Eduardo R. Miranda, Alexis Kirke, and Qijun Zhang
Interdisciplinary Centre for Computer Music Research (ICCMR)
University of Plymouth
Plymouth, PL4 8AA United Kingdom
{eduardo.miranda, alexis.kirke, qijun.zhang}@plymouth.ac.uk

Artificial Evolution of Expressive Performance of Music: An Imitative Multi-Agent Systems Approach

As early as the 1950s and early 1960s, pioneers such as Lejaren Hiller, Gottfried Michael Koenig, Iannis Xenakis, and Pietro Grossi, among a few others, started to gain access to computers to make music. It soon became clear that to render music with a so-called "human feel," computers needed to process information about performance (e.g., deviations in tempo and loudness), in addition to the symbols that are normally found in a traditional musical score (e.g., pitch and rhythm). This was especially relevant for those interested in using the computer to play back scores.

Indeed, the first ever attempt at creating a computer-music programming language, by Max Mathews at Bell Telephone Laboratories in 1957, was motivated by his wish to "write a program to perform music on the computer" (Park 2009 p. 10). It appears that this development began after Mathews and John Pierce went to a piano concert together. During the intermission, Pierce suggested that perhaps a computer could perform as well as the pianist. Mathews took up the challenge, which resulted in Music I, the ancestor of music programming languages such as Csound (Boulanger 2000).

Research into computational models of expressive performance of music (Widmer and Goebl 2004) is still an active area of study—particularly, research into devising increasingly more sophisticated automated and semi-automated computer systems for expressive music performance, hereinafter referred to as CSEMP.

A CSEMP is able to generate expressive performances of music. For example, software for music typesetting is often used to write a piece of music, but most packages play back the music in a "robotic" way, without expressive performance. The provision of a CSEMP engine would enable such systems to produce more realistic playback.

A variety of techniques have been used to implement CSEMPs (Widmer and Goebl 2004; Kirke and Miranda 2009; in press). These include (1) rule and grammar-based approaches (Sundberg, Askenfelt, and Frydén 1983; Clynes 1986; Bresin and Friberg 2000; Livingstone et al. 2007), including expert systems (Johnson 1991); (2) linear and non-linear regression systems (Canazza et al. 2000; Ishikawa et al. 2000), including artificial neural networks (Bresin and Vecchio 1995; Camurri, Dillon, and Saron 2000), Hidden Markov Models (Grindlay 2005), Bayesian Belief Networks (Raphael 2001), Sequential Covering methods (Widmer and Tobudic 2003), and Regression Trees (Ramirez and Hazan 2005); and (3) evolutionary computing methods (Zhang and Miranda 2006; Ramirez et al. 2008). In this article, we introduce a new approach using the *imitative multi-agents* paradigm.

Expressive Music Performance

How do humans make their performances sound so different from the so-called "robotic" performance a machine would normally give? In this article, the strategies and changes that are not marked in a score but which performers apply to the music are referred to as *expressive performance actions*. Two of the most common expressive performance actions in Western classical music are changing the tempo and the loudness of the piece as it is played. These are tempo and loudness changes not marked on the score; they are additional to notated tempo or loudness changes, such as *accelerando* or *mezzo-forte*. For example, a common expressive performance strategy is for the performer to slow down as they approach the end of the piece (Friberg and Sundberg

Computer Music Journal, 34:1, pp. 80–96, Spring 2010

1999). Another expressive performance action is the use of expressive articulation—for instance, when a performer chooses to play notes in a more staccato (short and pronounced) or legato (smooth) way. Those who play instruments with continuous tuning, for example string players, can also use expressive intonation, making notes slightly sharper or flatter, and such instruments also allow for expressive vibrato. Many instruments provide the ability to expressively change timbre as well.

There have been a number of studies into Western pre-20th-century classical music performance, notably involving the music of the Baroque, Classical, and Romantic periods. On of the earliest systematic studies was developed in the late 1930s (Seashore 1938), and more recently good reviews have been published (e.g., Palmer 1997; Gabrielsson 2003). One element of these studies has been to discover what aspects of a piece of music are related to a performer's use of expressive performance actions. An important factor of expressive music performance is the performer's structural interpretation of the piece. Performers have a tendency to express this structure in their performances (Palmer 1997). They often slow down at boundaries in the hierarchy, with the amount of slowing being correlated to the importance of the boundary (Clarke 1988). Thus, a performer would tend to slow more at a boundary between sections than between phrases. There are also regularities relating to other musical features in performers' expressive strategies. For example, in some cases, higher-pitched notes tend to be played more loudly. Also, notes that introduce tension relative to the key may be played more loudly. However, for every rule, there are always exceptions. For a discussion of other factors involved in human expressive performance, we refer the reader to Juslin (2003).

Evolutionary Computation

Evolutionary Computation (EC) methods have been successfully applied to algorithmic composition (please refer to Miranda and Biles 2007 for an introduction to a number of such systems). The great majority of these systems use genetic algorithms (Goldberg 1989), or GA, to produce melodies and rhythms. In these systems, music parameters are represented as "genes" of software agents, and GA operators are applied to "evolve" music according to given fitness criteria.

More recently, progress in applying EC to CSEMP has been reported (Ramirez and Hazan 2005; Zhang and Miranda 2006; Ramirez et al. 2008). EC-based CSEMPs have all applied the neo-Darwinian approach of selecting the musically fittest genes to be carried into the next generation. We are interested, however, in investigating the application of an alternative EC approach to expressive performance—one that is based on cultural transmission rather than genetic transmission.

Musical behavior in human beings is based both in our genetic heritage and also our cultural heritage (Dissanayake 2001). One way of achieving a cultural, as opposed to genetic, transmission is through imitation of behavior (Zentall and Galef 1988; Boyd and Richerson 2005). Work on the application of this imitative cultural approach to algorithmic composition was initiated by Miranda (2002). In this article, we follow up the cultural transmission methodology with an application of an imitative multi-agent systems approach to expressive music performance. We have developed a system referred to as Imitative Multi-Agent Performer, or IMAP, which is introduced subsequently.

In the GA model of behavior transmission, a population of agents is generated having its own behavior defined by their "genetic" code. The desirability of the behavior is evaluated by a global fitness function, and agents with low fitness are often discarded, depending on which version of the algorithm is adopted (Goldberg 1989). Then, a new population of agents is generated by combination and deterministic or non-deterministic transformation of the genes of the highest-scoring agents.

Conversely, in the imitation model of behavior transmission, an agent interacts with one or more other agents using a protocol that communicates the first agent's behavior to the other agents. The other agents evaluate the first agent's behavior based on some evaluation function, and if the evaluation scores highly enough, one or more of the other agents will change their own behaviors based on the first agent's behavior. The evaluation function in the imitation model plays a similar role to the fitness function in the GA model. However, in imitative multi-agent systems, the evaluation function is particularly suited for the design of EC systems using a non-global fitness function, for example, by giving each agent their own evaluation function.

The potential for diversity is a desirable trait in a system for generating novel expressive music performances—as opposed to replicating existing ones—because there is no objectively defined optimal performance for a musical score (Bresin and Friberg 2000; Ramirez et al. 2008). Performance is a subjective, creative act. Previous work on genetic transmission in generating expressive music performance has been significantly motivated by the desire to generate a variety of performances. As will be demonstrated herein, there is even more scope for such variety in IMAP because a multiplicity of evaluation functions is used. Furthermore, there is scope for easily controlling the level of diversity in IMAP.

It is not our intention to compare the imitative approach with the GA approach, because both approaches have their own merits and should be considered as complementary approaches. Ramirez et al. (2008) demonstrated the validity of a GA model, and the experiments later in this article demonstrate the validity of our imitative approach.

One obvious measure of validity is whether the system generates performances that are expressive. The other two measures of validity relate to those elements of the imitative approach, which differentiate it from the standard GA approach—in particular, the ability to easily provide the system with a number of parallel interacting fitness functions. Hence, IMAP will be evaluated in terms of (1) the expressiveness of IMAP-generated performances (note, however, that this is not assessed by means of experiments with human subjects; we assess how well the agents can generate performances that embody their preference weights); (2) performance-diversity generation and control of the level of diversity; and (3) the ability to control diversity when it is being affected by multiple musical elements simultaneously.

Imitative learning has been frequently used in other multi-agent systems research (De Boer 2000; Noble and Franks 2004). However, to the best of our knowledge, IMAP is the first application of such methods to the generation of expressive musical performances.

Imitative Multi-Agent Performer: IMAP

Each agent has two communication functions: It can listen to the performance of another agent, and it can perform to another agent. All agents are provided with the same monophonic melody—the melody from which expressive performances will be generated. In all interactions, all agents perform the same melody, usually with different expressive actions. Agents in IMAP have two types of expressive actions: changes in tempo and changes in note loudness. Each agent also has a musical evaluation function based on a collection of rules, where different agents give different weightings to the rules and use the combination to evaluate the performances they hear. Initially, agents will perform with random expressive actions. If they evaluate another agent's expressive performance highly enough through their evaluation function, then they will adjust their own future performances toward the other agent's expressive actions. As this process continues, a repertoire of different expressive performances evolves across the population.

Agent Evaluation Functions

The agents' evaluation functions could be generated in a number of ways. One of the most common methods used in CSEMPs is learning from human examples using machine-learning techniques (Bresin and Vecchio 1995; Widmer and Tobudic 2003; Grindlay 2005). A second common method is providing agents with rules describing what features an expressive performance should have (Sundberg, Askenfelt, and Frydén 1983; Todd 1985; Hashida, Nagata, and Katayose 2006; Livingstone et al. 2007). The second approach was chosen for IMAP because we wanted to provide the means to explicitly change the influence of various musical factors on the final expressive performance. Machine-learning approaches, such as those based on artificial neural networks, tend to develop a more implicit reasoning system (Ben-David and Mandel 1995). An explicitly described rule set allows for simpler controllability of a multi-agent system. However, unlike many rule-based CSEMPs, the agents in IMAP do not use their rules to generate their performances. Rather, they use them to evaluate performances (their own and those of other agents) and therefore choose which other agents to imitate. This will become clearer as we introduce the system. In short, the more highly another agent's performance is scored by the parameterized evaluation function of a listening agent, the more highly the listening agent will regard the performing agent.

An agent's evaluation function is defined at two stages: the Rule Level and the Analytics Level. The first stage—the Rule Level—involves a series of five rules derived from previous work on generative performance. The second stage—the Analytics Level—involves a group of musical analysis functions that the agent uses to represent the structure of the musical score. The Rule Level and the Analytics Level are both parameterized to allow the user to control which elements have most influence on the resulting performances.

For the Rule Level, we could have selected a large number of rules available from previous research into CSEMP. To keep the rule list of IMAP manageable, only five rules were selected, bearing in mind the application and controllability of the imitative approach. One should note, however, that these rules are not absolute; as will be demonstrated later, the agents often create performances that do not fully conform to all rules. For this reason we refer to these rules as *preference rules*.

The five preferences rules of the Rule Level relate to *Performance Curves*, *Note Punctuation*, *Loudness Emphasis*, *Accentuation*, and *Boundary Notes*. Each preference rule is based on previous research into music performance, as follows.

Rule 1: Performance Curves

Performance deviations for tempo between note group boundaries (e.g., motif and phrase boundaries) should increase for the beginning part of the group and decrease for the second part of the group; how these "parts" are defined is explained later. This is consistent with the expressive shapes, which are well established in the field of CSEMP (Todd 1985; Friberg, Bresin, and Sundberg 2006; Hashida, Nagata, and Katayose 2006; Livingstone et al. 2007). This shape should also occur for the loudness deviations (Todd 1992).

Rule 2: Note Punctuation

According to this rule, the ending note of a group of notes should be lengthened (Friberg, Bresin, and Sundberg 2006).

Rule 3: Loudness Emphasis

Performance deviations for loudness should emphasise the metrical, melodic, and harmonic structure (Clarke 1988; Sundberg et al. 1983).

Rule 4: Accentuation

Any note at a significantly accentuated position (as defined later) must either have a lengthened duration value or a local loudness maximum (Clarke 1988; Cambouropoulos 2001).

Rule 5: Boundary Notes

The last note in a note grouping should have an expressive tempo, which is either a local minimum or local maximum (Clarke 1988).

Evaluation Equations

These five preference rules of the Rule Level were implemented as a set of evaluation equations, which are detailed in the following sections. The user can change the influence of a preference rule in the final evaluation through the setting of weights. The rules take as input the result of a musical score analysis done by four analysis functions in the Analytics Level, namely *Local Boundary Detection Model (LBDM)*, *Metric Hierarchy*, *Melodic Accent*, and *Key Change*. A detailed explanation of these analysis functions is beyond the scope of this article; the reader is invited to consult the given references.

Local Boundary Detection Model (LBDM)

The first of these, LBDM, takes a monophonic melody as input and returns a curve that estimates the grouping structure of the music; i.e., where the note–group boundaries are and how important each boundary is (Cambouropoulos 2001). Each adjacent note pair is given an LBDM value. The higher the value, the more likely that the interval is at a grouping boundary; and the higher the value at a boundary, the more important the boundary is. This function allows an agent to express aspects of the grouping structure of the music.

Metric Hierarchy

The second function is the Metric Hierarchy function, which uses the Lerdahl and Jackendoff (1983) method of assigning notes a position in a metric hierarchy. In most Western European classical music, each note has a position in a metric hierarchy. For example, a piece in 4/4 time might have a note with a strong beat at the start of every bar and a weaker beat half way through each bar. The Metric Hierarchy function is implemented in IMAP as a function that takes as input a melody and returns the strength of each beat. (A detailed explanation of the implementation is beyond the scope of this article; it suffices to say that the representation does not explicitly include information about bar lines and time signatures.) Thus, it allows an agent to express aspects of the metric structure in its performance.

Melodic Accent

Another form of accent analysis used in the Analysis Level is the Melodic Accent. Thomassen (1982) proposes a methodology for analyzing the importance of each note in a melody; each note is assigned an importance value. This allows an agent to express aspects of the melodic structure in its performance.

Key Change

The fourth function in the Analysis Level is the Key Change analysis. Krumhansl (1991) introduces an algorithm, based on perceptual experiments, for analyzing changes of key in a melody. This algorithm allows an agent to express aspects of the harmonic structure in its performance.

Therefore, an agent will represent the score by its note groupings, metric hierarchy, melodic accents, and key changes, although different agents may see the music score differently depending on how they parameterize the functions in the Analytics Level. Then, based on the five preference rules, the agents will prefer certain expression deviations for different parts of the musical score, where the types of expressive deviations preferred depend on an agent's parameterization of the preference rules in the Rules Level.

Agent Function Definitions

The evaluation function $E(P)$ of an agent evaluating a performance P is defined as

$$E(P) = w_{Tem} * E_{Tem}(P) + w_{Lou} * E_{Lou}(P) \quad (1)$$

Here, E_{Tem} and E_{Lou} are the agent's evaluation of how well a performance fits with its preference for expressive deviations in tempo and loudness, respectively. (Although the weights in this two parameter equation are designed to add to unity and could therefore be rewritten in a single weight form with multipliers of w and $1–w$, both weights are explicitly written for reasons of clarity and for conformity with the format of the other equations below.) The preference weights w_{Tem} and w_{Lou} define how much an agent focuses on timing elements of expression in relation to loudness elements of expression. The evaluation functions for tempo and loudness are defined using evaluation sub-functions E_{iTem} and E_{iLou}, which evaluate all five preference rules discussed earlier. Subscripts 1–5 relate to preference rules 1–5, respectively:

$$\begin{aligned} E_{Tem} = {} & w_{1Tem} * E_{1Tem} + w_{2Tem} * E_2 + w_{4Tem} \\ & * E_{4Tem} + w_{5Tem} * E_5 \end{aligned} \quad (2)$$

$$\begin{aligned} E_{Lou} = {} & w_{1Lou} * E_{1Lou} + w_{3Lou} * E_3 \\ & + w_{4Lou} * E_{4Lou} \end{aligned} \quad (3)$$

The E_{1Tem} and E_{1Lou} functions refer to preference rule 1 and affect both tempo and loudness, respectively. Function E_2 refers to preference rule 2 and affects only tempo. Similarly, function E_3 refers to preference rule 3 and affects only loudness. Functions E_{4Tem} and E_{4Lou} refer to preference rule 4 and affects both loudness and tempo, and function E_5 refers to rule 5 and affects only tempo.

The weights w_{iTem}, and w_{iLou} allow the setting of agent preferences for each of the five rules, though not all rules need to be part of both functions, because some apply only to tempo or only to loudness. The sub-functions are defined in terms of the deviations of tempo and loudness from the nominal score values found in a performance. The sub-functions are given in Equations 4–10. Equations 4 and 5 implement preference rule 1:

$$E_{1Tem} = \sum_{1}^{n} \left(\sum_{i=s_{start}}^{s_{turn}-1} \begin{cases} 1 & (dev_{Tem}(i+1) > dev_{Tem}(i)) \\ 0 & (dev_{Tem}(i+1) \leq dev_{Tem}(i)) \end{cases} + \sum_{i=s_{turn}}^{s_{end}-1} \begin{cases} 1 & (dev_{Tem}(i+1) < dev_{Tem}(i)) \\ 0 & (dev_{Tem}(i+1) \geq dev_{Tem}(i)) \end{cases} \right) \tag{4}$$

$$E_{1Lou} = \sum_{1}^{n} \left(\sum_{i=s_{start}}^{s_{turn}-1} \begin{cases} 1 & (dev_{Lou}(i+1) > dev_{Lou}(i)) \\ 0 & (dev_{Lou}(i+1) \leq dev_{Lou}(i)) \end{cases} + \sum_{i=s_{turn}}^{s_{end}-1} \begin{cases} 1 & (dev_{Lou}(i+1) < dev_{Lou}(i)) \\ 0 & (dev_{Lou}(i+1) \geq dev_{Lou}(i)) \end{cases} \right) \tag{5}$$

The ith note's tempo and loudness expressive deviations are written as $dev_{Tem}(i)$ and $dev_{Lou}(i)$ in the sub-functions. By virtue of the first (outer) summation in each equation, the calculations are applied to each note grouping separately, and the scores are added across the whole performance. The index values s_{start} and s_{end} are the note indices at which a note grouping starts and ends, and s_{turn} is its *turning point*.

There is no fixed threshold for defining boundaries using the LBDM method. We opted for one that was found sufficient for the purposes of IMAP: for a note to be a boundary note, its LBDM value must be greater than the average LBDM value of the whole melody. The turning point of a grouping is the point at which the expressive tempo defined by preference rule 1 peaks before dropping; it is not defined explicitly by LBDM either. In IMAP, the "third most important note" in the group is selected as representing a boundary between the first part of the group and the last part. So the turning point is defined as the note having the third highest LBDM in the group; the start and end notes will be the two highest LBDM values. This definition of turning point was found to be more musically meaningful than simply taking the mid-point between the start and end notes. To ensure that every note grouping has at least one potential turning point, another constraint is placed on note groupings: they must contain at least four notes; i.e., three intervals.

Equation 6 is added over all note groups in the melody. This sub-function implements preference rule 2. A tempo deviation value of unity means the performance is the same as the nominal value in the score; a value greater than unity means louder or faster than the score. This is applied to each note group in the melody.

$$E_2 = \sum_{1}^{n} \begin{cases} 1 & (dev_{Tem}(s_{end}) < 1) \\ 0 & (dev_{Tem}(s_{end}) \geq 1) \end{cases} \tag{6}$$

Equation 7 implements preference rule 3. The curve $s_A(i)$ used in this equation is the *accentuation curve*, which is generated by a weighted sum of three other curves: *melodic accent*, *metrical hierarchy*, and the *key change*, thus representing multiple musical elements. (Note: the notion of "curve" here is broadly metaphorical; it is not a mathematical curve in the strict sense of the term.)

$$E_3 = \sum_{i=1}^{q-1} \begin{cases} 1 & (\Delta d * \Delta dev_{Lou} > 0) \\ 0 & (\Delta d * \Delta dev_{Lou} \leq 0) \end{cases} \quad \text{where}$$

$$\begin{aligned} \Delta d &= s_{A(i+1)} - s_{A(i)} \\ \Delta dev_{Lou} &= dev_{Lou}(i+1) - dev_{Lou}(i) \end{aligned} \tag{7}$$

The melodic-accent curve moves higher for more important melodic notes (Thomassen 1982), whereas the metrical hierarchy curves move higher for notes that are more important in the metrical hierarchy (Lerdahl and Jackendoff 1983). The key-change curve moves higher the further away the melody

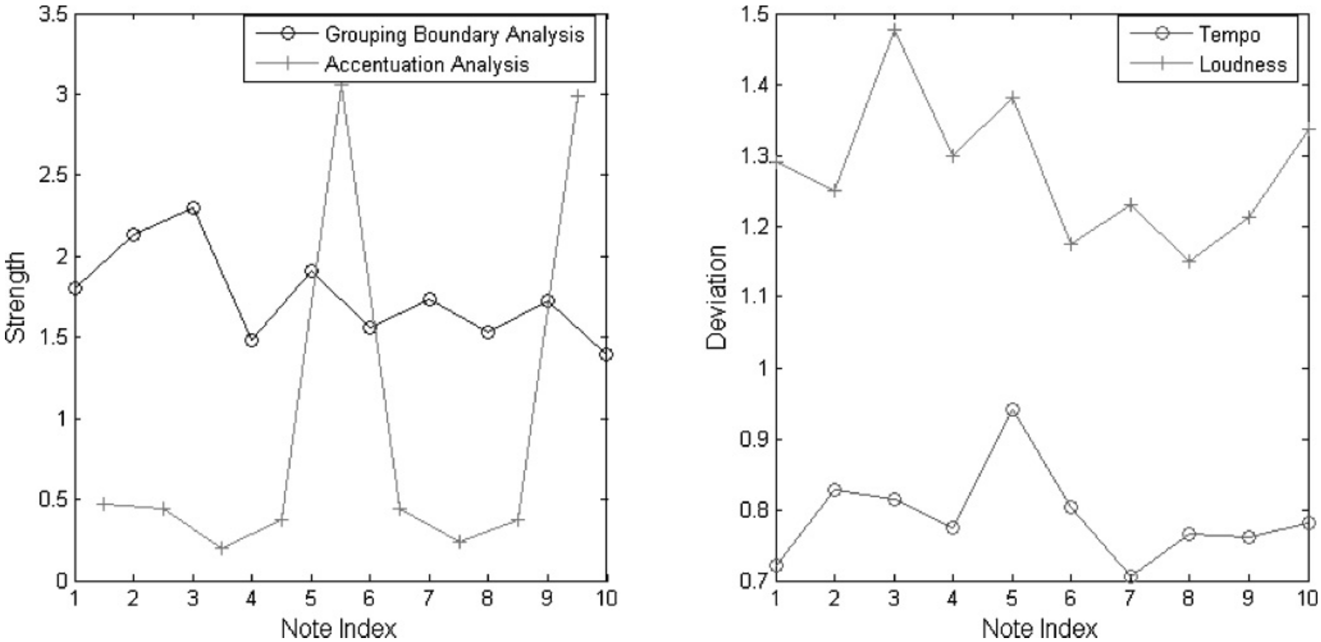


Figure 1. Example characteristics of a single agent with respect to a given sequence of ten notes.

moves from the estimated key (Krumhansl 1990) of the previous *N* bars, the default being two bars. These three curves are normalized, then weighted based on an agent's preferences, and finally added to generate the accentuation curve $s_A(i)$. Equation 7 will evaluate to a larger number if the loudness-deviation curve of a performance follows the same direction as this accentuation curve, encouraging the emphasis of the parts of the performance based on elements of their melodic, metric, and harmonic properties.

Figure 1 shows examples of accentuation and loudness curves (as well as the LBDM and tempo-deviation curves) for a single agent, given a sequence of ten notes. This sort of analysis is done once per agent.

In Figure 1, both *x*-axes refer to note index, where 1 is the first note in the score, 2 is the second note, etc. The left side of Figure 1 shows part of an example LBDM curve (circled points) used to define grouping boundaries, and an accentuation curve (crossed points) used for expressive loudness. The *y*-axis is the normalized strengths of the curves. The absolute strength is not important, but rather the relative values. The right side of Figure 1 shows the resulting deviation curves for tempo (circles) and loudness (crosses) after a number of iterations. A deviation greater than unity implies an increase in tempo, or an increase in loudness; a deviation less than unity implies a decrease in tempo or loudness.

Equations 8 and 9 implement preference rule 4. The rule is only applied to accentuated notes $\{a_1,\ldots, a_m\}$, which are defined as those notes *i* whose value on the accentuation curve $s_A(i)$ is a local maximum on the s_A curve. This definition chooses notes whose metric, melodic, or harmonic properties make them more significant than the notes surrounding them. The values of Equations 8 and 9 are higher if an accentuated note is reduced in tempo more than its neighbor notes (Equation 8), or played with a higher loudness (Equation 9).

$$E_{4Tem} = \sum_{j=a_1}^{a_m} \begin{cases} 1 & (dev_{Tem}(j) < dev_{Tem}(j-1) \quad \text{and} \\ & \quad dev_{Tem}(j) < dev_{Tem}(j+1)) \\ 0 & (otherwise) \end{cases} \qquad (8)$$

$$E_{4Lou} = \sum_{j=a_1}^{a_m} \begin{cases} 1 & (dev_{Lou}(j) \geq dev_{Lou}(j-1) \quad \text{and} \\ & \quad dev_{Lou}(j) \geq dev_{Lou}(j+1)) \\ 0 & (otherwise) \end{cases} \qquad (9)$$

Figure 2. The core algorithm of the agents' interaction cycle.

Begin of Cycle 1
An agent is selected to perform, say agent $\mathbf{A_1}$
Agent $\mathbf{A_1}$ performs
All agents $\mathbf{A_j}$ apart from $\mathbf{A_1}$ evaluate $\mathbf{A_1}$'s performance, to get $\mathbf{E_{j1}}$
If an agent $\mathbf{A_j}$'s evaluation $\mathbf{E_{j1}}$ is greater than its evaluation of its own performance,
then $\mathbf{A_j}$ moves its own expressive performance deviations closer to
$\mathbf{A_1}$'s performance by an amount defined by the learning rate.
An agent is selected to perform, say agent $\mathbf{A_2}$
Agent $\mathbf{A_2}$ performs
All agents $\mathbf{A_j}$ apart from $\mathbf{A_2}$ evaluate $\mathbf{A_2}$'s performance, to get $\mathbf{E_{j2}}$
If an agent $\mathbf{A_j}$'s evaluation $\mathbf{E_{j2}}$ is greater than its evaluation of its own performance,
then $\mathbf{A_j}$ moves its own expressive performance deviations closer to
$\mathbf{A_2}$'s performance by an amount defined by the learning rate.
•
•
•
Continue this process until all agents have performed, then Cycle 1 is complete
End of Cycle 1
Repeat cycles until some user-defined stopping condition is met.

Equation 10 implements preference rule 5, checking that notes at the end of a group have a higher or lower tempo deviation, compared to the notes on either side.

$$E_5 = \sum_{1}^{n} \begin{cases} 1 & (dev_{Tem}(s_{end}) - dev_{Tem}(s_{end} - 1)) \\ & \quad * (dev_{Tem}(s_{end}) - dev_{Tem}(s_{end} + 1)) > 0. \\ 0 & (otherwise) \end{cases} \tag{10}$$

With Equations 1–10, a user can set weights to control how an agent represents or, speaking metaphorically, "sees" the score. A user can also control how the agent prefers such a "seen" score to be performed.

Agent Cycle

Agents are initialized with evaluation weights for their evaluation functions and with a common monophonic score in MIDI form that they will perform. Agents are also initialized with an initial performance. This will be a set of expressive deviations from the score in loudness and tempo, which are implemented when the agent plays to another agent. These initial deviations are usually set randomly, but they can be set by the user should one wish. Default values used for tempo are 55–130% of nominal and 75–125% for loudness. These values were established intuitively after experimenting with different ranges. Agents have a learning rate between 0% and 100%. If an agent with a learning rate L% hears a performance P that it prefers to its own, then it will move its own performance deviations linearly toward P by L%. An agent with a learning rate of 100% will allow another agent's performance to influence 100% of its own performance. That is, the agent will replace its performance entirely with any it hears, which it prefers to its own. An agent with a learning rate of 0% will ignore all other performances it hears.

The core algorithm of the agents' interaction cycle is given in Figure 2. Note that the algorithm shown here is sequential, but in reality the agents are asynchronous, in the sense that all agents are operating simultaneously in separate threads.

User-Generated Performances with IMAP

Before describing how to generate expressive performances with IMAP, we would like to discuss some of the issues with practical performance generation. Kirke and Miranda (2009) introduced the term "performance creativity" to refer to the ability of a CSEMP to generate novel and original performances, as opposed to simulating previous human strategies. Such creative and novel performance is often applauded in human performers. For example, Glenn Gould created highly novel expressive performances of pieces of music and has been described as having a vivid musical imagination. Expressive computer performance provides possibilities for even more imaginative experimentation with performance strategies. Many CSEMPs, for example the Artificial Neural Network Piano System (Bresin and Vecchio 1995; Bresin 1998), are designed to simulate human performances—an important research goal—but not to create novel performances. IMAP is less constrained in the generation of performances than a number of systems that learn from human examples. It also has a parameterization ability, which can be manipulated creatively to generate entirely novel performances.

There are two important provisos here. First, "novel" does not necessarily mean "pleasant." Second, flexibility does not necessarily lead to creativity. A system that is totally manual would seem at first glance to have a high creativity potential, because the user could entirely shape every element of the performance. However, this potential may never be realized owing to the excessively time-consuming manual effort required to implement a performance. Not all CSEMPs are able to act in a novel way that is practically controllable. A number of them generate a model of performance, which is basically a vector or matrix of coefficients. Changing this matrix by hand (i.e., "hacking" it) would allow the technically savvy to generate novel performances. Still, the changes would entail an excessive amount of manual effort—or the results of such changes could be excessively unpredictable—thus requiring too many iterations or "try-outs." For performance creativity, a balance needs to exist between automation and creative flexibility.

As described earlier, in IMAP there are a number of weights that need to be defined for an agent's evaluation function. Table 1 lists all the weights that must be set in IMAP. Although a set of nine weights may seem too large for practical performance creativity, in reality, many of these weights can be fitted to default values, and the remaining weights would still provide a wide scope for creativity. For example, users could simply adjust the top two weights of the equation hierarchy (w_{Tem} and w_{Lou}) in Equation 1, fixing all other weights to their default values. This two-weight set could be simply extended by also allowing the user to adjust the weights w_{4Tem} and w_{4Lou} in Equations 2 and 3 to change the amount of tempo and loudness emphasis, respectively, of accentuated notes. It is worth noting that the parameters in the Analytics Level can also be made available to users. For example, the user could set weights that would indirectly change the shape of the accentuation curve shown in Figure 1.

Table 1. IMAP Weights That Can Be Set in Equations 1, 2, and 3 by the User to Influence the Final Expressive Performance

Preference Rule	*Weight*	*Equation*
All tempo-based effects	w_{Tem}	Equation 1
All loudness-based effects	w_{Lou}	Equation 1
Rule 1 tempo effects	w_{1Tem}	Equation 2, Tempo
Rule 2 tempo effects	w_{2Tem}	Equation 2, Tempo
Rule 4 tempo effects	w_{4Tem}	Equation 2, Tempo
Rule 5 tempo effects	w_{5Tem}	Equation 2, Tempo
Rule 1 loudness effects	w_{1Lou}	Equation 3, Loudness
Rule 3 loudness effects	w_{3Lou}	Equation 3, Loudness
Rule 4 loudness effects	w_{4Lou}	Equation 3, Loudness

These nine weights define the effects of the five preference rules in the Rules Level.

Another key element of IMAP is how agents can have different "views" of what makes a good expressive performance. This provides an ability, which will be demonstrated later in this article, for generating and controlling diversity in the results of the population learning. For example, a population with similar initial preference weights will tend to learn a group of far more similar performances than a population whose initial weight values differ widely.

We now describe how to generate expressive performances with IMAP. Before the first cycle of IMAP, a population size is defined—for example 3, 10, or 50 agents. (Larger populations may have the advantage of greater statistical stability and a larger choice of performances.) Then, a learning rate must be set. In this article, a global learning rate is used: All agents have the same learning rate, a default of 10%. A low learning rate was desired to allow agents to build up a good combination of performances through imitation. A learning rate closer to 100% would turn the system into more of a performance-swapping population rather than one for performance combining. However, too low a rate would result in slow convergence.

Concerning the question of how many cycles to run the system, one approach would be to define a fixed number of cycles. Another approach would be to define a more sophisticated stopping condition. A common form of stopping condition is a convergence criterion—for example, stopping when agents are no longer updating their performance deviations during the interactions. This normally occurs when no agent is hearing a performance better than its own performance. Yet another option is to base convergence on the average performance, i.e., the average deviations across the entire population. Once this ceases to change by a significant amount per cycle (that amount defined by the user), convergence can be considered to have been achieved.

Three experiments with IMAP are detailed in this article that test the system in terms of capability of expression generation, generation of diversity, and controlling the direction of the diversity.

Experiments and Evaluation

The melody of *Étude No. 3*, Op. 10 by Frédéric Chopin was used in the experiments that follow. Although IMAP is able to process whole pieces of (monophonic) music, for the sake of clarity, only the first five bars of Chopin's piece were considered herein.

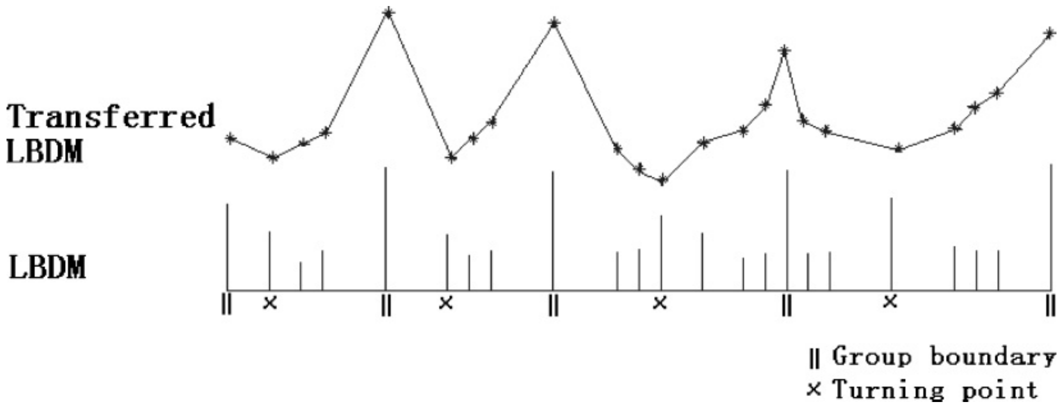
Experiment 1: Can Agents Generate Performances Expressing Their "Preference" Weights?

The purpose of this experiment is to demonstrate that the agents generate performances that express their "preference" weights. To show this clearly, two weight sets were used: set A, in which $w_{Tem} = 1$, $w_{1Tem} = 1$, and all other weights are 0; and set B, in which $w_{Lou} = 1$, $w_{3Lou} = 1$, and all other weights are 0. The first of set of weights will only lead to preference rule 1 being applied (and only to tempo). The second set of weights will lead to preference rule 3 being applied (and only to loudness). If agents express the music structure through their weights, then a multi-agent system where agents have only weight set A should generate performances whose tempo deviations clearly express the grouping structure (LBDM) of the music as defined by preference rule 1. Similarly, if the agents are given weight set B, then the generated loudness deviations should express the accentuation curve as implemented by preference rule 3.

Two groups of experiments were run: five with weight set A and five with weight set B. A system of 15 agents was used, and 20 iterations were used for each run. For each run in the experiment with weight set A, the initial agent performances were randomized. For comparison purposes, exactly the same set of initial performances was used for the parallel run with weight set B; hence, the ten runs only use five sets of 15 random initial performances. To enable meaningful results for the scenario with weight set A, a new curve is defined: the *transferred LBDM* curve. The transferred LBDM curve is our own adaptation of the LBDM curve into a form more easily comparable with the grouping expression. The transferred curve will have maxima at the boundary points on the LBDM curve and minima at the turning points within each note group. The transferred LBDM is concave between boundary points. An example is shown in Figure 3. Preference rule 1 can then be interpreted as saying that tempo curves should move in the opposite direction to the transferred LBDM curve—or equivalently, that the reciprocal of the tempo curve should move in the same direction as the transferred LBDM curve.

In Figure 3, the horizontal axis represents time. On the vertical axis, LBDM values do not have units as such. They indicate relative "boundary strength" rather than absolute values. The fitness function only needs to know the direction of the transferred LBDM curve rather than its absolute value. In the

Figure 3. *Example of a transferred LBDM curve for a melody from Chopin's* Étude No. 3, *Op. 10.*



lower graph, the LBDM values are plotted for each note pair/interval. The group boundaries and turning points are shown on the horizontal axis. Note that the transferred LBDM curve in the upper graph is concave between boundaries; it has maxima at boundaries and minima at the turning points.

In this experiment, the average performance across all agents was used to represent the performances evolved by the system. Thus, the deviations of the tempo and loudness generated by the system are represented by the deviations of the tempo and loudness in the average performance. The results of scenarios with weight sets A and B can be seen in Table 2, which shows the average correlations *Corr(x, y)* across the five runs for *x* set to the transferred LBDM curve *tLBDM*; *x* set to the accentuation curve *Acc*; *y* set to the reciprocal of performance tempo *rTem*; and *y* set to the performance loudness *Lou*.

It can be seen that for weight set A (a weight set that should cause grouping structure to be expressed using tempo deviations to express it), there is an increase in correlation between the transferred LBDM and the reciprocal performance tempo: *Corr*(*tLBDM, rTem*) = 0.11. For weight set B (a weight set that should cause the accentuation curve to be expressed by loudness deviations), the only increase in correlation is between the accentuation curve and the loudness: *Corr*(*Acc, Lou*) = 0.2. These results show that the average agent performances are expressing the preference weights in the system. Figure 4 shows expressive deviations evolved by two agents for the Chopin melody.

Table 2. Results from Experiment 1 Showing Correlations for Average Performance Across a Population of Agents

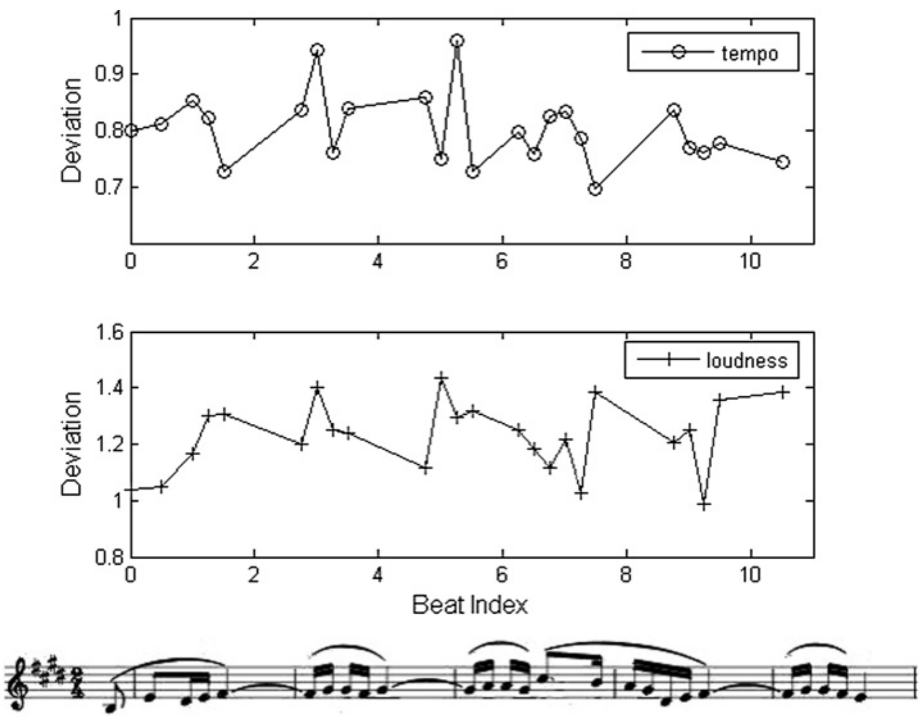
	Before Iterations	*After Iterations*	*Increase*
	Weight Set A (Tem)		
Corr(tLBDM, rTem)	0.49	0.61	0.11
Corr(tLBDM, Lou)	0.52	0.52	0
Corr(Acc, Lou)	0.5	0.52	0.02
	Weight Set B (Lou)		
Corr(tLBDM, rTem)	0.49	0.49	0
Corr(tLBDM, Lou)	0.52	0.48	–0.04
Corr(Acc, Lou)	0.5	0.7	0.2

An increase in correlation between the transferred LDBM and reciprocal performance tempo shows that the tempo deviations are expressing the grouping structure of the music. An increase in correlation between the accentuation curve and loudness shows that the loudness is expressing elements of the metric, melodic structure, and harmonic structure of the music, as defined in the accentuation curve.

Experiment 2: Can One Control the Extent of the Performances' Diversity?

The purpose of this experiment was to demonstrate that IMAP can generate a diversity of performances and that the user can control that diversity. In the experiment, a group of 15 agents was used, each with randomly initialized performance deviations. A set of default weights *W* for Table 1 was defined. The experiment was set with two conditions. In Condition 1, agents were assigned weights that could vary by no more than 10% from the corresponding

Figure 4. Expressive deviations of two agents from Experiment 1 after 20 iterations for the first 5 bars of the melody of Chopin's Étude No. 3, *Op. 10. (Each point in the plots corresponds to a note in the score, excepting the last point in each plot.) The top graph (circles) shows the weight set A of an agent (tempo expression only), hence only tempo expression is plotted. The bottom graph (crosses) shows the weight set B of another agent (loudness evaluation only), hence only loudness expression is plotted.*



default weight in set W. In Condition 2, this variation was raised to 60%. Thus, in Condition 2, the preference weights varied much more widely across agents than in Condition 1. In each condition, 30 iterations were performed, and the coefficient of variation (i.e., the ratio of standard deviation to mean for both tempo and loudness deviations) was calculated for deviations across the population. This experiment was repeated 10 times, each time with different initial random performance deviations.

After 30 iterations of Condition 1, the resulting average coefficient of variation for tempo and for loudness deviations was 0.2%. In Condition 2, with more diverse preference weights, the value was 1.9%. This supports the ability of IMAP to generate a diversity of performances and to control that diversity using the spread of preference weights.

Experiment 3: Controlling the Direction of the Performances' Diversity

The purpose of this experiment was to demonstrate that if agent preferences are biased a certain way in a subset of the population, then the resulting performances will become affected by that preference. This demonstrated that, although a diversity of performances can be produced as shown by Experiment 2, changing the distribution of weights enables one to change the distribution of outcomes in a coherent way. To show this, we used the same two weight sets as in Experiment 1: set A, in which $w_{Tem} = 1$, $w_{1Tem} = 1$, and all other weights are 0; and set B, in which $w_{Lou} = 1$, $w_{3Lou} = 1$, and all other weights are 0. Thus, weight set A only affects timing, and weight set B only affects loudness. The two weight sets do not overlap in their effect. In this experiment, the population of 15 agents from Experiment 1 had another 5 agents added to it. The 15 agents (labeled group G2) are assigned weight set B, and the 5 additional agents (labeled group G1) are assigned weight set A. The objective is to demonstrate that the addition of G1 to G2 leads to G1 influencing the performances of G2, despite the fact that G1 and G2 have mutually exclusive weight sets.

Before running the experiment, it is necessary to benchmark the level of random relative increase

Table 3. The Results of Benchmarking the Level of Random Fluctuations

	Run1		*Run2*		*Run3*		*Run4*		*Run5*	
Set B	*Lou*	*Tem*	*Lou*	*Tem*	*Lou*	*Tem*	*Lou*	*Tem*	*Lou*	*Tem*
Before	0.19	0.19	0.213	0.213	0.223	0.223	0.21	0.213	0.301	0.301
After	0.315	0.19	0.325	0.19	0.306	0.248	0.35	0.208	0.374	0.292
Change	0.125	0	0.112	–0.02	0.083	0.025	0.137	–0.005	0.073	–0.009
TempoRatio	0		–0.205		0.301		–0.037		–0.123	

After 25 iterations, the increase in loudness evaluation and tempo evaluation were measured with Equations 3 and 2, respectively. The ratio of tempo evaluation increase to loudness evaluation increase was calculated.

in evaluation that can be generated in the system. Specifically, given an agent system of 15 agents with preference weights that only affect loudness, how much would we expect their expressive tempo evaluation to increase relative to the increase in their expressive loudness evaluation, solely due to random fluctuations in tempo during iterations? These random fluctuations come from the randomized initial performances influencing each other. This was measured by taking a system of 15 agents with loudness-only weights (i.e., weight set B) and doing five runs of 25 cycles. (The authors ran a number of versions of this experiments, and it was clear that as few as five runs of 25 cycles were sufficient to generate meaningful random fluctuations in this context.)

The results are shown in Table 3. The column and row headings in this table are defined as follows: "Lou" refers to the expressive loudness evaluation by Equation 3, "Tem" refers to the expressive tempo evaluation by Equation 2, "Before" is the average evaluation before iterations, "After" is the average evaluation after 25 iterations, "Change" is the change in evaluation before and after 20 iterations, and "TempoRatio" is the change in tempo evaluation divided by the change in loudness evaluation. Essentially, this ratio is a measure of the increase of tempo expressiveness relative to the increase of loudness expressiveness:

$$TempoRatio(P) = \frac{Increase\_in\_E_{Tem}(P)}{Increase\_in\_E_{Lou}(P)} \tag{11}$$

The average value of *TempoRatio* across the five runs is equal to –0.013. This will be used as a measure of relative tempo evaluation increase owing to random fluctuations in performance, because during these five runs there was no evaluation function pressure to increase tempo expressiveness. This particular $TempoRatio = -0.013$ is referred to as the *baseline value* of *TempoRatio*.

Next, another set of runs were performed with 5 agents added to the system of 15 agents described previously. As mentioned, the 5 agents (group G1) were assigned tempo-only weight set A, as opposed to the 15 agents (group G2), which had loudness-only weight set B. The results after 25 iterations are shown in Table 4. The column heading "AP2" is the average performance deviation of agents in G2. For instance, G1(AP2) = 0.255 is G1's average evaluation of G2's performances in Run 2 after 25 iterations.

The key measurements in Table 4 are G1's evaluations of G2's performances AP2; this is written as G1(AP2). Note that all values in "Increase G1(AP2)" row are smaller than all the values in the "Increase G2(AP2)" row. These values are shown before and after iterations in rows 1 and 2 of Table 4, respectively. G1(AP2) is calculated using Equation 12, but this equation can be simplified into Equation 13, because w_{LouG1} is equal to 0 and w_{TemG1} is equal to 1 (weight set A):

$$G1(AP2) = E_{G1}(AP2) = w_{TemG1} * E_{TemG1}(AP2) + w_{LouG1} * E_{LouG1}(AP2) \tag{12}$$

$$G1(AP2) = E_{TemG1}(AP2) \tag{13}$$

Thus, because G1's evaluation functions measure only tempo expressivity, G1(AP2) provides a measure of the expressive tempo evaluation of G2's performance. The difference between G1(AP2)

Table 4. Results of Experiment 3

		Run1 AP2	Run2 AP2	Run3 AP2	Run4 AP2	Run5 AP2
G1(AP2)	Before	0.245	0.273	0.239	0.269	0.255
	After	0.252	0.255	0.274	0.276	0.291
G2(AP2)	Before	0.21	0.236	0.284	0.24	0.234
	After	0.335	0.307	0.349	0.322	0.305
Increase G1(AP2)		0.007	–0.018	0.035	0.007	0.036
Increase G2(AP2)		0.125	0.071	0.065	0.082	0.071
Cross-Group TempoRatio		0.056	–0.253	0.538	0.085	0.507

Results for a 20-agent system made up of 15 agents with weight set B (labeled G2), and 5 agents with weight set A (labeled G1). After 25 iterations, the increase in loudness evaluation and tempo evaluation for the average performance of G2 was measured for both groups. The ratio of tempo evaluation increase to loudness evaluation increase (*Cross-Group TempoRatio*) was then calculated.

before and after the iterations is a measure of how much G2's expressive tempo evaluation has increased, as evaluated by G1. Similarly, the measure of G2's expressive loudness evaluation is found by calculating G2's evaluation of its own performance, G2(AP2), as shown in Equation 14, which can be simplified into Equation 15, because w_{TemG2} is equal to 0 and w_{LouG1} is equal to 1 (weight set B):

$$G2(AP2) = E2_{G2}(AP2) = w_{TemG2} * E_{TemG2}(AP2) + w_{LouG2} * E_{LouG2}(AP2) \quad (14)$$

$$G2(AP2) = E_{LouG2}(AP2) \quad (15)$$

The increase in G2(AP2) before and after iterations gives the increase in G2's loudness expressivity as a result of iterations. The ratio of these two values is shown in Equation 16 and is the increase of expressiveness of G2's tempo deviations relative to the increase in expressiveness of G2's loudness deviations:

$$\frac{Increase\_in\_G1(AP2)}{Increase\_in\_G2(AP2)} = \frac{Increase\_in\_E_{TemG1}(AP2)}{Increase\_in\_E_{LouG2}(AP2)} = CGTR(AP2) \quad (16)$$

This could be interpreted as a form of "cross-group" *TempoRatio* (CGTR) of G2's performance *AP*2. However, Equation 16 is not G1's actual *TempoRatio* as defined in Equation 11; otherwise, the numerator in Equation 16 would have to be increase in $E_{TemG2}(AP2)$. A *TempoRatio* based on this numerator would always be equal to 0, because G2's evaluation function E_{TemG2} is defined by weight set B, in which all weights in E_{TemG2} are set to 0. Therefore, the only meaningful tempo ratio has G1's E_{TemG1} in the numerator. This is not just meaningful, but also relevant: the purpose of this experiment was to investigate how G1's view of expressive performance has influenced G2. Thus, when looking at the influence of G1's evaluation function on G2, we use G1's evaluation function—hence the use of the cross-group *TempoRatio*, or CGTR. This is calculated in the last row of the Table 4. The average value of CGTR for G2's performance is 0.219.

It would be tempting to say that the average CGTR = 0.219 supports the hypothesis that G1's tempo weights have influenced G2's tempo expression, just because it is a positive value. However, on its own, this positive average CGTR might just represent the result of random fluctuations in G2's tempo deviations caused during the iterations. But recall that we have shown in a previous set of five runs that the baseline value *TempoRatio* owing to random fluctuations in a dynamics-only agent set was on the order of –0.013. By comparing G2's CGTR of 0.219 to the baseline value *TempoRatio* of –0.013, and considering that G1 and G2 have mutually exclusive weight sets, one can see that the expressiveness of G2's tempo deviations relative to the expressiveness of G2's loudness deviations is significantly larger than could likely be explained by random fluctuations. This supports the hypothesis that G1 has significantly influenced the increase in G2's tempo expressivity relative to its loudness expressivity. This in turn supports the idea that if agent preferences are biased a certain way in a subset of the population, then the whole system's performances will become affected by that preference.

Conclusions and Recommendations for Further Work

This article introduced an imitative multi-agent system approach to generate expressive performances of music, based on agents' individual parameterized musical rules. We have developed a system called IMAP to demonstrate the approach. Aside from investigating the usefulness of such an application of the imitative multi-agent paradigm, there was also a desire to investigate the inherent feature of diversity and control of diversity in this methodology: a desirable feature for a creative application, such as synthesized musical performance. To aid this control of diversity, parameterized rules based on previous expressive-performance research were used. These were implemented in the agents using previously developed musical-analysis algorithms. When experiments were run, we found that agents were expressing their preferences through their music performances and that diversity could be generated and controlled.

In addition to the possibility of using IMAP in practical applications, there are also potential applications of IMAP in an area in which multi-agent systems are frequently used: modeling for sociological study, specifically in the sociological study of music performance (Clarke and Davidson 1998). However, the focus of this article was on the practical application of imitative multi-agent systems to generate expressive performance, rather than to investigate social modeling.

A priority piece of future work for IMAP would be to conduct formal listening tests to measure human judgments of automatically generated performances. Only then we would be in a better position to evaluate whether IMAP would indeed be more practical and more beneficial for music-making than simply allowing the user to control parameters directly. Another area of work would be listening experiments on how adjusting parameters such as the pitch and inter-onset intervals weights in the LBDM would affect performances, and how other variables such as the number-of-bars horizon in the key-change part of the accentuation curve impacts performances.

The effectiveness of IMAP is to a significant degree decided by the effectiveness of the Analysis Level. We acknowledge that the algorithms we have used are not absolutely perfect; for example, LBDM is known to only be a partial solution to the detection of local boundaries. Different analysis algorithms should be tested. The same could be said of the Rule Level: other sets of rules could be used in experiments. In both the case of the Rule Level and the Analysis Level, such work could include the investigation of explicitly polyphonic analysis functions and rules. Furthermore, despite the initial experience and thoughts regarding convergence criteria for the system, such criteria are by no means obvious in a creative application; thus, further work should be done at this front.

We believe that advanced learning rate functionality would be a fruitful area for further investigation. For example, agents with learning rates of 0% have the power to influence but not be influenced by the system. Another area of investigation is interaction control. The system currently assumes that all agents can always interact with all agents. In multi-agent systems, there are often "popularity" or "connection" measures (Kirke 1997; Wooldridge 2002) that define which agents interact with which. The addition of a social network, which could change conditionally over time, would be worth investigating.

IMAP has the potential to be influenced by human performances, and this is certainly an area worth investigating further. Suppose the system is set up with 50% of agents supplied with performance deviations from a single performance *M* by a human performer *A*. The other 50% would have random performances. Depending on preference weightings, the resulting performances would be influenced to a degree by Performer A's performance. Another approach would be to reverse engineer evaluation function weights from Performer A's performance, using a parameter search optimization technique (Winston and Venkataramanan 2002). Performer A's preference weights would affect the performances more strongly than just using Performer A's initial performances. The preference function would not necessarily contain Performer A's real preference, and there would not be a one-to-one relationship between function weights and a single performance. Nevertheless, such an approach would be worth investigating as a tool for generating new expressive performances. In fact, one could envision a "recipe book" of different agent preferences generated by deviations from different professional performers. These agents could then be added to IMAP in the proportions desired by the user. For example, a user might specify "I would like a performance repertoire of Bach's Piano Partita No. 2 based 30% on Daniel Barenboim's performance, 50% on Glenn Gould's performance, and 20% based on the preference weights I explicitly specify."

Another suggested future work for IMAP would be to study the effect of agent communication noise on the convergence of the system. For instance, Kirke and Miranda (in press) have introduced a multi-agent system in which agents communicate musical ideas and generate new ideas partially through errors in the communication. Similarly, allowing agents in IMAP to make small errors in their performances could be viewed as an imitative equivalent of a GA mutation operator. This would potentially lead to agents generating performances that more closely match their preferences.

Also, one should consider extending IMAP to expressive performance indicators other than tempo and loudness. However, the limitations of MIDI make this difficult with our current framework. Ideally, we should address this extension once we are in a position to deal directly with audio rather than MIDI.

Acknowledgments

This work was financially supported by the EPSRC-funded project "Learning the Structure of Music," grant EPD063612-1. Qijun Zhang was partially supported by the Faculty of Technology, University of Plymouth.

References

Ben-David, A., and J. Mandel. 1995. "Classification Accuracy: Machine Learning vs. Explicit Knowledge Acquisition." *Machine Learning* 18(1):109–114.

Boulanger, R., ed. 2000. *The Csound Book: Perspectives in Software Synthesis, Sound Design, Signal Processing, and Programming*. Cambridge, Massachusetts: MIT Press.

Boyd, R., and P. J. Richerson. 2005. "Solving the Puzzle of Human Cooperation." In S. Levinson, ed. *Evolution and Culture.* Cambridge, Massachusetts: MIT Press, pp. 105–132.

Bresin, R. 1998. "Artificial Neural Network Based Models for Automatic Performance of Musical Scores." *Journal of New Music Research* 27(3):239–270.

Bresin, R., and A. Friberg. 2000. "Emotional Coloring of Computer-Controlled Music Performances." *Computer Music Journal* 24(4):44–63.

Bresin, R., and C. Vecchio. 1995. "Neural Networks play Schumann." *Proceedings of the KTH Symposium on Grammars for Music Performance.* Stockholm: Department of Speech Communication and Music Acoustics, KTH, pp. 5–14.

Cambouropoulos, E. 2001. "The Local Boundary Detection Model (LBDM) and Its Application in the Study of Expressive Timing." *Proceedings of the 2001 International Computer Music Conference*. San Francisco, California: International Computer Music Association. Available online at hdl.handle.net/2027/spo.bbp2372.2001.021.

Camurri, A., R. Dillon, and A. Saron. 2000. "An Experiment on Analysis and Synthesis of Musical Expressivity." *Proceedings of 13th Colloquium on Musical Informatics*. L'Aquila, Italy: Istituto Gramma. Available online at ftp://infomus.dist.unige.it/Pub/Publications/CIM2000CDS.PDF.

Canazza, S., et al. 2000. "Audio Morphing Different Expressive Intentions for Multimedia Systems." *IEEE Multimedia* 7(3):79–83.

Clarke, E. F. 1988. "Generative Principles in Music Performance." In J. Sloboda, ed. *Generative Processes in Music: The Psychology of Performance, Improvisation, and Composition*. Oxford: Clarendon Press, pp. 1–26.

Clarke, E. F., and J. W. Davidson. 1998. "The Body in Music as Mediator Between Knowledge and Action." In W. Thomas, ed. *Composition, Performance, Reception: Studies in the Creative Process in Music*. Oxford: Oxford University Press, pp. 74–92.

Clynes, M. 1986. "Generative Principles of Musical Thought: Integration of Microstructure with Structure." *Communication and Cognition* 3:185–223.

De Boer, B. 2000. "Emergence of Vowel Systems through Self-Organisation." *AI Communications* 13:27–29.

Dissanayake, E. 2001. "Birth of the Arts." *Natural History* 109(10):84–92.

Friberg, A., R. Bresin, and J. Sundberg. 2006. "Overview of the KTH Rule System for Musical Performance." *Advances in Cognitive Psychology* 2(2):145–161.

Friberg, A., and J. Sundberg. 1999. "Does Music Performance Allude to Locomotion? A Model of Final Ritardandi Derived from Measurements of Stopping Runners." *Journal of the Acoustical Society of America* 105(3):1469–1484.

Gabrielsson, A. 2003. "Music Performance Research at the Millennium." *Psychology of Music* 31:221–272.

Goldberg, D. E. 1989. *Genetic Algorithms in Search, Optimization, and Machine Learning*. Cholchester: Addison-Wesley.

Grindlay, G. C. 2005. "Modeling Expressive Musical Performance with Hidden Markov Models." Master's Thesis, University of California Santa Cruz.

Hashida, M., N. Nagata, and H. Katayose. 2006. "Pop-E: A Performance Rendering System for the Ensemble Music that Considered Group Expression." *Proceedings of 9th International Conference on Music Perception and Cognition*. Bologna: ESCOM, pp. 526–534.

Ishikawa, O., et al. 2000. "Extraction of Musical Performance Rule Using a Modified Algorithm of Multiple Regression Analysis." *Proceedings of the 2000 International Computer Music Conference.* San Francisco, California: International Computer Music Association, pp. 348–351.

Johnson, M. L. 1991. "Toward an Expert System for Expressive Musical Performance." *Computer* 24(7):30–34.

Juslin, P. 2003. "Five Facets of Musical Expression: A Psychologist's Perspective on Music Performance." *Psychology of Music* 31(3):273–302.

Kirke, A. 1997. "Learning and Co-operation in Mobile Multi-Robot Systems." PhD Thesis, University of Plymouth.

Kirke, A., and E. R. Miranda. 2009. "A Survey of Computer Systems for Expressive Music Performance." *ACM Surveys* 42(1): Article 3.

Kirke, A., and Miranda, E. R. In press. "Using a Biophysically Constrained Multi-Agent System to Combine Expressive Performance with Algorithmic Composition." In E. R. Miranda, ed. *A-Life for Music: Music and Computer Models of Living Systems*. Middleton, Wisconsin: A-R Editions.

Krumhansl, C. 1991. *Cognitive Foundations of Musical Pitch*. Oxford: Oxford University Press.

Lerdahl, F., and Jackendoff, R. 1983. *A Generative Theory of Tonal Music*. Cambridge, Massachusetts: MIT Press.

Livingstone, S. R., et al. 2007. "Controlling Musical Emotionality: An Affective Computational Architecture for Influencing Musical Emotions." *Digital Creativity* 18(1):43–53.

Miranda, E. R. 2002. "Emergent Sound Repertoires in Virtual Societies." *Computer Music Journal* 26(2):77–90.

Miranda, E. R., and J. A. Biles, eds. 2007. *Evolutionary Computer Music*. London: Springer.

Noble, J., and D. W. Franks. 2004. "Social Learning in a Multi-Agent System." *Computing and Informatics* 22(6):561–574.

Palmer, C. 1997. "Music Performance." *Annual Review of Psychology* 48:115–138.

Park, T. H. 2009. "An Interview with Max Mathews." *Computer Music Journal* 33(3):9–22.

Ramirez, R., and A. Hazan. 2005. "Modeling Expressive Performance in Jazz." *Proceedings of 18th International Florida Artificial Intelligence Research Society Conference.* Menlo Park, California: Association for the Advancement of Artificial Intelligence Press, pp. 86–91.

Ramirez, R., et al. 2008. "A Genetic Rule-Based Model of Expressive Performance for Jazz Saxophone." *Computer Music Journal* 32(1):38–50.

Raphael, C. 2001. "Synthesizing Musical Accompaniments with Bayesian Belief Networks." *Journal of New Music Research* 30(1):59–67.

Seashore, C. E. 1938. *Psychology of Music*. New York: McGraw-Hill.

Sundberg, J., A. Askenfelt, and L. Frydén. 1983. "Musical Performance: A Synthesis-by-Rule Approach." *Computer Music Journal* 7:37–43.

Thomassen, J. M. 1982. "Melodic Accent: Experiments and a Tentative Model." *Journal of the Acoustical Society of America* 71(6):1596–1605.

Todd, N. P. 1985. "A Model of Expressive Timing in Tonal Music." *Music Perception* 3:33–58.

Todd, N. P. 1992. "The Dynamics of Dynamics: A Model of Musical Expression." *Journal of the Acoustical Society of America* 91(6):3540–3550.

Widmer, G., and W. Goebl. 2004. "Computational Models of Expressive Music Performance: The State of the Art." *Journal of New Music Research* 33(3):203–216.

Widmer, G., and A. Tobudic. 2003. "Playing Mozart by Analogy: Learning Multi-Level Timing and Dynamics Strategies." *Journal of New Music Research* 32(3):259–268.

Winston, W. L., and M. Venkataramanan. 2002. *Introduction to Mathematical Programming: Applications and Algorithms*. Pacific Grove, California: Duxbury Press.

Wooldridge, M. 2002. *An Introduction to Multi-Agent Systems*. Hoboken, New Jersey: Wiley.

Zentall, T., and B. G. Galef. 1988. *Social Learning: Psychological and Biological Perspectives*. Hillsdale, New Jersey: Lawrence Erlbaum.

Zhang, Q., and E. R. Miranda. 2006. "Evolving Musical Performance Profiles Using Genetic Algorithms with Structural Fitness." *Proceedings of the 8th Annual Conference on Genetic and Evolutionary Computation*. New York: Association for Computing Machinery, pp. 1833–1840.