SWARA HISTOGRAM BASED STRUCTURAL ANALYSIS AND IDENTIFICATION OF INDIAN CLASSICAL RAGAS

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ABSTRACT

This work is an attempt towards robust automated analysis of Indian classical ragas through machine learning and signal processing tools and techniques. Indian classical music has a definite heirarchical structure where macro level concepts like thaats and raga are defined in terms of micro entities like swaras and shrutis. *Swaras or notes* in Indian music are defined only in terms of their relation to one another (akin to the *movable do-re-mi-fa* system), and an inference must be made from patterns of sounds, rather than their absolute frequency structure. We have developed methods to perform scale-independent raga identification using a random forest classifier on swara histograms and achieved state-of-the-art results for the same. The approach is robust as it directly works on partly noisy raga recordings from *Youtube* videos without knowledge of the scale used, whereas previous work in this direction often use audios generated in a controlled environment with the desired scale. The current work demonstrates the approach for 8 ragas namely Darbari, Khamaj, Malhar, Sohini, Bahar, Basant, Bhairavi and Yaman and we have achieved an average identification accuracy of 94.28% through the framework.

1. INTRODUCTION

Music information retrieval(MIR) is an active and growing field of research as most music today whether available over the internet or otherwise is in digital form. The important feature of classical music, both western and Indian, that distinguishes it from other kinds of music is that it is supported by a proper well established theory and rules. There has been a lot of work on content analysis of western classical music in terms of information retrieval, genre detection and instrument/singer identification etc. for example (see [1], [3], [2]). Though Indian Classical music is also a major form of music, the current literature related to it is very limited, in comparison to its western counterpart. Indian classical music is known for its technical soundness and its well defined structure. A basic musical performance unit, akin to a song, is a *raga*. A *raga* has layers of additional finer structure that can help in content identification and classification, yet these aspects have been under-utilised by the music analysis community.

While an expert in Indian Classical music can identify a raga just by noticing the unique constituent patterns such as *swaras (notes), arohan, avarohan* and *pakad* in the performance (explained later), developing computational models for the same has been a challenging task for music researchers. The freedom that Indian classical music provides to an artist to give his/her own personal flavour to a raga makes it harder for a novice to identify two different performances of the same raga. Another key challenge is the fact that swaras are defined only in terms of their relation to one another, and inferences must be made from patterns of sounds, rather than their absolute frequency structure. This motivated us to move away from diretly trying to identify notes as features and conceptualize various features based on swaras and their structural form.

2. APPLICATIONS

Automatic Tagging/Annotation: Continued digitisation of old archives of classical music and the sole availability of newer classical performances in digital form has resulted in huge digital databases of music. Automatic content tagging of this unorganised media is important to generate metadata for available data and thus facilitate creation of easily accessible databases. Bertin-Mehiuex et al. have already created a tool [7] for music tagging, but the work does not include Indian ragas.

Music Recommendation System: Based on an user's earlier choices of music, a music recommendation system filters out and recommends music through tags or content analysis. In the Indian system ragas are associated with emotions, time of the day, and seasons of the year. For queries based on such criteria, a proper recommendation system can make appropriate choices using raga identification as a base.

Music Tutoring/Correctness Detection System: A probabilistic raga identification system can be modified to a tutoring [9] or correctness detection system as well. While achieving this for a complex professional musical performance might be difficult, yet using it for cleaner and simpler instrumental versions of a raga may give positive results. Mistakes like skipping some swaras or a particular rule not being followed, can be identified by such a tutoring system.

Raga Generation: Within some broad rules, Indian classical music allows a performer to modify the components of ragas according to his creativity to create his own personalised performance of that raga. Generative models induced from human raga performances can be used to synthesize new raga performances that can be made unique or personalized by injecting controlled randomness or variations.

3. RELATED WORK

For a novice human ear, the basic way of recognising a raga is to correlate two tunes on the basis of how similar they sound. A trained expert on the other hand looks for characteristic phrases like arohanam, avrohanam, pakad and constituent swaras, gamakas etc. to arrive at a conclusion about the raga. This well defined manner of raga identification using the above properties has motivated researchers to conceptualize computational models for them.

Sahasrabuddhe and Upadhye [10] (1992) modelled a raga as a finite state automaton based on the *swara* constituent sequential patterns. Pandey et al. (2003) [11] extended this idea of *swara* sequence in the "Tansen" raga recognition system where they worked with Hidden Markov Models on *swara* sequences. These swara sequences were extracted using two methods- hill peak heuristic and note duration heuristic. They also employed two separate *pakad* matching algorithms that improved the HMM based results. The first algorithm used substring matching for pakad identification and the second algorithm was based on counting occurences of n-grams of frequencies in the pakad. Tansen was able to perform with an accuracy of 87% on a dataset of two ragas.

In [13] Sreedhar and Geetha created a database of ragas and used the scale of the raga performance as the similarity metric. Within a scale, notes are matched with the existing sets of notes in the ragas in the database. The closest raga in the database is given as the output for the test raga. Chrodia and Rae [12](2007) derived Pitch-class Distributions (PCD) and Pitch-class Dyad Distributions (PCDD) from Harmonic Pitch Class Profiles (HPCP) and used these distributions for classification using SVMs. They achieved state-of-the-art results with accuracies of 78% for PCDs and 97.1% for PCDDs. The dataset they had used consisted of 17 ragas played by a single artist.

Inspired by the use of HMMs over swara sequences and PCDs and PCDDs in [11] and [12], we propose a new approach to raga identification using swara based features extracted from chromagrams. Similar to HPCP features, we extract feature vectors from chromagram patterns (details later). But instead of learning probability distributions and using their parameters for an SVM (support vector machine) based classification as in [12], we modify them to extract Swara based features that are then used for raga modelling and identification.

The novelty in our approach is in performing raga identification without the knowledge of the scale of the performance. We employ *swara* based features extracted from the chromagram using the concept of *vadi* (explained later) and perform random forest classifier based classification to achieve state-of-the-art results.

4. INDIAN CLASSICAL MUSIC: BASIC STRUCTURAL ELEMENTS

The theory of Indian classical music discussed in this chapter is based on the texts [8] of well known Indian musicologist and scholar Vishnu Narayan Bhatkhande. We first discuss some important concepts of Indian classical music that are needed to understand the methods used in this work.

4.1 Swaras

Swaras (or notes) correspond to the frequencies being performed vocally or by a musical instrument. Collectively the seven Swaras are symbols used for a set of frequency values. They are the constituent units of a raga and thus act as an alphabet. They are closely related to the solfege (do re mi fa so la ti) in western music. Basically, there are 7 *swaras* in Indian classical music: *Shadja (Sa), Rishab (Re), Gandhara (Ga), Madhyama (Ma), Panchama (Pa), Dhaivata (Dh), and Nishad (Ni)*. These *swaras* are related to each other by the fixed ratio of absolute frequency values they denote. Similar to notes in western music, we get the same *swara* one octave above or below a particular *swara*.

The notes Sa, Re, Ga, Ma, Pa, Dha and Ni are today known as "shuddha svaras" or "pure notes". This expression is used in contrast to "vikrta svaras" or "altered notes". Thus Re may be flattened to get the vikrta swara "Komal Re" and Ma can be "sharpened" to get the vikrata swara "tivra" Ma. *Sa* and *Pa* only have the *Shuddha*(pure) form, while the rest have variants in *Tivra*(sharp) or *Komal*(soft) forms. Table 1 describes relations between the various swaras and similarity to western notes if C is labelled as Sa.

Table 1. Scale of 12 Swaras used in Ragas (if the note C is labelled as the swara Sa)

Hindustani Name (Symbol)	Solfa	Scale of C	Ratio to Sa
Shadja (Sa)	Doh	C	1
Komal Rishabh (Re)		C#,Db	256/243
Shuddha Rishabh (Re)	Re	D	9/8
Komal Gandhr (Ga)		D#,Eb	32/27
Shuddha Gandhr (Ga)	Mi	E	5/4
Shuddha Madhyam (Ma)	Fa	F	4/3
Tvra Madhyam (M)		F#,Gb	45/32
Pancham (Pa)	Sol	G	3/2
Komal Dhaivat (Dha)		G#,Ab	128/81
Shuddha Dhaivat (Dha)	La	A	5/3
Komal Nishd (Ni)		A#,Bb	16/9
Shuddha Nishd (Ni)	Ti	B	15/8
Shadja (Sa)	Doh	C'	2

The swaras are related to each other through frequency value ratios. If the swara Sa is assigned some frequency value in hertz, the rest of the *swaras* are spread around *Sa* as per the ratios governing them. For example the *swara* *Pa* is always $\frac{3}{2}$ times *Sa* in terms of actual frequencies. The 12-note system which is mostly used with *Sa* as the 1^{st} note and *Ni* as 12^{th} is described in table 4.1 in terms of the frequency ratios.

4.2 Raga

A raga (Sanskrit meaning - "color/hue") is a complex melodic construction over swaras meant to induce a specific emotional response i.e. color the mind of the listener with a particular emotion.

A raga is not just a simple collection of *swaras*, but is typically identified by swara patterns, the presence or absence of certain *swaras*, the possible ornamentation (*alankars*) applied on these swaras and their relative importance while playing the raga.

Here we discuss some relevant raga related terminology.

4.2.1 Arohan, Avrohan and Pakad

Though two ragas may have the same constituent *swaras*, a unique differentiation between them is the ascending and descending sequences of *swaras* termed as *arohan* and *avarohan* respectively. *Pakad* is a small sequence of *swaras* in a raga that acts as a signature for the raga and an artist often visits and revisits the *pakad* over a performance.

4.2.2 Vadi and Samvadi

Vadi is the most prominent *swara* in a raga and is often described as the King of *swaras* for that raga. The *swara* second to *vadi* in importance is called the *samvadi*. An artist stays at the *vadi* and *samvadi* for significant durations and emphasises them in a performance. The *swaras* other than *vadi* and *samvadi* which constitute the raga are called *anuvadi swaras* whereas the *swaras* which are totally absent are called *vivadi*.

4.2.3 Scale of the Raga - Tonic Frequency

An artist always tunes his whole raga performance around a fixed tonic frequency which she chooses according to her own comfort. This frequency defines the scale in which the raga will be performed. Irrespective of the absolute value of this tonic frequency, it is termed as the *swara* Sa. The rest of the swaras get aligned in accordance with their ratios with the swara Sa.

4.2.4 Jati- Audhav/Shadav/Sampoorna

Ragas are classified based on the number of swaras in the arohan and avrohan. Sampoorna is all 7 swaras, shadhav is 6 swaras, audhav is 5 swaras and Surtar is 4 swaras. So, an audhav-audhav raga has 5 swaras in its arohan and 5 swaras in its avrohan.

5. FEATURE EXTRACTION

5.1 Chromagram

A chromagram [6] is a visual representation of energies in the 12 semitones(or chromas) of the western musical octave namely C, C#, D, D#, E, F, F#, G, G#, A, A# and B. So, it basically depicts the distribution of energy in the twelve pitch classes.

The western semitones are such that they are fixed with respect to absolute frequency values and the musical octave has the property that the semitone one octave below or above is equivalent to the current semitone. For example,

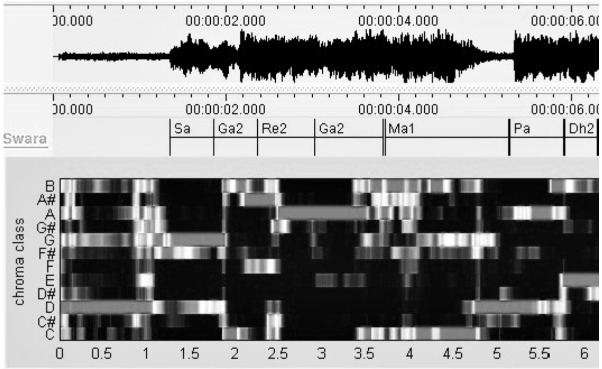


Figure 1. *Chromagram and Swara sequence for an arohan of Raga Bhairavi*

if one note has a frequency of 440 Hz, the note an octave above it is at 880 Hz, and the note an octave below is at 220 Hz. Since the semitones get repeated in each octave above and below, the energies in the chromagram for each semitone(chroma) is computed by wrapping and adding it up over different octaves.

Figure 1 depicts a chromagram generated from an *arohan* of raga Bhairavi. The arohan for raga bhairavi is:

Sa Re-Kom Ga-Kom Ma Pa Dh-Kom Ni-Kom Sa

The *Sa swara* of *Bhairavi* coincides with the semitone G and the rest of the *swaras* in the *arohan* get aligned with the semitone pattern in the chromagram. Note that, though this notes-to-swara alignment is not perfect and energies may spill over to the adjacent bins, still a signature pattern very close to the Bhairavi arohan is visible. This alignment is deduced using the swara and western seminotes equivalence discussed above and in Table 4.1.

These observations and previous use of chromagrams in audio analysis [14] and chord recognition [15] motivated us to use the chromagram to extract information about swaras. For processing chromagrams, the MIRToolbox [16], an open source toolbox for musical feature extraction was used to extract features.

5.2 Swara Histograms

From the chromagram, we extract the semitone with maximum energy in each frame and get a sequence of semitones for the raga. Though these sequences of semitones might have some identifying information about the raga, using them for raga identification is not appropriate since ragas are defined over patterns of *swaras* that in turn may get associated with different semitones depending on the tonic frequency selected by the artist for a particular performance.

In our approach, we assume that we do not have information about the tonic frequency of the raga performance. We must therefore find the mapping from the absolute frequency scale employed by the chromagram to the relative scale of the musical piece, so that the *swara* sequence can be identified. To do so, we use the concept of *vadi* discussed earlier to convert the semitone sequence to a *swara* sequence. We compute the most frequently occurring semitone from the semitone sequence and associate it with the *vadi* of a raga which is known for each raga. For example *vadi* for raga Khamaj is *swara* “Ga”. In an audio of Khamaj, if the semitone C# is most prominent, we label *swara* “Ga” at semitone C# and then convert the rest of the semitone sequence into a *swara* sequence.

The above procedure is raga specific, *i.e.* the conversion from semitone sequence to *swara* sequence utilizes the identity of the raga-specific *vadi* swara. Assume that we are building a system for n ragas and the actual raga for the test audio is not known, then for the given audio, we must compute separate *swara* transcriptions for each of the n ragas. They are combined into an unified representation in the algorithm below. The concatenation of 12-dimensional normalized frequency vectors $N_i's$ is done so as to capture the underlying raga's behavior even in the cases when it is being transcripted using a vadi of some other raga.

Algorithm 1 ***Computation of Swara based Features***

Step 1: From a raga audio, extract 3 minutes long snippets.
Step 2: Compute the snippet's western semitone transcription T from the chromagram by assigning each frame the highest energy semitone.
Step 3: Find the most frequently occuring semitone s in transcription T.
Step 4: Compute the snippet's *swara* transcription S_i for each raga R_i where $i = 1..n$ by matching semitone s to vadi v_i of raga R_i.
Step 5: From each transcription S_i, create a 12-dimensional normalized frequency vector N_i, that is a histogram of *swaras* over the 3 minute snippet.
Step 6: Concatenate all such N_i's to get k-dimensional feature vector where $k = 12 \times n$. We call this feature the **swara histogram** and use classification trees to identify the raga.

6. EXPERIMENTS

6.1 Raga Dataset

There does not exist any standard database for raga identification yet and the current dataset has been collected from YouTube videos. We include both vocal and instrumental performances by artists. In terms of quality, the relatively newer raga performances whose digital recordings are available have cleaner audio on YouTube. The older recordings do not have very clear vocal or instrument sounds. We believe that the methods used here should be unaffected by these. We demonstrate our system on 8 ragas whose details are in Table 2.

Raga	Number of Recordings	Time (in minutes)
Bahar	16	109
Basant	13	125
Bhairavi	18	162
Darbari	14	125
Khamaj	13	91
Malhar	13	124
Sohini	14	121
Yaman	16	151

Table 2. *Details of the Raga Dataset Used*

6.2 Random Forest Classifier over Swara Histograms

Data: Swara histograms were created for raga audios using Algortihm 1. For each snippet of 3 minutes, a hop factor of 0.025 seconds was used which gave 7200 frames. Each frame was tagged with a swara. We created a histogram of the 12 swaras over these 7200 frames and then normalised it to get swara frequencies that added up to 1. As explained earlier, for each snippet, we got 8 swara transcriptions corresponding to each possible raga. After concatenation of histograms from each such transcription, we finally got a 96 dimensional histogram feature for the snippet.

Random Forest Configuration: An ensemble of 100 trees was grown using the random forest algorithm [18]. For each tree, if there are N datapoints in the data, we choose N datapoints from them with repetition. This is called a bootstrap sample. Within each tree, when splitting criteria for a decision at a node are being calculated, a fixed number of dimensions are randomly sampled from the 96 dimensions. This number has to be less than the total number of dimensions and the best split on these dimensions is used to split the node. We take the square root of the number of dimensions i.e. $\lceil\sqrt{96}\rceil = 10$ for this.

7. RESULTS AND ANALYSIS

7.1 Results for Random Forest Classifier Experimrent

A 10-fold cross validated experiment has been done and the average accuracy attained for the 8 ragas is $\mathbf{94.28\%}$. Apart from Khamaj, all ragas have been identified with an accuracy of more than 90%.

Raga	Da	Kh	Ma	So	Ba	Bh	Bs	Ya
Da	**95.96**	0.83	0.77	0.00	0.00	0.00	0.83	1.60
Kh	1.11	**88.00**	2.22	0.00	0.00	2.11	0.00	6.56
Ma	0.77	0.00	**91.86**	0.00	8.00	4.17	0.00	3.21
So	0.00	0.00	0.00	**96.67**	0.00	1.11	0.00	2.22
Ba	0.00	0.91	0.91	0.00	**96.36**	0.00	0.00	1.82
Bh	4.23	0.00	0.00	0.00	0.59	**94.56**	0.00	1.82
Ba	0.00	0.00	0.00	1.11	1.11	1.11	**95.56**	1.11
Ya	0.67	2.67	0.67	0.00	0.00	1.33	0.00	**94.67**

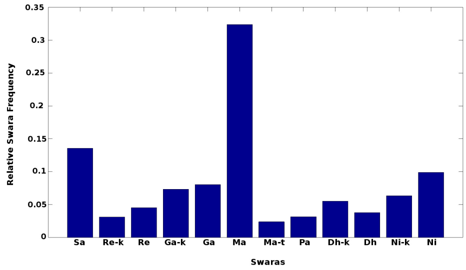
Table 3. *Confusion Matrix for the 8 ragas*

We make some important observations here:

1. Raga Malhar is being confused as Bahar and Bhairavi with 8% and 4% misclassifications respectively. The fact that all three of them have the same vadi (Ma) and samvadi (Sa) is the likely reason this happens.
2. Similarly, Khamaj and Yaman where 6.5% of Khamaj test cases are misclassified. Again, both have the same vadi (Ga) and samvadi (Ni) pair.
3. Raga Sohini is the only raga among the three which employs 6 *swaras*) (a class of ragas called *shadav*) whereas the rest are *sampoorna* and have 7 notes. This is a possible reason for its superior performance.

7.2 Plots for Swara Histograms

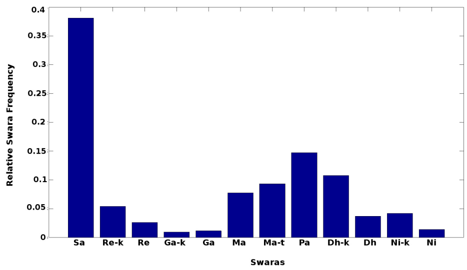
The swara histogram features have been plotted for all the 8 ragas and they reveal exact correspondence of our swara



(a) Swara Histogram for Bahar

Swara	Actual	Plot
Vadi-Sam	Ma-Sa	Ma-Sa
Anuvadi	Re,Ga-k,Pa,Dh,Ni-k	Ni,Ga,Ga-k,Ni-k,Dh-k,Re
Vivadi	Re-k,Ga,Ma-t,Dh-k	Ma-t,Re-k

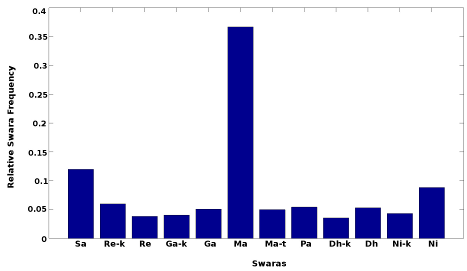
(b) Plot Observations vs. Actual Swaras in Bahar



(c) Swara Histogram for Basant

Swara	Actual	Plot
Vadi-Sam	Sa-Pa	Sa-Pa
Anuvadi	Re-k,Ga,Ma-t,Pa,Dh-k,Ni	Dh-k,Ma-t,Ma,Re-k
Vivadi	Re,Ga-k,Ma,Dh,Ni-k	Re,Ga-k,Ga,Dh,Ni-k,Ni

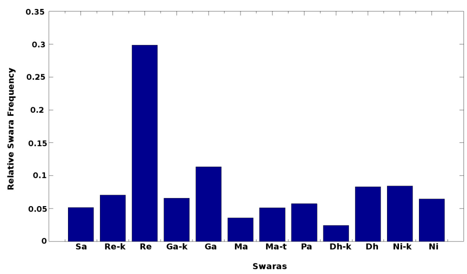
(d) Plot Observations vs. Actual Swaras in Basant



(e) Swara Histogram for Bhairavi

Swara	Actual	Plot
Vadi-Sam	Ma-Sa	Ma-Sa
Anuvadi	Re-k,Ga-k,Pa,Dh-k,Ni-k	Ni,Re-k,Pa,Ga,Ga-k
Vivadi	Re,Ga,Ma-t,Dh,Ni	ReDh-k

(f) Plot Observations vs. Actual Swaras in Bhairavi

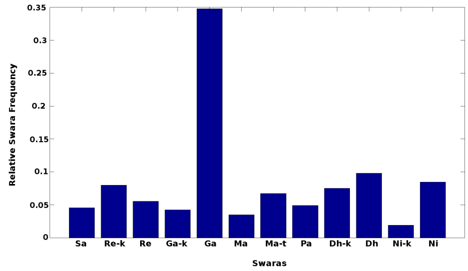


(g) Swara Histogram for Darbari

Swara	Actual	Plot
Vadi-Sam	Re-Pa	Re-Ga
Anuvadi	Sa,Ga-k,Ma,Dh-k,Ni	Re-k,Dh,Ni-k,Ni,Ga-k,Pa,Ma-t,Sa
Vivadi	Re-k,Ga,Ma-t,Dh,Ni	Dh-k,Ma

(h) Plot Observations vs. Actual Swaras in Darbari

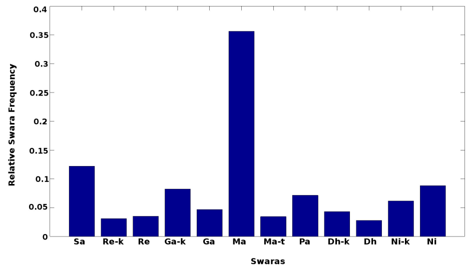
Figure 2. *Swara Histogram Plot for Bahar, Basant, Bhairavi and Darbari*



(a) Swara Histogram for Khamaj

Swara	Actual	Plot
Vadi-Sam	Ga-Ni	Ga-Dh
Anuvadi	Sa,Re,Ma,Pa,Dh,Ni-k	Ni,Dh,Re-k,Dh-k,Ma-t,Re,Pa,Sa
Vivadi	Re-k,Ga-k,Ma-t,Dh-k	Ni-k,Ma

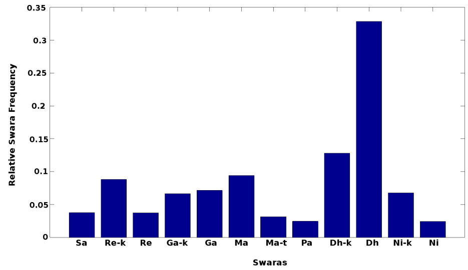
(b) Plot Observations vs. Actual Swaras in Khamaj



(c) Swara Histogram for Malhar

Swara	Actual	Plot
Vadi-Sam	Ma-Sa	Ma-Sa
Anuvadi	Re,Ga,Pa,Dh,Ni-k,Ni	Ga-k,Ni,Ni-k,Pa,Ga
Vivadi	Re-k,Ga-k,Ma-t,Dh-k	Re-k,Re,Ma-t,Dh

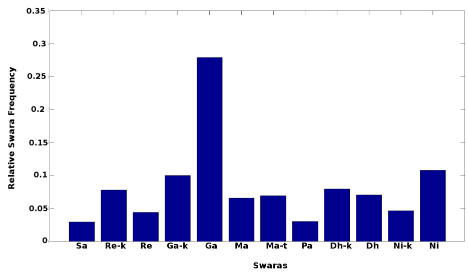
(d) Plot Observations vs. Actual Swaras in Malhar



(e) Swara Histogram for Sohini

Swara	Actual	Plot
Vadi-Sam	Dh-Ga	Dh-Ma
Anuvadi	Sa,Re-k,Ma-t,Ni	Ma,Dh-k,Re-k,Ga,Ga-k,Ni-k
Vivadi	Re,Ga-k,Ma,Dh-k,Pa,Ni-k	Sa,Re,Ma-t,Pa,Ni

(f) Plot Observations vs. Actual Swaras in Sohini



(g) Swara Histogram for Yaman

Swara	Actual	Plot
Vadi-Sam	Ga-Ni	Ga-Ni
Anuvadi	Sa,Re,Ma-t,Pa,Dh	Ga-k,Ma-t,Dh-k,Dh,Re-k
Vivadi	Re-k,Ga-k,Ma,Dh-k,Ni-k	Sa,Re,Pa,Ni-k

(h) Plot Observations vs. Actual Swaras in Yaman

Figure 3. *Swara Histogram Plot for Darbari, Malhar, Sohini and Yaman*

extraction approach to the musical theory of vadi, samvadi, anuvadi and vivadi. The plots are bar graphs of the swaras' relative frequency with respect to each other for each graph. The plots also strongly suggest the use of classification methods based on swara histograms. We have compared the observations we made from the plots with what the actual theory says about that raga in the tables below the histogram plots.

We note that while creating swara histograms, we had forcefully aligned the most frequent note with the vaadi. So, in all the plots, the vadi suggested by the plot matches with the actual vadi of the raga. What is important is that in most ragas, there is significant resemblence between the plot observations and the actual samvadi, anuvadi and vivadi. The discrepancies can be again attributed to the fact that actual raga performances are much more complex and contain variations that are not present in the written form of the raga. Since these discrepancies are present in the training as well as test data, it should have only a small impact on the results.

8. CONCLUSION AND FUTURE WORK

Our approach to raga identification relies heavily on the theoretical base for Indian classical music. The whole work confirms the premise that Indian classical music has a very well defined structure. The whole concept of a complex raga being built out of small substructures of arohan, avrohan and pakad which in turn are made up of swaras can be efficiently modelled efficiently if treated and analysed using these hierarchies. Breaking the ragas into swaras and successful identification can help to develop highly accurate applications for automatic tagging, raga tutoring, music recommendation, and possibly, raga generation.

We achieved an average accuracy of 94.28% which is the best current result for scale independent raga identification beating the previous best by Chordia [12]. We have achieved good accuracies in an experiment which excludes common audio features like MFCC, supports our initial hypothesis that the finer swara based substructure contains the defining information about ragas.

Most earlier approaches use raga audios which are performed with a specific tonic frequency by artists in controlled environments usually using only instrumental music. In comparison, we have attempted raga recognition without the knowledge of the tonic frequency, on performances downloaded from YouTube videos that have a good mixture of vocal (male and female) as well as instrumental music.

Competing with expert human identification is the final goal in raga identification and it can always be assumed that professional artists can perform this task with 100% accuracy. So, there is still scope for improvement in the results. Future work also lies in fusing the above approaches to achieve more efficiency and expanding our dataset to many more ragas. We also wish to investigate structure discovery through minimum entropy or maximum-structure learning methods. Chroma and swara features can also be tested for classification of genres and *taals* (rhythms).

9. REFERENCES

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