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Modeling melody similarity using music synthesis and perception

Velankar M.R.[a], Dr. Sahasrabuddhe H.V.[b], Dr. Kulkarni P.A.[c]

[a]*Faculty, Cummins College of Engineering, Pune, India*
[b]*Retired Professor, CRESIT IIT Mumbai, India*
[c] *Director,Chief Scientist, Eklat Research, Pune, India*

Abstract

Melody similarity in music is a perception of listeners based on cognitive method. Thus, the algorithms should be based on perceptually oriented computational model. We have used computer generated synthesized tune of popular song and its variations to understand similarity notion. We have generated variations of a tune by changing musical scale or relative duration of notes or notes itself and combination of them. The proposed approach to calculate similarity relationship between two tunes will be useful to model the melody similarity notion for various applications such as QBH (Query by humming), music classification and retrieval, music plagiarism etc.

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Keywords: music similarity; melody similarity perception; computational model.

1. Introduction

Tune or melody similarity in music has been a topic of research for a long time. It has major applications in content based music information retrieval such as query by humming (QBH) in which melody is submitted by user by humming a tune and the algorithm finds possible similar tune or tunes for the submitted tune. Melody similarity does have a diverse application in music industry for piracy detection and proving music copyright infringement.

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Melody or tune is developed based on the some musical notes and there combinations by the composers. From the limited set of notes, we have enormous possibilities of melodies possible with different set of notes, possible sequences, different relative durations and there amplitudes, rhythm associated with them etc. as possible changing parameters.

Many music composers claimed about a particular tune was stolen by other composer and it was first created by him or her. Some composers do admit that a particular tune was created with an inspiration based on some other tune. All said and done, it has been the topic of debate among music community since a long time and no concrete solution possible so far. Concluding on this matter is very difficult considering the issues involved such as how to decide the boundary line between inspiration or copy and exact definition of copy in musical tune.

Notion of tune or melody similarity is associated with the perception of the listener and his/her background of music. The tunes based on same Hindustani raga (specific note combination and rules associated for composition) might be considered as similar tunes for the seasoned listeners whereas novice listeners may have different opinions about the possible similarity.

We have attempted to find the notion of similarity among majority of listeners from the computer generated melody and possible variations among it. Computer generated music helped us to change different parameters of the tune and observe effect of it on similarity perception among listeners.

Our approach is to model the similarity notion and proposed the tune similarity model based on different variations in the tune. In this pilot experiment, we have not considered rhythm associated with the tune as it is inherent in most of the melodies and melody is considered as a note sequence and parameters associated with notes in broadly.

2. Related Work

Many researchers have worked on melody similarity and modeled music similarity on melody in different ways and various algorithms are proposed by them. Min Woo Park [1] has proposed overall similarity approach for music with more focus on one dimensional numeric string based on MIDI notations for melody comparison. They proposed Conditional Euclidean Distance measure as better measure for melody similarity. Naresh Vempala [2] has focused on psychological aspects and listeners responses on similarity measures with one note changed in two tunes. Melodic contour, pitch distance, pitch direction were the major deciding factors for melody similarity as per their findings. Petri Toiviainen [3] suggested a computational model of melodic similarity based on multiple representations and self organizing maps.

Geometric melodic representation with melody representation in pitch time plane and sequence alignment is another approach used by Juli´an Urbano [4]. Limin Xiao [5] presented a Graphical Processing Unit (GPU) acceleration approach for melody accurate matching. Margaret Cahill [6] focused on listening experiments to gather similarity ratings for a piece in theme and variations part. Emilios Cambouropoulos [7] has focused on fundamental concepts of identity, similarity, categorization and melodic cue and proposed an algorithm for monophonic tunes. Ning Hu [8] presented a work on sung queries and retrieval for query by humming (QBH).

Emilios Cambouropoulos [9] proposes an efficient pattern extraction algorithm that can be applied on melodic sequences that are represented as strings of abstract intermittent symbols. Ruben Hillewaere [10] evaluated different approaches for folk music genre classification and concluded that the n-gram models outperform both the string methods and the global feature models. Teppo E. Ahonen [11] presented compression method based on mapping the values of binary chromagrams extracted from MIDI files in symbolic polyphonic music. Julián Urbano [12] proposes an alternative to generate similarity lists by using crowdsourcing to gather music preference judgments without the need for experts.

Matthias Robine [13] evaluated Existing algorithms that can be applied to detect near-duplicate music documents rely on string matching or geometric algorithms. They found out that musical sequences composed of very different notes can be musically very similar and proposed some improvements specific to the musical context for plagiarism detection. Pierre Hanna [14] proposed optimizing the editing algorithms for evaluating similarity between monophonic musical sequences. Their optimization techniques are suitable for specific musical applications and imply significant improvements of the editing algorithm. Bryan Pardo [15] have studied different approaches for melody matching and concluded that no approach is clearly superior, string matching having slight advantage.

Moreover, neither approach surpasses human performance. Christian André Romming [16] has proposed and evaluated algorithms for polyphonic music retrieval using hausdorff metric and geometric hashing. They mentioned need of further research work on ways to improve results.

Most of the research papers focused on already existing musical compositions and proposing algorithms to find similarity among them. Although many of them shown acceptable results for the musical melodies under consideration, they have mentioned need of further research in melody similarity for better results.

3. Our Approach

We have used computer generated music for our study of tune similarity. The reference tune was first generated using a program in chuck. Chuck is a software tool for computer music generation using synthesis. This reference tune selected was a familiar tune for majority of the listeners. We have purposely selected familiar tune for the similarity perception. The reference tune familiarity helps; as listeners can co-relate the similarity easily as one tune pattern is already registered within listener's brain. Association and similarity pattern with known tune removes the need of registering the reference tune pattern. New variations of the tune were generated by changing different parameters such as changing scale, changing durations, change in notes etc.

We have initially done the experiments by changing only one parameter and generating few tunes for each parameter in order to understand impact of individual parameter and later tried to vary two parameters at a time and finally changing all parameters. Although various permutations were possible for each, the attempt was to generate different possible sounding tunes and understand the similarity notion.

3.1 Changing scale/transpose of melody

In this variation of generating tune, we have only shifted the scale as playing the same note sequence in different octaves or shifting the note sequence by specific number of notes. During these tune generations, the note distance was mentioned as say T T T T, where T stands for tone. Following examples will explain the use of change of scale concept with different sequence generated.

1. C, D, E, D, E.
2. F, G, A, G, A.
3. A, B, C#, B, C#.

Transpose or change scale can be shown with MIDI sequence of notes with possible transpose of same tunes as shown with 3 tunes sequence below. All sequences are generated based on transpose concept of same tune sequence.

Tune 1 MIDI sequence – 60, 64, 66.
Tune 2 MIDI sequence- 58, 62, 64.
Tune 3 MIDI sequence- 62, 66, 68.

If we refer first note at 0 then subsequent notes can be mapped as per increase or decrease of MIDI value from the previous note as 0, +4, +2 in the above example. These values indicate distance of next note from the previous note.

3.2 Changing relative duration/time stretching

Here in this tune generation experiments, we have generated tunes with same notes played but by changing relative duration of notes played. Relative duration is important here as we have reduced duration of each note by say double or half. Following examples with duration for each note and sequence generated with different duration illustrates the concept of relative duration. Time shown here is representation in second of notes played subsequently.

1. 1, 0.6, 0.6, 0.4, 1.

2. 2, 1.2, 1.2, 0.8, 2.
3. 0.5, 0.3, 0.3, 0.2, 0.5.

First duration sequence shows the duration of 5 notes played in the tune sequence. Second duration sequence represents duration doubled with respect to first duration sequence which sounds as the same notes played slowly compared to first sequence. Third sequence shown is half compared to first duration sequence which makes the same notes played at faster pace compared to first sequence.

3.3 Change in one note

We have studied the note pattern and different variations were generated from them as to consider less impact change to high impact change. Less impact is considered as a change in note with less duration and few or very less appearance in the overall tune. High impact is the change of note with more duration and more appearance in tune. In these experiments, we have changed only one note in the sequence with change of particular note occurring at different occasions. We have attempted to give more thrust on this experiment as tune is generally perceived note sequence in particular order.

Despite of many possibilities, we have selected the sequences with possibly more similar to more dissimilar generated tunes to understand the possible impact of change in notes.

3.4 Change in scale and duration

For change in scale and duration experiment, relative scale and relative duration of notes were modified with similar principles mentioned above. This experiment was conducted to understand impact of change in both parameters at a time and its response is cumulative or different than individual parameter’s response.

3.5 Change in one note and duration

For the combined experiments with change of one note, actual change was with respect to one note only. i.e. the duration of changed note was modified. Possible low impact change was considered as change in note with less duration/ occurrences and possible high impact is considered as note with more duration and frequency in the sequence.

3.6 Change in one note and scale

In this case the only one note was changed in different scale. Despite of enormous possibilities present in this, we have selected few representative tune variations to understand the impact on similarity perception.

3.7 Change in all 3 parameters

We have changed all three parameters as scale, duration and one note to understand the collective effect to recognize impact on similarity perception. We have used consistent scale changes, duration changes and one note changes through out all experiments to understand the similarity response. Our aim was to understand the cumulative impact.

We have used staff notations for the Indian music considering familiarity of notations to majority of music researchers. However, we have also presented the Indian notations for the tune representation. Following example illustrates the sample notation equivalence. “C D E D E E D C” sequence in western notation is similar to “Sa Re Ga Re Ga Ga Re Sa” as a possible sequence in Indian notations.

4. Results

We have attempted to understand the notion of similarity of tune on the perception scale of 1 to 10 with 10 refers to identical or similar tune and 1 refers to dissimilar tune. We have taken responses from about 10 listeners for each experiment and similarity perception given in Table 1 is the average response value. The value indicates impact of parameter/ parameters change on similarity. Although the perception study of only 10 different listeners is carried out, the values indicate the overall possible perception. More detailed perception study with listeners of different age groups and cultural diversities can result into more accurate similarity perception values by averaging; however individual opinions may vary.

Table 1. Similarity perception with change in reference tune

Tunes	Experimental tune with change	Similarity perception
1	Change in scale	9.2
2	Change in relative duration	8.8
3	Change in one note with less impact	8.1
4	Change in one note with medium impact	7.8
5	Change in one note with high impact	7.2
6	Change in scale and duration	8.6
7	Change in scale and high impact note	5.6
8	Change in duration and high impact note	5.1
9	Change in scale, duration and high impact note	4.4

As per the results related to similarity perceptions, change in relative scale or relative duration does not have major impact on dissimilarity and the tunes perceived to be similar despite of change in these parameters. However, the relative change in scale such as shift of sequence by one tone or more tones needs to be noted as it can have possible impact on emotions perceived. To clarify the point we can consider following note sequences with change in scale or transpose of melody concept.

1. C, D, E, D, E.
2. F, G, A, G, A.

Similar sequence can be generated with starting note as A or B or any other note. We need to record the distance of scale change as here the distance between C and F in the above example needs to be noted. Similarly the duration change in time stretching also needs to be noted with possible multiples of duration. More study on similarity cognition can throw more light on the process of melodic similarity notion among majority of listeners.

5. Proposed Methodology

Considering the notion of similarity with different parameters, it is essential to perform some pre-processing on the notes pattern in order to compute the distance between two tunes. We have not considered rhythms associated as tune is considered as note sequence with relatively very less impact of rhythm. Proposed model does not consider different parameters such as rhythm, timbre, triads etc. as they are generally independent of tune or melody in the music.

5.1 Identification of transpose or change of scale

The tune can be represented as sequence of numbers with step up by + and step down by – to indicate next note is above or below previous note and by how much distance.

As an example a tune with following MIDI notations can be represented as follows.

MIDI sequence: 62, 64, 65, 65, 63, 62.
Representation: 0, +2, +1, 0, -2, -1.

This proposed representation represents melodic contour in a simpler manner. This representation can be useful to understand the change in scale or transpose and compare the two sequences. For example, MIDI sequence: 58, 60, 61, 61, 59, 58 will have similar representation as mentioned in the previous example and we can identify transpose or change of scale easily.

5.2 Change in relative duration or time stretching

We need to consider some reference note for such comparison from both tunes under consideration. We have used prominent note concept here as a reference note, Prominent note is the note with maximum duration in the tune. In case the total duration is same for two notes in a tune then maximum occurrences and maximum loudness features can be used to decide prominent note in the tune. Two tunes can be compared for change of scale or relative duration with reference to prominent notes in both tunes. We can make duration of such prominent notes in both melodic sequence same at an instance of maximum duration in both to understand impact of time stretching.

5.3 Change in note

About the note change, we need to consider the number of occurrences and duration of the note to find the possible impact on similarity. This notion of importance can be represented by some weight associated with each note in a particular sequence. We can order the notes from higher duration to lower duration and assign the weights accordingly. In case of similar duration, occurrences and /or loudness can be useful to assign different weight.

5.4 Distance measure

For transpose, the distance between two reference notes of tunes can be noted as d1 along with weight w1. In case both the tunes have same reference note then d1 will be zero. For time stretching, the stretching of one tune with respect to other tune in view of reference note can be considered as d2 along with weight w2. Similarly, in case the duration of reference notes in both tunes is same then d2 will be zero.

We can consider following MIDI sequences with 6 notes to explain the computation of d1.

Tune 1 sequence with 6 notes: 62, 64, 65, 65, 63, 62 (1)
Tune 2 sequence with 6 notes: 58, 60, 60, 60, 59, 57 (2)

With first note as the reference note, the difference between them (62 and 58) is considered as d1. In the above example (1) and (2), d1 will be 4.

We can consider following MIDI sequences with note durations in unit time to explain the computation of d2.

Tune 1 note duration for 6 notes: 2, 1, 2, 2, 1, 1 (3)
Tune 2 note duration for 6 notes: 4, 4, 4, 4, 4, 2 (4)

With first note as the reference note, the first note duration difference (2 and 4) is considered as d2. In the above example (3) and (4) d2 will be 2.

After pre-processing of both tunes referred above, distance measure can be computed as a parameter representing for change of notes pattern and also change in respective durations of notes. Sample data presented below is with pre-processing for the reference note as first note for which transpose and time stretching is applied.

Following table shows the concept of sequence and duration distance measure calculation proposed.

Table 2: Calculation of sequence distance and duration distance

	note 1	note 2	note 3	note 4	note 5	note 6
Tune 1 sequence	0	+2	+1	0	-2	-1
Tune 2 sequence	0	+2	0	0	-1	-2
Sequence Distance (d3)	0	0	1	0	1	1
Tune 1 duration	2	1	2	2	1	1
Tune 2 duration	2	2	2	2	2	1
Duration Distance (d4)	0	1	0	0	1	0

In the example shown in table 2, total distance measure for sequence is 3 (d3) and total distance measure for duration is 2 (d4), which is summation of individual values. 0 in the tune sequence represents no change with respect to previous note.

5.5 Summary of proposed methodology

The proposed distance measure formula can be combination of all parameters mentioned above with different weights for each parameter. In order to make simple calculations for distance measure for sequence and duration distances, we can simply compute the total distance with weights as w1 to w4 respectively and arrive at a simple formula for distance as

$$D = d1.w1 + d2.w2 + d3.w3 + d4.w4. \quad (5)$$

The weights can be associated according to importance of parameter in similarity perceptions such as values for w1 and w2 can be less as these parameters have less impact on similarity notion whereas w3 with note sequence should have maximum value as it has major impact as compare to other parameters. Value for w4 can be more than w1 and w2 but less than w3 considering impact of duration of note on similarity opinion.

Sample calculation of D for the tunes and durations mentioned by (1), (2), (3) and (4) with computation of d1, d2, d3 and d4 shown above will be as under. Values of w1, w2, w3 and w4 are considered as 0.2, 0.2, 0.6 and 0.4 for the sample calculation. More similarity perception experiments and result analysis will be useful to decide values of weights w1, w2, w3 and w4.

$$D = 4 \times 0.2 + 2 \times 0.2 + 3 \times 0.6 + 2 \times 0.4$$
$$= 3.8.$$

Lesser the value of D shows more similarity whereas, bigger the value of D shows less similarity. More complex and may be a better version can be with association of weight according to actual duration of note where change is noticed and importance or prominence of the note. This can be done using probabilistic model with calculating duration of each note and associating probability of occurrence to it for a specific melody.

6. Conclusion

In order to compute similarity between given tunes, we have proposed a methodology which can consider different important parameters for melody similarity concept and compute the similarity value associated with the tunes. Pre-processing of tune for relative scale change and duration change is proposed. The proposed algorithm and distance measure requires extensive testing on different tunes, and its performance has yet to be compared with other similar algorithms. This study, however, has presented a novel approach in terms of melodic representation and melody pattern matching, and has attempted to provide an efficient solution to it that can be used for further testing and evaluation.

References

1. Min Woo Park and Eui Chul Lee. Similarity Measurement Method between Two Songs by Using the Conditional Euclidean Distance**.** Wseas Transaction On Information Science And Applications issue 12 vol 10 Dec.2013
2. Naresh N. Vempala and Frank A. Russo. A Melodic Similarity Measure Based on Human Similarity Judgments. 12th International Conference on Music Perception and cognition July 2012 thelsinki Greece.
3. Petri Toiviainen & Tuomas Eerola. A Computational Model Of Melodic Similarity Based On Multiple Representations And Self-Organizing Maps. Proceedings of the International Conference on Music Perception and Cognition Sydney 2002.
4. Juli´an Urbano, Juan Llor´ens, Jorge Morato and Sonia S´anchez-Cuadrado. Symbolic Melodic Similarity: Hybrid Sequence Alignment with Geometric Representations. MIREX 2012.
5. Limin Xiao, Yao Zheng, Wenqi Tang, Guangchao Yao, and Li Ruan. GPU Acceleration of Melody Accurate Matching in Query-by-Humming. the Scientific World Journal 2014.
6. Margaret Cahill, Donncha Ó Maidín. Melodic Similarity Algorithms – Using Similarity Ratings For Development And Early Evaluation. Centre for Computational Musicology and Computer Music University of Limerick, Ireland.
7. Emilios Cambouropoulos. Melodic Cue Abstraction, Similarity, and Category Formation: A Formal Model. Music Perception An Interdisciplinary Journal, Vol. 18, No. 3 (Spring 2001)
8. Ning Hu and Roger B. Dannenberg. A Comparison of Melodic Database Retrieval Techniques Using Sung Queries. Joint Conference on Digital Libraries, (2002), New York: ACM Press.
9. Emilios Cambouropoulos, Maxime Crochemore, Costas Iliopoulos, Manal Mohamed, Marie-France Sagot. A Pattern Extraction Algorithm For Abstract Melodic Representations That Allow Partial Overlapping Of Intervallic Categories. International Conference On Music Information Retrieval (Ismir 2005)
10. Ruben Hillewaere, Bernard Manderick, Darrell Conklin. String Methods For Folk Tune Genre Classification. International Society For Music Information Retrieval 2012
11. Teppo E. Ahonen, Kjell Lemstr¨Om, Simo Linkola. Compression-Based Similarity Measures In Symbolic, Polyphonic Music. International Society For Music Information Retrieval Conference (ISIMR 2011)
12. Julián Urbano, Jorge Morato, Mónica Marrero and Diego Martín. Crowdsourcing Preference Judgments for Evaluation of Music Similarity Tasks. Proceedings of the SIGIR 2010 Workshop on Crowdsourcing for Search Evaluation (CSE 2010)
13. Matthias Robine, Pierre Hanna, Pascal Ferraro and Julien Allali. Adaptation of String Matching Algorithms for Identification of Near-Duplicate Music Documents. Workshop on Plagiarism Analysis, Authorship Identification, and Near-Duplicate Detection SIGIR '07 Amsterdam.
14. Pierre Hanna, Pascal Ferraro And Matthias Robine. On Optimising The Editing Algorithms For Evaluating Similarity Between Monophonic Musical Sequences. Journal Of New Music Research 36 (2007)
15. Bryan Pardo, Jonah Shifrin and William Birmingham. Name That Tune: a Pilot Study in Finding a Melody From a sung Query. Journal Of The American Society for Information Science and Technology 2004.
16. Christian André Romming, Eleanor Selfridge-Field. Algorithms For Polyphonic Music Retrieval: The Hausdorff Metric And Geometric Hashing. Austrian Computer Society 2007.