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Music Pattern Mining: A Machine Learning Approach via Neural Networks and a Music Style Classification Technique

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Abstract

In this paper we propose a new algorithm and introduce a data structure for music pattern mining. In the proposed method, we search both vertical and horizontal patterns in some pieces of music and classify each piece to specific classes. A learning process based on fuzzy neural networks is developed so that in the learning phase the system is trained with the vertical and horizontal patterns. In the test phase a new musical piece is introduced to the system. The system locates the patterns based on their characteristics and classifies the piece of music applying its dynamic rules and employing its knowledge base. The structure of this paper is as follows. First we briefly introduce a stochastic analysis of music and introduce a new mathematical model and develop its data structure. Then we will demonstrate the proposed algorithm for music pattern mining. Simultaneously a case study has prepared for explaining these concepts. This is an innovative practical way that can be used both in multimedia systems and in computer-aided music composition systems.

Keywords

Computer-aided Music Analysis, Music Theory, Fuzzy Neural Networks, Machine Learning, Classification Algorithms, Pattern Recognition.

1. Introduction

Music is an intuitive phenomenon and has a mathematical structure with complex interrelations between its stochastic elements and iterative segments. We listen to audio signals and enjoy these structures while we recognize undesirable noise, random irregular perturbations which are not related to the pure desirable signal.

By paying attention to repetitions and remember what we have heard, we can predict what might come next. We also can understand the structure of music by structural relationships that we perceive, based on both repetition and function [1]. However in this paper, according to our application we look at musical patterns and repetitions from a different point of view. The theory of music is highly involved in some parts of this manuscript. A computer program is developed to implement the mentioned concepts. A visual presentation of which is depicted in Fig. 1 and we will discuss different modules and data streams. For case study there are 30 waltz musical pieces which are randomly selected from different composers to be analyzed. But this is important to notice that this program works only with waltz musical pieces and it may not work with other musical styles. This technique is applicable for automatic analyzes and pattern mining of waltz musical pieces [2].

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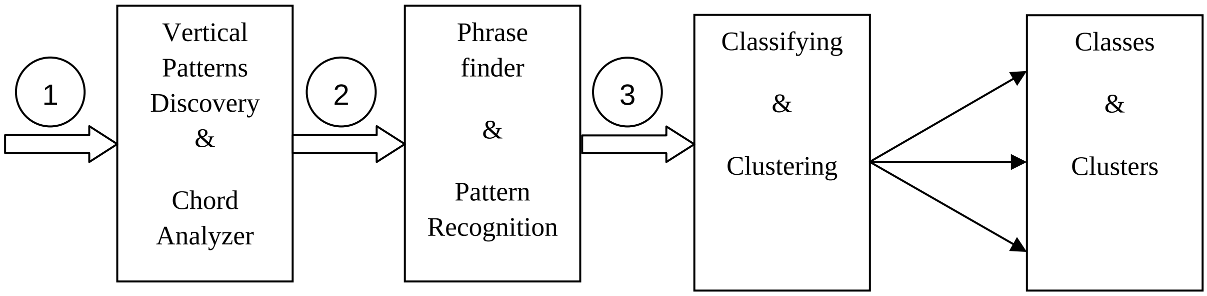

Figure 1: Diagram of the System- Numbers in the figure are: 1-MIDI Input Data 2-Monophonic Note Matrix 3-A linked-list structure contains collection of phrases

1.1. Related Work

Many researchers have considered the importance of patterns and repetition in music. Roger Dannenberg [1] has mentioned patterns, similarities and clustering from recorded audio. David Cope [3] explored pattern processing to analyze music, generally with the goal of finding commonalities among different compositions. This work is based on symbolic music representations and is aimed at the composition rather than the listening process. Eugene Narmour [4] has published a large body of work on cognitive models for music listening. In his recent publication, Narmour explores structural relationships and analogies that give rise to listeners' expectations. Narmour quotes Schenker as saying that "repetition … is the basis of music as an art." The more elaborate rules developed by Narmour are complex examples of structural relationships described here. Some other researchers have noticed that data compression relies upon the discovery and encoding of structure, and so data compression techniques have been applied to music as a form of analysis. An application to music generation is seen in work by Lartillot, Dubnov, Assayag, and Bejerano [5], [1].

Here we discuss another application of pattern mining. Accordingly related parts like data structures, methods, and techniques which are used in this application are different.

2. A Practical Data Structure

A hidden markov model-based data structure that uses Gaussian random variables which are including observable quantities like note onset times, and unobservable quantities, such as local tempo that can represent the solo notes [6]. This model is an appropriate model for rhythmic parsing and learning purposes [7] and also an appropriate model for pattern recognition because of having matrix-based structure. To simplify this project we prefer to use MIDI protocol which has a matrix structure

ONSET (BEATS)	DURATION (BEATS)	MIDI CHANNEL	MIDI PITCH	VELOCITY	ONSET (SEC)	DURATION (SEC)

Figure 2-a: Conventional MIDI structure

ONSET (BEATS)	DURATION (BEATS)	MIDI CHANNEL	MIDI PITCH	VELOCITY	ONSET (SEC)	DURATION (SEC)	CHORD POINTER

Figure 2-b: MIDI structure with one additional column

Figure 2: MIDI Structure

as can be observed in Fig. 2-a that we have modified it by adding another column named chord-pointer according to our application that it has been shown in Fig 2-b.

2.1. Weaknesses and Capabilities of MIDI Structure

It is lucid that MIDI has weaknesses such as having 16 channels which form 16 groups of notes and each group has a set of controllers such volume and pitch-bend which gives MIDI a limited 2-level structure. MIDI has some other weaknesses including no mechanism for flow control, error control, and error correction [8]. Although MIDI has these weaknesses, because we do not have real-time application or music data propagation here therefore; we do not need any error control or error correction.

In spite of MIDI weaknesses, because of discrete MIDI structure- which represents events at a point in time- for indicating music information such as beat, duration and time [8] in a matrix-based structure, we have used midi structure in our application for music analysis, pattern recognition and classification.

3. Chord Analyzer and Vertical Pattern Recognizer

The first module of our system receives a MIDI matrix as an input data which we call it “note matrix” [2] for further uses. This note matrix may include polyphonic information of more than one musical instrument which appears in more than one MIDI channel. We then examine these vertical structures and using full expansion method and other structuring and partitioning techniques to separate these channels to have some polyphonic unrelated pieces of music [9] that each of which will be stored in a separate note matrix.

Now each note matrix must become a monophonic one for being used in other modules therefore we need a module which is able to analyze and replace each chord with one main note.

3.1. Chord Analyzer Module

To replace each chord with one of its notes-which the note can be either root note or bass note. It is important to know the characteristics of each chord for example triad chords (chords with 3 notes) which belong to one of the following four categories [10]:

1-Major Common Chord (M)

2-Minor Common Chord (m)

3-Diminished Triad (/5)

4-Augmented Triad (+5)

The most important factor to find the root note is to specify the type of input chord which is as follow [10]:

1-Normal (a five-three chord)

2-First Inversion (a six-three chord)

3-Second Inversion (a six-four chord)

According to our experimental results about these 30 Waltzes as our case studies we have found that the bass note almost characterizes each chord better than root or other notes as it is demonstrated in Fig. 3. Therefore, in our research we will use bass notes most of the time instead of a chord to convert a polyphonic piece to monophonic one.

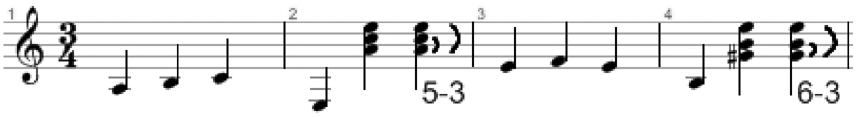

Figure 3: A 5-3 and a 6-3 chord example in an instance waltz piece which in the 5-3 chord bass and root note is A but in the 6-3 chord the root note is E and the bass note is G# and this module will choose G# for this chord situation.

4. A Pattern Recognition Technique

The next step is to specify patterns for further uses. In our case-study patterns are made of simple phrases which are made of one or more bars. There are some techniques available for phrase finding like analyzing temporal and pitch structures [11] and other available algorithms and monophonic or polyphonic pattern searching [12]. For waltzes we have used new simple rules to distinguish phrases other than methods mentioned above.

4.1. Finding musical phrases in a note matrix

There is a tonal note that is named tonal center [10] which its attraction effects on other notes that the listener feels there is an overall tendency to return to this note and is demonstrated in Fig. 4 for one of the waltz studies and also there is a tonality like this which there is a general tendency

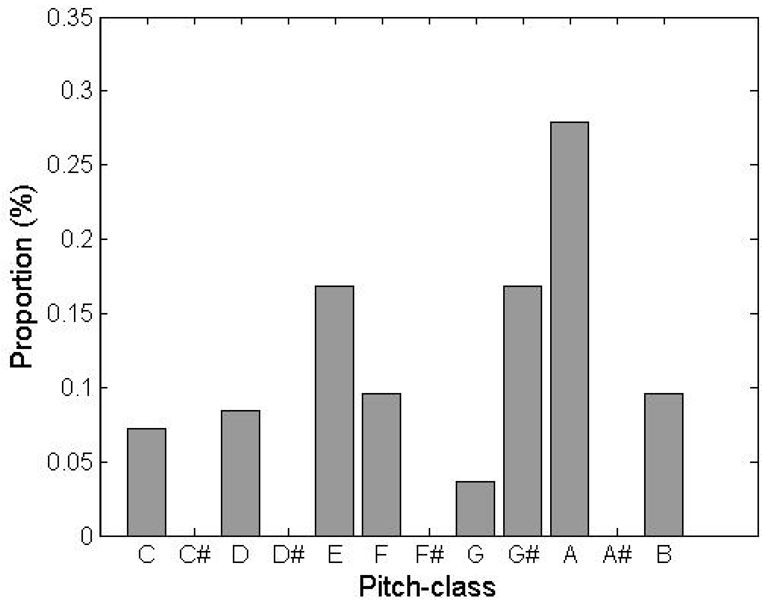

Figure 4: This bar chart demonstrates that the A note is the tonic or tonal center of this melody which is in A minor Scale.

over the piece to return to it when tonality changes temporarily. An example is mentioned in Fig. 5 and the general shape of this melody is demonstrated in Fig. 6.

Figure 5: Waltz piece that is examined here.

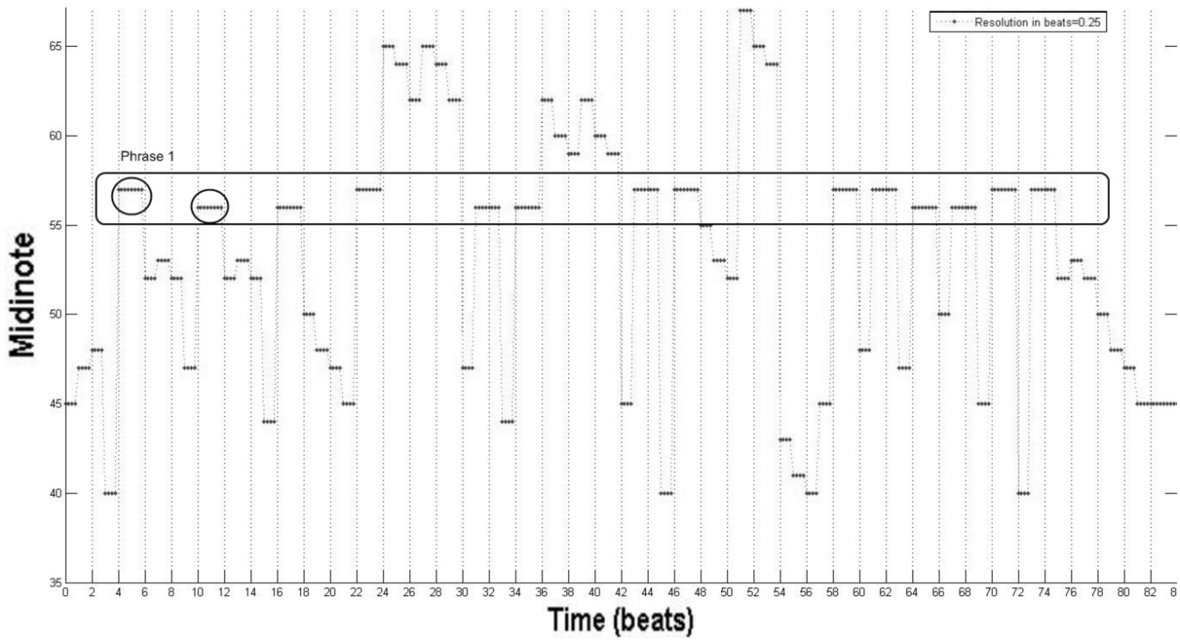

Figure 6: This figure describes the overall shape of melody that the rectangle and each circle in it show a repetitive phrase.

Finally, most of the time the last note of each phrase has a longer duration than other notes in the phrase. When phrases are ready, the system will distinguish the type of each phrase because each phrase belongs to one the following categories:

1-Repetitive phrases

2- Leading phrases

3-Melodic phrases

4.1.1. Repetitive Phrases

Repetitive phrases are phrases which are repetitively appeared in melody line like those demonstrated in Fig. 6. These phrases can be found by melodic similarity techniques. For example an efficient way is to compute probabilistic distributions of phrases and using dynamic programming techniques [13,2] to find the distances of each phrase with others. Then, by counting the number of repetition of each phrase by comparing it to all other phrases, the phrases with higher degree of similarity which are repeated more than others are belonging to this category.

4.1.2. Leading Phrases

Leading phrases are phrases which when listener hear them, he or she is awaited until hear one repetitive phrase as soon as possible. These phrases appear most of the time just before one repetitive phrase[3].

4.1.3. Melodic Phrases

Phrases which are belonging to none of those previous phrase groups are melodic phrases that the main melody line is carried on these phrases.

4.2. Data Structure Made of Phrases

The output of this module can be represented by a linked-list shown in Fig. 7. Each phrase is a piece of note matrix and has one pointer to next phrase and a pointer to a collection of note matrices which make the chords of that phrase.

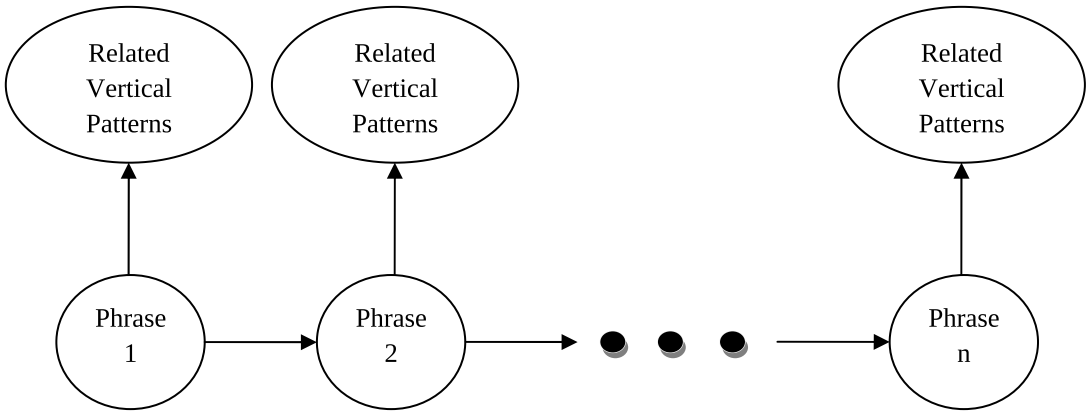

Figure 7: A linked-list data structure made of phrases and their chords

5. Style and Pattern Classification

The last step is to classify each waltz musical piece. For achieving this goal we can use either a Bayesian, linear or neural network classifier which is passed through a learning phase then can be used as an excellent classifier. According to performance measurements results we conclude that neural network has higher performance on few classes and the other applications such as pattern

[3] Surely after each leading phrase a repetitive phrase exists but there may be some repetitive phrases that there is not any leading phrase before them.

clustering [14]. This classifier receives a linked-list which is a collection of matrices as explained in previous section, analyzes it according to its structure (the elements that make this musical piece like general duration of notes, overall shape of melody, pitch specifications, number of strong beats and other statistical information of each musical piece). Then puts it in one of the classes such as Vals (musical piece like waltz with two strong beat at the first of each bar), complex waltz or simple waltz. Percentage of correct classification by different classes is approximately 99% for our classifier. The importance of this part is that each of these classes contains a cluster which is used in pattern clustering process.

5.1. Pattern Clustering

After distinguishing that to which class the current musical piece belongs, the system analyzes all patterns and attaches them to that class cluster. Some patterns may be different from the others but all of them will be clustered with a minimum distance clustering method. Using fuzzy methods for clustering, clusters will have some degree of similarity. The system uses characteristics of each pattern and its phrases to cluster them.

After learning phase, we have a classifier which usually performs well and some clusters full of related waltz patterns in each class which will increases at time pass by.

6. Conclusions

Although the music theory is used frequently for pattern recognition and phrase searching, it is important to find out how human listen to music, recognize musical patterns and their interrelations. This guides us to find more efficient solutions for music pattern mining.

Even though there are many work on pattern recognition and music style classifications, clustered patterns in music style classes has some more advantages and more usages. For example in computer-aided music composition systems, ready patterns which are classified according to their characteristics can be efficient because they can be changed, used and their vertical information be modify in compositions. Another way is to use them with adaptive algorithms [15] to compose music. Eventually it can be used in multimedia systems which need content less music for entertainment. By joining and playing patterns on some related branches in a cluster with same structure gives us the opportunity to have an interesting but meaningless music.

In spite of these advantages and applications this system is limited to waltz musical pieces and there is a huge effort required to advance this system to support other music styles. Also for optimizing the system better data structures, more efficient music pattern recognition and higher performance music style classifiers are needed and each of which requires more researches and efforts.

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