Classification of Dance Music by Periodicity Patterns

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Outline

- Aims
- Musical Background
- Periodicity Detection
  - IOI Clustering
    (Dixon, Goebl & Widmer, ICMAI2002)
  - Bandwise Autocorrelation
    (Paulus & Klapuri, ISMIR2002)
- Experimental Results
- Current and Future Work

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Aims

- Genre classification for standard & Latin ballroom dance music
  - common characteristics: strong beat, constant tempo
  - recognisable differences (e.g. tango, waltz, jive)
- Using temporal features only
- Comparison of methods for determining periodicities
- Evaluation of information provided by periodicities

Musical Background

- Pulse: a regularly spaced stream of accents

- Beat: the primary pulse

- Meter: (hierarchical) grouping of pulses

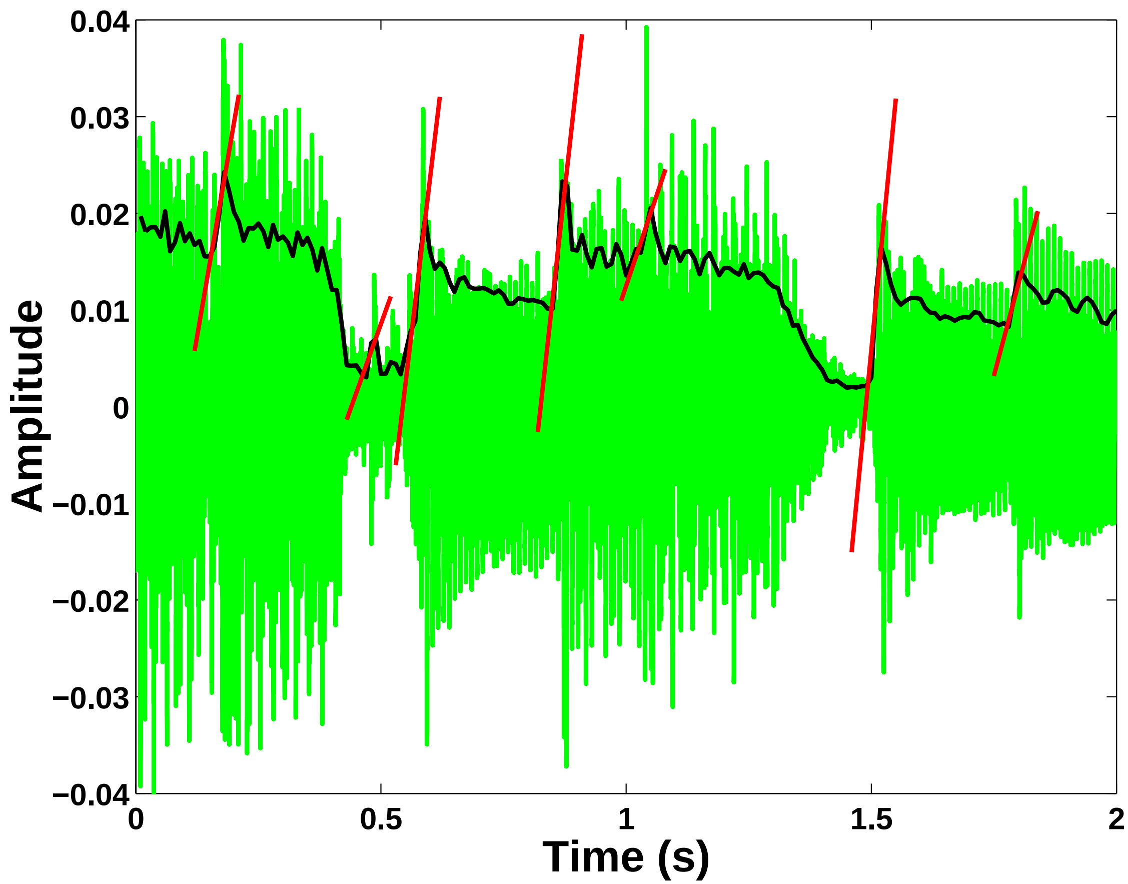
- Metrical level: a level of the metrical hierarchy

Method 1: IOI Clustering

- Single frequency band
- Onset detection
- Calculation of inter-onset intervals (IOIs)
- Clustering of IOIs (weighted IOI histogram)

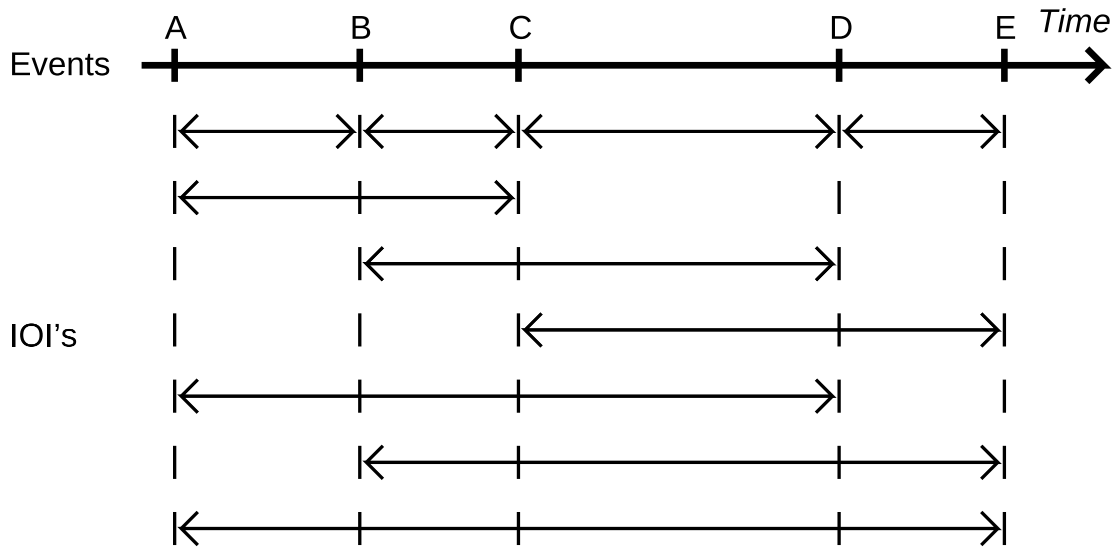
Onset detection

- 40ms windowed RMS smoothing with 75% overlap
- Find peaks in slope of envelope

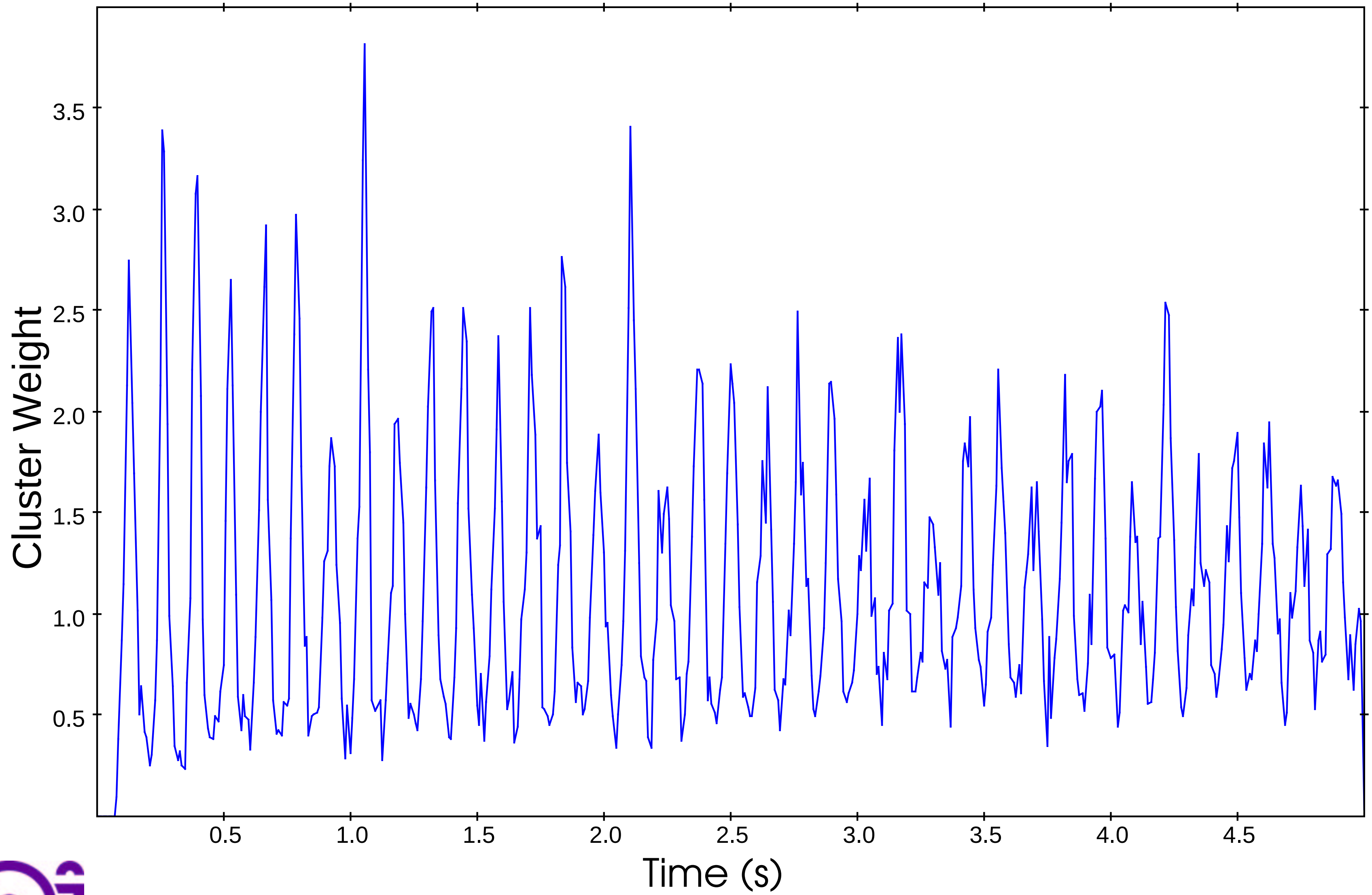


Clustering: IOI calculation

Clusters correspond to musical time units

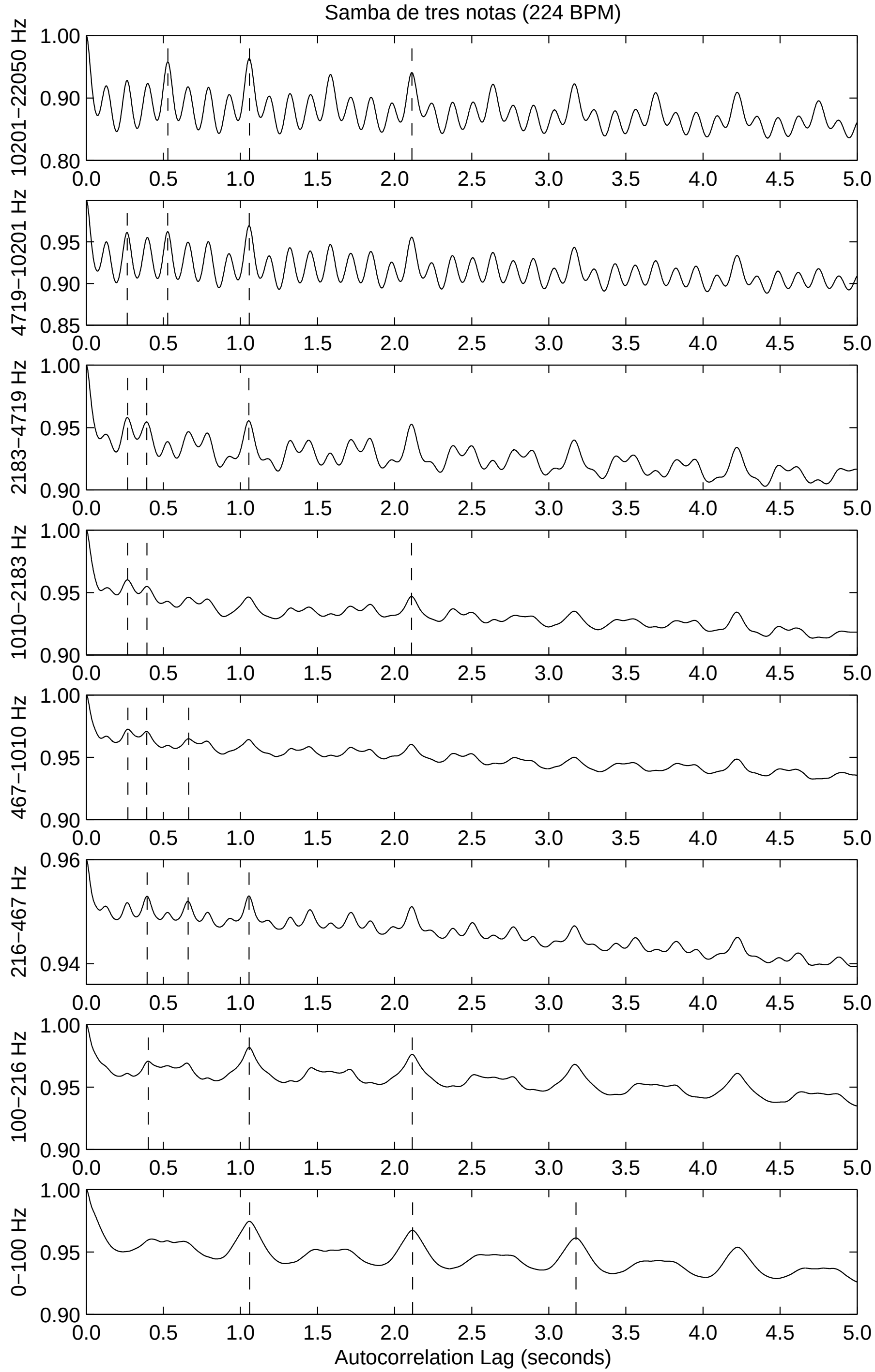


Clustering: Results



Method 2: Autocorrelation

- Multiple frequency bands: 0–100Hz, then 7 logarithmically spaced bands to 22050Hz
- Amplitude envelopes: each band was rectified, squared, decimated to 980Hz sampling rate and smoothed with a 20Hz LP filter
- Dynamic range compression (logarithmic)
- Autocorrelation calculated for lags of 0–5 seconds


Samba de tres notas (224 BPM)
10201–22050 Hz
4719–10201 Hz
2183–4719 Hz
1010–2183 Hz
467–1010 Hz
216–467 Hz
100–216 Hz
0–100 Hz
Autocorrelation Lag (seconds)

Autocorrelation: Peak Selection

- Normalisation by peak at lag 0
- Peak at lag 0 discarded
- 3 highest peaks from each band selected
- Peaks within 20ms combined
- Peaks weighted by number of bands plus (average) autocorrelation

Determination of Meter and Beat

- Same method for both types of input data
- Distinguish beat and meter from other metrical levels
- Assign a musical meaning to each periodicity
- Exhaustive approach: all possible interpretations are evaluated

Evaluation of Meter Hypotheses

- Ratio of periodicity to beat is calculated as a simple fraction
- Error and complexity of each fraction are estimated
- Weighted sum of periodicity weights computed for even and odd meters
- Weights are corrected for tempo and the errors and complexities of fractions

Genre Classification

- Simple rule-based approach
- Based on known features of genres
- Hand-coded
- Uses tempo, meter and periodicity distribution

Sample Rules

```
viennesewaltz(Meter, Tempo) :-
        Meter = 3,
        Tempo > 40.

slowwaltz(Meter, Tempo) :-
        Meter = 3,
        Tempo <= 40.

quickstep(Meter, Tempo) :-
        Meter = 4,
        Tempo <= 54,
        Tempo > 48,
        weight(3/8) <= 3.
```

Test Data

- Tested with dance CDs (genre and/or tempo specified)
- Small set (161 tracks with style specified, 96 with tempo)
- 17 styles (several with only 1 or 2 examples)

Results: Ranking of Periodicities

Where did the bar and beat levels appear in the rankings?

Rank:		1	2	3	4	5	6	7	8	9	none
Method 1: Clustering	Bar	13	16	16	9	11	13	13	3	2	0
	Beat	11	16	18	15	9	12	10	1	1	3
Method 2: Correlation	Bar	19	20	25	10	13	1	1	0	0	7
	Beat	30	25	20	7	4	0	0	0	0	10

The beat and bar level were ranked among the highest 10 periodicities in almost all cases.

Results: Classification Rate

	IOI-Clustering	Correlation
Tempo	53/96	65/96
Meter	142/161	150/161
Style	36/52	52/65

Tzanetakis and Cook (2002) report 61% correct classification for 10 (non-similar) genres, using features representing timbre, rhythm and pitch

Results: Tempo Error Types

	IOI-Clustering	Correlation
Half tempo	4	10
Double tempo	24	16
Wrong meter	14	5
Other	1	0

Confusion Matrix

	PD	SA	TA	SF	QU	RR	RU	SW	CH	BO	WW	FO	JI	MA
PD	5	-	-	-	-	-	-	-	-	-	-	-	-	-
SA	-	3	-	-	-	-	-	-	-	-	-	-	-	1
TA	-	-	6	-	-	-	-	-	1	-	-	-	-	-
SF	-	-	-	4	-	-	-	-	1	-	-	-	1	-
QU	-	3	-	-	6	-	-	-	-	-	-	-	-	-
RR	-	-	-	-	-	-	-	-	-	-	-	-	-	-
RU	-	-	1	-	-	-	4	-	-	-	-	-	-	-
SW	-	-	-	-	-	-	-	6	-	-	-	-	-	-
CH	-	-	-	-	-	-	-	-	-	-	-	-	-	-
BO	-	-	-	-	-	-	-	-	-	-	-	-	-	-
WW	-	-	-	-	-	-	-	-	-	-	2	-	-	-
FO	-	-	-	-	-	-	-	-	-	-	-	-	-	-
JI	-	-	-	-	-	1	-	-	-	2	-	2	16	-
MA	-	-	-	-	-	-	-	-	-	-	-	-	-	-

Current (Future) Work

- Analysis of sequences of events
- Estimation of metrical boundaries
- Encoding and catalaguing temporal patterns
- Similarity and genre estimation based on these patterns
- Machine learning of categories (more data required)