Performance Comparison of Musical Instrument Family Classification Using Soft Set

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Abstract

Nowadays, it appears essential to design automatic and efficacious classification algorithm for the musical instruments. Automatic classification of musical instruments is made by extracting relevant features from the audio samples, afterward classification algorithm is used (using these extracted features) to identify into which of a set of classes, the sound sample is possible to fit. The aim of this paper is to demonstrate the viability of soft set for audio signal classification. A dataset of 104 (single monophonic notes) pieces of Traditional Pakistani musical instruments were designed. Feature extraction is done using two feature sets namely perception based and mel-frequency cepstral coefficients (MFCCs). In a while, two different classification techniques are applied for classification task, which are soft set (comparison table) and fuzzy soft set (similarity measurement). Experimental results show that both classifiers can perform well on numerical data. However, soft set achieved accuracy up to 94.26% with best generated dataset. Consequently, these promising results provide new possibilities for soft set in classifying musical instrument sounds. Based on the analysis of the results, this study offers a new view on automatic instrument classification.

Keywords: Traditional Pakistani Musical Instruments Sounds, Classification, Soft Set, Fuzzy Soft Set.

1. INTRODUCTION

Classification is one of the most important and significant machine learning areas, capable of handling musical data effectively and efficiently, once the dataset is categorized into different families. In general, the need for musical data analysis arises in different contexts, which leads to many practical applications such as effective data arrangement, music transcription, indexing and comprehensive digital libraries [1].

Generally, audio signal classification can be cast into musical genre, musical instruments, composer, artist, music segmentation and so on. Thus, musical instruments classification is not only subject matter for musicologists but also become an important research field for Music Information Retrieval (MIR) [2]. Much of existing research focuses on the achievable classification accuracy of different machine learning algorithms. The studies have shown that a number of different algorithms are able to achieve high classification accuracy rate. Such as support vector machine [3], [4], [5], artificial neural networks [6], [7] and rough set [8].

Even though in the work of Ali & Smith [9], they conducted comprehensive study on eight different classification algorithms. The author compared different eight classification algorithms with hundred different datasets. The relative weighted performance measurers showed that there was no single classifier to solve all classification problems with best performance over the different experimental setups. This leads that no single method has been found to be superior over all datasets. Nevertheless, rough set has been successfully applied for musical instruments sounds data [10], [11], [12]. Therefore, it is interesting to see the application of soft set theory for classification of musical instruments sounds. Moreover, to observe the viability, efficiency and effectiveness of soft set, while performing this classification task.

Molodtsov [13] introduced the notions of a soft set as a collection of approximate description of an object. The initial description of an object has as approximate nature, and there is no need of to introduce the notions of exact solution. The applications of this theory boom in recent years and are extended to data analysis [14], [15], decision-making [16], [17], [18] to texture classification [19].This furnishes motivation from the advancement in soft set to apply classification algorithm based on notions soft set theory (named as soft set classifier), which was proposed by [19] for texture classification. This paper focuses to asses the performance of soft set classifier towards classification of musical instruments. Moreover, the contemporary study expands the usual work of using western musical instruments to the non-western musical instruments i.e. Traditional Pakistani musical instruments.

The reminder of paper is organized as follows: Section 2 presents the dataset details. Feature extraction producer is discussed in Section 3. Section 4 illustrates an overview of classification algorithms followed by results and discussion in the Section 5. Finally the conclusions are made in Section 6.

2. DATASET

Musical instruments have universal appeal, richness and soothing tones without language and regional barriers. The history of Traditional Pakistani musical instruments (TMPI) can be gathered from various sources such as literature (folk, music), visual representation (painting, sculptures, and models). Interestingly, most of the Pakistani musical instruments remain still in use. Pakistani music is represented by a wide variety of forms. It ranges from traditional styles such as qawwali, sufism and ghazal to more recent shapes that is fusion of traditional music with western music.

Generally, these instruments can be cast into religious, geographic and tribal categories. For instance: harmonium and tabla comes under the religious category and their purpose is for spiritual uplifts. Likewise, under the umbrella of geographic category, instruments are: algoza, dhol, dholok and ektara. Benjo, rubab, gheychak, santoor are under the tribal category. TPMI play a significant role in Pakistani culture. They are used in wedding ceremonies, in traditional dances such as bhangra, jhumar and khattak. The primary instrument that defines bhangra and jhumar is the dhol. Whilst, the instruments for qawwali and sufism are harmonium and tabla [20].

Traditional Pakistani musical instruments play a significant role in Pakistani culture. In order to perform classification of Traditional Pakistani musical instruments a dataset is designed. Table 1 shows the taxonomy of TMPI based on Hornbostel and Sachs system. Dataset consists of three families which are string, woodwind, percussion and nine musical instruments. The dataset consist of 104 pieces of Traditional Pakistani musical instruments from compact disks and via internet. All pieces were solo music from three instrument families. The sampling rate was 44.1 kHz which was later resample to 22.1 kHz with mono .wav files. Table 1 presents the three families with their description which is partially based on Sachs-Hornbostel system [21].

Family	Instruments
String	Benju, Ghaychak, Rubab, Sarood, Tumbi
Woodwind	Bainsuri, Harmonium
Percussion	Tabla, Dholok

TABLE 1: Description of musical instruments

3. FEATURE EXTRACTION

Feature extraction is the significant phase in musical instrument classification. Depending on the characteristics of the problem domain; the crucial step in the classification is to identify the relevant features. Though, 'feature", "attribute" or "variable" refers to the aspect of data. Moreover, feature can be discrete, continuous or nominal. Therefore, usually during data collection, features are specified or chosen. As, extracted features are an input to the classifier (machine learning algorithm), therefore it is important to extract the right features which can help classifier to produce encouraging results.

Many feature schemes have been proposed in the literature for audio classification. It is worth to state that improving feature extraction process will be probably enhancing performance of the classification algorithm. As mention earlier, diverse features have been proposed and identified by different studies; each study either work on individual features or combination of features [7]. In general, designing a classification algorithm for musical instrument, feature extraction techniques are mostly taken from speech and speaker recognition system as they have proved a significant role to extract valuable information from the dataset [6], [7]. For this study, Mel–Frequency Cepstral Coefficient (MFCCs) and perception based are adopted from the work of [6] for extracting features. On the other hand, these features are reflecting different aspects of signal spectrum, which are discussed in the following sub-section.

3.1 Perception–Based

The most popular features related to perception based are spectral centroid (brightness), spectral flux and bandwidth (spectral range), which have popularity across the literature. These spectral features are computed from the Fast Fourier Transform (FFT) of the segmented signals. Besides, time domain zero crossing and root mean square are also included which reflects the temporal properties of the signals.

3.2 Mel-Frequency Cepstral Coefficients

Mel-frequency cepstral coefficients are proven to be useful in an extensive range of classification tasks such as speech classification [22], speaker identification [23] and musical genre classification [24]. MFCCs proved to be a successful candidate for classification and recognition For MFCCs, the steps derived in the work of [6] are adapted. The input signal is first divided into frames. Afterwards, fast Fourier transform (FFT) is used to get the power spectrum of the each frame. Finally, the Mel filter bank is generated to scale the frequencies logarithmically. To conclude, the mean and standard deviations has been then calculated for each of the feature vectors. Table 2 provides the depiction of features utilized

No.	FEATURES
1	Zero Crossings
2-3	Zero Crossing Rate(Mean and Standard deviation)
4-5	Root Mean Square(Mean and Standard deviation)
6-7	Spectral Centriod(Mean and Standard deviation)
8-9	Bandwidth(Mean and Standard deviation)
10-11	Spectral Flux(Mean and Standard deviation)
12-37	MFCC (Mean and Standard deviation of the first 13 values)

TABLE 2: Features Descriptions

Prior to the classification stage, vector normalization was done to make sure that data must lie between the ranges of $[0,1]$.

4. CLASSIFICATION ALGORITHMS

As it was mentioned in Section 1, automatic classification of musical audio data can be performed in many ways. However, in the described research, two algorithms have been used. The reason for considering soft set is to see the viability of this mathematical tool, even though rough set has been successfully applied to audio signal classification. Moreover, soft set theory is straightforward, simple and it allows reducing important problems to well-known Boolean ones using model assumptions. On the other hand, Maji *et al* [16] proposed an algorithm for decision making problems. This algorithm has similarity with soft set classifier proposed by Mushrif *et al*, [19] I in particular for texture classification.

While in case of fuzzy soft set, this algorithm has similarity with the work of Mushrif *et al*, [19], where building the model is same (training set), however for the classification phase which involves construction of comparison table is replaced by the similarity measurement function. Next subsection provides an overview of soft set and fuzzy soft set.

4.1 Soft Set

In 1999, Molodtsov [13] introduced the notion of a soft set as collections of approximate descriptions of an object. This initial description of the object has an approximate nature, and hence there is no need to introduce the notions of exact solution. The absence of restrictions on the approximate description in soft set makes this theory suitable and easily applicable in real world problems. Soft set theory is a newly emerging mathematical tool to deal with uncertain problems. The applications of this theory boom in recent years and are extended to data analysis [14], [15], decision-making [16], [17], [18], classification [19].

Maji, Roy & Biswas [16] presented some new definitions on soft set in decision making problems. Afterwards, Mushrif [19] offered a novel method for classification of natural texture using the notions of soft set theory. All features from the natural textures were consists of real numbers. For the dataset, 25 texture classes with 14 textures features were used. Out of 49 images, 14 images were randomly selected for training and 35 remaining for testing. The proposed method successfully classifies natural textures. In this section, soft set classifier has been explained in details.

The soft set classifier learns by calculating the average value of each attributes (features) from the entire objects. In other words, an object in the universe represents data which is derived from the same class label. Afterwards, to classify the test data, first to construct a comparison table as designed in the case of decision making problem.

Soft Set Classifier (SSC)
Training phase
1. Given N samples obtained from the data class w.
2. Calculate the cluster center vector $E_{wi}, i = 1,2,..,N$.
3. Obtain soft set model (F, E) which is $W \times D$.
4. Repeat the process for all W classes.
Classification phase
1. Obtain the unknown class data.
2. Obtain a soft set (F, A) which have elements p_{wd}.
3. Compute comparison table of soft set (F, A)
4. Compute the score vector S.
5. Assign the unknown data to class w if $w = \max S$

For calculating cluster center vector, the following expression is used [19].

$$E_w = \frac{1}{N} \sum_{i=1}^{N} E_{wi} \tag{1}$$

where E_w is mean of feature vectors in the same class label. Moreover, $W \times D$ is table in which element of each table is g_{wd}, where $w = 1,2,..,W$ and $d = 1,2,..,D$. In this way, a row g_{wd} is a cluster center vector for every class w having D features.

Similarly, for calculating element p_{wd}, the following expression is used [19].

$$p_{wd} = 1 - \frac{g_{wd} - Efd}{\max(g_{wd})} \tag{2}$$

where $w = 1,2,..,W$ and $d = 1,2,..D$.

The comparison table is constructed (for more details please refer to [19]). Afterwards, the score S is computed. The score vector S is a vector containing largest element in S. The score vector expression is as follows [19].

$$w = \arg\left[\max_{w=1}^{W}(S)\right] \tag{3}$$

4.2 Fuzzy Soft Set

In 1965, Zadeh [25] introduced the concept of fuzzy set, where he stated that fuzzy set is a kind of soft set. Let A be a fuzzy set and μ_A be a member function where μ_A be a mapping of U into $[0,1]$. Later, fuzzy set has been studied by Roy *et al.* [27] where this general concept has been combined with soft set, named as fuzzy soft set. The results from fuzzy soft set further expand the scope of applications of soft set theory.

Interestingly, Maji *et al* [16] proposed an algorithm for decision making problems. This algorithm has similarity with soft set classifier proposed by Mushrif *et al* [19] I in particular for texture classification. In addition, the concept of measuring similarity between two soft set has been studied by [28], [29] and [30].

4.2.1 Similarity Between Two Soft Sets

Measuring similarity between two entities is a key step for several data mining tasks such as classification and clustering. The similarity measure calculates the extent to which different image or signal patterns are alike [30]. Later, Majumdar & Samanta [28] defined and studied the generalised fuzzy soft sets where the degree is attached with the parameterization of fuzzy sets while defining a fuzzy soft set and provides similarity measured of soft set and fuzzy soft set. Next sub-section provides the preliminaries for general fuzzy soft sets

a) Preliminaries

In this sub-section, similarity between the two general fuzzy soft sets are explained by Majumdar & Samanta [28]. Let $U = \{x_1, x_2, ..., x_n\}$ be the universal set of elements and $E = \{e_1, e_2, ..., e_m\}$ be the universal set of parameters. Let F_ρ and G_δ be two general fuzzy soft sets over the parameterized family universe (U, E). So $F_\rho = \{(F(e_i), \rho(e_i)), i = 1,2,...,m\}$ and $G_\delta = \{(G(e_i), \delta(e_i)), i = 1,2,...,m\}$.

Therefore, $\tilde{F} = \{F(e_i), i = 1,2,..,m\}$ and $\tilde{G} = \{G(e_i), i = 1,2,..,m\}$ are two families of fuzzy soft sets. As a result, similarity between $\tilde{F}$ and $\tilde{G}$ is determined and it is denoted by $M(\tilde{F}, \tilde{G})$. Next the similarity between the two fuzzy soft sets ρ and δ is found and is denoted by $m(\rho, \delta)$. Later, the similarity between the two fuzzy soft sets F_ρ and G_δ is denoted as $S(F_\rho, G_\delta) = M(\tilde{F}, \tilde{G})$ and $\rho = \delta = 1$. Now the formula for similarity measure is

$$S(F_\rho, G_\delta) = M_i(\tilde{F}, \tilde{G}) = 1 - \frac{\sum_{j=1}^{n} \left|\tilde{F}_{ij} - \tilde{G}_{ij}\right|}{\sum_{j=1}^{n} \left(\tilde{F}_{ij} + \tilde{G}_{ij}\right)} \tag{4}$$

where F and G are two families of fuzzy soft sets.

5. RESULTS AND DISCUSSION

Sample data from compact disks and via internet was set up for the different experiments. Seven datasets were utilized. Table 3 sums up the characteristics of different experimental sets carried out during dataset formations. In the first experimental setup, the parameter audio length (duration) will be evaluated to the performance of classification algorithm. Since, there is lack of uniform approach for audio length of sounds. Therefore, this study investigates three audio lengths which are 10 seconds, 20 seconds and 30 seconds. Likewise, this is done in order to generate diverse datasets and to examine whether this identified parameter plays major role in determining the classification results [6].

Afterwards, the second set focused on finding the optimal frame size (window analyzes). For feature extraction it is assumed that only short-term audio streams are present. For classifying longer audio streams, segmentation is necessary. Each of the audio samples is divided into frames [31]. In addition, the reason to look into the frame size 256 samples and 1024 samples, these two frame sizes have been commonly used, when it comes to expands the usual work of using western musical instruments to non-western musical instruments such as in the work of [6], [32]. Moreover, for analyzing features of audio and speech algorithms, they are computed on frame basis. By doing so, the amount of data to be processed may possibly reduce.

The remaining of the datasets dealt with finding the best starting point of audio files by providing the overall better classification results in terms of accuracy rate. The reason for taking this parameter into consideration is to look into the problem of locating the beginning of the sound. The purpose is observed and to identify whether noise is there at the beginning of the sound or not [8]. Therefore; the starting points of each dataset were altered to 0 second, 0.05 seconds and 0.3 seconds. The small size of the starting points are considered since, few of the original sounds in the datasets have shorter length (less then 1 second).

NO.	PARAMETERS	DATASET	VALUES
1	Audio Length (Duration)	L1	0.1 to 10 Seconds
		L2	0.1 to 20 Seconds
		L3	0.1 to 30 Seconds
2	Frame Size (Segmentation)	FS1	256 Samples
		FS2	1024 Samples
3	Starting Point Of Audio File	SP1	0 Second
		SP2	0.05 Second
		SP3	0.3 Second

TABLE 3: Experimental setup designed for study

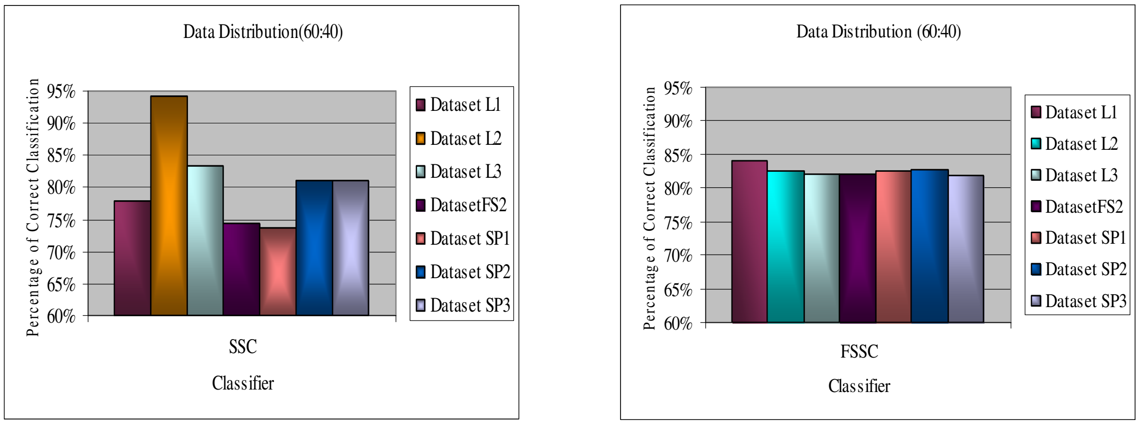
The experiments were performed on two different models: comparison table and similarity measure of two soft sets. For the comparisons of both classification algorithms, performance measurement was classification accuracy. Table 4 shows the classification accuracy. As mentioned earlier, the dataset consists of three families with nine musical instruments. Feature extraction in these experiments are implemented in an overlapped analysis window of 256 samples at 22050Hz, calculated the means and standard deviations of all 37 attributes. After feature extraction, we utilize soft set classifier and fuzzy soft set classifier on those extracted features.

	Comparison Table (SSC)		Similarity Measure (FSSC)	
Data Distribution	60:40	70:30	60:40	70:30
DatasetL1	77.91	86.84	83.97	84.20
DatasetL2	94.26	92.27	82.44	81.87
DatasetL3	83.45	85.98	82.15	81.90
DatasetFS2	74.29	69.83	82.03	82.58
DatasetSP1	73.75	81.22	82.47	82.41
DatasetSP2	81.19	88.23	82.63	82.05
DatasetSP3	81.13	88.34	81.80	81.50

TABLE 4: Percentage of correct classification for all datasets

Figure 1 presents the performance comparison of classification accuracy of different datasets with SSC and FSSC. In case of SSC, the classification accuracy gradually increases when the modified starting points are used, instead of zero. The highest achievement occurred in the Dataset L2 with accuracy 94.26%, while, the lowest achievement 73.75% occurred in the DatasetSP1. In case of FSSC, the highest classification hit rate was 83.97%, while the lowest achievement was 81.80%.

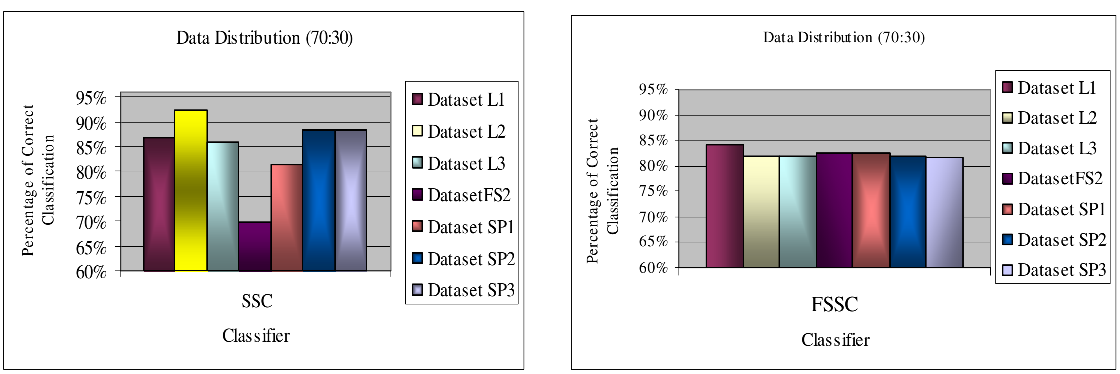
Though, the results for FSSC are about 1.64% better on mean average with data partition 60:40. Some what the results from SSC are little weaker then of that sophisticated method (FSSC). However, the simplicity of SSC makes it appealing and can be pretty helpful in classifying musical instruments sounds.



(a) (b)

FIGURE 1: Classification performance of both classifiers (a) and (b) with data distribution 60:40

While, Figure 2 shows the graphical comparison with data fraction 70:30 for both classifiers. It can be seen that classification range is 69.83% to 92.27% for SSC. Whilst, for FSSC the range from 81.50% to 84.20%. Interestingly, the results for SSC are about 2.32% better on mean average. And the hypothesis that larger the training set make sure classifier to gain knowledge of data, this graph plots the evidence of that myth.



(a) (b)

FIGURE 2: Classification performance of both classifiers (a) and (b) with data distribution 70:30

6. CONCLUSIONS

Classification is a key intervention for initiating process of labeling monophonic sounds. Most of the studies conducted to find differences and similarities with features schemes, afterwards evaluate and compare with various classifiers. At the same time as, the right extracted features can simplify the design of a classification algorithm, whereas lousy features can hardly be compensated with any of the classification algorithm. Therefore, it is likely to state that appropriate parameterization of audio sounds allows efficacious classification of musical instruments. Additionally, the choice of classification algorithm makes a quite sophisticated approach towards classification task. However, despite the massive research has been carried out on this filed, studies have mainly dealt with western musical instruments and few works can be found on non-western musical instruments. However, individual musical instrument has different behavior and so does Pakistani musical instruments. Therefore, this study incorporates soft set theory for classification of Traditional Pakistani musical instrument and investigates the impact of three factors, which are length of audio file, frame size and starting point towards classification performance of soft set classifier.

A small–scale database of instrumental music was built, in line with popular taxonomy known as Sachs & Hornbostel, categorizing instruments into three families: string, woodwind and percussion. With experiments on 37 features and two classifiers, all music clips were automatically classified by instrument families. In the light of obtained results from the both classifiers, provides a relatively new picture about instrument classification. The experiments testified that FSSC suits well for automatic instruments classification, while applied SSC best to it.

In addition, based on the obtained results, this study offers a new view on automatic instrument classification. Thus, the soft set can be considered to be employed in musical instrument classification problem. Nevertheless, it is experimentally demonstrated that this classification algorithm yields better accuracy when compared with fuzzy soft set. These results have further expanded the scope of soft set for real world problems. Future work will consider the selection of the most relevant features in discriminating between different instruments and extension of the present feature set.

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