite the user	Neutral Valence, Low Arousal	Neutral Valence, High Arousal

Table 2. Objectives tested during of the online aBCMI testing session.

Each of these objectives were evaluated 10 times during the testing session over 10 trials presented to the participant in a random sequence. In addition, these objectives were supplemented with other related objectives, drawn randomly from the set of supplementary objectives listed in Table 3.

Objective	Initial affective state	Target affective state
Make the user happy	Low Valence, Low Arousal	High Valence, Low Arousal
Make the user happy	Low Valence, High Arousal	High Valence, High Arousal
Calm the user	Low Valence, High Arousal	Low Valence, Low Arousal
Calm the user	High Valence, High Arousal	High Valence, Low Arousal
Excite the user	Low Valence, Low Arousal	Low Valence, High Arousal
Excite the user	High Valence, Low Arousal	High Valence, High Arousal

Table 3. Supplementary objectives tested during the online aBCMI testing session.

2.3. Analysis

2.3.1. Online artefacts During the final online testing session artefact removal was not performed online due to computational limitations of the measurement computer. Instead, offline post-hoc artefact rejection was used to identify trials containing artefacts and to discount them from the final analysis. Specifically, trials were rejected from analysis if they were observed to contain any amplitudes during the 60 s music listening period that were greater than ±100 uV. Additionally, visual spot checking of random trials from each participant was used to confirm the absence of artefacts from the dataset.

2.3.2. Evaluation To evaluate the success of the aBCMI system during the final online testing session a set of evaluation criteria are defined.

First, the success of the aBCMI in meeting its objectives is evaluated. For each of the key objectives, the participants FEELTRACE reports of their current felt emotions are compared against the targeted affective states. Relative changes in affective states are considered as the measurable objectives. Specifically, each of the aBCMIs' objectives attempts to first place the participant in a starting affective state and then move them to a new target affective state. If the relative change in the participant's affective state, as a result of the use of the aBCMI, is in the right direction significantly more often than chance the objective can be said to be successfully accomplished.

This is measured by first fitting a 1st order polynomial function to the participant's mean FEELTRACE reports of their felt valence and arousal. The angle of deflection of this polynomial function from the horizontal was then calculated for each trial. This set of angles represents the responses of the participants after attempts to manipulate their affective states. The distribution of these angles over all trials with a single objective was then compared to a null distribution representing the null hypothesis that the attempted manipulation was unsuccessful and, therefore, participants were equally likely to report increases or decreases in their valence and arousal.

A normal distribution (mean = 0, STD. = 1) was used to represent this null hypothesis. The observed deflection angles from each participant under each condition were normalised to a standard deviation of 1 and the mean of the distribution of deflection angles was compared to the null distribution via a Kolmogorov-Smirnoff test. If the distribution of angles of the trends of the user's FEELTRACE reports for a given objective were significantly different from a normal distribution, and visual inspection of the FEELTRACE reports confirms the trajectory was moving in the right direction, the objective can be said to be met.

Second, an additional criterion used to determine the success of the aBCMI system was the performance of the online affective state detector. The participant's mean FEELTRACE report from 10 s to 20 s relative to the start of the music is taken as the ground truth measure of their affective state. This is compared to the detected affective state, which is derived from the same time period.

Because the exact values of the participant's FEELTRACE reports can differ between participants and trials, depending on the individual proclivities and moods of the participants, it is not possible to compare the absolute values of the FEELTRACE reports to the detected affective states. Therefore, in order to determine which trials the affective state detection system worked for a classification approach is taken. A support vector machine (SVM) is used to attempt to classify the detected affective state from the participant's reports of their felt affective state. For trials for which this classification was correct it may be observed that the affective state detection system detected an affective state that was significantly closer to the participant's reported affective state than could have occurred by chance. Due to the likelihood of unbalanced class sizes, accuracies were calculated via the balanced accuracy measure, which is more robust to unbalanced class sizes (Brodersen et al. 2010). Chance level classification was estimated via a bootstrapping approach with 4,000 bootstrapped accuracies calculated from data with shuffled class labels. Significance was then estimated by comparing this null distribution to the reported accuracy via a t-test.

Finally, the case-based reasoning system was evaluated for its ability to move participants from their initial affective state to the target affective state. This was done by identifying trials for which the affective state detector worked (trial group A) and trials for which it did not (trial group B). If the case-based reasoning system is having a significant effect on the ability of the system to move participants to the correct final affective state than trials in group A should be significantly closer to the final target affective state than trials in group B. In other words, if the aBCMI detects the correct initial affective state, the case based reasoning system should be able to apply an optimal set of transformations that move the aBCMI user to the correct final target affective state. This means that, if the case-based reasoning system had a significant effect on the performance of the aBCMI, then, if the initial affective state detection were wrong, the CBR would not be able to easily move the aBCMI user to the final target affective state.

All analysis was conducted in Matlab (2014) with the statistics toolbox used for significance testing.

3. Results

3.1. Participants

Participants were asked to attend multiple consecutive sessions spread over a period of several months for this study. However, due to various reasons (including participants graduating) several participants were not able to attend the final session of the experiment. As a result the final online study was conducted with 8 participants.

3.2. Artefact rejection

Artefact rejection was performed in post-hoc analysis after the online testing session. This resulted in a mean of 5.37 ($\pm$6.69) trials being removed from each participant's dataset, leaving a mean of 53.12 ($\pm$7.74) artefact free trials from the online testing session.

3.3. Distraction task

The efficacy of the distraction task was evaluated by inspecting the audio ERP generated during the beep counting distraction task. ERPs are found for each participant during

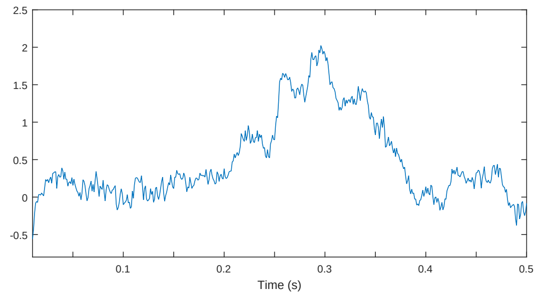

Figure 4. Grand average P300 ERP recorded from participant 7 during the beep counting distraction task.

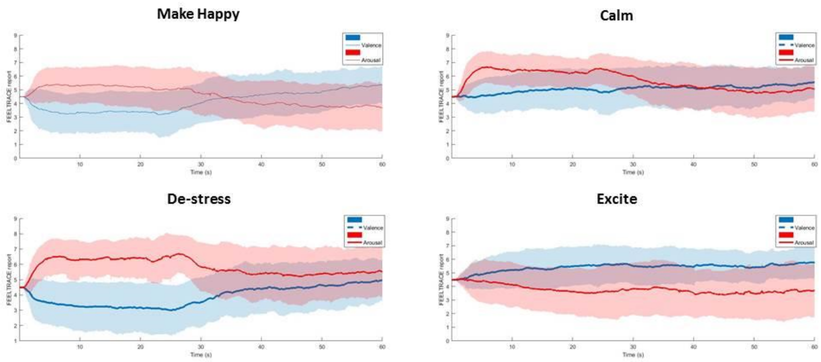

Figure 5. Mean FEELTRACE trajectories reported by all participants over the 60s music listening trials for each objective. The shaded areas indicate ±1 standard deviation.

the beep counting task, an example of which is illustrated in Figure 4. This indicates that the participants were attending to the distraction task.

3.4. Objectives

The affective state trajectories reported by all participants during each of the target objectives are illustrated in Figure 5.

It may be observed that participants report affective states corresponding to the starting affective state from about 2 s after the start of the trial in the majority of cases. For example, when the target objective is to make the user happy the experiment is structured such that the first 20 s of generated music will aim to first induce a reduction in valence (i.e. we first aim to put the user in a reduced valence, less happy, condition and then explore whether we can increase their felt valence via the aBCMI). This initial reduction in mean reported valence may be seen in the figure. From 10 s onwards the aBCMI aims to detect the participant's felt affective state from their physiological signals and EEG, based upon this detected affective state the aBCMI then attempts to generate music to move them from this affective state towards the final target affective state. Thus, when the final objective is to make the user happy the aBCMI aims to

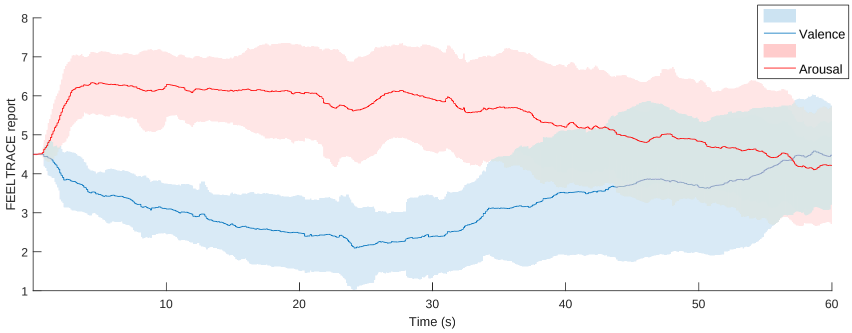

Figure 6. FEELTRACE trends reported by participant 2 during the "de-stress" objective. The objective in this case was to both increase the valence felt by the participant and decrease their felt arousal. This was achieved with a significant increase in valence ($p = 0.003$) and a significant decrease in arousal ($p < 0.001$) observed.

play music to increase the user's valence from 20 s after the start of the trial. This may be seen in Figure 5 where, after a short delay, the average valence reported by the participants increases.

This effect may be seen more clearly when inspecting the FEELTRACE reports of felt affective states produced by individual participants. Figure 6 illustrates the FEELTRACE reports from participant 2 during the objective 'de-stress'.

The trajectory angles produced by each participant during each objective are tested to determine whether they could have occurred by chance. The results of each significance test for each participant and objective are listed in Table 4.

These results are also summarised in Table 5. It may be noted that for the objectives "make happy", "calm", and "de-stress" the system is able to cause participants to report the targeted affective state change trajectory significantly more often than chance in the majority of cases. The exception is the "excite" objective, which was only successful with three participants.

It may also be observed that valence and arousal are not independent. For example, when the objective of the aBCMI is to make the user happy, the arousal is also seen to decrease in conjunction with the reported increase in valence. Indeed, the correlation between valence and arousal appears to change as a function of the objective of the aBCMI system. For each of the objectives there is a significant (but small) correlation between valence and arousal. Specifically, for the objective "make happy" the correlation is $r = -0.172$ ($p < 0.05$), for the objective "calm" $r = -0.020$ ($p < 0.05$), for "de-stress" $r = -0.145$ ($p < 0.05$), and for "excite" $r = -0.097$, ($p < 0.05$). It may be observed that the correlations are negative, i.e. as valence increases arousal decreases.

3.5. Affective state detection

The features that are automatically selected for use in the affective state detection stage differ between participants. The EEG features selected to classify affective states for two

	Objective				
	Make happy	Calm	De-stress		Excite
Participant	Increase valence	Decrease arousal	Increase valence	Decrease arousal	Increase arousal
1	0.001	0.009	0.023	0.035	0.046
2	<0.001	<0.001	0.003	<0.001	0.145
3	<0.001	<0.001	<0.001	0.004	0.005
4	<0.001	0.002	<0.001	0.003	<0.001
5	<0.001	<0.001	<0.001	<0.001	<0.001
6	0.156	0.074	0.517	0.055	0.167
7	<0.001	<0.001	0.021	<0.001	0.376
8	<0.001	<0.001	<0.001	0.032	0.003

Table 4. Summary statistics for each participant and objective detailing which objectives were achieved by the aBCMI system for each participant. The p-values indicate the difference between the first 10 s and the last 10 s of the FEELTRACE reports from each participant while the aBCMI system attempted to achieve the 4 objectives: "make happy" (increase valence), "calm" (decrease arousal), "de-stress" (increase valence and decrease arousal), and "excite" (increase arousal).

Objective	Count of participants reporting correct trajectories
Make happy	7
Calm	7
De-stress	7
Excite	5

Table 5. Count of the number of participants reporting an affective state change trajectory matching the objective trajectory significantly more often than chance ($p < 0.05$).

randomly drawn example participants are illustrated in Figure 7. It may be observed that different proportions of features from different frequency bands are selected for use in classifying affective states for each of these participants, suggesting a large amount of inter-participant variability in the effect of affective state changes on the recorded physiological signals.

The scalp topographies of the EEG features that are most frequently selected are illustrated in Figure 8. Note that the selected features from all participants over all classification problems are illustrated. It can be observed that the theta, alpha, and beta bands are most often used for classification and that features in the right hemisphere

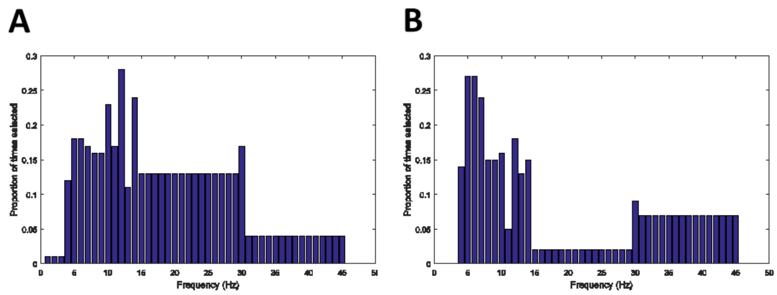

Figure 7. EEG Features selected to classify affective states for participant 1 (A) and 3 (B). The feature selection procedure is run 100 times in the 10x10 cross-fold training scheme and the y-axis indicates the proportion of folds in which features from each frequency band are selected.

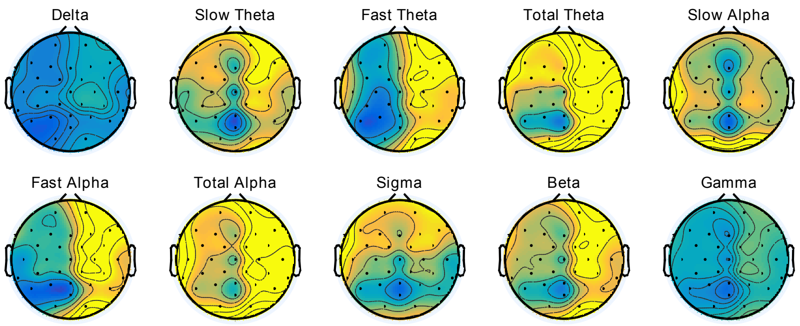

Figure 8. EEG features selected for online EEG classification, averaged over all participants and classification problems. Each scalp plot represents a histogram of the number of times features extracted from each of the channels were selected for use in the online aBCMI system.

are selected slightly more often than those in the left hemisphere.

Mean EEG band-powers within the theta, alpha, and beta frequency bands recorded over the right hemisphere were observed to most frequently relate to the participants reports of their felt emotions. Thus, the specific EEG patterns, that we most frequently observe, that may be used for online affective state detection are the magnitude of the ongoing, non-phase locked root mean squared frequency band-powers over the right cortical hemisphere.

Other physiological features, that don't include EEG, are also used for classification. On average, over all participants, physiological features were selected 18.99 % of the time, while EEG features were selected 81.01 % of the time. The physiological features that were selected for use in online affective state detection are illustrated in Figure 9.

The classification performance of the affective state detection stage of the aBCMI system is reported in Table 6. It may be observed that significant affective state detection accuracies ($p < 0.05$) are achieved with 7/8 participants when classifying valence and 3/8 participants when classifying arousal.

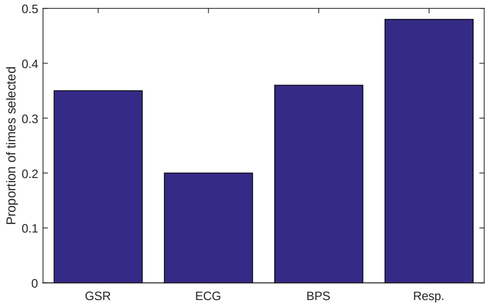

Figure 9. Relative proportion of times physiological features were selected for use in classifying affective states.

	Valence		Arousal	
Participant	Accuracy	p	Accuracy	p
1	0.577	< 0.01	0.628	< 0.01
2	0.552	< 0.01	0.475	0.376
3	0.500	0.016	0.670	< 0.01
4	0.658	0.426	0.634	< 0.01
5	0.491	< 0.01	0.646	0.912
6	0.551	0.012	0.469	0.400
7	0.471	< 0.01	0.482	0.439
8	0.517	< 0.01	0.300	0.654
Mean	0.539	-	0.538	-

Table 6. Affective state detection performance, reported in terms of balanced accuracies.

3.6. Case-based reasoning

The effect of the affective state detection on the overall performance of the aBCMI system is measured in terms of the effect of the success of the detection method on the reported affective state trajectories. An example of the mean affective state trajectories reported during the 'calm' objective, for trials in which the affective state detection method was correct, is illustrated in Figure 10.

These may be compared to the mean affective state trajectories, for the same 'calm' objective, for trials in which the affective state detection was not correct, which are illustrated in Figure 11.

From these examples, it may be observed that when the affective state detection is correct the trajectory of the arousal exhibits a steeper gradient change. Specifically, when the aBCMI is able to correctly detect the user's initial affective state it is able to

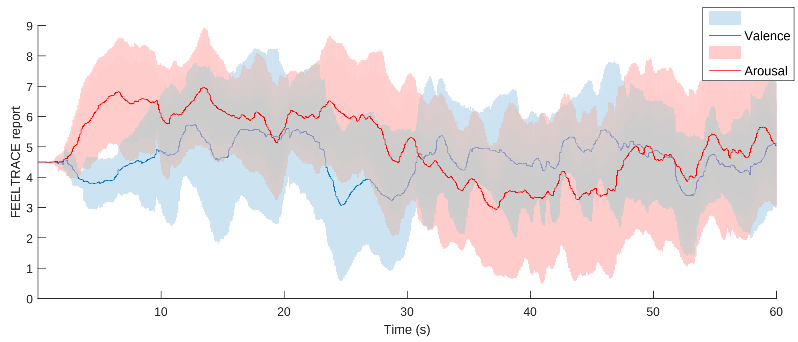

Figure 10. Affective state trajectories reported by participant 7 during the "calm" objective during trials in which the aBCMI correctly detected the initial affective state.

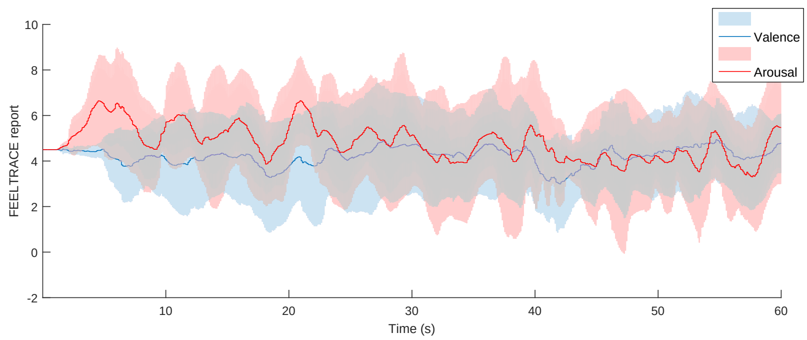

Figure 11. Affective state trajectories reported by participant 7 during the "calm" objective during trials in which the aBCMI did not correctly detect the initial affective state.

more successfully reduce the user's arousal.

The significance of this effect is tested by fitting a linear regression to relate the reported affective states to the independent variables: 'objective', 'correct affective state detection', 'measured affective state' (valence or arousal), and 'participant number'. The regression model fits with an adjusted R^2 of 0.275 and with significant effects of the independent variables 'correct affective state detection' ($p = 0.022$), 'measured affective state' ($p < 0.001$), and 'participant number' ($p < 0.001$). Thus, it may be concluded that the affective state detection result significantly improves the outcome of the aBCMI.

4. Discussion

Affective brain-computer music interfacing (aBCMI) is a novel neuro-modulation technology, which we propose for a range of applications such as physiologically / neurologically driven music therapy or entertainment.

Our proposed aBCMI is able to modulate its user's affective states via first detecting their current affective state and then using a case-based reasoning system to identify the best approach to move them to a targeted affective state. An affectively-driven music composition system is used to generate musical stimuli to move users to a target affective state.

The aBCMI is able to change the majority of the participant's affective states in order to meet the objectives "make happy", "calm", and "de-stress". However, for the majority of the participants the aBCMI was not able to "excite" them. Specifically, the majority of participants reported either no change in arousal or a significant reduction in arousal when the system was trying to excite them. At the same time the majority of participants also reported an increase in valence, which was not intended. The reasons for this are unclear, although it is speculated that it could be the result of the type of music (monophonic piano) generated by the aBCMI not being able to induce this particular change in affective states.

The affective state detection method is personalised for each user of the aBCMI and achieves statistically significant online single trial classification accuracies when classifying the user's valence in 7 out of 8 participants and significant accuracies when classifying the user's arousal in 3 out of 8 participants. This affective state detection method significantly improves the success of the aBCMI in achieving its objectives. Specifically, for trials in which the affective state detection method was correct the final affective state trajectories reported by the participants were significantly closer to the aBCMI systems objectives.

The mean affective state detection accuracies of 53.96 % (valence) and 53.80 % (arousal) compare favourably to other efforts to classify affective states from the EEG. For example, in a recent study Atkinson & Campos reported median accuracies of 62.33 % (valence) and 60.7 % (arousal) (Atkinson and Campos 2016). However, although these accuracies are somewhat higher than those we obtain, they were obtained from a 2-class problem (in which the threshold of statistical significance is higher) and during offline EEG analysis (which may be considered less challenging, in terms of classification efforts, than online BCI use).

The automatically selected features used by the affective state detection method contain both neurological and physiological features. Indeed, given that the probability of selecting a physiological feature by chance (3.8 %) is much lower than the probability of selecting an EEG feature (96.1 %) this indicates the importance of physiological features in identifying affective states and reinforces the idea that emotional responses to music are a function of both the brain and the body (Niedenthal et al. 2009).

Our affective brain-computer music interface may be contrasted with other efforts to passively translate brain-states into music. This is known as sonification and has been reported to be useful for real-time monitoring of brain states via EEG (Wu et al. 2009) and via joint EEG and functional magnetic resonance imaging (fMRI) (Lu et al. 2012). Sonification provides a method for passively monitoring affective states and translating them into audio output in a way that, it is suggested, may be useful for music therapy. In contrast, our aBCMI system first aims to classify a users' current affective state and then actively modulate that affective state via a music generator. Specifically, sonification generally provides a linear mapping between the neural signals

(EEG or fMRI) and music, whereas our method is able to produce a wide range of different non-linear streams of auditory cues in response to the affective states encoded within the neural signals.

Over all participants and classification problems features in the delta, slow theta, total alpha, and beta frequency bands were selected most frequently. This corresponds well to previous reports in the literature that delta, theta, alpha, and beta bands are involved in different emotional responses to music (Daly, Malik, Hwang, Roesch, Weaver, Kirke, Williams, Miranda and Nasuto 2014, Kabuto et al. 1993, Lin et al. 2010, Sammler et al. 2007). Additionally, there is a slight right hemisphere bias to the selected features, which further supports the general understanding that the right hemisphere is more involved in the processing of emotional stimuli (Silberman and Weingartner 1986).

Interpreting spatial information from EEG is not as reliable as other neuro-imaging modalities, such as fMRI, due to the effects of volume conduction (Nunez and Srinivasen 2006). However, it is still possible to make broad statements about hemispheric localisation of affect. Thus, the observation that band-power features are more frequently selected in the right hemisphere than the left may be interpreted to mean that the magnitude of the ongoing EEG oscillations in these frequency bands recorded over the right hemisphere is more likely to change with respect to participants felt emotions while they listen to music.

It has been observed elsewhere that there is a change in relative activity in the alpha (Schmidt and Trainor 2001) and beta (Daly, Malik, Hwang, Roesch, Weaver, Kirke, Williams, Miranda and Nasuto 2014) frequency bands between pre-frontal cortical hemispheres while listening to emotionally evocative music. It has been suggested that the right hemisphere is dominant in processing the majority of emotional stimuli, regardless of the modality of the stimuli, and that this is performed via the right hemisphere sub-cortical route, via which emotional stimuli are routed to the amygdala (Gainotti 2012). Our observation that EEG band-powers on the right hemisphere change with respect to the induced affective state of our musical stimuli further support this view.

Finally, it is important to note that the selected features do not correspond well to the left motor cortex. The participants all used their right hand to report their felt emotions and it could be possible that some element of these small right hand movements was being used to classify their reported emotions. However, as band powers over the left motor cortex in the alpha and sigma bands were selected much less frequently than other features, this is unlikely to be the case.

Our EEG recordings were referenced to a single EEG reference electrode placed at position FCz. This is a common approach taken in many EEG and BCI studies. However, it is also well-known that the use of a single EEG reference such as this can distort the measured scalp potentials such that they do not completely accurately reflect the underlying cortical sources. There are several different approaches that may be taken to attempt to solve this, such as common average referencing Nunez et al. (1997), Schiff (2005) or the Reference electrode standardisation technique (REST) Yao (2001).

However, as reported by Nunez (2010), neither of these techniques can qualify as a "gold standard" as both are limited by the number of electrodes and incomplete electrode coverage (Nunez 2010). In addition, REST is limited by the choice of head model employed. When an accurate, personalised, head model is available REST has been reported to be superior to other referencing methods in its ability to identify patterns of connectivity (Chella et al. 2016). However, head models that are completely accurate in their representations of paths of electrical resistance in the brain are difficult to obtain, limiting the utility of this method. Furthermore, applying such transforms to the EEG moves the EEG away from clinical standard EEG, which is most commonly used to understand and diagnose electrophysiological activity.

Therefore, it was decided that for the present study single reference electrode EEG would be used for classification of affective states in the brain. This also allowed for rapid online EEG signal processing to be possible, a requirement for online brain-computer interfacing, and something that is not possible with current computational implementations of REST.

Nonetheless, both common average referencing and REST are acknowledged to be superior to single referenced EEG in terms of the accuracy with which the original electrophysiological sources may be derived (Nunez 2010). Therefore, the lack of such a transformation in our current aBCMI implementation is a potential caveat of our study and we will attempt to resolve this in future work.

It is important to consider the potential effects of local minima in the feature selection method used. Specifically, stepwise linear regression is a hill-climb search algorithm and is, therefore, subject to local minima (Alpaydin 2004). Nonetheless, many features for each participant are repeatedly selected for the majority of folds of the cross-fold train and validation procedure. This suggests they are robust to changes in the starting position of the search and are, hence, more likely to reflect the global optima.

There are a number of caveats that must be considered with regard to this study. First, the size of the population of participants is relatively small. This study was conducted longitudinally, with each participant returning for multiple sessions over a period of several months. However, unfortunately, several participants were not able to continue for the entire length of the study. Hence, the final online experiment was conducted with 8 of the initial 20 participants.

Second, the music generation process was used to produce mono-phonic piano music. This allowed a relatively simple musical structure to be used in the experiments. However, it also means that the music is not as evocative as it perhaps could be if polyphonic music were used or if different types of instrumentation were explored. Future work will explore these issues.

Additionally, although robust steps were taken to remove trials containing artefacts from the final analysis it would be more optimal to remove artefacts from the EEG and other physiological signals during online use of the aBCMI. This would allow the system to respond more reliably to a wider range of users. This will be investigated in future work.

Finally, the online affective state detection method, although often able to perform above chance level, is not able to achieve very high classification accuracies. This may be a result of inter-trial variabilities within participants and non-stationarities in the data. It may also be a result of inadequate candidate feature sets used to describe the participant's EEG and physiological activity. Therefore, future work will seek to explore neurological and physiological correlates of music induced affective states in more detail. For example, it has recently been reported that independent component analysis has been used to identify specific cortical regions involved in valence and arousal responses during music listening (Rogenmoser et al. 2016) and we could adopt a similar approach in our future work to improve the accuracy of our affective state detector.

The aBCMI system developed and tested in this study is able to modulate an individual's affective state. By using physiological measurements it is possible to obtain an objective estimate of an individual's affective state. This is coupled with a case-based reasoning system to identify and exploit optimal methods to modulate affective states. Finally, an affectively-driven algorithmic composition system is used to allow the aBCMI to produce a theoretically infinite amount of emotionally evocative music.

Thus, the complete aBCMI system provides a unique tool for monitoring and modulating user's emotions. Future work will seek to explore the possibilities for the aBCMI system to be used with patients suffering from emotional problems and other patients who, it has also been suggested, could benefit from music therapy, such as those with brain injury (Bradt et al. 2010).

Acknowledgements

This work was supported by the EPSRC grants EP/J003077/1 and EP/J002135/1.

References

Alpaydin, E. (2004), *Introduction to Machine Learning*, MIT Press.

Atkinson, J. & Campos, D. (2016), 'Improving BCI-based emotion recognition by combining EEG feature selection and kernel classifiers', *Expert Systems with Applications* **47**, 35–41.

Bajaj, V. & Pachori, R. (2014), Detection of Human Emotions Using Features Based on the Mulitwavelet Transform of EEG Signals, *in* 'Brain-Computer Interfaces: Current Trends and Applications', Vol. 1, Springer, chapter 8, p. 416.

Bhattacharya, J. & Lee, E.-J. (2012), 'Modulation of EEG Theta Band Signal Complexity by Music Therapy'.

Bradt, J., Magee, W. L., Dileo, C., Wheeler, B. L. & McGilloway, E. (2010), 'Music therapy for acquired brain injury.', *The Cochrane database of systematic reviews* (7), CD006787.

Brodersen, K. H., Ong, C. S., Stephan, K. E. & Buhmann, J. M. (2010), The Balanced Accuracy and Its Posterior Distribution, *in* '2010 20th Int. Conf. on Patt. Recon.', IEEE, pp. 3121–3124.

Chella, F., Pizzella, V., Zappasodi, F. & Marzetti, L. (2016), 'Impact of the reference choice on scalp EEG connectivity estimation', *Journal of Neural Engineering* **13**(3), 1–21.

Cowie, R., Douglas-Cowie, E., Savvidou, S., McMahon, E., Sawey, M. & Schröder, M. (2000), 'FEELTRACE': An Instrument For Recording Perceived Emotion In Real Time, *in* 'Proceedings of the ISCA Workshop on Speech and Emotion', pp. 19–24.

Daly, I., Billinger, M., Laparra-Hernández, J., Aloise, F., García, M. L., Faller, J., Scherer, R. & Müller-Putz, G. (2013), 'On the control of brain-computer interfaces by users with cerebral palsy.', *Clinical neurophysiology : official journal of the International Federation of Clinical Neurophysiology* **124**(9), 1787–97.

Daly, I., Billinger, M., Scherer, R. & Mueller-Putz, G. (2013), 'On the automated removal of artifacts related to head movement from the EEG', *IEEE Transactions on neural systems and rehabilitation engineering* .

Daly, I., Malik, A., Hwang, F., Roesch, E., Weaver, J., Kirke, A., Williams, D., Miranda, E. & Nasuto, S. J. (2014), 'Neural correlates of emotional responses to music: an EEG study', *Neuroscience Letters* **573**, 52–57.

Daly, I., Malik, A., Weaver, J., Hwang, F., Nasuto, S., Williams, D., Kirke, A. & Miranda, E. (2015*a*), Identifying music-induced emotions from EEG for use in brain-computer music interfacing, *in* '6th Affective Computing and Intelligent Interaction'.

Daly, I., Malik, A., Weaver, J., Hwang, F., Nasuto, S., Williams, D., Kirke, A. & Miranda, E. (2015*b*), Towards Human-Computer Music Interaction: Evaluation of an Affectively-Driven Music Generator via Galvanic Skin Response Measures, *in* '7th Computer Science and Electronc Engineering Conference'.

Daly, I., Scherer, R., Billinger, M. & Muller-Putz, G. (2014), 'FORCe: Fully Online and automated artifact Removal for brain-Computer interfacing.', *IEEE transactions on neural systems and rehabilitation engineering* **23**(5).

Gabrielsson, A. (2001), 'Emotion perceived and emotion felt: Same or different?', *Musicae Scientiae* **Spec Issue**, 123–147.

Gainotti, G. (2012), 'Unconscious processing of emotions and the right hemisphere.', *Neuropsychologia* **50**(2), 205–18.

Juslin, P. N. & Sloboda, J. A. (2001), *Music and emotion: Theory and research. Series in affective science.*

Kabuto, M., Kageyama, T. & Nitta, H. (1993), 'EEG power spectrum changes due to listening to pleasant music and their relation to relaxation effects.', *Nihon eiseigaku zasshi. Japanese journal of hygiene* **48**(4), 807–18.

Kübler, A. & Birbaumer, N. (2008), 'Brain-computer interfaces and communication in paralysis: extinction of goal directed thinking in completely paralysed patients?', *Clin Neurophysiol* **119**(11), 2658–2666.

Larsen, R. (2000), 'Toward a Science of Mood Regulation on JSTOR'.

Leeb, R., Friedman, D., Müller-Putz, G. R., Scherer, R., Slater, M. & Pfurtscheller, G. (2007), 'Self-paced (asynchronous) BCI control of a wheelchair in virtual environments: a case study with a tetraplegic', *Computational Intelligence and Neuroscience* .

Lin, Y.-P., Wang, C.-H., Jung, T.-P., Wu, T.-L., Jeng, S.-K., Duann, J.-R. & Chen, J.-H. (2010), 'EEG-based emotion recognition in music listening.', *IEEE transactions on bio-medical engineering* **57**(7), 1798–806.

Livingstone, S. R., Palmer, C. & Schubert, E. (2012), 'Emotional response to musical repetition.', *Emotion (Washington, D.C.)* **12**(3), 552–67.

Lu, J., Wu, D., Yang, H., Luo, C., Li, C. & Yao, D. (2012), 'Scale-free brain-wave music from simultaneously EEG and fMRI recordings.', *PloS one* **7**(11), e49773.

McDermott, O., Crellin, N., Ridder, H. M. & Orrell, M. (2013), 'Music therapy in dementia: a narrative synthesis systematic review.', *International journal of geriatric psychiatry* **28**(8), 781–94.

Miranda, E. R. (2006), 'Brain-Computer music interface for composition and performance', *IntJ Dis Human Dev* **5**(2).

Miranda, E. R., Magee, W. L., Wilson, J. J., Eaton, J. & Palaniappan, R. (2011), 'Brain-Computer Music Interfacing (BCMI): From Basic Research to the Real World of Special Needs', *Music and Medicine* **3**(3), 134–140.

Müller-Putz, G. R., Daly, I. & Kaiser, V. (2014), 'Motor imagery induced EEG patterns in spinal cord injury patients and their impact on Brain-Computer Interface accuracy', *Journal of neural engineering* **(online)**.

Niedenthal, P. M., Winkielman, P., Mondillon, L. & Vermeulen, N. (2009), 'Embodiment of emotion concepts.', *Journal of personality and social psychology* **96**(6), 1120–36.

Nijboer, F., Morin, F. O., Carmien, S. P., Koene, R. A., Leon, E. & Hoffmann, U. (2009), Affective brain-computer interfaces: Psychophysiological markers of emotion in healthy persons and in persons with amyotrophic lateral sclerosis, *in* '2009 3rd International Conference on Affective Computing and Intelligent Interaction and Workshops', IEEE, pp. 1–11.

Nijholt, A. & Desney, T. (2009), *BCI for games: A state of the Art survey*, Vol. 5309/2009 of *Lecture notes in computer science*, Springer Berlin / Heidelberg.

Nunez, P. L. (2010), 'REST: a good idea but not the gold standard.', *Clinical neurophysiology : official journal of the International Federation of Clinical Neurophysiology* **121**(12), 2177–80.

Nunez, P. L., Srinivasan, R., Westdorp, A. F., Wijesinghe, R. S., Tucker, D. M., Silberstein, R. B. & Cadusch, P. J. (1997), 'EEG coherency', *Electroencephalography and Clinical Neurophysiology* **103**(5), 499–515.

Nunez, P. & Srinivasen, R. (2006), *Electric fields of the brain*, Oxford University Press.

Rentfrow, P. J. & Gosling, S. D. (2003), 'The do re mi's of everyday life: the structure and personality correlates of music preferences.', *Journal of personality and social psychology* **84**(6), 1236–56.

Rogenmoser, L., Zollinger, N., Elmer, S. & Jäncke, L. (2016), 'Independent component processes underlying emotions during natural music listening.', *Social cognitive and affective neuroscience* pp. 1–12.

Russell, J. A. (1980), 'A circumplex model of affect.', *Journal of Personality and Social Psychology* pp. 1161–1178.

Sammler, D., Grigutsch, M., Fritz, T. & Koelsch, S. (2007), 'Music and emotion: electrophysiological correlates of the processing of pleasant and unpleasant music.', *Psychophysiology* **44**(2), 293–304.

Schiff, S. J. (2005), 'Dangerous phase.', *Neuroinformatics* **3**(4), 315–318.

Schmidt, L. A. & Trainor, L. J. (2001), 'Frontal brain electrical activity (EEG) distinguishes valence and intensity of musical emotions', *Cognition & Emotion* **15**(4), 487–500.

Silberman, E. K. & Weingartner, H. (1986), 'Hemispheric lateralization of functions related to emotion', *Brain and Cognition* **5**(3), 322–353.

Stikic, M., Johnson, R. R., Tan, V. & Berka, C. (2014), 'EEG-based classification of positive and negative affective states', *Brain-Computer Interfaces* **1**(2), 99–112.

Verma, K. L., Jaiswal, A. K., Mishra, M. & Shukla, A. K. (2014), 'EEG Interface Module for Cognitive Assesment Through Neurophysiologic Tests'.

Vuoskoski, J., Thompson, W., McIlwain, D. & Eerola, T. (2012), 'Who Enjoys Listening to Sad Music and Why? on JSTOR', *Music Perception* **29**(3), 311–317.

Williams, D., Kirke, A., Miranda, E., Daly, I., Hallowell, J., Hwang, F., Malik, A., Roesch, E., Weaver, J. & Nasuto, S. (2015), Affective calibration of a computer aided composition system by listener evaluation, *in* 'Proceedings of the Ninth Triennial Conference of the European Society for the Cognitive Sciences of Music (ESCOM2015)'.

Wolpaw, J. R. (2007), 'Brain-computer interfaces as new brain output pathways.', *The Journal of physiology* **579**(Pt 3), 613–619.

Wu, D., Li, C.-Y. & Yao, D.-Z. (2009), 'Scale-free music of the brain.', *PloS one* **4**(6), e5915.

Wu, D., Li, C., Yin, Y., Zhou, C. & Yao, D. (2010), 'Music composition from the brain signal: representing the mental state by music.', *Computational intelligence and neuroscience* **2010**, 267671.

Yao, D. (2001), 'A method to standardize a reference of scalp EEG recordings to a point at infinity.', *Physiological measurement* **22**(4), 693–711.

Zander, T. O. & Kothe, C. (2011), 'Towards passive brain-computer interfaces: applying brain-computer interface technology to human-machine systems in general.', *Journal of neural engineering* **8**(2), 025005.