Weighted Markov Chain Model for Musical Composer Identification

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Abstract. Several approaches based on the 'Markov chain model' have been proposed to tackle the composer identification task. In the paper at hand, we propose to capture phrasing structural information from inter onset and pitch intervals of pairs of consecutive notes in a musical piece, by incorporating this information into a weighted variation of a first order Markov chain model. Additionally, we propose an evolutionary procedure that automatically tunes the introduced weights and exploits the full potential of the proposed model for tackling the composer identification task between two composers. Initial experimental results on string quartets of Haydn, Mozart and Beethoven suggest that the proposed model performs well and can provide insights on the inter onset and pitch intervals on the considered musical collection.

1 Introduction

Various methods for computer aided musical analysis have been proposed, which focus on two different classes of data extraction models. Namely, the *global feature extraction models* [10], which encapsulate global features of a musical piece in a single value, and the *event models* which view the piece as a sequence of events that are described by their own value [6]. Global feature models have been used for musical genre identification [10,13] as well as for style and composer recognition [8]. Event models, have been utilized for chordal analysis [12], composer identification [4,5,7] and music composition [11] among others.

The composer identification task has been tackled through various event models, with the most successful approaches being with n-grams or $(n-1)$-th order *Markov chain models* [5,6,19]. These models utilize the Markov assumption that only the prior local context, i.e. some last few notes, may affect the next notes. A simple first order Markov chain model for composer identification has been recently proposed in [9]. This model provides information only for the sequence of scale degrees that form the melody, without incorporating any insights about their position in a phrase.

In the paper at hand, we propose to capture phrasing structural information from *inter onset* and *pitch intervals* of pairs of consecutive notes, and incorporate that information into the simple Markov chain model. To this end, assumptions can be made about which pairs of consecutive notes are of more or less musical importance. The proposed model is a weighted variant of the first order Markov chain model, namely the *Weighted Markov Chain* (WMC) model. Additionally, we propose an evolutionary

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procedure to automatically tune the two introduced parameters of the WMC model and consequently exploit its full potential for tackling the composer identification task between two composers. The performance of the proposed approach has been evaluated on string quartets of Haydn, Mozart and Beethoven with promising results.

The rest of the paper is organized as follows: Section 2 briefly describes how monophonic melodies can be expressed as Markov chains and how did that motivate us to propose the weighted variation of the Markov chain model, which is extensively described in Section 3. In Section 4, an automatic procedure for the application of the weighted Markov chain model on the musical composer identification task is presented. Section 5 presents experimental results of the proposed approach on a musical collection of string quartets of Haydn, Mozart and Beethoven. The paper concludes in Section 6 with a discussion and some pointers for future work.

2 Monophonic Melodies as Markov Chains

Monophonic melodies can be easily represented through a discrete Markov Chain (MC) model. A discrete MC is a random process that describes a sequence of events from a set of finite possible states, where each event depends only on previous events. Thus, each monophonic melody, as a sequence of discrete musical events (the scale degrees), can be formulated as a discrete MC model. Each MC is characterized by a *transition probability matrix* that represents the probability of transition from one state to an other. The aforementioned representation has been proposed in [9] to tackle a two way composer identification task between the string quartets of Haydn and Mozart.

To formulate each monophonic melody, and proceed with the construction of the probability transition matrix, we have to assume that any single note in the melody depends only on its previous note. This assumption has nothing to do with over-simplification of a musical composition, it is just a statistical compliance that lets us consider each monophonic melody as a first order MC. It is evident that, if one would like to utilize more information in each transition probability, a higher order MC should be incorporated [19], i.e. if each note is assumed to depend on its past two notes, we should incorporate a second order Markov chain.

Markov chain model intends to capture a composer's preferences on creating harmonic structures independently of the key signature of the piece, e.g. the $V \rightarrow I$ cadences. In [9], Markov chain models are built up for scale degree transitions in one octave, thus all musical pieces were transposed in the same key. To this end, a transition matrix of a musical piece M can be formally described by a square matrix T_M, where each pair (row, column) represents one possible state. Each element $T_M(i, j)$ of the transition matrix, describes the probability that scale degree class i is followed by scale degree class j.

Motivation: The Markov chain model as used so far, provides information only for the sequence of scale degrees that form the melody, regardless of the phrasing structure they are embodied. Two elements that could be possibly utilized to define phrasing structure are the *inter onset interval* and the *pitch interval* of a pair of consecutive notes that form each transition. The *inter onset interval* is the distance between two consecutive note start times, while *pitch interval* is the difference in semitones between two notes. A statistical refinement of the aforementioned two elements in a monophonic melody may lead to criteria about which transitions are of more or less musical importance.

For example, two consecutive notes with a great magnitude of their inter onset interval, possibly belong to a different phrase, thus their transition should not be considered of great importance. On the contrary, pairs of consecutive notes that are separated by small inter onset intervals may not constitute vital elements of the phrase they belong to, since they possibly form stylistic articulations. Similarly, a transition between notes that share pitch distance of great magnitude, e.g. over one octave, possibly reveals that these two notes belong to different phrases. The first one may belong to the end of the current phrase, while the second one to the beginning of the next phrase.

On the contrary, pairs of consecutive notes in a musical piece whose inter onset interval value is near to the mean value of all the inter onset intervals, probably constitute a pair of notes that demonstrates greater phrasing coherence. Thereby, they contain more information about the composer's musical character. The same holds for pitch intervals. It is evident that to capture the aforementioned characteristics, a weighting procedure on the transitions should be incorporated. This procedure should take into account both the inter onset and pitch interval of the notes.

3 Weighted Markov Chain Model

Motivated by the aforementioned comments, we try to capture qualitative statistical characteristics of musical nature and construct an enhanced transition probability matrix for each monophonic voice. The new transition probability matrix is constructed in a similar manner as the Markov chain model, with the difference that transitions are biased according to some musical criteria, that we will briefly discuss bellow. A general rule that can be deducted by the comments on Section 2, is that pairs of more distant time and pitch events provide less information than less distant ones. Thus an obvious question to face is: In which way that distance affects musical information? For example, do more distant notes contain linearly or exponentially less information than less distant ones?

An answer to the above questions could be provided by studying the distributions of the inter onset and pitch intervals of pairs of consecutive notes within a piece. Here, we study string quartets from classical composers such as, Haydn, Mozart and Beethoven. The string quartets of the classic music composers are perfectly suited for the composer identification problem since each string quartet is composed in four monophonic voices, where note transitions are clearly distinguished. A detailed description of the utilized musical piece collection along with their characteristics will be explained in the experimental results section (Section 5).

To this end, we have observed that all four voices from the string quartets of Haydn, Mozart and Beethoven follow a Gaussian-like inter onset and pitch interval distribution. Thus, we take as a test case a randomly chosen musical piece of each composer, to demonstrate the aforementioned behavior. Figure 1 illustrates normalized bar plots of pitch and inter onset intervals of the first violin for a string quartet of Haydn, Mozart and

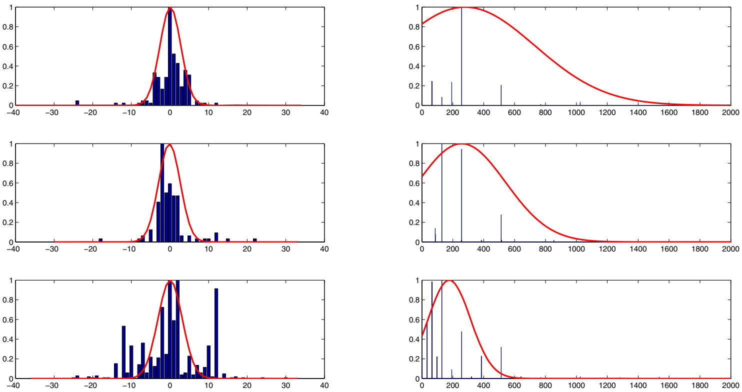

Fig. 1. Demonstration of the pitch (left) and inter onset intervals (right) along with their fitted Gaussian curves for the first violin of a musical piece of Haydn (top), Mozart (middle) and Beethoven (bottom)

Beethoven. The bar plot distribution of both pitch and inter onset intervals, exhibit that intervals follow a Gaussian-like distribution. This can be fairly justified by the Gaussian curves that are properly adjusted to fit the distributions.

It has been observed that all pieces in the considered collection, in all four violins demonstrate the same behavior. This observation provides insights on our question about how less important are more distant events. Since some intervals are preferred over others, they should contain more musical information. It would be reasonable to assume that pairs of consecutive notes that fall into an interval class that is more frequently used, should be given a greater weight than others. In other words, it could be assumed that there is a reciprocal relation on the usage frequency and the information contained in any inter onset or pitch interval. It is expected that each piece contains unique compositional information, thus different Gaussian distribution should be properly defined for the inter onset and pitch intervals of each piece.

Based on these observations it is rational to exploit the statistical characteristics of each piece and define a weighted variant of the Markov Chain (MC) model, that adjusts the weight of each transition within a piece, namely, the Weighted Markov Chain (WMC) model. More specifically, for a musical piece M we can define a Gaussian curve for the pitch intervals, $\mathrm{Pitch}_M(x, y)$, and the inter onset, $\mathrm{Time}_M(x, y)$, as follows:

$$\mathrm{Pitch}_M(x, y) = \exp\left(\frac{\big(p(x, y) - m_p(M)\big)^2}{2s_p(M)^2}\right), \tag{1}$$

$$\mathrm{Time}_M(x, y) = \exp\left(\frac{\big(t(x, y) - m_t(M)\big)^2}{2s_t(M)^2}\right), \tag{2}$$

where, x and y represent two consecutive notes of the current piece M that form a transition, $p(x, y)$ denotes the pitch interval, $t(x, y)$ denotes the inter onset interval,

$m_p(M)$ and $m_t(M)$ represent the mean values of all pitch and inter onset intervals respectively on the entire musical piece at hand, while $s_p(M)$ and $s_t(M)$ denote the standard deviation values of all pitch and inter onset intervals respectively.

Equations (1) and (2) capture the probabilistic characteristics that we have formerly discussed, and are capable to weight each transition $\mathrm{Trans}_M(x, y)$ from note x to note y, as the product of the multiplication of the inter onset and pitch intervals distribution values. More formally, $\mathrm{Trans}_M(x, y) = \mathrm{Time}_M(x, y)\,\mathrm{Pitch}_M(x, y)$. It is evident that, the distributions are different from piece to piece, since every piece has unique $m_t(M)$, $s_p(M)$ and $s_t(M)$ values. To keep the identical pitch transition $\mathrm{Pitch}_M(x, x)$ to a maximum weighted value 1, we consider from now on $m_p(M) = 0$ for all musical pieces. In Equation (1) a transition from pitch x to pitch x has a value $p(x, x) = 0$, to ensure that $\mathrm{Pitch}_M(x, x) = 1$, we should set $m_p(M) = 0$ for every musical piece. One can observe that some values of the distributions vanish to zero, even in cases where exist some transitions worth mentioning. For example, on the bottom left plot of Fig. 1, we observe that transitions with pitch interval value $p(x, y) = 12$, exhibit a high value bar plot and should not be ignored. Although the value of the fitted Gaussian curve tends to vanish that transition.

To overcome the aforementioned problem, we introduce two parameters, r_1 and r_2, to properly adjust the *stiffness* of the Gaussian-like curves, described by Eqs. (1)-(2). The adjusted distribution values can be defined according to the following equations:

$$\mathrm{Pitch}_M^{r_1}(x, y) = \exp\left(r_1 \frac{\big(p(x, y) - m_p(M)\big)^2}{2s_p(M)^2} \right), \tag{3}$$

$$\mathrm{Time}_M^{r_2}(x, y) = \exp\left(r_2 \frac{\big(t(x, y) - m_t(M)\big)^2}{2s_t(M)^2} \right), \tag{4}$$

where $r_1, r_2 \geqslant 0$. In the extreme case where $r_1 = r_2 = 0$ all transitions will have the same weight value, equal to 1, which is the simple Markov chain model. In cases where both parameters are $r_1, r_2 > 1$ the fitted distribution exhibits a tight "bell"-shape around the mean value, while in the opposite case a less tight one.

To demonstrate this behavior, we exhibit in Fig. 2 the effect of the r_1 and r_2 variables on pitch and inter onset interval curves, for three different values ($0.1, 1$, and 10 respectively). Finally, we define and use from now on, as weight of the transition from note x to note y the product of the aforementioned Eqs. (3)-(4).

$$\mathrm{Trans}_{(r_1,r_2)}(x, y) = \mathrm{Pitch}_M^{r_1}(x, y)\,\mathrm{Time}_M^{r_2}(x, y). \tag{5}$$

The construction of the new transition matrix follows the same procedure as in the Markov model, with the only exception that not all transitions are equally weighted, but given a set of $r1, r2$ parameters, the (x, y) element of the matrix will be weighted by Eq. (5).

4 Weighted Markov Chain Model for Composer Identification

In this section, we incorporate the *Weighted Markov Chain* (WMC) model into a general procedure to effectively tackle the musical composer identification task between

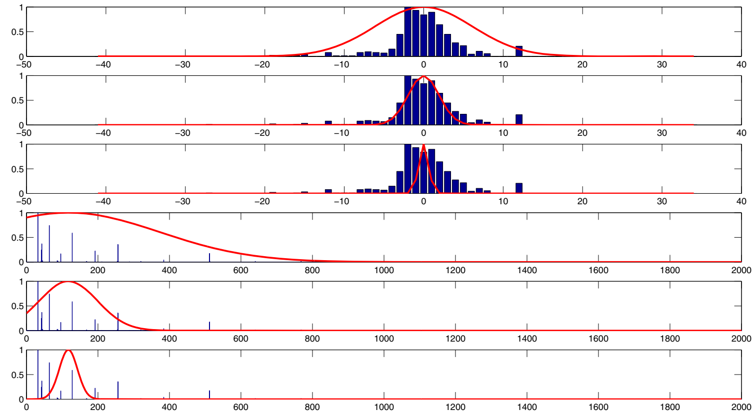

Fig. 2. Adjusted Gaussian curves over the pitch intervals distribution (top three), with $r_1 = 0.1$, $r_1 = 1$ and $r_1 = 10$ respectively, and over the inter onset intervals distributions (bottom three), with $r_2 = 0.1$, $r_2 = 1$ and $r_2 = 10$ respectively

two composers. The WMC model is a properly defined model for the representation of a musical piece, since it captures some essential characteristics for both pitch and inter onset intervals. The WMC model utilizes two parameters for adjusting the Gaussian curves that estimate the distributions of pitch and inter onset intervals of a given piece. These parameters should be automatically tuned to properly capture the characteristics of the composer style. Thereby, we propose the incorporation of any intelligent optimization algorithm to efficiently tune WMC model parameters and consequently tackle the musical composer identification task by maximizing the classification performance, i.e. the identification accuracy, of the proposed methodology.

Suppose that we have a collection of monophonic melodies of musical pieces composed by two composers. In order to achieve maximum composer identification accuracy with the WMC model, we perform the following five steps:

1. Provide an intelligent optimization algorithm to properly adjust r_1 and r_2 parameters.
2. Given r_1 and r_2 values, transform the monophonic melody of each piece in the collection into a weighted transition probability matrices through the WMC model.
3. Classify the weighted transition probability matrices by performing a leave one out classification task, using any supervised classifier.
4. Calculate the success percentage of the classification task and use it as a fitness value of the optimization algorithm for the r_1 and r_2 parameters.
5. Repeat the above procedure until either a termination criterion is reached or the r_1 and r_2 values produce the best composer identification accuracy for the utilized classifier.

More specifically, in this work, we propose to utilize as a supervised classifier, the well known Support Vector Machine (SVM) classifier [3,16], which has been successfully applied to a wide range of difficult classification problems [16]. SVM is a supervised binary classifier which is trained with a set of paradigms. It classifies a paradigm to one of the two categories by representing it as a point in the classification space. It is mapped in a way that all paradigms of the two categories can be separated by a clear gap which is as wide as possible. When a new paradigm is presented, SVM classifies it based on which side of the aforementioned gap, i.e. respective class, will fall into.

Additionally, to optimize the r_1 and r_2 parameters, we employ a global optimization algorithm that can handle nonlinear, (possibly) non-differentiable, multi-modal functions, namely the Differential Evolution (DE) [15,17]. DE is a population-based stochastic algorithm, which utilizes concepts borrowed from the broad class of the Evolutionary Algorithms. It exploits a population of potential solutions to effectively explore the search space and evolve them by simulating some basic operations involved in the evolution of genetic material of organism populations, such as natural selection, crossover and mutation. A thorough description of DE can be found in [15,17].

5 Experimental Results and Concluding Remarks

In this section, we perform an experimental evaluation of the proposed methodology over a musical piece collection formed by string quartet movements of Haydn, Mozart and Beethoven. The compilation contains 150 movements of string quartets in MIDI format from collections [2,14], 50 pieces for each composer. All movements were composed in a major scale and transposed in the key of C major.

It has to be noticed that, string quartets have a strictly specified structure, which makes them a difficult musical collection for composer identification. Every string quartet is composed in four voices, each of which play a certain role in the composition. The voice of the higher pitch register plays the leading voice role, the others form the harmony and the lower voice also forms almost always the bass line. The four voices are almost always monophonic and can be easily separated in four different monophonic tracks. When polyphony occurs, the skyline algorithm is performed to keep only the higher note of the polyphonic cluster [18]. For the rest of the paper, we refer to the highest voice, as the first voice, the next lower as second and similarly for the third and fourth.

More technically, in this work we utilize for the optimization task the DE/rand/1/bin strategy, with a population of 20 individuals, and default values for the parameters as stated in [17] i.e. $F = 0.5, CR = 0.9$. The number of maximum generations is kept fixed and equal to 200. Additionally, we utilize as a classification method the SVM with default parameters as stated in the libSVM library [1]. It has to be noted that the transition matrix of each voice is reshaped into a normalized vector to meet the SVM formality. For each of the 150 movements, we have four separate monophonic voices. Thus, we can split the experimental procedure and perform four different simulations to study and observe the composers unique compositional style of every voice.

Table 1 exhibits experimental results of the Markov Chain (MC) model and the Weighted Markov Chain (WMC) model for all four voices of three different composer identification tasks, namely Haydn–Mozart, Beethoven–Haydn and Mozart–Beethoven. The following notation is used in Table 1: *Voice* indicates which voice we refer to; *MC–success performance* indicates the classification success performance of the simple Markov Chain model; similarly *WMC–success performance* indicates the mean value of the classification success performance over 30 independent simulations produced by the

Table 1. Experimental results for the simple Markov Chain (MC) model, the Weighted Markov Chain (WMC) model and the corresponding r_1 and r_2 mean values

Haydn – Mozart					
Voice	MC Success Performance	WMC Success Performance	Improvement	r_1	r_2
First	63%	65%	2%	0.6760	15.1925
Second	53%	70%	17%	0.8025	5.7154
Third	57%	67%	10%	2.7398	18.1810
Fourth	55%	63%	8%	3.0347	9.9962
Beethoven – Haydn					
Voice	MC Success Performance	WMC Success Performance	Improvement	r_1	r_2
First	66%	88%	22%	3.1389	0.1204
Second	71%	75%	4%	1.3641	0.8872
Third	61%	59%	-2%	3.5439	2.3682
Fourth	64%	78%	14%	0.0071	8.9264
Mozart – Beethoven					
Voice	MC Success Performance	WMC Success Performance	Improvement	r_1	r_2
First	82%	87%	5%	6.5461	0.9697
Second	68%	74%	6%	3.9459	0.4409
Third	67%	71%	4%	0.1840	2.9747
Fourth	70%	77%	7%	0.7016	5.1395

weighted Markov chain model; *Improvement*, denotes the improvement percentage of the WMC versus the simple MC model. Finally, for the aforementioned WMC–success performance results, we exhibit the mean best values of the r_1 and r_2 parameters.

A first comment is that, in the majority of the considered cases, the WMC model improves the simple MC model, even by a small amount. In the third voice of the Beethoven–Haydn identification task, DE has been trapped in a local maximum, since when $r_1 = r_2 = 0$ the identification success would be the same as the simple MC model. The WMC model exhibits a good overall improvement in the Beethoven–Haydn and Haydn–Mozart tasks. In the data sets of Mozart–Beethoven and Beethoven–Haydn, we observe that in the first two voices $r_2 < 1$, while $r_1 > 1$. The opposite happens for the third and the fourth voice, with exception of the r_1 factor in the third voice of the Beethoven–Haydn set. This might indicate that Beethoven's aspect for the operation of the four voices in the string quartets, is different compared to Haydn's and Mozart's. Thereby, Beethoven seems to utilize smaller pitch intervals within phrases for the first two voices, and smaller inter onset internals within phrases for the third and the fourth voice.

Next we proceed with some comments of musical nature that we can make about the Haydn–Mozart pair which is one of the most difficult identification task considered in this work. In this task, we observe that the smallest improvement was made for the first voice. This could be due to the fact that the first voice already contains most of the information, since it plays the role of the leading voice. It also explains the fact that in this voice the simple Markov chain model produced its best success performance over the utilized collection. Additionally, the r_1 values were kept at a low level near to zero, which possibly means that distant pitch intervals contain considerable information. Musically, this signifies that notes with distant pitches may belong to same phrases. A similar behavior also holds for the second voice. On the contrary, in the first voice, values of the r_2 parameter were kept in high levels, near 15, which possibly means that distant time events are less important, resulting that distant time events are used as phrase separators. A similar behavior can also be observed for the third voice. Finally, the third and the fourth voices exhibit best results for high values of the r_1 parameter. Thus, it could be said that different use of closely neighboring pitches is unique for the string quartets of Haydn and Mozart.

Similar comments can be made for the remaining identification tasks, by analyzing pairs of the r_1 and r_2 parameter values of different voices. A further analysis should be made by musicologists, who could extract refined information by the aforementioned comments, in the considered musical collection. To collect more musical structural meanings, we can enhance the proposed model by incorporating more variables that could probably capture additional characteristics of the musical collection.

6 Conclusions

In this work, a weighted version of the simple Markov chain model for the representation of a monophonic musical piece, which includes further information about its pitch and inter onset intervals has been proposed. Furthermore, to tackle the composer identification task an automatic procedure based on an evolutionary algorithm for tuning the parameters of proposed model has been presented. Initial experimental results suggest that it is a promising model. The proposed model has two main aspects. Firstly, as the results suggest, the weighted Markov chain model performs better than the simple Markov chain model and in some cases exhibit high classification performance. Secondly, the incorporation of the proposed weighted Markov chain model representation can provide insights about the behavior and the characteristics of the pitch and inter onset intervals on each monophonic voice in a given musical collection. Thereby, models like the proposed one, in accordance with the essential opinion of a musicologist, could lead to significant insights for identification of classical composers.

Several interesting aspects should be considered in a future work. The proposed approach should be further studied in a bigger collection with either string quartets or pieces that share similar voice structures. The combination of all four voices into a single transition matrix may further enhance the performance and the musical quality of the proposed approach. Additionally, the proposed approach could be also tested for sub-genre classification, since the compositions within a genre, often utilize certain combinations of musical instruments and very similar voice structures. Furthermore, genre classification could be performed, with a proper matching of the roles of monophonic voices between different genres.

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