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PMFCC Features for Music Classification Using the Modified KNN Algorithm

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Abstract— From ancient period Music is a integral part of human life. People prefered to listen Music while relaxing. All over the world nowadays music is used as supporting medication for healing mental illness and many other diseases. The origin of Indian Music is Indian Classical Raga, having a melodious combination of Rhythm and notes. There are various users like music-composers, e-learners, music therapists are frequently retrieving Indian classical Raga based music. The vast retrieval of Raga based music made it necessary to classify Indian music on Raga. This paper proposes an a new algorithm to classify an Indian Music using Raga information which further will be useful for song recommendation, personalizing collection, and musicologists for various purpose.

In this paper, the combined Pitch and MFCC based PMFCC features are extracted and processed by Modified K Nearest Neighbor algorithm. The performance of PMFCC and Pitch Class Distribution features is compared using traditional machine learning classification algorithms and Modified Variant K Nearest Neighbor (MVKNN). The PMFCC features outperformed with the Modified KNN algorithm. The accuracy of PMFCC features with Modified KNN algorithm is found 96.11% for our Our dataset and 93.65% for Compmusic standard dataset.

Keywords- Indian Classical Music; Feature Extraction; Mel Frequency Cepstrum Coefficient; Pitch; Pict Class Distribution; Classification algorithms

I. INTRODUCTION *(HEADING 1)*

Music is a medium that expresses ethnicities, activities, and sentiments. The research says that Music expresses as well as controls the feelings and the activities of the people [1]. This insisted doctors, Music Therapists to make use of Music as supporting medication to recover the patients. The research in music therapy supports its effectiveness in many areas such as maintaining overall physical fitness, increasing mental strength, and emotional support [2, 3]. The ancient Music Scientist documented emotions associated with Raga [4]. The advances in technologies such as the Internet of Things (IoT), storage devices, embedded systems, etc. created a huge amount of musical tracks in digital form. This gave birth to Content-Based Music Information Retrieval (CBMIR) for personalization of Music collection, Tagging [5], and Recommendation based on time [6]. Many Indian folks, and movie songs are based on the Raga framework. There are many Music Information Retrieval systems are available which are indexed on artist name, genre, instruments used in a song, sentiments, and so on [7, 8, 9]. If the Music is properly tagged, or indexed with the Raga name will improve retrieval of Music from an enormous collection of Music on the web. The identification of the Raga, and its properties in a song will really be helpful for e-learners, composers, musicians, and musicologists.

The retrieval and recommendation may work more effectively by correct feature representation and efficient algorithm implementation. The 7 Swar namely Shadaj(Sa), Rishabh(Re), Gandhar(Ga), Madhyam(Ma), Pancham (Pa), Dhaiwat (Dha), Nishad(Ni) are main components in Indian Classical Music (ICM). In ICM the seven swar are sung in three different ways Natural (Shuddha), Flat (Komal), and Sharp (Tivra). All seven Swar can be sung in a Natural way, Re, Ga, Dha, and Ni can be sung in a flat way, and Ma can be sung in a Sharp way. This way 12 swar form one octave. ICM have three types of octaves, Lower Octave called as Mandra Saptak, Middle Octave names as Madhya Saptak, and Higher Octave known as Tar Saptak. The trained musicians easily identify in which octave music is played and which swar is Wadi swar i.e. appearing the highest number of times, Samwadi Swar i.e, swar appearing a second largest number of times, Varjya Swar i.e. not used in a song. The properties like Wadi Sanwadi swar, Varjya swar, ascending descending sequence of swar are used for Raga Recognition [10]. The accurate Tonic value helps in finding Swaras of audio signal [12, 13]. Identification of Tonic itself is one of the research issues so many researchers proposed Mel Frequency Cepstrum Coefficients (MFCC) based Raga Identification, which will not require Tonic information. In this paper, we proposed hybrid features with a modified KNN algorithm for Raga Identification.

The paper covers review of existing work done for Raga identification in Section II. In Section III the proposed methodology is described. Section IV gives experimentation details. Section V Conclusion.

II. Related Work

The Loudness, Pitch and Timbre are three important perceptual parameters in human sound recognition. Pitch is subjective and closely correlated with the fundamental frequency F0 [14]. Analysis of ICM based on Raga requires various properties such as melodic motifs, chalan to be explored. To explore these properties Pitch features are necessary to be extracted. Most Pitch Detection Algorithms (PDAs) extract F0 from the acoustic signal, i.e. they are based on the repetition rate of specific temporal features, or by detecting the harmonic structure of its spectrum. Zero-Crossing Rate (ZCR), Autocorrelation-based, Harmonic Product Spectrum (HPS), Maximum Likelihood (ML), Cepstrum biased HPS algorithms are few Pitch Detection Algorithms (PDA) [15]. There are various systems developed [15, 16, 17] for Tonic detection using these algorithms as base. In this paper, we identified Pitch values using the Autocorrelation method and the Tonic of a signal using the Praat Tool [18].

In [19] researchers developed an algorithm for identifying Tonic for Polyphonic music. The algorithm is predominant melody (f0) extraction for Polyphonic music Tonic identification. This method is used by many researchers in their work [20, 21].

After extracting Pitch values, the researchers represented these values in different distribution forms such as Pitch Class Distribution (PCD), Pitch Class Dyad Distribution (PCDD), Fine-grained Pitch Distribution (FPD), and Kernel-Density Pitch class Distribution (KPD) and used for Raga Identification [20, 21, 22, 23, 24]. Pitch Distribution is distributing one-octave pitches in different bins. In Music, if the first octave starts at 110Hz then the second will start at 220Hz and the third at 440Hz, and so on. In western music, one octave is divided into 12 semitones. Similarly in Indian Classical music we have 12 Swaras which is collection of 7 swaras indicating Normal Notes, Flat Notes, and Sharp Notes. The representation of Pitch values using class distribution methods leads to the loss of sequential occurrence of Swaras and concentrates only on the total count of each swar in a sample.

The accurate Swar identification correct tonic identification is expected so to avoid this, few researchers used Chroma [25, 26] or MFCC features, which provides Timbre information for Raga identification in [27, 28, 29].

In the Identification module mainly KNN classification algorithm, Decision Tree algorithm, Random Forest, and Support Vector Machine algorithms are used. The widely used classification algorithm is KNN. KNN has the limitation of selecting the K value. It gives effective results if the training data is large. In [11, 12 20, 22, 23, 24] authors got satisfactory results using the KNN algorithm with different distance metrics for Raga Identification. The Tree-based classifiers uses a greedy approach for building the tree. Decision tree algorithm is suitable for the small set of data as for a large dataset the tree will be created with more depth, and so retrieval becomes inefficient. It works only on discrete value attributes so continuous values are necessary to quantized into discrete form. In [12, 22] Random Forest is implemented for Raga classification using PCD features. Support Vector Machine (SVM) classifier classifies linear, nonlinear data efficiently by constructing a hyper-plane or set of hyperplanes. The SVM requires more memory for both training, and testing. The selection of best kernel makes non-linearly separable data classification efficient. In ICM, SVM is used successfully in Raga Identification [12, 21, 25, 26].

In the referred literature author used traditional classifiers by selecting its most suitable parameters by trial-and-error method like the value of K in KNN, a number of trees in Random Forest, or kernel function in SVM. But from the study, it is identified that as the application changes, then modifications in classifiers are also expected.

The use of PCD shows a loss of temporal characteristics. To overcome the limitation of PCD, in this paper the Pitch values are combined with the MFCC feature, and created PMFCC feature vector to input to the classifier. In the next section implementation of PCD, PMFCC, and Modified Variant KNN is explained.

III. Ease of Use

The Musical signal is a combination of various melodic patterns, which can be differentiated easily by variations in pitch values but automatic identification of patterns is a challenging job. While using PCD, we are only concentrating on a count of occurrence of any node but when Indian Music we are considering, the movement of Swara from one to another is also important. So in the proposed method, the combination of the Pitch value and MFCC features is done. The Pitch values and MFCC features are extracted for each sample in a dataset. The MFCC features are extracted as per the steps followed in [30]. The Pitch values are calculated using Autocorrelation as follows

Step 1: Divide the input signal into frames of size 20msec with 25% overlap.

Step 2: Perform framewise Autocorrelation using eq.1.

$$Y\_auto_{\tau} = \frac{1}{N}\sum Y_n * Y_{n+\tau} \qquad (1)$$

Where frame is having length N, and lag τ .

Step 3: Identify the first two peak values in the auto-correlated signal

Step 4: Divide Sampling Frequency with the difference in the location of two peak values as shown in eq. 2

$$P_{auto(i)} = \frac{f_s}{peak1(Y_{auto}) - peak2(Y_{auto})} \qquad (2)$$

A singer has scope to sing a song with a different tonic at different instance. So, it is necessary to identify the Tonic of each sample. In this paper, the Tonic value (T) is calculated using the Praat Tool. T is considered 'Sa' of Middle octave.

Step 5: Calculate 'Sa' values in three octaves and store them in PCP.
PCP[13] = T, PCP[1] = T/2, PCP[25] = T *2

Step 6: The remaining values in (Octave) PCP are calculated as per the ratios in [31].

Step 7: The normalization is done to map all the pitch values in PCP to T = 220.

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Step 8: Original Pitch values of every frame are mapped to nearest Pitch value to 220. The Following Fig I and II shows original Pitch values and Pitch values mapped to 220 for one sample of Raga Asavari.

From Normalized Pitch values, PCD of size 36 is calculated. The PCD for above sample is shown in Table I. After calculating features separately, the process of augmentation is implemented. From the Pitch features the consecutive frames of a same Pitch value are identified and it is replaced by single a row with (Pi,Ci) where Pi is Pitch value and Ci is count of occurrence. The mean of MFCC features of frames having consecutive same Pitch value is taken and merged with (Pi,Ci). Tables II and III show samples of augmentation.

After combining, every frame will have15 values. If the first coefficient of MFCC and Pitch value are non-zero then the frame is considered for further processing. The Min-Max normalization method is applied to normalize the combined features. The length of every audio sample is different. So, to make the feature vector of a same size, Principal Component Analysis (PCA) algorithm is applied on PMFCC features of each sample and converted to [15]X[15] size vector.

The comparison of various classifiers Decision Tree, KNN, SVM, and MVKNN is done using PCD and PMFCC features. MVKNN is a Modified Variant K Nearest algorithm, which is proposed in [32] for Raga identification. In MVKNN algorithm, identifies the optimal K value for every class in training phase. In this algorithm, binary Min-Heap data structure is used to store the nearest K samples. By creating the Min-Heap of size 2*K, the complexity of testing is reduced. The experimental results for all algorithms are discussed in next section.

Table I PCD for one sample of Raga Asavari

	Sa	r	R	g	G	M	M'	P	Dha	Dha	ni	Ni
Lower Octave	2	13	42	162	1373	251	1210	1109	639	2221	378	437
Middle Octave	986	659	617	946	748	196	107	205	85	92	168	326
Higher Octave	817	259	127	64	75	27	18	16	13	8	16	9

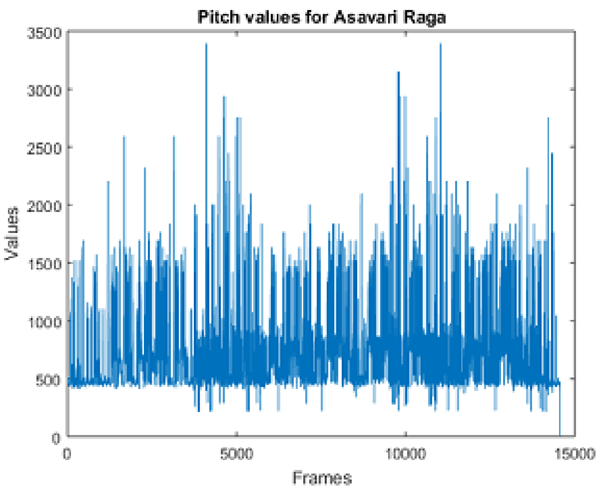

Figure 1. Pitch values for one sample of Asavari Raga

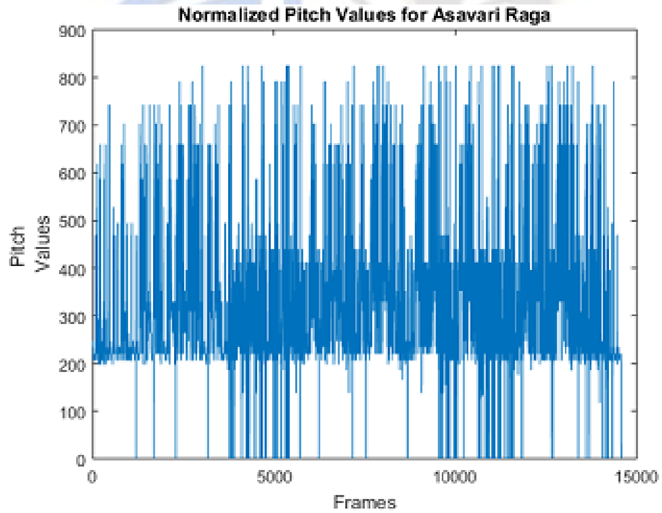

Figure 2. Normalized Pitch values for one sample of Asavari Raga

Table II Pitch and MFCC features for few frames in Raga Asavari

Pitch	MFCC1	MFCC2	MFCC3	MFCC4	MFCC5	MFCC6	MFCC7	MFCC8	MFCC9	MFCC10	MFCC11	MFCC12	MFCC13
330	0.0337	1.0000	0.4083	0.3134	0.7983	0.6058	0.0274	0.0038	0.0000	0.0029	0.0090	0.0299	0.0738
330	0.0338	1.0000	0.4662	0.2969	0.7629	0.5367	0.0303	0.0042	0.0000	0.0016	0.0086	0.0308	0.0690
154.68	0.0602	1.0000	0.4148	0.3051	0.6652	0.4924	0.0488	0.0110	0.0000	0.0025	0.0083	0.0268	0.0747
154.68	0.0330	1.0000	0.5451	0.3841	0.7471	0.5744	0.0453	0.0025	0.0034	0.0000	0.0105	0.0351	0.0956
154.68	0.0417	1.0000	0.5500	0.4223	0.8507	0.6490	0.0293	0.0113	0.0050	0.0000	0.0058	0.0262	0.0792
330	0.0079	1.0000	0.4938	0.3483	0.8401	0.5820	0.0283	0.0160	0.0082	0.0000	0.0180	0.0405	0.0857
330	0.0092	0.7531	0.4708	0.2805	1.0000	0.7893	0.0181	0.0069	0.0000	0.0080	0.0136	0.0376	0.0991
330	0.0318	0.5620	0.3895	0.3691	1.0000	0.7280	0.0180	0.0038	0.0019	0.0000	0.0074	0.0407	0.1021
330	0.0207	0.4984	0.2988	0.2652	1.0000	0.7174	0.0302	0.0160	0.0017	0.0000	0.0071	0.0265	0.0561

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330	0.0254	0.2783	0.1779	0.2354	1.0000	0.7231	0.0244	0.0077	0.0057	0.0000	0.0060	0.0192	0.0601
330	0.0166	0.4695	0.2861	0.2362	1.0000	0.6949	0.0279	0.0091	0.0145	0.0000	0.0103	0.0203	0.0667
330	0.0364	0.4094	0.1447	0.2571	1.0000	0.7469	0.0148	0.0090	0.0150	0.0000	0.0113	0.0303	0.0564
330	0.0370	0.7983	0.3231	0.3089	1.0000	0.7898	0.0190	0.0000	0.0146	0.0022	0.0047	0.0290	0.0829
330	0.0276	0.4985	0.1739	0.2798	1.0000	0.8005	0.0105	0.0000	0.0095	0.0031	0.0104	0.0256	0.0722

Table III PMFCC features for few frames in Raga Asavari

Pitch	Count	MFCC1	MFCC2	MFCC3	MFCC4	MFCC5	MFCC6	MFCC7	MFCC8	MFCC9	MFCC10	MFCC11	MFCC12	MFCC13
330	2	0.0338	1.0000	0.4372	0.3052	0.7806	0.5713	0.0288	0.0040	0.0000	0.0023	0.0088	0.0303	0.0714
154.68	3	0.0450	1.0000	0.5033	0.3705	0.7543	0.5719	0.0412	0.0083	0.0028	0.0008	0.0082	0.0294	0.0832
330	9	0.0236	0.5853	0.3065	0.2867	0.9822	0.7302	0.0213	0.0076	0.0079	0.0015	0.0099	0.0300	0.0757

IV. Experimental Result

Our data and CompMusic data are used for the experimentation. In Our data 1600 samples are recorded with electronic Tabla and Tanpura as accompanying instruments in isolated environment. 25 samples sung by each of 8 singers for 8 different Raga namely Asavari, Bageshree, Bhairavi, Bhupali, Darbari Kanada, Malkauns, Vrindavani Sarang, Yaman. The file is stored in .wav format with sampling frequency 44100Hz, and 16bps. The frame size is considered as 20ms with 25% overlapping.

CompMusic dataset [11, 12] includes full length audio recordings with Raga label. It is a collection of several artists' vocal as well as instrumental performances. The clips were extracted from the live performances and CD recordings of 13 artists. Total 128 tunes for 08 ragas same as Our data. The average duration of each tune in CompMusic dataset is 5-6 minutes. The tunes are downloaded [33] and converted with same configuration parameters of Our data.

The splitting of data is done into training and testing data by considering 70:30 ratio. The test data is given as input to KNN, Decision Tree, SVM, and MVKNN and calculated confusion matrix for multiclass classifiers. Accuracy and F1- score is calculated for all classifiers for both PCD and PMFCC features. Tables IV and V show Accuracy and F1-score of PCD with all classifiers. Tables VI and VII show Accuracy and F1-score of PMFCC with all classifiers.

Table IV Accuracy for PCD features

	KNN	Decision Tree	SVM	MVKNN
Our data	87.16%	93.69 %	83.12%	94.82%
Compmusic data	86.02%	86.33%	82.72%	89.45%

Table V F1-score for PCD features

	KNN	Decision Tree	SVM	MVKNN
Our data	56.66%	74.79%	38.99%	83.28%
Compmusic data	44.11%	49.13%	38.70%	57.81%

Table VI Accuracy for PMFCC features

	KNN	Decision Tree	SVM	MVKNN
Our data	89.65%	93.95 %	91.92%	96.11%
Compmusic Data	87.34%	89.04%	83.33%	93.65%

Table VII F1-score for PMFCC features

	KNN	Decision Tree	SVM	MVKNN
Our data	59.72%	75.83%	67.70%	86.45%
Compmusic Data	49.38%	69.89%	74.98%	74.60%

The results of PCD and PMFCC shows that there is not much change in the Accuracy and F1 score when the Decision Tree classifier is used, this may be because pruning has happened in Decision tree. In case of SVM, Accuracy and F1 score for both the dataset is improved due to the size of feature vector of PMFCC is higher dimensional than PCD and SVM works effectively even on non-separable, high dimensional data. MVKNN has higher accuracy and F1 score for both features than KNN. An increase in F1-score concludes that True Positive cases are increased and even variable K value for each test sample is more effective than constant value for all the samples. Though in our dataset number of samples are the same for all classes but when applying train-test-split, it takes number of samples for every class differently in the training set so the use of the same K for all classes is not exactly the correct solution.

V. Conclusion

The combination of Pitch and MFCC features creates a more robust model as Pitch overcomes the lacuna of MFCC for Raga Identification and vice-versa. The Pitch gives melody information and MFCC gives spectral information. While extracting Pitch single dominant value for every frame is considered, in this, it may happen important information of that frame is missing but this could be overcome by MFCC features as it is taking multiple coefficients for one frame. It is observed that if the same song from the same Raga is sung by a different singer it is accurately identified by combining Pitch and MFCC features, which was not happening with only PCD features. The modified KNN outperformed for both datasets with PMFCC features for classifying music based on Raga. In the future our aim to automatically identify repeated patterns in every sample without considering complete signals and apply modified versions of classifiers and also Neural Network variant algorithms.

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