Artificial Affective Listening towards a Machine Learning Tool for Sound-Based Emotion Therapy and Control

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ABSTRACT

We are extending our work in EEG-based emotion detection for automated expressive performances of algorithmically composed music for affective communication and induction. This new system will involve music composed and expressively performed in real-time to induce specific affective states, based on the detection of affective state in a human listener. Machine learning algorithms will learn: (1) how to use EEG and other biosensors to detect the user's current emotional state; and (2) how to use algorithmic performance and composition to induce certain affective trajectories. In other words the system will attempt to adapt so that it can – in real-time - turn a certain user from depressed to happy, or from stressed to relaxed, or (if they like horror movies!) from relaxed to fearful. As part of this we have developed a test-bed involving an artificial listening affective agent to examine key issues and test potential solutions. As well as giving a project overview, prototype design and first experiments with this artificial agent are presented here.

1. INTRODUCTION

The aim of our research is to develop technology for implementing innovative intelligent systems that can monitor a person's affective state and induce a further specific affective states through music, automatically and adaptively. [1] investigates the use of EEG to detect emotion in an individual and to then generate emotional music based on this. These ideas have been extended into a 4.5 year EPSRC research project [2] in which machine learning is used to learn, by EEG emotional feedback, what types of music evoke what emotions in the listener. This paper introduces the key background elements behind the project: Music and Emotion, Emotional Expressive Performance and Algorithmic Composition, and EEG Affective Analysis; then details some preparatory work being undertaken, together with the future project plans.

2. MUSIC AND EMOTION

Music is commonly known to evoke various affective states (popularly referred to as "emotions") [3]. There have been a number of questionnaire studies supporting the notion that music communicates affective states (e.g., [4, 5]) and that music can be used for affect regulation and induction (e.g., [6, 7]). However the exact nature of these phenomena is not fully understood. The literature makes a distinction between perceived and induced affectivity with music being able to generate both types [4]. The differences between induced affective state and perceived affective state have been discussed by Juslin and Sloboda [3]. For example a listener may enjoy a piece of music like Barber's Adagio, which most people would describe as a "sad" piece of music. However, if they gain pleasure from listening, the induced affective state must be positive, but the perceived affective state is sadness; i.e., a negative state. Despite the differences between perceived and induced affective state, they are highly correlated [4, 8]. Zentner et al. [9] reported on research into quantifying the relationship between perceived and induced affective state in music genres.

3. EMOTION-BASED ALGORITHMIC COMPOSITION

One area of algorithmic composition which has received more attention recently is affectively-based computer-aided composition. A common theme running through some of the affective-based systems is the representation of the valence and arousal of a participant's affective state [11]. Valence refers to the positivity or negativity of an affective state; e.g., a high valence affective state is joy or contentment, a low valence one is sadness or anger. Arousal refers to the energy level of the affective state; e.g., joy is a higher arousal affective state than happiness. Until recently the arousal-valence space was a dominant quantitative two-dimensional representation of emotions in research into musical affectivity. More recently, a new theory of emotion with the corresponding scale, referred to as GEMS (Geneva Emotional Musical Scale) has been proposed [9].

Many of the affective-based systems are actually based around re-composition rather than composition; i.e. they focus on how to transform an already composed piece of music to give a different emotional effect – e.g. make it sadder, happier, etc. This is the case with the best known and most thoroughly tested system - the Computational Music Emotion Rule System (CMERS) [11]. The rules for expressing emotions map valence and arousal onto such elements as modes and pitch class. These rules were developed based on the combining a large number of studies by psychologists into music and emotion. However it was found these needed to be supplemented by rules for expressive performance of the transformed music to express the emotion successfully. Hence CMERS is actually an integrated composition and expressive performance. CMERS key limitation as a composition system is that it is designed for re-composition, not for generating new material.

Oliveira and Cardoso [13] also perform affective transformations on MIDI music, and utilize the valence-arousal approach to affective specification. These are to be mapped on to musical features: tempo, pitch register, musical scales, and instrumentation. A knowledge-base of musical features and emotion was developed based on musical segments with a known affective content. This knowledge-base was then used to train a generalized mapping of affective state to required music and a model was then generated based on Support Vector Machine regression. The model was tested for transforming the emotion of classical music – the current results are not as good as CMERS.

Although Legaspi et al. [14] utilize pre-composed music as its heart, it is more fo-cused on composing new music. An affective model is learned based on score fragments manually labeled with their appropriate affective perception – this maps a desired affective state on to a set of musical features. The model is learned based on the machine learning approaches Inductive Logic Programming and Diverse Density Weighting Metric. This is then used as a fitness function for a Genetic Algorithm – however the GA is also constrained by some basic music theory. The GA is then used to generate the basic harmonic structure, and a set of heuristics are used to generate melodies based on the harmonic structure. The system was trained with emotion label dimensions "favourable-unfavourable", "bright-dark", "happy-sad", and "heartrending-not heartrending". Listening tests were done on a series of eight bar tunes and the results obtained were considered promising, but indicated more development was needed.

4. EEG AND EMOTION

EEG measurements have been found to be useful in a clinical setting for diagnosing brain damage, sleep conditions and epilepsy; e.g. [17]. It is well known in the literature that it is possible to relate different EEG spectral bandwidths (often referred to as "EEG rhythms") to certain characteristics of mental states, such as wakefulness, drowsiness, etc. As early as the 1970s researchers have reported on the relationship between EEG asymmetry and affective state. Reviews of EEG asymmetry and affective state can be found in [18, 19] and one of the most recent sets of results can be found in [20]. Davidson [21] proposed a link between asymmetry of frontal alpha activation and the valence and arousal of a participant's affective state.

Musha and co-workers [22] developed one of the earliest computer EEG affective state detection systems and a number of detection methods have been investigated since then; e.g., [23]. More recently detection and analysis of weak synchronization patterns in EEG have been shown to be indicators of cognitive processing; growing evidence suggests that synchronization may be a carrier of information about the information processing in the brain [24]. There are different ways in which signals may co-vary. For instance, there is the hypothesis that information about many cognitive phenomena is preserved not necessarily in the intensity of the activation, but rather in the relationship between different sources of activity. There are an in-creasing number of studies investigating the role of synchronization in cognitive processing using various techniques, e.g. [25]. A particularly promising form of synchronization is called Phase–locking, which has been studied extensively by the third author and co-workers, e.g. [26]. Moreover, there is growing evidence supporting the role of synchronization in music perception [27] and also in response to affectively charged non-musical stimuli [28].

5. EMOTIONAL FEEDBACK EEG MUSIC

The above sections show that there is increasing evidence in the literature that musical traits such as rhythm, melody, tonality and expressive performance, can communicate specific affective states. There is also increasing evidence (e.g. [12]) that these states are detectable in the EEG of the listener. There are fewer studies into establishing which musical traits are useful for implementing a system to induce affective states. Amongst the techniques available, the analysis of synchronisation patterns in the EEG signal is a promising option for detecting affective states induced by music. Other techniques (as discussed in the literature) will also be considered in the project and the most suitable will be adopted. Thus the detection of affective state by EEG is a research area which this project will contribute to as well. Although initially a valence-arousal model will be used in development, other models will be utilized if found to be more effective. The valence-arousal model will be calibrated using tests involving marked-up emotional picture databases.

As was mentioned earlier, [1] investigates the use of EEG to detect emotion in an individual and to then generate emotion-inducing music based on this. The work done previously in [1] was not real-time and did not involve any machine learning process. The research and implementation of a real-time version of a more advanced detection method would allow us to monitor affective states induced by music on the fly. We hypothesise that once we establish specific musical traits associated with specific affective states, then we will be able to parameterise such traits in order to exert control in a musical composition; e.g., speed up the tempo to induce affective state X, use a “harsher” timbre to induce state Y, etc. The parameterisation of musical traits will allow for the design of algorithms capable of generating music (e.g., rule-based) embodying musical traits aimed at inducing specific EEG-observed trajectories correlated to affective states. Such a generative system can be rendered intelligent and adaptive by means of machine learning techniques (e.g., case-based reasoning and reinforcement learning) that are able to learn to recognize complex patterns and make decisions based on detected patterns in real-time.

6. AFFECTIVE LISTENING PROTOTYPE

For full real-time tests to be run, a controlled laboratory environment will need to be available together with EEG lab assistants and various types of equipment. Given the project is geographically spread it was decided to investigate the development of a simulated testing environment. In addition to providing a potential way of testing elements of the system without a human lab set-up, these investigations would help to highlight issues which may come up in the listening tests, and allow these to be included earlier in design discussions.

One potentially useful element of a simulated testing environment would be a virtual “emotional listener”. Such a listener would take as input music, and respond to the music with artificial emotions. This would not be useful for simulating EEG results. However once the artificial listener became sufficiently developed through iterative design to give advanced and adaptive responses, it could be placed in the machine learning and algorithmic composition / performance loop as a way of prototyping strategies without having to find a human test subject and use an EEG lab for all phases of development.

Figure 1 shows the schematic for the prototype machine listening test-bed, labeled the Affective Reactive Trajectories Harnessing Unit Response (ARTHUR). The main purpose of ARTHUR is to receive as input a MIDI tune and output an affective response to the tune. The units in ARTHUR are now described.

6.1 Music Feature Affective Response

The Affective Linear Estimator (ALE) [29] is the heart of the ARTHUR system which takes as input a monophonic tune, and responds with an estimate of the tunes’ valence and arousal. A linear equation is used to model agent B’s the affective estimate of a Tune A – this is shown in equations (1) and (2):

$$valenceEst = x_p mean(pitchA) + x_l mean(loudA) + x_k mean(keyModeA) + x_{IOI} mean(IOIA) + x_0 \quad (1)$$

$$arousalEst = y_p mean(pitchA) + y_l mean(loudA) + y_{IOI} mean(IOIA) + y_0 \quad (2)$$

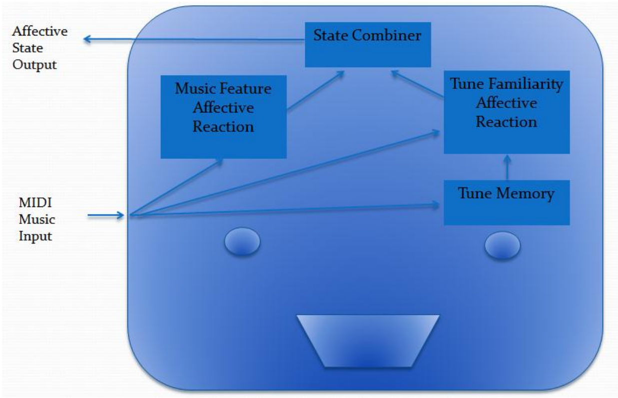

Figure 1. ARTHUR Schematic

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The parameters of ALE were estimated in a one-off process as follows. A set of 1920 random MIDI files was generated, of random lengths between 1 and 128 notes. Each MIDI file was transformed for 10 known and equally spaced valence and arousal values between -1 and 1 using transformation equations developed from a well-tested system for generating emotion-communicating music features [11] (there is not space here to detail these transformations).

	x	**y**
Pitch	-0.00214	0.003025
Loudness	0.012954	0.052129
keyMode	1.1874	-1.4301
IOI	-0.6201	0.59736
Constant	0.61425	-4.5185

Table 1. Regression Results

Then a linear regression was run on the resulting transformed MIDI files against the known arousal and valence values. The resulting coefficients are shown in Table 1. The average percentage errors – when tested on a separate 1920 transformed random files - were 10% for valence and 9% for arousal. These are considered to be sufficiently accurate. Actual human musical emotion recognition error rates can be as high as 23% [30]; and other far more complex artificial musical emotion detection systems have rates such as 81% [31].

ARTHUR does not wait until it has heard the whole tune to respond emotionally. It has an input buffer of fixed size. Once the buffer is filled it processes the music segment, then the buffer is cleared and the next segment of the music is shifted into the buffer.

6.3 Tune Familiarity Affective Reaction

ARTHUR stores all past buffer content in its memory. When hearing a new tune T*, having heard a series of tunes T_i in the past, ARTHUR adjusts its valence reaction based on both the tune affective features using equations (1) and (2), and the tune familiarity. The "mere exposure effect" is the effect that suggests that tune familiarity increases a listener's liking ratings on a tune [32]. Krugman [33] observed that valence increases with familiarity. Others have proposed a balance is needed between predictability and novelty [34]. ARTHUR's familiarity calculation is now explained.

First the similarity is compared between new tune segment T* and all past tunes T_i. The similarity is only calculated up to the length of the shortest tune. So if T* is 10 seconds long and T_i is 20 seconds long, only the first 10 seconds are compared. The system also does a simple form of pattern recognition. Rather than simply comparing each pitch and onset step by step, it moves through T* and then finds the notes that are closest in time to the notes in Ti. Then it looks at the pitch direction from a note to its next note in T*, does the same for the closest note in Ti, and compares the two. For onset times the system finds the closest note in Ti in time to each note in T* and for each of these notes compares the onsets. For similarity purposes, more weighting is given to pitch than to timing. Equations (3) to (6) detail the similarity calculations.

$$pitchDistance = distance(closest\ pitch\ directions) \quad (3)$$

$$onsetDistance = distance(closest\ onsets) \quad (4)$$

$$distance = 0.75*pitchDistance + 0.25*onsetDistance \quad (5)$$

$$similarity = 1-distance \quad (6)$$

The mean similarity of the new tune T* to all other tunes is calculated, denoted *sim*. Then this is compared to the mean similarity of all previous tunes to each other and a delta is calculated, as in equation (7). This delta is added to ARTHUR's estimate of the valence communicated by the tune on the basis of its musical features, to give the valence update.

$$deltaFamiliarity = W * (sim-meanSim) \quad (7)$$

$$valenceDelta = valenceFeatures + deltaFamiliarity \quad (8)$$

W in equation (8) is the variable which instantiates the balance between novelty and familiarity. It is calculated as in conditional equation (9).

$$W = \begin{cases} sim - (meanSim + 0.1 * stdSim) & [\text{sim} < \text{meanSim} + 0.1 * \text{stdSim}] \\ -sim + meanSim + stdSim & [\text{sim} > \text{meanSim} + \text{stdSim}] \\ 1 & [\text{Otherwise}] \end{cases} \quad (9)$$

To show how the tune familiarity and feature affective reaction elements combine, a couple of examples are now given.

6.4 Tune Familiarity Example

In these examples ARTHUR starts with 8 tunes in **its** memory, of length 12 notes, generated so that they have a variety of affective features. ARTHUR is then played a tune with a specific set of affective features repeatedly (32 times). Figure 2 shows a tune whose features are predominantly of higher valence. The pitches are fairly high and suggest a major key profile.

ARTHUR's valence reaction to being played this tune 32 times is shown in Figure 3. To understand the response it is helpful to first look at Figure 4. In Figure 4 ARTHUR's internal valence response purely to the musical features is shown.

It can be seen in Figure 4 that ARTHUR responds uniformly positively to being played the tune, and in fact ARTHUR "feels" more and more positive **the** more times it hears the tune. However in Figure 3, where tune familiarity is included, it can be see that there is a**n initial** period of very positive response from ARTHUR to the tune. In fact the gradient increase**s** the first 4 or 5 hearings. However after this the gradient drops off very fast until there is no positive response. It fact it can be seen that ARTHUR reacts *negatively* on the 32^{nd} play. So initially ARTHUR's rate of valence increase goes up, because it is being affected not only the positive music features, but because the tune is becoming more familiar. But eventually the tune becomes too familiar and ARTHUR becomes "sick" of it leading the reducing valence in spite of positive valence tune features.

A second example is shown in Figure 5. This tune is a lower pitch tune than in Figure 2. Also it has a pitch profile which indicates a minor key (C minor), so is a lower valence tune than that in Figure 2. When played repeatedly to ARTHUR the resulting valence response is that shown in Figure 6. It can be seen that valence initially decreases then increases and then drops off rapidly. The reason for this is clarified again by showing ARTHUR's internal response valence-wise to just the tune features, graphed in Figure 6.

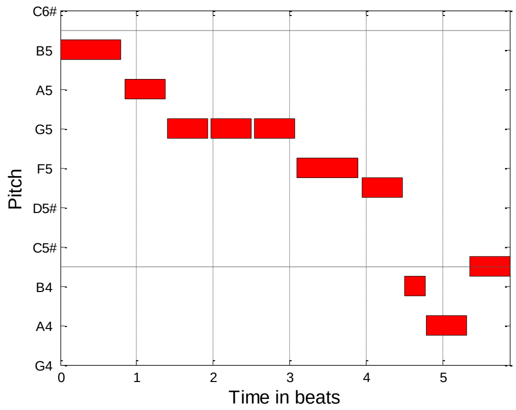

Figure 2. Higher Valence Tune 1 played to ARTHUR

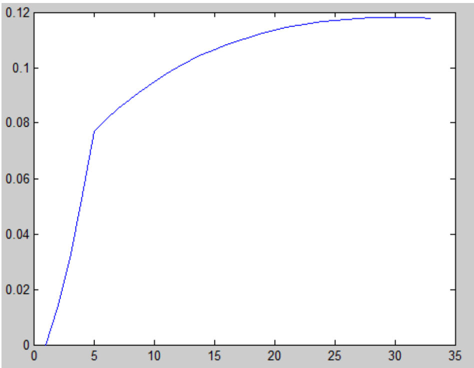

Figure 3. ARTHUR's Valence Response to repeatedly hearing Higher Valence Tune 1, with Familiarity response and Tune Memory

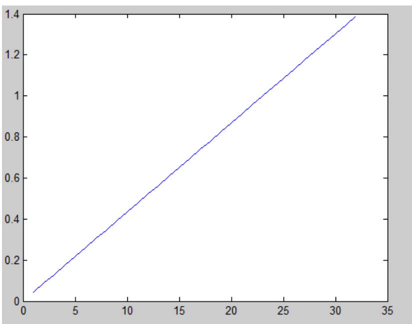

Figure 4. ARTHUR's Valence Response to repeatedly hearing Higher Valence Tune 1 without Tune Memory

It can be seen in Figure 7 that, as expected, ARTHUR's detection of the valence of the tune features will attempt to lower its valence repeatedly. So it is now possible to clarify that the initial decrease in valence in Figure 6 is partly due to ARTHUR being unfamiliar with the tune. Then there is a short period of valence increase where ARTHUR's increasing familiarity outweighs the low valence features of the tune. Then it can be seen that on repeated plays eventually the rate of valence decrease actually starts to increase, as ARTHUR gets "sick" of the tune.

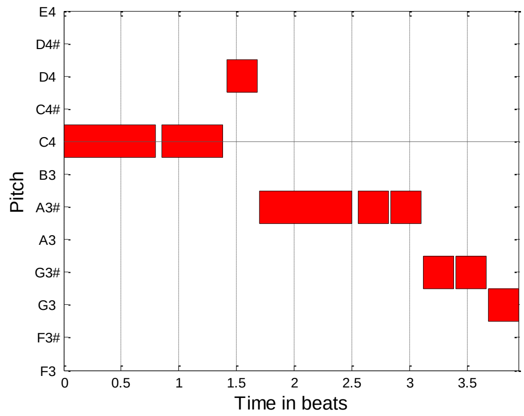

Figure 5. Lower Valence Tune 2 played to ARTHUR

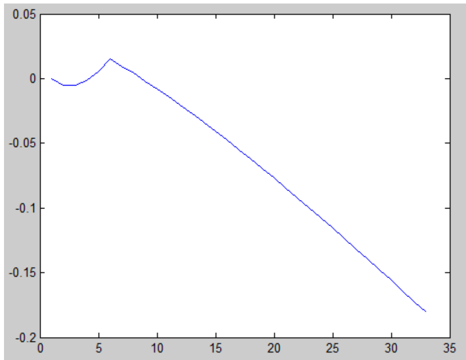

Figure 6. ARTHUR's Valence Response to repeatedly hearing Lower Valence Tune 2, with Familiarity response and Tune Memory

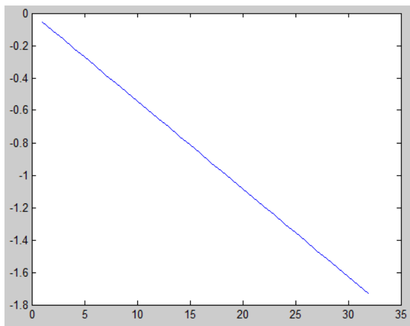

Figure 7. ARTHUR's Valence Response to repeatedly hearing Lower Valence Tune 2 without Tune Memory

This ability of ARTHUR to respond not only to the valence and arousal communicated by the tune as well as to the familiarity will hopefully make the system more useful as an offline test-bed for the brain-computer music interface system. Two key elements to highlight in ARTHUR's response are that it is highly dependent on the accuracy of simplified affective feature equations (1) and (2), and that it responds linearly. Furthermore it is based on communicated emotion research, rather than induced emotion research. However even in its simplified form ARTHUR has already highlighted some of the issues which will come up in testing, and directed the project team towards previous research on tune novelty. It also provides a starting point for developing a test bed with more advanced affective reactions.

7. CONCLUSIONS AND FUTURE WORK

A new method for utilizing the emotion-inducing nature of music and sound has been introduced. The background elements have been detailed, including affective representation, computer expressive performance, affective algorithmic composition and EEG-based machine learning. One of the initial steps in this research has been the develop of a prototype offline test bed based on a computer-listening music system (ARTHUR). This system is designed to allow for quicker and lower cost experiments to be done to test out machine learning and algorithm composition frameworks. Just as importantly it also helps to highlight and address key issues such as tune novelty response, early on in the research process.

Future work in the broader project includes characterising synchrony patterns corresponding to different induced affective states from the EEG recordings while participants listen to music stimuli. Initially, the analysis and the system for learning the emotional control music generation will be developed based on the valence arousal emotional scale, due to its widespread acceptance and availability of tagged databases. We will subsequently develop a GEMS representation for the images and will evaluate the usefulness of the two scales for developing our system.

Then, we shall progressively move towards the final goal of real-time assessment of affective states using reinforcement learning (RL). Initially, the affective state estimation will be updated at a slower time scale consistent with the computational demands of the synchronisation analysis. However, our aim is to create a system for a fast real-time assessment of affective state based on efficient analysis using feature selection and dimensionality reduction.

We plan to develop further algorithms for generating music featuring the various musical traits that have been discussed in the literature. Some musical features are more universal determinants of affective response, invariant across populations with common cultural background [9]. Other features may show more variation dependent on contextual effects of culture, personality and environment. Our initial results will be driven by more universal musical determinants of emotional response than context-specific. Thus, they will be based on results averaged across a test population. The later stages of the project will extend the former to include context-specific emotional responses.

We plan to test our initial generative music algorithms for inductive effects using an offline EEG affective state detector. The results of these tests will be used to initialize a case-based reasoning (CBR) system for affective induction by music. Then, we will extend the CBR system by investigating specific musical genres. A recent study [9] also suggested the importance of genre selection for the induction of certain affective states. The benchmark will be a classical solo piano genre, as classical music has well known computational approaches for eliciting certain affective states, but expansions on this will be investigated utilizing ideas from pop and electroacoustic music genres.

In order to have a real-time, dynamic assessment of the affective state – so as to increase accuracy and effectiveness - we will use the CBR system to initialise an automatic music generation system based on reinforcement learning (RL). RL has been successfully used in optimising the stimulation patterns in deep brain stimulation therapy of the epileptic seizures [35]. The RL system we plan to build will be used in action selection optimizing a desired affective response of this participant. The move towards more on-going assessment of affective state will be important because it will enable us to extend the system beyond the music composition based on manipulation of the musical traits eliciting generic affective responses, to a more adaptive individual-oriented system taking into account participants' states; thus utilising also the contextual effects of an individual and the environment.

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