An Approach to Discover Similar Musical Patterns

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ABSTRACT:

An algorithm has been developed to find the similarity between given songs. The song pattern similarity has been determined by knowing the note structures and the fundamental frequencies of each note of the two songs, under consideration. The statistical concept namely Correlation of Coefficient is used in this work. Correlation of Coefficient is determined by applying 16 Note-Measure Method. If Correlation of Coefficient is near to 1, it indicates that the patterns of the two songs under consideration are similar. Otherwise, there exists a certain percentage of similarity only. This basic principle is used in a set of Indian Classical Music (ICM) based songs. The proposed algorithm can determine the similarity between songs, so that alternative songs in place of some well-known songs can be identified, in terms of the embedded raga patterns.

A digital music library has been constructed as a part of this work. The library consists of different songs, their raga name, and their corresponding healing capabilities in terms of music therapy.

The proposed work may find application in the area of music therapy. Music therapy is an area of research which is explored significantly in recent time. This work can also be exploited for developing intelligent multimedia tool that is applicable in healthcare domain.

A multimedia based mobile app has been developed encapsulating the above mentioned idea that can recommend alternative or similar songs to the existing ICM based songs. This mobile app based music recommendation system may be used for different purposes including entertainment and healthcare.

As a result of the applications of the proposed algorithm, similar songs in terms of raga patterns can be discovered from within the pool of a set of songs. A music recommendation system built on this algorithm can retrieve an alternative song from within the pool of songs as a replacement to a well-known song, which otherwise may be used for a particular music therapy.

Results are reported and analyzed thoroughly. Future scope of the work is outlined.

INDEX TERMS: Fundamental Frequency Measure (FFM), Correlation of Coefficient, Computational Musicology, Music Recommendation System (MIR), Music Therapy, Electronic Healthcare.
I INTRODUCTION

Music has capability to heal some of the illnesses of human body. Thus music is said to have therapy capabilities. Indian Classical Music (ICM) consists of one basic component known as raga. The seven basic notes of music, i.e., Sa, Re, Ga, Ma, Pa, Da and Ni are exploited to create a particular raga [10]. Computational Musicology is an emerging field which draws various basic principles from Computer Science. In the 16 Note-Measure System, the notes Re, Ga, Da, and Ni have three variations and the note Ma has two variations. The 16 different notes are as mentioned below: Sa, Re1, Re2, Re3, Ga1, Ga2, Ga3, Ma1, Ma2, Pa, Da1, Da2, Da3, Ni1, Ni2, and Ni3 [11]. Music therapy is an area of para medicine field in which music is being employed for different therapy applications. Music therapy can be used in curing even psychological and physiological problems like mesothelioma, peritoneal mesothelioma asthma, asbestos cancer, depression etc [11]. The raga of a music is the primary element considered for music therapy. There are various ragas that can be used for different purposes, for example, Ahirbhairav and Todi are used for hypertension, Punnagavarali is used to control anger and violence, Todi is used to relief from cold and headache, Shivaranjani is used for memory related problems, Bhairavi is used to get relief from sinus, cold, phlegm, tooth ache etc [12]. Similarly, Chandrakauns raga is used to treat the heart problems and diabetes, Darbari is used to reduce the tension and to provide relaxation [12].

Therefore, a specific ICM based song of a specific raga is applicable for some health and mind issues [15]. This work introduces an approach by which two similar songs in terms of raga, can be identified. Thus similar musical patterns are possible to identify, computationally. This approach can also be applied to develop an intelligent multimedia mobile application. In turn, such a mobile application may be applied in the electronic healthcare field. This mobile application can recommend alternate music in place of the ICM based songs, having similar healing capabilities. Challenge is to identify similar songs which are suitable for music therapy. ICM is the backbone of this work, as there are a lot of ragas known to be applicable for different therapies. The song pattern similarity can be established by knowing the note structures, and the fundamental frequencies of each note of the songs under consideration. The Correlation of Coefficient is identified by applying 16 Note-Measure Method. If Correlation of Coefficient is close to 1, then it indicates that the patterns of the two songs under consideration are similar. Otherwise, it indicates a certain percentage of similarity only, between the songs. This method has been used in a set of ICM based songs. The ICM based songs are stored in a digital music library along with their raga name, and the corresponding healing capabilities. After applying the algorithm reported in this paper, a set of new songs are discovered as an alternative to the ICM based songs. A multimedia based mobile app has been developed and also reported in this paper that can recommend alternative songs in place of the established ICN based songs, for a particular music therapy. The system that has been reported here has potential to act as an electronic healthcare system for some specific purposes based on music therapy.

Correlation is a statistical concept that helps to analyse and determine the degree of relationship that exists among series of data variables. The degree of relationship among different series of data is expressed by Correlation Coefficient which ranges from $-1 \leq r \leq +1$. The direction of change is determined by a sign. Fig. 1 depicts one example of positive, negative, and zero correlation.

Correlation of Coefficient deals with the association among series of variables and for that reason it has been assumed that it is the basis of similarity mapping between two song structures. The paper proposes a statistical approach for computing the similarity between two different songs or music structures or music patterns by using Correlation Coefficient of the fundamental frequencies of the two given songs.

Following are the possible correlations:

1. If $r = +1$, then the relation of the two series of data variables is said to be positively similar.
2. If $r = -1$, then the relation of the two series of data variables is said to be negatively similar.
3. If $r = 0$, then there exists no similarities between the two series of data variables.

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3. If $r = 0$, then there exists no similarities between the two series of data variables.
Music recommendation system plays an important role in music therapy. Music recommendation system recommends music for the users depending on various factors like, human moods, human behaviours, choices, similarities, fundamental frequencies, time slots, etc. Fig. 2. depicts the overall relationship between music recommendation system and music therapy.

Motivation:

There are different folk songs available in different parts of the world. The folk songs are less explored in terms of computational musicology. It is already explored and recommended by competent authority that Indian Classical Music has therapy capabilities and can be used for different treatment, e.g., to treat health and mental problems. A very fundamental question that motivates to do this work is “Does the Indian Folk Music (IFM) too have music therapy capabilities like the Indian Classical Music (ICM)?”. Although addressing this question is a larger study with wider scope, in this work, we are motivated to develop a method to find out similarity between songs (for example, ICM based and IFM based songs) from computational musicology perspectives. If alternate songs can be recommended from computing perspective, to use as an alternative to ICM based songs, then in the next stage, the music therapy capabilities of the alternate songs may be examined. This fact motivates to develop an approach to identify similar music patterns and recommend alternate songs for music therapy.

The contributions made in this work are as mentioned below.

i) An algorithm is proposed to identify similar song patterns. The statistical measure Correlation Coefficient has been exploited in order to find similar music patterns.

ii) A music database has been created comprising of ICM based and IFM based songs. In this song repository, the raga information of the ICM based songs and the healing capabilities of different ragas are also stored.

iii) A mobile app has been developed that works as a Music Recommendation System. The app implements the proposed algorithm (as mentioned in i)) to identify similar songs and it works over the database developed (as mentioned in ii).

iv) The process of finding similar song patterns has been demonstrated through rigorous experiments and statistical analysis of the obtained experimental results.

The proposed algorithm may be used to identify two similar songs considering the frequency as the basis. Thus this is the first step toward identifying ICM music or other music (for example, IFM) with similar therapeutic effects. In fact, establishing similar therapeutic effect of IFM in comparison to ICM is the next step of this work, in which rigorous experiments involving human has already been planned by this group.

The rest of the paper is organized as follows. Section II reports few related works. The proposed algorithm is detailed in section III followed by the section IV, in which experimental results are analysed. The paper is concluded in section V.

II RELATED WORK

There are quite a lot of research works that motivate to work further and explore even new dimensions of musicology research. Computational musicology is the most emerging area that depends on different concepts of computer science. Indian Classical Music (ICM) is
relatively complex and a vast area which has not been explored significantly in terms of computational musicology.

Music recommendation system has been explored in [27]. The work provides a personalized music recommendation service with the help of polyphonic music objects using MIDI (Musical Instrument Digital Interface) format. The user analyses the profiles for user grouping based on the behaviours and interests of the users. They use pitch density for track selection that contains the melody which can be calculated as:

\[
Pitch\ Density = \frac{NP}{AP}
\]  

(1)

Where,
NP = Number of distinct pitches in the track
AP = Number of all distinct pitches in MIDI standard

The pitch entropy (PE) can be derived as follows:

\[
PE = -\sum_{j=1}^{NP} (P_j \log P_j)
\]

(2)

where,

\[
P_j = \frac{N_j}{T}
\]

(3)

Nj = Total number of notes with the corresponding pitch in the representative track,

T = Total number of notes in the representative track.

The music group containing highly accessed musical objects hold the higher weight than other groups. The weight of music group (GWi) can be calculated as:

\[
GW_i = -\sum_{j=1}^{n} TW_j \times MO_j, i
\]

(4)

where

TWj = Weight of the transaction Tj
n = Number of latest transactions used for analysis
MOj,i = Number of music objects which belong to music group Gi in transaction Tj.

Different numbers (Ri) of musical objects from music groups are computed (also recommended) according to the GWi, as follows [18]:

\[
R_i = \left[ N \times \frac{GW_i}{\sum_{k=1}^{m} GW_k} \right]
\]

(5)

Although this work is based on music recommendation system, it does not explore Indian Classical Music and associated ragas.

There is a specific relationship between Raga and Rasa. Raga means music origin, and rasa means music emotions. Therefore, music and emotions are directly related to each other and that have been established. A content-based culture-specific music recommendation system model has been proposed in [13]. The paper [14] describes a research project that is aimed at developing a music analysis system which presents an analysis of clinical music therapy. Music is a very effective mode of mental treatment and human mental management can be controlled by music therapy, based on ICM [5].

The paper [16] is a reference of website that illustrates different raga names and their respective healing powers. The work reported in [17] introduces music recommendation technique based on content and context information mining. The work reported in [18] introduces a context-aware mobile music recommendation system.

The work reported in [19] is a modeling technique and useful tool that formalizes the music composition rules; the technique increases music analysis speed with the help of Music Petri nets that introduces Schoenberg’s rules. The work presented in [20] introduces an approach that determines the similarity mapping between two songs; this is achieved by the notes and the fundamental frequencies of each note of the two songs. The Pearson’s Correlation of Coefficient is exploited in this work. The work presented in [21] is a method to generate song list for listening; the songs may be downloaded according to age factor of the online users. It is a web-based application that recommends different songs depending on the listeners’ choice that too based on their age group. Songs are downloaded from the music library and unknown songs are classified depending on the review of the users.

The work presented in [22] introduces a model of musical creativity rather than algorithmic music variations with the help of genetic algorithms. The implementation of this model is based on Genome software. A statistical approach has been exploited to find similar song patterns with the help of coefficient of variance [23]. A time based raga recommendation system has been developed by using Neural Networks.
Some important characteristics of ICM are enlisted in Table 1.

**TABLE 1**

**CHARACTERISTICS OF INDIAN CLASSICAL MUSIC**

| ICM Features | Descriptions |
|--------------|--------------|
| Thaat | (Raga Origin) These are known as Raga origin which consists of a set of ragas. Ragas are organized in thhts. Some of the thhts are - Kalyan, Bhairav, Kafi, Asavari, Bilabal, Khannaj, Bhairavi, Purbi and Torhi etc. |
| Raga | Ragas are the backbone of Indian Classical Music. It is the combinations of different note structures. Ragas are used for different music compositions that provide different melodies to music. |
| Notes | Note can be a beat or combination of beats. |
| Aroha | (Ascending Notes) The ascending order note frequency sequence from the tonic of the scale is called Aroha. Example: Ni Sa, ga Ma Pa, Ni Sa (Next Octave). |
| Aboroha | (Descending Notes) The descending order note frequency sequence from the tonic of the scale is called Aboroha. Example: Sa, Ni dha Pa, Ma Ga, re Sa (Next Octave). |
| Notation | Combinations or series of different notes that indicate various aspects regarding how a piece of music is to be performed. |
| Pitch | Pitch is the number of times a musical sound wave can repeat in one second. It can be measured by Hz. |
| Tempo | Tempo is the speed of music rendition and it is denoted by bits per minute. |
| Melody | Melody is the combination of two most important musical elements: pitch and rhythm. |
| Tonic | Tonic is one of the most important attributes of music patterns which is reserved for tonal context of music. Normally, tonic means the first degree scale of note from which all other notes are referenced hierarchically. For example ga (Minor) and Ga (Major) both are known as tonic GA. |
| Shruti | (Microtones) Shrutis ordinarily refers to the frequency of notes which means it is a group of frequencies with different amplitude levels. Therefore, the note frequencies which have the maximum amplitude level are known as Shruti. In Indian Classical Music, there are three types of Shruti-System existing. They are: 12 Shruti-System, 16 Shruti-System, 22 Shruti-System. |
| Tala | (Rhythm) Rhythm is the style or pattern of sound in musical piece that combines with the recurrence of notes and rests. |
| Genre | Genre is the style of musical phrases like traditional music, classical music, folk music, devotional music, rock music, pop music, etc. |
| Aalap | (Rendition) Aalap is the melodic distribution of musical notes of a particular raga in which the combinations of all possible valid note combinations are performed without any fixed rhythm. |
| Timbre | Music Timbre is the quality of music sound or quality of music tone or the quality of music notes. Several instruments can play the same musical pitches or same notes in same volume but can produce different timbres. |

Though some of the above characteristics of ICM are applicable for measuring the similarity between two songs, pitch is one of the most important features to find the similarity between the music patterns. Therefore, computing pitch or fundamental frequencies of any song is the primary task to find similarity of two songs using pitches of the songs. Pitch values of the songs can be extracted by any standard music software like Wavesurfer. Wavesurfer has been adopted in this work.

Music Information Retrieval (MIR) involves series of activities like, music recommendation, song detection, music genre recognition, pitch tracking, music score generation, beat tracking, music transcription, music mood similarity mapping, music melodic similarity, musical instrument recognition, tempo estimation, query by humming etc.

Content based Music Information Retrieval System is the combinations of different research fields like computational musicology, music cognition, music perception, and these research fields are applied for intelligent music recommendation system for advanced searching, processing, and retrieval of music. The overall architecture of Content based Music Retrieval System is depicted in Fig 3.
In the first phase of Fig. 3, the required data are gathered and organized. The phase consists of the three sub-phases - feature extraction, normalization, and storage. Feature extraction includes pitch processing, timbre generation, computation of loudness from several audio files. In data normalization phase the extracted data are normalized using some standard form, and finally, date are stored in database using indexing. In the next phase, music similarity mapping can be achieved by using different similarity measuring algorithm [1].

As per [2], the music similarity mapping in MIR has two basic research areas, first, exploring the overall functionalities and application areas of MIR, and second, music similarity mapping through different procedures and comparative performance analysis among these procedures.

Some relevant music similarity mapping approaches using the different features of ICM are enlisted in Table 2.

### TABLE 2
MUSIC SIMILARITY MAPPING APPROACHES USING DIFFERENT FEATURES OF ICM

| Work                               | ICM elements or other elements | Evaluation metric | Results & discussion |
|------------------------------------|--------------------------------|-------------------|----------------------|
| Signal processing for music analysis [3]. | Pitch, timbre, melody, harmony, rhythm | Different digital signal processing (DSP) techniques | Some DSP techniques addressing musical features like melody, harmony, rhythm, timbre, etc are used. |
| Measuring disruption in song similarity networks [5]. | Musical disruption and genre trajectory | Mel-frequency cepstral coefficients (MFCCs) as feature for audio similarity estimation | This is work focused to the music disruption using similarity through metadata-networks. |
| Automatic mood classification of Indian popular music [6]. | Genre, mood, style, pitch, rhythm, harmony, timbre | Random forests using bootstrap aggregation, K-means algorithm | This work finds the music emotions automatically. |
| Mood based music categorization system for Bollywood music [7]. | Timbre, intensity, rhythm | K-means algorithm | Automatically identifies the mood of the Bollywood movie songs. |
| Audio similarity-based retrieval [8]. | Fingerprinting, remixes / sampling, cover songs, genre, artist | Gaussian mixture models (GMM) of MFCC features | The work has been applied to the wide spectrum of collective audio for similarity retrieval. |
| Symbolic melody similarity [9]. | Notes, pitch contour, | String-based methods for monophonic melodies | The work searches the database for entries with matching regular expressions. |

## III PROPOSED METHOD

In this section, an algorithm has been proposed that can be used to identify a similar song to a benchmark song. For validation of the algorithm, a song library has been created containing different ICM based songs. Different songs, their associated raga, and corresponding healing capabilities of various ragas are also stored in the library. After applying the algorithm on the library / database, a new song database has been created containing the songs having the same healing power. Thus groups of similar songs are getting created automatically. It is expected that songs of a particular group can be used alternatively as they have similarity in terms of their embedded ragas.

In order to find the similarities of the frequency patterns of two given songs, a statistical method based on Correlation Coefficient has been proposed which is the...
core of the proposed algorithm. The primary objective of the Correlation Coefficient is to examine whether the two series of fundamental frequencies of two given song structures are similar. Moreover, Correlation Coefficient may also be used to determine whether the fundamental pitches of the two songs are significantly similar or not.

Finally, an app (for mobile) has been developed embedding the proposed algorithm, and the song database as mentioned above. The app is able to find the similarity between two songs running the proposed algorithm. Depending on the fundamental frequency patterns, similar songs are discovered. It is already known that some songs based on ICM have healing power that can be used in music therapy for treating different health and mind issues. This app is implemented in such a way that it can function as a search engine and also a music recommender that recommends alternate songs instead of the standard ICM that may have similar healing capability. Thus the app functions as a music recommendation system. Moreover, the app contains a large collection of Indian Folk Music (IFM). Thus as an alternative to the ICM, an IFM from within the database may be recommended. Such an app may be used as an E-Healthcare application. The structure of the app is outlined below.

**App Name: MMES (Multimedia Mobile E-Healthcare System)**

The app consists of eight different components:

1. **Playlist**: It is a list of video or audio files that can be played on a media player.
2. **Artists**: It is a list of artists that can be played on a media player.
3. **Albums**: It is a collection of audio or video recordings treated as a collection of songs.
4. **Songs**: It is a collection of note structures performed by singers.
5. **TV & Movies**: Some media from where music files can be downloaded.
6. **Downloaded Music**: It is the digital transfer of music through the Internet into a device capable of storing locally.
7. **Song Similarity Mapping**: It is the primary focus of this app; using the proposed algorithm, the similarity between two or more songs is determined.
8. **Music Therapy in E-Healthcare**: It is another focus of this app; it may be used as a tool for music therapy. This part functions as a multimedia based mobile E-Healthcare application.

**Proposed Algorithm for Song Similarity Mapping:**

In this sub-section, the proposed algorithm has been detailed that can be used to find song similarity. It is necessary to know the note structures and the fundamental frequencies of each note of the two songs in order to find the similarity between the two songs through the algorithm designed.

In order to create the pitch file and determine the fundamental frequency of the songs, the wave surfer software has been used. The following procedure describes how to use the wave surfer software in order to create the pitch file (pre-processing); the proposed algorithm to find song similarity has also been presented in this procedure.

**Proposed Procedure:**

**Pre-Processing:**

1. **Pick a song of a particular Raga that has some healing power and another normal song from the available song library/repository.**

2. **Click on the wave surfer button to open the software. Run one song through the Wave Surfer which is used to generate the pitch values of that song. Firstly “.mp3” song file is used to build the pitch file of the song with the extension of .f0. This file consists of all the pitches that are used in the song.**

3. **The basic steps to create the .f0 format file from a given song are:**
   a. **Click on the File of Wave Surfer.**
   b. **Open and choose a song and then click on Transform and then choose Convert button with sample rate 22050, sample...**
encoding Lin 16, and fix the channel as Mono.
c. Right click on the black line.
d. Then click on Create Pane and choose Pitch Contour.
e. Now Right click on the black dots and click on Properties and then Pitch Contour and set Pitch Method is AMDF (Average Magnitude Difference Formula) and finally click on OK button. The other basic properties of Pitch Contour are -
   i. Max Pitch Value: 400 Hz
   ii. Min Pitch Value: 60 Hz
   iii. Analysis Window Length: 0.0075
   iv. Frame Interval: 0.01
   v. Tuning (C1): 65.4064
   vi. Scalar Color: Gray
   vii. Record Scroll Speed: 250 Pixel/second

f. After that click on the black dots and save the data file.

(4) The .f0 file consists of huge number of frequencies of monotonic song. This file format is converted into “.csv” format.

Proposed Algorithm:

**Input:** Two Songs

**Output:** Song Similarity Scores

**Steps:**

**Step1:** Calculate the number of occurrences of all the fundamental frequencies of each song.

**Step2:** Fix sixteen (16) frequencies which have highest occurrences respectively, from the list of frequencies of the .f0 file of each of the songs, as it applies 16 Note - Measure Method.

**Step3:** Compute total pitch value of individual note of Song 1 using the following expression:

\[ S_1 f_i = S_1 f_i \times S_1 o_i \]  \hspace{1cm} (6)

Where, \( i = 1, 2, 3, \ldots, n \)

\( S_1 f_i \) = Total Pitch value of individual note of Song 1,

\( S_1 f_i \) = Frequency of individual note of Song 1,

\( S_1 o_i \) = Occurrence of individual note of Song 1.

**Step4:** Compute total pitch value of individual note of Song 2 using the following expression:

\[ S_2 f_i = S_2 f_i \times S_2 o_i \]  \hspace{1cm} (7)

Where, \( i = 1, 2, 3, \ldots, n \)

\( S_2 f_i \) = Total Pitch value of individual note of Song 2,

\( S_2 f_i \) = Frequency of individual note of Song 2,

\( S_2 o_i \) = Occurrence of individual note of Song 2.

**Step5:** Now find the value of \( \bar{S}_1 f_i \) and \( \bar{S}_2 f_i \) as follows:

\[ \bar{S}_1 f_i = \text{Mean of } S_1 f_i = \frac{\sum S_1 f_i \times S_1 o_i}{n} \]  \hspace{1cm} (8)

\[ \bar{S}_2 f_i = \text{Mean of } S_2 f_i = \frac{\sum S_2 f_i \times S_2 o_i}{n} \]  \hspace{1cm} (9)

Now consider the sum of square (SoS) values of a set of \( n \) fundamental frequencies of (\( S_1 f_i, S_2 f_i \)) about \( \bar{S}_1 f_i \) and \( \bar{S}_2 f_i \) respectively as:

\[ \text{SoS}_{S_1 f_i,S_2 f_i} = \sum S_1 f_i^2 - n \bar{S}_1 f_i^2 \]

\[ \text{SoS}_{S_1 f_i,S_2 f_i} = \sum S_1 f_i^2 - 2n \bar{S}_1 f_i^2 + n \bar{S}_1 f_i^2 \]

\[ \text{SoS}_{S_1 f_i,S_2 f_i} = \sum S_1 f_i^2 - 2 \bar{S}_1 f_i \sum S_1 f_i + n \bar{S}_1 f_i^2 \]

\[ \text{SoS}_{S_1 f_i,S_2 f_i} = \sum (S_1 f_i - \bar{S}_1 f_i)^2 \]  \hspace{1cm} (10)

Again

\[ \text{SoS}_{S_1 f_i,S_2 f_i} = \sum S_2 f_i^2 - n \bar{S}_2 f_i^2 \]

\[ \text{SoS}_{S_1 f_i,S_2 f_i} = \sum S_2 f_i^2 - 2n \bar{S}_2 f_i^2 + n \bar{S}_2 f_i^2 \]

\[ \text{SoS}_{S_1 f_i,S_2 f_i} = \sum S_2 f_i^2 - 2 \bar{S}_2 f_i \sum S_2 f_i + n \bar{S}_2 f_i^2 \]
Now the song similarity can be measured by Pearson’s Correlation formula using the following expression:

\[
\text{Song Similarity} = \frac{SS_{S_{1}F_{i}S_{2}F_{i}}}{\sqrt{SS_{S_{1}F_{i}S_{1}F_{i}}SS_{S_{2}F_{i}S_{2}F_{i}}}}
\]

(13)

\[
\text{Song Similarity} = \frac{\sum_{i}(S_{1}F_{i} - S_{1}F_{i})(S_{2}F_{i} - S_{2}F_{i})}{\left(\sum_{i}(S_{1}F_{i} - S_{1}F_{i})^{2}\right)^{\frac{1}{2}}\left(\sum_{i}(S_{2}F_{i} - S_{2}F_{i})^{2}\right)^{\frac{1}{2}}}
\]

(14)

Using the above mentioned algorithm, song similarity may be computed in terms of percentage.

In this section, different results derived based on the proposed algorithm are presented. Different ICM based songs taken from Hindi movies, and a few Indian folk songs are considered for experiments. The data sets are available and kept as .f0 format files. To be more specific, total five songs are considered in the experiments. One ICM based song has been considered as the basis, and then the similarity patterns are identified considering other four songs. Four test cases are presented in this work. The base song that has been considered is titled as “Laaga Chunri Mein Daag”; this was sang by Manna Dey. The raga of this song is Raga Bhairavi. Raga Bhairavi is used to reduce sinus problem, cold, and toothache. Experiments were carried out to find out the similarities of other five songs with the base song according to their similarity values. The Waveform, Spectrogram and Pitch Contour of this song are depicted in Fig 5, and Mean plus Standard Deviation of Song 1 (Laaga Chunri Mein Daag) are depicted in Fig. 6.

| Song 1:          | Laaga Chunri Mein Daag |
|------------------|------------------------|
| Movie Name:      | Dil Hi to Hai          |
| Song Type:       | Indian Classical Music |
| Singer:          | Manna Dey              |
| Raga Name:       | Bhairavi               |
| Solve Disease:   | Sinus Problem, Cold, Toothache |
Thus the first test case is, Test Case 1: Song 1 is compared with Song 2.

**Song 3:** Kande Kanai Bajeya re Sanai  
**Song Type:** Indian Folk Music  
**Singer:** Jubin Garg

The Waveform, Spectrogram, and Pitch Contour of Song 3 are depicted in Fig 9 and Mean plus Standard Deviation of Song 3 (Kande Kanai Bajeya re Sanai) are presented in Fig. 10.

Thus the second test case is, Test Case 2: Song 1 is compared with Song 3.

**Song 4:** Oh Jeebon re  
**Song Type:** Indian Folk Music  
**Singer:** Jubin Garg

The Waveform, Spectrogram, and Pitch Contour of Song 4 are depicted in Fig. 11, and Mean plus Standard Deviation of Song 4 (Oh Jeebon re) are presented in Fig. 12.
Thus the third test case is, Test Case 3: Song 1 is compared with Song 4.

**Song 5:** Sankar Guru  
**Song Type:** Indian Folk Music  
**Singer:** Rameswar Pathak

The Waveform, Spectrogram, and Pitch Contour of Song 5 are depicted in Fig 13 and Mean plus Standard Deviation for the same song (Sankar Guru) are presented in Fig. 14.

In Table 3, $S_1f_i$ = Pitch frequency, $S_1o_i$ = Pitch occurrence, $S_1F_i$ = total Pitch frequency of Song 1; and $S_2f_i$ = Pitch frequency, $S_2o_i$ = Pitch occurrence, $S_2F_i$ = total Pitch frequency of Song 2.

Table 4 depicts the song similarity between Song 1 and Song 2 and its value is $0.7240924 \equiv 72.40924\%$.
TABLE 4

COMPUTATION OF SONG SIMILARITY

| $s_{I1}$ | $s_{I2}$ | $s_{I1}/s_{I2}$ | $\Delta = s_{I1}/s_{I2}$ | $\Delta/s_{I1} - s_{I2}$ | $\Delta/s_{I1} + s_{I2}$ | $\text{TD}^1$ | $\text{TD}^2$ | $\text{TD}^1$ | Song Similarity |
|----------|----------|----------------|--------------------------|--------------------------|--------------------------|----------------|----------------|----------------|----------------|
| 0000     | 10000    |                |                          |                          |                          |                |                |                |                |
| 0547     | 9412     |                |                          |                          |                          |                |                |                |                |
| 0925     | 5860     |                |                          |                          |                          |                |                |                |                |
| 1760     | 7115     |                |                          |                          |                          |                |                |                |                |
| 5000     | 8128     |                |                          |                          |                          |                |                |                |                |
| 5419     | 5180     |                |                          |                          |                          |                |                |                |                |
| 5520     | 5032     |                |                          |                          |                          |                |                |                |                |
| 5620     | 5078     |                |                          |                          |                          |                |                |                |                |
| 5139     | 5918     |                |                          |                          |                          |                |                |                |                |
| 5238     | 5675     |                |                          |                          |                          |                |                |                |                |
| 5816     | 5333     |                |                          |                          |                          |                |                |                |                |
| 5764     | 5145     |                |                          |                          |                          |                |                |                |                |
| 5398     | 5039     |                |                          |                          |                          |                |                |                |                |
| 5024     | 5352     |                |                          |                          |                          |                |                |                |                |
| 4155     | 5535     |                |                          |                          |                          |                |                |                |                |
| 3904     | 5133     |                |                          |                          |                          |                |                |                |                |

In Table 5, $\text{OF}(S1)$ = Observed Pitch Frequency of Song 1, $\text{OF}(S2)$ = Observed Pitch Frequency of Song 2, $\text{EF}(S1)$ = Expected Pitch Frequency of Song 1, and $\text{EF}(S2)$ = Expected Pitch Frequency of Song 2.

Expected frequencies may be computed depending on the observed frequencies as given in (15).

\[
(\text{EF}(S_1), f_1) = \frac{\text{OF}(S_1) \times \text{OF}(S_1) + \text{OF}(S_2)}{N}
\]

In order to determine the degree of association between Song 1 and Song 2, Chi-Square measure and Coefficient of Contingency are computed by using the equations (16) and (17), respectively.

\[
\chi^2 = \sum_{i=0}^{N} \frac{(O_i - E_i)^2}{E_i}
\]

Where,
- $\chi^2$ = Chi-Square
- $O$ = Observed Frequency
- $E$ = Expected Frequency

\[
C = \frac{\sqrt{\chi^2}}{\sqrt{N + \chi^2}}
\]

Where,
- $C$ = Coefficient of Contingency
- $N$ = Total Population

Degree of Freedom ($df$) = $(r - 1) \times (c - 1)$ (18)

Where,
- $r$ = Number of rows
- $c$ = Number of columns

The 16 Shruti-Measure systems applied for all the computations in order to measure song similarity; in each test case, it has been compared between one pair of songs.

Therefore, for each comparison, the value of $r = 16$ and $c = 2$. Therefore, the Degree of Freedom for each song comparison = $(16 - 1) \times (2 - 1) = 15$.

Table 6 presents the computation of Chi-Square measure, and Coefficient of Contingency between Song1 and Song2.

Validation of Test Case 1:

Table 5 presents the expected frequencies depending on observed frequencies of Song1 and Song2.

TABLE 5

CONTINGENCY TABLE BETWEEN SONG 1 AND SONG 2

| $\text{OF}(S1)$ | $\text{OF}(S2)$ | $\text{OF}(S1+S2)$ | $\text{EF}(S1)$ | $\text{EF}(S2)$ | $\text{EF}(S1+S2)$ |
|---------------|---------------|-------------------|---------------|---------------|-------------------|
| 110           | 160           | 270               | 107.6946498   | 162.3053502   | 270               |
| 123           | 179           | 302               | 120.4584602   | 181.5415398   | 302               |
| 113           | 180           | 293               | 116.8686385   | 176.1313615   | 293               |
| 111           | 159           | 270               | 107.6946498   | 162.3053502   | 270               |
| 119           | 177           | 296               | 118.0709004   | 177.9290996   | 296               |
| 109           | 162           | 271               | 108.0935189   | 162.9064811   | 271               |
| 121           | 176           | 297               | 118.4641448   | 178.5358852   | 297               |
| 116           | 182           | 298               | 118.8629839   | 179.1370161   | 298               |
| 117           | 158           | 275               | 109.6889952   | 165.3110048   | 275               |
| 114           | 175           | 289               | 115.2731622   | 173.7268378   | 289               |
| 98            | 157           | 255               | 101.7116317   | 153.2883883   | 255               |
| 136           | 165           | 301               | 120.0959911   | 180.904089    | 301               |
| 108           | 183           | 291               | 116.0709004   | 174.9209996   | 291               |
| 126           | 164           | 290               | 115.6720313   | 174.3279687   | 290               |
| 107           | 173           | 280               | 111.6833406   | 168.3166594   | 280               |
| 106           | 214           | 320               | 127.6381035   | 192.3618965   | 320               |

$\Sigma = 1834$ $\Sigma = 2764$ $\Sigma = 4598$ $\Sigma = 1834$ $\Sigma = 2764$ $\Sigma = 4598$
TABLE 6
COMPUTATION OF CHI-SQUARE, AND COEFFICIENT OF CONTINGENCY

| Pairs | Observed Pitch | Expected Pitch | Square of difference between Observed and Expected Pitch | Chi-Square | Coefficient of Contingency of Song1 and Song2 |
|-------|----------------|----------------|----------------------------------------------------------|------------|---------------------------------------------|
| (S1, F1) | 110 | 107.6946 | 0.049349151 | 14.259 | 0.049621326 |
| (S1, F2) | 123 | 120.4585 | 0.053623669 | 6795 | 0.049621326 |
| (S1, F3) | 113 | 116.8686 | 0.12806142 | 118.0652 | 0.0074007 |
| (S1, F4) | 111 | 107.6946 | 0.101447379 | 118.0652 | 0.0074007 |
| (S1, F5) | 119 | 118.0652 | 0.007601825 | 118.0652 | 0.0074007 |
| (S1, F6) | 109 | 108.0935 | 0.007601825 | 118.0652 | 0.0074007 |
| (S1, F7) | 121 | 118.4601 | 0.054284065 | 118.4601 | 0.054284065 |
| (S1, F8) | 116 | 118.863 | 0.068959036 | 118.863 | 0.068959036 |
| (S1, F9) | 117 | 109.689 | 0.487294018 | 109.689 | 0.487294018 |
| (S1, F10) | 114 | 115.2732 | 0.014061747 | 115.2732 | 0.014061747 |
| (S1, F11) | 98 | 101.7116 | 0.13544251 | 101.7116 | 0.13544251 |
| (S1, F12) | 136 | 120.0596 | 2.116420967 | 120.0596 | 2.116420967 |
| (S1, F13) | 108 | 116.0709 | 0.561203825 | 116.0709 | 0.561203825 |
| (S1, F14) | 126 | 115.672 | 0.922149774 | 115.672 | 0.922149774 |
| (S1, F15) | 107 | 111.6833 | 0.196391683 | 111.6833 | 0.196391683 |
| (S1, F16) | 166 | 127.6381 | 3.668242556 | 127.6381 | 3.668242556 |
| (S2, F1) | 160 | 162.3054 | 0.032744997 | 162.3054 | 0.032744997 |
| (S2, F2) | 179 | 181.5415 | 0.035580973 | 181.5415 | 0.035580973 |
| (S2, F3) | 180 | 176.1314 | 0.084972737 | 176.1314 | 0.084972737 |
| (S2, F4) | 159 | 162.3054 | 0.067313492 | 162.3054 | 0.067313492 |
| (S2, F5) | 177 | 177.9348 | 0.004910594 | 177.9348 | 0.004910594 |
| (S2, F6) | 162 | 162.9065 | 0.005044047 | 162.9065 | 0.005044047 |
| (S2, F7) | 176 | 178.5359 | 0.036019166 | 178.5359 | 0.036019166 |
| (S2, F8) | 182 | 179.137 | 0.045756466 | 179.137 | 0.045756466 |
| (S2, F9) | 158 | 165.311 | 0.323334743 | 165.311 | 0.323334743 |
| (S2, F10) | 175 | 173.7268 | 0.009330406 | 173.7268 | 0.009330406 |
| (S2, F11) | 157 | 153.2884 | 0.08987032 | 153.2884 | 0.08987032 |
| (S2, F12) | 165 | 180.9404 | 1.404311162 | 180.9404 | 1.404311162 |
| (S2, F13) | 183 | 174.9291 | 0.372376199 | 174.9291 | 0.372376199 |
| (S2, F14) | 164 | 174.328 | 0.611875067 | 174.328 | 0.611875067 |
| (S2, F15) | 173 | 168.3167 | 0.130311992 | 168.3167 | 0.130311992 |
| (S2, F16) | 214 | 192.3619 | 2.433930707 | 192.3619 | 2.433930707 |

In Test Case 1, Degree of Freedom (df) = 15 and χ² between Song 1 and Song 2 = 14.2596795. From the chi-square table, for df = 15, chi-square value at 0.05 level is 24.996 and at 0.025 level is 27.488. Therefore, calculated value of chi-square is less than the both tabulated value and the value of coefficient of contingency is near to zero. Therefore, there is no significant difference between the two series. Thus, it is mostly significant and rejects the null hypothesis and the conclusion is that Song 1 and Song 2 are similar at a certain percentage.

Fig. 15 presents the comparison between Song 1 and Song 2 with respect to Observed Frequency and Expected Frequency.

![Fig 15. Comparison between Song1 and Song 2 with respect to Observed Frequency and Expected Frequency](image-url)

Findings from Test Case 2:
Table 7 represents 16 fundamental pitch values and their corresponding occurrences in Song 1 and Song 3.

### Table 7

**TOTAL PITCH VALUES OF SONG 1 AND SONG 3**

| $S_1 f_i$ | $S_1 o_i$ | $S_2 F_i$ | $S_3 f_i$ | $S_3 o_i$ | $S_3 F_i$ |
|----------|----------|-----------|-----------|-----------|-----------|
| 110      | 546      | 60660     | 175       | 731       | 127925    |
| 123      | 529      | 65067     | 173       | 654       | 113142    |
| 113      | 525      | 59325     | 176       | 603       | 106128    |
| 111      | 519      | 57609     | 196       | 536       | 105056    |
| 119      | 495      | 58905     | 177       | 493       | 87261     |
| 109      | 461      | 50249     | 198       | 441       | 87318     |
| 121      | 449      | 54329     | 172       | 432       | 74304     |
| 116      | 445      | 51620     | 195       | 404       | 78780     |
| 117      | 438      | 51246     | 232       | 396       | 91872     |
| 114      | 428      | 48792     | 220       | 371       | 81620     |
| 98       | 426      | 41748     | 179       | 370       | 66230     |
| 136      | 424      | 57664     | 170       | 366       | 62220     |
| 108      | 405      | 43740     | 147       | 350       | 51450     |
| 126      | 399      | 50274     | 200       | 331       | 66200     |
| 107      | 388      | 41516     | 169       | 312       | 52728     |
| 106      | 339      | 35934     | 234       | 310       | 72540     |

Validation of Test Case 2:

Table 9 presents the expected frequencies depending on observed frequencies of Song 1 and Song 3.

### Table 9

**CONTINGENCY TABLE OF SONG 1 AND SONG 3**

| OF(S1) | OF(S2) | OF(S1+S2) EF(S1) | EF(S2) | EF(S1+S2) |
|--------|--------|------------------|--------|------------|
| 110    | 175    | 285              | 107.8378378 | 177.1621622 | 285 |
| 123    | 173    | 296              | 112     | 184        | 296 |
| 113    | 176    | 289              | 109.3513514 | 179.6486486 | 289 |
| 111    | 196    | 307              | 116.1621622 | 190.8378378 | 307 |
| 119    | 177    | 296              | 112     | 184        | 296 |
| 109    | 198    | 307              | 116.1621622 | 190.8378378 | 307 |
| 121    | 172    | 293              | 110.8846846 | 182.1351351 | 293 |
| 116    | 195    | 311              | 117.6756757 | 193.3243243 | 311 |
| 117    | 232    | 349              | 132.0540541 | 216.9459459 | 349 |
| 114    | 220    | 334              | 126.3783784 | 207.6216216 | 334 |
| 98     | 179    | 277              | 104.8108108 | 172.1891892 | 277 |
| 136    | 170    | 306              | 115.7837838 | 190.2162162 | 306 |
| 108    | 147    | 255              | 96.4864864 | 158.5135135 | 255 |
| 126    | 200    | 326              | 123.3513514 | 202.6486486 | 326 |
| 107    | 169    | 276              | 104.4324324 | 171.5675676 | 276 |
| 106    | 234    | 340              | 128.6486486 | 211.3513514 | 340 |

### Table 10

Table 10 presents the computation of Chi-Square measure, and Coefficient of Contingency between Song 1 and Song 3.
In Test Case 2, Degree of Freedom (df) = 15 and $\chi^2$ between Song 1 and Song 3 = 17.6666808. From the chi-square table, for df = 15, chi-square value at 0.05 level is 24.996 and at 0.025 level is 27.488. Therefore, calculated value of chi-square is less than the both tabulated values, and the value of coefficient of contingency is near to zero. Therefore, there is no significant difference between the two series. Thus it is mostly significant and rejects the null hypothesis; thus the conclusion is that Song 1 and Song 3 are similar at a certain percentage.

Fig. 16 presents the comparison between Song 1 and Song 3 with respect to Observed Frequency and Expected Frequency.

In Test Case 2, Degree of Freedom (df) = 15 and $\chi^2$ between Song 1 and Song 3 = 17.6666808. From the chi-square table, for df = 15, chi-square value at 0.05 level is 24.996 and at 0.025 level is 27.488. Therefore, calculated value of chi-square is less than the both tabulated values, and the value of coefficient of contingency is near to zero. Therefore, there is no significant difference between the two series. Thus it is mostly significant and rejects the null hypothesis; thus the conclusion is that Song 1 and Song 3 are similar at a certain percentage.

Fig. 16 presents the comparison between Song 1 and Song 3 with respect to Observed Frequency and Expected Frequency.

Findings from Test Case 3:

Table 11 represents 16 fundamental pitch values and their corresponding occurrences in Song1 and Song4.
TABLE 11
TOTAL PITCH VALUES OF SONG 1 AND SONG 4

|    | S₁f₁ | S₁o₁ | S₄F₁ | S₄o₁ | S₄F₁ |
|----|------|------|------|------|------|
| 110| 546  | 60060| 220  | 946  | 208120|
| 123| 529  | 65067| 222  | 880  | 195360|
| 113| 525  | 59325| 218  | 855  | 186390|
| 111| 519  | 57609| 216  | 679  | 146664|
| 119| 495  | 58905| 225  | 608  | 136800|
| 109| 461  | 50249| 214  | 575  | 123050|
| 121| 449  | 54329| 196  | 526  | 103096|
| 116| 445  | 51620| 195  | 521  | 101595|
| 117| 438  | 51246| 198  | 515  | 101970|
| 114| 428  | 48792| 212  | 451  | 95612|
| 98 | 426  | 41748| 227  | 431  | 97837|
| 136| 424  | 57664| 200  | 426  | 85200|
| 108| 405  | 43740| 193  | 418  | 80674|
| 126| 399  | 50274| 210  | 408  | 85680|
| 107| 388  | 41516| 191  | 396  | 75636|
| 106| 339  | 35934| 190  | 371  | 70490|

In Table 11, \( S₁f₁ \) = Pitch frequency, \( S₁o₁ \) = Pitch occurrence, \( S₄F₁ \) = total Pitch frequency of Song 1; and \( S₄f₁ \) = Pitch frequency, \( S₄o₁ \) = Pitch occurrence, \( S₄F₁ \) = total Pitch frequency of Song 4.

Table 12 presents the song similarity between Song1 and Song3 and its value is 0.7860254 ± 78.60254%.

TABLE 12
COMPUTATION OF SONG SIMILARITY

|    | S₁f₁ | S₁o₁ | S₄F₁ | S₄o₁ | EF(S₁+S₄) | OF(S₁+S₄) | S₁(EF) | S₄(EF) | OF(S₁+O₁) | S₁(OF) | S₄(OF) |
|----|------|------|------|------|-----------|-----------|--------|--------|-----------|--------|--------|
| 110| 546  | 60060| 220  | 946  | 208120    | 330       | 117    | 267    | 330       | 212    | 730    |
| 123| 529  | 65067| 222  | 880  | 195360    | 330       | 112    | 253    | 330       | 222    | 406    |
| 113| 525  | 59325| 218  | 855  | 186390    | 330       | 112    | 253    | 330       | 222    | 406    |
| 111| 519  | 57609| 216  | 679  | 146664    | 330       | 112    | 253    | 330       | 222    | 406    |
| 119| 495  | 58905| 225  | 608  | 136800    | 330       | 112    | 253    | 330       | 222    | 406    |
| 109| 461  | 50249| 214  | 575  | 123050    | 330       | 112    | 253    | 330       | 222    | 406    |
| 121| 449  | 54329| 196  | 526  | 103096    | 330       | 112    | 253    | 330       | 222    | 406    |
| 116| 445  | 51620| 195  | 521  | 101595    | 330       | 112    | 253    | 330       | 222    | 406    |
| 117| 438  | 51246| 198  | 515  | 101970    | 330       | 112    | 253    | 330       | 222    | 406    |
| 114| 428  | 48792| 212  | 451  | 95612     | 330       | 112    | 253    | 330       | 222    | 406    |
| 98 | 426  | 41748| 227  | 431  | 97837     | 330       | 112    | 253    | 330       | 222    | 406    |
| 136| 424  | 57664| 200  | 426  | 85200     | 330       | 112    | 253    | 330       | 222    | 406    |
| 108| 405  | 43740| 193  | 418  | 80674     | 330       | 112    | 253    | 330       | 222    | 406    |
| 126| 399  | 50274| 210  | 408  | 85680     | 330       | 112    | 253    | 330       | 222    | 406    |
| 107| 388  | 41516| 191  | 396  | 75636     | 330       | 112    | 253    | 330       | 222    | 406    |
| 106| 339  | 35934| 190  | 371  | 70490     | 330       | 112    | 253    | 330       | 222    | 406    |

\[ \Sigma = 1834 \]

Table 12 presents the expected frequencies depending on the observed frequencies of Song 1 and Song 4.

Table 13 presents the computation of Chi-Square measure, and Coefficient of Contingency between Song 1 and Song 4.
In Test Case 3, Degree of Freedom (df) = 15 and $\chi^2$ between Song 1 and Song 4 = 12.01. From the chi-square table, for df = 15, chi-square value at 0.05 level is 24.996 and at 0.025 level is 27.488. Therefore, calculated value of chi-square is less than the both tabulated values and the value of coefficient of contingency is near to zero. Therefore, there is no significant difference between the two series. Thus it is mostly significant and rejects the null hypothesis; the conclusion is that Song 1 and Song 4 are similar at a certain percentage.

Fig. 17 presents the comparison between Song 1 and Song 4 with respect to Observed Frequency and Expected Frequency.

![Relation between Observed & Expected Pitch, Chi-Square and Coefficient of Contingency](image)

**TABLE 14**

**COMPUTATION OF CHI-SQUARE, AND COEFFICIENT OF CONTINGENCY**

| Pairs   | Observed Pitch | Expected Pitch | Square of difference between Observed and Expected Pitch | Chi-Square | Coefficient of Contingency |
|---------|----------------|----------------|----------------------------------------------------------|------------|---------------------------|
| (S1, F1) | 110            | 117.268        | 0.459450419                                             |            |                           |
| (S1, F2) | 123            | 122.5983       | 0.00135971                                              |            |                           |
| (S1, F3) | 113            | 117.6233       | 0.181725593                                             |            |                           |
| (S1, F4) | 111            | 116.2019       | 0.232868416                                             |            |                           |
| (S1, F5) | 119            | 122.243        | 0.086032711                                             |            |                           |
| (S1, F6) | 109            | 114.7805       | 0.291110683                                             |            |                           |
| (S1, F7) | 121            | 112.6483       | 0.619188014                                             |            |                           |
| (S1, F8) | 116            | 110.5162       | 0.272107605                                             |            |                           |
| (S1, F9) | 117            | 111.9376       | 0.228942704                                             |            |                           |
| (S1, F10) | 114          | 115.8465       | 0.029433034                                             |            |                           |
| (S1, F11) | 98            | 115.4912       | 2.64904648                                              |            |                           |
| (S1, F12) | 136           | 119.4001       | 2.307838111                                             |            |                           |
| (S1, F13) | 108           | 106.9626       | 0.010061369                                             |            |                           |
| (S1, F14) | 126           | 119.4001       | 0.364810908                                             |            |                           |
| (S1, F15) | 107           | 105.8965       | 0.011498415                                             |            |                           |
| (S1, F16) | 106           | 105.1858       | 0.006302128                                             |            |                           |
| (S4, F1)  | 220           | 212.732        | 0.248309669                                             |            |                           |
| (S4, F2)  | 222           | 222.4017       | 0.000725425                                             |            |                           |
| (S4, F3)  | 218           | 213.3767       | 0.100175755                                             |            |                           |
| (S4, F4)  | 216           | 210.7981       | 0.128368102                                             |            |                           |
| (S4, F5)  | 225           | 221.757        | 0.047425306                                             |            |                           |
| (S4, F6)  | 214           | 208.2195       | 0.160473998                                             |            |                           |
| (S4, F7)  | 196           | 204.3517       | 0.341325764                                             |            |                           |
| (S4, F8)  | 195           | 206.4838       | 0.149989801                                             |            |                           |
| (S4, F9)  | 198           | 203.6064       | 0.12606544                                              |            |                           |
| (S4, F10) | 212           | 210.1535       | 0.01624882                                              |            |                           |
| (S4, F11) | 227           | 209.5088       | 1.460279906                                             |            |                           |
| (S4, F12) | 200           | 216.5999       | 1.27218969                                              |            |                           |
| (S4, F13) | 193           | 194.0374       | 0.00554630                                              |            |                           |
| (S4, F14) | 210           | 216.5999       | 0.20110505                                              |            |                           |
| (S4, F15) | 191           | 192.1035       | 0.006338471                                             |            |                           |
| (S4, F16) | 190           | 190.8142       | 0.003474031                                             |            |                           |
Findings from Test Case 4:

Table 15 represents 16 fundamental pitch values and their corresponding occurrences in Song 1 and Song 5.

**TABLE 15**

| S₁f₁ | S₁o₁ | S₁F₁ | S₂f₁ | S₂o₁ | S₂F₁ |
|------|------|------|------|------|------|
| 110  | 546  | 60600| 206  | 946  | 194876|
| 123  | 529  | 65067| 208  | 880  | 183040|
| 113  | 525  | 59325| 204  | 855  | 174420|
| 111  | 519  | 57609| 202  | 679  | 137158|
| 119  | 495  | 58905| 210  | 608  | 127680|
| 109  | 461  | 50249| 229  | 575  | 131675|
| 121  | 449  | 54329| 200  | 526  | 105200|
| 116  | 445  | 51620| 234  | 521  | 121914|
| 117  | 438  | 51246| 227  | 515  | 116905|
| 114  | 428  | 48792| 198  | 451  | 89298|
| 98   | 426  | 41748| 185  | 431  | 79735|
| 136  | 424  | 57664| 212  | 426  | 90312|
| 108  | 405  | 43740| 183  | 418  | 76494|
| 126  | 399  | 50274| 186  | 408  | 75888|
| 107  | 388  | 41516| 196  | 396  | 77616|
| 106  | 339  | 35934| 195  | 371  | 72345|

In Table 15, S₁f₁ = Pitch frequency, S₁o₁ = Pitch occurrence, S₁F₁ = Total Pitch frequency of Song 1; and S₂f₁ = Pitch frequency, S₂o₁ = Pitch occurrence, S₂F₁ = total Pitch frequency of Song 5.

Table 16 represents the song similarity between Song 1 and Song 5 and its value is 0.8040744 $\approx$ 80.40744%.

**TABLE 16**

**COMPUTATION OF SONG SIMILARITY**

Validation of Test Case 4:

Table 17 presents the expected frequencies depending on observed frequencies of Song 1 and Song 5.

**TABLE 17**

**CONTINGENCY TABLE OF SONG 1 AND SONG 5**

|       | S₁(OF) | S₁(EF) | S₃(OF) | S₃(EF) | EF(S₁+S₃) | OF(S₁+S₃) |
|-------|--------|--------|--------|--------|-----------|-----------|
| 110   | 206    | 113.4358974 | 316    | 118.8205128 | 331 |
| 123   | 208    | 118.8205128  | 331    | 113.7948718  | 327 |
| 113   | 204    | 113.7948718  | 327    | 112.3589744  | 313 |
| 111   | 202    | 112.3589744  | 313    | 110.1025641  | 309 |
| 119   | 210    | 110.1025641  | 309    | 118.9743595  | 305 |
| 109   | 229    | 118.9743595  | 305    | 121.3333333  | 302 |
| 121   | 200    | 121.3333333  | 302    | 115.2307692  | 298 |
| 116   | 234    | 115.2307692  | 298    | 125.6410256  | 294 |
| 117   | 227    | 125.6410256  | 294    | 123.4871795  | 290 |
| 114   | 198    | 123.4871795  | 290    | 112.1166667  | 287 |
| 98    | 185    | 112.1166667  | 287    | 101.5897436  | 283 |
| 136   | 212    | 101.5897436  | 283    | 124.9230769  | 279 |
| 108   | 183    | 124.9230769  | 279    | 104.4615385  | 275 |
| 126   | 186    | 104.4615385  | 275    | 186.5384615  | 271 |
| 107   | 196    | 186.5384615  | 271    | 108.7692308  | 267 |
| 106   | 195    | 108.7692308  | 267    | 108.0512821  | 263 |

| Σ=1834 | Σ=3275 | Σ=5109 | Σ=1834 | Σ=3275 | Σ=5109 |

Table 18 presents the computation of Chi-Square measure, and Coefficient of Contingency between Song 1 and Song 5.

**TABLE 18**

| S₁(OF) | S₂(OF) | S₁(EF) | S₂(EF) | EF(S₁+S₂) | OF(S₁+S₂) | χ² | Contingency Coefficient |
|--------|--------|--------|--------|-----------|-----------|----|------------------------|
| 110    | 206    | 113.4358974 | 316    | 118.8205128 | 331 |
| 123    | 208    | 118.8205128  | 331    | 113.7948718  | 327 |
| 113    | 204    | 113.7948718  | 327    | 112.3589744  | 313 |
| 111    | 202    | 112.3589744  | 313    | 110.1025641  | 309 |
| 119    | 210    | 110.1025641  | 309    | 118.9743595  | 305 |
| 109    | 229    | 118.9743595  | 305    | 121.3333333  | 302 |
| 121    | 200    | 121.3333333  | 302    | 115.2307692  | 298 |
| 116    | 234    | 115.2307692  | 298    | 125.6410256  | 294 |
| 117    | 227    | 125.6410256  | 294    | 123.4871795  | 290 |
| 114    | 198    | 123.4871795  | 290    | 112.1166667  | 287 |
| 98     | 185    | 112.1166667  | 287    | 101.5897436  | 283 |
| 136    | 212    | 101.5897436  | 283    | 124.9230769  | 279 |
| 108    | 183    | 124.9230769  | 279    | 104.4615385  | 275 |
| 126    | 186    | 104.4615385  | 275    | 186.5384615  | 271 |
| 107    | 196    | 186.5384615  | 271    | 108.7692308  | 267 |
| 106    | 195    | 108.7692308  | 267    | 108.0512821  | 263 |
| Σ=1834 | Σ=3275 | Σ=5109 | Σ=1834 | Σ=3275 | Σ=5109 |
COMPUTATION OF CHI-SQUARE, AND COEFFICIENT OF CONTINGENCY

| Pairs   | Observed Pitch | Expected Pitch | Square of difference between Observed and Expected Pitch | Chi-Square | Coefficient of Contingency |
|---------|----------------|----------------|----------------------------------------------------------|------------|-----------------------------|
| (S1, F1) | 110            | 113.4359       | 0.104071032                                              | 0.019071032| 0.042711198                  |
| (S1, F2) | 123            | 118.8205       | 0.147012606                                              | 0.019071032| 0.042711198                  |
| (S1, F3) | 113            | 113.7949       | 0.06552282                                               | 0.019071032| 0.042711198                  |
| (S1, F4) | 111            | 112.359        | 0.016436706                                              | 0.019071032| 0.042711198                  |
| (S1, F5) | 119            | 118.1026       | 0.006819422                                              | 0.019071032| 0.042711198                  |
| (S1, F6) | 109            | 121.3333       | 1.253662997                                              | 9.33710823  | 0.042711198                  |
| (S1, F7) | 121            | 115.2308       | 0.288846671                                              | 0.042711198 | 0.042711198                  |
| (S1, F8) | 116            | 125.641        | 0.739801145                                              | 0.042711198 | 0.042711198                  |
| (S1, F9) | 117            | 123.4872       | 0.340792445                                              | 0.042711198 | 0.042711198                  |
| (S1, F10)| 114            | 112            | 0.035714286                                              | 0.042711198 | 0.042711198                  |
| (S1, F11)| 98             | 101.5897       | 0.126846064                                              | 0.042711198 | 0.042711198                  |
| (S1, F12)| 136            | 124.9231       | 0.982190028                                              | 0.042711198 | 0.042711198                  |
| (S1, F13)| 108            | 104.4615       | 0.119859519                                              | 0.042711198 | 0.042711198                  |
| (S1, F14)| 126            | 112            | 1.75                                                      | 0.042711198 | 0.042711198                  |
| (S1, F15)| 107            | 108.7692       | 0.028778154                                              | 0.042711198 | 0.042711198                  |
| (S1, F16)| 106            | 108.0513       | 0.039842233                                              | 0.042711198 | 0.042711198                  |
| (S5, F1) | 206            | 202.5641       | 0.058279778                                               | 0.042711198 | 0.042711198                  |
| (S5, F2) | 208            | 212.1795       | 0.082327059                                              | 0.042711198 | 0.042711198                  |
| (S5, F3) | 204            | 203.2051       | 0.003190278                                              | 0.042711198 | 0.042711198                  |
| (S5, F4) | 202            | 200.641        | 0.009204555                                              | 0.042711198 | 0.042711198                  |
| (S5, F5) | 210            | 210.8974       | 0.003818876                                              | 0.042711198 | 0.042711198                  |
| (S5, F6) | 229            | 216.6667       | 0.702051278                                              | 0.042711198 | 0.042711198                  |
| (S5, F7) | 200            | 205.7692       | 0.161754135                                              | 0.042711198 | 0.042711198                  |
| (S5, F8) | 234            | 224.359        | 0.414288641                                              | 0.042711198 | 0.042711198                  |
| (S5, F9) | 227            | 220.5128       | 0.198043769                                              | 0.042711198 | 0.042711198                  |
| (S5, F10)| 198            | 200            | 0.02                                                      | 0.042711198 | 0.042711198                  |
| (S5, F11)| 185            | 181.4103       | 0.071033796                                              | 0.042711198 | 0.042711198                  |
| (S5, F12)| 212            | 223.0769       | 0.550026527                                              | 0.042711198 | 0.042711198                  |
| (S5, F13)| 183            | 186.5385       | 0.067121331                                              | 0.042711198 | 0.042711198                  |
| (S5, F14)| 186            | 200            | 0.98                                                      | 0.042711198 | 0.042711198                  |
| (S5, F15)| 196            | 194.2308       | 0.016115766                                              | 0.042711198 | 0.042711198                  |
| (S5, F16)| 195            | 192.9487       | 0.021807651                                              | 0.042711198 | 0.042711198                  |

In Test Case 4, Degree of Freedom (df) = 15 and \( \chi^2 \) between Song 1 and Song 5 = 9.33710823. From the chi-square table, for \( df = 15 \), chi-square value at 0.05 level is 24.996 and at 0.025 level is 27.488. Therefore, calculated value of chi-square is less than the both tabulated values and the value of coefficient of contingency is near to zero. Therefore, there is no significant difference between the two series. Thus it is mostly significant, and rejects the null hypothesis; the conclusion is that Song 1 and Song 5 are similar at a certain percentage.

Fig. 18 presents the comparison between Song 1 and Song 5 with respect to Observed Frequency and Expected Frequency.

**Comparative Performance Evaluation:**

In this subsection, a comparative performance analysis is presented. Apart from considering the findings from
the above mentioned four test cases using the proposed method (i.e., using correlation co-efficient), outcomes regarding the similarity level determined between two songs have been calculated by using different sound analysis methods such as mean and standard deviation. Then all the computed values are presented in Table 19.

Table 19 presents the song similarity values between (Song 1 & Song 1), (Song 1 & Song 2), (Song 1 & Song 3), (Song 1, & Song 4), and (Song 1 & Song 5) that have been computed using different measures such as mean, standard deviation, and the proposed algorithm.

![Fig. 19. Song pattern similarity between (Song1, Song1), (Song1, Song2), (Song 1, Song3), (Song1, Song4), and (Song1, Song5)](image)

| Compare          | Mean Similarity % (A) | Standard Deviation Similarity % (B) | Song Similarity % using Correlation Coefficient (C) |
|------------------|-----------------------|--------------------------------------|---------------------------------------------------|
| Song (1,1)       | 100                   | 100                                  | 100                                               |
| Song (1,2)       | 55.9262               | 82.7096                              | 72.40924                                          |
| Song (1,3)       | 65.5347               | 87.3243                              | 71.44741                                          |
| Song (1,4)       | 83.7016               | 96.2287                              | 78.60254                                          |
| Song (1,5)       | 78.0493               | 97.8049                              | 73.84429                                          |

As a summary, it is found through rigorous experiments that all the four songs of IFM are similar to the ICM based song titled as “Laaga Chunri Mein Daag”. The Song 4 of IFM (that is “Oh Jeebon re”) is highly similar to Song 1 (that is “Laaga Chunri Mein Daag”). Thus, all the four IFM based songs are applicable as the alternative to the ICM based song “Laaga Chunri Mein Daag”. However, out of these four IFM based songs the Song 4 (that is “Oh Jeebon re”) of IFM database, may be considered as the best alternative.

V CONCLUSION AND FUTURE SCOPE

In this paper, an algorithm has been proposed that can identify similar music patterns based on the statistical measure like Correlation Coefficient. A mobile app has also been developed that implements the proposed algorithm to identify the alternate songs for Indian Classical Music (ICM) based songs, from a pool of Indian Folk Music (IFM). Rigorous experiments have been carried out and results are presented in this paper to identify the alternate songs, algorithmically.

Correlation Coefficient is one of the most suitable parameters to calculate the similarities between two different song samples. If computed value of Correlation Coefficient is near to +1, it indicates that the two song structures are similar to each other, and otherwise, it indicates presence of a certain percentage of similarity.

Two other similarity measures used for sound analysis, namely, Mean Similarity and Standard Deviation Similarity have also been explored for determining similarity levels between two input songs.

The goal of this work is to develop a methodology to identify similar songs in terms of their corresponding raga contents. Such a methodology may be applicable in the broad areas of music information retrieval (MIR). An application of such a method may be found in recommending an alternate but similar song to a standard song having well-known therapy capability or healing power. Based on the similarity value of two songs determined by the proposed method, it may be decided to replace one song by the other for music therapy like applications.
In future, rigorous experiments shall be carried out to measure the actual impact of the alternate songs identified by the proposed method in terms of their therapy capabilities, so that alternate music therapy can also be applied to the prospective users. These alternate songs are planned to be picked up from IFM like Goalparia Lokgeet, Kamrupia Lokgeet and Boul Geet.

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Annexure I: List of variables with corresponding significance

| Variable Names | Significance |
|----------------|-------------|
| PD Pitch Density | |
| NP Number of distinct Pitches in the track | |
| AP Number of All distinct Pitches in MIDI standard | |
| PE Pitch Entropy | |
| Nj Total number of notes with the corresponding pitch in the representative track | |
| T Total number of notes in the representative track | |
| GiWi Weight of music group | |
| TWj Weight of the transaction Tj | |
| MOj,1 Number of music objects which belongs to music group Gi in transaction Tj | |
| $S_1F_i$ Total Pitch value of individual note of Song 1 | |
| $S_1f_i$ Frequency of individual note of Song 1 | |
| $S_1o_i$ Occurrence of individual note of Song 1 | |
| $S_2F_i$ Total Pitch value of individual note of Song 2 | |
| $S_2f_i$ Frequency of individual note of Song 2 | |
| $S_2o_i$ Occurrence of individual note of Song 2 | |
| $\overline{S_1F_i}$ Mean of $S_1F_i$ | |
| $\overline{S_2F_i}$ Mean of $S_2F_i$ | |
| SoS Sum of Square | |
| OF(S1) Observed Pitch Frequency of Song 1 | |
| OF(S2) Observed Pitch Frequency of Song 2 | |
| EF(S1) Expected Pitch Frequency of Song 1 | |
| EF(S2) Expected Pitch Frequency of Song 2 | |
| (EF($S_i$), $f_i$) Expected Frequencies computed with respect to Observed Frequencies | |
| $\chi^2$ Chi-Square | |
| O Observed Frequency | |
| F Expected Frequency | |
| C Coefficient of Contingency | |
| N Total Population | |
| df Degree of Population | |
| r Number of rows | |
| c Total population | |
| $S_3f_i$ Pitch frequency of Song 3 | |
| $S_3o_i$ Pitch occurrence of Song 3 | |
| $S_4f_i$ Pitch frequency of Song 4 | |
| $S_4o_i$ Pitch occurrence of Song 4 | |
| $S_5f_i$ Pitch frequency of Song 5 | |
| $S_5o_i$ Pitch occurrence of Song 5 | |

Annexure II: Data set description

The data set (song) has been created using the following features of ICM.

1. Thaat (Raga Origin): These are known as Raga origin which consists of a set of ragas. Ragas are organized in terms of the thaths are - Kalyan, Bhairav, Kafi, Asavari, Bilalab, Khamaj, Bhairavi, Purbi and Torhi etc.

2. Raga: Ragas are the backbone of ICM. It is the combinations of different note structures for different music compositions that are providing different melodies to music.

3. Notes: Notes can be a beat or combinations of beats.

4. Notation: Combination or series of different notes that indicate various aspects of how a piece of music is to be performed.

5. Pitch: Pitch is the number of times a musical sound wave can repeat in one second. It can be measured in Hz.

6. Shruti (Microtones): Shrutis ordinarily refers to the
frequency of notes which means it is a group of frequencies with different amplitude levels. Therefore, the note frequencies which have the maximum amplitude level are known as Shruti. In ICM, there are three types of Shruti-Systems. They are: 12 Shruti-System, 16 Shruti-System, and 22 Shruti-System.

Thus the data set used in this work is totally based on different characteristics of ICM.
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