Memetic network of musical agents

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Introduction

Mazzola (1998) argues that musicology should be more precise in order to become a big science. He notes that mathematics is divided into several thousand subdomains, yet the unified discipline remains a coherent whole due to its precision. Currently, such precision does not exist across different branches of musicology. In particular, neuromusicology and the social psychology of music are seen as two separate disciplines with different research domains and vocabularies. Furthermore, most of the current literature on biomusicology (Wallin, 1991) are limited to neurophysiological and neuropsychological experiments on isolated human subjects, and as such cannot explain social phenomena such as culture. As a first step towards bridging this gap, we propose a a preliminary, multilevel memetic test bed for musicological modelling.

Background

Neuroscience

The hippocampus and cerebellum are responsible for the coordination of recognition learning, reinforcement learning, and sensory-motor learning (Grossberg and Merrill, 1996). The cerebellum is also related to auditory rhythm reproduction (Penhune et al., 1998). Existing system models include the dynamic synapse, a neural network based on hippocampal dynamics (Liaw and Berger, 1996); the sparse distributed memory (SDM), an idealised model of the cerebellum (Kanerva, 1988); and the SDM Signal model, an improved SDM (Hely et al., 1997).

At the sociocultural level, Cacioppo and Berntson (1992) pioneer the doctrine of multilevel analysis in neuroscience, and coin the term social neuroscience. Kennepohl (1999) proposes a preliminary model of cultural neuropsychology, focusing on cultural influences on individual brains. In computational simulations, the multi-agent systems approach has been proposed to integrate sociocultural processes and cognition, resulting in the CLARION architecture (Sun, 2001).

Biomusicology

The field of biomusicology (Wallin, 1991) consists of evolutionary musicology, neuromusicology and comparative musicology, and the memetics of music belongs to evolutionary musicology (Brown et al., 2000).

The *meme* is “a unit of cultural transmission, or a unit of imitation” (Dawkins, 1976).

Jan (2000) applies Dawkins’ approach to classical music, and presents a preliminary model of the memetics of music. Cox (2001) presents the mimetic hypothesis for musical sounds, which holds that music cognition involves tacit imitation drawing on previous embodied experience in music making. Majoros (2002) demonstrates that the Chomsky hierarchy is not a necessary condition for birdsongs to evolve, because simulated memetic recombination at the note level is shown to be able to reconstruct the higher syntatic structures found in the recorded songs of *carpodacus mexicanus*. In computational modelling, Gabora (1997) studies the relationship between memes, creativity and SDM, and Conte (2000) points out the importance of multi-agent systems in memetic modelling.

In neuromusicology, it has been postulated that music breaks the epistemological solipsistic barrier between different human brains, which leads to social bonding and the evolution of culture (Freeman, 2000). Unlike other primates, all normal humans today are musical to a certain degree (Koelsch et al., 2000): weakly chaotic music elicits a higher EEG dimension on musically sophisticated subjects than less sophisticated ones (Birbaumer et al., 1996).

In comparative musicology, Reybrouck (2001) claims that music is a tool for sonic adaptation, and musical knowledge is generated enactively by sensorimotor integration in the *Umwelt*.

Algorithmic Composition

Spector and Alpern (1994) claim that analytical and generative rules in intelligent music systems have implicit cultural contexts imparted by their programmers. Viewed in this light, all intelligent music systems have a fixed culture (e.g. Horner and Goldberg, 1991; Spector and Alpern, 1995; Papadopoulos and Wiggins, 1998). Spector and Alpern (1994) further propose the parameterisation of culture as a case-base of valuable works. Biles (2001) presents an autonomous genetic jammer based on an evolving library of jazz licks, which is completely memetic, although he does not label it as such.

Memetic Network of Musical Agents (MNOMA)

Scope

Motivated by the lack of sociocultural models in computational musicology, we propose MNOMA (pronounced *noma*), a multilevel (Cacioppo and Berntson, 1992) memetic model of musical behaviour. It models selected parts of an artificial mammalian brain and its social interactions, incorporating cultural development (Cross, 2001) into the evolutionary model of music. Specifically, the following regions are selected: auditory cortex, hippocampus, cerebellum and motor cortex.

Assumptions

As a starting point, we assume that the unselected parts of the brain are insignificant for memetic transmission. We suppose internal memes and external memes (Conte, 2000) reside in the SDM's and the auditory outputs, respectively. We further assume that the representation of internal memes is implicitly shaped by its inputs (embodied meaning) as in the subsumption architecture (Brooks, 1991; Bryson et al., 1992). Extrapolating from Majoros's (2002) experimental results, we postulate that external memes are musical fragments and we do not account for higher-level generative structures.

System Architecture

The proposed architecture will be a network of n identical agents, where n is a parameter. Each musical agent (MA) has the same neuronal architecture (Figure 1) and is connected to the same auditory transceiver. MNOMA is similar to an interaction model (Hudak and Berger, 1995), and since each MA is implicitly both a composer and a critic, it can also be viewed as a Frankensteinian model (Todd and Werner, 1999).

Below is a breakdown of the architecture:

- **AUDITORY**. This module receives MIDI note-on messages from the auditory transceiver, and forwards them to the STM and SDM.
- **STM (HIPPOCAMPUS)**. The architecture for this module is taken from Liaw and Berger (1996). The parameters for this module are n (number of neurons) and M_H (connectivity matrix).
- **SDM (CEREBELLUM)**. The module is implemented as a SDM Signal model (Hely et al., 1997). The parameters are n (giving 2^n soft locations), m (giving 2^m hard locations), l (signal loss ratio) and M_C (connectivity matrix).

- **MOTOR**. This module receives motor commands from the SDM, and forwards them to the auditory transceiver as MIDI note-on messages.

Operational Validity

Sargent (1999) shows us how to validate simulation models. We are interested in his idea of *operational validity*, which is defined as “determining that the model’s output behavior has sufficient accuracy for the model’s intended purpose over the domain of the model’s intended applicability” (Sargent, 1999). In MNOMA, our intended domain is the basic mechanisms of music communications at the neural, individual, and sociocultural levels.

Of particular interest are the following validation techniques (Sargent, 1999):

- **Animation**. MNOMA activities are plotted graphically on a computer screen. Unreasonable patterns (such as a complete silence) can then be spotted easily.
- **Comparison to Other Models**. Simulation results are compared statistically to other validated models’ outputs.
- **Extreme Condition Tests**. MNOMA’s outputs are tested under extreme conditions, such as an extremely low number of agents. Simulation results should remain reasonable.
- **Face Validity**. Consult neuroscientists and musicologists to assess the plausiblity of the model and the choice of parameters.
- **Empiricism**. Validate at least some of the assumptions and simulation outputs empirically.
- **Internal Validity**. Check the consistency of MNOMA outputs across different simulation runs. For example, it should do similar things each time if the parameters are fixed.
- **Predictive Validation**. Simulation results are compared to future experimental data to determine the predictive power of MNOMA.

As the scope of this model is still open-ended, it is impossible to validate all aspects of the model at once. Instead, we should revalidate it each time as new research questions come along.

Discussion

Amit (1998) notes that the simulation of neurobiology in detail will not tell us anything new about cognitive neurophysiology; however, simulation results can be useful for theoretical predictions. In other words, we can make testable predictions from MNOMA. Following Rosenbloom and Newell (1986), who derive the power law of practice empirically from a simulation of Seibel's task with a chunking model, we expect to be able to do the same for the inverted-U curve of musical popularity vs originality in a social setting (Simonton, 1997).

Although our model are not biologically plausible at this point, we can reuse Edelman and Reeke, Jr.'s excuse in their now-classic Darwin II paper:

> "Darwin II is not an explicit model of either the whole or part of any nervous system. Nevertheless, it was designed heuristically with nervous systems in mind and it would not be surprising if it reflected some aspects of their performance [...] Demonstration of their reality obviously will depend on direct experimentation in real nervous systems" (Edelman and Reeke, Jr., 1982, p. 2095).

To recapitulate, the computational memetic approach enables the testing of hypotheses across neuroscience and social psychology under a unifying framework. We speculate that this approach would significantly enlarge the scope and investigative power of systematic musicology.

Future Directions

We claim that MNOMA will be a good compositional tool for generating creative music, regardless of its biological validity. Specifically, Gabora (1997) claims that SDM is capable of generating creative variations, and MNOMA is a convenient platform to test this hypothesis. As regards creativity (Boden, 1990), we will also formalise the "conceptual space" in our simulation model using more precise terms (Wiggins, 2001).

When the model is mature, we will be able to directly test the hypothesis proposed by Lerdahl (1988), who claims that the best music "utilizes the full potential" of our cognitive capabilities, by sampling MNOMA output and correlating the level of neuronal activities with the aesthetic value (judged by a panel of musical experts).

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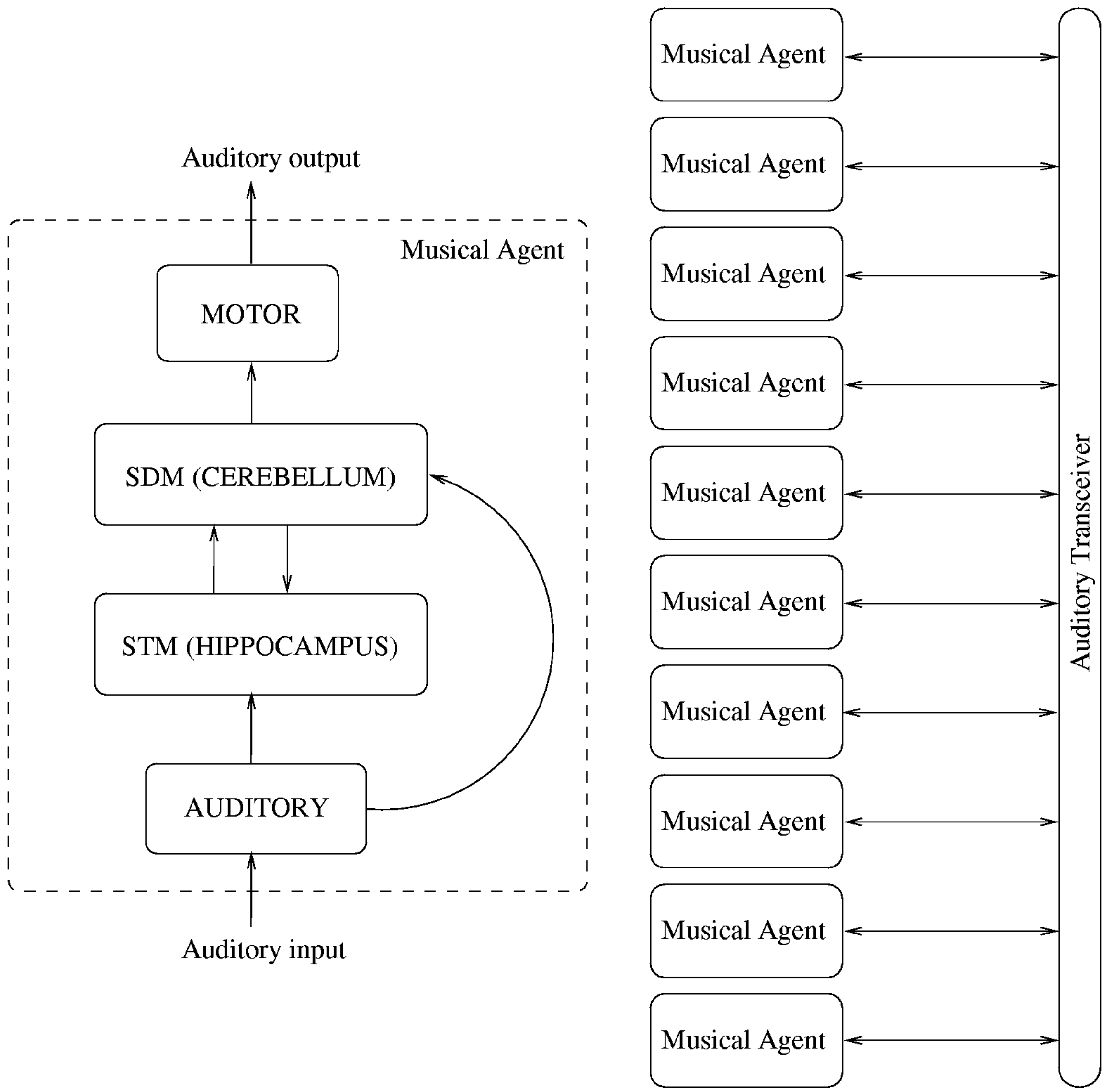

Figure 1: Memetic Network of Musical Agents