# Development of a Rhythm Similarity Model for Electronic Dance Music

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## ABSTRACT

This research investigates rhythmic similarity in Electronic Dance Music (EDM). Rhythm in EDM is built on the concept of a 'loop', a repeating pattern often associated with a four-measure percussive pattern. In our model, music tracks are segmented using a structural segmentation algorithm developed in previous research, and features are extracted from the audio. A segment is split into different streams of rhythmic patterns, where each pattern is described with three attributes: a) characterization of attacks, b) periodicity of rhythmic elements, and c) metrical distribution of onsets. These attributes for all patterns within a segment contribute to the rhythm characterization of that segment. Finally, an algorithm is developed to measure similarity between segments.

## 1. INTRODUCTION

Electronic dance music (EDM) is an umbrella term consisting of the 'four on the floor' genres such as techno, house, trance, and the 'breakbeat-driven' genres such as jungle, drum 'n' bass, breaks. These genres are characterized by a specific rhythmic pattern. In general, four on the floor genres are characterized by four steady bass-drum quarter notes whereas breakbeat-driven exploit rhythm irregularity [2]. However, multiple types of subtle rhythmic variations and embellishments exist. Our goal is to develop a rhythm similarity model that captures these embellishments and allows for a fine inter-song rhythm similarity.

A large and diverse literature deals with the challenges of audio rhythm similarity. This includes approaches on onset detection [1], tempo estimation [7], rhythmic pattern description and genre classification [6]. Specific to EDM, [3] investigate temporal and structural features for automatic music generation.

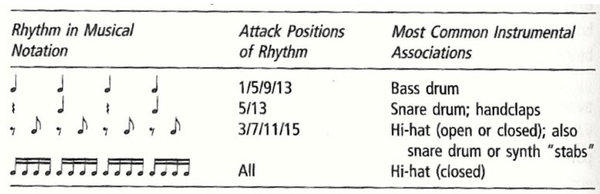
The aim of this study is to develop a rhythm similarity algorithm that models both EDM characteristics as well as rhythm perceptual attributes. In future research, the model will be evaluated with human annotations.

## 2. DATASET

Our music dataset consists of a total of 1236 audio recordings from 60 well-known artists of a balanced number of EDM genres and subgenres. As a preprocessing step, the segmentation algorithm developed in [5] is applied. This detects structural boundaries based on timbral features and music heuristics, resulting in a total of 21676 segments. For the preliminary evaluation of the model, a subset of segments from this dataset is used.

## 3. METHODOLOGY

Rhythm in EDM is described based on the following music characteristics: a) Musical structure in EDM is built on the concept of a loop, a repeating pattern associated with a particular instrument or instruments. This often exhibits a certain rhythm polyphony (see Fig. 1). To analyze this polyphony, we split the rhythmic elements into different perceptual streams. b) Typically, loops consist of drum patterns although loops of other instruments are also used. To differentiate between percussive and non-percussive loops, we characterize the attack phase of the onsets. c) A loop may refer to a pattern consisting of multiple repeating sequences, hence, we analyze onset layers with different periodicities. d) Finally, we model the metrical aspects of the rhythmic pattern. Based on the above characteristics, a feature vector is extracted for each segment and is used to measure rhythm similarity. Details for each step are provided below.



| Rhythm in Musical Notation | Attack Positions of Rhythm | Most Common Instrumental Associations |
|---|---|---|
| | 1/5/9/13 | Bass drum |
| | 5/13 | Snare drum; handclaps |
| | 3/7/11/15 | Hi-hat (open or closed); also snare drum or synth "stabs" |
| | All | Hi-hat (closed) |

**Fig. 1:** Example of a common (symmetrical) rhythm in electronic dance music [2, p. 82].

### 3.1. Rhythmic Streams

An onset detection method with psychoacoustic modeling is considered and perceptual streams are estimated with respect to the frequency domain. In particular, the FFT is computed and magnitude spectra, transformed in logarithmic scale, are assigned to bark bands. Synchronous masking is modelled using Schroeder's spreading function, and temporal masking is modelled using a smoothing window of 100 ms. A self-similarity matrix is computed from the 24-band spectral representation, and the novelty approach [4] is applied to detect which bands should be grouped to the same stream. The difference of magnitude spectra is computed on each band prior summing to the different streams, and onsets are detected via peak extraction within each stream. This onset detection approach incorporates similar methodological concepts with the best performing algorithm for the task of audio onset detection [1] in MIREX 2012, and the best performing tempo estimation methods described in [7]. Features are extracted within each stream, and combined accordingly to a feature vector as described below.

### 3.2. Attack Characterization

To differentiate between percussive and non-percussive loops we extract features that characterize the attack phase of the onsets. For all onsets in all streams, the mean and standard deviation of the attack time and attack slope is computed (a total of 4 features).

### 3.3. Rhythm Periodicity

To model the different rhythm periodicities, features are extracted from the autocorrelation of the onset function. These include the lag time of maximum autocorrelation, entropy, and harmonicity of peaks (a total of 3 features).

### 3.4. Metrical Distribution

To model the metrical aspects of the rhythmic pattern we compute the metrical profile [6]. To do this, we detect the first downbeat by simply estimating the first onset in the stream of the lowest frequencies (i.e., the first beat of the bass drum), quantize the onsets assuming a $4/4$ meter and 16-th note resolution [2], and finally collapse the pattern to 2 measures. This gives a total of 32 features. From this profile, we measure syncopation, density, and the center of gravity of events (a total of 3 more features).

## 4. PRELIMINARY EVALUATION

A preliminary across-segment similarity was computed using the cosine distance. Similarity via different sets of features was also addressed. Four subjects evaluated the algorithm's output and the following was noted: a) the metrical profile is essential in modelling rhythm similarity (a finding also supported in [6]), b) more investigation on the relation of rhythmic elements amongst the different streams might improve the output.

## 5. CONCLUSION

We have presented a model for investigating rhythm similarity in EDM based on music-specific characteristics as well as rhythm perceptual aspects. For each segment in our database, features related to these characteristics were extracted, and inter-segment similarity was preliminary addressed via the cosine distance. Further investigation and evaluation is considered in future work.

## 6. REFERENCES

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