Classification of Different Indian Songs Based on Fractal Analysis

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In this paper some of the prevailing classifications of Indian songs are quantified by measuring their fractal dimension. Samples were collected from three categories: Classical, Semiclassical, and Light. After appropriate processing, the samples were converted into time series datasets and their fractal dimension was computed. Based on these results, an online method for classification is offered.

1. Introduction

Even though mathematical analysis of music is not new there is no standard method and different analysts apply different tools. In this paper we try to apply nonlinear tools to quantify some of the prevailing classifications in Indian songs. Our method can be generalized and applied to other areas of music. We confine our discussion to music as a purely acoustic phenomenon.

The basic point is that the way music is composed makes it fall into three categories: Classical, Semiclassical, and Light. This categorization is largely from popular perception and is not very rigorous in nature. A detailed study of the origin and classification of Indian music can be found in [1]. Here we consider only vocal performances; that is, songs, more particularly, the melodic lines from each of the categories. Classical songs are composed by strictly following a set of compositional rules that are of fundamental importance for this type of composition. This type of song is quite difficult to learn and is supposed to be the foundation for all other types of songs. The procedure results in a complex melodic line that is a characteristic for a variety of songs in this category. In Light music, in contrast, more stress is given to lyrics, the melodic line is less complex, and the song is sung more "smoothly."

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Semiclassical songs lie in between. See [2, 3] for a brief discussion on Indian songs. See [4, 5] for the addresses of some Internet sites to listen to songs. Here, we shall attempt to find if the mentioned categories can be mathematically defined using fractal dimension (D) as a measure.

Voss and Clark [6, 7] determined that music exhibits $1/f$-power spectra at low frequencies. This fact allows us to consider music as a time series and analyze the fractal dimension of a particular piece of music. Bigerelle and Iost [8] found the global D to be an invariant for different types of music. In another work [9], D in the music of Mozart and Bach was calculated. Hsu and Hsu [10] discussed the application of D to music in detail and for a work of Bach, found D to be 2.418.

We collected several data samples of each category as discussed in section 2. We discuss the tools in section 3. We then apply the tools in section 4 to calculate D of proposed excerpts and compare the result derived from examples of different types of melodic lines. Some figures are drawn for frequency analyses. Based on the results obtained, some conclusions are made in section 5.

2. Data

We have selected three samples, each from a different category of song. The original soundtracks are in MP3 format and we extracted a roughly 11 second clip from each song. The selection had to contain the least amount of usual accompanying musical instruments since they are not a subject of our analysis and act as "unwanted noise." Also, spectrogram analysis shows that even a highly trained voice produces several frequencies simultaneously due to the very nature of human voice production. For more details on this see, for example, [11].

We extracted the waveforms of the musical excerpts and converted them to ASCII data; that is, in text form to produce a data file for each song. While recording and converting audio files on a computer, we used the following parameters: single channel, 8 bit, and and a sampling rate of 11 kbps. These parameters were chosen in order to keep the data file size small (each file still has nearly 120000 data points). These data files are fed to a computer program that plays back the original soundtracks and makes a real-time calculation of D simultaneously.

We may add that all of the musical excerpts, regardless of their complexity, were performed by great singers. Our selections were not intended to reflect any aspect of the performance of the songs in question, they only present a particular category of song.

3. Analysis of the data

The repetition of frequency in the time scale may lead to some self-similarity in the time series plot. To investigate this property, standard statistical tools are not sufficient and a more appropriate tool seems to be the fractal dimension.

3.1 Fractal dimension (*D*)

D is a measure of the extent to which trajectories on the attractor fill a region in the phase space, a strange attractor has a noninteger dimension. There are at least five different well-established definitions of D, although their interrelations are by no means completely understood [12]. If we try to cover, suppose, a line segment with squares of some finite side, say R, then let N be the number of squares of that size required to cover the set. Now let us make the square small enough so that the curve (whose D is being estimated) is approximated well. If we plot in phase space, each point represents a state of the system. In the limiting case where scaling R makes each square contain approximately a single point, then N represents the number of states. So, for one-dimensional objects with a finite set, in the general form, we can write

$$D = \lim_{R \to 0} \left[\frac{\log N}{\log R} \right]. \tag{1}$$

Since the number of data points is so large for each sample, we used a real-time analysis program to find D which takes a chunk of 20000 points at a time from the input file as described in section 2. Details of D and the program used have been discussed in our earlier work [13]. We also used the software *Dataplore* 2.0-6 and *Nlyzer* 3.2. In this case, we have six D for each file and present the minimum (Min. D) and maximum (Max. D) of them for each sample. Details of the results are given in Table 1 and the values of parameters used are given in Table 2. The same parameter values are used to calculate D for each sample.

3.2 Frequency histograms

Every song, being a musical sound, has its own harmonics and subharmonics repeated over time. So frequencies are repeated in each sample following the rules depending on which category of song the sample belongs to. To visualize this feature, we have drawn frequency histograms for each sample.

4. Numerical results

From the results, we can see that Classical songs have higher values of maximum D (well above three) than Light songs (below three) while D from Semiclassical songs lie in between the other two types. This is well expected as D measures how "kinky" a curve is. On the other hand, a curve, which has several folds that are self-similar, has higher D. This fact is also evident in Figure 1 where we have plotted two time series,

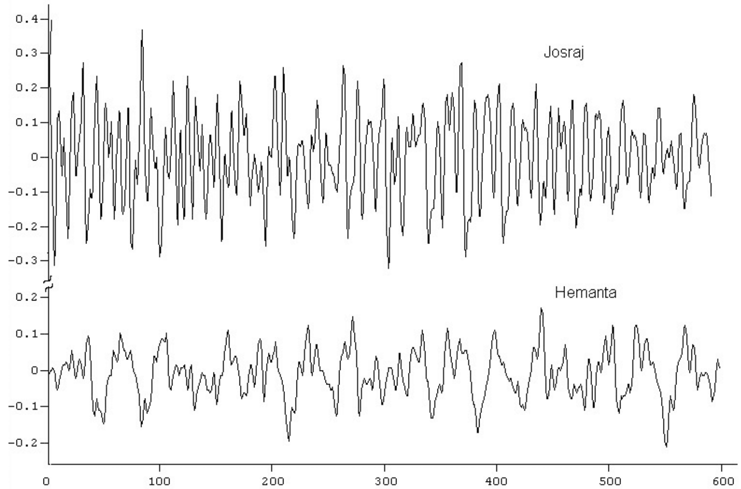

Figure 1. Comparing Classical (above) song sample "Josraj" to Light (below) song sample "Hemanta" to show the more complex nature of the former. Only 600 datapoints of each sample are plotted.

Number	Sample	Maximum D	Minimum D
A. Light			
A.1	*Hemanta*	2.45	0.79
A.2	*Nachiketa*	1.83	0.53
A.3	*Bhupen*	0.81	0.51
B. Semiclassical			
B.1	*Manna*	2.90	1.63
B.2	*Firoza*	3.14	0.53
B.3	*Sandhya*	2.21	0.93
C. Classical			
C.1	*Rashid*	4.09	0.51
C.2	*Josraj*	3.14	0.66
C.3	*Ajoy*	3.46	1.88

Table 1. Sample name, type of sample, and maximum and minimum value of D calculated for each.

Embedding Dimension	Delay	Reference Points	Data Points
8	4	512	20000

Table 2. Parameter values (with usual meaning) used in calculating D.

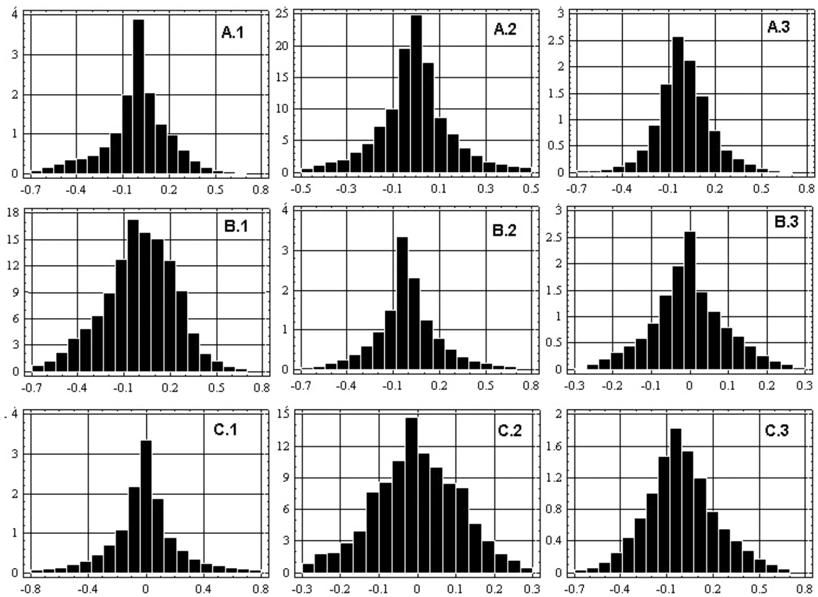

Figure 2. Frequency histograms for all of the samples. The sample number shown in the right-hand corner of each box is taken from Table 1. The vertical scale for A.2, B.2, and C.2 is 1000 and for all others is 10000.

one each from a Classical and a Light song. To have a closer look, we used only 600 points for each series.

In a Classical song the singer stresses producing a wide range of frequencies or repetition of frequencies over a short period. Naturally, this produces a more fractal curve associated with higher D. Also, from the frequency histograms in Figure 2, one can see that the data range is much wider for Classical songs than the other two types.

5. Discussion

The analysis presented here can be generalized to categorize different types of songs. Taking larger samples, in both number and time-scale, can give a more accurate analysis. We further propose to build up a full-fledged online system to classify Indian songs whose type is unknown. The scheme can be represented by Figure 3.

For this purpose, huge computational resources are needed to handle more samples of longer duration. Samples can be chosen from playing a prerecorded song or directly from the recorder device. Samples would be filtered to remove sounds from accompanying musical instruments to get only the sound of the voice. In the present case this was done manually. For a large number of samples a more efficient vocal-extracting program

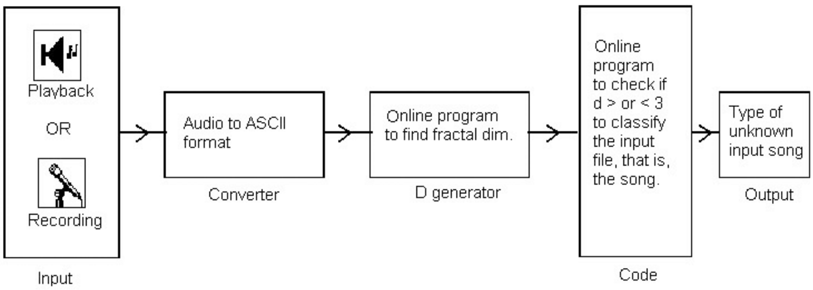

Figure 3. Showing how an online Indian song categorization scheme can be implemented.

is needed. But in any case, the method demonstrated here is quite applicable.

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[3] Theoretical discussion on Indian music can be found at http://www.lsi.usp.br/usp/rod/sounds/indian/indian.html.

[4] Listen to any kind of Indian music, Classical or Light at http://www.musicindiaonline.com or http://www.indianmelody.com.

[5] Freely downloadable vocal and instrumental Classical Indian music clips are available at http://homepage.mac.com/patrickmoutal/macmoutal/rag.html.

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