Towards Automatic Transcription of Expressive Oral Percussive Performances

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ABSTRACT

We describe a tool for transcribing voice generated percussive rhythms. The system consists of: (a) a segmentation component which separates the monophonic input stream into percussive events (b) a descriptors generation component that computes a set of acoustic features from each of the extracted segments, (c) a machine learning component which assigns to each of the segmented sounds of the input stream a symbolic class. We describe each of these components and compare different machine learning strategies that can be used to obtain a symbolic representation of the oral percussive performance.

Categories and Subject Descriptors

H.5.2 [**Information Interfaces and Presentation**]: User Interfaces—*Voice I/O*; H.5.5 [**Information Interfaces and Presentation**]: Sound and Music Computing

General Terms

Human Factors, Performance

Keywords

Knowledge-based approaches, speech processing, performance transcription

1. INTRODUCTION

This paper focuses on information retrieval in voice generated rhythms. The aim of this work is to develop a system able to reduce the gap between the user and a device (namely keyboard, drum pad or GUI) in order to get a symbolic rhythmic representation. This is relevant as many musicians who just have an intuitive notion of rhythm and groove can not easily transcript a beat they have in mind. Furthermore, in both non western music and recent western urban genres, the oral tradition of music and especially rhythm is predominant. Few works have focussed in automatically indexing non standard drum based rhythms and an effort towards finding a representation that can apply to a whole range of acoustic oral rhythms from beat boxing to Indian tabla oral recitals has to be done. This can be achieved in several ways, from finding an appropriate instrument taxonomy asserting that any performer tries to imitate some drum percussion, to using a completely data-driven model with non supervised methods. Between theses extremes, one can consider the taxonomy of human phonemes as a starting point to identify recurrent oral drum clusters. The other issue raised by this work is that even though each percussive event was perfectly segregated and transcribed, the resulting drum score would lack information describing how the performer has modulated the produced sounds, that is, oral performance expressivity. Thus, a representation of oral percussion expressive effects (e.g. energy and resonance frequency variation, use of harmonic sounds, distortion) has to be defined along with effective computational methods to track them. We must provide enough flexibility to the system so that it is able to assign the same instrument to a family of somehow modulated sounds and at the same time being able to track the expressive modulation events. Recent works in non standard drum percussive signals transcription and sax expressive performance analysis suggest that we can take advantage of performing some contextual analysis of the oral drum part instead of just considering the description of each isolated percussive event. As a starting point we present a system that performs automatic transcription of oral percussive performance into a 4 drum-class score. The system performs percussive event segmentation of the input audio stream, descriptors generation of the percussive segments and classification regarding the generated descriptors. The user interface and signal processing components were designed and implemented within the Object Oriented CLAM framework [1] and are presented below. In continuation we test different Machine Learning techniques on multi-user training and test sets and discuss the results. Finally some related work is presented.

2. SOUND SEGMENTATION

In order to segment the input audio stream, that is, to index each percussive event with an onset time and a duration, we used an energy based algorithm that decomposes the input stream into successive and possibly overlapping frames, computes each frame energy, and indexes successive frames with an overall energy greater than a user-defined threshold.

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[1]http://www.iua.upf.es/mtg/clam

This simple method fits well to monophonic oral percussive recordings and requires few computational resources, compared to more complex and time consuming method, such as the multi-band processing using psychoacoustic knowledge used in [6].

3. ORAL PERCUSSIVE DESCRIPTORS

We defined a compact representation of oral percussive sounds, based on [1] which focussed on classifying acoustic and synthetic drum sounds and which highlighted the importance of some descriptors to classify unpitched sounds. We believe that the noisy nature of oral percussive can lead to good results using similar features. Each percussive event was split into an attack part and a release part with another segmentation algorithm that finds the maximum of the sound envelope to detect the attack/decay boundary. In the case of oral percussive sounds the attack part is considerably shorter than the release. Therefore, we only extracted temporal descriptors from the attack and both temporal and spectral descriptors from the decay part.

Temporal Features: We included in our system the following temporal features. **Duration** refers to the duration of the segmented attack or decay part and **LogDuration** to its natural logarithm, **Energy** refers to the mean energy of the segmented part. **Zero-crossing rate** is calculated as the rate the signal changes sign in a given period of time, that is, the duration of the segmented part. **Temporal centroid** refers to the time averaged over of the energy enveloppe.

Spectral Features: To compute the spectral features, we performed a Fast Fourier Transform of the successive frames of the decay part of the oral percussive event, and for each of the frames, we computed the descriptors presented below. **Energy** refers the calculated energy of the spectrum at a given frame, while **Centroid** refers the the center of gravity of the spectrum. **Flatness** is the ratio between the geometrical mean and the arithmetical mean of the spectrum. A flat spectrum sound tends to be perceived as noisy while low flatness reflects more harmonic sounds. **Kurtosis** is the fourth-order central moment and gives information about whether the sound spectrum is peaky or not. Finally, **Mel Frequency Cepstrum Coefficients (MFCC)** have been used in speech recognition and musical application due to their capacity to give a compact representation of the spectrum based on a source-filter model. We retained the first five MFCC. In order to obtain a summary of the evolution of these spectral features along the decay part, we retained their respective mean and the variance of each one. Consequently we generated a training set which was composed by instances of 28 features, namely 10 temporal features and 18 spectral features.

4. MACHINE LEARNING TECHNIQUES

A taxonomy of 4 standard drum sounds was defined i.e the classes were *Bass Drum*, *Snare Drum*, *Closed Hat* and *Open Hat*. A set trained from the recordings of 4 performers, 2 men and 2 women, was used (they were asked to imitate the sound of each of the drum classes), totalizing 242 training instances. Different machine learning techniques that were tested on this dataset are presented below.

Tree induction algorithms build a tree model by selecting at each node the most relevant attribute. We compare the results of C4.5 [2], C4.5 with boosting, and C4.5 with bagging. Boosting refers to a meta algorithm that can improve the results of any classification algorithm by giving to each instance of the training set a particular weight proportional with the difficulty to classify such instance. That is, a first classification model is proposed giving the same weight to all the training instances. Misclassified instances with this model are then given a greater weight, and so on. After a user defined number of iterations (in our case 10 iterations) the resulting model is able to deal with "difficult" training instances. This boosting method can drastically improve the results of an inaccurate model, thought overfitting can occur. Bagging helps improving classification by sampling the training set in smaller training sets, and calling the induction tree to build a model for each of these subsets. The classification decision is then taken combining the votes of each of the sub-models.

Lazy Methods: The notion of lazy learning subsumes a family of algorithms that store the complete set of given (classified) examples without building a compact model. They delay all further calculations until requests for classifying yet unseen instances are received. We included in our experiment K-Nearest Neighbor algorithm, one of the most popular instanced-based algorithm, which handles well noisy data if the training set has an acceptable size. The main idea of this algorithm is to compare a test set with its nearest neighbors (which number is determined by the user, we empirically found the best accuracy for K=1).

5. CLASSIFICATION RESULTS

The presented classification results of our system come from 2 experiments. In the first one, we performed a 10 fold cross validation of the training set, that is, the model was built 10 times, putting apart a bag of training instances in order to test them against this model. This methods gives a preliminary idea of the the classification accuracy of the system, and the results are presented in Table 1. In the second experiment we simulated a real world situation of the system, as we tested the classification model with 2 new performers recordings that were not used in the training set. The results of the experiments are presented in Table 2. The classification accuracy, denoted C.A, has to be compared with the accuracy of a random classification i.e. 25%.

Algorithm	C.A(%)
kNN	75.7
C4.5	81.6
C4.5 w/Boosting	89.3
C4.5 w/Bagging	**86.9**

Table 1.Cross validation results of the training set

Algorithm	C.A(%)
kNN	79.0
C4.5	79.0
C4.5 w/Boosting	87.0
C4.5 w/Bagging	**90.0**

Table 2. Classification accuracy for a test set with recording from unseen performers

6. DISCUSSION AND FUTURE WORK

A classification accuracy of 90% has been obtained in a test involving 2 performers whose recordings were not used in the training set, the test set being composed of 62 instances. This last experiment gives an idea of the accuracy that can be reached in a real world application, and the results are encouraging. The percussive event descriptors presented before have shown to be useful, especially attack and decay durations and zero crossing rate among the temporal descriptors, kurtosis, second and fourth MFCC means among the spectral descriptors. Nevertheless the system performs classification into a fixed 4 class taxonomy, and the results fall quickly if we use a test set in which the user produces the rhythm using quite different phonemes compared to these that were used during the training. To improve the robustness of the system, we plan to consider a rhythmic role based analysis which would use the human phoneme taxonomy, considering that 2 different successions of phonemes can describe the same rhythmic pattern, especially if the user performs expressive modulations of the oral beat. As mentionned earlier, and unlike in [3] or [4], this work aims to consider the oral percussive expressivity that does not appear in a symbolic drum pattern and to define a corresponding representation. To achieve this, we plan to increase the amount of training data and the diversity of the sources. We finally plan to study the modalities of a fast recognition system using results from [5], in order to design a real time application.

7. RELATED WORK

Automatic audio analysis has been widely studied during the past years, and a growing interest has been shown in developing high level content extraction systems able to process automatically large amounts of data. Some works have largely helped the developments of the automatic drum classification branch. In [6] a system that performs sound segmentation using psychoacoustic knowledge (i.e using the characteristics of human auditive perception) has been designed. Automatic drum transcription has been studied in [1] using the standard drum taxonomy at 3 levels of abstraction. [8] deals with the problem of beat induction and meter detection of segmented signals. The problem of analyzing audio percussive excerpts which are not generated using standard drum sounds is studied in [9, 10] when some context analysis of the percussive events is considered. In [9], which focuses on the automatic labelling of tabla signals into tabla recital vocabulary, a Hidden Markov Model is considered to represent the contextual dependencies between percussive strokes and because the representation symbols may be context dependent. In [10], arbitrary sounds such as voice, or hand claps can be segregated into 3 labels that represent a rhythmic role rather than an instrument, and thus concentrate on the pattern context of each rhythmical event. Context analysis has also been used in [11] to study expressive transformations in monophonic sax performances of jazz standards. In this work, melodic context of each score notes is taken into account to induce performance transformations rules. The basis of the presented work was defined and a preliminary implementation of the system was done in [7]. Two systems based on Beat Boxing signal analysis for drum pattern retrieval are presented in [3] and [4].

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