INTERNATIONAL AUDIO LABORATORIES ERLANGEN

Lecture
Music Processing

Tempo and Beat Tracking

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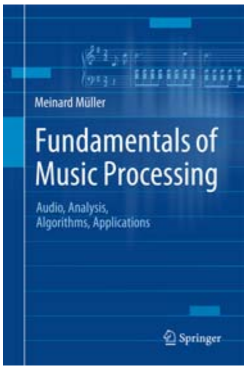
Fraunhofer IIS

Book: Fundamentals of Music Processing



Meinard Müller
Fundamentals of Music Processing
Audio, Analysis, Algorithms, Applications
483 p., 249 illus., hardcover
ISBN: 978-3-319-21944-8
Springer, 2015

Accompanying website:
www.music-processing.de

Book: Fundamentals of Music Processing

Chapter	Music Processing Scenario
1	Music Represenations
2	Fourier Analysis of Signals
3	Music Synchronization
4	Music Structure Analysis
5	Chord Recognition
6	Tempo and Beat Tracking
7	Content-Based Audio Retrieval
8	Musically Informed Audio Decomposition

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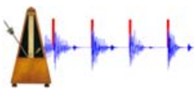
Chapter 6: Tempo and Beat Tracking



Tempo and beat are further fundamental properties of music. In Chapter 6, we introduce the basic ideas on how to extract tempo-related information from audio recordings. In this scenario, a first challenge is to locate note onset information—a task that requires methods for detecting changes in energy and spectral content. To derive tempo and beat information, note onset candidates are then analyzed with regard to quasiperiodic patterns. This leads us to the study of general methods for local periodicity analysis of time series.

Introduction

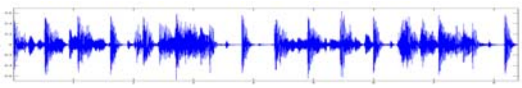
Basic beat tracking task:

Given an audio recording of a piece of music, determine the periodic sequence of beat positions.

“Tapping the foot when listening to music’’

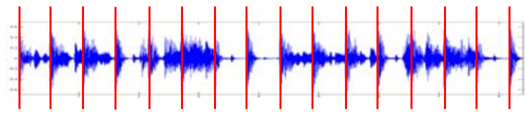
Introduction

Example: Queen – Another One Bites The Dust



Introduction

Example: Queen – Another One Bites The Dust



Introduction

Example: Happy Birthday to you

Pulse level: **Measure**

Introduction

Example: Happy Birthday to you

Pulse level: **Tactus (beat)**

Introduction

Example: Happy Birthday to you

Pulse level: **Tatum (temporal atom)**

Introduction

Example: Chopin – Mazurka Op. 68-3

Pulse level: Quarter note

Tempo: ???

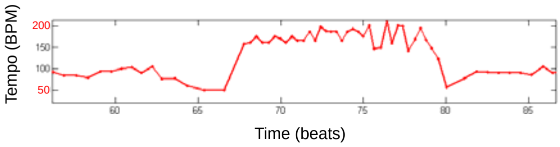
Introduction

Example: Chopin – Mazurka Op. 68-3

Pulse level: Quarter note

Tempo: 50-200 BPM

Tempo curve



Introduction

Example: Borodin – String Quartet No. 2

Pulse level: Quarter note

Tempo: 120-140 BPM (roughly)

Beat tracker without any prior knowledge

Beat tracker with prior knowledge on rough tempo range

Introduction

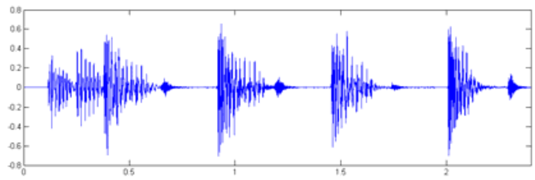
Challenges in beat tracking

- Pulse level often unclear
- Local/sudden tempo changes (e.g. rubato)
- Vague information
  (e.g., soft onsets, extracted onsets corrupt)
- Sparse information
  (often only note onsets are used)

Introduction

Tasks

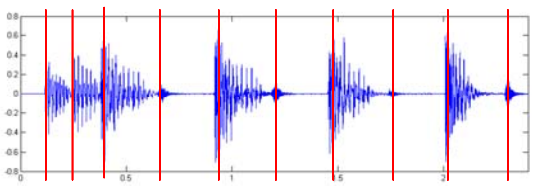
- Onset detection
- Beat tracking
- Tempo estimation



Introduction

Tasks

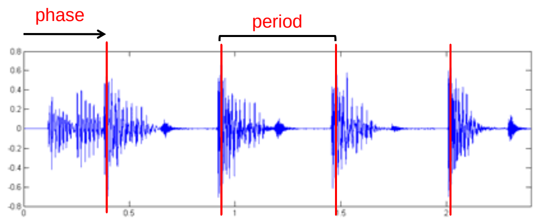
- Onset detection
- Beat tracking
- Tempo estimation



Introduction

Tasks

- Onset detection
- Beat tracking
- Tempo estimation



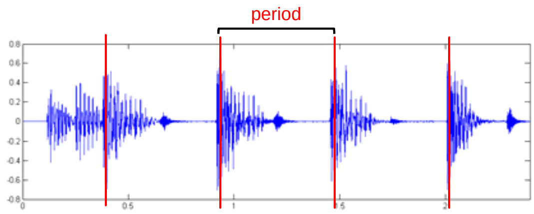
Introduction

Tasks

- Onset detection
- Beat tracking
- Tempo estimation

Tempo := 60 / period

Beats per minute (BPM)



Onset Detection

- Finding start times of perceptually relevant acoustic events in music signal
- Onset is the time position where a note is played
- Onset typically goes along with a change of the signal's properties:
  - energy or loudness
  - pitch or harmony
  - timbre

Onset Detection

- Finding start times of perceptually relevant acoustic events in music signal
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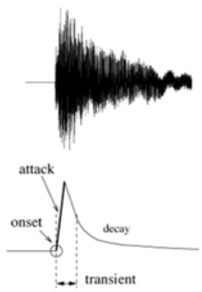
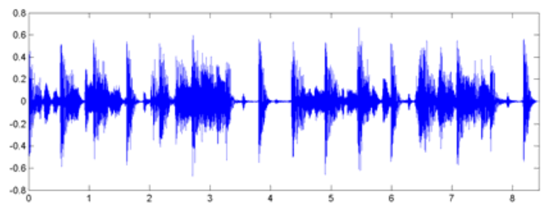


[Bello et al., IEEE-TASLP 2005]

Onset Detection (Energy-Based)

Steps

Waveform



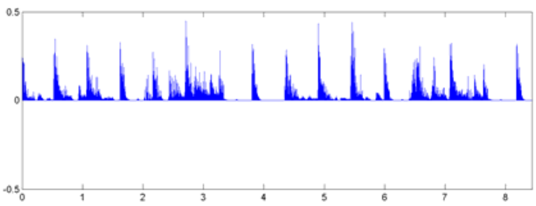
Time (seconds)

Onset Detection (Energy-Based)

Steps

1. Amplitude squaring

Squared waveform



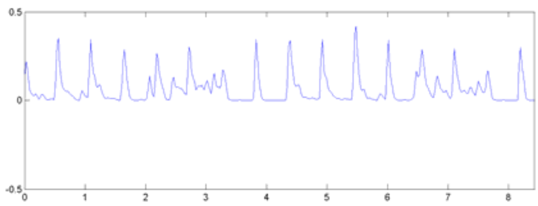
Time (seconds)

Onset Detection (Energy-Based)

Steps

1. Amplitude squaring
2. Windowing

Energy envelope



Time (seconds)

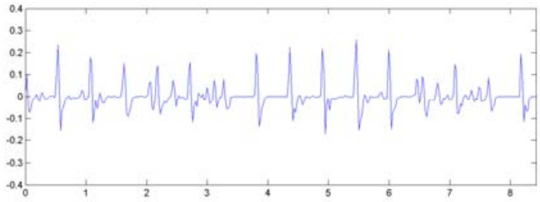
Onset Detection (Energy-Based)

Steps

1. Amplitude squaring
2. Windowing
3. Differentiation

Capturing energy changes

Differentiated energy envelope



Time (seconds)

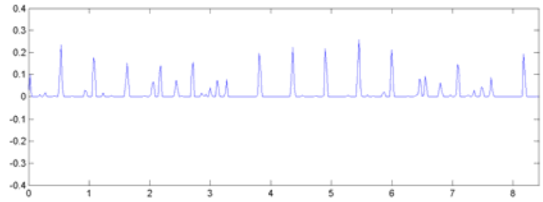
Onset Detection (Energy-Based)

Steps

1. Amplitude squaring
2. Windowing
3. Differentiation
4. Half wave rectification

Only energy increases are relevant for note onsets

Novelty curve



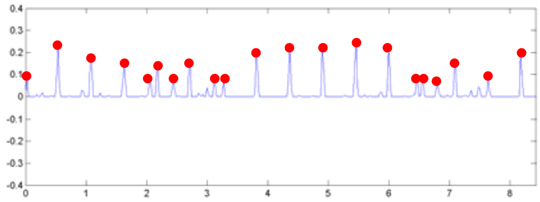
Time (seconds)

Onset Detection (Energy-Based)

Steps

1. Amplitude squaring
2. Windowing
3. Differentiation
4. Half wave rectification
5. Peak picking

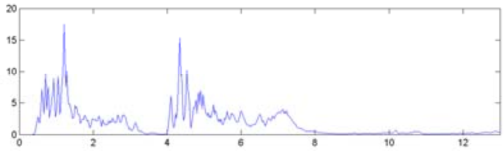
Peak positions indicate note onset candidates



Time (seconds)

Onset Detection (Energy-Based)

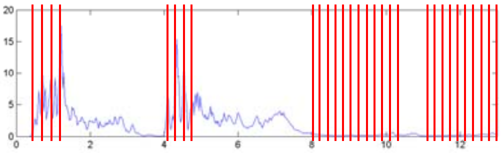
Energy envelope



Time (seconds)

Onset Detection (Energy-Based)

Energy envelope / note onsets positions

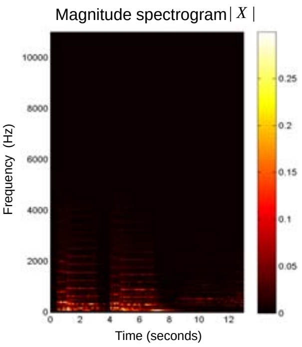


Time (seconds)

Onset Detection

- Energy curves often only work for percussive music
- Many instruments such as strings have weak note onsets
- No energy increase may be observable in complex sound mixtures
- More refined methods needed that capture
  - changes of spectral content
  - changes of pitch
  - changes of harmony

Onset Detection (Spectral-Based)

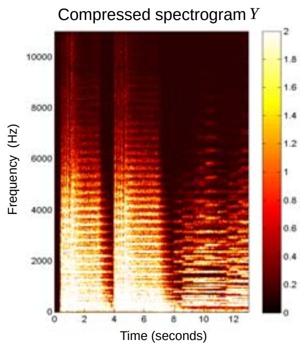


Steps:

1. Spectrogram

- *Aspects concerning pitch, harmony, or timbre are captured by spectrogram*
- *Allows for detecting local energy changes in certain frequency ranges*

Onset Detection (Spectral-Based)



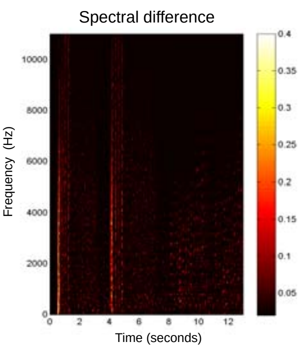
Steps:

1. Spectrogram
2. Logarithmic compression

$$Y = \log(1 + C \cdot |X|)$$

- *Accounts for the logarithmic sensation of sound intensity*
- *Dynamic range compression*
- *Enhancement of low-intensity values*
- *Often leading to enhancement of high-frequency spectrum*

Onset Detection (Spectral-Based)

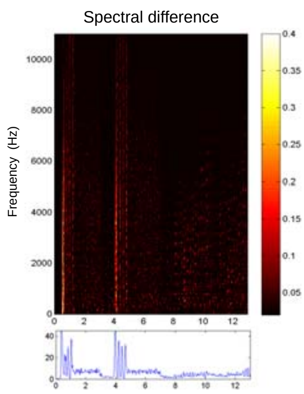


Steps:

1. Spectrogram
2. Logarithmic compression
3. Differentiation

- *First-order temporal difference*
- *Captures changes of the spectral content*
- *Only positive intensity changes considered*

Onset Detection (Spectral-Based)



Steps:

1. Spectrogram
2. Logarithmic compression
3. Differentiation
4. Accumulation

- *Frame-wise accumulation of all positive intensity changes*
- *Encodes changes of the spectral content*

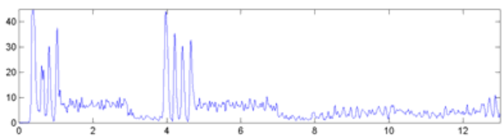
Novelty curve

Onset Detection (Spectral-Based)

Steps:

1. Spectrogram
2. Logarithmic compression
3. Differentiation
4. Accumulation

Novelty curve



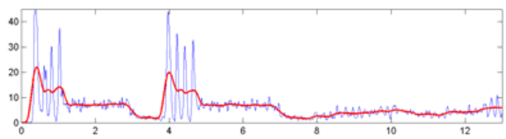
Onset Detection (Spectral-Based)

Steps:

1. Spectrogram
2. Logarithmic compression
3. Differentiation
4. Accumulation
5. Normalization

Novelty curve

Substraction of local average

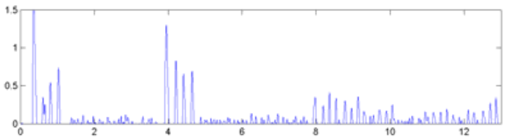


Onset Detection (Spectral-Based)

Steps:

1. Spectrogram
2. Logarithmic compression
3. Differentiation
4. Accumulation
5. Normalization

Normalized novelty curve

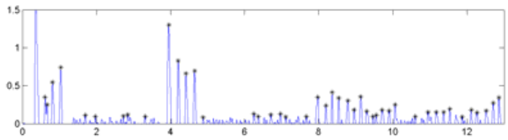


Onset Detection (Spectral-Based)

Steps:

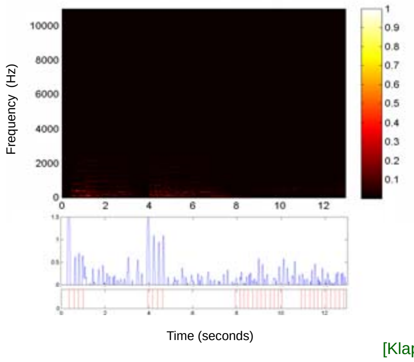
1. Spectrogram
2. Logarithmic compression
3. Differentiation
4. Accumulation
5. Normalization
6. Peak picking

Normalized novelty curve



Onset Detection (Spectral-Based)

Logarithmic compression is essential



$|X|$

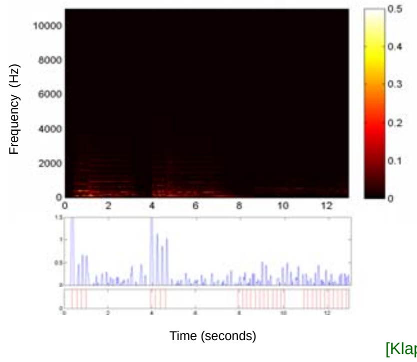
Novelty curve

Ground-truth onsets

[Klapuri et al., IEEE-TASLP 2006]

Onset Detection (Spectral-Based)

Logarithmic compression is essential



$Y = \log(1 + C \cdot |X|)$

C = 1

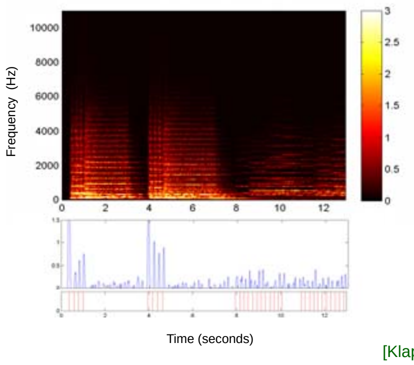
Novelty curve

Ground-truth onsets

[Klapuri et al., IEEE-TASLP 2006]

Onset Detection (Spectral-Based)

Logarithmic compression is essential



$Y = \log(1 + C \cdot |X|)$

C = 10

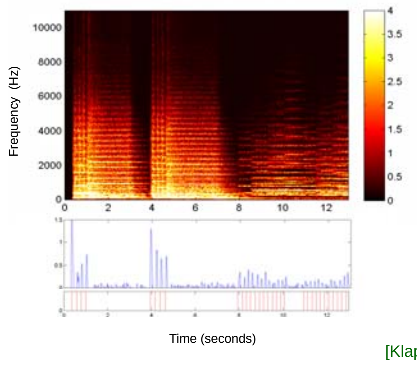
Novelty curve

Ground-truth onsets

[Klapuri et al., IEEE-TASLP 2006]

Onset Detection (Spectral-Based)

Logarithmic compression is essential



$Y = \log(1 + C \cdot |X|)$

C = 1000

Novelty curve

Ground-truth onsets

[Klapuri et al., IEEE-TASLP 2006]

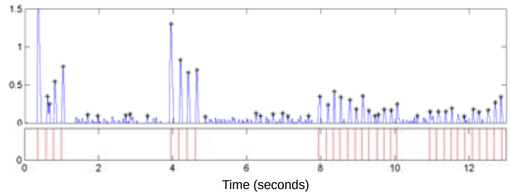
Onset Detection (Spectral-Based)

- Spectrogram $X = (X(t,k))_{t,k}$ $\quad t \in [1:T]$, $k \in [1:K]$
- Compressed Spectrogram $Y := \log(1 + C \cdot |X|)$ $\quad C > 1$
- Novelty curve $\Delta : [1:T-1] \to \mathbb{R}$

$$\Delta(t) := \sum_{k=1}^{K} |Y(t+1,k) - Y(t,k)|_{\geq 0}$$

Onset Detection

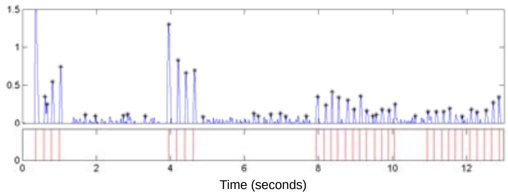
Peak picking



- Peaks of the novelty curve indicate note onset candidates

Onset Detection

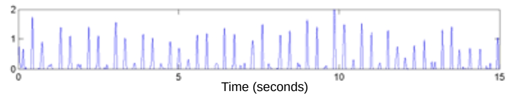
Peak picking



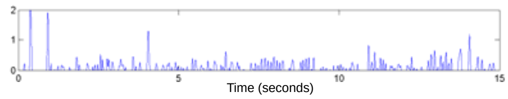
- Peaks of the novelty curve indicate note onset candidates
- In general many spurious peaks
- Usage of local thresholding techniques
- Peak-picking very fragile step in particular for soft onsets

Onset Detection

Shostakovich – 2nd Waltz



Borodin – String Quartet No. 2



Onset Detection

Drumbeat

Going Home

Lyphard melodie

Por una cabeza

Donau

Beat and Tempo

What is a beat?

- Steady pulse that drives music forward and provides the temporal framework of a piece of music
- Sequence of perceived pulses that are equally spaced in time
- The pulse a human taps along when listening to the music

[Parncutt 1994]
[Sethares 2007]
[Large/Palmer 2002]
[Lerdahl/ Jackendoff 1983]
[Fitch/ Rosenfeld 2007]

The term tempo then refers to the speed of the pulse.

Beat and Tempo

Strategy

- Analyze the novelty curve with respect to reoccurring or quasi-periodic patterns
- Avoid the explicit determination of note onsets (no peak picking)

Beat and Tempo

Strategy

- Analyze the novelty curve with respect to reoccurring or quasi-periodic patterns
- Avoid the explicit determination of note onsets (no peak picking)

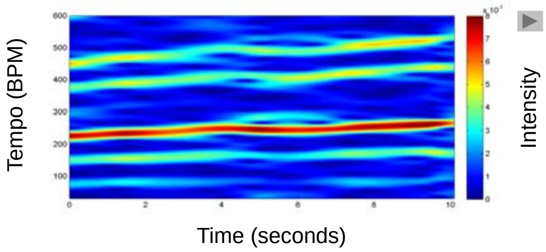
Methods

- Comb-filter methods
- Autocorrelation
- Fourier transfrom

[Scheirer, JASA 1998]
[Ellis, JNMR 2007]
[Davies/Plumbley, IEEE-TASLP 2007]
[Peeters, JASP 2007]
[Grosche/Müller, ISMIR 2009]
[Grosche/Müller, IEEE-TASLP 2011]

Tempogram

Definition: A tempogram is a time-tempo representation that encodes the local tempo of a music signal over time.



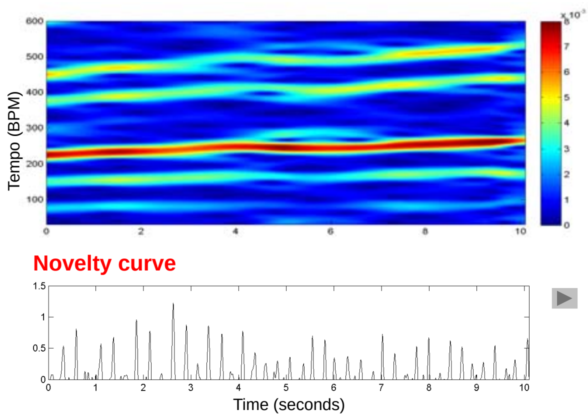
Tempogram (Fourier)

Definition: A tempogram is a time-tempo represenation that encodes the local tempo of a music signal over time.

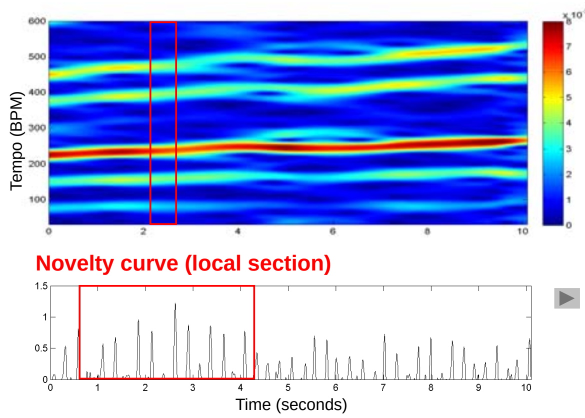
Fourier-based method

- Compute a spectrogram (STFT) of the novelty curve
- Convert frequency axis (given in Hertz) into tempo axis (given in BPM)
- Magnitude spectrogram indicates local tempo

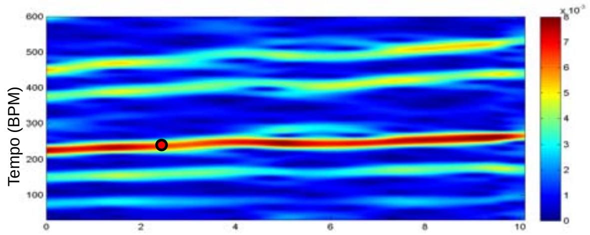
Tempogram (Fourier)



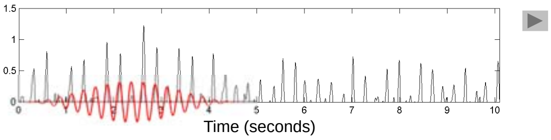
Tempogram (Fourier)



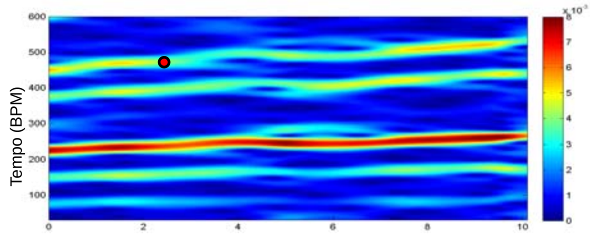
Tempogram (Fourier)



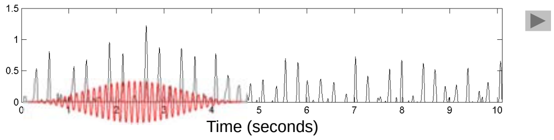
Windowed sinusoidal



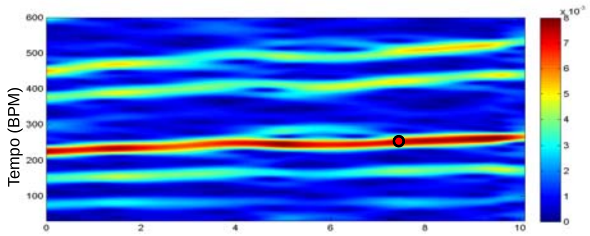
Tempogram (Fourier)



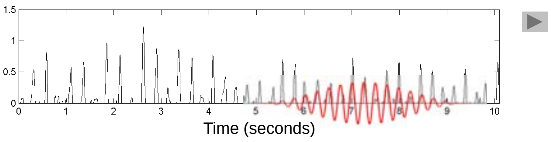
Windowed sinusoidal



Tempogram (Fourier)



Windowed sinusoidal



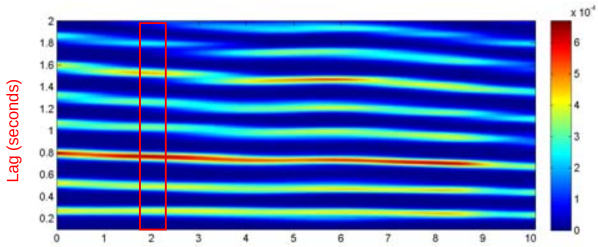
Tempogram (Autocorrelation)

Definition: A tempogram is a time-tempo represenation that encodes the local tempo of a music signal over time.

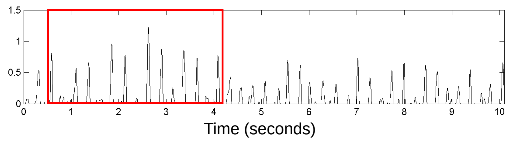
Autocorrelation-based method

- Compare novelty curve with time-lagged local sections of itself
- Convert lag-axis (given in seconds) into tempo axis (given in BPM)
- Autocorrelogram indicates local tempo

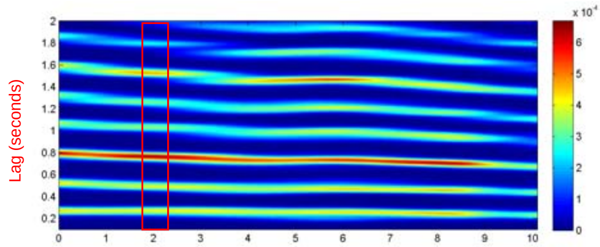
Tempogram (Autocorrelation)



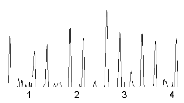
Novelty curve (local section)



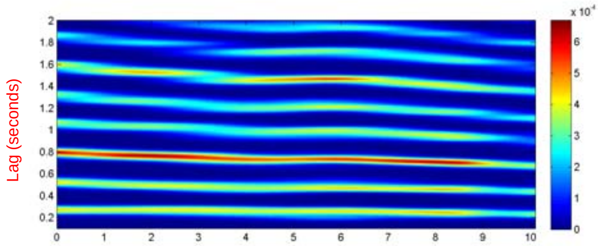
Tempogram (Autocorrelation)



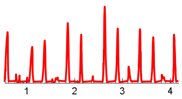
Windowed autocorrelation



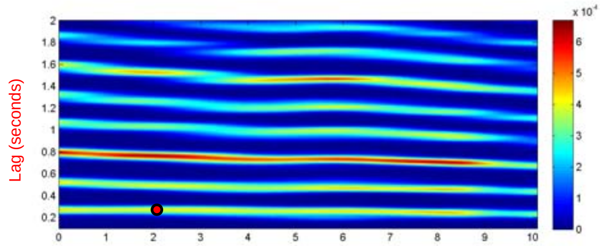
Tempogram (Autocorrelation)



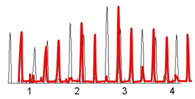
Lag = 0 (seconds)



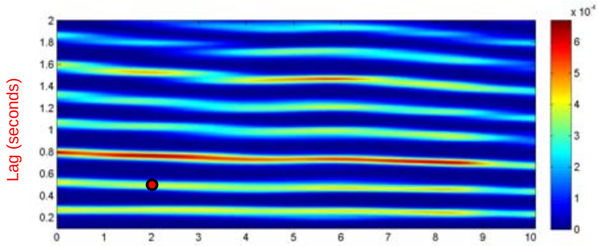
Tempogram (Autocorrelation)



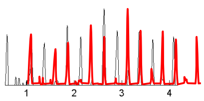
Lag = 0.26 (seconds)



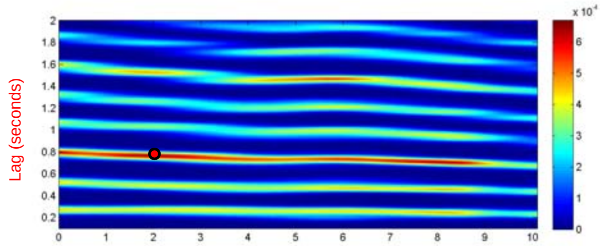
Tempogram (Autocorrelation)



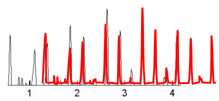
Lag = 0.52 (seconds)



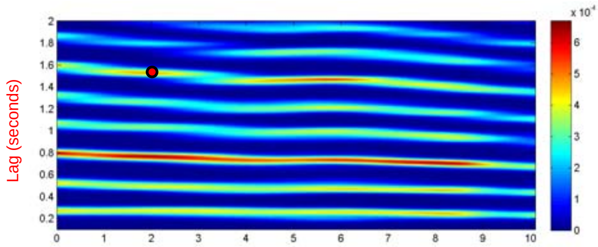
Tempogram (Autocorrelation)



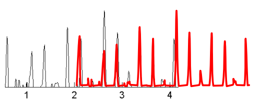
Lag = 0.78 (seconds)



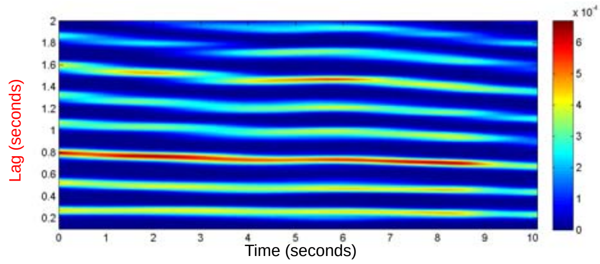
Tempogram (Autocorrelation)

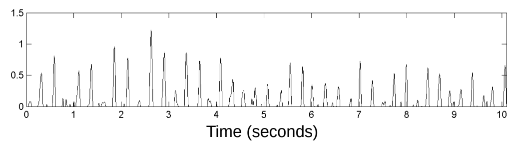


Lag = 1.56 (seconds)

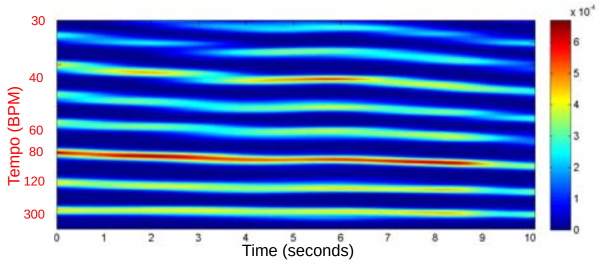


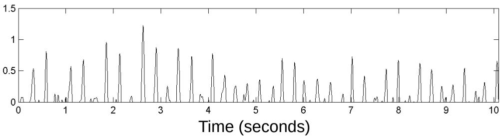
Tempogram (Autocorrelation)



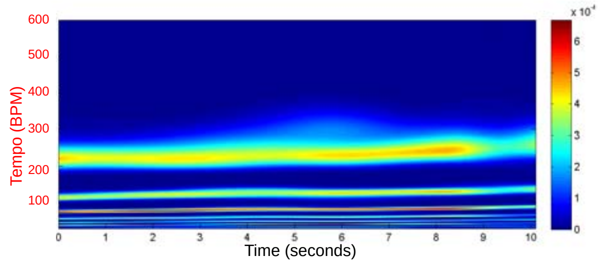


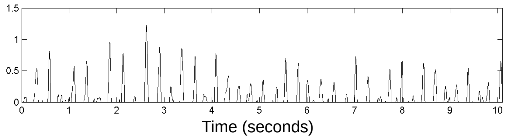
Tempogram (Autocorrelation)





Tempogram (Autocorrelation)

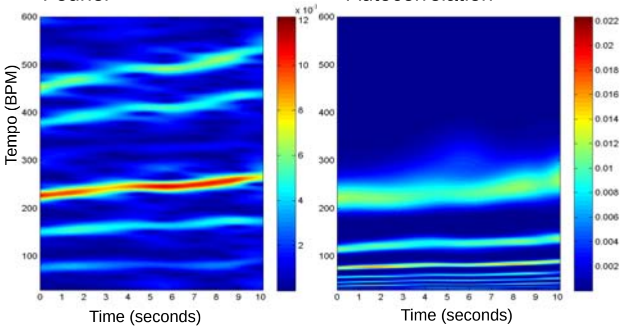




Tempogram

Fourier

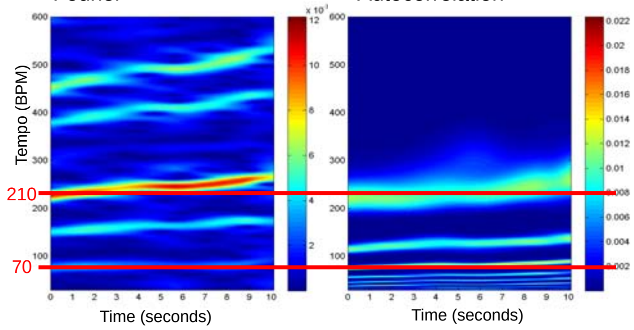
Autocorrelation



Tempogram

Fourier

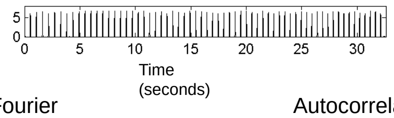
Autocorrelation



Tempo@Tatum = 210 BPM

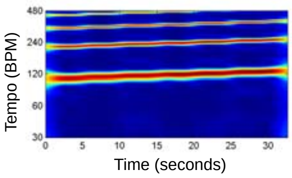
Tempo@Measure = 70 BPM

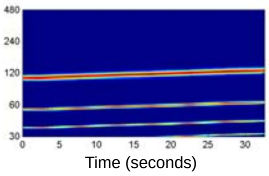
Tempogram



Fourier

Autocorrelation





Emphasis of tempo harmonics (integer multiples)

Emphasis of tempo subharmonics (integer fractions)

[Peeters, JASP 2007][Grosche et al., ICASSP 2010]

Tempogram (Summary)

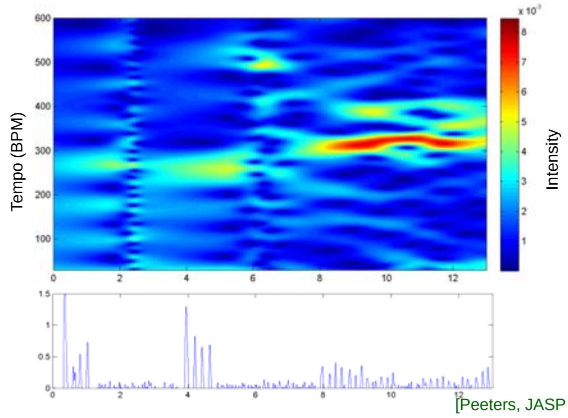
Fourier	Autocorrelation
Novelty curve is compared with sinusoidal kernels each representing a specific tempo	Novelty curve is compared with time-lagged local (windowed) sections of itself
Convert frequency (Hertz) into tempo (BPM)	Convert time-lag (seconds) into tempo (BPM)
Reveals novelty periodicities	Reveals novelty self-similarities
Emphasizes harmonics	Emphasizes subharmonics
Suitable to analyze tempo on tatum and tactus level	Suitable to analyze tempo on tactus and measure level

Beat Tracking

- Given the tempo, find the best sequence of beats
- Complex Fourier tempogram contains magnitude and phase information
- The magnitude encodes how well the novelty curve resonates with a sinusoidal kernel of a specific tempo
- The phase optimally aligns the sinusoidal kernel with the peaks of the novelty curve

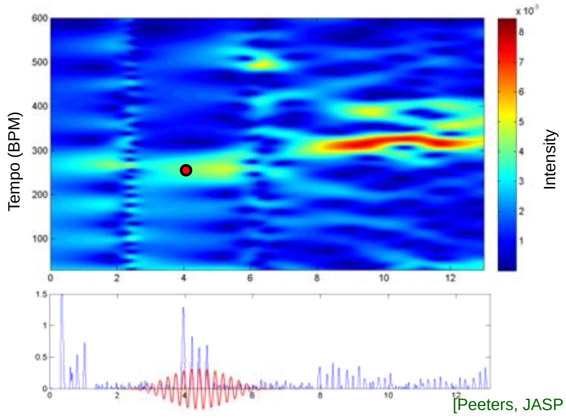
[Peeters, JASP 2005]

Beat Tracking



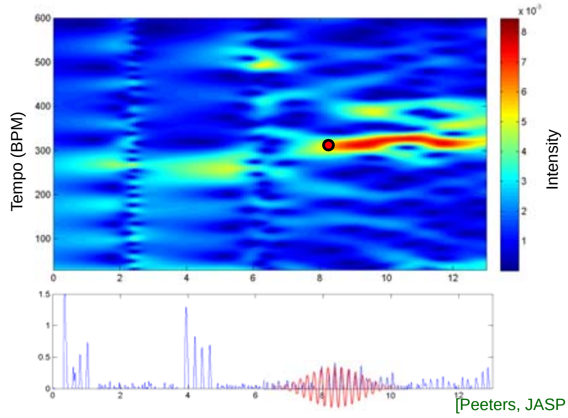
[Peeters, JASP 2005]

Beat Tracking



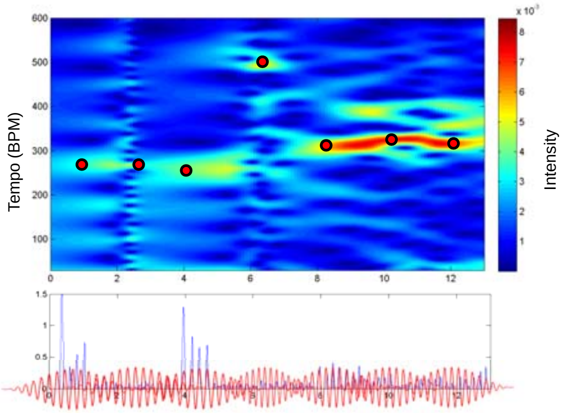
[Peeters, JASP 2005]

Beat Tracking

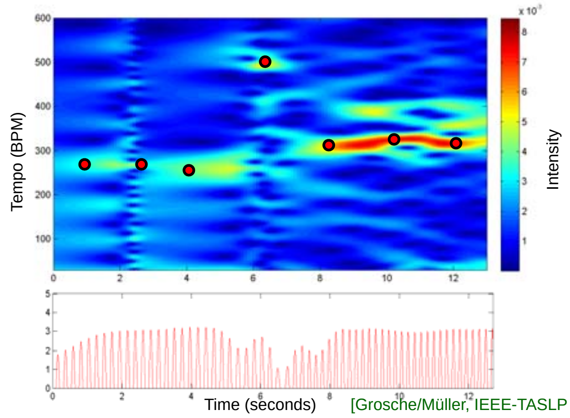


[Peeters, JASP 2005]

Beat Tracking



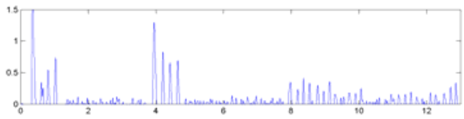
Beat Tracking



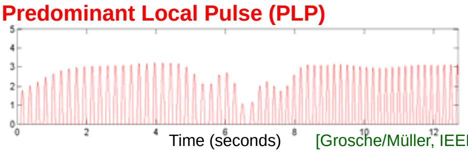
[Grosche/Müller, IEEE-TASLP 2011]

Beat Tracking

Novelty Curve



Predominant Local Pulse (PLP)



[Grosche/Müller, IEEE-TASLP 2011]

Beat Tracking

Novelty Curve

- Indicates note onset candidates
- Extraction errors in particular for soft onsets
- Simple peak-picking problematic

Predominant Local Pulse (PLP)

- Periodicity enhancement of novelty curve
- Accumulation introduces error robustness
- Locality of kernels handles tempo variations

[Grosche/Müller, IEEE-TASLP 2011]

Beat Tracking

- Local tempo at time t : $\tau_t \in \Theta$ $\qquad \Theta =$ [60:240] BPM
- Phase $\varphi_t := \frac{1}{2\pi} \arccos\left(\frac{\mathrm{Re}(\mathcal{T}(t,\tau_t))}{|\mathcal{T}(t,\tau_t)|}\right)$
- Sinusoidal kernel $\kappa_t : \mathbb{Z} \to \mathbb{R}$

$$\kappa_t(n) := W(n-t)\cos(2\pi(\tau_t/60 \cdot n - \varphi_t)) \qquad n \in \mathbb{Z}$$

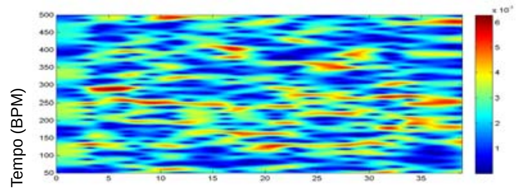
- Periodicity curve $\Gamma : [1:T] \to \mathbb{R}_{\geq 0}$

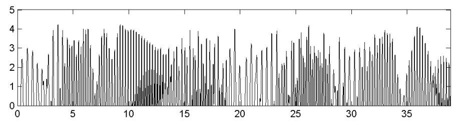
$$\Gamma(n) = \left| \sum_{t \in [1:T]} \kappa_t(n) \right|_{\geq 0} \qquad n \in [1:T]$$

[Grosche/Müller, IEEE-TASLP 2011]

Beat Tracking

Borodin – String Quartet No. 2



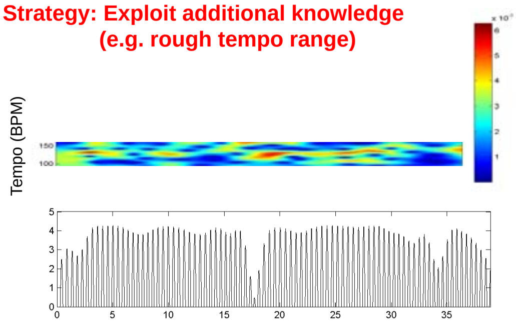


[Grosche/Müller, IEEE-TASLP 2011]

Beat Tracking

Borodin – String Quartet No. 2

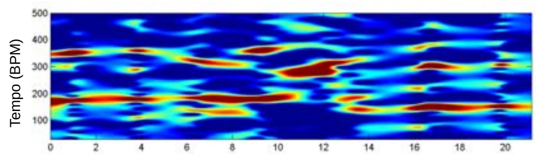
Strategy: Exploit additional knowledge (e.g. rough tempo range)



[Grosche/Müller, IEEE-TASLP 2011]

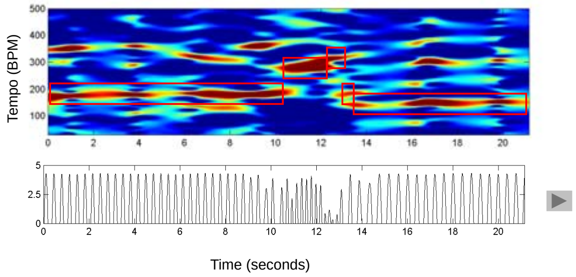
Beat Tracking

Brahms Hungarian Dance No. 5



Beat Tracking

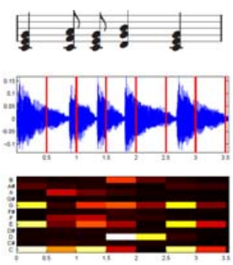
Brahms Hungarian Dance No. 5



Applications

- Feature design
  (beat-synchronous features, adaptive windowing)
- Digital DJ / audio editing
  (mixing and blending of audio material)
- Music classification
- Music recommendation
- Performance analysis
  (extraction of tempo curves)

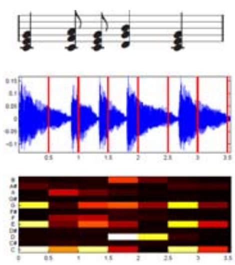
Application: Feature Design



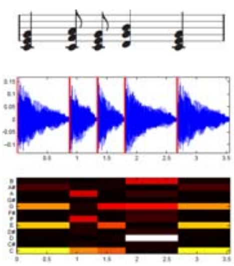
Fixed window size

[Ellis et al., ICASSP 2008] [Bello/Pickens, ISMIR 2005]

Application: Feature Design



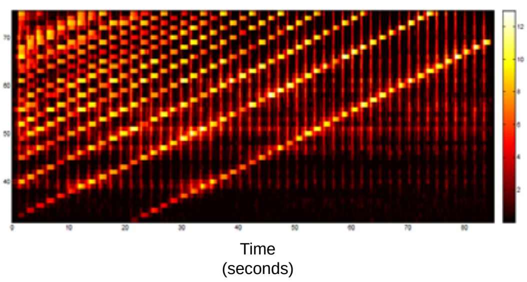
Fixed window size



Adaptive window size

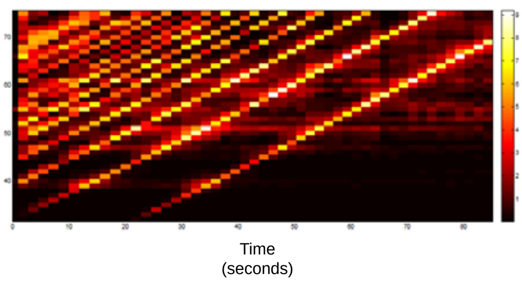
[Ellis et al., ICASSP 2008] [Bello/Pickens, ISMIR 2005]

Application: Feature Design



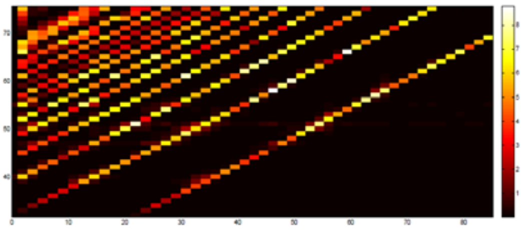
Fixed window size (100 ms)

Application: Feature Design



Adative window size (roughly 1200 ms)
Note onset positions define boundaries

Application: Feature Design



Adative window size (roughly 1200 ms)
Note onset positions define boundaries

Denoising by excluding boundary neighborhoods

Application: Audio Editing (Digital DJ)

http://www.mixxx.org/

Application: Beat-Synchronous Light Effects

Summary

1. Onset Detection
   - Novelty curve (*something is changing*)
   - Indicates note onset candidates
   - Hard task for non-percussive instruments (strings)
2. Tempo Estimation
   - Fourier tempogram
   - Autocorrelation tempogram
   - Musical knowledge (tempo range, continuity)
3. Beat tracking
   - Find most likely beat positions
   - Exploiting phase information from Fourier tempogram