TOWARDS AFFECTIVE ALGORITHMIC COMPOSITION

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Abstract

Automated systems for the selective adjustment of emotional responses by means of musical features are driving an emerging field: affective algorithmic composition. Strategies for algorithmic composition, and the large variety of systems for computer-automation of such strategies, are well documented in literature. Reviews of computer systems for expressive performance (CSEMPs) also provide a thorough overview of the extensive work carried out in the area of expressive computer music performance, with some crossover between composition and performance systems. Although there has been a significant amount of work (largely carried out within the last decade) implementing systems for algorithmic composition with the intention of targeting specific emotional responses in the listener, a full review of this work is not currently available, creating a shared obstacle to those entering the field which, if left unchecked, can only continue to grow. This paper gives an overview of the progress in this emerging field, including systems that combine composition and expressive performance metrics. Re-composition, and transformative algorithmic composition systems are included and differentiated where appropriate, highlighting the challenges these systems now face and suggesting a direction for further work. A framework for the categorisation and evaluation of these systems is proposed including methods for the parameterisation of musical features from semiotic research targeting specific emotional correlates. The framework provides an overarching epistemological platform and practical vernacular for the development of future work using algorithmic composition and expressive performance systems to monitor and induce affective states in the listener.

Keywords: Algorithmic composition, Affect

1. Introduction

Algorithmic composition, and the large variety of techniques for computer automation of algorithmic composition processes, are well documented in literature (Collins, 2009; Miranda, 2001; Nierhaus, 2009; Papadopoulos and Wiggins, 1999). Surveys of expressive computer performance systems such as that carried out by (Kirke and Miranda, 2009) also provide a thorough overview of the extensive work carried out in the area of emotionally targeted computer aided music performance, giving rise to the popular Computer Systems for Expressive Performance (CSEMP) paradigm, which has been used to carry out perceptual evaluations of computer aided performative systems (Katayose et al., 2012). Although there has been a significant amount of work carried out by researchers implementing musical features in algorithmic composition with the intention of targeting such specific emotional responses, an overview of this work (largely carried out within the last decade) is not currently available. This paper therefore presents an overview of existing compositional systems that use some emotional correlation to shape the use of musical features in their output.

A dimensional model of the functionality of existing systems is then presented, with each system assessed against the model. Systems covering the largest number of dimensions are then outlined in greater detail in terms of their affective model, emotional correlates, and musical feature-sets.

2. Background: terminology

This section introduces the terminology that forms the basis for assessment of the various affective algorithmic systems outlined in section 3. A hierarchical approach to musical features is proposed, whereby a combined musical or acoustic feature-set can be linked to specific emotional correlates in an affective algorithmic composition system.

Emotional models and music

The 'circumplex model of affect' (Russell, 1980) is often used synonymously with the 2-Dimensional emotion space model (Schubert, 1999a), and/or interchangeably with other models of mood or emotion focussing on arousal (activation energy, or intensity of response) and valence (high or low positivity in response) as independent dimensional attributes of emotion, such as the vector model (Bradley et al., 1992). The two-dimensional model is usually presented with arousal shown on the vertical axis and valence on the horizontal axis, giving quartiles that correspond broadly, to happy (high arousal and valence), sad (low arousal and valence), angry (high arousal, low valence), and calm (low arousal, high valence). These models of affect are general models of emotion, rather than musical models, though they have been adopted by much work in affective composition. Other models of emotion, less commonly found in the literature shown in Table 3 include the Geneva Emotional Music Scale (Zentner et al., 2008) GEMS, and the Pleasure, Arousal, Dominance model (PAD) of (Mehrabian, 1996). The GEMS was specified in order to give a model for musical emotion, by analysing a list of musically meaningful emotion terms for both induced and perceived emotions to create a nine-factorial model of emotions that can be induced by music. These factors (including nine first-order and three second-order factors) can then be used in categorical cluster analysis as an emotional measurement tool. GEMS can be considered a *categorical,* and *dimensional* musical emotion model, as opposed to more generalized *dimensional* models which comprise fewer, less complex dimensions.

Perceived vs Induced

The distinction between 'perceived' and 'induced' emotions has been well documented in much of the literature (see for example (Västfjäll, 2001; Vuoskoski and Eerola, 2011) (Gabrielsson, 2001a)), though the precise terminology used to differentiate the two does vary, as summarised in **Table 1.**

Table 1. Synonymous descriptors of 'Perceived/Induced' emotions that can be found in the literature. For detailed discussion the reader is referred to (Gabrielsson, 2001a; Kallinen and Ravaja, 2006; Scherer, 2004)

"What is the composer trying to express?"	*"How does/did the music make me feel?"*
Perceived	Felt
Conveyed	Elicited
Communicated	Induced
Cognitivist	Emotivist
Observed	Experienced
Expressed	Experienced
"a response made about the stimulus"	"a description of the state of the individual responding" (Schubert, 1999b)

Musical parameters for *induced* emotions are not well documented, though some work in this area has been undertaken (Juslin and Laukka, 2004; Scherer, 2004). For a fuller discussion of the differences in methodological and epistemological approaches to perceived and induced emotional responses to music, the reader is referred to (Gabrielsson, 2001a; Scherer et al., 2002; Zentner et al., 2000).

3. Introducing algorithmic composition

Musical feature-sets, and rules for creation or manipulation of specific musical features, are often used as the input for algorithmic composition systems. Algorithmic composition (either computer assisted or otherwise) is now a well-understood and documented field (Collins, 2009, 2009; Miranda, 2001; Nierhaus, 2009; Papadopoulos and Wiggins, 1999). An overview of a basic affective algorithmic composition, in which emotional correlates determined by literature review of perceptual experiment might be used to inform the selection of generative or transformative rules in order to target specific affective responses, is presented in **Figure 1.**

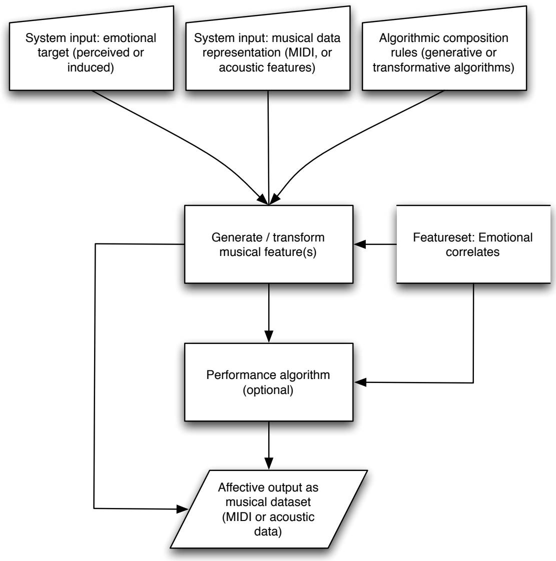

Figure 1. Overview of an affective algorithmic composition system. A minimum of three inputs are required: algorithmic compositional rules (generative, or transformative), a musical (or in some cases acoustic) dataset, and an emotional target.

This section introduces the musical and/or acoustic features used in algorithmic composition systems that are also found in literature as perceptual correlates for affective responses. An evaluation of the overlap between these two distinct types of feature is presented in the context of affective algorithmic composition, and a hierarchical approach to the implementation of musical feature-sets is proposed.

Musical and acoustic features

Musicologists have a long-established, though often evolving, grammar and vocabulary for the description of music, in order to allow detailed musical analysis to be undertaken (Huron, 1997, 2001). In computational musicological tasks, such as machine listening or music information retrieval for semantic audio analysis, complex feature-sets are often extracted for computer evaluation by means of various techniques (Mel-Frequency Cepstral Coefficients, acoustic fingerprinting, meta-analysis and so on) (Eidenberger, 2011). For the purposes of evaluating systems for affective algorithmic composition, the musical features involved necessary lie somewhere in-between the descriptive language of the musicologist and the sonic fingerprint of the semantic audiologist. The feature-set should include meaningful musical descriptors as the musical features themselves contribute to the data that informs any generative or transformative algorithms.

Whilst some musical features might have a well-defined acoustic cue (pitch and fundamental frequency, vibrato, tempo etc.), some features have more complicated acoustic (and/or musical) correlations. Therefore an awareness of the listeners' method for perceiving such features becomes important. Meter, for example (correlated with some emotions by (Kratus, 1993)), has been shown to be affected by both melodic and temporal cues (Hannon et al., 2004), as a combination of duration, pitch accent, and repetition (which might themselves then be considered 'low-level' features, with meter a 'higher-level', composite feature). Many timbral features are also not clearly, or universally, correlated (Aucouturier et al., 2005; Bolger, 2004; Schubert and Wolfe, 2006), particularly in musical stimuli, presenting similar challenges.

Musical features alone do not create a musical structure. Musical themes emerge as temporal products of these features (melodic and rhythmic patterns, phrasing, harmony and so on). An emotional trajectory can be derived in response to structural changes by listener testing (Kirke et al., 2012). For example, a reduction in tempo has been shown to correlate strongly with arousal, with a change in mode correlated with valence (Husain et al., 2002). A fully affective compositional algorithm should include some consideration of the effect of structural change — transformative systems would lend themselves particularly well to such measurement.

4. Existing systems, dimensions, and feature-sets

Existing systems for algorithmic composition targeting affective responses can be categorised according to their data sources (either musical features, emotional models, or both), and by their dimensional approach. These dimensions can be considered to be broadly bipolar as follows:

- *Compositional / Performative.* Does the system include both compositional processes and affective performance structures? Compositional systems refer synonymously to structural, score, or compositional rules. Performative rules are also synonymously referred to by some research as interpretive rules for music performance. The distinction between structural and interpretive rules might be interpreted as differences that are marked on the score (for example, dynamics might be marked on the score, and rely on a musicians interpretive performance, yet are part of the compositional intent). For a fuller examination of these distinctions, the reader is referred to (Gabrielsson, 2001).

- *Communicative / Inductive.* Does the system target affective communication, or does it target the induction of an affective state?

- *Adaptive / Non-adaptive.* Can the system adapt its output according to its input data (whether this is emotional, musical, or both)?

- *Generative / Transformative.* Does the system create output by purely generative means, or does it carry out some transformative / repurposing processing of existing material?

- *Real-time / Offline.* Does the system function in real-time?

A summary of the use, or implied use, of these dimensions amongst existing systems is given in **Table 2.** None of the systems listed target affective induction through generative or transformative algorithmic composition in real-time. This presents a significant area for further work.

Table 2. A summary of dimensionality (where known or implied by literature) in existing systems for affective algorithmic composition

System	Emotional reactions to audio signal structure	Affective music production	athenaCL	Herman	RaPScoM, GeMMA	Affective variation in computer-generated musical sounds	Inmamusy	Ossia	KTH	ROBOSER, EmotoBot, Curvasom	Multiple agents communicating emotion	CMERS	Mind Music	Moodtrack	Neuromuse
Data source(s)	Affective responses derived by statistical audio signal analysis, no direct musical feature-set	Emotion model	Circumplex model of affect, two musical features (tempo and harmonic complexity)	Single emotional control, musical features defined as rules	Circumplex model of affect, semantic categorisation of existing musical content	Pre-composed music with spectral modification	Multiagent control of musical featurset	Musical feature-set generated and evaluated by genetic algorithm	2-D model of affect (valence and arousal), musical feature-set as performance rules by weighted 'k-value'	Cell-based evolutionary algorithm and MIDI musical features	Emotion model	2-D model of affect (valence and arousal), musical feature-set as performance rules by weighted 'k-value'	Neural network of nodes with 2-D model of valence and arousal, time-signature used as musical feature	Hevner adjective cycle of emotion, bipolar musical feature-sets	EEG and parameterised synthesis model
Reference(s)	(Dubnov et al., 2006)	(Oliveira and Cardoso, n.d.)	(Mattek, 2011)	(Stapleford, 1998; Wiggins, 1999)	(Doppler et al., 2011; Rubisch et al., n.d.)	(Bailes and Dean, 2009)	(Delgado et al., 2009)	(Dahlstedt, 2007)	(Bresin and Friberg, 2000; Friberg et al., 2006)	(Eng et al., 2003; Manzolli and Verschure, 2005)	(Kirke, 2012) (Kirke and Miranda, 2011b)	(Livingstone et al., 2010)	(Eladhari et al., 2006)	(Vercoe, 2006)	(Le Groux and Verschure, 2009)
Compositional?	x		x	X	x	x	x	x	x	x	x	x	x	x	x
Performative?										x	x	x			
Inductive?															
Communicative?	x	x	x	X	x	x	x		x	x	x	x	x	x	x
Adaptive?								x	x		x	x	x	x	x
Generative?			x	X			x	x		x	x				x
Transformative?		x				X	x	x	x		x	x	x	x	
Real-time?		x			X	x			x	x		x	x	x	x

System	Automated composition system	Emotional situated data integration	Generative model for musical emotion	EIS	Emotional Musical Data Abstraction	GERM	AMEE	CAUI, SDM	Primary music-emotion structural rules	Emotion-driven interactive music system	ELM	Experience-driven procedural music generation	DM	EMGUIGA	Combined EEG system
Data source(s)	Neural network of affect, with genetic algorithm for generation of musical feature vectors	2-D model of affect (valence and arousal), musical feature-set for sieve based algorithmic composition	Genetic algorithm populated by musical feature-set	2-D emotion map and musical feature-set	Emotion model (listener defined affective responses to compositional features)	Musical feature-set and emotional model	Hevner adjective cycle of emotion, bipolar musical feature-sets	Affective responses to corpus with genetic algorithm, limited set of musical features	Musical feature-set and emotional model	Parameterized musical feature-set	Emotional cue model with eight musical features	Parameterized musical feature-set and weighted metrics for three moods	2-D model of affect (valence and arousal), musical feature-set as performance rules by weighted 'k-value'	2-D model of affect (valence and arousal), musical feature-set evaluated by genetic algorithm	2-D model of affect hierarchical structure of random motifs with algorithmically generated left-hand accompaniment
Reference(s)	(Jiang and Zhou, 2010)	(Huang, 2011)	(Birchfield, 2003)	(Chih-Fang and Yin-Jyun, 2011)	(Dzuris and Peterson, 2003)	(Juslin et al., 1999)	(Hoeberechts and Shantz, 2009; Hoeberechts et al., 2007)	(Legaspi et al., 2007; Numao et al., 2002a, 2002b; Sugimoto et al., 2008)	(Livingstone and Brown, 2005; Livingstone et al., 2007)	(Oliveras Castro, 2009)	(Juslin and Lindström, 2010; Winter, 2005)	(Plans and Morelli, 2012)	(Bresin et al., 2002; Friberg et al., 2000)	(Zhu et al., 2008)	(Kirke and Miranda, 2011a)
Compositional?	x	x	x	X	x	x	x	x	x	x	x	x	x	x	x
Performative?									x		x		x	x	x
Inductive?															
Communicative?	x	x		X	x	x	x	x	x	x	x	x	x	x	x
Adaptive?			x		X		x	x		x	x		x	x	x
Generative?	x	x	x	X		x		x		x	x	x		x	x
Transformative?					X		x		x	x		x	x	x	x
Real-time?				x		x	x	x				x	x	x	

Musical features in existing systems

The systems outlined in **Table 2** utilise a variety of musical features. Deriving a ubiquitous feature-set is not a straightforward task, due to the lack of an agreed lexicon – perceptual similar and synonymous terms abound in the literature. Though the actual descriptors used vary, a summary of the major musical features found in these systems is provided in **Table 3.** Major terms are presented left to right in decreasing order of number of instances. Minor terms are presented top to bottom in decreasing order of number of instances, or alphabetically by first word if equal in number of instances. These 'major' features are derived from the full corpus of terms by a simple verbal protocol analysis. The most prominent features are used as headings, with an implied perceptual hierarchy.

Perhaps not surprisingly, the largest variety of sub-terms comes under the 'Melody (pitch)' and 'Rhythm' headings, which perhaps indicate the highest level of perceptual significance in terms of a hierarchical approach to musical feature implementation. Tempo is the most unequivocal – it seemingly has no synonymous use in the corpus. Whilst 'mode' and its synonyms are nominally the most common, the results also show a lower number of instances of the word 'mode' or 'modality' than 'pitch' or 'rhythm', suggesting those major terms to be better understood, or rather, more universal descriptors. Whilst 'timbre' appears only 3 times in the group labelled 'Timbre', which includes 5 instances of noise/noisiness and 4 instances of harmonicity/inharmonicity, it does seem a reasonable assumption timbre should be the heading for this umbrella set of musical features given the particular nature of the other terms included within it (timbre is the commonality between each of the terms in this heading). A similar assumption might be made about dynamics and loudness, where loudness is in fact the most used term from the group, but the over-riding meaning behind most of the terms can be more comfortably grouped under dynamics as a musical feature, rather than loudness as an acoustic feature.

Under the 'Melody (pitch)' label, there could be an eighth major division, pitch direction (with a total of 8 instances in the literature, comprising synonymous terms such as melodic direction, melodic change, phrase arch, melodic progression), implying a feature based on the direction and rate of change in the pitch.

Table 3. Number of generative systems implementing each of the major musical features as part of their system. Terms taken as synonymous for each feature are expanded in italics.

Modality	*Rhythm*	*Melody (pitch)*	*Timbre*	*Dynamics*	*Tempo*	*Articulation*
29	29	28	23	17	14	13
Mode / Modality (9) *Harmony (5)* *Register (4)* *Key (3)* *Tonality (3)* *Scale (2)* *Chord Sequence (1)* *Dissonance (1)* *Harmonic sequence (1)*	*Rhythm (11)* *Density (3)* *Meter (2)* *Repetitivity (2)* *Rhythmic complexity (2)* *Duration (1)* *Inter-Onset duration (1)* *Metrical patterns (1)* *Note duration (1)* *Rhythmic roughness (1)* *Rhythmic tension (1)* *Sparseness (1)* *Time-signature (1)* *Timing (1)*	*Pitch (11)* *Chord Function (2)* *Melodic direction (2)* *Pitch range (2)* *Fundamental frequency (1)* *Intonation (1)* *Note selection (1)* *Phrase arch (1)* *Phrasing (1)* *Pitch clarity (1)* *Pitch height (1)* *Pitch interval (1)* *Pitch stability (1)* *Melodic change (1)*	*Noise / noisiness (5)* *Harmonicity / inharmonicity (4)* *Timbre (3)* *Spectral complexity (2)* *Brightness (2)* *Harmonic complexity (1)* *Ratio of odd/even harmonics (1)* *Spectral flatness (1)* *Texture (1)* *Tone (1)* *Upper extensions (1)*	*Dynamics (3)* *Loudness (5)* *Amplitude (2)* *Velocity (2)* *Amplitude envelope (1)* *Intensity (1)* *Onset time (1)* *Sound level (1)* *Volume (1)*	*Tempo (14)*	*Articulation (9)* *Micro-level timing (2)* *Pitch bend (1)* *Chromatic emphasis (1)*

5. Conclusions

An overview of affective algorithmic composition systems has been presented, including a basic vernacular for classification of such systems (by proposed dimensionality and data source), and an analysis of musical feature-sets and emotional correlations employed by these systems. Three core questions have been investigated:

Which musical features are most commonly implemented?

Modality, rhythm, and pitch are the most common features found in the surveyed affective algorithmic composition systems, with 30, 29, and 28 instances respectively found in the literature. These features include an implicit hierarchy, with, for example, pitch contour and melodic contour features making a significant contribution to the instances of pitch features as a whole.

Which emotional models are employed by such systems?

Other dimensional approaches exist, but the 2-Dimensional model (or circumplex model) of affect is by far the most common of the emotional models implemented by affective algorithmic composition systems, with multiple and single bipolar dimensional models employed by the majority of remaining systems. The existing range of emotional correlates, and even in some cases the bipolar adjective scales used, are not necessarily evenly spaced in the two-dimensional model. Therefore selecting musical features that reflect emotions that are as dissimilar as possible, (i.e., as spatially different in the *emotion-space*) would be advisable when testing the applicability of any musical features implemented at the stimulus generation stage of an affective algorithm. The GEMS specifically approaches musical emotions, allowing for a multidimensional approach (Fontaine et al., 2007) and providing a categorical model of musical emotion with nine first-order and three second-order factors, which provides the opportunity for emotional scaling of parameterised musical features in an affective algorithmic composition system.

How can existing systems be classified by dimensional approach?

A number of dimensions are proposed, which could be considered to be bipolar in nature:

- Compositional and/or performative
- Communicative or inductive
- Adaptive or non-adaptive
- Generative or transformative
- Real-time or offline

A number of systems cover several of these dimensions, but a system for the real-time, adaptive induction of affective responses by algorithmic composition (either generative or transformative), including music which has been informed by listener responses to the effect of structural remains a significant area for further work.

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