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Music Instrument Sound Classification using KNN

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Abstract: Automatic instrument sound classification is very useful in music analysis. This system tested in ten different classes of musical instrument sound from two different instruments. The accuracy of the classification relies on the strength of the features and classification scheme. In this paper, Mel-Frequency cepstral coefficients (MFCC) features are extracted from the input Signal and describes a technique that uses K-Nearest Neighbour (KNN) to classify music. The proposed feature extraction and classification models results in better accuracy in music genre classification.

Index Terms **- Music Instrument Signal, Feature Extraction, Mel-Frequency cepstral coefficients (MFCC), K-Nearest Neighbour (KNN)**

I. Introduction

Musical instrument sound classification have a complex interaction between the public, marketing, historical, and cultural factors [1]. This perception has driven a few analysts to propose the meaning of another sort order conspire only for the reasons for music data recovery [2]. The classification of musical instruments was a lengthy manual process. Everyone in the present era listens to and plays music. Music is diverse all around the world. It is the fulcrum of all the arts and a language that speaks for itself. We might argue that this immaculate art's vast history extends to infinity and beyond [3]. Each instrument has different acoustic and physical properties that define their own particular timbre. Humans can reliably identify the sources of sounds based on listening, which must be due to some properties in the sound that can be related to timbre [4]. In this proposed work, the musical instruments sound classification is done in three steps, first is the preprocessing of musical data, then the features are extracted and finally the classification process. Figure 1 shows block diagram of the proposed work.

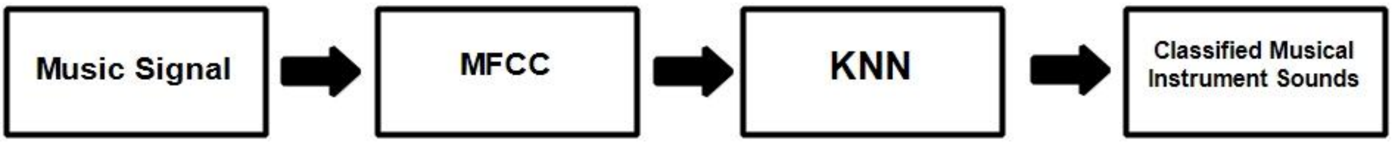

Fig. 1 Block diagram of the proposed work

II. Mel-Frequency Cepstral Coefficients (MFCC)

Mel-frequency cepstral coefficients (MFCCs) are extensively used in music Analysis [5]. The Mel-frequency cepstrum has shown to be profoundly compelling in perceiving construction of music signals and in demonstrating the abstract pitch and recurrence content of sound signs [6]. MFCCs depend on the known variety of the human ears basic transfer speeds with recurrence, channels divided straightly at low frequencies and logarithmically at high frequencies to catch the phonetically significant qualities of discourse and sound [7]. The sound signs were divided and windowed into short casings. Greatness range was figured for every one of these edges utilizing quick Fourier change (FFT) and changed over into a bunch of Mel scale channel bank yields. Logarithm was applied to the filter bank outputs followed by discrete cosine trans-formation to obtain the MFCCs [8]. The filter bank has a triangle bandpass frequency response, and the bandwidth distance is determined by the mel-frequency interval constant [9].
In this work, a 14th order MFCC analysis is used to approximate the spectral samples and hence obtained a 14-dimensional feature vector for a speech signal of frame size of 20 milliseconds is obtained.

III. K-NEAREST NEIGHBOUR (KNN)

KNN classifier is non- parametric strategy utilized for order [10]. KNN is a supervised learning technique a new instance is classified based on the closest training samples present in the feature space [11]. It does not use any model to fit, and is only based on memory. At the point when a test information is entered, it is alloted to the class that is generally basic among its k closest neighbors. KNN classifier is non- parametric strategy utilized for order. It needn't bother with any earlier information about, the structure of the information in preparing set. On the off chance that the new preparing design is added to existing preparing set. Any ties can be broken indiscriminately. The KNN algorithm uses the neighbourhood classification as the prediction value of the new query instance. The KNN algorithm is sensitive to the local structure of the data. The K-Nearest Neighbour is one of those algorithms that are very simple to understand but works incredibly well in practice [12].

IV. RESULTS AND DISCUSSION

4.1 The database

The data is collected from databases with distinct characteristics for instruments classification. In our work dataset consists of 661 audio tracks each 30 seconds long. It contains 4 instruments. The tracks are all 22050Hz Mono 16-bit audio files in .wav format.

Table 1 Classes and number of samples in the database

Instruments	Samples
Violin	200
Guitar	156
Flute	136
Trumpet	169

4.2 Acoustic feature extraction

In this work fixed length frames with duration of 20 ms and 50 percentages overlap (i.e., 10 ms) are used. The objective of overlapping neighbouring frames is to consider the harmonic information characteristic of audio content. An input wav file is given to the feature extraction techniques. MFCC 14 dimensional feature values will be calculated for the given wav file. The above process is continued for 661 number of wav files.

4.3 Classification

The training process analyzes music training data to find an optimal way to classify music frames into their respective classes. The feature vectors are given as input and compared with the output to calculate the error. Experiments were conducted to test the performance of the system using KNN. Figure 2 shows the performance of music classification using KNN for different duration respectively.

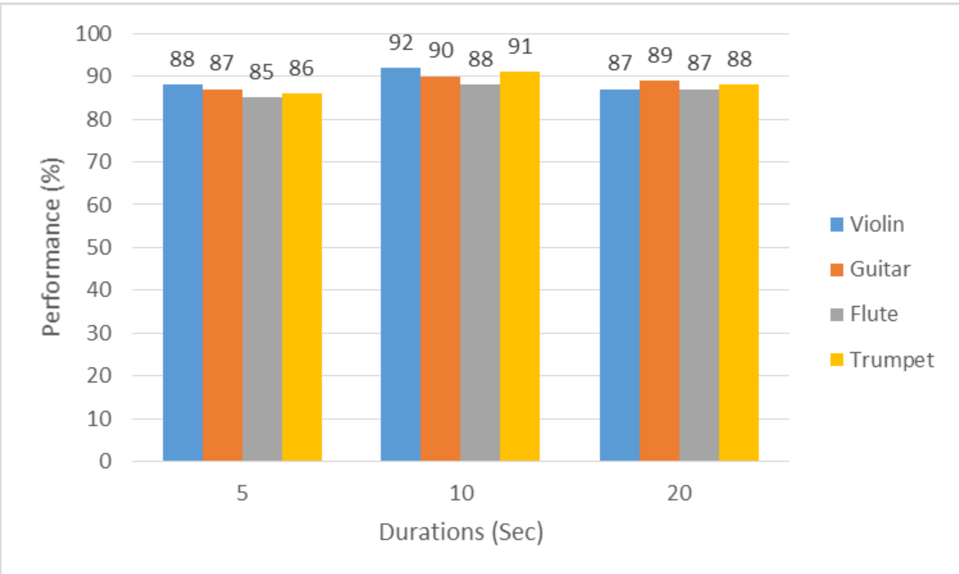

Fig. 2 Performance of music instrument classification for different duration of music clips using KNN

IV. CONCLUSION

In this paper, a music instrument classification system using KNN. MFCC is determined as elements to describe music content. KNN learning algorithm has been used for the classification of a music instrument classification by learning from training data. It shows that the proposed method can achieve better classification accuracy than other approaches. Experimental results show that the proposed audio KNN method has good performance in musical genre classification scheme is very effective and the accuracy rate is 92%.

REFERENCES

[1] R. Thiruvengatanadhan, “Music Genre Classification using Chromagram and GMM”, International Journal of Innovative Research in Computer and Communication Engineering, Vol. 6, Issue 3, March 2018.

[2] O.M. Mubarak, E. Ambikai rajah and J. Epps, “Novel Features for Effective Speech and Music Discrimination,” IEEE Engineering on Intelligent Systems, pp. 342-346, 2006.

[3] Shreevathsa, P. K., Harshith, M., A. R. M. & Ashwini, "Music Instrument Recognition using Machine Learning Algorithms," 2020 International Conference on Computation, Automation and Knowledge Management (ICCAKM), 2020, pp. 161-166, doi: 10.1109/ICCAKM46823.2020.9051514.

[4] Thomas D Rossing and Folden B Stumpf. The science of sound, 1982.

[5] R. Thiruvengatanadhan, P. Dhanalakshmi, and S. Palanivel, “GMM Based Indexing and Retrieval of Music Using MFCC and MPEG-7 Features,” Emerging ICT for Bridging the Future, Springer Advances in Intelligent Systems and Computing, Volume 1, pp. 363-337, 2014.

[6] Nagavi, T.C., Anusha, S.B., Monisha, P., Poornima, S.P.: Content based audio retrieval with MFCC feature extraction, clustering and sort-merge techniques Computing. In: 2013 Fourth International Conference on Communications and Networking Technologies (ICCCNT), July 4-6, pp. 1–6 (2013)

[7] Kinnunen, T., Saeidi, R., Sedlak, F., Lee, K.A., Sandberg, J., Hansson-Sandsten, M., Li, H.: Low-Variance Multitaper MFCC Features: A Case Study in Robust Speaker Verification. IEEE Transactions on Audio, Speech, and Language Processing 20(7), 1990–2001 (2012)

[8] Krishna Kishore, K.V., Krishna Satish, P.: Emotion recognition in speech using MFCC and wavelet features. In: 2013 IEEE 3rd International Advance Computing Conference (IACC), February 22-23, pp. 842–847 (2013)

[9] F. Amelia and D. Gunawan, "DWT-MFCC Method for Speaker Recognition System with Noise," 2019 7th International Conference on Smart Computing & Communications (ICSCC), 2019, pp. 1-5, doi: 10.1109/ICSCC.2019.8843660.

[10] R. Thiruvengatanadhan, “AANN and KNN based Music Classification using Chromagram”, GIS SCIENCE JOURNAL, VOLUME 8, ISSUE 1, 2021.

[11] U. Rajendra Acharya, Filippo Molinari, S. Vinitha Sree, Subhagata Chattopadhyay,Kwan-Hoong Nge, and Jasjit S. Suri, “Automated diagnosis of epileptic EEG using entropies,” Elsevier Biomedical Signal Processing and Control, vol. 7, pp. 401–408, 2012.

[12] Subhas Halder, An Approach to Diagnosis of Cancer Using k-Nearest Neighbour (k-NN) Algorithm, Ph. D thesis, Jadavpur University Kolkata, May, 2013.