Oriental Musical Instruments Identification by Selecting Optimized Features and Suitable Classifier

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DECLARATION

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ABSTRACT

The research field of Music Information Retrieval is a particular subcategory, which brings out data from the audio signal by the expedient of digital signal analysis. This thesis deals with temporal and spectral features of music instruments. Particularly, the formant concept of timbre is the main subject all through. This theory expresses that auditory musical instrument sounds may be classified with the aid of their formant structures. Ensuring this concept, our method aims to suggest a computer based implementation for constructing tools for musical instrument recognizable proof and grouping systems.

One of the most crucial aspects of musical instrument classification is selecting the relevant set of features, which are very important steps in musical instrument identification. Feature selection is an important task in musical instrument identification. Feature selection is one routine of reaching dimension reduction, and after an ephemeral debate of various feature selection techniques, the study endorses a derived technique for predominant feature selection in a sequential forward feature selection with a greedy algorithm. This technique is empirically selected to optimize the best set of features by using train data and it is displayed to gain classification accuracy with a diminished predominant set of features much like that gained with a complete set of features. This study extracted the 44 features from 20 musical instruments with three musical families.

The three classifiers used in this task, were Decision Tree, kNN, SVM and CNN. The best-selected features have been used in the classification. The confusion matrix got from each classification for evaluation to the performance of the classifiers. The SVM classifier contains the lowest error rate, and the highest AUC scores most values are 1 and a few are within the range of 0.99 - 0.98. Finally, the approval results are finished. SVM classifier is found to be the best classifier among the four classifiers. The predominant features are selected by the Greedy algorithm with SFFS technique for individual musical instrument and selected features are used for polyphonic music identification.

Keywords: Predominant features, Feature selection techniques, Musical instrument.

Polyphonic music

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LIST OF ABBREVIATIONS

Acronym Definition

AC Autocorrelation Coefficients

AUC Area Under the receiver operating characteristics Curve

BT Binary Tree Classifier

CNN Convolutional Neural Network

CPNN Counter Propagation Neural Network

DNN Deep Neural Network

DT Decision Tree

FFT Fast Fourier Transformation

HC Hierarchical Cluster

kNN k-Nearest Neighbors

LDB Local Discriminant Bases

LiFT likelihood-frequency-time

LPC Linear Prediction Coefficient

LPCC Linear Predictive Coding coefficients

MFCC Mel-Frequency Cepstral Coefficient

MIMN Multiple Instrument Multiple Note

MIR Musical Information Retrieval

MPEG-7 Moving Picture Exports Group - Multimedia Content

Description Framework

Acronym Definition

MUMS McGill University Master Sample

NMF Non-negative Matrix Factorization

OMII Oriental Musical Instruments Identification

PDF Probability Density Function

RANSAC Random sample consensus

ROC Receiver Operating Characteristics

SFFS Sequential Forward Feature Selection

SIMN Single Instrument Multiple

SISN Single Instrument Single Note

SVM Support Vector Machine

VZCR Variance of Zero Crossing Rates

ZCR Zero Crossing Rates