Identifying music-induced emotions from EEG for use in brain-computer music interfacing

Ian Daly, Asad Malik, James Weaver,
Faustina Hwang, Slawmoir J. Nasuto
Brain Embodiment Lab, School of Systems Engineering,
University of Reading, Reading, UK
Email: i.daly@reading.ac.uk

Duncan Williams, Alexis Kirke,
Eduardo Miranda
Interdisciplinary Centre for Music Research,
University of Plymouth,
Plymouth, UK

***Abstract*—Brain-computer music interfaces (BCMI) provide a method to modulate an individuals affective state via the selection or generation of music according to their current affective state. Potential applications of such systems may include entertainment of therapeutic applications. We outline a proposed design for such a BCMI and seek a method for automatically differentiating different music induced affective states.**

Band-power features are explored for use in automatically identifying music-induced affective states. Additionally, a linear discriminant analysis classifier and a support vector machine are evaluated with respect to their ability to classify music induced affective states from the electroencephalogram recorded during a BCMI calibration task. Accuracies of up to 79.5 % ($p < 0.001$) are achieved with the support vector machine.

Keywords- ***Brain-computer music interfaces; Linear discriminant analysis; Support vector machines; EEG***

I. Introduction

Brain-computer music interfaces (BCMIs) provide a method for interacting with music without the need for movement [1], [2]. They may be used for applications such as entertainment.

BCMIs, as music composition systems, have been proposed based upon the use of event-related potentials and steady-state visual evoked potentials to select musical choices, such as chords and key sets. An example of this is given in work reported by Miranda et al. [3] in which steady-state visual evoked potentials are used to select musical notes.

However, music is also a powerful method for influencing emotional states. Consequently, BCMIs may be used as a form of affective computing [4]. In this application, a BCMI is used as a form of passive brain-computer interface, in which an attempt is made to identify the listeners current affective state and, consequently, move them more positive affective states.

This type of BCMI may be used as a tool for music therapy. Music therapy attempts to produce long term changes in a listener's emotional state by playing them carefully selected pieces of music [5], [6]. It has been suggested that music therapy could benefit to a range of user groups, including those with depression [7], acquired brain injury [8], or stroke [9].

We propose to use a BCMI as a tool for modulating a user's affective state. The BCMI is designed to detect a user's current affective state. New music may then be played to the user to move them into a different affective state, with the intention of producing long-term beneficial changes to their affective state.

In our proposed design music is automatically generated to target specific emotional states. This allows the BCMI to produce a theoretically infinite number of different pieces of music to suit a very wide range of affective requirements.

One of the challenges of developing a BCMI system is the accurate identification of music-induced affective states from EEG signals. This has been attempted by a number of authors [10], [11], [12]. However, accurate affective state identification during music listening remains a considerable challenge.

This manuscript first introduces our proposed BCMI design. It then goes on to detail the initial stages of the development of the BCMI. Specifically, it discusses the identification of music-induced affective state changes within the electroencephalogram (EEG) and describes our initial experimental results.

II. Brain-Computer Interface Design

The brain-computer music interface (BCMI) we propose has four key components, recording physiological signals from the user, identifying the user's current affective state, identifying what music to generate and play to the user to move from their current affective state to a target affective state, and generating and playing music to the user.

The design of the proposed BCMI is illustrated in Figure 1.

III. Methods

A. Aims

In this manuscript we aim to identify a method for automatically determining the BCMI user's current music-induced affective state from their electroencephalogram (EEG). This allows us to construct the proposed BCMI system.

Twenty healthy participants are recruited to a longitudinal study designed to allow us to identify a method for recognising a user's current music-induced affective states. A range of features and two different classifiers are explored.

B. Data Collection

1) Participants: Twenty individuals were recruited to participate in the study via email advertisement. The mean age of the participants was 22 (range 19 - 30, standard deviation 1.45). All participants were right handed and nine were female. All participants gave informed consent prior to participating

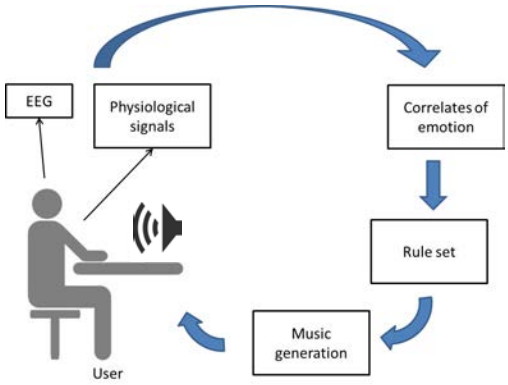


Fig. 1: Our proposed BCMI design for use in automated music therapy. EEG and physiological signals are recorded in order to identify the user's current affective state. Based upon this affective state a rule-set is used to determine which music to generate in order to move the user into a new affective state that meets the system's current objective.

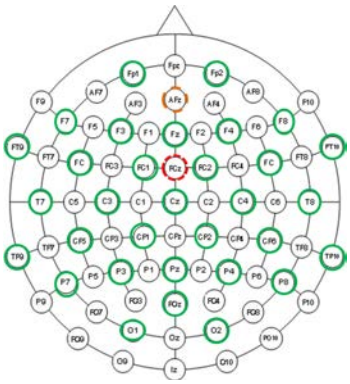


Fig. 2: EEG recording channels used.

in the study. Each participant received £10.00 (GBP) for their participation in each session of the study.

All participants attended multiple sessions. Each session lasted approximately 2 hours and ran over different days according to a schedule that was convenient for the participants.

Upon visual inspection of the recorded EEG 3 participants were noted to have large amounts of artefact in their EEG. These participants were discounted from the current analysis, leaving a total of 17 participants.

2) Recording: Electroencephalogram (EEG) was recorded from 32 electrodes positioned using a standard 10/20 recording montage. The channels used are illustrated in Figure 2.

EEG was recorded at a sample rate of 1,000 Hz via a Brain Products BrainAmp system (Brain Products, Germany). Impedances were kept below 10 kΩ for the duration of the experiment for all participants and sessions.

In addition, galvanic skin response (GSR), electrocardiogram (ECG), respiration, head movement acceleration, and blood oxygenation level were also recorded.

GSR was recorded from the ventral medial phalanx positions on the participants index and middle fingers of the left hand. ECG was recorded using a standard two-channel electrode positioning system with electrodes placed on the participant's right and left wrists. Respiration was recorded via a respiration belt placed over the base of the participant's rib cage. Head movement was recorded via a three-dimensional accelerometer placed at position CPz on the participant's head. Finally, blood oxygenation levels were measured via a pulse oximeter placed on the participant's left thumb.

These physiological signals are analysed elsewhere.

3) Ethics: Ethical approval for the experiments was obtained via the University of Reading School of Systems Engineering ethics approval procedures.

4) Experiment: Participants were asked to attend multiple consecutive sessions as part of a longitudinal study. These are categorised as either calibration sessions or training sessions. Each participant first attended 1 calibration session and then 3 training sessions. Within this manuscript we consider the data recorded during the calibration session.

The sessions were composed of multiple trials with the same structure. First the participant was presented with a fixation cross for a random duration of time lasting between 1-2 s (randomly drawn with replacement from a uniform distribution). They were then played music for either 20 s in the calibration session or 40 s in the training sessions.

During this period of time they were also asked to continuously report their current affective state via the FEELTRACE interface for reporting emotional states [13]. Participants used a track-ball mouse to interact with the FEELTRACE interface. This allowed control of the mouse cursor, while minimising movement to the participant's wrist.

After the music stopped participants were asked to report their current felt valence and arousal using self-assessment manikins [14]. This was followed by an auditory event (a beep) counting task, which acted as a distractor. Finally, an inter-stimulus interval was imposed for 2.5 s.

Trials were grouped into runs of duration 18 trials. Each calibration session contained 5 runs. Participants were given a break of at least 2 minutes duration between each run.

C. Music

To provide a range of stimuli an affectively-driven algorithmic composition (AAC) system is used [15], [16], [17].

A number of models have been adopted to measure affective responses to music. The circumplex (2-Dimensional) model is common, and is adopted in this experiment. In this model, valence represents affective state positivity, as plotted on the horizontal axis of a 2-D space, and arousal represents the intensity of the state, plotted on the vertical axis [18].

The AAC system uses a range of musical features with known affective correlates; tempo, mode, pitch range, timbre, and amplitude envelope. Specific variations in each musical feature are exploited in a generative ruleset of an AAC system to imply different affective states in newly generated music samples, via a 3x3 Cartesian grid across the affective space.

The AAC system is used to produce a stimulus set for experiments. Each stimulus is generated to consist of 20 s

TABLE I: FREQUENCY BANDS OF INTEREST.

Frequency band	Range (Hz)
Delta	1 - 4
Slow Theta	4 - 5.5
Fast Theta	5.5 - 7
Total Theta	4 - 7
Slow Alpha	8 - 10
Fast Alpha	10 - 12
Total Alpha	8 - 12
Sigma	12 - 14
Beta	14 - 30
Gamma	30 - 45

TABLE II: SCALP REGIONS OF INTEREST.

Scalp region	EEG channels
Whole scalp	All channels
Frontal	FP1, FP2, F7, F3, Fz, F4, F8
Central	C3, Cz, C4, CP5, 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

of monophonic piano music designed to target one of the 9 different affective states in the 3x3 Cartesian grid.

Ninety pieces of music are produced, with 10 pieces targeting each affective state. The participants are not informed which affective state is being targeted for each stimulus.

D. Analysis

1) Pre-processing and artefact rejection: Artefacts are identified and removed from the EEG signals via an automated artifact removal method. Specifically, the method Fully automated and online artefact removal for Brain-computer interfacing (FORCe) was employed to remove artefacts [19].

Additionally, trials were band-pass filtered in the range 4-45 Hz (2'nd order Butterworth filter). Trials were discounted from use if the maximum amplitude of the EEG within the filtered trial exceeded $\pm 200\,\mu$V. If the trial was not discounted from analysis, the original trial, after cleaning via FORCe, but before filtering, was included in subsequent analysis.

Finally, random visual spot checking of the included cleaned EEG trials was used to confirm the absence of artefacts.

2) Features: Features were extracted from the EEG via the method originally described in [20]. Specifically, the mean band-power within a range of frequency bands of interest was calculated from a range of scalp locations of interest.

Band-power was calculated as the log of the EEG after band-pass filtering into the frequency range of interest. They were calculated in the frequency bands listed in table I.

Band-power values were calculated for every channel individually and then the mean band-power was calculated within each scalp region of interest. The scalp regions of interest used in this study are listed in table II.

3) Trial segmentation: Music was played to participants continuously for 20 s. The participant continuously reported their affective state, which was expected to change continuously over time as they listened to the music. Therefore, to attempt to identify the user's current affective state with high temporal resolution, music listening periods are split into new "trials" of non-overlapping 1 s durations. Features are extracted from each of these new trials along with the corresponding mean affective states reported by the participants within these 1 s periods. This results in 1800 new trials per participant.

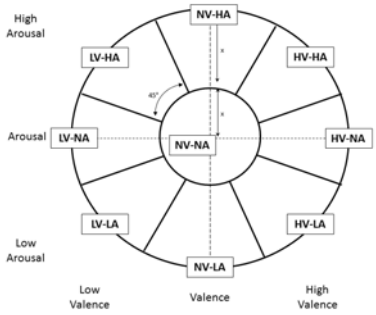


Fig. 3: The segmentation of the FEELTRACE response space into discrete regions. Regions are labelled as low (L), neutral (N), and high (H) arousal (A), or valence (V).

4) Affective states: Participants report their current affective states via FEELTRACE. This provides a circular area in which to position a cursor to report current affective states. We coarse grain participants' reports of their affective states by segmenting this space into discrete zones corresponding to high, neutral, and low valence and arousal (see figure 3).

Each zone within the FEELTRACE response space has the same area and is given a unique arbitrary numeric label. This allows a discrete set of labels to be constructed corresponding to the participant's report of their current music-induced affective state during each 1 s trial.

5) Feature selection: Feature selection is performed via stepwise linear regression. A regression model is sought between the candidate features and the coarse grained reports of participants' music-induced affective states. Features are added and removed from the regression model if doing so significantly improves the fit of the regression model ($p < 0.05$).

6) Verification: In order to account for inter-participant differences in EEG and affective responses to music each participant is analysed individually. A 10x10 cross-fold train and validation approach is used to select features and train a classifier to differentiate trials according to the participants reports of their current music-induced affective states.

Two different classifiers are used; a linear discriminant analysis (LDA) classifier and a support vector machine (SVM).

TABLE III: CLASSIFICATION ACCURACIES AT DIFFERENTIATING TRIALS BY PARTICIPANTS' REPORTS OF THEIR MUSIC-INDUCED VALENCE (HIGH VALENCE VS. LOW VALENCE). AN LDA CLASSIFIER IS USED. SIGNIFICANCE (P) IS ESTIMATED FROM THE BINOMIAL DISTRIBUTION.

Participant	Acc. (mean)	Acc. (STD)	p
1	0.686	0.065	< 0.001
2	0.701	0.059	0.001
3	0.654	0.057	0.003
4	0.709	0.079	0.002
5	0.708	0.068	0.002
6	0.567	0.064	0.047
7	0.533	0.079	0.116
8	0.648	0.079	0.002
9	0.761	0.061	< 0.001
10	0.594	0.107	0.097
11	0.671	0.044	< 0.001
12	0.610	0.048	0.009
13	0.649	0.051	0.004
14	0.694	0.059	< 0.001
15	0.663	0.054	0.002
16	0.661	0.067	< 0.001
17	0.637	0.151	0.025
Avg.	0.656	0.068	-

The SVM is trained with a quadratic kernel using a least squares programming method. This is motivated by the widely made observation that, for EEG classification, non-linear classifiers can outperform linear classification methods [21].

Classification accuracy is measured via balanced accuracy [22]. This is more robust to changes in class size due to artefact trial rejection than traditional accuracy calculations.

Two binary classification problems are considered in this study. These are, differentiating trials in which the participants report high levels of music-induced valence from low levels of music-induced valence and differentiating trials in which participants report high arousal from trials in which they report low arousal. These classification problems provide a proof-of-principle demonstration for differentiating between key affective states and may be used as the basis for a more thorough classification approach for use in BCMI systems.

IV. Results

A. Classification Accuracy

The classification results achieved with the Linear discriminant analysis (LDA) classifier in differentiating high valence and low valence trials are listed in table III.

The classification accuracies achieved when differentiating high and low arousal trials via an LDA are listed in table IV.

These results may be compared to those achieved with a support vector machine (SVM). These results for high valence and low valence trials are listed in table V.

Additionally, we attempt to classify high and low arousal via an SVM. The results for this are listed in table VI.

The classification accuracies achieved with the LDA and the SVM are compared via a paired t-test. It is found that the SVM classifier produces significantly higher classification

TABLE IV: CLASSIFICATION ACCURACIES AT DIFFERENTIATING TRIALS BY PARTICIPANT REPORTS OF MUSIC-INDUCED AROUSAL (HIGH AROUSAL VS. LOW AROUSAL). AN LDA CLASSIFIER IS USED. SIGNIFICANCE (P) IS ESTIMATED FROM THE BINOMIAL DISTRIBUTION.

Participant	Acc. (mean)	Acc. (STD)	p
1	0.738	0.066	< 0.001
2	0.597	0.059	0.032
3	0.619	0.084	0.019
4	0.609	0.087	0.055
5	0.628	0.069	0.014
6	0.533	0.079	0.034
7	0.629	0.081	0.038
8	0.599	0.057	0.018
9	0.671	0.063	0.009
10	0.537	0.122	160
11	0.629	0.048	006
12	0.649	0.048	0.002
13	0.647	0.067	006
14	0.705	0.072	< 0.001
15	0.549	0.068	
16	0.604	0.069	0.021
17	0.568	0.059	0.053
Avg.	0.624	0.071	-

TABLE V: CLASSIFICATION ACCURACIES AT DIFFERENTIATING TRIALS BY PARTICIPANT REPORTS OF MUSIC-INDUCED VALENCE (HIGH VALENCE VS. LOW VALENCE). AN SVM CLASSIFIER IS USED. SIGNIFICANCE (P) IS ESTIMATED FROM THE BINOMIAL DISTRIBUTION.

Participant	Acc. (mean)	Acc. (STD)	p
1	0.739	0.066	< 0.001
2	0.597	0.059	0.032
3	0.619	0.084	0.019
4	0.609	0.087	0.055
5	0.628	0.069	0.014
6	0.633	0.079	0.034
7	0.629	0.081	0.038
8	0.599	0.057	0.018
9	0.671	0.063	0.009
10	0.537	0.122	0.160
11	0.629	0.048	0.006
12	0.649	0.054	0.002
13	0.647	0.067	0.006
14	0.705	0.0.072	< 0.001
15	0.549	0.068	0.067
16	0.604	0.069	0.021
17	0.568	0.059	0.053
Avg.	0.624	0.071	-

TABLE VI: CLASSIFICATION ACCURACIES AT DIFFERENTIATING TRIALS BY PARTICIPANT REPORTS OF MUSIC-INDUCED AROUSAL (HIGH AROUSAL VS. LOW AROUSAL). AN SVM CLASSIFIER IS USED. SIGNIFICANCE (P) IS ESTIMATED FROM THE BINOMIAL DISTRIBUTION.

Participant	Acc. (mean)	Acc. (STD)	p
1	0.724	0.048	< 0.001
2	0.726	0.074	< 0.001
3	0.694	0.065	< 0.001
4	0.779	0.061	< 0.001
5	0.746	0.061	< 0.001
6	0.561	0.060	0.061
7	0.591	0.099	0.081
8	0.701	0.050	< 0.001
9	0.795	0.056	< 0.001
10	0.598	0.099	0.097
11	0.700	0.051	< 0.001
12	0.659	0.053	< 0.001
13	0.677	0.059	0.002
14	0.733	0.057	< 0.001
15	0.694	0.052	< 0.001
16	0.729	0.055	< 0.001
17	0.688	0.144	0.003
Avg.	0.694	0.067	-

accuracies when classifying high vs. low arousal, compared to the LDA classifier ($p = 0.001$). However, the SVM classifier does not produce significantly higher accuracies when classifying high vs. low valence trials ($p = 0.072$).

Additionally, the features selected during the cross-fold training procedure for classifying high vs. low valence and high vs. low arousal trials are illustrated in figure 4. Note, the scalp maps illustrate the normalised probability that features from each channel will be selected in each frequency band.

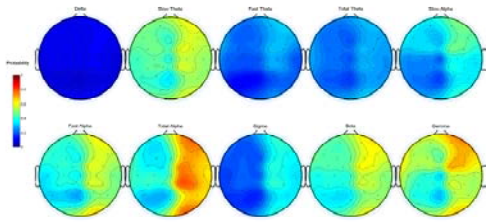
It may be observed that, in order to classify trials into high vs. low valence, features from the right hemisphere and in the central and frontal regions are most likely to be selected. Features within the total alpha, beta, and gamma frequency bands are also the most likely to be selected.

In contrast, to classify high vs. low arousal trials features in the slow theta, slow and fast alpha, and sigma frequency bands are most likely to be selected. These features are also more likely to be selected from the right hemisphere but are also frequently selected from the occipital electrodes.

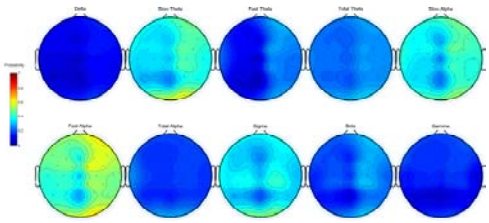
V. Discussion

Brain-computer music interfaces (BCMIs) have the potential to be useful as a form of affective brain-computer interface (aBCI). By detecting a BCMI user's current affective state it is possible to play music which is able to change their current affective state and lead to beneficial emotional changes.

A key component in the development of BCMIs for affective computing is the accurate identification of the users' current affective state. We have presented a design for a BCMI for use as an aBCI. We have also explored a method for detecting a BCMI user's current affective state.



(a) High vs. Low Valence



(b) High vs. Low Arousal

Fig. 4: Normalised probabilities of selecting features from each scalp region in each frequency band to differentiate either high vs. low valence or high vs. low arousal trials.

By using an SVM we are able to accurately identify users' current affective states with an accuracy of up to 79.5 %. This can be used to allow us to accurately determine whether the music played to a BCMI user is inducing changes in their current affective state. This accuracy may be compared to slightly higher accuracies achieved in [10] of 82.3 %. However, these results were achieved with film soundtracks created with full orchestras, which are likely to be more emotionally stimulating than the piano music used in our study.

Only binary classification was considered. However, to identify music-induced emotions during BCMI use it is necessary to perform classification with more than two classes. In future work we will investigate the use of multiple binary classifiers and voting methods to identify music-induced emotions. We will also seek to investigate the use of multi-class classifiers.

The selected features for differentiating periods when the BCMI user indicated a high music-induced valence compared to a low level of music-induced valence are concentrated in the right hemisphere. This is broadly in line with the widely known hemispheric lateralisation of emotional processing within the brain [23]. Specifically, the right hemisphere is widely reported to be more involved with emotions [24].

A similar pattern of lateralisation is also found when attempting to differentiate arousal. Additionally, the identification of features on the occipital channels for differentiating arousal conditions is reported elsewhere. For example, in [25] occipital channels are shown to exhibit different levels of band-power when threatening images are shown to participants

compared to when pleasant images are shown.

Our findings also match other attempts to identify affective states from the EEG. For example, Reuderink et al. [26] report changes in frontal theta and alpha bandpower relating to arousal and alpha assymetry relating to valence, which are among the features we find. However, they also report changes in delta related to arousal, which we do not find.

Participants report their current affective states on a continuous basis via the use of FEELTRACE. This involves continuous use of the mouse with the movements of the mouse correlated with the reported affective states. Therefore, it is possible that either movement artefacts or EEG related to movement are contaminating the results.

To reduce the risk of artefact contamination a track-ball mouse was used to minimise participant movements. Additionally, artefact removal, trial rejection via thresholding, and random visual spot-checking of the data were used to reduce the risk of artefact contamination due to movements.

Hand movement produces an event-related (de) synchronisation in the EEG, which is a change in relative band-power in the alpha and beta bands [27]. It is possible that instead of classifying emotion-related events we are classifying motor-related events. However, this is highly unlikely. The selected features are concentrated in the right hemisphere (known to be involved in emotional processing), while the contralateral hemisphere is known to be involved in movement planning.

All the participants were right handed and used FEELTRACE with their dominant hand, thus movement related activity is expected to be dominant in the left motor cortex. Additionally, this is expected to be concentrated in the alpha and beta frequency bands [27]. These features were very unlikely to be selected by the feature selection method (see figure 4). Therefore, it is unlikely that EEG activity related to motor control is used by the classifiers.

It is possible that the classification approach is identifying EEG features related to different musical features, not to music-induced emotions. For example, the change in music tempo used by the AAC system may be causing the classification results, not the change in music-induced emotions. However, this is unlikely as the EEG features used by the classifiers are similar to features used in other literature to identify emotional responses to music and other modalities.

VI. Conclusion

Two classifiers were investigated for their ability to identify music-induced emotions from EEG signals. They are intended for use in a Brain-computer music interface (BCMI).

The non-linear SVM produced significantly better performance in differentiating arousal trials. However, although the mean accuracy for high vs. low valence trials was higher with the SVM, this was not significant. This reinforces earlier findings that, although non-linear classifiers can produce higher accuracy, this improvement is often small [21].

We plan to use our classification method to build and evaluate a BCMI for changing users' affective state. We also plan to evaluate user's experiences of the system and the overall success of the final BCMI in future work.

Acknowledgment

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References

[1] R. Knapp and H. Lusted, "A Bioelectric Controller for Computer Music Applications on JSTOR." [Online]. Available: http://www.jstor.org/stable/3680115?seq=1#page_scan_tab_contents

[2] E. R. Miranda, "Brain-Computer music interface for composition and performance," *IntJ Dis Human Dev*, vol. 5, no. 2, 2006.

[3] E. R. Miranda, W. L. Magee, J. J. Wilson, J. Eaton, and R. Palaniappan, "Brain-Computer Music Interfacing (BCMI): From Basic Research to the Real World of Special Needs," *Music and Medicine*, vol. 3, no. 3, pp. 134–140, Mar. 2011.

[4] I. Daly, D. Williams, F. Hwang, A. Kirke, A. Malik, E. Roesch, J. Weaver, E. Miranda, and S. J. Nasuto, "Investigating music tempo as a feedback mechanism for closed-loop BCI control," *Brain-Computer Interfaces*, pp. 1–12, Nov. 2014. [Online]. Available: http://www.tandfonline.com/doi/abs/10.1080/2326263X.2014.979728#.VJGE-DGsWQA

[5] A. S. Maratos, C. Gold, X. Wang, and M. J. Crawford, "Music therapy for depression." *The Cochrane database of systematic reviews*, no. 1, p. CD004517, Jan. 2008. [Online]. Available: http://www.ncbi.nlm.nih.gov/pubmed/18254052

[6] O. McDermott, N. Crellin, H. M. Ridder, and M. Orrell, "Music therapy in dementia: a narrative synthesis systematic review." *International journal of geriatric psychiatry*, vol. 28, no. 8, pp. 781–94, Aug. 2013. [Online]. Available: http://www.ncbi.nlm.nih.gov/pubmed/23080214

[7] J. Erkkilä, M. Punkanen, J. Fachner, E. Ala-Ruona, I. Pöntiö, M. Tervaniemi, M. Vanhala, and C. Gold, "Individual music therapy for depression: randomised controlled trial." *The British journal of psychiatry : the journal of mental science*, vol. 199, no. 2, pp. 132–9, Aug. 2011. [Online]. Available: http://bjp.rcpsych.org/content/199/2/132.short

[8] J. Bradt, W. L. Magee, C. Dileo, B. L. Wheeler, and E. McGilloway, "Music therapy for acquired brain injury." *The Cochrane database of systematic reviews*, no. 7, p. CD006787, Jan. 2010. [Online]. Available: http://www.ncbi.nlm.nih.gov/pubmed/20614449

[9] J. Tamplin and F. Baker, *Music Therapy Methods in Neurorehabilitation: A Clinician's Manual*. Jessica Kingsley Publishers, 2006. [Online]. Available: http://books.google.com/books?hl=en&lr=&id=iIu3rAsairEC&pgis=1

[10] Y.-P. Lin, C.-H. Wang, T.-P. Jung, T.-L. Wu, S.-K. Jeng, J.-R. Duann, and J.-H. Chen, "EEG-based emotion recognition in music listening." *IEEE transactions on bio-medical engineering*, vol. 57, no. 7, pp. 1798–806, Jul. 2010. [Online]. Available: http://www.ncbi.nlm.nih.gov/pubmed/20442037

[11] K. Li, X. Li, Y. Zhang, and A. Zhang, "Affective state recognition from EEG with deep belief networks," in *2013 IEEE International Conference on Bioinformatics and Biomedicine*. IEEE, Dec. 2013, pp. 305–310. [Online]. Available: http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=6732507

[12] M. Soleymani, S. Asghari-Esfeden, M. Pantic, and Y. Fu, "Continuous emotion detection using EEG signals and facial expressions," in *2014 IEEE International Conference on Multimedia and Expo (ICME)*. IEEE, Jul. 2014, pp. 1–6. [Online]. Available: http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=6890301

[13] R. Cowie, E. Douglas-Cowie, S. Savvidou, E. McMahon, M. Sawey, and M. Schröder, "'FEELTRACE': An Instrument For Recording Perceived Emotion In Real Time," in *Proceedings of the ISCA Workshop on Speech and Emotion*, 2000, pp. 19–24. [Online]. Available: http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.58.7528

[14] M. M. Bradley and P. J. Lang, "Measuring emotion: the Self-Assessment Manikin and the Semantic Differential." *Journal of behavior therapy and experimental psychiatry*, vol. 25, no. 1, pp. 49–59, Mar. 1994. [Online]. Available: http://www.ncbi.nlm.nih.gov/pubmed/7962581

[15] A. Mattek, "Emotional Communication in Computer Generated Music: Experimenting with Affective Algorithms," in *Proceedings of the 26th Annual Conference of the Society for Electro-Acoustic Music in the United States*, 2011.

[16] D. Williams, A. Kirke, E. R. Miranda, E. Roesch, I. Daly, and S. Nasuto, "Investigating affect in algorithmic composition systems," *Psychology of Music*, pp. 1–24, Aug. 2014. [Online]. Available: http://pom.sagepub.com/content/early/2014/08/14/0305735614543282

[17] D. Williams, A. Kirke, J. Eaton, E. Miranda, I. Daly, J. Hallowell, E. Roesch, F. Hwang, and S. J. Nasuto, "Dynamic Game Soundtrack Generation in Response to a Continuously Varying Emotional Trajectory," in *Audio Engineering Society Conference: 56th International Conference: Audio for Games*. Audio Engineering Society, Feb. 2015. [Online]. Available: http://www.aes.org/e-lib/browse.cfm?elib=17593

[18] J. A. Russell, "A circumplex model of affect." *Journal of Personality and Social Psychology*, pp. 1161–1178, 1980.

[19] I. Daly, R. Scherer, M. Billinger, and G. Muller-Putz, "FORCe: Fully Online and automated artifact Removal for brain-Computer interfacing." *IEEE transactions on neural systems and rehabilitation engineering*, Aug. 2014. [Online]. Available: http://www.ncbi.nlm.nih.gov/pubmed/25134085

[20] M. Stikic, R. R. Johnson, V. Tan, and C. Berka, "EEG-based classification of positive and negative affective states," *Brain-Computer Interfaces*, vol. 1, no. 2, pp. 99–112, May 2014. [Online]. Available: http://www.tandfonline.com/doi/abs/10.1080/2326263X.2014.912883

[21] D. Garrett, D. A. Peterson, C. W. Anderson, and M. H. Thaut, "Comparison of linear, nonlinear, and feature selection methods for EEG signal classification." *IEEE transactions on neural systems and rehabilitation engineering : a publication of the IEEE Engineering in Medicine and Biology Society*, vol. 11, no. 2, pp. 141–4, 2003. [Online]. Available: http://www.ncbi.nlm.nih.gov/pubmed/12899257

[22] K. H. Brodersen, C. S. Ong, K. E. Stephan, and J. M. Buhmann, "The Balanced Accuracy and Its Posterior Distribution," in *2010 20th Int. Conf. on Patt. Recon.* IEEE, Aug. 2010, pp. 3121–3124.

[23] R. J. Davidson and N. A. Fox, "Asymmetrical brain activity discriminates between positive and negative affective stimuli in human infants." *Science (New York, N.Y.)*, vol. 218, no. 4578, pp. 1235–7, Dec. 1982. [Online]. Available: http://www.ncbi.nlm.nih.gov/pubmed/7146906

[24] N. A. Fox, "If it's not left, it's right. Electroencephalograph asymmetry and the development of emotion." *The American psychologist*, vol. 46, no. 8, pp. 863–72, Aug. 1991. [Online]. Available: http://www.ncbi.nlm.nih.gov/pubmed/1928939

[25] L. Aftanas, "Trait anxiety impact on the EEG theta band power changes during appraisal of threatening and pleasant visual stimuli," *International Journal of Psychophysiology*, vol. 50, no. 3, pp. 205–212, Nov. 2003. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0167876003001569

[26] B. Reuderink, C. Mühl, and M. Poel, "Valence, arousal and dominance in the EEG during game play," *International Journal of Autonomous and Adaptive Communications Systems*, vol. 6, no. 1, Dec. 2012. [Online]. Available: http://www.inderscienceonline.com/doi/abs/10.1504/IJAACS.2013.050691

[27] G. Pfurtscheller and F. Lopes da Silva, "Event-related EEG/MEG synchronization and desynchronization: basic principles," *Clinical Neurophysiology*, vol. 110, no. 11, pp. 1842–1857, Nov. 1999.