Analysis and application of audio features extraction and classification method to be used for North Indian Classical Music's singer identification problem

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Abstract: The Singer identification process requires extraction of useful musical information and classification. In literature, various methods of extracting the features of audio signal have been proposed. Depending upon the application, for which the information is to be extracted, there are various approaches of extraction and viewpoints for the signal analysis. The features are mainly analysed in time or frequency domains. Different classifiers such as K-means clustering, Hidden Markov model etc. have been utilized according to the applications such as singing voice detection, musical instrument classification or genre recognition. The performance efficiencies of these classifiers differ with difference in input, feature extractors used and application for which classification has been done. In this paper, we have analysed majority of the contributions done in this regards and have proposed the best suitable audio feature descriptor and the classifiers to be used for the problem of Singer identification in North Indian classical music. This type of music requires special attention and careful selection of feature extractors because of the involvement of accompanying instruments and melodic structure of the raga. There exist more than 52 audio descriptors in literature including all low level descriptors specified in MPEG7 standards. If all of them are considered as features to be used for classification and probabilistic models of classification are used then the system becomes complex and messy. In contrast to the western music, which is harmonious in nature, north Indian classical music is more complex structure and requires perceptual analysis along with less number of audio descriptors and a simple method of classification so as to reduce the computational complexity of the system. We have analysed various approaches and then proposed and implemented a singer identification process that reduces the complexity and increase the efficiency of solution to the problem of identification of a singer in North Indian Classical Music. The efficiency achieved by combining RMS energy, Brightness and Fundamental Frequency has been found to be 70% when K-means clustering has been used for classification of the singer of north Indian classical music- vocal.

Keywords: North Indian Classical Music, Audio descriptor, K-Means Clustering, Hidden Markov Model, MPEG 7 standards. RMS energy, Brightness, Fundamental Freq.

I. INTRODUCTION

Singing voice is extracted by various methods from the piece of an audio file for the applications such as querying a database for a particular song, karaoke generation, and genre classification and so on. In order to calibrate the success of any such application one has to first know and calibrate the audio feature extraction method being used and the classifier or a decision making unit identifying the singer.

This paper elaborates various audio feature extraction methods applied till now to the best of our knowledge and the classifiers used with the analysis of their input environment , the constraints on the system and the results been generated in controlled result space. Comprehensive analysis of various audio features, methods of feature extraction and classification techniques with results is presented in this paper. Here, we have treated human voice, a kind of musical instrument, so that all audio related feature extractors, especially timbre, can be compared. In later part of the paper we have proposed and

implemented a method of selecting the suitable audio descriptors and classifier.

II. CONCEPT OF AUDIO DESCRIPTOR

Transformations such as Fourier Transform are used to convert sound described in one domain to the other domain. A sound, in physics, is an air pressure disturbance that results from vibration [1]. Typically properties of sound signal such as its volume (amplitude, measured in dB), its pitch (frequency, measured in Hz) and duration (time, measured in seconds), are all characterized by one dimension. However, according to psycho-acoustic properties of sound another term is popularly used called as *timber*. Timbre itself is multidimensional in nature [2].The attributes of the sound are called as audio descriptors. These descriptors carry unique information of the audio file. The audio descriptors can be one dimensional or *scalar values* or a series of values resulting in a *feature vector*. There are various ways in which these

descriptors can be grouped depending upon the application [3].

Following ways are used to extract the audio descriptors from an audio file:-
a. Applying the functions on entire signal to find the audio descriptors.
b. Transforming the signal into another domain and then finding the audio descriptors.
c. Representing the single using standard model such as 'source-filter model' and then extracting the audio descriptors.
d. Emulating human ear (hearing) system.

The exact classification of audio descriptors is very difficult because it mostly depend on type of application.

III.   THE TIMBRE

Unfortunately, the term timber has neither been yet clearly understood nor defined accurately. It has no unit of measurement. More than 20 definitions are collectively given in [2]. It is to be noted that timber is a complex multidimensional structure component of sound.

Some attributes of the timber are:
a. A timbre has a number of harmonics together.
b. It has a harmonic structure such that all components of these harmonics are difficult to extract.
c. It contains loudness and f0 that is fundamental frequency.
d. It contains noise and has important consideration of phase.
e. It is multidimensional in nature.
f. It is perceptual and subjective non tangible component of sound.
g. It cannot fit into any subjective scale available today.

There may be two musical instruments, emitting same loudness, pitch and duration but there always will remain a difference between these two sounds produced through same type of musical instrument. That is how timber can be thought of as a powerful tool to separate the two sounds and identify the two sources. Different researchers have used different names for timber such as [4], who identifies timbre as 'tonal quality', while [5] as 'sound colour' and [6] as 'tone colour'.

Interesting fact of timbre is that, since it is a complex portion of sound wave, to one side, it cannot be mapped to a single dimensional scale at the same time , to the other side, we cannot decompose timbre from other components of sound that are one dimensional in nature. Additionally, it does not have any MKS/CGS or SI unit assigned. Timbre has been later mapped onto various perceptual features of sound as Brightness (mid-point distribution of signal energy), Fullness (even-odd harmonics) and Roughness (6 onwards harmonic present)

Mac Adams [7] proposed the 'timbre space' concept. This timbre space can be obtained by applying multidimensional scaling (MDS) method to reduce the number of dimensions to 2 or 3. Howard [8] concluded that if up to 5 specific rating scales are used we can identify almost any timbre. Researchers further added 'log of raise time' and 'irregularity' timbre attribute which [9]substituted spectral irregularity with 'spectral flux'. We have considered all above audio descriptors to represent the entity 'timber'.

There are very acute seventeen low level descriptors proposed [10] which, they classify into *Basic, Basic spectral, Signal parameters, and Temporal Timbral, Timbral* and *Spectral* basis representations categories. This MPEG group has used a standard classification of either AudioLLDScalarType or AndioLLDVectorType.

IV.   STRUCTURE OF NORTH INDIAN CLASSICAL MUSIC

In North Indian classical music all notes sung by a performer stick to one particular group of notes in a scale. The groups are formed on the basis of 'raga'. A raga uses a series of five or more musical notes upon which a melody is constructed [11]. The complexity of this type of restricted yet melodious singing lies in the way the voice is produced. There are various accompanying instruments that follow the singer. Tanpura, Violin, Harmonium and Tabla are some basic instruments used in a concert that are tuned and played in the same musical scale in which the singer is singing. This makes the computer system difficult to identify which sound is of the singer and which sound is of the instruments. Whereas, harmonium(for male and female singers) and violin(specially for female singers) produce the sound pitch so much similar to the human singer that many times it becomes difficult even to humans to identify which timbre is of the singer and that of an instrument?

This structure of reciting a raga by a singer makes the system more complicated since the audio that contain the sound contains both the components which are very much indistinguishable. Huge research has been done till date for identification of an instrument and very few singer identification of western music. While very rarely there has been designed a robust system identifying a singer reciting North Indian Classical music.

V. THE SINGING VOICE DETECTION PROCESS

The singer identification models work in three modules viz. input module (feature extraction module), query module (training and testing) and a classification module (singer identification) [12]. The input audio files have various attributes such as file type (.wav, mp3), sampling rate (44.1k, 16 kHz), audio type (mono, stereo) and bit rates etc. Some standard feature extraction methods such as Linear Predictive coding (LPC), Mel Frequency Cestrum Coefficient (MFCC), Wavelet Transform (WT), Fourier Transform (FT) etc. are frequently used in speaker identification. This gives various features of the audio sample. The coefficients generated out of LPC and MFCC are some numbers representing the audio signal.

These values are then used to train the model. Various classifiers are available depending upon the type of applications. Some typical classifiers are K-Nearest Neighbour (KNN), Gaussian mixture model (GMM),

Hidden Markov Model (HMM) or Bayesian Classifier etc. When a new audio sample is presented to the system, audio descriptors of that file are calculated and mapped on to the trained clusters to declare whether the singer is known (identified) or unknown (not identified).

Overall there is found a relationship in type of feature extractor and the corresponding classifier used with given constraints on both, the input data file and the classifier. Following section summarizes this to the best of our knowledge. There may be some more such examples of feature extractions and classifiers but we have selected the prominent feature extractors useful because of the accuracy of the results produced. A short summary of such algorithms and their performances restricted to the application of instrument classification has been presented also by [13].

However, major research has been done on audio feature extraction for identification of a musical instrument and to some extent of identification of a singer. Various classifier used for different audio features in the application of identification of Timbre of an instrument are reviewed by [14]. They have concluded that K-Nearest Neighbour (KNN) is more sensitive to feature selection than Decision Tree (DT) in instrument classification. On the other hand harmonic peaks feature fits DT better than KNN. There is no comprehensive analysis of all the audio descriptors and classifiers used in the identification of north Indian classical singer.

VI.   AUDIO FEATURE EXTRACTION METHODS AND CLASSIFIERS

In genre classification application used by [15], continuous wavelet like transform has been used to extract the Spectral Histogram by making use of 1024 bins. They had used mono recordings of 8 KHz sampling frequency, 16 bit PCM recording in .mp3 format. Each recording has been of the duration of 20 sec. Using k= 15(number of genres) for K nearest Neighbour classifier they have generated a 2D histogram trained by 1873 audio samples of 822 artists. The result has not been very impressive as the accuracy achieved was only 52.7%.

In classifying the musical instruments [2] it is suggested that most of the frequency domain analysis is based on Fourier Transform and its variants due to the fact that human hearing system make frequency analysis of the sound much like Fourier transform. Experiments have been carried on mono recordings of musical instruments with sampling frequency 22 kHz, 16 bit PCM, of duration 2 seconds. Total 12 different musical instruments have been considered with total number of audio samples 829. Out of these 292 samples were taken from string instruments such as Electric bass, cello, violin etc., 190 audio samples from woodwind instruments such as flute and 248 audio samples of brass instruments such as trumpet.

Various audio feature descriptors have been extracted in frequency and time domain analysis of the sound signal such as Inharmonicity, Harmonic Expansion/Compression,

Harmonic Slope, Shimmer and Jitter,Spectral Envelope, Synchronicty, Tristimulus, Spectral Centroid, Spectral Irregularity, Spectral Flux , Log Spectral Spread, Roll-off ,Phase and Spectral Flatness Measure in Frequency domain and Attack , Steady-State and Decay, Attack Time (rise-time), Amplitude Modulation (Tremolo) , Temporal Centroid, Pitch , Autocorrelation Method for Pitch Extraction, Autocorrelation withAdaptive Lag Length Method ,Zero-Crossing Rate (ZCR) and Linear Predictive Coding (LPC) in time domain.

The extensive utilization of almost all the features of an audio singal made the system complicated and slow. For training and classification purpose neural networks have been used. An accuracy of 78% has been achieved when Radial Basis function network (RBFN) has been used as classifier and 81% classification accuracy has been achieved when used elliptical basis function network (EBFN) with number of epochs used as 2000.

Another combination of audio descriptors has been used in [16]. The audio descriptors that are used usually in speech recognition such as linear prediction coefficients (LPC), LPC derived cepstrums (LPCC), Mel-frequency cepstral Coefficients (MFCC), spectral power (SP), short time energy(STE), and zero crossing rates (ZC) , have been used for the application of classification of musical audio. Mono recordings of .wav file format with 16 bit PCM representation and 44.1 kHz sampling frequency have been used. In total 6 Support Vector Machines (SVMs) were used for the purpose of classification and the results were cross verified by Gaussian Mixture model classifier output. The accuracy achieved from various music classification tasks was on an average above 85%. Major drawback of the system has been the high computational complexity in calculating various audio descriptor features.

There are various similar methods deployed in calculating the audio descriptor values and fed to the variety of classifiers. More or less all these methods are similar to MFCC or LPC or from the philosophy of Fourier transform usage. Harmonic pitch class profile with KNN classifier with 130 samples of each, 60 sec duration has given an accuracy of training to testing ratio of 60/40% respectively [17]. MFCC and Spectral features [18] along with two new features, namely, Normalized Harmonic Energy (NHE) and Sinusoidal Track Harmonic Energy (STHE) give improvement over the accuracy. The Gaussian mixture model (GMM) for classification has been trained for 75 vocal samples and 80 instrumental samples. With the testing data of 39 vocal and 43 instrumental samples the classifier could achieve accuracy of 92.17% for vocal and 56.14% for instruments.

An important conclusion has been given by [19] regarding the signal to noise ratio that decreases with the performance of the classifier. That means in other way, the signal to noise ratio, if is high, then the classifier works better. This seems obvious. They have used MFCC, LPC, Perceptual Linear Prediction (PLP) and a4 Hz harmonic coefficient as audio features and various combinations of

typical classifiers such as Gaussian Mixture model (GMM), Support Vector Machines (SVM) and Multi-layer perceptron (MLP) for the application of separation of the singing voice from background music. The feature extraction purpose has been to identify only the singing and non-singing portion from an audio file. Important contribution is that they have worked upon the complex structure of music in polyphonic environment. They have used 25 audio clips for training from 10 songs with average duration of 3.9 seconds with the introduction of four different signal- noise ratios (SNR) as -5, 0, +5 and +10 dB.

Voice coding based on Linear Predictive Coding (LPC) has been used by [20]. They have used linear scale data, wrapped data and combination of both of these and cross validated the classification using GMM and SVM. The major drawback of their system has been that it could not clearly detect the vocal region. This resulted in poor accuracy of classification of the singer.

Logically we may consider that singing voice is also a kind of musical instrument, we should be able to use the same system of feature extraction and classification as what can be used for a simple problem of instrument identification. Interesting part is that no research has been done, to the best of our knowledge, on identification of different units of instruments from same family. For example, we can have a robust system of classification of various musical instruments as violin, flute, guitar or drum but we have no system yet that tells which violin? Which flute? Which guitar? Hence, this system may fail our basic assumption of considering singing voice as another kind of simple musical instrument. Moreover, the complexity of North Indian classical music has to be considered which is based on melody in contrast with western classical music which is based on harmony.

This led us to a conclusion that traditional timber identification and musical instrument classification methods are not sufficient to correctly identify the problem of singer identification of North Indian classical music. A lot of parameters are to be separately analysed and studied by considering the complexity of the music. Also, the typical methods of extracting the singing voice from accompanying instruments will not be sufficient since there is noise like merger of other musical instruments running continuously with the voice of the singer. On the other hand, if all audio features are considered, so as to increase the accuracy of the result, the performance of the system degrades with respect to the complexity and robustness of the system performance. Hence, special method has to be derived to select the audio descriptors and also the classifiers.

VII.   EXPERIMENTS, RESULTS AND IMPROVEMENTS

There are three places of improvement, an input, the feature extractor & the audio features used and the classifier. Merely considering the input without any accompaniment would help us to test the feature selection

and classification methods we are using.   In this section, we propose improvement on some important aspects of audio descriptor selection and training and classification methods to be used for the problem of singer identification in North Indian Classical Music. A hybrid selection method of audio descriptors proposed by [12] makes sense in dynamically reducing the number of audio descriptors. This reduced set of inputs, to be given to the classifier, makes the system simpler and robust. Music Information Retrieval (MIR) community has designed a unique Toolbox of MatLab called, MIRTOOLBOX, containing its own way of describing the classification of the audio descriptors and has provided various functions to extract these features. The Toolbox functions have been used on input data of audio samples of 9 singers. Seven samples per singer were used for training each with duration of 5 sec. These studio recorded audio files were recorded from north Indian classical singers singing with only Tanpura as supportive instrument. The Tanpura drone itself has to be treated as noise and was been removed by making use of inverse comb filtering technique. These 63 audio files were further re-sampled at 16000 Hz and converted into mono channel. By making use of simple K-Means clustering classifier the results were tested for the combination of various audio descriptors. The experiments were carried out using systematic approach for selection of audio descriptors. First, all single audio descriptors were used. Total 20 audio samples were used for testing out of which 10 samples were the one used in training (known) and 10 samples were out the training dataset (unknown). The classification accuracy that comparatively Brightness gave was 50%. Then all combinations of brightness with other audio descriptors were done yielding 60% of accuracy and so on. With implementation of this method and thus exploring all results one by one gave further accuracy of 70% for the combination of RMS, BRIGHTNESS and F0(fundamental Freq) and 60% for RMS,BRIGHTNES and ENTROPY. Out of this for the combination of RMS, BRIGHTNESS and F0 the accuracy for known sample was 80% and 60% for unknown samples. The table1 explains the results.

Unfortunately, if we proceed for all the other possible combinations of RMS, BRIGHTNESS, F0 and other descriptors the results degrade considerably. The very basic reason behind this could be the combined effect of all the audio descriptors on the singer identification process. The nature and behaviour of each descriptor is unique hence they may degrade the classification accuracy when combined together. Also, k-means clustering though is simple, not robust to such complex problem of singer identification of north Indian classical music. When all statistical, timbrel and energy related audio descriptors were used the classification efficiency degraded to almost to 20%.

If we divide the audio descriptors found from hybrid selection method into two major parts of scalar and vector descriptors then separate treatment can be given to them with respect to the classifier. For scalar values Decision Tree classifier would perform better while to the vector

values (MFCC etc) KNN classifier would improve the accuracy. At the end of both the results there could be a decision making unit giving final verdict of the class to which current audio sample belongs.

VIII.   CONCLUSION

The problem of identification of singer becomes more complex if the input belongs to North Indian Classical Music. In this paper we have studied and analysed various music information retrieval techniques used so far along with the classification techniques used. The methods here described have been taken from the application point of view. At the beginning we have elaborated what is an audio descriptor and what are various audio descriptor types for a sound file. As Shown in Figure 1.

Model	Kmeans	Total Training Audio Samples d=(b*c)	63	Testing Data Samples	
Number of Ads (a)	3			Sample(K) (f)	5
# of Singers (b)	9	Total Training Values of Ads e=(a*b*c)	189	Sample(TK) (g)	5
# of Samples (c)	7			Total Data samples (h)	10

SP#	Ads Used	Recognition Result for		Total Recognized Samples	Total Not Recognized Samples	% Recognition Accuracy		Overall % Recognition Accuracy	Overall Recognition Failure
		Sample(K)	Sample(TK)			Sample(K)	Sample(TK)		
1	RMS+BRIGHTNESS+LE	4	1	5	5	80	20	50	50
2	RMS+BRIGHTNESS+ZCR	3	2	5	5	60	40	50	50
3	RMS+BRIGHTNESS+ROLLOFF	4	1	5	5	80	20	50	50
4	RMS+BRIGHTNESS+ROUGHNESS	2	0	2	8	40	0	20	80
5	RMS+BRIGHTNESS+IRREGULARITY	3	0	3	7	60	0	30	70
6	RMS+BRIGHTNESS+MODALITY	3	1	4	6	60	20	40	60
7	RMS+BRIGHTNESS+HCDF	4	0	4	6	80	0	40	60
8	RMS+BRIGHTNESS+INHARMONICITY	2	2	4	6	40	40	40	60
9	RMS+BRIGHTNESS+CENTROID	3	0	3	7	60	0	30	70
10	RMS+BRIGHTNESS+SPREAD	2	1	3	7	40	20	30	70
11	RMS+BRIGHTNESS+SKEWNESS	2	3	5	5	40	60	50	50
12	RMS+BRIGHTNESS+KURTOSIS	0	0	0	10	0	0	0	100
13	RMS+BRIGHTNESS+FLATNESS	2	3	5	5	40	60	50	50
14	RMS+BRIGHTNESS+ENTROPY	4	2	6	4	80	40	60	40
15	RMS+BRIGHTNESS+MFCC	2	1	3	7	40	20	30	70
16	RMS+BRIGHTNESS+LPC	3	2	5	5	60	40	50	50
17	RMS+BRIGHTNESS+F0	4	3	7	3	80	60	70	30
18	RMS+BRIGHTNESS+PITCH	3	1	4	6	60	20	40	70

Figure 1: Showing RMS, BRIGHTNESS and F0 giving maximum Accuracy

We have also emphasized on a very complex and non-tangible structure of sound-the timbre. Timbre becomes useful attribute of sound while identifying an instrument or a singer. We have explained various complexities of North Indian Classical Music and how it is difficult to use traditional approaches towards information retrieval from this complex music structure.

The literature mainly divides the features into frequency domain and time domain but there exists many other approaches towards finding useful information of sound such as perceptual analysis of the sound. From various approaches, results and their analysis, it is concluded that singing voice cannot be treated as a kind of musical instrument since classifiers are not classifying which unit of instrument but only type of instrument.

Thus a new improvised approach has been proposed that uses Hybrid selection algorithm of selection of correct audio descriptors on the basis of the application and then dividing the descriptors into two major categories. K-means classifier has been used for various audio

descriptors combinations and the highest classification accuracy was found with RMS, BRIGHTNESS and F0 combination as 70%. That shows these audio descriptors definitely are important in singer identification process and if combined with traditional feature extractors such as MFCC or LPC a better singer recognition system can be derived.

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