Computational Musicology: An Artificial Life Approach

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***Abstract*— Artificial Life (A-Life) and Evolutionary Algorithms (EA) provide a variety of new techniques for making and studying music. EA have been used in different musical applications, ranging from new systems for composition and performance, to models for studying musical evolution in artificial societies. This paper starts with a brief introduction to three main fields of application of EA in Music, namely *sound design*, *creativity* and *computational musicology*. Then it presents our work in the field of computational musicology. Computational musicology is broadly defined as the study of Music with computational modelling and simulation. We are interested in developing A-Life-based models to study the evolution of musical cognition in an artificial society of agents. In this paper we present the main components of a model that we are developing to study the evolution of musical ontogenies, focusing on the evolution of rhythms and emotional systems. The paper concludes by suggesting that A-Life and EA provide a powerful paradigm for computational musicology.**

Index Terms — **Artificial Life, Music, Computational Musicology, Synchronization and Evolution of Rhythm, Musical Ontogensis, Emergence of Emotion.**

I. Introduction

Acoustics, Psychoacoustics and Artificial Intelligence (AI) have greatly enhanced our understanding of Music. We believe that A-Life and EA have the potential to reveal new understandings of Music that are just waiting to be unveiled.

EA have varied applications in Music, with great potential for the study of the artificial evolution of music in the context of the cultural conventions that may emerge under a number of constraints, including psychological, physiological and ecological constraints.

We identify three main fields of application of EA in Music: *sound design*, *creativity* and *computational musicology*. The following sections briefly survey these three main fields of application. Then we introduce our work in the field of computational musicology, inspired on A-Life techniques and EA.

A. Sound Design

The production of sound faced a revolution in the middle of the 20^{th} century with the appearance of the digital computer [1]. Computers were given instructions to synthesise new sounds algorithmically. Synthesisers (or *software synthesisers*) soon became organized as a network of functional elements (signal generators and processors) implemented in software. Comprehensive descriptions of techniques for computer sound synthesis and programming can be found in the literature [2].

The vast space of parameter values that one needs to manage in order to synthesise sounds with computers led many engineers to cooperate with musicians in order find effective ways to navigate in this space. Genetic algorithms (GA) have been successfully used for this purpose [3]. EA have also been used to develop topological organizations of the functional elements of a software synthesiser, using Genetic Programming (GP) [4].

The use of extremely brief time-scales gave rise to granular synthesis [5], a technique that suits the creation of complex sounds [6], adding more control problems to the existing techniques. One of the earliest applications of EA to granular synthesis is *Chaosynth*, a software designed by Miranda [7] that uses Cellular Automata (CA) to control the production of sound grains. *Chaosynth* demonstrates the potential of CA for the evolution of oscillatory patterns in a two-dimensional space. In most CA implementations, CA variables (or cells) placed on a 2D matrix are often associated with colours, creating visual patterns as the algorithm evolves in time. However, in *Chaosynth* the CA cells are associated with frequency and amplitude values for oscillators. The amplitude and frequency values are averaged within a region of the 2D CA matrix, corresponding to an oscillator. Each oscillator contributes a partial to the overall spectrum of a grain. The spectra of the grains are generated according to the evolution of the CA in time (Fig. 1).

More recently, Mandelis and Husbands [8] developed *Genophone*, a system that uses genetic operators to create new generations of sounds from two sets of preset synthesis parameters. Some parameters are left free to be manipulated with a data-glove by an external user, who also evaluates the fitness of the resulting sounds. Offspring sounds that are ranked best by the user will become parents of a new population of sounds. This process is repeated until satisfactory sounds are found.

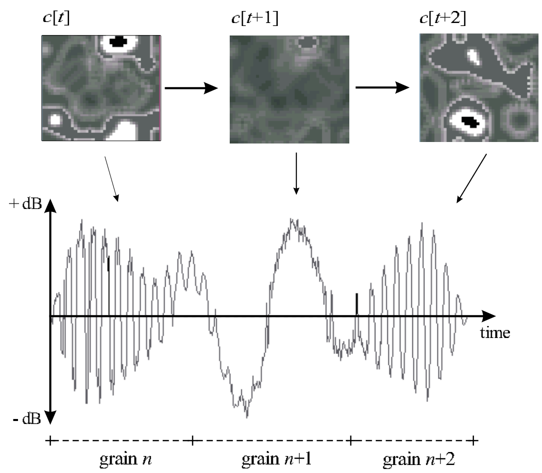

Fig. 1. Each snapshot of the CA produces correspond to a sound-grain. (Note, however, that this is only a schematic representation, as the grains displayed here do not actually correspond to these particular snapshots.)

B. Creativity

One interesting question with respect to the use of computers for aiding musical creativity is whether computers can create new kinds of musical compositions. In this case, the computer should neither be embedded with particular well-known compositional models at the outset nor learn from selected examples, which is not the case with most Artificial Intelligence-based systems for generating musical compositions.

Composers have used a number of mathematical models such as combinatorial systems, grammars, probabilities and fractals [9][10][11] to compose music that does not imitate well-known styles. Some of these composers created very interesting pieces of new music with these models and opened innovative grounds in compositional practices, e.g., the techniques created by Xenakis [12].

The use of the emergent behaviour of EA, on the other hand, is a new trend that is becoming very popular for its potential to generate new music of relatively good quality. A great number of experimental systems have been used to compose new music using EA: Cellular Automata Music [13], CA Music Workstation [14], CAMUS [15], MOE [16], GenDash [17], CAMUS 3D [18], Living Melodies [19] and Genophone [20], to cite but a few.

For example, *CAMUS* [15] takes the emergent behaviour of Cellular Automata (CA) to generate musical compositions. This system, however, goes beyond the standard use of CA in music in the sense that it uses a two-dimensional Cartesian representation of musical forms. In this representation the coordinates of a cell in the CA space correspond to the distances between the notes of a set of three musical notes.

As for GA-based generative music systems, they generally follow the standard GA procedures for evolving musical materials such as melodies, rhythms, chords, and so on. One example of such system is Vox Populi [21], which evolves populations of chords of four notes, through the operations of crossover and mutation.

EA have also been used in systems that allow for interaction in real-time; i.e., while the composition is being generated. In fact, most GA-based systems allow for this feature by letting the user to control GA operators and fitness values while the system is running. For example, Impett proposed an interesting swarm-like approach to interactive generative musical composition [22]. Musical composition is modelled here as an agent system consisting of interacting embodied behaviours. These behaviours can be physical or virtual and they can be emergent or preset. All behaviours co-exist and interact in the same world, and are adaptive to the changing environment to which they belong. Such behaviours are autonomous, and prone to aggregation and generation of dynamic hierarchic structures.

C. Computational Musicology

Computational musicology is broadly defined as the study of Music by means of computer modelling and simulation. A-Life models and EA are particularly suitable to study the origins and evolution of music. This is an innovative approach to a puzzling old problem: if in Biology the fossils can be studied to understand the past and evolution of species, these "fossils" do not exist in Music; musical notation is a relatively recent phenomenon and is most prominent only in the Western world. We are aware that Musicology does not necessarily need computer modelling and simulation to make sense. Nevertheless, we do think that "*in silico*" simulation can be useful to develop and demonstrate specific musical theories. These theories have the advantage that they can be objective and scientifically sound.

Todd and Werner [23] proposed a system for studying the evolution of musical tunes in a community of virtual composers and critics. Inspired by the notion that some species of birds use tunes to attract a partner for mating, the model employs mating selective pressure to foster the evolution of fit composers of courting tunes. The model can co-evolve male composers who play tunes (i.e., sequences of notes) along with female critics who judge those songs and decide with whom to mate in order to produce the next generation of composers and critics. This model is remarkable in the sense that it demonstrates how a Darwinian model with a pressure for survival mechanism can sustain the evolution of coherent repertoires of melodies in a community of software agents. Miranda [24] [25] proposed a mimetic model to demonstrate that a small community of interactive distributed agents furnished with appropriate motor, auditory and cognitive skills can evolve from scratch a shared repertoire of melodies (or tunes) after a period of spontaneous creation, adjustment and memory reinforcement. One interesting aspect of this model is the fact that it allows us to track the development of the repertoire of each agent of the community. Metaphorically, one could say that such models enable us to trace the musical development (or "education") of an agent as it gets older.

From this perspective we identify three important components of an Artificial Musical Society: agents synchronization, knowledge evolution, and emotional content in performance.

The first presents itself as the basis for musical communication between agents. The second, rooted on the first, allows musical information exchange, towards the creation of a cultural environment. Finally we incorporate the indispensable influence of emotions in the performance of the acquired music knowledge. The following sections present this three aspects separately. Even though they are parts of the same model, experiments were run separately. We are working towards the complete integration of the model, and co-evolution of the musical forms: from motor response to compositional processes and performances.

II. Emergent Beat Synchronisation

A. Inspiration: Natural Timing

Agents interacting with one another by means of rhythm need mechanisms to achieve beat synchronisation.

In his book *Listening*, Handel [26] argues that humans have a biological constrain referred to as *Natural Timing* or *Spontaneous Tempo*. This means that when a person is asked to tap an arbitrary tempo, they will have a preference. Furthermore, if the person is asked to tap along an external beat that is faster or slower, and if the beat suddenly stops, then they will tend to approximate to their preferred tempo. The tap interval normally falls between 200 msec and 1.4 sec, but most of the tested subjects were in the range of 200 - 900 msec [27]. The claim that this phenomenon is biologically coded rises from the extreme proximity of these values when observed in identical twins. The same disparity observed for unrelated subjects is observed in fraternal twins. The time interval between two events is called Inter-Onset Interval (IOI).

In our model, the agents "are born" with different natural timings by default. As they interact with each other, each agent adapts its beat to the beats of the other agents.

B. Synchronisation Algorithm

Computational modeling of beat synchronisation has been tackled in different ways. Large and Kolen devised a program that could tap according to a rhythmic stimulus with nonlinear-oscillators [28], using the gradient descendant method to update their frequency and phase. Another approach, by Scheirer, consisted of modelling the perception of meter using banks of filters [29]. We propose an algorithm based on Adaptive Delta Pulse Code Modulation (ADPCM) that enables the adaptation of different agents to a common ground pulse, instead of tracking a given steady pulse. Our algorithm proved to be more compatible with Handel's notion of natural timing, as discussed in the previous section. As in ADPCM for audio, where a variable time step tracks the level of an audio signal, the agent in our model uses a variable time step to adjust its IOI to an external beat. The agent counts how many beats from the other agents fit into its cycle and it determines its state based on one of the following conditions: SLOW (listened to more than one beat), FAST (no beats were listened), or POSSIBLY_SYNCHRONISED (listened to one beat). Depending on whether the agent finds itself in one of the first two states, it increases or decreases the size of their IOIs. Delta corresponds to the amount by which the value of an IOI is changed. If the agent is in the POSSIBLY_SYNCHRONISED state and the IOIs do not match, then there will be a change of state after some cycles, and further adjustments will be made until the IOIs match. However, the problem is not solved simply by matching the IOI of the other agent. Fig. 2(b) illustrates a case where the IOIs of two agents are the same but they are out of phase. An agent solves this problem by delaying its beat until it produces a beat that is close to the beat of the other agent (Fig. 2(c)).

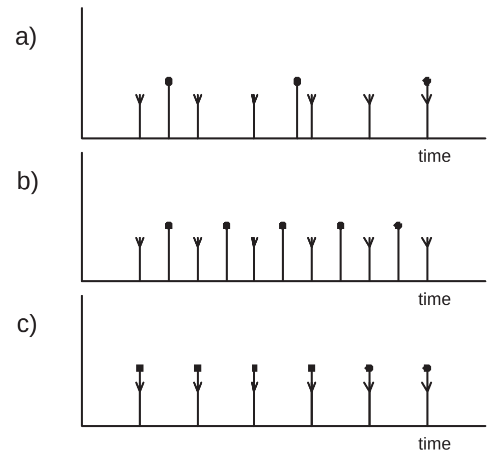

Fig. 2. (a) The agents have different IOIs; (b) The agents have the same IOI but they are out of phase; (c) The IOIs are synchronised.

C. Experiment and Result

In this section we present the result of an experiment with two agents adapting to each other's beats. Fig. 3 shows the temporal evolution of the IOIs of the agents. The minimum value for Delta, which is also the initial value of the time step, is different for the two agents. If the agent recognises that it is taking too long to change its state, the former value of Delta is multiplied by 2. Oscillatory patterns were observed when they were close to finding a common beat, due to the fact that both agents changed their IOIs and phases when they realised that they were not synchronised. The solution to this problem was solved by letting only one of the agents to change the phase after hearing one beat from the other agent.

Agent 1 started with an IOI equal to 270 ms and it had an initial adaptation step of 1 ms. Agent 2 started with an initial IOI equal to 750 ms and it had an initial adaptation step of 3 ms. Fig. 3 shows that the agents were able to find a matching IOI of 433 ms and synchronise after 26 beats. Notice that they found a common IOI after 21 beats, but they needed 5 more beats to synchronise their phases.

One interesting alternative that requires further study is the interaction between the agents and a human player. In the present case study the system requires many beats to reach synchronisation, but it is expected that the ability that humans have to find a common beat quickly may introduce a shortcut into the whole process.

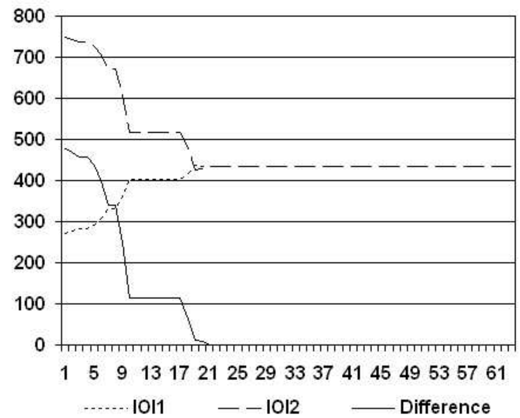

Fig. 3. Evolution of IOIs and their difference.

In this experiment, the "spontaneous tempo" and the Delta values of the agents were initialised by hand. But once the synchronisation algorithm is embedded in a model to study the evolution of musical rhythm one needs to implement a realistic way to initialise these values. Different agents can be implemented with different default Delta value but it would be more realistic to devise a method to modulate such value in function of some form of musical expression, or semantics. In order to do this, we are looking into ways in which we could program the agents to express emotions. In this case, the agents should be given the ability to modulate Delta coefficients and initial deviations from their "spontaneous tempo" in function of their emotional state. In section IV we present the first phase of an emotional system that we are developing to implement this.

III. Musical Ontogenesis in an Artificial Society

In Philosophy of Science, ontogenesis refers to the sequence of events involved in the development of an individual organism from its birth to its death. We therefore use the term musical ontogenesis to refer to the sequence of events involved in the development of the musicality of an individual. Intuitively, it should be possible to predict the music style of future musicians according to restrained music material that is absorbed during their formative stages. But would it be possible to objectively study the way in which composers or improvisers create music according to their educational background? Although it may be too difficult to approach this subject with real human musicians, we suggest that it should be possible to develop such studies with artificial musicians. A model of musical ontogenesis is therefore useful to study the influence of the musical material learned during the formative years of artificial musicians, especially in systems for musical composition and improvisation. A growing number of researchers are developing computer models to study cultural evolution, including musical evolution ([30] [31] [32] [33]). Gimenes [34] presents RGeme, an artificial intelligence system for the composition of rhythmic passages inspired by Richard Dawkin's theory of memes. Influenced by the notion that genes are units of genetic information in Biology, memes are defined as basic units of cultural transmission. A rhythmic composition would be understood as a process of interconnecting ("composition maps") sequences of basic elements ("rhythmic memes"). Different "rhythmic memes" have varied roles in the stream. These roles are learned from the analysis of musical examples given to train the system.

A. RGeme

The overall design of the system consists of two broad stages: the learning stage and the production stage. In the learning stage, software agents are trained with examples of musical pieces in order to evolve a "musical worldview". The dynamics of this evolution is studied by analysing the behaviour of the memes logged during the interaction processes.

At the beginning of a simulation a number of Agents is created. They sense the existence of music compositions in the environment and choose the ones with which they will interact, according to some previously given parameters such as the composer's name and the date of composition.

Agents then parse the chosen compositions to extract rhythmic memes (Candidate Memes) and composition maps. The new information is compared with the information that was previously learned and stored in a matrix of musical elements (Style Matrix). All the elements in the Style Matrix possess a weight that represents their relevance over the others at any given moment. This weight is constantly changing according to a transformation algorithm that takes into account variables such as the date the meme was first listened to, the date it was last listened to and a measure of distance that compares the memes stored in the Style Matrix and the Candidate Memes. These features can be seen in more detail in [34].

At last, in the production phase the Agents execute composition tasks mainly through the reassignment of the various Composition Maps according to the information previously stored in the learning phase.

B. Experiment and Result

The different Style Matrices that are evolved in an agent's lifetime represent the evolution of its musical worldview. One can establish the importance of the diversity of the raw material (in terms of developing different musical worldviews) based on the data stored in the Style Matrix's log files. It is possible to directly control the evolution of an agent's worldview, for instance, by experimenting with different sets of compositions originated from different composers.

In Fig. 4 we show the results obtained from an experiment involving a simple learning scenario. During a given period of time an agent only interacted with a particular set of compositions by Brazilian composer Ernesto Nazareth. Afterwards, the agent interacted with a different set of compositions by another Brazilian composer, Jacob do Bandolim. In the same figure, each line represents the evolution of the relative importance (weight) of a small selection of memes that the agent learned during the simulation. Fig. 5 shows the musical notation for each one of these memes. We can observe different behaviours in the learning curves, which means that the agent was exposed to each one of these memes in different ways.

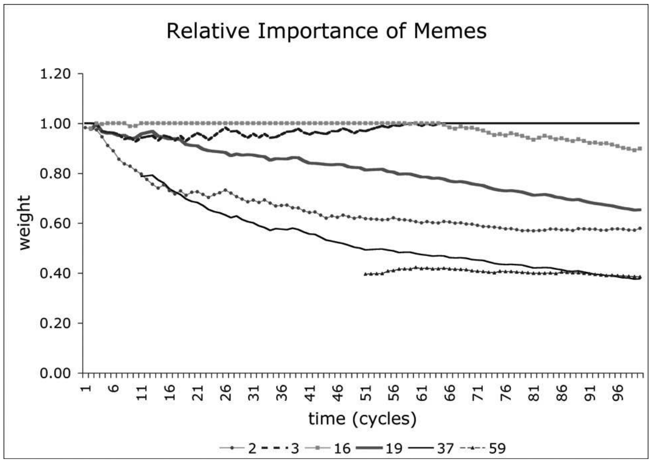

Fig. 4. Relative importance of memes in time.

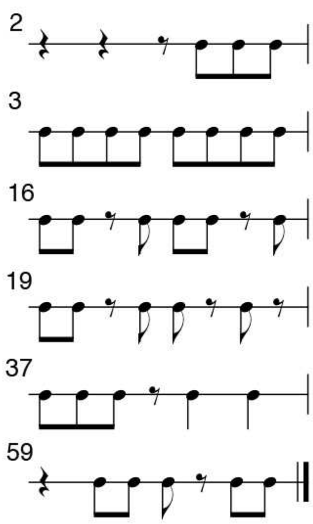

Fig. 5. Musical representation of rhythmic memes.

RGeme has the potential to execute intricate simulations with several Agents learning at the same time from rhythms by composers from inside and outside the system's environment. We believe that this model will allow for the objective establishment of a sophisticated musical ontogenesis through which one will be able to control and predict the musical culture of the inhabitants of artificial communities.

There is however a number of problems that needs to be addressed in order to increase the complexity of this model. One such problem is beat synchronisation, which has been discussed in the previous section. It is possible to observe the behaviour of thousands of male fireflies flashing synchronously during their mating season. Each insect has its own preferred pulse but they gradually adjust their pulses to a single global beat by observing each other [35]. Different humans also have their own preferred pulses, which are driven towards synchrony when engaged in collective musical performance with other humans, non-humans or both. As with fireflies, this mechanism is believed to be biologically coded in humans.

Nonetheless, music is mostly the result of a cultural context [36]. Specially in our research, the rules for composition and performance should emerge from social interactions of agents.

IV. Modelling Emotions

A. Expressivity

The use of expressive marks by Western composers documents well the common assumption that emotions play an important role in music performance.

Expressive marks are performance indications, typically represented as a word or a short sentence written at the beginning of a movement, and placed above the music staff. They describe to the performer the intended musical character, mood, or emotion as an attribute of time, as for example, *andante con molto sentimento*, where *andante* represents the tempo marking, and *con molto sentimento* its emotional attribute.

Before the invention of the metronome by Dietrich Nikolaus Winkel in 1812, composers resorted to words to describe the tempo (the rate of speed) in a composition: Adagio (slowly), Andante (walking pace), Moderato (moderate tempo), Allegretto (not as fast as allegro), Allegro (quickly), Presto (fast). The metronome's invention provided a mechanical discretization of musical time by a user chosen value (beat-unit), represented in music scores as the rate of beats per minute (quarter-note = 120). However, after the metronome's invention, words continued to be used to indicate tempo, but now often associated with expressive marks. In some instances, expressive marks are used in lieu of tempo markings, as previous associations indicate the tempo being implied (e.g. *funebre* implies a slow tempo).

The core "repertoire" of emotional attributes in music remains short. Expressions such as *con sentimento*, *con bravura*, *con affetto*, *agitato*, *appassionato*, *affetuoso*, *grave*, *piangendo*, *lamentoso*, *furioso*, and so forth, permeate different works by different composers since Ludwig van Beethoven (1770-1827) (for an example see Fig. 6) . But what exactly do these expressions mean?

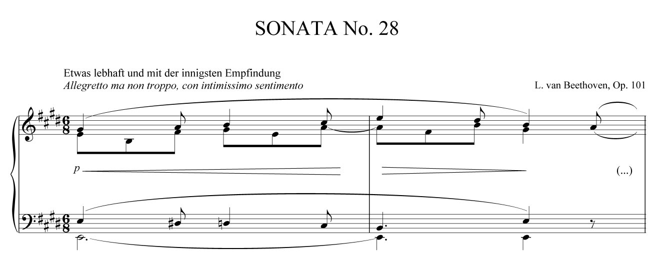

Fig. 6. Beethoven score: example of use of emotional attributes.

Each performer holds a different system of beliefs of what expressions such as *con sentimento* represent, as our understanding of emotions has not yet reduced them to a lawful behaviour. Without consensus on the individual meaning of such marks, a performance *con sofrimento* is indistinguishable from one *con sentimento*, since both expressions presume an equally slow tempo. Although we have no agreement on the meaning of expressive marks and their direct musical consequences, musicians have intuitively linked expressivity with irregularity within certain boundaries. Celebrated Polish pianist and composer Ignacy Jan Paderewski (1860-1941) stated: "every composer, when using such words as *espressivo*, *con molto sentimento*, *con passione*, and so on, demands (...) a certain amount of emotion, and emotion excludes regularity... to play Chopin's G major Nocturne with rhythmic rigidity and pious respect for the indicated rate of movement would be (...) intolerably monotonous (...). Our human metronome, the heart, under the influence of emotion, ceases to beat regularly - physiology calls it arrhythmic, Chopin played from his heart. His playing was not rational, it was *emotional*" [37].

Composers are well aware that a clear representation of the musical idea reduces ambiguity in the interpretation of the message (the music score). However, the wealth of shadings, accents, and tempo fluctuations found in human performances are, at large, left unaccounted by the composer as the amount of information required to represent these type of nuances carries, in practice, no linear bearing in the detail human performers can faithfully reproduce.

While the electronic and computer music mediums provide composers the power to discretize loudness and time related values in very small increments (for example, MIDI systems [38] use 128 degrees of loudness, and time measured in milliseconds), we note that music scores for human performances use eight approximate levels of loudness (ppp, pp, p, mp, mf, f, ff, fff), and time is discretized in values hundreds of milliseconds long. If we compare any two "faithful" human performances of a work, we conclude that, from performance to performance, only the order of notes remains strictly identical.

Expression marks operate as synesthesia, that is, the stimulation of one sense modality to rise to a sensation in another sense modality [39]. Although their direct musical consequences remain unclear, we can deduce which musical levels are susceptible of being influenced: time and loudness.

These are structural levels where small value changes produce significantly different results. The amount of information needed to describe such detail in fine resolution falls outside the precision limits with which human performers process a music score to control time and the mechanics of traditional music instruments.

> "*Look at these trees!*" Liszt told one of his pupils, "*the wind plays in the leaves, stirs up life among them, the tree remains the same. That is Chopinesque rubato*[1]."

[1] *Rubbato*: from the Italian "robbed", used to denote flexibility of tempo to achieve expressiveness.

B. Emotions

We go back to the 19^{th} century to find the earliest scientific studies: Darwin's observations about bodily expression of emotions [40], James's studies on the meaning of emotion [41], and Wundt's work on the importance of emotions for Psychology [42]. But studies on behaviour focused for many years only on higher level cognitive processes, discarding emotions [43]. Still, emotions were occasionally discussed, and the ideas changed considerably within the last decade or so. Research connecting mind and body, and the role of emotions in rational thinking gained prominence after the work of Cannon and Bard [44]. In short, they suggested that there are parallel neural paths from our senses to the experience of an emotion and to its respective physiological manifestation. Later Tomkins [45][46], Plutchik [47][48] and Izard [49][50][51][52] developed similar theories. They suggested that emotions are a group of processes of specific brain structures and that each of these structures has a unique concrete emotional content, reinforcing their importance. Ekman proposed a set of basic (and universal) emotions [53], based on cross-cultural studies [54]. These ideas were widely accepted in evolutionary, behavioural and cross-cultural studies, by their proven ability to facilitate adaptive responses.

Important insights come from Antonio Damasio [55][56][57], who brought to the discussion some strong neurobiological evidence, mainly exploring the connectivity between body and mind. He suggested that, the process of emotion and feeling are part of the neural machinery for biological regulation, whose core is formed by homeostatic controls, drives and instincts. Survival mechanisms are related this way to emotions and feelings, in the sense that they are regulated by the same mechanisms. Emotions are complicated collections of chemical and neural responses, forming a pattern; all emotions have some regulatory role to play, leading in one way or another to the creation of circumstances advantageous to the organism exhibiting the phenomenon. The biological function of emotions can be divided in two: the production of a specific reaction to the inducing situation (e.g. run away in the presence of danger), and the regulation of the internal state of the organism such that it can be prepared for the specific reaction (e.g. increased blood flow to the arteries in the legs so that muscles receive extra oxygen and glucose, in order to escape faster). Emotions are inseparable from the idea of reward or punishment, of pleasure or pain, of approach or withdrawal, or personal advantage or disadvantage.

Our approach to the interplay between music and emotions follows the work of these researchers, and the relation between physiological variables and different musical characteristics [58]. Our objective is to develop a sophisticated model to study music performance related to an evolved emotional system. The following section introduces the first result of this development.

Physiological Data	Drives	Variation
Adrenaline	Explore	neural activity (arousal)
Blood Sugar	Hunger	metabolism, food
Endorphine	Boredom	metabolism, toys
Energy	Fatigue	metabolism, bed
Vascular Volume	Thirst	metabolism, water
Pain	Withdraw	metabolism, obstacles
Heart Rate	-	metabolism, all objects

TABLE I

PHYSIOLOGICAL DATA, DRIVES, AND THEIR DYNAMICS.

C. The Model

The current version of our model consists of an agent with complex cognitive, emotional and behavioural abilities. The agent lives in an environment where it interacts with several objects related to its behavioural and emotional states. The agent's cognitive system can be described as consisting of three main parts: Perceptual, Behavioural, and Emotional systems.

The Perceptual system (inspired in LIVIA [59] and GAIA [60]) receives information from the environment through a retina modelled as close as possible to a biological retina in functional terms. It senses a bitmap world through a *ray tracing* algorithm, inspired by the notion that photons travel from the light-emitting objects to the retina. The Behavioural system is divided into two sub-systems: Motivational and Motor Control. These sub-systems define the interaction of the agents with their environment. While the agents interact with objects and explore the world, the Motivational sub-system uses a feed-forward neural network to integrate visual input and information about their internal and physiological states. The network learns through a reinforcement learning algorithm. As for the Motor Control sub-system, the agents control their motor system by means of linear and angular speed signals, allowing them to navigate in their world; this navigation includes obstacle avoidance and object interaction. The Emotional system considers the role of emotions as part of an homeostatic mechanism [56]. The internal body state of an agent is defined by a set of physiological variables that vary according to their interaction with the world and a set of internal drives. The physiological variables and the internal drives in the current version of the model are listed in Table I. The agents explore the world and receive the stimuli from it. Motor Control signals are also controlled by the neural network. There are several types of objects: food, water, toys, beds, and obstacles. Each of them is related to one or more physiological variables. Interacting with objects causes changes in their internal body state. For instance, the Vascular Volume (refer to Table 1) of an agent will be increased if it encounters water and manifests the desire to drink it. The agent's own metabolism can also change physiological data; e.g. moving around the world decrease the energy level of an agent. An emotional state reflects the agent's well-being, and influences its behaviour through an amplification of its body alarms. For further details on the model, refer to [61].

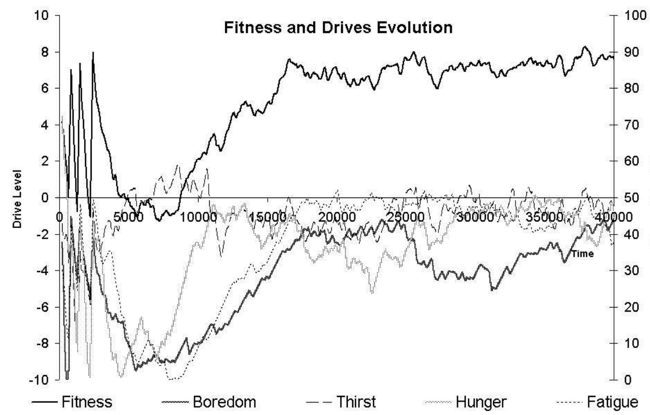

Fig. 7. Fitness vs Drives Evolution.

We propose that these emotional states affect music performance, reflecting the agent emotional state in the music. There are a few studies regarding the communication of emotions through music; for further details please refer to [58]. We simulated different musical performance scenarios inspired by these studies, and the next section presents the outcome from running the Emotional part of our model.

D. Experiment and Result

The objective of this experiment was to analyze the ability of an agent to regulate its homeostasis. To achieve this task we studied the emergence of associations between world stimuli with internal needs; in other words, an implicit world/body map. Fig. 7 shows the relation between fitness function (reflecting the agent's well-being) and the evolution of the agent's drives. The values are averages for each 200 iterations intervals. An overall increase of fitness is shown, suggesting that the agent is capable to adapt itself to new environments. Fig. 7 also shows a decrease of the amplitude of the drives as time evolves. By looking at the evolution of the drives in time we can observe that they were maintained within a certain range. This reflects the ability of the agent to respond to its "body needs". Apparently the agent not only learned how to adapt to the environment, but also did it effectively, maintaining a "healthy behaviour" by self-regulation of the homeostatic process.

A complete analysis of the system is presented in [61] .

E. Performance

Two physiological variables, selected for their influence in actual human performances [58], *Heart Rate* and *Adrenaline*, control *tempo* and *velocity* (loudness) in the performance of a piece of music [62], reflecting neural activity and emotions valence (whether positive or negative), mirroring the agent's emotional state. *Heart Rate* values modulate the on-times of events within each measure (bar), in this case 4000 ms, with a maximum deviation of +/- 640 ms. *Adrenaline* values modulate events' velocity (loudness) between user chosen limits, in this case, 80 and 127. The results can be heard at http://cmr.soc.plymouth.ac.uk/ecoutinho/ (link *Polymnia*).

Fig. 8. Score: J.S.Bach - *Prelude no I, BWV 846, from the Well Tempered Klavier I*

Heart Beat	**Note duration**	**Adrenaline**	**Amplitude**	**MIDI**
71.000	226.387	5.207	92	[145 60 92]
69.263	239.539	9.228	94	[145 64 94]
69.649	246.098	9.652	97	[145 67 97]
69.991	257.054	9.538	97	[145 72 97]
69.770	233.929	9.466	86	[145 76 86]
70.269	264.449	9.962	112	[145 67 112]
70.659	249.279	9.962	98	[145 72 98]
70.548	255.966	10.239	121	[145 76 121]
70.890	237.331	10.335	99	[145 60 99]
70.902	278.871	10.334	102	[145 64 102]
70.908	256.56	10.363	105	[145 67 105]
70.950	250.47	10.288	109	[145 72 109]
71.301	265.184	10.392	85	[145 76 85]
71.323	237.109	10.084	107	[145 67 107]
71.322	261.263	10.078	90	[145 72 90]
71.655	240.51	10.169	112	[145 76 112]

TABLE II

PERFORMANCE DATA (MIDI MESSAGES: [INSTRUMENT PITCH VELOCITY] - PIANO.

We collected the data from the simulation in the previous section to "perform" a piece of music [62]; in this case to playback a MIDI recording of a piece. In Fig. 8 we present the first measure of the piece. The anatomy of each note here represented by three parameters (MIDI messages): note-number, note-duration (measured in ms), and velocity (loudness). In the original MIDI file notes are played every 250 ms. In our piece their duration varies according to *Heart Rate* value(see Fig. II). Velocity (or loudness) is controlled by the level of *Adrenaline*. The system related *Heart Rate* onto music by mirroring stable or unstable situations, relaxation or anxiety with deviations from original rhythmic structure of each measure of music, and *Adrenaline*, by, on the one hand, mirroring excitement, tension, intensity, or, on the other hand, boredom, low arousal, by changes in note-velocity (loudness); refer to Table II.

We are currently testing the model with different conditions and metabolism, specifically the amount of resources needed to satisfy drives and the way in which these drives decrease and increase in time. A deep analysis of the behaviour of the model may reveal that performance in different environments and with different agent metabolisms can play a strong role in the affective states.

V. CONCLUDING REMARKS

At the introduction of this paper we indicated that EA has been used in a number of musical applications, ranging from sound synthesis and composition to computational musicology. An increasing number of musicians have been using EA for artistic purposes since the early 1980s. However, the potential of EA for computational musicology started to be explored only recently, after the works by researchers such as Todd, Kirby and Miranda [23] [24] [25] [63].

This paper presented three components of an A-Life model (using EA) that we are developing to study the development of musical knowledge, rooted on the problem of beat synchronisation, knowledge evolution and emotional systems.

Although the A-Life approach to computational musicology is still incipient, this paper reinforced the notion that a new approach to computational musicology is emerging.

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REFERENCES

[1] M. V. Mathews, "The digital computer as a music instrument," *Science*, vol. 142, no. 11, pp. 553–557, 1963.

[2] E. R. Miranda, *Computer Sound Design: Synthesis Techniques and Programming*. Oxford, UK: Focal Press, 2002.

[3] A. Horner, J. Beauchamp, and L. Haken, "Machine tongues XVI: Genetic algorithms and their application to fm matching synthesis," *Computer Music Journal*, vol. 17, no. 4, pp. 17–29, 1993.

[4] R. Garcia, "Growing sound synthesizers using evolutionary methods," in *Proceedings of ALMMA 2002 Workshop on Artificial Models for Musical Applications*, E. Bilotta, E. R. Miranda, P. Pantano, and P. M. Todd, Eds. Cosenza, Italy: Editoriale Bios, 2002, pp. 99–107.

[5] D. Gabor, "Acoustical quanta and the theory of hearing," *Nature*, no. 1044, pp. 591–594, 1947.

[6] P. Thomson, "Atoms and errors: towards a history and aesthetics of microsound," *Organised Sound*, vol. 9, no. 2, pp. 207–218, 2004.

[7] E. R. Miranda, *Composing Music with Computers*. Oxford, UK: Focal Press, 2001.

[8] J. Mandelis and P. Husbands, "Musical interaction with artificial life forms: Sound synthesis and performance mappings," *Contemporary Music Review*, vol. 22, no. 3, pp. 69–77, 2003.

[9] C. Dodge and T. Jerse, *Computer Music*. London, UK: Schimer Books, 1985.

[10] D. Cope, *Computers and Musical Style*. Oxford, UK: Oxford University Press, 1991.

[11] D. Worral, "Studies in metamusical methods for sound image and composition," *Organised Sound*, vol. 1, no. 3, pp. 183–194, 2001.

[12] I. Xenakis, *Formalized Music: Thought and Mathematics in Composition.* Bloomington (IN), USA: Indiana University Press, 1971.

[13] D. Millen, "Cellular automata music," in *International Computer Music Conference ICMC90*, S. Arnold and D. Hair, Eds. San Francisco (CA), USA: ICMA, 1990, pp. 314–316.

[14] A. Hunt, R. Kirk, and R. Orton, "Musical applications of a cellular automata workstation," in *International Computer Music Conference ICMC91*. San Francisco (CA), USA: ICMA, 1991, pp. 165–168.

[15] E. R. Miranda, "Cellular automata music: An interdisciplinary music project," *Interface (Journal of New Music Research)*, vol. 22, no. 1, pp. 03–21, 1993.

[16] B. Degazio, "La evolucion de los organismos musicales," in *Musica y nuevas tecnologias: Perspectivas para el siglo XXI*, E. R. Miranda, Ed. Barcelona, Spain: L'Angelot, 1999, pp. 137–148.

[17] R. Waschka II, "Avoiding the fitness bottleneck: Using genetic algorithms to compose orchestral music," in *International Computer Music Conference ICMC99*. San Francisco (CA), USA: ICMA, 1999, pp. 201–203.

[18] K. McAlpine, E. R. Miranda, and S. Hogar, "Composing music with algorithms: A case study system," *Computer Music Journal*, vol. 223, no. 2, pp. 19–30, 1999.

[19] P. Dahlstedt and M. G. Nordhal, "Living melodies: Coevolution of sonic communication," *Leonardo*, vol. 34, no. 2, pp. 243–248, 2001.

[20] J. Mandelis, "Genophone: An evolutionary approach to sound synthesis and performance," in *Proceedings of ALMMA 2001 Workshop on Artificial Models for Musical Applications*, E. Bilotta, E. R. Miranda, P. Pantano, and P. M. Todd, Eds. Cosenza, Italy: Editoriale Bios, 2001, pp. 37–50.

[21] J. Manzolli, A. Moroni, F. von Zuben, and R. Gudwin, "An evolutionary approach applied to algorithmic composition," in *VI Brazilian Symposium on Computer Music*, E. R. Miranda and G. L. Ramalho, Eds. Rio de Janeiro, Brazil: EntreLugar, 1999, pp. 201–210.

[22] J. Impett, "Interaction, simulation and invention: a model for interactive music," in *Proceedings of ALMMA 2001 Workshop on Artificial Models for Musical Applications*, E. Bilotta, E. R. Miranda, P. Pantano, and P. M. Todd, Eds. Cosenza, Italy: Editoriale Bios, 2001, pp. 108–119.

[23] P. M. Todd and G. Werner, "Frankensteinian methods for evolutionary music composition," in *Musical networks: Parallel distributed perception and performance*, N. Griffith and P. M. Todd, Eds. Cambridge (MA), USA: MIT Press/Bradford Books, 1999, pp. 313–339.

[24] E. R. Miranda, "At the crossroads of evolutionary computation and music: Self-programming synthesizers, swarm orchestras and the origins of melody," *Evolutionary Computation*, vol. 12, no. 2, pp. 137–158, 2004.

[25] E. R. Miranda, S. Kirby, and P. Todd, "On computational models of the evolution of music: From the origins of musical taste to the emergence of grammars," *Contemporary Music Review*, vol. 22, no. 3, pp. 91–111, 2003.

[26] S. Handel, *Listening: An Introduction to the Perception of Auditory Events*. Cambridge (MA), USA: The MIT Press, 1989.

[27] P. Fraisse, *The Psychology of Time*. New York, USA: Harper & Row, 1963.

[28] E. W. Large and J. F. Kolen, "Resonance and the perception of musical meter," *Connection Science*, vol. 6, pp. 177–208, 1994.

[29] E. Scheirer, "Tempo and beat analysis of acoustic musical signals," *Journal of the Acoustical Society of America*, vol. 103, no. 1, pp. 588–601, 1998. [Online]. Available: http://web.media.mit.edu/ eds/beat.pdf

[30] R. Dawkins, *The Blind Watchmaker*. London, UK: Penguin Books, 1991.

[31] A. Cox, "The mimetic hypothesis and embodied musical meaning," *MusicæScientiæ*, vol. 2, pp. 195–212, 2001.

[32] L. M. Gabora, "The origin and evolution of culture and creativity," *Journal of Memetics - Evolutionary Models of Information Transmission*, vol. 1, no. 1, pp. 1–28, 1997.

[33] S. Jan, "Replicating sonorities: towards a memetics of music," *Journal of Memetics - Evolutionary Models of Information Transmission*, vol. 4, no. 1, 2000.

[34] M. Gimenes, E. R. Miranda, and C. Johnson, "Towards an intelligent rhythmic generator based on given examples: a memetic approach," in *Digital Music Research Network Summer Conference 2005*. Glasgow, UK: The University of Glasgow, 2005, pp. 41–46.

[35] S. Strogratz and I. Stewart, "Coupled oscilators and biological synchronization," *Scientific American*, vol. 26, pp. 68–74, 1993.

[36] J. A. Sloboda, *The Musical Mind: The Cognitive Psychology of Music*. Oxford, UK: Clarendon Press, 1985.

[37] "Paderewski," http://www.wyastone.co.uk/nrl/gpiano/8816c.html, Last visited 27 April 2005.

[38] P. White, *Basic Midi*. London, UK: Sanctuary Publishing, 2000.

[39] "An essay on chopin," http://www.geocities.com/Vienna/3495/essay1.html, Last visited 27 April 2005.

[40] C. Darwin, *The Expression of the Emotions In Man and Animals*, P. Ekman, Ed. New York, USA: Oxford University Press, 1998.

[41] W. James, "What is an emotion?" *Mind*, vol. 9, pp. 188–205, 1884.

[42] W. Wundt, *Outlines of Psychology*. London, UK: Wilhelm Engelmann, 1897.

[43] R. Lazarus, *Emotion and Adaptation*. New York, USA: Oxford University Press, 1991.

[44] W. Cannon, *Bodily Changes in Pain, Hunger, Fear and Rage*. New York, USA: Appleton, 1929.

[45] S. S. Tomkins, "The positive affects," *Affect, imagery, consciousness*, vol. 1, 1962.

[46] ——, "The role of facial response in the experience of emotion," *Journal of Personality and Social Psychology*, vol. 40, pp. 351–357, 1981.

[47] R. Plutchik, "Emotion: Theory, research, and experience," *Theories of emotion*, vol. 1, pp. 3–33, 1980.

[48] ——, *The Emotions*. University Press of America, 1991.

[49] C. E. Izard, *The face of emotion*. New York, USA: Appleton-Century-Crofts, 1971.

[50] ——, *Human Emotions*. New York, USA: Plenum Press, 1977.

[51] ——, "Differential emotions theory and the facial feedback hypothesis activation," *Journal of Personality and Social Psychology*, vol. 40, pp. 350–354, 1981.

[52] ——, "Four systems for emotion activation: Cognitive and noncognitive processes," *Psychological Review*, vol. 100, no. 1, pp. 68–90, 1993.

[53] P. Ekman, "Basic emotions," in *The Handbook of Cognition and Emotion*, T. Dalgleish and T. Power, Eds. Sussex, UK: John Wiley and Sons, Ltd., 1999, pp. 45–60.

[54] ——, *Darwin and facial expression: A century of research in review*. New York, USA: Academic, 1973.

[55] A. Damasio, *Descartes' Error: Emotion, Reason, and the Human Brain*. New York, USA: Avon Books, 1994.

[56] ——, *The Feeling of What Happens: Body, Emotion and the Making of Consciousness*. London, UK: Vintage, 2000.

[57] ——, *Looking for Spinoza: Joy, Sorrow and the Feeling Brain*. New York, USA: Harcourt, 2003.

[58] P. N. Juslin and J. A. Sloboda, Eds., *Music and Emotion: Theory and Research*. Oxford University Press, 2001.

[59] E. Coutinho, H. Pereira, A. Carvalho, and A. Rosa, "Livia - life, interaction, virtuality, intelligence, art," Faculty of Engineering - University of Porto (Portugal), Tech. Rep., 2003, ecological Simulator Of Life.

[60] N. Gracias, H. Pereira, J. A. Lima, and A. Rosa, "Gaia: An artificial life environment for ecological systems simulation," in *Artificial Life V: Proceedings of the Fifth International Workshop on the Synthesis and Simulation of Living Systems*, C. Langton and T. Shimohara, Eds. MIT Press, 1996, pp. 124–134.

[61] E. Coutinho, E. R. Miranda, and A. Cangelosi, "Towards a model for embodied emotions," *Accepted to the Affective Computing Workshop at EPIA 2005*, 2005.

[62] J. S. Bach, *The Well-Tempered Clavier, Book I*, vol. BWV 846, ch. Prelude I (C major).

[63] E. R. Miranda, "Creative evolutionary systems," in *On the Origins and Evolution of Music in Virtual Worlds*, P. J. Bentley and D. W. Corne, Eds. Morgan Kaufmann, 2002, ch. 6, pp. 189–203.