Self Organizing Feature Map Network for Musical Instrument Sounds

Gulhane Sushen R., Shirbahadurkar Suresh D., Badhe Sanjay S

Abstract - Self Organizing Feature Map Network is used as a classifier for classification of features extracted of the sound database of Musical Instruments. However, the database of Indian Classical Musical Instruments is prepared for 15 instruments. The different types of features such as Temporal, Spectral and Cepstral features are available out of which we have considered Spectral features i.e. Roll off, Centroid, RMS Energy, Zero Crossing Rate, Spectral Irregularity & Spectral Brightness.

Keywords - Roll off, Centroid, RMS Energy, Zero Crossing Rate, Spectral Irregularity & Brightness.

I. INTRODUCTION

The cultural activity whose medium is sound organized in time, terms as Music. There are no. of important elements of Music out of which Timbre, Rhythm, Pitch are considered mostly. Timbre is element which shows the color of sound. The different types of music may emphasize, de-emphasize or omit some of these elements.

As we know, every god is associated with Musical Instrument such as Saraswati with Veen, Shiva with Damaru, etc. There are lot of Musical instrument using from ancient times out of which some were going to be used for the conveying the messages. During war also, some instruments were going to be used for giving message. In Ramayana and Mahabharata, Drums were used to convey message of peace [30].

In India, there are no. of caves, temples and at these places it has been found that there are no. musical instruments in the sculpture existing. From the early decade, it has understood the salutary use of musical instruments. Musical Instrument are manufactured using different types of materials. The materials such as skin, cotton thread, wood, clay. Tata Vadya, Sushir Vadya, and Avanaddha Vadya & Ghana Vadya are the different types of musical instruments classified according to the material used [30].

Feature Extraction is termed as the way of extracting the features of signal. They are temporal features, Spectral Features, and Cepstral features. The Spectral features are extracted from the musical instrument sound signals.

In this paper, Spectral (timbral) features of Musical Instrument Sounds are extracted using Music Information Retrieval (MIR) toolbox 1.6. After extracting the features, they are analyzed and used for further classification of Musical Instrument for Identification.

For database generation of Musical Instrument Sounds, 15 Musical Instruments are considered. Out of which, 4 Indian Woodwind Musical Instruments, 3 Western Woodwind Musical Instruments, 5 Indian String Musical Instruments, and 3 Western String Musical Instruments and each have 15 samples. So in all 225 samples database is created.

II. THEORY

Artificial Neural Network is a boom technology now a day's. ANN is a network of group of nodes wherein they are interconnected. There are no. of types of ANN out of which Self organizing feature map is a network which is trained using unsupervised learning technique. It produces a low-dimensional, discretized representation of the input space of the training samples, called a map, and is, therefore, a method to do dimensionality reduction [29]. SOFM uses competitive learning instead of error-correction learning. It uses neighborhood function to restore the similar properties of the input space due to which it differs from other artificial neural networks [29].

Self Organizing Map neural network model need no human interaction or supervision during the training due to which it comes under unsupervised learning and hence it is considered as the most popular neural network model and it needs something to be known about the features of the input data [29]. We could, for example, without knowing the class membership of the input data sample, SOM has been used for congregating the data samples. SOM can be deployed to discover the features immanent to the problem and due to which it has also been known as the Self-Organizing Feature Map (SOMF).

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Self Organizing Map algorithm is based on unsupervised, competitive learning. The SOM can thus present as a group analyzing tool of huge-dimensional data. Also, the SOM has the capability to generalize [29].

A number of classifiers are available for classification. Here, we have used SOMF Classifier for the Musical Instrument Classifier.

Musical instrument Identification is the way to identify the musical instrument to which belongs. For identification of Musical Instrument System following is the block diagram.

A. Block Diagram:

Here, Audio Input signal is provided to the Pre-processing stage. Then features are extracted and fed to Classifier. Similarly, the same steps are to be performed for the testing phase. Then both phases’ inputs are to be given classifier. The classifier will compare the inputs and according classify/identify the instruments.

III. EXPERIMENT RESULTS

The number of experiments is performed for feature extraction of audio signals. For experimentation, audio input is taken. In the proposed system, audio timbral features are extracted of the sound samples.

Timbral feature extractors

The experiments are performed for extracting the timbral features. The results are shown below: Here results have shown in Table 1 of only eight instruments. The features for all 15 instruments are extracted and are used for classification.

| Type of Instrument | Type of Instrument | ZCR | Roll-off | Brightness | Roughness | Irregularity | Rms Energy | Centroid |
|--------------------|--------------------|-----|----------|------------|------------|-------------|------------|----------|
| Indian Woodwind    | Flute              | 0.00008 | 2.2564 | 0.0003 | 0.0000 | 0.0005 | 0.0003 | 1.2135 |
|                    | Shehnai            | 0.00041 | 4.2966 | 0.0009 | 0.0007 | 0.0007 | 0.0003 | 2.9422 |
|                    | Piccolo            | 0.00017 | 2.0422 | 0.0004 | 0 | 0.0016 | 0.0000 | 1.6670 |
|                    | Saxophone          | 0.00017 | 2.0377 | 0.0006 | 0 | 0.0007 | 0 | 1.8483 |

Graph 1 shows the comparison of different timbral features of Various Musical Instruments which is drawn from Table 1.

Here, after extracting the features, the Self Organizing Feature Map Network is used for classification. In this out of 100% created database, 60% database is used for training, 40% database is used for testing and 15% database is used for cross-validation. The results are as follows:

Graph 2: Std. Deviation Avg. MSE Boundaries

Here, Graph 2 shows the Avg. MSE parameter with std.
deviation boundaries for 3 iterations for training and Cross-validation.

| Table 2: Avg. Minimum & Avg. of Final MSEs of Training |
|--------------------------------------------------------|
| **All Runs**                                      | **Training. Min.** | **Training Std. Dev.** | **Cross Validation Min.** | **Cross Validation Std. Dev.** |
|-----------------------------------------------------|--------------------|------------------------|---------------------------|-------------------------------|
| Avg. of Min. MSEs                                   | 0.0001845          | 4.65045E-05            | 0.0402969                 | 0.0035645                     |
| Avg. of Final MSEs                                  | 0.0001845          | 4.64996E-05            | 0.1247007                 | 0.0304680                     |

Here, Table 2 shows the result of Avg. Min. and Avg. of Final MSE of Training & Cross-Validation.

| Table 3: Training & Cross Validation Data with Iterations & Epochs |
|--------------------------------------------------------------------|
| **Best N/w.s**                                                                 |
| Iteration #            | Training | Cross Validation |
|------------------------------------------|-----------|-------------------|
| Epoch #                        | 998       | 20                |
| Min. MSE                     | 0.000130869 | 0.036477847       |
| Final MSE                    | 0.000130878 | 0.104271808       |

Here, Table 3 shows the result of Training & Cross-Validation Data with Iterations & Epochs.

![Graph 3: Training MSE](image)

Here, Graph 3 shows the result of Training MSE with three Runs for 1000 epochs.

![Graph 4: Showing Cross-Validation MSE](image)

Here, Graph 4 shows the result of Cross-Validation MSE with three Runs for 1000 epochs.

The following table 4 shows the result as shown;

| Table 4: Result of MII using SOFM Network |
|------------------------------------------|
| **Statistical Analysis**                          | **Self Organizing Feature Map Network** |
|                                               | Training | Testing | Cross-Validation |
| MSE                                          | 0.017533313 | 0.014402717 | 0.022517189 |
| NMSE                                         | 0.290747859 | 0.25610934 | 0.352838952 |
| MAE                                          | 0.060287812 | 0.061996583 | 0.071996975 |
| Min Abs Error                                | 0.001976062 | 0.001051081 | 0.002316751 |
| Max Abs Error                                | 0.530555095 | 0.587123778 | 0.49674898 |
| r                                            | 0.824768936 | 0.864429812 | 0.810862319 |
| Percent Accuracy                             | 84.78771044 | 89      | 82            |

Table 4 shows the results of musical instrument identification using Self Organizing Feature Map Network with parameters as MSE, NMSE, MAE, r and Percentage Accuracy for Training, Testing and Cross-Validation phases.

IV. CONCLUSIONS:

Numbers of experiments are performed to extract Timbral features which are required to identify the musical instruments & analyzed and performed experimentation using Self Organizing Feature Map Network as classifier and concluded that SOFM Network gives 89% accuracy for Testing with 82% accuracy for Cross-Validation.
V. FUTURE SCOPE:
The above techniques can be used for image identification as well as image features extraction.

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