Investigation on the musical features of carnatic ragas using neutrosophic logic

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Abstract. Carnatic music is rich in its own style but more complex in the way the notes are arranged and rendered. Each Carnatic raga possess definite rules to be followed to frame its musical notes. But the significance of musical notes arrangement of the Carnatic music is unknown. This paper provides an attempt to find the significant relationship between the combinations of musical notes with the musical parameters. The objective of this work is to find the influence of various musical parameters on the Carnatic raga notes using Neutrosophic Cognitive Maps (NCMs). An analysis is made and the influences of musical parameters are cross checked with those of the Neutrosophic Cognitive Maps (NCMs). The values of the musical features of each raga are obtained using MIR MATLAB Toolbox.

1. INTRODUCTION

Music is an art form and its medium is sound. The definition of music varies according to culture and social content [1]. Music organises sounds in a fashion that follows definite natural principles and provides an inner feeling of happiness. Indian music is generally classified into two - South Indian Carnatic music and North Indian Hindustani music. Both these systems of music are rich in their own style. But Carnatic music is more complex in the way the notes are arranged and the way it is rendered, compared to any other type of music. The complexity of Carnatic music is mainly because of the use of gamakas (the sequence of swaras in the ragas) is not fixed and various improvisations called gamakas are allowed. A detailed analysis on each raga of Carnatic music is made using 49 different musical parameters. In this paper an attempt is made to analyze the relationship between the musical parameters and the structure of various musical notes of each of the 72 Melakarta ragas.

2. CARNATIC MUSIC

A raga in Carnatic music is nothing but a set of rules for building a melody. It set out rules for movements up (arohanam) and down (avarohanam) on the musical scale. It also describes which notes should be given more importance and which notes should be used more sparingly. Raga also describes which notes may be sung with gamak and which phrases should be used/avoided, and so on. A raga can either be a Janaka (root) raga or a Janya (derived) raga [2]. Ragas are based on Swaras. There are seven basic swaras in Indian Classical music namely, Shadjam (Sa), Rishabam (Ri), Gandharam (Ga), Madhyamam (Ma), Panchamam (Pa), Dhaivatham (Da) and Nishadam (Ni) and are called as Saptha Swaras. Different combination of these swaras results in different ragas. The first four swaras of the Saptha Swaras – Sa, Ri, Ga, and Ma form a group known as the Purvanga. The last three notes – Pa,
Da, and Ni form a group known as Uttharanga [3], Swara Rishabham can have variation denoted as R1, R2, R3; Swara Gandharam have variations denoted by G1, G2, G3; Swara Madhyamam have two variations denoted by M1, M2; Swara Dhaivatham has three variations denoted by D1, D2,D3; Swara Nishadham has three variations N1, N2, N3. Swara Shadjam (Sa) and Panchama (Pa) are the same in all ragas.

Ragas can be divided into two classes: janaka ragas or parent ragas and janya ragas or descendant ragas of a particular janaka raga. Janaka Ragas which are popularly known as Melakarta Ragas has all the seven swaras in its ascending and descending scale. Jayna ragas are obtained from janaka ragas by leaving some notes in its ascending or descending phases. In Carnatic Music, there are seventy-two melakarta ragas. The first thirty-six ragas are known SudhaMadhyamaMelas. The remaining thirty-six are called as PrathiMadhyamaMelas. Names of Melakarta Ragas are determined using Katapayadisankhya system. Swara Sa and Pa are fixed. Ri and Ga can take any combination of two notes from R1, R2/G1, R3/G2, G3. Da and Ni can take any combination of two notes from D1, D2/N1, D3/N2, N3. Ma can take any of the two notes M1 or M2. Thus a total of $2 \times 4C_2 \times 4C_2 = 72$ Janaka Ragas are possible [4]. SudhaMadhyama ragas use M1 as the middle note Ma, and PrathiMadhyama ragas use M2 as middle note Ma. Each of these thirty-six ragas are further divided into 6 parts called Chakras; each chakra has 6 ragas within it.

3. EXISTING WORK

Compared to Western Music, research work in Carnatic music retrieval is on a slow pace. To classify ragas based on the scale estimation was proposed. In this method scale of sample raga was found and compared it with the scale stored in the database [5]. The test data set consists of 30 samples of 3Melakarta ragas sung by four musicians. The database has raga name, arohana and avarohana of ragas in swara component form. Harmonic product spectrum algorithm was used to extract the pitch. This work mainly focuses on raga identification by estimating the singer’s fundamental frequency. A method for Identifying Ragas using MIDI was proposed [6]. After the note transcription, scale matching was done. Scale matching is done with the help of pitch detection, frequency mapping, raga annotation and use of swara features. 70 songs were used for training the proposed system. Various musical features are extracted from these songs and the system was trained using extracted features and tested using a neural network. Another method for raga recognition is done by note identification using frequency Spectrum [7]. This method takes audio files as input and its frequency spectrum and frequency domain characteristics are analyzed and then depending on that characteristics, it is mapped to notes. The major difference between Hindustani Raga pattern and Carnatic Raga pattern is that in Hindustani music have R1, R2 as against R1, R2, R3 in Carnatic Music. Likewise, G, D, N all has three different frequencies in Carnatic music but only two frequencies in Hindustani music.

‘Tansen’, the raga recognition system is based on Hidden Markov Model. It is used to recognize two Hindustani ragas Bhupali and Yamankalyan [8]. In this work, HMM algorithm uses Baum-Welch learning algorithm is used for identification of transition and initial state probability. This work focusses on the identification of ragas in same Thaat. It did not mention about the identification of ragas belonging to different Thaats. The authors have considered only vocal signal as input. Another raga recognition system for Hindustani raga identification by using swara intonation was proposed [9]. Peak, Mean, Sigma and probability corresponding to most likely position are calculated for each sware. From each performance segment, overall probability of a swara are extracted from folded pitch distribution (FPD). For classification of the ragas, Nearest Neighborhood Classifier with leave one out cross validation is used. KullbackLibeler (KL) was used to compute the distance between various instances. Raga Identification system based on Pitch-class Distributions (PCDs) and Pitch-class Dyad Distributions (PCDDs) was proposed [10]. PCDs and PCDDs represent the probabilities of the dyads. The database consisted of 20 hours of unaccompanied ragas along with some commercial recordings which were split into 30 s and 60 s segments. There were a total of 31 distinct ragas. With an SVM
classifier and 10-fold cross-validation, 75.2% and 57.1% accuracy was achieved with PCDs and PCDDs respectively.

4. NEUTROSOPHIC COGNITIVE MAP FOR RAGA

Each raga has its own characteristics. The musical features of each raga are extracted using Music Information Retrieval (MIR) MATLAB Toolbox [11]. Musical features can be categorized into five perceptual dimensions namely Dynamic, Timbre, Tonal, Spectral and Rhythmic. Dynamic features indicate the degree of loudness in music piece. Root Mean Square (RMS) is the dynamic feature. Timbre feature indicates the quality in musical piece. Zero-cross, Low energy, Spectral Flux are the important timbre features. Tonal features include Chromagram Peak, Chromagram Centroid, Key Clarity, Mode and Harmonic Change Detection Function (HCDF) indicate the features responsible for balancing of harmonics present in the musical piece. Spectral features are the shape descriptors which include Spectral Centroid, Spectral Brightness, Spectral Spread, Spectral Skewness, Spectral Kurtosis, Roll-off 95, Roll-off 85, Spectral Entropy, Flatness, Roughness, and Irregularity. The Rhythmic features include Peak, Centroid, Tempo, Attack Time, Attack Slope indicate the nature of musical piece as time progress. But all the musical parameters extracted do not have an equal level of influence on a raga. The parameters influencing on each raga to a larger degree are found using Neutrosophic Cognitive Maps (NCMs). Neutrosophic Cognitive Maps (NCMs) is a generalization of Fuzzy Cognitive Maps (FCMs). When the data under analysis is indeterminate, then it is difficult to express by a mathematical expression. This problem is solved by introducing an additional expression called Indeterminate (I) so that fuzzy becomes neutrosophic [12]. Neutrosophic logic is the one of the best tool known to us, which deals with indeterminacy, and brief description of it is explained below.

Let C_1, C_2… C_{50} be the nodes of a NCM, with feedback. Let node C_1 refer to a raga and C_2 … C_{50} refer to the various musical parameters of a raga. Let A_i be the instantaneous state neutrosophic vector and N be the neutrosophic adjacency matrix of the NCM. The neutrosophic adjacency matrix refers to the relationship among the various parameters and the raga. To find the relationship between the raga and the parameters, C_1 is switched on and the input is given as the initial instantaneous state neutrosophic vector A_i = (1, 0… 0). The data should pass through the neutrosophic matrix N. This is done by multiplying A_1 by the matrix N. Let A_1N be (a_1, a_2… a_n). A threshold operation is done to form the updated vector that is, by replacing a_i by 1 if a_i> k and a_i by 0 if a_i<k (k – a suitable positive integer) and a_i by I if a_i is not an integer. The concept C_1 is included in the updated vector by making the first coordinate as 1 to form the resulting vector, A_2. Suppose A_1N → A_2 then consider A_2N and repeat the same procedure. This procedure is repeated till a limit cycle or equilibrium state is reached [13][14].

All the musical parameters extracted using MIR Toolbox are made as the nodes of the NCM. All the ragas used for the study are collected from the instrument Veena and each with 12 seconds duration. For better accuracy and statistical analysis, mean and variance of each parameter are considered. The weights of each edge are obtained by considering a threshold value which is the average value of each feature of all the 72 ragas. Each parameter value is compared with the corresponding parameter’s threshold value. The edge weight is made as +1 if it is greater than threshold and 0 if it is lesser than threshold. The Indeterminate edges are found by considering the relationship between parameters that tend to exist but are unknown. The musical feature denoting each node is listed below:

C_1 → Respective raga (Raga 37 is used here)  
C_2 → Root Mean Square (RMS) Mean  
C_3 → Root Mean Square Variance (RMS)  
C_4 → Peak Mean  
C_5 → Peak Variance  
C_6 → Centroid Mean  
C_7 → Centroid Variance  
C_8 → Tempo Mean  
C_9 → Tempo Variance  
C_{10} → Attack time Mean
Figure 1. Neutrosophic Cognitive Maps for raga 37 (Raga Salagam)

The Neutrosophic graph based on the assumptions made is drawn for raga 37 and is shown in figure 1. The corresponding neutrosophic adjacency matrix N1 related to the neutrosophic directed graph is given below.
To find the higher influencing parameters for raga 37 (Salagam), node C1 that is, raga 37 namely the node C1 is made ON and rest of the nodes OFF to form the instantaneous state neutrosophic vector A1. Initially A1 vector signifies that there is no prominent relationship for the node C1 that is, raga 37 with all other nodes that is, all musical parameters.

\[ A_1 = (1 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0) \]

To see the effect of A1 on N1, A1 is multiplied with N1. To the vector A1N1 the node C1 is made 1 to form the resulting vector A2. A2 is then multiplied with N1. This procedure is repeated until an equilibrium state is reached that is, \( A_n = A_{n-1} \).

\[ A_1 N_1 = (0 \ 1 \ 0 \ 0 \ 0 \ 0 \ 0 \ 1 \ 1 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0) \]

\[ / \]

\[ = A_2 \]

\[ A_2 N_1 = (0 \ 1 \ 0 \ 0 \ 0 \ 0 \ 0 \ 1 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 1 \ 1 \ 0 \ 1 \ 0 \ 1 \ 0) \]

\[ = A_3 \]

\[ A_3 N_1 = (0 \ 1 \ 0 \ 0 \ 0 \ 0 \ 0 \ 1 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0) \]

\[ / \]

\[ = A_4 = A_3 \]

As \( A_3 = A_4 \), the equilibrium state is reached. The nodes C2, C10, C38, C44, C45, C47, and C49 are in the ON state. So raga 37 is highly influenced by the parameters RMS mean, attack time mean, lowenergy, chromogram centroid variance, keyclarity mean, mode mean and HCDF mean. Similarly, the influencing parameters for all the 72 Melakarta ragas are found by following the above steps.

5. ANALYSIS

5.1. Parameter characterizing SuddhaMadhyama and PrathiMadhyama

It is observed that ragas of SuddhaMadhyama and PrathiMadhyama cannot be distinguished through a single parameter but by a combination of Lowenergy, Spectralflux Mean and Zerocross Mean. When the parameters influencing 72 ragas are found using Neutrosophic Logic Cognitive Maps (NCMs), it is observed that at least one of these parameters are found in all the ragas. The fact that a single musical parameter cannot differentiate between SuddhaMadhyama ragas and PrathiMadhyama ragas is understandable because ragas of SuddhaMadhyama and PrathiMadhyama are not only differentiated by the notes M1 and M2 but also by the notes denoting the ‘RiGa’ and ‘DaNi’ combination.

5.2. Parameters characterizing chakras

To characterize the features of each chakra or in other words the different ‘RiGa’ combination, the musical features influencing the various ragas in each chakra are analyzed. To characterize the ‘RiGa’ combination, common parameters within the chakras are found. Since the chakras 1 and 7, 2 and 8, 3 and 9, 4 and 10, 5 and 11, 6 and 12 vary only by one note namely M1 and M2 respectively in the ‘Ma’ position, a common parameter that is present in the respective chakras that vary only in the use of M1 and M2, but common in ‘RiGa’ combination is found. By identifying the common parameters among the chakras, a conclusion can be made that the ‘RiGa’ combination which is constant within the chakra is characterized by that common parameter. The influencing parameters for the ragas of chakra 1 and chakra 7 are shown in Table 1.

A Parameter is chosen such that they are common within all the ragas of chakra 1 and 7. In the table shown above for chakra 1 and 7, Attack Time Mean parameter is seen common for all the ragas.
within chakra. The above analysis is also cross checked with the help of Neutrosophic Cognitive Maps (NCMs), drawn against a musical parameter and all chakras. The Attack Time Mean and 12 chakras are made as nodes in the Neutrosophic Cognitive Maps (NCMs). The edge weight in the graph is updated by comparing the respective parameter average of the chakras with the parameter average of all 72 ragas. Edge weight is made +1 if chakra average is greater than the average of all 72 ragas. The Neutrosophic graph for Attack Time Mean is shown in figure 2.

### Table 1. Influencing Parameters of Chakra 1 and Chakra 7.

| Raga | Musical parameters |
|------|--------------------|
| 1    | RMS Mean, Attack Time Mean, Zerocross Mean, Chromogram Centroid Variance, Keyclarity Mean, Mode Mean, HCDF Mean. |
| 2    | RMS Mean, Attack Time Mean, Zerocross Mean, Lowenergy, Chromogram Centroid Variance, Mode Mean, HCDF Mean. |
| 3    | RMS Variance, Attack Time Mean, Low energy, Spectralflux Mean, Chromogram peak Variance, Mode Mean. |
| 4    | RMS Variance, Attack Time Mean, Lowenergy, Spectralflux Mean, Chromogram peak Variance, Chromogram Centroid Variance, Mode Mean, HCDF Mean. |
| 5    | RMS Mean, Attack Time Mean, Lowenergy, Chromogram peak Variance, Chromogram Centroid Variance, Mode Mean, HCDF Mean. |
| 6    | RMS Mean, Attack Time Mean, Zerocross Mean, Lowenergy, Chromogram peak Variance, Mode Mean, HCDF Mean. |
| 37   | RMS Mean, Attack Time Mean, Lowenergy, Chromogram Centroid Variance, Keyclarity Mean, Mode Mean, HCDF Mean. |
| 38   | RMS Mean, Attack Time Mean, Roughness Mean, Irregularity Mean, Zerocross Mean, Spectralflux Variance, Mode Mean, HCDF Mean. |
| 39   | RMS Mean, Attack Time Mean, Zero cross Mean, Lowenergy, Chromogram peak Variance, Mode Mean, HCDF Mean. |
| 40   | RMS Variance, Attack Time Mean, Roughness Mean, Irregularity Variance, Lowenergy, Spectralflux Variance, Chromogram peak Variance, Chromogram Centroid Variance, Mode Mean, HCDF Mean. |
| 41   | RMS Mean, Attack Time Mean, Roughness Mean, Zerocross Mean, Spectralflux Variance, Chromogram peak Variance, Mode Mean, HCDF Mean. |
| 42   | RMS Mean, Attack Time Mean, Zerocross Mean, Chromogram peak Mean, Mode Mean, HCDF Mean. |

![Figure 2. Neutrosophic Cognitive Maps (NCMs) for chakras.](image)
By making Attack time Mean as node C1 and Chakras 1 to 12 as nodes C2 .. C13 respectively, the
neutrosophic adjacency matrix N2 related to the neutrosophic directed graph shown above is as below:

|   | C1  | C2  | C3  | C4  | C5  | C6  | C7  | C8  | C9  | C10 | C11 | C12 | C13 |
|---|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| C1 | 0   | 1   | 0   | 0   | 0   | 0   | 0   | 1   | 1   | 0   | 1   | 0   | 1   |
| C2 | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   |
| C3 | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   |
| C4 | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   |
| C5 | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   |
| C6 | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   |
| C7 | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   |
| C8 | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   |
| C9 | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   |
| C10| 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   |
| C11| 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   |
| C12| 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   |
| C13| 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   |

The chakras which are highly influenced by the parameter Attack time mean is found by finding the
hidden pattern for the above Neutrosophic graph. The instantaneous state neutrosophic vector A1 is
obtained by making node C1 as 1 and the rest of the nodes as 0. Vector A1 denotes that relationship of
Attack Time Mean with all the chakras is kept unknown initially.

\[ A_1 = (1 0 0 0 0 0 0 0 0 0 0 0 0) \]

To see the effect of A1 on N2, A1 is multiplied with N2. To the vector A1N2 the node C1 is made 1 to
form the resulting vector A2. A2 is then multiplied with N2. This procedure is repeated until an
equilibrium state is reached that is, \( A_n = A_{n-1} \).

\[ A_1 N_2 = (0 1 0 0 0 0 0 1 1 0 1 0 1) \Rightarrow (1 1 0 0 0 0 0 1 1 0 1 0 1) = A_2 \]
\[ A_2 N_2 = (0 1 0 0 0 0 0 1 1 0 1 0 1) \Rightarrow (1 1 0 0 0 0 0 1 1 0 1 0 1) = A_3 = A_2 \]

As \( A_2 = A_3 \), the equilibrium state or limit cycle is reached. The nodes C2, C8, C9, C11 and C13 are in the
ON state during limit cycle condition. Chakras 1, 7, 8, 10 and 12 are highly influenced by the
parameter Attack Time Mean. This is also cross checked with the Attack Time Mean parameter values
obtained using MIR Toolbox. The Attack Time Mean values for the ragas in Chakra 1 and 7 are
higher compared to that of all ragas of other chakras. So Attack Time Mean parameter may be used to
categorize the ‘RiGa’ combination of chakra 1 and 7.

Similarly, the parameters that are present common among the influencing parameters of all the ragas
within the chakra which vary only by the use of F, F# can signify the chakra characteristics that is,
‘RiGa’ combination. The parameters that are noted common within the chakra to denote the ‘RiGa’
combination is shown in Table 2.
Table 2. Parameters influencing each chakra

| Chakra   | Parameter          |
|----------|--------------------|
| 1 and 7  | Attack time Mean   |
| 2 and 8  | Attack Slope Mean  |
| 3 and 9  | Irregularity Mean  |
| 4 and 10 | HCDF Variance      |
| 5 and 11 | Spectralflux Mean  |
| 6 and 12 | Chromogram Centroid Mean |

5.3. Parameter characterizing Ragas
The musical notes arrangement of the first two ragas of every chakra has the same ‘DaNi’ combination but has different ‘RiGa’ combination. When comparing the influencing parameters of the first two ragas of the same chakra, the uncommon parameters may signify the A and A# difference.

Some of the important facts that are observed during the analysis are:

- Average value of parameter ‘Lowenergy’ is higher for SuddhaMadhyama compared to that of the PrathiMadhyama. Lowenergy is defined as the percentage of frames which is less than the average energy, which makes clear that if a signal has lower lowenergy value then the energy of that signal is higher. So it is clear that most of the ragas in SuddhaMadhyama have lower energy compared to those of PrathiMadhyama. It is also noted that the first three chakras in SuddhaMadhyama has higher energy.
- Dynamic parameters namely RMS Mean and RMS Variance, Tonal features namely HCDF and Mode and Timbre features namely Lowenergy and ZeroCross Mean are present as influencing parameter in most of the ragas. So these parameters can be used to characterise the ragas.
- Timbre features namely, ZeroCross Variance and Spectralflux Variance, Tonal features namely, Chromogram Centroid Variance and Chromogram peak Variance and Spectral features namely, Roughness Mean and Irregularity Mean are used to identify the ragas.
- Among the influencing parameters of all the 72 ragas, PrathiMadhyama ragas have either Attack Time Mean or Attack Slope Mean as one of their influencing parameters. Attack time is defined as the time difference between the initial points of lowermost amplitude to the highest amplitude. Similarly the value of slope is the ratio between the magnitude difference at the commencement and the termination of the attack time. Attack time and Attack slope comes under the rhythmic feature. So Attack time Mean and Attack slope Mean can be used to characterise the ragas.
- The Chromogram peak Mean difference is maximum between first and sixth raga of every chakra and it is minimum between third and fourth raga of every chakra.
- The Chromogram Centroid Mean difference is maximum between third and fourth raga of every chakra.
- For the tonal parameters namely, Chromogram peak Mean, Chromogram peak Variance, Keyclarity Mean, Keyclarity Variance and Mode Variance, the difference is maximum between the first and sixth raga of all chakras.
- The Keyclarity Mean difference is minimum between second and fourth raga of every chakra.
- For Mode Mean, the difference between fourth and sixth raga of every chakra is having the highest value.
- The difference in Mode variance is minimum either for the combination of second and fourth or second and fifth raga of all chakras

6. CONCLUSION
In this paper, the theory of Neutrosophic Cognitive Map is used for identify the features which influence the ragas. As Melakarta ragas have intricate nature, Neutrosophic logic is found suitable to
analyze these ragas. The concepts of Neutrosophic Cognitive Maps (NCMs) are used to identify the significant relationship between the musical note combinations with the musical features of the ragas. A single musical note is not related to a particular musical feature because as the musical feature not only depends on the note itself but also on position of a musical note and also the way of arrangement with other musical notes. It is also observed that it is difficult to identify the relationship between the musical features and a specific musical note. The features signifying the difference between SuddhaMadhyama and PratiMadhyama ragas, and also for each chakra are found using NCMs.

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