Functional Scaffolding for Composing Additional Musical Voices

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Amy K. Hoover, Paul A. Szerlip, and Kenneth O. Stanley
Department of Electrical Engineering and Computer Science (CS Division)
University of Central Florida
Orlando, FL 32816-2362 USA
{ahoover@eecs.ucf.edu, paul.szerlip@gmail.com,kstanley@eecs.ucf.edu}

Abstract

Many tools for computer-assisted composition contain built-in music-theoretical assumptions that may constrain the output to particular styles. In contrast, this article presents a new musical representation that contains almost no built-in knowledge, but that allows even musically untrained users to generate polyphonic textures that are derived from the users' own initial compositions. This representation, called *functional scaffolding for musical composition* (FSMC), exploits a simple yet powerful property of multipart compositions: The pattern of notes and rhythms in different instrumental parts of the same song are *functionally related*. That is, in principle, one part can be expressed as a function of another. Music in FSMC is represented accordingly as a functional relationship between an existing human composition, or *scaffold*, and a generated set of one or more additional musical voices. A human user without any musical expertise can then explore how the generated voice(s) should relate to the scaffold through an interactive evolutionary process akin to animal breeding. By inheriting from the intrinsic style and texture of the piece provided by the user, this approach can generate additional voices for potentially any style of music without the need for extensive musical expertise.

1 Introduction

Because musical structure is well-established and understood by music theoreticians, researchers often impart this expertise to the compositional tools that they create. However, such formalized rules or carefully extracted statistical relationships inevitably yield a musical space that constrains results to particular styles and genres, thus limiting the users' ability to explore outside their bounds (Todd and Werner 1999; Chuan 2009; Cope 1987; McCormack 1996; Conklin 2003; Pachet 2003).

In contrast, this paper introduces a new representation for computer-assisted musical composition that includes almost no built-in knowledge of musical structure (apart from the key and the smallest unit of rhythm) yet still helps users compose starting from some preexisting music, called a *scaffold*, that contains one or more simultaneous musical voices. Called *functional scaffolding for musical composition* (FSMC), this approach exploits two rarely explored mathematical properties of music: (1) that music can be represented as a function of time (Putnam 1994) and (2) that multiple simultaneous voices in a coherent piece are functionally related to each other. Interestingly, these properties alone are sufficient to be harnessed to create additional musical voices. In particular, the existing parts from the scaffold are functionally transformed into one or more additional voices through a neural-network-like representation called a compositional pattern-producing network (CPPN; Stanley 2007), which inputs the scaffold and outputs a corresponding generated voice. The key insight that makes this approach interesting is that simply creating a functional relationship between one sequence of notes and another, with no other musical principles, is enough to create the effect that one sequence is a plausible simultaneous countermelody, harmony, or accompaniment of the other.

To implement this idea in practice, a program called MaestroGenesis (freely available at `http://maestrogenesis.org`) was introduced to allow users to explore the space of computer-generated musical voices created by such CPPN-based transformations. It helps users navigate the space of possible transformations (i.e. additional voices) by presenting the user with a set of candidate generated voices and allowing the user to choose the best. A new set of candidate generated voices then inherit some of the appealing traits of those chosen from the previous generation. This process, called interactive evolutionary computation (IEC) (Takagi 2001; Dawkins 1986; Sims 1991), can be repeated many times to evolve towards a desired feel. The underlying evolutionary algorithm that enables this process is called NeuroEvolution of Augmenting Topologies (NEAT), through which the music-generating CPPNs can gradually increase in complexity (Stanley and Miikkulainen 2002).

Because FSMC emphasizes the importance of functional relationships between parts of a song, the hope is that MaestroGenesis can create high quality computer-generated additional voices through functional transformations. This paper is the first to present such a comprehensive overview of FSMC and MaestroGenesis by distilling and expanding the results from a series of prior conferences papers (Hoover et al. 2011a,b, 2012) and also presenting an entirely new study exploring experiences of amateur musicians with MaestroGenesis. FSMC is a significant step toward assisted music generation based on the surprisingly simple hypothesis that functional relationships alone are sufficient to generate plausible musical voices. While the impact of this technology on the musical creativity of amateurs will emerge from its use over time, the identification of such a simple and generic principle can potentially broaden the application of assistive musical technologies in the future.

The next section provides relevant background and Section 3 introduces the FSMC approach. Four experiments and their results are then described in Section 4. This point and implications of these results are finally discussed in Section 5.

2 Background

Much of the expressive potential of computer-generated music derives from the power of chosen musical representations. This section discusses prior approaches and representations in computer-generated music and describes a precursor to the FSMC method called NEAT Drummer.

2.1 Representations in Computer Music and Human-Computer Collaboration

Many musical representations have been proposed before FSMC, although their focus is not necessarily on representing the functional relationship between parts. For example, Holtzman (1981) describes a musical grammar that generates harp solos based on the physical constraints faced by harpists. Similarly, Cope (1987) derives grammars from the linguistic principles of haiku to generate music in a particular style. While grammars can produce a plausible rhythmic and melodic structure, deciding which aspects of musical structure should be represented by them is often difficult and ad hoc (Kippen and Bel 1992; Marsden 2000).

An alternative to manually constructing grammars is to discover important musical relationships through statistical analyses of musical corpora that then guide decision-making (Ponsford et al. 1999; Gillick et al. 2009). While this approach represents a significant contribution towards understanding how music can be generated by computers, the challenge is to gather sufficient data to generate plausible music without being too restrictive.

There have been many different approaches to incorporating human input into computer-generated music. The grammar-based program Impro-Visor helps users create monophonic jazz solos by automatically composing any number of measures in the style of famous jazz artists (Keller et al. 2006). Styles are represented as grammars that the user can invoke to complete compositions. While Impro-Visor is an innovative tool for teaching jazz styles to experienced musicians, it focuses on emulating prior musicians over exploration of a new sound. Another program, MySong, generates chord-based accompaniment for a vocal piece from hidden Markov models (Simon et al. 2008). However, MySong also requires a significant database of specific examples that must be carefully constructed by the programmers. Some programs address the need for data by offloading the responsibility of rule and database construction to the user (Zicarelli 1987; Chuan 2009).

In contrast to works that depend upon specific rules or trained transition tables, the aim in this paper is to exploit very general, high-level principles that can be applied across a broad range of compositions and styles while still taking users' input in the tradition of interactive evolution, described next.

2.2 Interactive Evolutionary Computation

A popular approach to facilitating creativity in non-experts in a variety of domains is a process similar to animal breeding called *interactive evolutionary computation* (IEC; Takagi 2001; Dawkins 1986; Sims 1991). The idea is that humans, rather than hard-coded rules, can rate candidate generated music in place of an explicit fitness function. IEC originated in Richard Dawkins' book, *The Blind Watchmaker*, in which he described a simple program called *Biomorphs* that is meant to illustrate evolutionary principles (Dawkins 1986). The program displays a set off several pictures (called Biomorphs) on the screen at one time. The user then selects from among those pictures (called the *population*) his or her favorite. From that selection, a new generation of *offspring* is spawned that replace the original population. Because the offspring are generated through slight mutations of the underlying genes of the selected parents, they tend to resemble their parents while still suggesting novel traits. In this way, over many generations, the user in effect *breeds* new forms.

Music composition is a popular application of IEC, wherein users specify the candidate compositions they like best, which are then mutated to create new candidates (Johanson and Poli 1998; Nelson 1993; Biles 1994, 2007; Collins 2002; Hoover and Stanley 2009; Tokui and Iba 2000). Most such systems impose explicit musical rules (often grammatical) conceived by the developer to constrain the search spaces of possible musical voices, thereby narrowing the potential for discovery. Thus the unexploited opportunity at the focus of this paper is to borrow from the creative seed already present in the user-created scaffold to enhance the generated output with very few formalized constraints.

2.3 NEAT Drummer and CPPNs

FSMC builds upon previous work by Hoover et al. (2008) and Hoover and Stanley (2009) on an IEC-based system called NEAT Drummer that creates percussion patterns for existing compositions. The drum generator transforms an input song into a drum pattern that embellishes the pitch and rhythmic patterns of the original song.

This transformation occurs through a special type of function representation called a compositional pattern-producing network (CPPN; Stanley 2007), which is also the representation in FSMC. The CPPN is a network of interconnected nodes similar to a neural network. However, unlike traditional neural networks, each node in a CPPN can compute a different type of function. In both NEAT Drummer and MaestroGenesis, hidden node activation functions include Gaussian, sigmoid, linear, sine, and multiplicative functions. These induce different types of symmetries and patterns with particular regularities. For example, in addition to generating drum patterns in NEAT Drummer, they are the representation behind the images evolved interactively by users in the Picbreeder and Endlessforms online services (Secretan et al. 2011; Clune and

Lipson 2011), which yielded spatial patterns with regularities and symmetries. CPPNs are in effect generic pattern generators capable of producing patterns in space (such as images) just as they can produce patterns in time (such as music).

CPPNs are typically evolved by an algorithm called NeuroEvolution of Augmenting Topologies (NEAT; Stanley and Miikkulainen 2002), which produces a new generation of CPPNs from those selected in the current generation. While the NEAT method was originally developed to solve difficult control and sequential decision tasks, in both NEAT Drummer and MaestroGenesis it is chosen for its ability to evolve minimal CPPN topologies. Both programs begin evolution with simple random CPPNs, each with one hidden node and a variable number of input and output nodes chosen by the user; the weights and activation functions are assigned through uniform random numbers at the beginning. NEAT then incrementally evolves CPPNs by gradually adding nodes and connections through crossover and mutation, which means the patterns they generate can become more complex. Only those structures survive that are found to be useful through interactive fitness evaluations. By starting with simple networks, NEAT searches through a minimal number of weight dimensions to find the appropriate complexity level for the problem.

NEAT Drummer (Hoover and Stanley 2009), the predecessor to FSMC, demonstrated that the generic pattern-generating capability of CPPNs can indeed be applied to musical patterns by generating percussion accompaniment. In NEAT Drummer, users breed percussion accompaniments by selecting those with the most appealing musical qualities. While NEAT Drummer showed that functional scaffolding (implemented through CPPNs) can produce credible percussion accompaniment, it left open the question of whether such an approach can produce complete orchestration from monophonic or polyphonic pieces, which is the aim of FSMC.

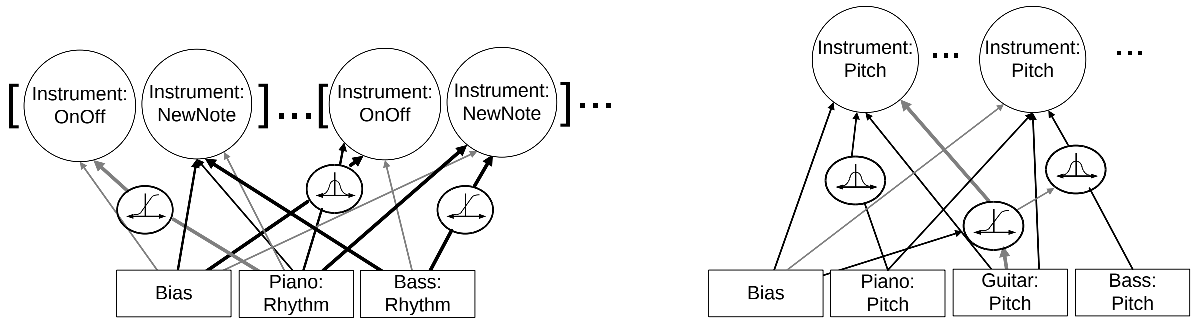
3 Approach

Extending the idea of NEAT Drummer to pitch as well as rhythm, instrumental parts in FSMC are generated from existing compositions. These compositions form a *scaffold* from which generated musical voices are built. However, unlike in NEAT Drummer, these scaffolds include timing information and pitch information, thereby providing the foundation for melodic and harmonic creation.

To understand the idea behind FSMC, consider the proposition that if different simultaneous instrumental parts in the same composition were not somehow related to each other, they would probably sound inappropriate together. This relationship can be conceived as a function that describes how one part might be transformed into another. That is, theoretically there exists a function that can transform one sequence of notes and rhythmic information into another. The idea in FSMC is to exploit this fact by literally evolving the function that relates one part to another. That way, instead of searching for a sequence of notes, FSMC can search for a transforming function that bootstraps off the existing parts (i.e. called the scaffold) to generate the additional voices. In effect, FSMC is the hidden function that relates different simultaneous parts of a composition to each other.

In particular, this transforming function is encoded in FSMC by CPPNs (Stanley 2007), as detailed shortly. However, it is important to note that in principle any representation of functional relationships could serve the role of CPPNs in FSMC, which are chosen in the presented implementation for their practical convenience and precedent in NEAT Drummer.

Users help to define the search space in FSMC by first selecting the musical starting point, i.e. an existing piece (either monophonic or polyphonic) called the scaffold. The terms monophonic and polyphonic indicate the number of voices contained in the piece,



(a) Rhythm (b) Pitch

Figure 1. ***CPPNs Compute a Function of the Input Scaffold.*** *The rhythm CPPN in (a) and pitch CPPN in (b) together form the generated music of FSMC. The inputs to the CPPNs (at bottom) are the scaffold rhythms and pitches for the respective networks and the outputs (at top) indicate the rhythms and pitches of the generated voices. The internal topologies of these networks, which encode the functions they perform, change over evolution. While these particular CPPNs depict an evolved arrangement of hidden nodes and activation functions (i.e. Gaussian and sigmoid functions), through evolution an unlimited number and arrangement of hidden nodes can occur. In MaestroGenesis, each hidden node is represented by either a Gaussian, sigmoid, linear, sine, or multiplicative function. In this example two generated voices are depicted, but the number of instrument outputs is in principle unlimited. The number of input instruments selected by the user also can vary depending on how many voices from the scaffold the user includes.*

i.e. a single voice versus multiple voices. Initial scaffolds can be composed in any style and at almost any level of expertise. Advanced users who may only need a single new part for existing compositions can start with a polyphonic composition, while single monophonic parts needing multiple layers of generated voices can be composed by users within a wide range of musical skill and expertise. The main insight behind the representation in FSMC is that a robust space of generated musical voices can be created with only this initial scaffold. Because of the relationship of different generated voices to the scaffold and therefore to each other, the space is easily created and explored.

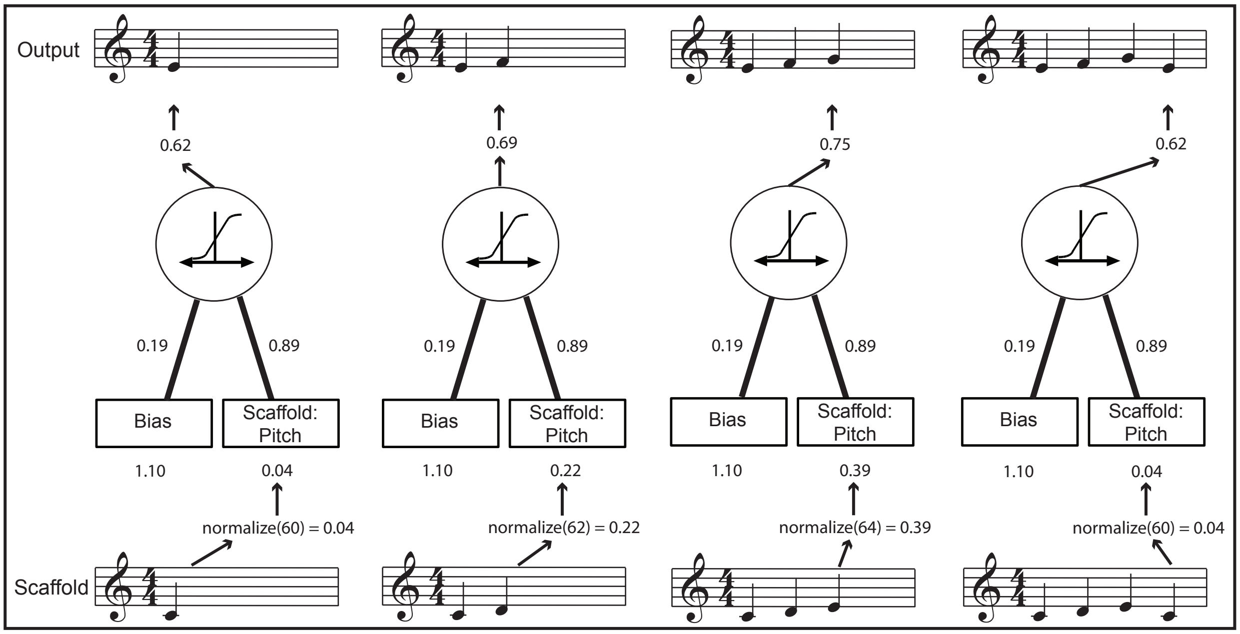
Recall that a CPPN is in effect a kind of neural network with heterogeneous activation functions at its nodes. The CPPNs depicted in figure 1 implement the idea of functional scaffolding. Each generated voice is encoded by two CPPNs: one for rhythm and one for pitch. Each CPPN is itself just a formalism for specifying a function that can be artificially evolved. The inputs to the CPPNs are the pattern of notes and durations within the scaffold and the outputs form the generated voice. In this way, each CPPN is literally a function of the scaffold that transforms it into a functionally-related rhythm or pitch pattern.

The hidden nodes in the CPPNs depicted in figure 1 are added by mutations that occasionally occur over the evolutionary process. They in effect increase the complexity of the transforming function by adding intervening nonlinearities. For example, the Gaussian function introduces symmetry (i.e. such as the same sequence of notes ascending and then descending) and the sigmoid is nonlinear yet asymmetric. By accumulating such transformations within a single CPPN, the relationship between scaffold and generated voice can become more complex.

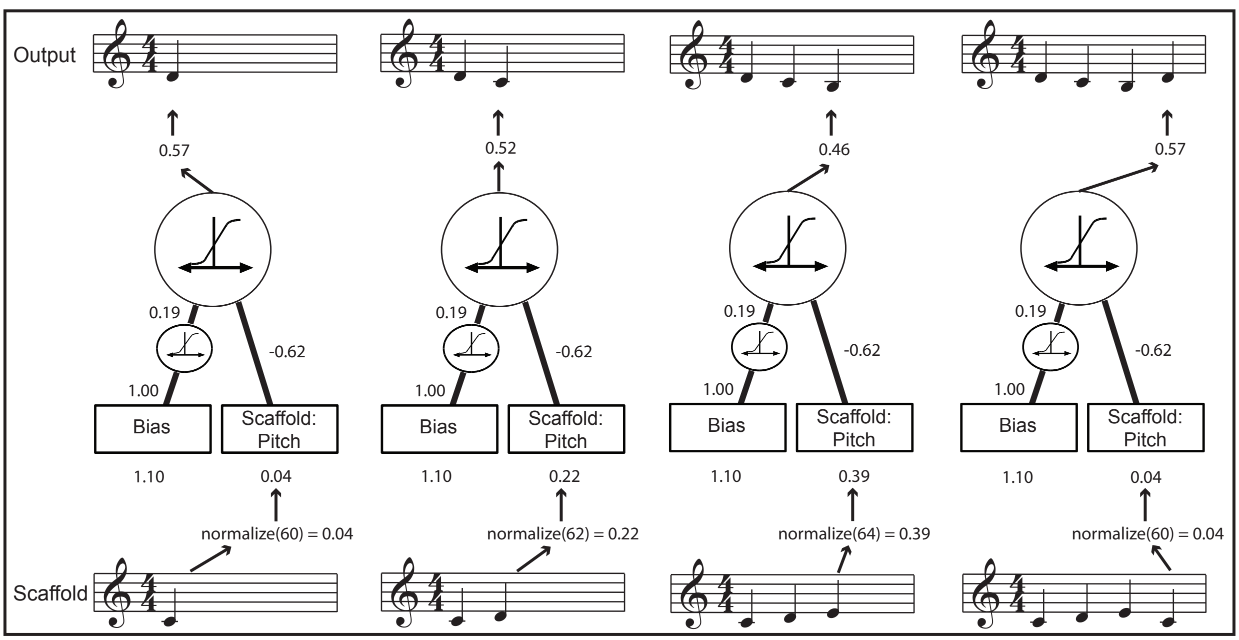
Each instrumental voice in the output is the result of the two separate functions that independently relate rhythmic and pitch information in the scaffold (i.e. the inputs) to the computer-generated additional voice, as shown in figure 1. It is important to note that the rhythm and pitch CPPNs are separated intentionally because combining them into a single CPPN would in effect imply that times within a piece are semantically similar to pitches of notes. Such a conflation leads to incoherent patterns, as preliminary experiments with such a setup confirmed. As figure 1 shows, multiple instruments can be input simultaneously and multiple instruments can be similarly output by the same CPPN. In effect, pitch information from the scaffold is fed into the pitch CPPN at the same time as rhythmic information is fed into the rhythm CPPN. Both CPPNs then output how the generated voice should behave in response. That way, they compute a function of the scaffold, establishing the essential functional relationship.

FSMC’s musical outputs are divided into a series of discrete time intervals called *ticks* that are concatenated together to form an entire piece. Each tick typically represents the length of an eighth note, though it could be a shorter or longer unit. Outputs are gathered from both the rhythmic and pitch CPPNs at each tick that are combined to determine the particular note (or rest) at that tick. As shown in figure 1a, the two outputs of the rhythm network for each generated voice are *OnOff*, which indicates whether a note or rest is played and (in the former case) its volume, and *NewNote*, which indicates whether or not to sustain the previous note. The single pitch output for each generated voice in figure 1b determines instrument pitch at the current tick (if a note is played) relative to a user-specified key.

To help illustrate intuitively how CPPNs work to encode functional transformations in FSMC, figure 2 shows how pitch outputs are calculated at each tick and how CPPN mutations can affect the generated output. The sequence in figure 2 is a simple example of both how CPPNs calculate their outputs and also how mutations to the CPPN in figure 2a alter the output it produces for the same scaffold (shown in figure 2b). While this example focuses on the pitch CPPN, the rhythm CPPN computes its transformations in an analogous manner. Each of the four identical pitch CPPNs in figure 2a and the four identical CPPNs in figure 2b represent a calculation made at a particular tick from both a bias (which is just a constant input) and scaffold input. To calculate the output value for the simple CPPN in figure 2a (which has just one activation function), the bias value of 1.1 and the particular scaffold value (which represents a normalized MIDI pitch) at the given tick are multiplied by their respective connection weights within the CPPN (0.19 and 0.89) and added together to produce a sum called $ActivationSum$. The value that results from $\mathrm{sigmoid}(ActivationSum) = \frac{1}{1+e^{-2 \cdot ActivationSum}}$ is a real number between $[0, 1]$ that is then mapped to one of fifteen notes in a two octaves of a diatonic key set by the user. For example, if the CPPN outputs a number between $[0, 0 + \frac{1}{15})$, the additional generated voice plays the tonic of the selected key whereas an output value between $[\frac{1}{15}, \frac{2}{15})$ would generate the supertonic. While the output of MaestroGenesis is constrained to standard diatonic keys, scaffold values can be input as any chromatic note. This example shows that it is in effect the weights of the connections within the CPPN (which act like coefficients) and the particular activation functions with its nodes



(a) Initial Generation Pitch CPPN over Time



(b) Second Generation Pitch CPPN over Time (with Mutations)

Figure 2. ***Pitch CPPNs over Two Generations*** *The pitch CPPNs in (a) and (b) illustrate how scaffolds are transformed to musical outputs. Each of the four identical CPPNs in (a) and the four identical CPPNs in (b) represent a calculation made at the four quarter-note-length ticks in this one measure scaffold. The CPPN in (a) is from the first generation and has yet to evolve hidden nodes, while the CPPN in (b) from the second generation has evolved an hidden node between the bias and output and mutated the existing connection weights.*

that determine what it outputs for a particular scaffold input.

Unlike the network in figure 2a, the CPPN in figure 2b has evolved the existing connection weights and a new sigmoid hidden function between the bias input and the output. Because there are now two activation functions in the CPPN, two separate activation sums and values must be considered. Starting from the bottom of the CPPN, the activation sum for the hidden node is calculated first and input to its sigmoid activation function such that the output (activation level) for the hidden node is $mathrmsigmoid(1.1 \cdot 1.0)$. For the second activation sum, the previously calculated hidden node value is multiplied by its connection weight of -0.19 and added to the scaffold input value multiplied by its connection weight, $\mathrm{normalize}(midi) \cdot -0.62$. The final output depends on the current tick, but is represented by the function, $\mathrm{output} = \mathrm{sigmoid}(\mathrm{sigmoid}(1.1 \cdot 1.0) \cdot -0.19 + (\mathrm{normalize}(\mathrm{midi}) \cdot -0.98))$. While the generated melody in 2a is transposed a diatonic third from the scaffold pitches, the additional hidden function and corresponding weight mutations in figure 2b in effect transpose and mirror invert the melody generated in figure 2a down a diatonic second.

In total, the example in figure 2 shows how it is possible for a network of weights and activation functions (the CPPN) to compute functional transformations of a sequence of pitches, and how mutations to the CPPN can perturb the nature of such transformations, enabling the discovery of different relationships through an evolutionary process.

Figure 3 illustrates through another example how FSMC interprets the rhythmic (at left) and pitch (at right) information contained in the scaffold. In this example, the scaffold is from the folk song Scarborough Fair. Each instrument in the scaffold, i.e. oboe, nylon guitar, clavinet I, and clavinet II, is input to both the rhythm and pitch CPPNs (which were evolved as explained in the next section) to create the computer-generated additional voice for Scarborough Fair. To produce the outputs, rhythmic and pitch information from the scaffold is sent to the CPPN at each tick. To encode rhythm, when a note strikes or a rest begins, it is represented as a maximum input level that decays linearly over time (i.e. over a number of ticks) until the note ends. The decay does not affect audio or amplitude envelope, and instead indicates to the CPPN how many ticks have elapsed since the note was struck. At the same tick, pitch information on the current note is input as a MIDI pitch value modulus 24 into the pitch CPPN. That is, C4 and C5 are differentiated, but C4 is equivalent to C6. The net effect is that the time within each note, or the number of elapsed ticks, and its pitch are known to the rhythm and pitch CPPNs at every tick.

To implement FSMC in practice, the program called *MaestroGenesis* (URL given in Section 1) provides an interface to help the user explore possible CPPN-encoded transforms to user-chosen scaffolds (figure 4). The sound of instruments in FSMC can be altered through instrument choice or key. A user can pick any of 128 pitched MIDI instruments and can request any of the major or natural minor keys. While FSMC can potentially generate additional voices in any key, MaestroGenesis outputs are restricted to the seven pitch classes of the current key signature. Once the user decides from what preexisting piece the scaffold is provided and the output instruments most appropriate for the piece, candidate CPPNs can be generated, thus establishing the musical space of generated voices. The theory behind this approach is that by exploring the potential relationships between scaffolds and their extra generated voices (as opposed to exploring direct representations of the voice itself), the user is constrained to a space in which candidate generated voices are almost all likely coherent with respect to the scaffold.

Of course, selecting the scaffold itself an important task. It requires selecting an existing composition and then choosing to which instrument tracks the rhythm and pitch networks should listen. For example, whether or not the rhythm network listens to

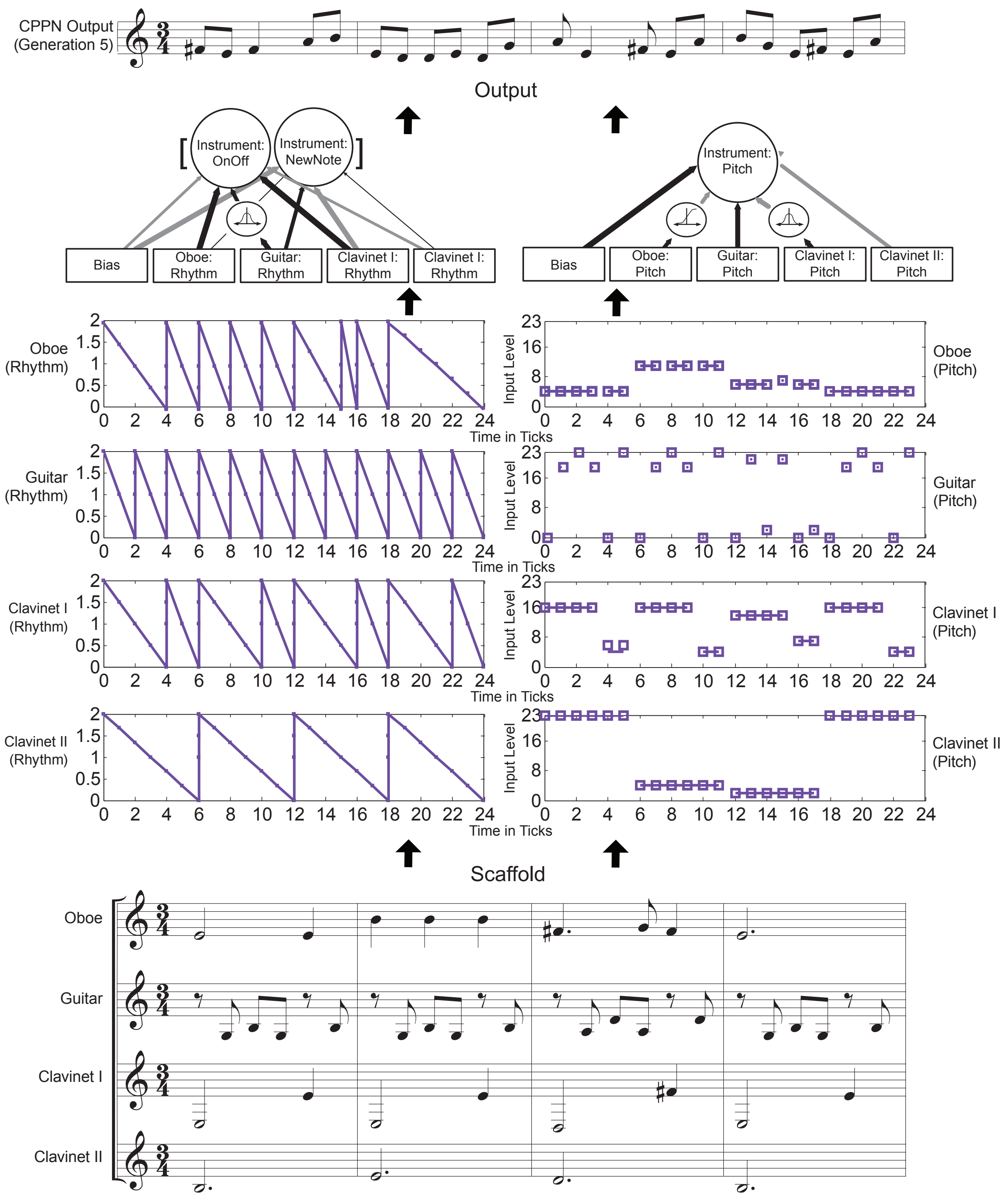


Figure 3. ***Representing the Scaffold.*** *This additional voice for Scarborough Fair (top) is generated from the four instruments in the scaffold (bottom). Each of these instruments is input to both the rhythmic CPPN (middle left) and the pitch CPPN (middle right). This example can be heard at* `http://eplex.cs.ucf.edu/fsmc/cmj`*. (See text for further explanation.)*

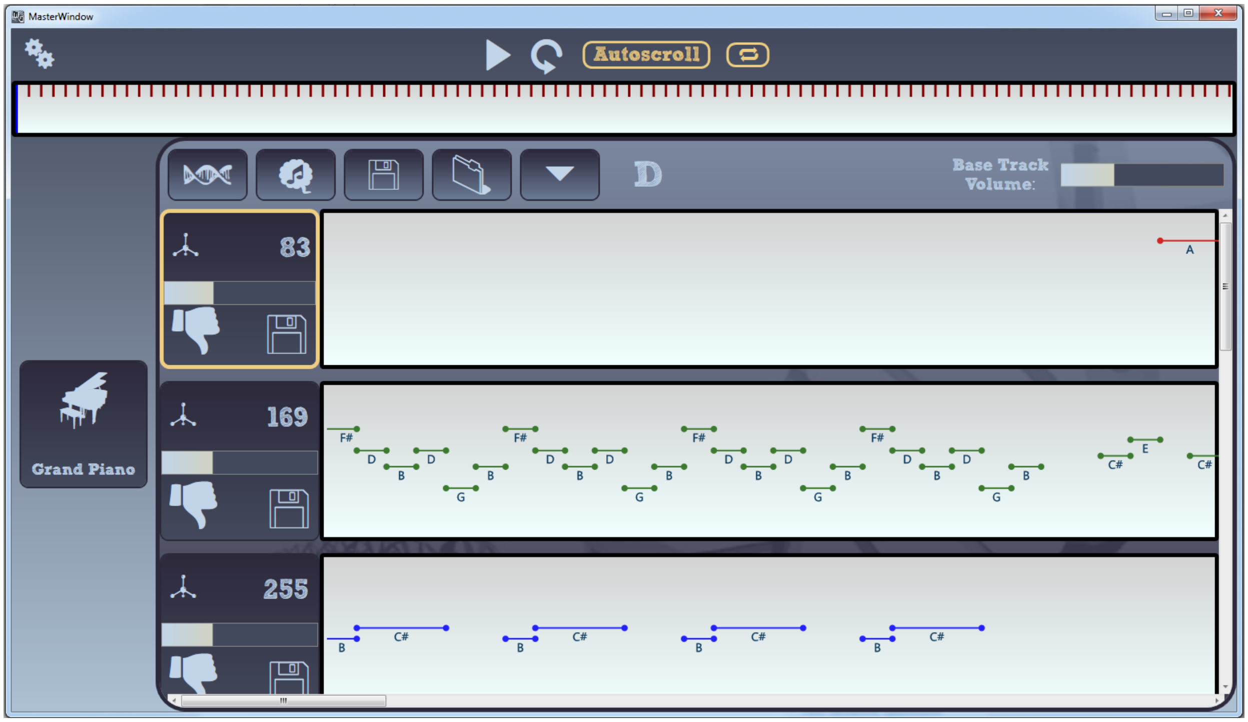


Figure 4. ***Program Interface.*** *This screenshot of the program (called MaestroGenesis;*`http://maestrogenesis.org`*) that implements FSMC shows generated voices for a melody input by the user. The user selects his or her favorites and then requests a new generation of candidates.*

a fast-changing instrument can impact the perceived complexity of the corresponding generated output. In fact, chosen tracks do not have to be the same for each network (e.g. the rhythm network can have piano and guitar inputs while the pitch network only has a bass guitar input).

Exploration of musical space in FSMC begins with the presentation to the user of the output of ten randomly-generated CPPN pairs, each defining the musical relationships between the scaffold and generated output (as shown in figure 4). These can be played through either MIDI or MP3 formats, the latter resulting from the open source FluidSynth soundfont simulator available at `http://sourceforge.net/apps/trac/fluidsynth/`. The user-guided process of exploration that combines and mutates these candidates is IEC, which was explained in Section 2.2: The user explores musical voices in this space by selecting and rating one or more of the computer-generated voice(s) from one generation to parent the individuals of the next. The idea is that the good musical ideas from both the rhythmic and pitch functions are preserved with slight alterations or combined to create a variety of new but related functions, some of which may be more appealing than their parents. The space can also be explored without combination by selecting only a single generated voice. The next generation then contains slight mutations of the original functions.

While IEC has previously been applied to music generation (Nelson 1993; Moroni et al. 2000; Bäckman and Dahlstedt 2008; Biles 1994), instead of manipulating single notes or features of a composition, FSMC permits the evolution of entire functional relationships, thereby ensuring that the search space at least only considers generated voices with some relationship to the scaffold. Because the parts of the scaffold themselves are human-composed and thereby sound appealing, generated voices built from any combination of such tracks end up acknowledging and transforming the pitch and rhythmic patterns of the original song.

One application of FSMC is generating single-instrument voices for an existing monophonic or polyphonic human composition, where the term monophonic means only a single voice versus the multiple voices implied by polyphony. For this purpose, the user selects any number of precomposed tracks and generates a single generated voice for the piece. Because this approach requires an existing polyphonic composition, it can help composers with writer's block who only would like creative assistance with single voice or amateurs with little composition experience.

To achieve a polyphonic feel, another application is to evolve multiple generated voices from monophonic melodies, rather than from polyphonic pieces. A natural approach to generating such polyphony is through a layering technique whereby generated voices from previous generations can serve as inputs to new CPPNs that then generate more layers of harmony. The result is the ability to spawn an entire multi-layered piece from a single monophonic starting melody.

With any of these approaches or a combination of them users can further influence their generated output by holding constant the rhythm CPPN or pitch CPPN while letting the other evolve. When two generated voices share the same rhythm network but differ in the pitch network slightly, the two monophonic instruments effectively combine (which can be accomplished manually) to create the rhythmic and melodic structure of a single polyphonic instrument. Similarly, the pitch networks can be shared while the rhythm networks are evolved separately, creating a different rhythmic and melodic feel. Notice that no musical expertise is needed in any of these scenarios to generate multiple musical voices.

4 Experiments

FSMC exploits the insight that music is a function of time and that musical parts are functionally related to one another. The experiments in this section are designed to address the hypothesis that the functional relationship is sufficient to enable users to discover plausible musical voices. While these experiments focus on the generation of folk music, with slight modification in MaestroGenesis the musical domain of the technique could be applied to more experimental styles of contemporary art music. The first experiment explores the structure of the search space by tracking musical quality over the evolution of a particular generated voice. Independent listeners to the generated works are thus asked to rate the quality of the pieces at the beginning, middle, and end of evolution.

A separate but related issue is the level of quality of generated voices that are completed. For example, is it possible to tell that such pieces are partly computer composed? To answer this question, the next experiment tests whether listeners can distinguish between two partially computer-composed and fully human-composed pieces. It also explores the internal structure of evolved voices.

In the experiments outlined so far, the scaffolds are polyphonic, thereby providing a rich context for generating additional musical voices. The third experiment thus examines whether there is enough information in a single monophonic melody to scaffold an entire multipart piece. If there is, then FSMC can potentially enhance the creativity of amateur musicians who may only feel comfortable or capable of composing their own monophonic melodies. The third experiment concludes accordingly with a study of user self-assessment to provide a perspective on the users' own perceptions of their experience with FSMC.

4.1 System Parameters and Setup

In each experiment, the user chooses the number and type of inputs based on the number of voices contained in the scaffold. The selected voices can be a subset of the scaffold voices or can be the entire piece itself. Each CPPN in the initial population also has a random number of hidden nodes between zero and one. During reproduction, the probability of crossover is 30%. Otherwise, the offspring is created by mutating only a single parent. In that case, each individual connection weight has an 80% chance of being mutated by adding uniform random noise between $[-2.0, 2.0]$. The activation functions within each node (except output nodes that are required to be sigmoidal) also can mutate with 80% probability to sigmoid, Gaussian, linear, sine, or multiplication. However, it is important to note that the user is free to adjust mutation rates through the MaestroGenesis interface to provide more or less variability, thereby avoiding the potential for too many trivial variations. The NewNote threshold is 0.3, which was found in preliminary tests to ensure a reasonable quality of generated music for many different scaffolds. Furthermore, when the OnOff output in the rhythm network (which also indicates volume) falls below 0.3, no note is played. Population size is ten per generation. The initial random weights in the first generation of CPPNs are chosen from a uniform distribution ranging between $[-2.0, 2.0]$. The next generation is created through mutation and recombination of solely the choices of the user. In general, all these settings were found effective through preliminary testing and minor variations of these parameters will likely yield similar results.

4.2 Investigating the Evolution of Generated Musical Voices

To begin to study the capabilities of FSMC, it is helpful to analyze in detail a representative evolutionary progression of generated musical voices. Such an analysis, coupled with a user study of perceived quality over generations helps to illuminate how generated voices are evolved and the contribution of interactive evolution to the results.

In this experiment, the focus is on the evolution of the generated musical voice. Therefore, the scaffold, i.e. music for which the additional voice will be evolved, is chosen to meet an established level of quality. That way, it is possible to determine whether the generated voice can maintain and complement the original quality in the scaffold. For this purpose, the well-known folk song Bad Girl's Lament is chosen, which was sequenced and provided with permission by musician Barry Taylor.

The interactive evolutionary process for the example piece was guided by the authors. They applied no musical knowledge (such as avoidance of non-chord tones) beyond simply choosing which candidates sounded best. The process proceeded as follows: A set of ten random CPPNs corresponding to an initial population of FSMC-generated voices was first created by MaestroGenesis. Among these, those that sounded best were selected by the user. From the selected candidates a new generation of CPPNs was created that are offspring (i.e. mutations and crossovers) of the original generation. This process of listening to candidates, selecting the best, and creating new generations was repeated until a satisfactory generated voice appeared. While user input is an important aspect of this process, no session lasted more than 12 generations (i.e. no more than 12 preference decisions were ever made), highlighting the overriding importance of the FSMC relationship to constraining generated musical voices to a reasonable set of candidates. Thus, interestingly, in contrast to data-intensive approaches, the only human knowledge aside from the key needed to generate musical voices through this approach is imparted in ten to 15 clicks of IEC.

To explore the space created by FSMC, an evolutionary progression of an instrumental voice for Bad Girl's Lament between generations 1 and 12 is studied by highlighting important milestones at generations 1, 6, and 12. Each sequence represents the one parent chosen out of ten possible candidates. This 12-generation progression took about thirty minutes in total for the user to complete; most of the time was spent listening to candidate generated voices. Inputs to the rhythm CPPN are the piano and harpsichord channels from the scaffold while the pitch CPPN input is only the harpsichord. For both networks, the smallest rhythmic unit is the sixteenth note.

Audio of the results are available at `http://eplex.cs.ucf.edu/fsmc/cmj`. Figure 5 shows measures 17, 18, and 19 of the generated voices for Bad Girl's Lament in generations 1, 6, and 12. The pitches in measures 17 and 18 of the first generation differ from those created for generations 6 and 12. Pitches in generation 1 ascend across notes A and B in measure 17 followed by C# and B in measure 18. However, in generations 6 and 12, the pattern more closely follows the harpsichord input from the scaffold with notes B and D occurring at beats one and two and a half in measure 17 and 18, demonstrating the influence of the functional relationship to the harpsichord on the evolved progressions. However, in the third measure, generation 12 descends to a C# thereby echoing the same note in the piano input even though the CPPN is only aware of pitch changes in the harpsichord. This variation adds a chord tone missing in the nineteenth measure of generations 1 and 6.

Overall, while the three depicted generations in Bad Girl's Lament exhibit some

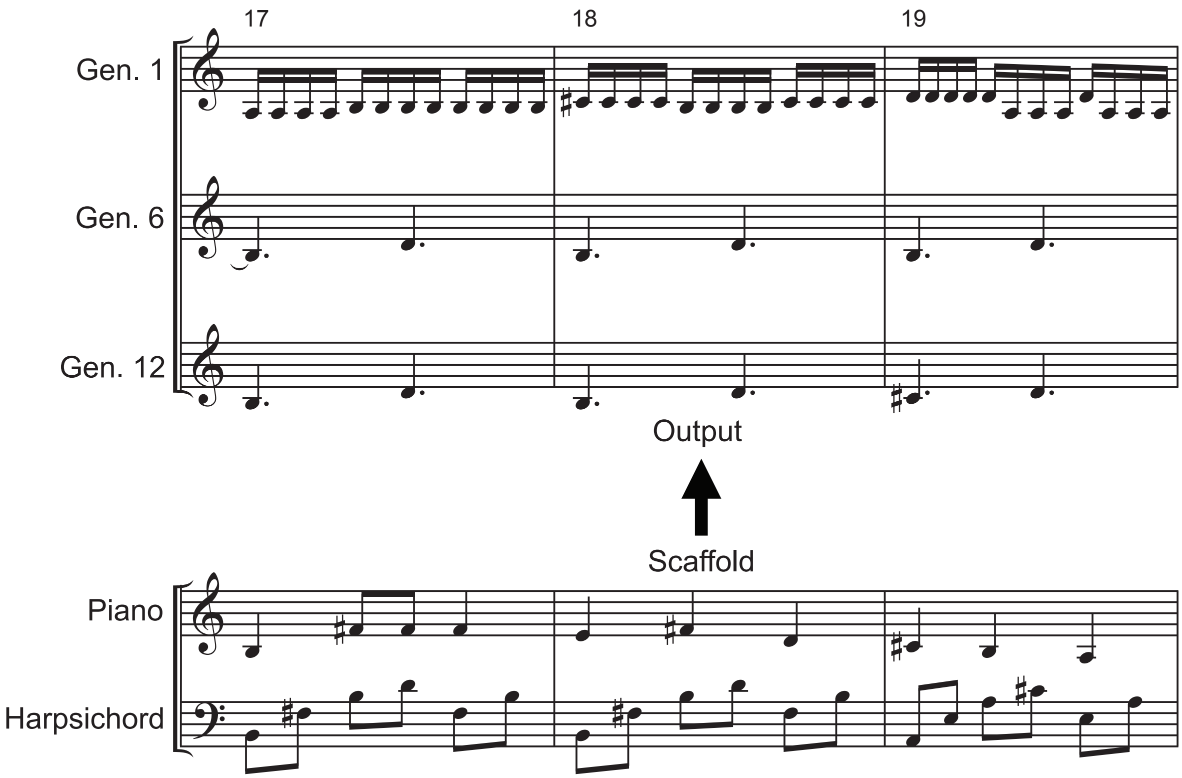


Figure 5. ***Evolutionary Musical Sequence for Bad Girl's Lament*** *Three measures of the evolved steel guitar voice from generations 1, 6, and 12 of Bad Girl's Lament is shown at top, followed by the pitch and rhythm inputs to the CPPN from the scaffold. In this experiment, the tick length or smallest rhythmic unit is a sixteenth note.*

Voices	Dissimilarity by Pitch Class	Dissimilarity by Contour
Gen. 12 v. Piano	5.8916	3.3074
Gen. 12 v. Harpsichord	4.9616	3.9240
Piano v. Harpsichord	5.08401	4.1073

Table 1. ***Similarity Comparison Results*** *Comparisons illustrate that differences between the human-composed voices are similar to those between the generated voice and human-composed voices. Pitch Class looks at differences between notes between two voices, while Contour looks at differences between note transitions between two voices. For both metrics, the square root of the mean squared error is calculated for pitch values at sixteenth note intervals. In this piece, the sixteenth note is the smallest rhythmic unit.*

similar characteristics, they progressively change over evolutionary time. For example, while generations 6 and 12 are rhythmically similar, generation 1 sounds significantly shorter notes. The pitch evolution progresses similarly to rhythm. From generation 1 to 6 many pitches change, but generations 6 and 12 differ in pitch by only a few choice notes.

Because the different voices within a folk piece are conventionally related, it is reasonable to expect that appealing computer-generated voices in the same context would exhibit a degree of similarity roughly equivalent to the similarity exhibited between the preexisting human-composed voices. To investigate the relationship of the generated voice to the scaffold, table 1 shows actual similarity comparisons within Bad Girl's Lament. To obtain these measurements, voices are broken into pitch components (measured in semitone increments) that are calculated at sixteenth note intervals. In column 1 of table 1, voices are compared by pitch class or note name, whereas column 2 shows differences in melodic contour (i.e. changes from one sixteenth note to the next). For both metrics, the dissimilarity in table 1 is obtained by first taking the mean squared difference at each sixteenth-note interval. The reported number is then the square root of this number, which thereby reveals on average how many semitone pitch increments separate a sixteenth-note interval or interval change (in the case of contour) within one voice from another.

Given that FSMC generated the pitches for the additional voice from the harpsichord alone, it is not surprising that pitch classes in the generated voice would differ more from the piano than the harpsichord (as shown in column 1 of table 1). However, with the pitch class metric, the difference between the generated voice and the harpsichord and between the generated voice and the piano is similar to the difference between the piano and the harpsichord, which are both part of the original human-composed piece. Thus the new voice varies in pitch as much relative to the preexisting voices as these human-composed voices do to each other. Furthermore, the values of these differences, at about 5.3 increments on average for pitch class (averaged over both scaffold voices), represents a nontrivial gap, thereby suggesting that the evolved transformation is itself nontrivial.

However, from pitch class alone the nature of this relationship cannot be fully elucidated. For example, the generated voice could potentially be a simple transposition of the human-composed scaffold. Therefore, the dissimilarity in melodic contour between the voices is also calculated (column 2). In this case, at each sixteenth note, instead of comparing the instantaneous pitch class differences, the difference between the previous and current sixteenth note's pitch class is calculated. These differences are then further compared between two voices. Interestingly, this contour-based metric shows that the generated voice moves more like the piano melody than the arpeggiated chords in the harpsichord from which pitches were generated. However, the slightly higher similarity to the contour of the piano is mainly due to the fact that the piano sustains its notes for longer than the harpsichord, as does the generated voice. More importantly, as with pitch class, the contour difference between both the generated voice and the harpsichord and the generated voice and the piano is similar to the contour difference between the piano and the harpsichord, which again are both part of the original human-composed piece. Thus the new voice varies in melodic contour similarly relative to the preexisting voices as these human-composed voices do compared to each other. The absolute average dissimilarity of 3.6 (averaged over both scaffold voices) also demonstrates that the generated voice is following a substantially different contour than either of the other scaffold voices, in effect different in its movement by almost 4 semitones on average for every single sixteenth-note increment in the entire composition. Together, this result along with the pitch class difference reinforces again the nontriviality of the evolved transformation.

To understand the effect of evolution on subjective appreciation, a total of 60 listeners, all of whom are students in a diversity of majors at the University of Central Florida, participated in a survey after listening to the evolved variants of Bad Girl's Lament. In particular, without knowing which is which, they listened to (1) an intentionally poor-quality control with inappropriate additional generated voice (which helps to establish that participants indeed generally agree on something subjective), (2) the original Bad Girl's Lament without additional voicing, (3) the song with FSMC-generated additional voice selected from the first generation of IEC, (4) the song with the generated voice selected from the sixth generation of IEC, and (5) the final selected song with the additional voice from generation 12. It is important to note that the control, which is from a randomly generated CPPN, benefits from the same key and rhythmic constraints as other results, ruling out that these alone account for the music's plausibility. For each of the variants, the listener was asked: *Rate MIDI i on a scale of one to ten. (1 is the worst and 10 is the best)*, where i refers to one of the five variants, which are available for listening online at `http://eplex.cs.ucf.edu/fsmc/cmj`.

By establishing the perceived quality of a respected composition, it becomes possible to estimate how well evolution can maintain that professional standard even though FSMC with IEC incorporates no prior musical knowledge or expertise beyond the guidance imparted by the non-expert human user. The results from the 60-person listener study, which focused on the same IEC-evolved voices for Bad Girl's Lament from the previous section, are shown in table 2. As expected, the control is rated

MIDI Name	Mean	Std. Dev.
Poor Control	4.35	1.93
BGL without Addit. Voice	7.30	1.85
BGL, Generation 1	5.15	2.20
BGL, Generation 6	6.07	1.96
BGL, Generation 12	6.83	1.98

Table 2. **Perceived Quality by Survey Participants**. *This table shows the average ratings and the mean and standard deviation for the control and four Bad Girl's Lament (BGL) MIDIs.*

significantly worse than every other example in the survey (at least $p < 0.05$ for all pair-wise comparisons with Student's t-test). This result establishes that listeners likely understood the questions in the survey.

Importantly, generation 6 is judged significantly higher quality than generation 1 ($p < 0.05$) and generation 12 is judged significantly better than generation 6 ($p < 0.05$). Furthermore, although the original MIDI without any additional generated voices is judged significantly better than generation 6 ($p < 0.001$), it is not judged significantly better than generation 12. Thus evolution guided by the human user eventually achieves in a short number of generations a level of quality that the participants could not distinguish from that of the original, hinting that FSMC-generated parts can meet an acceptable level of quality.

4.3 Comparing FSMC to Fully Human Compositions

The aim of this experiment is to explore whether additional voices generated by FSMC can sound human. To explore this question, an additional voice is generated for the folk song Nancy Whiskey, also originally arranged in MIDI format by Barry Taylor and redistributed with his permission. Then, the generated voicing for Nancy Whiskey and the final generation of Bad Girl's Lament from the previous section are included in a "musical Turing Test" to determine whether they are distinguishable from completely human-composed pieces.

It is important to note that these pieces are chosen for this experiment because they exemplify entirely human compositions that meet a minimum standard of recognizable quality. That way, it is possible to discern whether the generated additional voices reduce the human plausibility of the work, or whether they complement it successfully.

4.3.1 *Evolved Voice for Nancy Whiskey*

Like the experiment in Section 4.2, the interactive evolutionary process for Nancy Whiskey was guided by the authors with the same experimental settings as in the previous section. The main result, which is from only two generations of evolving an additional voice for Nancy Whiskey, can be seen and heard at `http://eplex.cs.ucf.edu/fsmc/cmj`. The low number of generations necessary to obtain this result is a result of the strong bias provided by FSMC towards generating additional voices related to the scaffold. In totality, the generated voice incorporates pitch and rhythmic elements from all three scaffold instruments while also varying and combining them in new ways, yielding an original pattern that complements the whole.

The internal structure of the CPPNs that generate the additional voices from Bad Girl's Lament in the previous section and Nancy Whiskey can also be seen at `http://eplex.cs.ucf.edu/fsmc/cmj`. Their structures are surprisingly simple, each with no more than one hidden node. It is important to understand that the simplicity of these relationships resulted from a process of human selection through IEC that ended when the human was satisfied, which means it reflects the human user's implicit preferences.

These results show that simple relationships in the CPPN can yield appealing and convincing musical relationships

4.3.2 *Musical Turing Test*

In this second listener study, anonymous participants were asked to rate examples with and without FSMC-generated voices. The key focus in the study is on whether the fact that a computer is involved in generating some of the examples can be discerned by the listeners. Thus the survey is a kind of *musical Turing Test*. This perspective is interesting because FSMC is based on no musical principle or theory other than establishing a functional relationship; if such a minimalist approach (guided by users' preferences) can generate plausible musical voices it suggests that the theory behind it is at least promising.

For this study, a total of 66 listeners, all of whom are students in a diversity of majors at the University of Central Florida, participated in the study. The full survey, including the human compositions, is provided at `http://eplex.cs.ucf.edu/fsmc/cmj`. Participants are asked to rate five different MIDIs by answering the following question:

> Based on your impression, how likely is it that any of the instrumental parts in the musical piece found at the following link, were composed by a computer? "Composed" means that the computer actually came up with the notes, i.e. both their pitch and duration, on its own. (1 means very unlikely and 10 means very likely).

The participants rated a total of five MIDIs: (1) an obviously computer-generated control that is restricted to notes generated in the same key as the scaffold (which helps to establish that participants understand the question), (2) the version of Nancy Whiskey with a computer-generated additional voice, (3) fully human-composed Chief Douglas' Daughter, (4) fully human-composed Kilgary Mountain, and (5) the version of Bad Girl's Lament with the computer-generated voice from generation 12. Thus the main issue is whether participants judge piece 2 and piece 5, which have additional voices evolved with FSMC, as distinguishable from piece 3 and piece 4, which are entirely composed by

MIDI Name	**Mean**	**Std. Dev.**
Control	7.82	2.15
Nancy Whiskey with Addit. Voice.	5.45	2.65
Chief Douglas' Daughter	4.32	2.61
Kilgary Mountain	4.86	2.39
Bad Girl's Lament with Addit. Voice.	4.82	2.44

Table 3. ***Survey Results (lower means more human-like).***

humans.

The complete results of this study are shown in table 3. On average, the 66 participants judge the intentionally-poor example as significantly more likely to be computer-generated than any other song in the survey ($p < 0.001$ according to Student's t-test). This difference indicates that participants understand the survey.

Although the accompanied Nancy Whiskey is judged significantly more likely ($p < 0.05$) to be computerized than the human song Chief Douglas' Daughter, it is not judged significantly more likely than Kilgary Mountain to be computerized. This result indicates that the accompanied Nancy Whiskey can pass the musical Turing test, i.e. the participants could not distinguish it from a song that was entirely human-generated. The generated voice for Bad Girl's Lament is even more difficult for participants to differentiate. It is not judged significantly more likely to be computer-assisted than either of the human pieces, i.e. Chief Douglas' Daughter or Kilgary Mountain. In fact, on average, FSMC-accompanied Bad Girl's Lament scored slightly less likely to be computerized than the entirely human song Kilgary Mountain.

These results validate that evolved additional generated voices are at least plausible enough to fool human listeners into confusing partly computer-generated compositions with fully human-composed ones, even though FSMC has almost no a priori musical knowledge programmed into it beyond the guidance of the human user.

4.4 Generating Polyphonic Additional Voices

The experiments in this section are designed to show how users can generate multipart pieces from just a single monophonic melody with FSMC. A creative self-assessment from users of the program studies their experience of the process. The ability to generate convincing polyphonic pieces from just a simple monophonic initial concept would open up musical creativity to anyone who can compose a simple monophonic melody. Thus this experiment explores an important issue in establishing the breadth of potential applications of FSMC.

For this experiment, three undergraduate independent study students, (Marie E. Norton, Trevor A. Brindle, and Zachary Merritt) composed in total three monophonic melodies. From each of these user-composed melodies, each student then added multiple generated voices through FSMC to their original melodies to create a polyphonic feel. Two other sets of multipart additional voices were generated by one of the students for the folk song *Early One Morning*, illustrating that results even with the same scaffold are not deterministic. The most important point is that no musical expertise was necessary to apply to the final creations beyond that needed to compose the initial monophonic melody in MIDI format. Thus, although results may sound consciously arranged it is important to bear in mind that all the polyphony you hear is entirely the output of FSMC. The original melodies, generated voices, and CPPNs are available at `http://eplex.cs.ucf.edu/fsmc/cmj`.

FSMC provides significant freedom to the user in how to accumulate the layers of a multipart piece. In general, the user has the ability to decide from which parts to generate other parts. For example, from the original melody, five additional parts could be generated at once by outputting all of them from both a single pitch and single rhythm CPPN. Or, instead, the user might accumulate layers incrementally, feeding each new part into a new CPPN pair to evolve yet another layer. Some layers might depend on one previous layer, while others might depend on multiple previous layers. In effect, such decisions shape the subtle structural relationships and hence aesthetic of the final composition. For example, evolving all of the new parts from just the melody gives the melody a commanding influence over all of the generated voices, while incrementally training each layer from the last induces a more delicate and complex set of complementary partnerships. Overall, the student composers took advantage of this latitude in a variety of ways. Scores, audio, and the full details of the procedures followed in each case are at `http://eplex.cs.ucf.edu/fsmc/cmj`.

Interestingly, the two versions of Early One Morning (Song 1), illustrate how a single user can generate different voices from the same initial monophonic starting melody and how the initial melody exerts its influence both rhythmically and harmonically but in different ways. Songs 2, 3, and 4 exhibit a similar effect: rhythmic and harmonic influence from the original melody, yet distinctive and original generated voices nevertheless. The result is that the overall arrangements sound composed even though they are evolved through a breeding process.

A key motivation for these polyphonic experiments is that they reflect a likely common mode of usage for FSMC in which users who can only create a monophonic melody on their own expand the initial melody into a full multipart piece with FSMC. Thus to evaluate the effect of the program on their own creative self-expression, the three undergraduates who composed the polyphonic pieces in this section were asked several questions designed to investigate how FSMC affects the composition process of its users. Each of the three students also had experience composing without FSMC, providing a unique opportunity to learn their perspective on its contribution. The aim of this study is to provide a qualitative perspective on the experience of composing with FSMC. Survey questions are at `http://eplex.cs.ucf.edu/fsmc/cmj`.

Results indicate that the users were satisfied with ideas suggested by

MaestroGenesis. For instance, when asked if "FSMC helped me explore a broader range of creative possibilities than I could before," each respondent indicated that MaestroGenesis helped them explore new areas of their creative search space. In fact, one student claimed that "FSMC freed me from my normal stylistic tendencies," while another indicated that "I typically follow a sort of pattern when I compose, but FSMC expanded my thinking." Said another, "Specific parts of the output harmonies were very good, and I could see myself applying them in many places throughout the song."

Furthermore, when asked to describe the advantage of integrating FSMC into the respondents' own musical creativity process, one student replied, "It would provide as a great source of ideas and inspiration for any work. I could very easily input my composition, evolve it, and develop FSMC outputs to cater to my piece." Another said, "a few of my stylistic elements will come through," but that "other elements will surface" that had not been considered. The third student claimed that FSMC was "great for writer's block." Thus the innovations pushed users outside of their normal musical boundaries, but tended to respect the musical direction that was intended.

There were several instances where users found FSMC more limiting than hoped. All three participants indicated that although they liked the holistic motifs presented by FSMC, they would like more control over the form of the pieces. One user said, "I could not shape the harmony produced to suit my melody's form...I would need to input the harmony produced into Sibelius [a sequencing program from Avid Technology, Inc.] to make final corrections and changes." Although the functional representation ensures that the generated voice is based on the pitch and rhythmic patterns of the original piece in its entirety, sometimes different evolved functional relationships might be appropriate for different sections. That is, one function can be more appropriate for an introduction, another for the next section, and so on, which is being addressed in future work.

While the users wanted more, they all indicated that they would generate ideas with FSMC in the future. One student summarized, "I often get writer's block, where nothing sounds how I want. By plugging my unfinished composition into FSMC, I would be able to find inspiration for new techniques, rhythms, or styles."

5 Discussion and Future Work

While many approaches in automated composition focus on generating music through formalized musical theory (Temperley 2004; Keller et al. 2006) or statistical analysis of large corpora (Rhodes et al. 2007; Kitani and Koike 2010; Ponsford et al. 1999; Simon et al. 2008; Gillick et al. 2010), FSMC takes a different tack by starting with almost no rules or assumptions. By starting with so few assumptions, FSMC facilitates exploration of both monophonic and polyphonic generated voices while still maintaining musical plausibility through its functional scaffolding. Most importantly, experimental results support the hypothesis that functional relationships alone are sufficient (in conjunction with human selection of candidates) to generate plausible musical voices, thereby suggesting a novel perspective on the nature of musical appreciation.

5.1 Implications for Musical Appreciation

While experienced human composers draw on knowledge of musical rules and techniques, FSMC composition occurs only through functional transformations of a given scaffold (guided by the choices of a human who need not have musical training). However, such transformations are powerful because they can generate a wide spectrum of meaningful relationships ranging from simple uniform transposition (e.g. from the key of C to that of D) to more complicated and subtle juxtapositions that elude traditional formalization.

An interesting aspect of FSMC is that the formal concepts that correspond to discovered transformations are never explicitly encoded in the representation. For example, a change in CPPN connection weights can mutate a perfect authentic cadence into a half or even plagal cadence. Yet neither MaestroGenesis users nor its own designers need to recognize cadence types, specify where they should occur, or even know what a cadence is.

In fact, because the emphasis is on generating plausible voices rather than conforming to musical rules, the search process has the potential to yield satisfying generated voices that nevertheless do not follow the rules. Interestingly, as illustrated by the studies in this paper, the average listener can enjoy the generated musical voices even if they do not completely adhere to compositional tradition. This observation suggests FSMC may be exposing an important factor in musical appreciation that is typically not considered: that an implicit recognition of the functional relationships in music may be important for its appreciation. As Nicholas Cook wrote in Music, Imagination, and Culture (Cook 1992),

> So it is not the enjoyment of the musical connoisseur who knows something about classical harmony and form that is perplexing: it is the degree of involvement that people who know nothing of these things feel in music, and their ability to respond to music in an appropriate and meaningful manner.

Because an essential aspect of appreciation may be functional relationships, listeners can potentially gain an appreciation for different genres and musical styles by studying the relationships that typify them. For instance, many musicians develop an appreciation for “art music” through their formal musical educations. They study atonal works, analyze their composition structures, and compose in such a style while working toward understanding and appreciating these types of pieces. Perhaps at an abstract level they are learning the functional relationships that relate parts of such music to each other. However, these functional relationships may also in part explain how even the most educated musicians can appreciate a good riff from a popular song: we are inundated in our own culture with such simple, tonal relationships, from advertisement jingles to nursery rhymes and Christmas carols. FSMC thus hints at the possibility of a simple new approach to understanding the elusive nature of music appreciation.

5.2 Practical Applications

The experiments in this paper hint at the potential for humans to collaborate with FSMC to discover novel musical inspiration. Many approaches in this area are restricted by the representation of musical knowledge in the system; a successful composition in such approaches depends in part on the designer's ability to identify and reasonably apply key compositional rules (Marsden 2000). However, while built-in rules may result in appealing musical pieces, they constrain a full exploration of musical possibilities. In contrast, because FSMC requires almost no explicit encoding of musical knowledge, the space of generated voices can be theoretically expanded over evolution through the increasing complexity of CPPNs to represent almost any musical relationship.

While the results only show a sampling of the possibilities in the folk-song genre, FSMC has the potential to help users compose additional musical voices for almost any style of music. Instead of first having the user specify a predefined style and then generating additional voices, FSMC-generated voices inherit style through the user-chosen scaffold. Future versions will also allow multiple simultaneous voices to be generated all in one step. Another idea is to allow FSMC to evolve not just the transforming function, but also which inputs from the scaffold to include. Interesting future work also lies in not only developing filters to present the user with melodies that fit the constraints of a particular musical style, but also exploring the nature of the particular CPPN itself by applying the same CPPNs to different scaffolds even as the search itself iterates. With all of these potential future extensions, an interesting experiment would be to explore how the FSMC-generated outputs and the user experience with MaestroGenesis compare to other established generative systems in the field.

In fact, the idea of functional scaffolding extends in principle beyond music. Recently, inspired by FSMC, Clune et al. (2013) showed that a three-dimensional model can act as a scaffold for related three-dimensional objects. In general, the complexity inherent in any pre-existing artifact is a potential scaffold for a search that inherits such complexity from the start.

In his best-selling book, Levitin (2006) points out that “the chasm between musical experts and everyday musicians has grown so wide in our culture” that people are easily discouraged from experiencing the satisfaction of creating their own performances or compositions. In this context, research efforts like FSMC and MaestroGenesis open the possibility of bringing the joy of making music back to people whose lack of expertise heretofore has forced them only to consume.

6 Conclusion

This paper presented functional scaffolding for musical composition (FSMC), a method that can generate with only minimal musical knowledge monophonic or polyphonic voices from as little as a single, human-composed monophonic starting track or *scaffold*. The approach facilitates exploration by helping the user search candidate generated voices through interactive evolutionary computation (IEC). FSMC results in musical compositions that sometimes can be confused with fully human-composed works. FSMC is the first approach to explore the simple hypothesis that functional relationships may play a significant role in music appreciation.

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