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Affective Brain Computer Music Interfacing: A Case Study Of Use By An Individual With Huntington's Disease

I. Daly[1], A.K. Ho[5,6], J. Marcon[4] F. Hwang[2], D. Williams[3], A. Kirke[3], E. Miranda[3], S. J. Nasuto[2]

[1]Brain-Computer Interfaces Laboratory, School of Computer Science and Electronic Engineering, University of Essex, Colchester, CO4 3SQ, UK
[2]Brain Embodiment Lab, Biomedical Engineering Section, School of Biological Sciences, University of Reading, Reading, RG6 6AY, UK
[3]Interdisciplinary Centre for Music Research, University of Plymouth, Plymouth, Devon, PL8 4AA, UK
[4]Ecole Polytechnique Grenoble, University Grenoble Alps, BP 5314 place du conseil nacional de la resistance, 38041 Grenoble Cedex 9, France
[5]School of Psychology and Clinical Language Sciences, University of Reading, UK
[6]Royal Berkshire NHS Foundation Trust, UK

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

ABSTRACT: An affective brain-computer music interface (aBCMI), developed for use as an aid to music therapy, is trialled in a case study with an individual with Huntington's disease. The aBCMI aims to detect a users current affective state and modulate music generated and played to that user in order to manipulate their affective state in a way that has potential therapeutic benefits. We have previously demonstrated the efficacy of this aBCMI on a population of healthy participants but it is unclear whether it could work with individuals with Huntington's.
Our case study demonstrates that there is some potential for aBCMI systems to be used by individuals with Huntington's disease. However, we also highlight some key challenges that need to be overcome in adapting aBCMI systems to this user group. Specifically, we identify a need for more robust measures of ground truths of affective states to allow the aBCMI to be trained with this user group.

INTRODUCTION

Brain-computer music interfaces (BCMIs) provide a method for allowing a user to interact with music via modulations of their brain activity and without the need for movement [17, 11, 10]. We have previously described and presented an evaluation of an affective BCMI (aBCMI) that was able to identify an individual's current affective state from their neural and physiological activity and use this to modulate music played to the individual [7, 8].
We previously demonstrated the ability of this system to modulate the affective states of a cohort of healthy individuals in a manner that has potential applications for music therapy. Specifically, we were able to use our aBCMI to increase felt valence (happiness), decrease felt stress (increase valence and decrease arousal), and decrease felt arousal (calm) reported by our participants [8]. Our aBCMI system was developed with intended applications in music therapy for individuals with a range of different neurological, psychological, or physiological conditions. One example application area is in the treatment of affective changes resulting from Huntington's disease. Huntington's disease is a progressive disorder of the central nervous system that causes damage to the brain and, over a period of typically 10-12 years leads to increased difficulties with movement, cognition and behavior. It also leads to disruption of an individual's ability to effective regulate their affective states. Therefore, there is potential utility in providing an aBCMI system to individuals with Huntington's disease [1].
Huntington's disease affects approximately between 7 to 12 in 100,000 people and there is currently no cure available [13]. Early symptoms of Huntington's disease can include change to personality, mood swings, cognitive processing, and fidgety movement [14].
To begin to explore whether a physiologically informed affective music therapy could be beneficial for individuals with Huntington's disease, we provided our aBCMI system to one individual with Huntington's disease as a case study. We had the following objectives in this study.

1. To determine if is it possible to deploy the aBCMI with an individual with Huntington's disease.
2. To explore how affective state reporting and detection may differ for this individual.
3. To determine whether we could accurately identify affective states from an individual with Huntington's disease.
4. To determine whether we could modulate affective states for this individual.

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MATERIALS AND METHODS

Patient: We recruited one individual with genetically confirmed Huntington's disease (male, 43 years old), who was at a very early stage of the disease.
Our participant received £20.00 (GBP) for each of the sessions attended. The study was given a favorable ethical opinion according to the research ethics procedures of the School of Systems Engineering, University of Reading.

Brain-computer music interface: The aBCMI includes 4 stages: (1) data measurement, (2) affective state detection, (3) case based reasoning, and (4) music generation. These are illustrated in Figure 1.

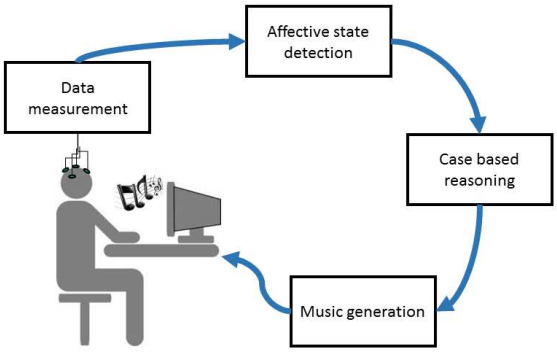

Figure 1: A schematic diagram of our aBCMI.

Data measurement: The data measured included electroencephalogram (EEG), electrocardiogram (ECG), galvanic skin response (GSR), blood pulse oximetry data, and head movement data recorded via an accelerometer. All data was recorded at a sample rate of 1,000 Hz via a BrainAmp EEG amplifier and ExG amplifier (BrainProducts, Germany).
EEG was recorded from 32 channels positioned according to the international 10/20 system for EEG electrode placement. The reference channel was placed at electrode FCz and the ground electrode was placed at position AFz. The impedances on all the channels throughout the study was less than 10 kΩ.
The ECG was recorded from the ventral positions on the participant's left and right wrists. GSR was recorded from the ventral medial phalanx positions of the participant's index and middle fingers on the left hand. The blood pulse oximetry information was recorded from the participant's left thumb with a pulse oximeter. Finally, the participant's head movement was recorded with an accelerometer placed at position CPz.

Affective state detection: Affective state detection was performed by first selecting features that were most frequently associated with changes in affective states and then classified via a combination of support vector machines (SVMs).
Features were extracted from the EEG by first segmenting the EEG into spatial regions depending on the region of the scalp the EEG was recorded from. Specifically, the EEG was subdivided into ten spatial regions, which are listed in Table 1.

Table 1: Spatial regions of EEG features.

Region	Channels
Whole head	All channels
Frontal	FP1, FP2, F7, F3, F4, F8
Central	C3, Cz, C4, CP5, CP6, CP1, CP2
Parietal	P7, P3, Pz, P4, P8, POz
Occipital	O1, O2
Left temporal	FT9, T7, TP9
Right temporal	FT10, T8, TP10
Midline	Fz, Cz, Pz, POz
Left hemisphere	FP1, F7, F3, FT9, FC5, FC1, T7, C3, TP9, CP5, CP1, P7, P3, O1
Right hemisphere	FP2, F4, F8, FC2, FC6, FT10, C4, T8, CP2, CP6, TP10, P4, P8, O2

Features were then subdivided further into 10 frequency bands. Specifically, the EEG within each spatial region was filtered into the delta (1-4 Hz), slow theta (4-5.5 Hz), fast theta (5.5-7 Hz), total theta (4-7 Hz), slow alpha (8-10 Hz), fast alpha (10-12 Hz), total alpha (8-12 Hz), sigma (12-14 Hz), beta (14-30 Hz), and gamma (30-45 Hz) frequency bands.

From the physiological signals the mean peak-to-peak interval time was extracted from the ECG and the blood pulse oximeter. Additionally, the mean amplitude of the GSR within a 1 s window was extracted and baseline corrected against the previous 1 s of data.

This resulted in a set of 103 candidate features. A subset of these features was then selected via a stepwise linear discriminant analysis approach. Features were iteratively added and removed from a linear regression model relating features (independent variables) to the participant's reported affective state over different trials (the dependent variable). This process continued until the addition or subtraction of further features did not significantly improve the fit of the regression further. The remaining set of features were then taken as the selected features for use in classifying affective states via a set of SVMs during online use of the aBCMI. Further details of this approach are reported in [4].

Case based reasoning: The case based reasoning system was used to identify the specific musical modulations that are most effective at modulating our participant's affective state in the desired direction during each trial. Specifically, case based reasoning was used to build a rule set that determines, for a given current affective state experienced by the participant and a target final affective state that we want them to be moved to, what is the best set of modulations of the music generator that should be applied.

The rule set of the case based reasoning system was trained from the participant's responses to the music played during a series of 3 training sessions. Each trial in these runs included different modulations to the music generator. The participant's felt affective states were

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recorded throughout the trial and used to determine the relationships between the music manipulations and the participant's felt affective states.

Music generator: A music generator was used to produce the music stimuli use throughout this study for both the offline training sessions and the online testing sessions. This allowed a very large amount of varying musical stimuli to be produced for the experiments, preventing well known effects of repeated listening on an individual's affective state [9]. An affectively driven algorithmic composition system was used to generate the music used in this study. This system has been previously described in [15, 16] and validated in [5].

Experiments: We attempted to train our aBCMI system to identify affective states and modulate music to achieve 4 key goals related to music therapy. Specifically, we attempted to use the aBCMI to achieve the following.

1. Make the participant happier: increase their reported valence.
2. Calm the participant: reduce reported arousal.
3. Reduce stress in the participant: simultaneously increase valence and decrease arousal.
4. Excite the participant: increase reported arousal.

The experiments were split over 4 sessions conducted over a 2 week period. The first three sessions were offline training sessions in which the participant was played a series of pieces of generated music intended to induce a range of different affective states. The affective state detector and case based reasoning system were trained based on the data from these sessions. Finally, the fourth session was an online session in which the aBCMI was used to attempt to achieve each of the four goals listed above.

Each training session contained 4 runs and was split into 18 trials per run (72 trials per session). In each trial the participant first observed a fixation cross for 2 s and then listened to music for 40 s. Each piece of music was generated to attempt to modulate the affective state of the participant from one of nine discrete regions on the valence arousal circumplex (high, neutral, and low valence and arousal tuples) to a new position on the circumplex. Specifically, the first 20 s of the music attempted to induce the first affective state and the next 20 s attempted to induce the second affective state.

While listening to the music the participant was instructed to report their currently felt affective state at each moment in time via the use of the, joystick controlled, FEELTRACE interface [3]. Before using the interface the system was explained to the participant via a written document, a power-point presentation, a video, and verbally. The participant was also given the opportunity to run through a practice session with the interface.

Between trials a distraction task was used to minimize serial effects of changes in affective states between trials. Specifically, the participant was asked to listen to a series of beep tones, one of which was at a higher pitch and occurred 20 % of the time and other occurred 80 % of the time. The tones were played in random order and the participant was asked to count the number of high pitch tones they heard.

The online session consisted of 6 runs, each of which contained 10 trials. In this session the aBCMI attempted to move the participant from a current affective state to a target affective state as described above. The affective state detector and the case based reasoning system were used to determine which modulations of the music generator were to be applied in each trial. The trial structure was the same as the training sessions.

Evaluation: The success of the aBCMI was measured by whether it was able to modulate our participant's affective state in the desired way significantly more often than chance during the online testing session. This was determined by inspecting the FEELTRACE reports provided by the participant during the online session. A first order polynomial function was fitted to these complete (40 s) traces over each trial and the angle of the resulting line was measured. The distribution of these angles was evaluated to determine if it differed significantly from a standard normal distribution (mean = 0, standard deviation = 1) via a Kolmogorov-Smirnov test. Specifically, if the distribution of these angles did not differ significantly from a standard normal distribution this would indicate that the participant's affective state had not been significantly altered by the aBCMI.

Furthermore, in cases where the distribution of the angles of the FEELTRACE reports was observed to differ significantly from chance the mean angle of the reports was inspected to determine whether it was moving in the correct direction for a particular goal. For example, for trials in which the aBCMI was attempting to increase the valence felt by the participant the FEELTRACE report of valence is expected to increase significantly over the course of the trial.

RESULTS

The aBCMI was able to significantly increase the participant's reported valence during trials in which the goal of the system was to make the participant happier ($p < 0.01$, ks-test, average of 17 trials per participant). This is illustrated in Figure 2.

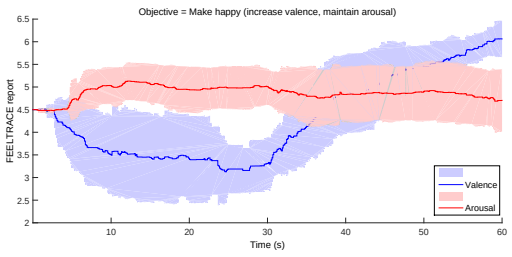

Figure 2: The participant's reported mean FEELTRACE responses over trials during the online session while us-

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ing the aBCMI to attempt to increase the valence.

Additionally, the affective state detection system was observed to be able to correctly identify the participant's felt valence in 43.8 % of the trials ($p < 0.001$) and the participant's felt arousal in 50.8 % of the trials ($p = 0.007$). These classification results, and their statistical significance, were calculated using methods first described in our earlier work [6].
However, unlike in the cohort of healthy participants reported in [8], the aBCMI was not able to successfully calm our participant. Specifically, no significant change in arousal was noted. Additionally, the aBCMI was not able to de-stress the participant, although it is worth noting that a non-significant trend of increased valence (illustrated in Figure 3) was observed during trials for which the goal was to reduce the stress of the participant. Finally, the aBCMI was not able to excite the participant. A significant increase in valence was noted during these trials but no significant change in arousal (the intended outcome of this goal) was noted.

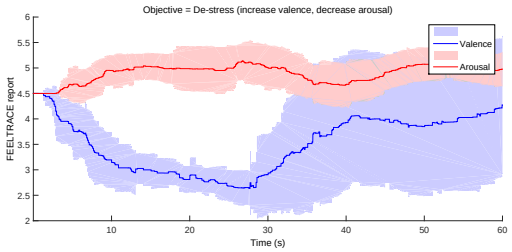

Figure 3: The participant's reported mean FEELTRACE responses over trials during the online session while using the aBCMI to attempt to de-stress (increase valence and reduce arousal).

DISCUSSION

It is not, of course, possible to draw general population wide conclusions from a single case study. Nonetheless, a number of observations may be drawn which should be considered when developing aBCMIs (and other types of affective BCIs) for use by individuals with Huntington's disease.
First, the aBCMI was able to correctly increase our participant's reported valence during trials in the online session in which the goal was to make our participant feel happier. This suggests that there is some potential for this aBCMI to be useful for at least some individuals with Huntington's disease.
Second, it is important to note that our participant had some difficulty using the 2-dimensional, joystick controlled, FEELTRACE interface to report their affective states. Although our participant was carefully briefed on what was meant by "valence" and "arousal" and how to use FEELTRACE, they had difficulty with simultaneously reporting their valence and arousal. For example, when the music attempted to first convey a neutral affective state (in terms of both valence and arousal) followed by a high valence and high arousal affective state we observed that our participant would only report an increase in valence.
In cases where only the arousal of the music changed, the participant used the FEELTRACE interface to report an increase in arousal. However, in cases where both the music's valence and arousal changed our participant reported only the change in valence. Upon careful questioning our participant reported that they felt a change in both the experienced valence and arousal while listening to the music. However, these were not reflected in his FEELTRACE report.
It may be the case that the use of FEELTRACE to report felt affect via continuously controlling a joystick is effecting the participant's affective state. Continuous use of the joystick requires a degree of concentration, and this is likely to distract from conscious awareness of the current felt affective state. However, FEELTRACE is used continuously for all affective states, thus, this effect is likely to be uniform over all affective states.
It may also be the case that, as a construct, arousal is more complex and less amenable to immediate self reporting than valence. Thus, it may have been harder for our participant to make judgments on their arousal and, consequently, their responses tended not to differ from the default middle range of the reporting space.
This suggests that FEELTRACE may not always be the most suitable tool for obtaining a ground truth measure of felt affective states. Alternative tools, such as GTRACE, which allows independent reporting of valence and arousal [2], and an alternative training process, which doesn't include any trials in which both valence and arousal are simultaneously changed, may be needed in these cases.
It is important to note that there is no completely agreed upon method to measure affective state from the individual [12]. Subjective measurements (such as FEELTRACE) and objective measures (such as physiological measurements) are both subject to error. The inaccuracy in reporting may also, in part, explain the relatively lower performance of the aBCMI with this participant compared to our previous cohort of healthy participants [8]. If we are not always able to obtain an accurate ground truth measure of changes in valence and arousal this is going to lead to lower classification accuracies in the affective state detection system and lower performance during the aBCMI's online session.
Third, we did not observe noticeable signal quality problems with our participant. Some individuals with Huntington's disease exhibit difficulties with movement and fidgeting, which may lead to increased amounts of artefact in the observed EEG. However, this was not observed to be the case in our study. Nonetheless, in general robust artefact removal methods are needed to assist with acquiring good quality EEG signals from such patient groups.
Finally, our case study suggests that there may be some

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potential for our aBCMI as a tool to aid with some aspects of therapy for individuals with Huntington's disease. However, a number of adjustments may need to be made to the aBCMI in order for it to be more useful for this population (for example by replacing the FEELTRACE interface with a more appropriate measure of the ground truth of the individuals affective state, such as GTRACE, for training the system). Further research in this area is needed.

Acknowledgments

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