Musical Composer Based on Detection of Typical Patterns in a Human Composer's Style

Horacio Alberto García Salas, Alexander Gelbukh

Laboratorio de Lenguaje Natural,
Centro de Investigación en Computación,
Instituto Politécnico Nacional, 07738, DF, Mexico
itztlii@gmail.com, www.gelbukh.com

Abstract. We present an evolutionary automatic music composer that finds and emphasizes typical patterns in the style of a human composer according to training. First, from a training corpus of melodies the system learns a matrix of conditional probabilities of note transitions; the music is generated as a sequence of notes representing a Markov process with this probability distribution. Then, the probability matrix is iteratively modified by learning from the system's own output; this emphasizes frequent patterns. After such evolution, the system's output becomes rich in patterns typical for this composer.

Keywords. Automatic music composition, typical patterns mining, Markov processes, evolutionary systems.

1   Introduction

The advance in information technology and the use of computational tools make it possible to develop models of music in order to automate composition processes and eventually build systems that automatically generate music. The following are possible applications of such systems:

–   Creation of new styles of music by finding patterns of different styles and mixing them,
–   Helping people to compose music. Providing tools that allow the user to edit the compositions generated by the system, resulting in a user composition, but which contains patterns that great musicians create and thus, people without musical knowledge can make good music.
–   Enabling computers have the capacity to carry out a process until now reserved for humans. Making this, machines will get human characteristics creating another way of human-machine communication.
–   Breaking the monopoly of large music companies that currently decide what music is to be listened to.

- Having machinery for the generation of live music for restaurants, offices, shops, etc. with compositions created in real time by indefatigable musicians.
- Providing tools that allow children from a very young age to have direct contact with the process of musical composition, which according to studies stimulates the mind for better performance in all other human activities.

When using supervised learning techniques is important to learn and generate as much resemblance to the examples with which the system is trained. In the case of music automatically generated that is not entirely true, because the closest composition to the style of an author would be the original piece. So to generate a similar melody but different is important to determine the meaningful features of a piece of music and alter the least important to get innovation in the compositions generated.

We believe that one of the important features of a melody has to do with the patterns of the sequences of notes used for each author. These patterns of transition can be measured statistically to determine the probability of moving from one state to another in a Markov process, what can be used to generate music which reflects these patterns of transition making it similar.

This paper is organized as follows. In Section 2 we describe different algorithms to develop the same task we do. In Section 3 we explain our system. In Section 4 we present some results and a discussion about how we can improve our model. In Section 5 is the future work we endeavor to accomplish. Then we present some conclusions and finally the references.

2   Related Work

The works [1, 2] provide a comprehensive study of different methods that have been used to develop systems of music composition based on: noise [3], knowledge, cellular automata, grammars [6], evolutionary methods, fractals, genetic algorithms [7], and neural networks [5]. Some systems are called hybrid since they combine several of these techniques.

For example, Harmonet [5] is a system based on connectionist networks, which has been trained to produce coral style J. S. Bach. It focuses on the essence of musical information, rather than restrictions on the structure of music. The authors of [13] believe that music composed by recurrent neural networks lacks structure, as they do not maintain memory of distant events, and developed a model based on LSTM (Long Short Term Memory) to represent the overall and local structure of music, generating blues compositions.

The work [8] describes a system for automatic recognition of music genre based solely on signal's audio content, focusing only on melodies of three music genres: classical, metal and dance. The work [9] presents a system to navigate through the contents of a music database, which includes audio files (MIDI), with the idea to make search based on contours of music, i.e. in a representation of relative changes in a melody frequencies, regardless of tone or time.

There is a number of works based on evolutionary ideas for music composition. For example, [6] used generative context-free grammars for modeling the melody,

through genetic algorithms making grammar evolves to improve the melody and produce an acceptable composition. GenJam [7] is a system based on a genetic algorithm that models a novice jazz musician learning to improvise. Musical phrases are generated at random and human feedback the system, allowing it to generate new compositions that through several generations are improving. In [2], a genetic algorithm with coevolution, learning, and rules, is used in a music composer system. In it, male individuals produce music and female critics evaluate it to mate with suitable males.

3 Evolving Composer System

Our system consists of a matrix which describes a bigram model to generate a musical composition through a Markov process. From human musical compositions is determined the way a Markov chain representing those examples should be built. We focus on finding the typical patterns over monophonic melodies, modeling solely the notes sequences.

The matrix consists of 60 rows by 60 columns and will store the number of times a musical note is used after another reflecting the typical patterns of notes sequences the author uses with more regularity.

Let *Notes[n]* be an array in which are stored the numbers corresponding to the notes of a melody. Where *n* is the index which refers to each of the elements of the array. Let M_{ij} be a matrix with *i* rows and *j* columns. Then:

for each i ∈ Notes[n], j ∈ Notes[n+1] do
  $M_{i,j} = M_{i,j} + 1$.

To determine the probability that a note succeeds another note, we need to determine the cumulative sum of each row of the matrix. Let M_{ij} be a matrix, with *i* counting rows and *j* columns. We calculate the cumulative sum for each row *i* and for each value of a column *j* such that $M_{ij} \neq 0$. The partial sum of the row *i* is stored in each non-zero cell. In a column S the total cumulative sum for each row *i* is stored.

for each i ∈ M do
  $S_i = S_i + M_{i,j}$,
$M_{i,j} = S_i$ *for each* $M_{i,j} \neq 0$.

While the system generates a musical composition with each note it modifies itself, increasing the likelihood for that note to be generated again. Besides we added a forgetting mechanism to ensure that the values do not overflow, which causes the notes played the least, lesser probability to be played again.

The algorithm to generate a musical composition is as follows:

1. Randomly choose one of the rows of the matrix (the first note of the composition).
2. Choose a random number between zero and the value of the S column of this row.
3. Compare this random number with each non-zero value in that row until one greater than or equal to this number if found. The note of the column where it is

stored this number indicates the following note of the composition and the following row to be processed.
4.   Repeat this algorithm indefinitely from the second step.

4 Results and discussion

In Fig. 1 is presented the score of a composition generated by the system having learned 4 fragments of Paganini. We made some recordings that have been compiled in a commercially available music CD.

The development of automatic music generators has been faced with the problem of deciding between structure and novelty of the musical compositions. The more restrictions applied to the system, the better shape of the structure that is usually found in the music results, the cost is in the novelty of the music generated, which makes it predictable and monotonous.

Fig. 1. Composition generated by the system after learning 4 fragments by Paganini.

In the case of the system presented in this paper it has only been modeled the frequency and it's been used only a short corpus to train it. We have obtained novelty results comparable with those obtained by other developments [4, 7].

To the ears of musicians compositions generated by our system sound similar to the examples used. However we are developing other algorithms in order to shape the musical structure. We consider that if a greater number of examples are provided the results will considerably improve.

On the other hand, it is necessary to develop more sophisticated forgetting functions to prevent the system stabilize, as this happens after a few hours of execution, although this depends on the music examples used.

5 Conclusions and Future Work

The evolving systems have proved to be a versatile tool that can be used to model various phenomena of reality. In the case of our system we have obtained satisfactory results and the opportunity to hear compositions forever different.

The development of this work is open as part of an overall process of composition and will be more complete if it manages to inspire a person to engage in development of computer music.

We are currently developing systems to improve the different sounds and effects that can be obtained, in addition to using matrices of 3, 4 or n dimensions, which may reflect the many variables involved in a musical work.

We are also interested in the development of models that can generate musical compositions that not only reflect the patterns of typical sequences of sounds, but also incorporate the emotional content of music [10–12].

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