

Evolving Music with Emotional Feedback

Paul Cohen, Geoff Nitschke
chnpau006@uct.ac.za, gnitschke@cs.uct.ac.za
Department of Computer Science
University of Cape Town, South Africa

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EXTENDED ABSTRACT

Computer based music generation (synthesis) has a rich history spanning several decades [1]. Current music evolution methods are *interactive* (periodic user evaluation to drive evolutionary selection), or otherwise *feature-based* where specific musical feature metrics are incorporated into the fitness function for synthesized music evaluation and selection [2]. In the former case, various musical styles and compositions have been evolved to suit user preferences, though evolved composition diversity and complexity are limited by user fatigue and the fitness function (for example, what musical features the user evaluates). In the latter case, evolved music diversity and complexity is similarly limited by fitness function metrics. Thus, metrics conforming to specific musical styles or genres will only result in the artificial evolution of musical compositions that resemble such styles or genres [1], [2].

This research aims to develop evolutionary methods that automate the synthesis of a diverse range of complex consonant digital music with minimal user interaction. The key notion is that such music evolution is mainly directed by physiological feedback from the user's parasympathetic responses to evolving music.

Methods and Experiments

Digital music was synthesized using an NSGA-II *Multi-Objective Evolutionary Algorithm* with *non-dominated sorting* and *crowding distance* [7] based on *Evolutionary L-System* [10] (Multi-Evol-S). Multi-Evol-S was initialized with a population of random rule-sets (genotypes) encoding (50) musical pieces. Such generated musical pieces were short (10 second) electronic (*synth-pop*) melodies. Each piece comprised five musical features: *musical scales*, *pitch register*, *tempo*, *articulation*, and *instruments* [6]. Each musical feature was in the range: [0, 1], 0 indicating the feature was *off* (no sound for the given feature) and 1 the maximum value.

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Experiments ran Multi-Evol-S for (N=50) generations. Music piece (parent) selection was driven by a multi-objective fitness function using multiple *subjective* and *objective* metrics.

Objective metrics were four participant physiological readings recorded in response to each musical piece. These readings were: average time between heartbeats (IBI: *Inter-Beat Intervals*), *Rhythmic Sinus Arrhythmia* (RSA), *Heart Rate* (HR) and *Respiration Rate* (RR). Electrodes connected to the *Vrije Universiteit Ambulatory Measurement System* (VU-AMS) [8] and to the user monitored these physiological metrics (figure 1). Metric values were normalized to the range: [0, 1], where 0 was no reading and 1 the maximum value. Measurements were taken per millisecond and averages calculated over 30 seconds (musical piece duration).

The subjective component of music evaluation was *perception self-assessment* by each user. That is, rating (on a 10-point scale) their own *valence* and *arousal* (emotional) [6] response to each musical piece. For *valence*, extremes were from negative to positive and for *arousal* from calm to excited. That is, valence measured the user's positive versus negative reaction to the music stimulus and arousal measured any agitation. Thus this self-assessment indicated the user's own emotional response to evolving music.

A multi-objective fitness function (F) was used where objective physiological values: (IBI, RSA, HR, RR), were multiplied by the user *perception self-assessment* factor, and F values normalized to succinctly indicate overall user responses. A value close to 1.0 indicated a strong positive response (in terms of valence, arousal or physiological response or some combination of these metrics). Whereas, F close 0.0 indicated a strong overall negative response.

One generation of Multi-Evol-S evaluated the population of (50) musical pieces. A generation was completed when a participant had listened to 50 separate musical pieces, with 10 second intervals between each music piece, and all music pieces were assigned a *score vector* (multi-objective fitness). After each generation, specialized genetic *crossover* and *mutation* operators [5] were applied to the population's fittest 20% and child L-system rules (music pieces) replaced the least fit 20%. These operators were selected to enable sufficient genetic (and thus musical) diversity in the population. The execution of (N=50) generations constituted one experiment with the Multi-Evol-S music evolution process.

For statistical integrity and to mitigate *user* and *environmental bias* [4], experiments were replicated 10 times for each of 20 users. Thus, 50 independent experiment sets were conducted, where overall evolved music evaluation (fitness) was measured as averages

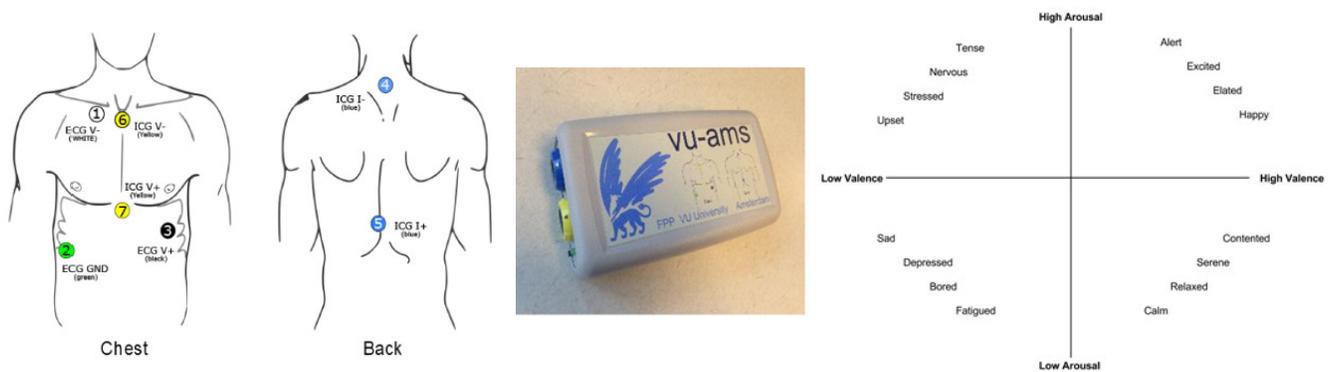


Figure 1: Left-Center: Several electrodes attached to the *Vrije Universiteit Ambulatory Measurement System (VU-AMS)* measured user physiological responses such as heart and respiration rate. Right: Diagram of emotional responses to musical stimuli graphed on axes of *arousal* and *valence*. For example, music resulting in emotional responses such as stress or nervousness were indicative of users with low valence but high arousal.

taken over all 10 replications of each experiment and over all 50 experiment sets (that is, for all the 20 users). To facilitate an analysis of evolved music, averages (per experiment and overall) of subjective and objective metrics (composing total fitness), versus corresponding variations in music feature ranges were also recorded.

To effectively evaluate whether physiological feedback (indicative of emotional reactions to musical stimuli) is an effective means to direct digital music evolution, we also conducted a set of control experiments with the same group of 20 users. These control experiments did not use physiological feedback to direct music evolution over subsequent trials, though to mitigate bias users were unaware of this. Rather, each control experiment consisted of only (10) randomly generated musical pieces (thus, no music evolution) and physiological and self-assessment readings were recorded as per usual. For consistency with the evolution experiments each control experiment was also replicated 10 times per user.

Preliminary results indicated that the given *physiological* metrics (in combination with the *perception self-assessment* metric) were suitable as synthesized music evaluation metrics to effectively direct the evolutionary synthesis of music such that the user’s own emotional and physiological responses regulated the nature (defined by the given musical features) of evolving music. Thus for example, if the synthesized music resulted in increased user IBI, RSA, HR or RR, and the user did not have adverse emotional reactions to such physiological (parasympathetic) reactions, selection in the next generation would be music pieces with similar music feature values. That is, similar sounding music pieces evoking similar emotional and physiological responses were produced.

The multi-objective fitness function (evaluating music pieces) weighted the multiple physiological metrics by user *perception self-assessment* corresponding to the strength of *valence* and *arousal* responses, meaning music piece evolution was directed by each user’s emotional reaction to their own physiological responses. Hence

music evoking strong positive or negative valence and arousal responses (and elevated physiological readings) enticed users to direct music composition evolution to synthesize music pieces that reinforced positive emotional reactions. Overall results (for all users and experiments) indicated that, on average, user reactions enabled the efficient evolution (within 10 generations) of a diverse range (in terms of musical feature values) of consonant music pieces that were tailored to individual user music tastes.

These results support hypotheses from related work postulating strong correlations between perceived emotions (valence and arousal in this study) and specific musical features such as tempo, pitch and rhythm [9], [3]. However, ongoing work is investigating purely objective based fitness functions (using parasympathetic feedback) for music evolution, where the end goal is automated music synthesis to suit one’s mood and emotions.

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