Advanced Course Computer Science

Music Processing

Summer Term 2010

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Tempo and Beat Analysis

Introduction

Musical Properties:

- Harmony
- Melody
- Rhythm
- Timbre

Introduction

Musical Properties:

- Harmony
- Melody
- Rhythm: Tempo and beat analysis
- Timbre

Introduction

Example 1: Britney Spears – Oops!...I Did It Again

Tempo: 100 BPM

Introduction

Example 2: Queen – Another One Bites The Dust

Tempo: 110 BPM

Introduction

Example 3: Burgmueller – Op100-2

Tempo: 130 BPM

Introduction

Example 4: Chopin – Mazurka Op. 68-3

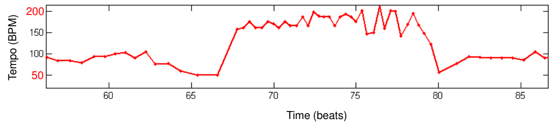
Tempo:

Introduction

Example 4: Chopin – Mazurka Op. 68-3

Tempo: 50-200 BPM

Tempo curve



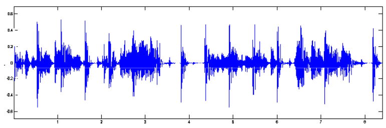
Introduction

Example 5: Borodin – String Quartet No. 2

Tempo: 120-140 BPM (roughly)

Introduction

Given a recording of a musical piece

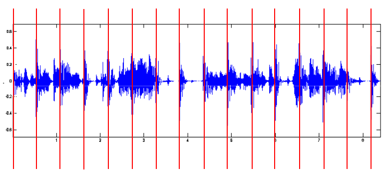


determine the periodic sequence of beat positions:

Tapping the foot to a piece of music

Introduction

Given a recording of a musical piece



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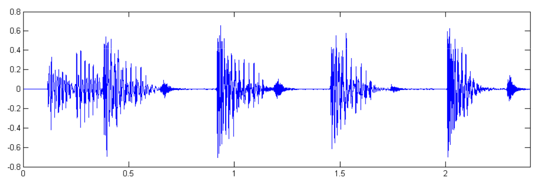
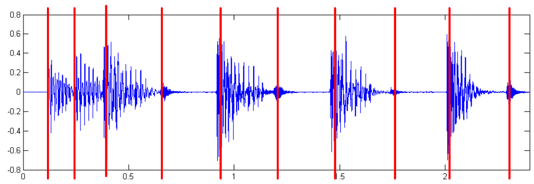
Tapping the foot to a piece of music

Introduction



Introduction

1. Note onset detection
2. Tempo estimation
3. Beat tracking



Introduction

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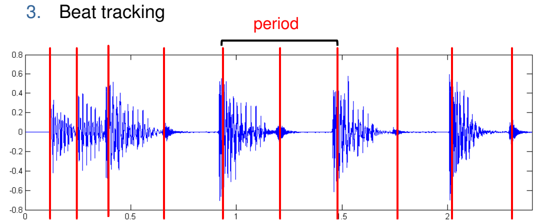

Tempo (BPM) := 60 / period (seconds)

Introduction

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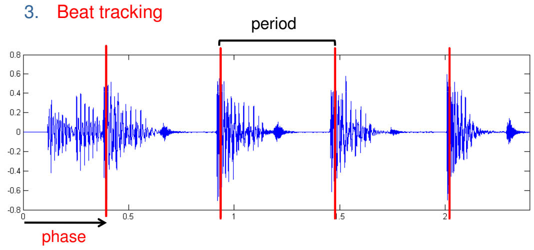


Introduction

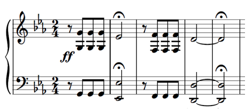
Beat
Sequence of equally spaced impulses, which periodically occur in music. The perceptually most salient pulse (foot tapping rate).

Tempo
The tempo of a piece is the inverse of the beat period. Instead of frequency in Hz, we think beats per minute (BPM).

Introduction

- Tempo and beat are fundamental properties of music
- The beat provides the temporal framework of music (musical meaningful time axis)
- Beat-synchronous audio features
- Rhythmic similarity for music recommendation, genre classification, music segmentation
- Music transcription

- Commercial applications
  - automatic DJ / mixing
  - light effects



Introduction

Tasks

1. Note onset detection
2. Tempo estimation
3. Beat tracking

Overview

Tasks

1. Note onset detection
2. Tempo estimation
3. Beat tracking

Challenges

- Non-percussive music
- Soft note onsets
- Time-varying tempo

Overview

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Challenges

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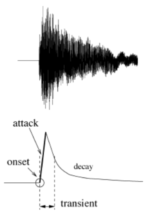
Note Onset Detection

- Finding perceptually relevant impulses in a music signal
- Musical accents, note onsets

Onset:

- The exact time, a note is hit
- One of the three parameters defining a note (pitch, onset, duration)



- Change of properties of sound:
  - Energy or Loudness
  - Pitch or Harmony
  - Timbre

[Bello et al. 2005]

Note Onset Detection

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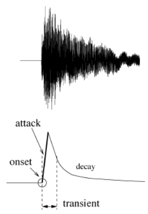

- Change of properties of sound:
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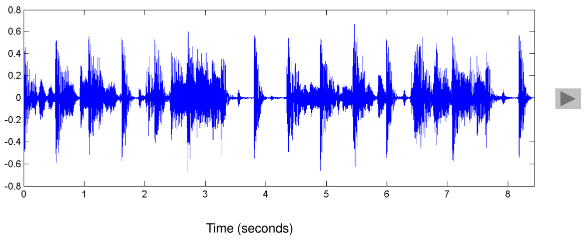
[Bello et al. 2005]

Note Onset Detection

- Amplitude Squaring
- Windowing
- Differentiation
- Half wave rectification

Waveform



Note Onset Detection

- Amplitude Squaring
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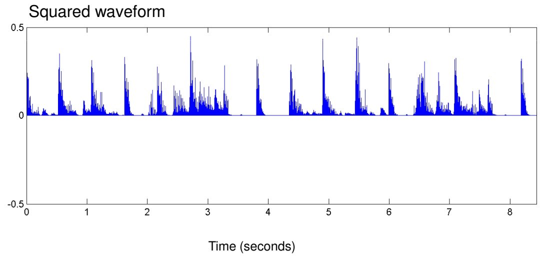
Squared waveform



Note Onset Detection

- Amplitude Squaring
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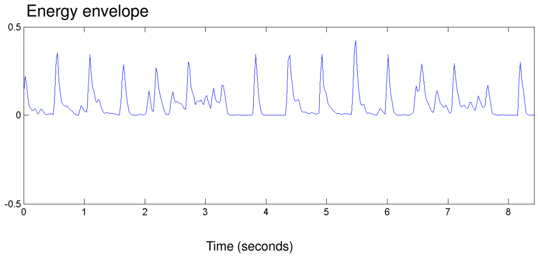
Energy envelope

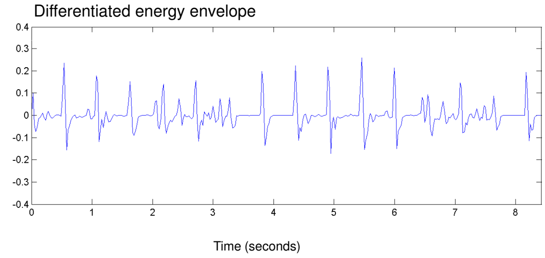


Note Onset Detection

- Amplitude Squaring
- Windowing
- Differentiation
- Half wave rectification

capture energy changes

Differentiated energy envelope

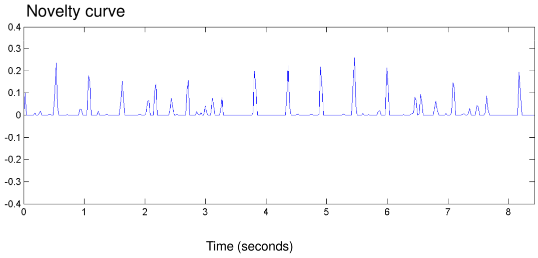


Note Onset Detection

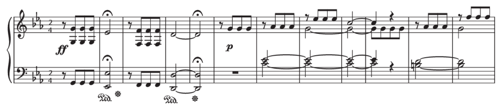
- Amplitude Squaring
- Windowing
- Differentiation
- Half-wave rectification

only energy increases are relevant for note onsets

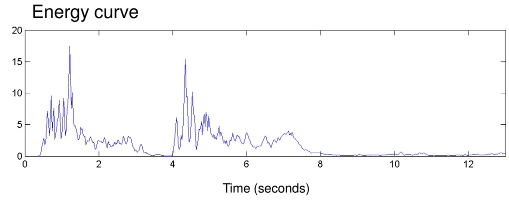
Novelty curve



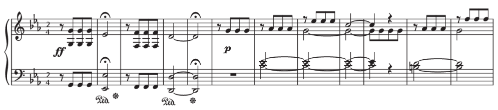
Note Onset Detection



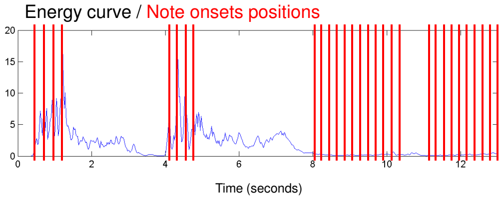
Energy curve



Note Onset Detection



Energy curve / Note onsets positions



Onset Detection

- Energy curves only work for percussive music
- Many instruments have weak note onsets (strings)
- No energy increase observable in complex mixtures

- More refined methods addressing different signal properties:
  - Change of spectral content
  - Change of pitch
  - Change of harmony

Onset Detection

- Energy curves only work for percussive music
- Many instruments have weak note onsets (strings)
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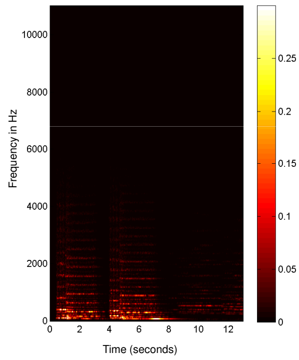
- More refined methods addressing different signal properties:
  - Change of spectral content
  - Change of pitch
  - Change of harmony

Onset Detection

Magnitude spectrogram $|X|$



Steps:

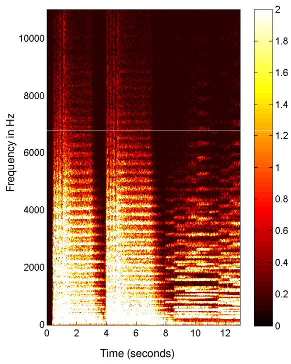
1. Spectrogram (STFT)

- allows for detecting local energy increases in certain frequency ranges
- pitch, harmony, or timbre changes are captured

[Bello et al. 2005]

Onset Detection

Compressed spectrogram Y



Steps:

1. Spectrogram (STFT)
2. Logarithmic intensity

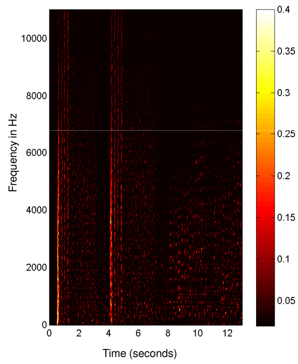
$$Y = \log(1 + C \cdot |X|)$$

- follows the human sensation of intensity
- dynamic range compression
- enhances low intensity values
- reduces influence of amplitude modulation

[Bello et al. 2005]

Onset Detection

Spectral difference



Steps:

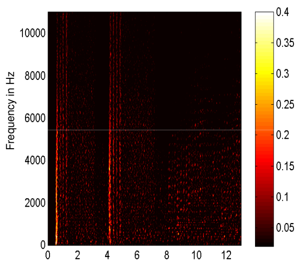
1. Spectrogram (STFT)
2. Logarithmic intensity
3. Differentiation

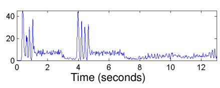
- first-order temporal difference
- captures changes of the spectral content
- only positive intensity changes considered

[Bello et al. 2005]

Onset Detection

Spectral difference





Steps:

1. Spectrogram (STFT)
2. Logarithmic intensity
3. Differentiation
4. Accumulation

- for each time step, accumulate all positive intensity changes
- encodes changes of the spectral content

Novelty curve

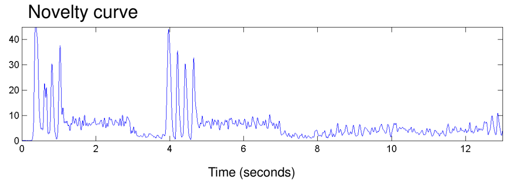
[Bello et al. 2005]

Onset Detection

Steps:

1. Spectrogram (STFT)
2. Logarithmic intensity
3. Differentiation
4. Accumulation

Novelty curve

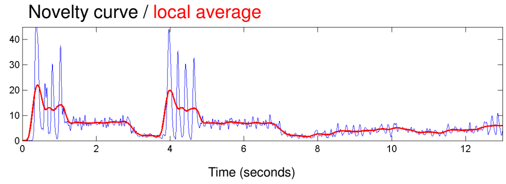


Onset Detection

Steps:

1. Spectrogram (STFT)
2. Logarithmic intensity
3. Differentiation
4. Accumulation

Novelty curve / local average

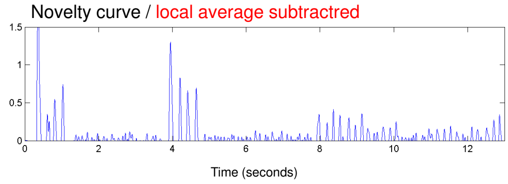


Onset Detection

Steps:

1. Spectrogram (STFT)
2. Logarithmic intensity
3. Differentiation
4. Accumulation
5. Mean Subtraction

Novelty curve / local average subtracted

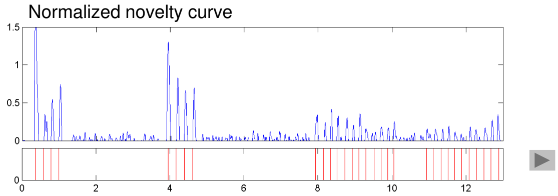


Onset Detection

Steps:

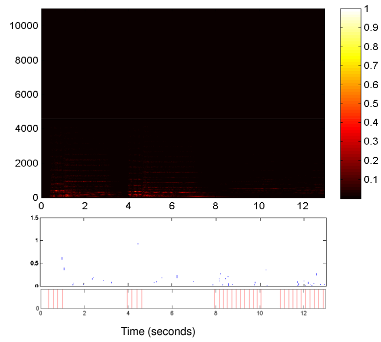
1. Spectrogram (STFT)
2. Logarithmic intensity
3. Differentiation
4. Accumulation
5. Mean Subtraction

Normalized novelty curve



Onset Detection

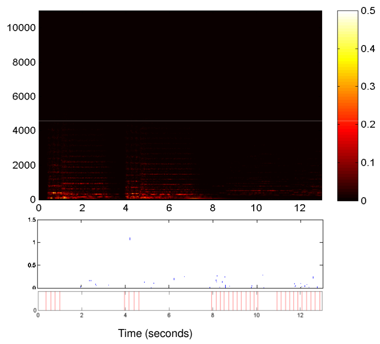
- Logarithmic compression is essential



linear intensity

Onset Detection

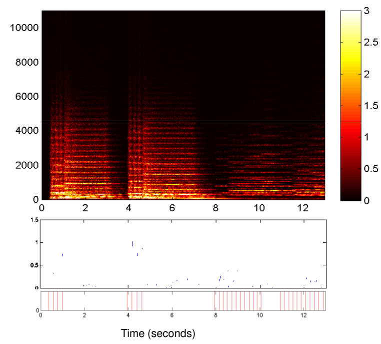
- Logarithmic compression is essential



logarithmic intensity
C = 1

Onset Detection

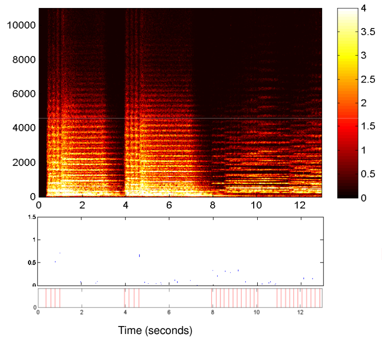
- Logarithmic compression is essential



logarithmic intensity
C = 10

Onset Detection

- Logarithmic compression is essential



logarithmic intensity
C = 1000

Onset Detection

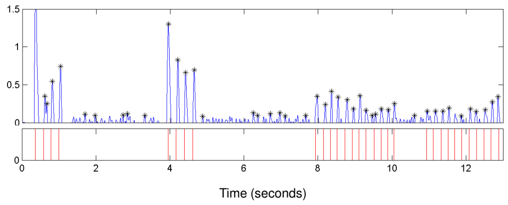
- Spectrogram $X = (X(t,k))_{t,k}$ $\quad t \in [1:T]$, $k \in [1:K]$
- Compressed Spectrogram $Y := \log(1 + C \cdot |X|)$ $\quad C > 1$
- Novelty curve $\Delta : [1 : T-1] \to \mathbb{R}$

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

Onset Detection

- Peaks of the novelty curve are note onset candidates
- Extraction of note onsets by peak-picking methods (thresholding)

Peak picking

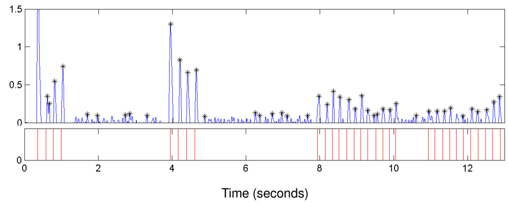


[Bello et al. 2005]

Onset Detection

- Peaks of the novelty curve are note onset candidates
- Extraction of note onsets by peak-picking methods (thresholding)
- Peak-picking is a very fragile step in particular for soft onsets (strings)
- How to distinguish between true onset peaks and spurious peaks?

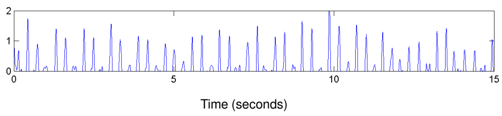
Peak picking



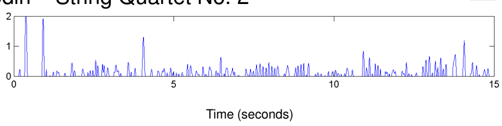
[Bello et al. 2005]

Onset Detection

Shostakovich – 2nd Waltz



Borodin – String Quartet No. 2



Onset Detection

Drumbeat

Going Home

Lyphard melodie

Por una cabeza

Donau

Onset Detection, Summary

- Compute a novelty curve that captures changes of certain signal properties
  - Energy
  - Spectrum
  - Pitch, harmony, timbre

- Energy based methods work for percussive music only
- Peaks of the novelty curve indicate note onset candidates
- Extraction of note onsets by peak-picking methods (thresholding)
- Peak-picking is a very fragile step in particular for soft onsets (strings)

[Bello et al. 2005]

Overview

Tasks

1. Note onset detection
2. Tempo estimation
3. Beat tracking

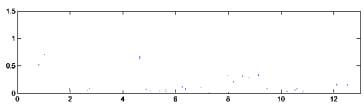
Tempo Estimation

[Peeters 2007]

- The beat is a *periodic* sequence of impulses
- Reveal periodic structure of the note onsets
- Avoid the explicit determination of note onsets (no peak picking)
- Analyze the novelty curve with respect to periodicities

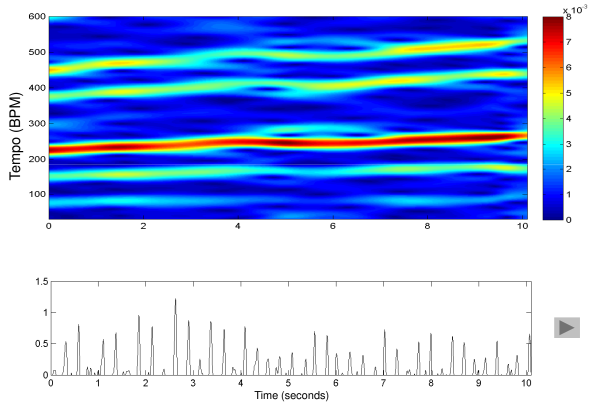
Methods for frequency / tempo estimation:

1. Fourier Transform
2. Autocorrelation



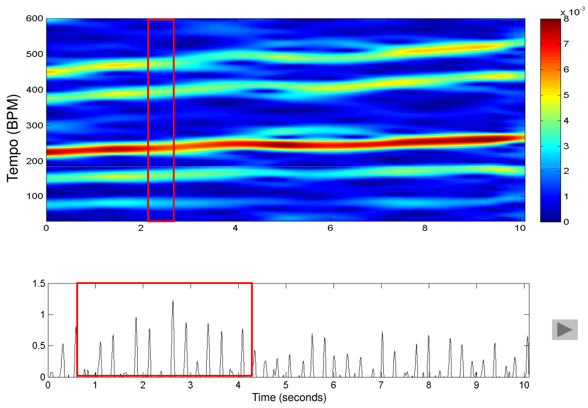
Fourier-Tempogram

[GroscheMueller 2009]



Fourier-Tempogram

[GroscheMueller 2009]



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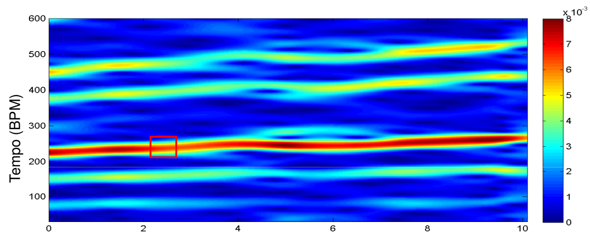
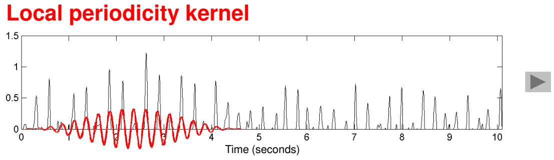


Local periodicity kernel



Fourier-Tempogram

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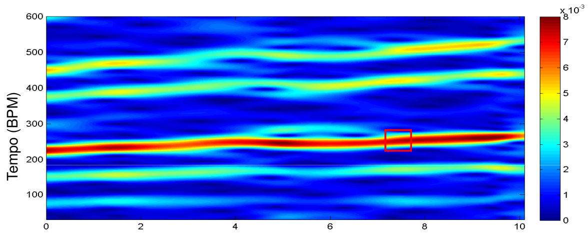
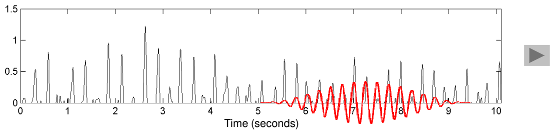


Local periodicity kernel



Fourier-Tempogram

[GroscheMueller 2009]

- A time / tempo representation that encodes the local tempo of the piece
- A spectrogram (STFT) of the novelty curve
- Frequency axis is interpreted as tempo in BPM instead of frequency in Hz
- Reveals periodicities of the note onsets

Fourier-Tempogram

[GroscheMueller 2009]

- Fourier coefficient $\mathcal{F}(t,\omega) = \sum_{n\in\mathbb{Z}} \Delta(n)\cdot W(n-t)\cdot \mathrm{e}^{-2\pi i\omega n}$

window function $W:\mathbb{Z}\to\mathbb{R}$ centered at $t=0$ $\omega\in\mathbb{R}_{\geq 0}$

- Fourier tempogram $\mathcal{T}:[1:T]\times\Theta\to\mathbb{C}$

$$\mathcal{T}^{\mathrm{F}}(t,\tau) = \mathcal{F}(t,\tau/60)$$

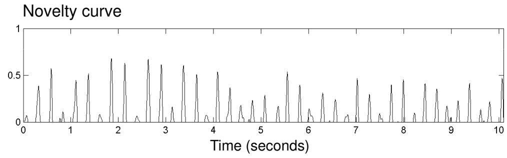
for the tempo parameter $\tau = 60\cdot\omega$ in BPM

and the set of tempo parameters $\Theta\subset\mathbb{R}_{>0}$ $\Theta =$ [30:600]

Autocorrelation-Tempogram

[Peeters 2007]

Novelty curve



Autocorrelation-Tempogram

[Peeters 2007]

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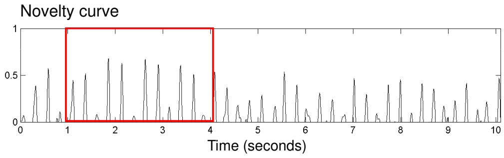
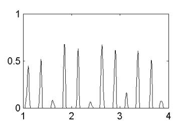


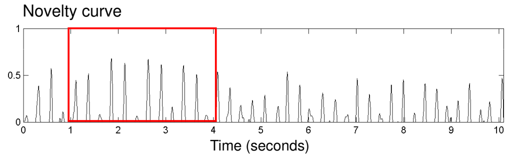
Autocorrelation-Tempogram

[Peeters 2007]



Windowed Autocorrelation

Novelty curve

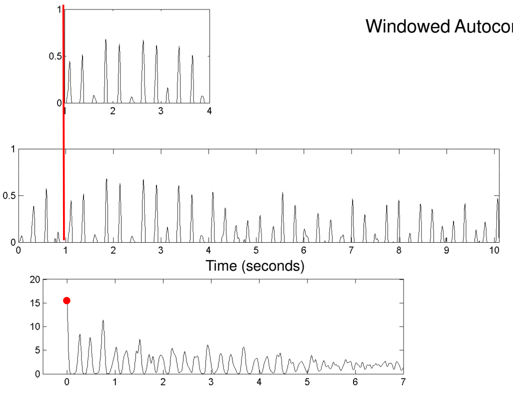


Compare the novelty curve with time-shifted copies of itself

Autocorrelation-Tempogram

[Peeters 2007]

Windowed Autocorrelation



Autocorrelation-Tempogram

[Peeters 2007]

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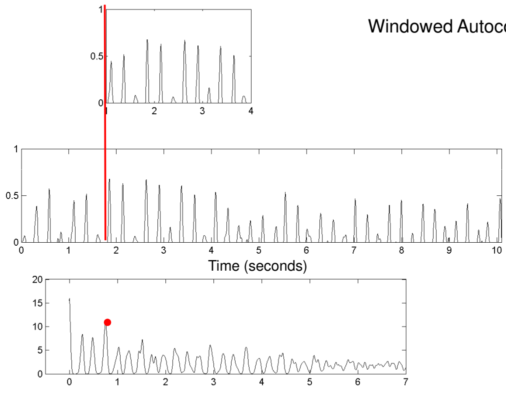
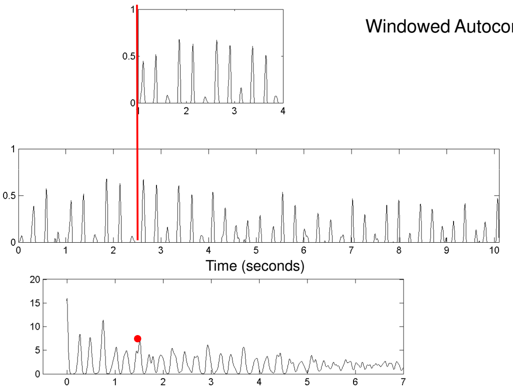


Autocorrelation-Tempogram

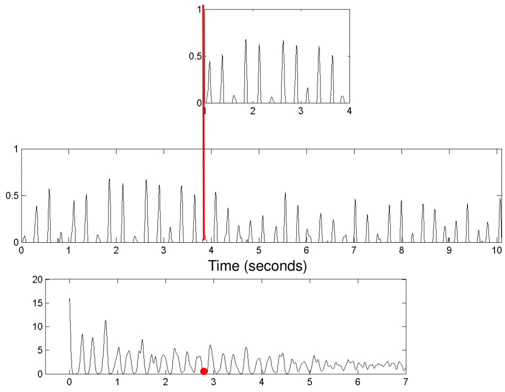
[Peeters 2007]

Windowed Autocorrelation



Autocorrelation-Tempogram

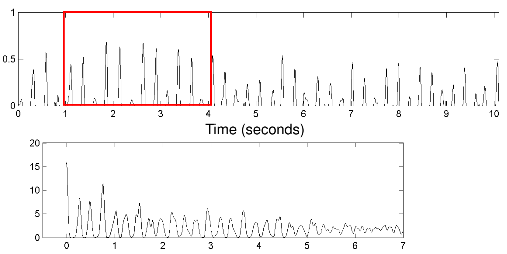
[Peeters 2007]



Autocorrelation-Tempogram

[Peeters 2007]

Windowed Autocorrelation

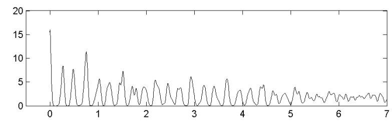


Autocorrelation-Tempogram

[Peeters 2007]

- High values for time lags with high correlation
- Reveals periodic self-similarities
- Maximum for a lag of zero (no shift)

Autocorrelation



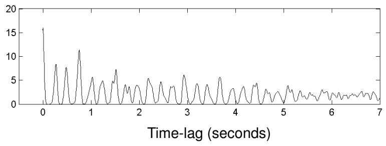
Autocorrelation-Tempogram

[Peeters 2007]

- High values for time lags with high correlation
- Reveals periodic self-similarities
- Maximum for a lag of zero (no shift)

- Time-lag is not intuitive for music signals

Autocorrelation



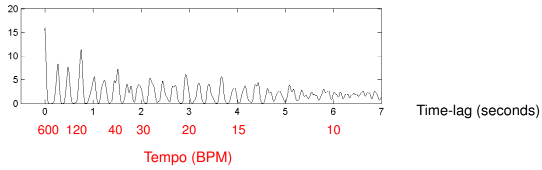
Autocorrelation-Tempogram

[Peeters 2007]

1. Convert time-lag into tempo in BPM

$$\mathit{Tempo}\ (\text{in BPM}) = 60\ /\ \mathit{Lag}\ (\text{in sec})$$

Autocorrelation / Tempo (BPM)



Autocorrelation-Tempogram

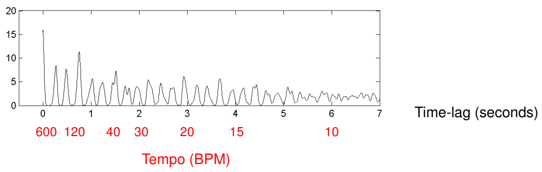
[Peeters 2007]

1. Convert time-lag into tempo in BPM

$$\mathit{Tempo}\ (\text{in BPM}) = 60\ /\ \mathit{Lag}\ (\text{in sec})$$

- Still not a meaningful tempo axis

Autocorrelation / Tempo (BPM)



Autocorrelation-Tempogram

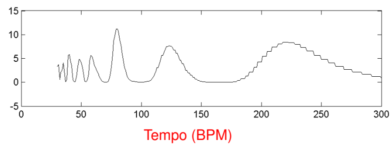
[Peeters 2007]

1. Convert time-lag into tempo in BPM

$$\mathit{Tempo}\ (\text{in BPM}) = 60\ /\ \mathit{Lag}\ (\text{in sec})$$

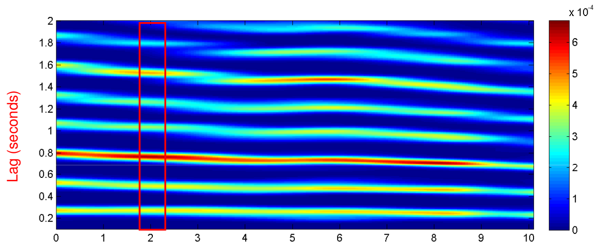
2. Interpolate to a linear tempo axis in a musically meaningful tempo range

Tempo mapped autocorrelation

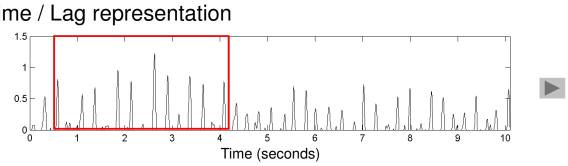


Autocorrelation-Tempogram

[Peeters 2007]

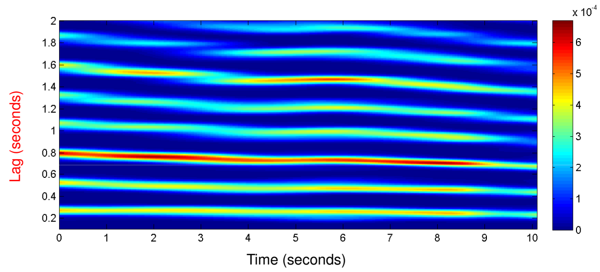


Time / Lag representation



Autocorrelation-Tempogram

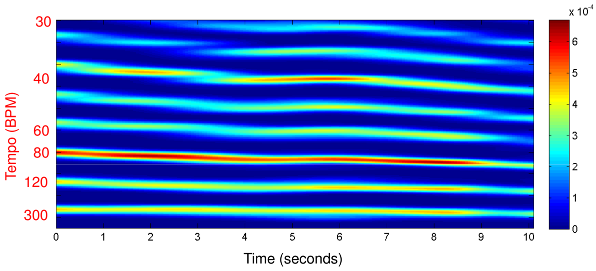
[Peeters 2007]



Time – Lag is not musically meaningful

Autocorrelation-Tempogram

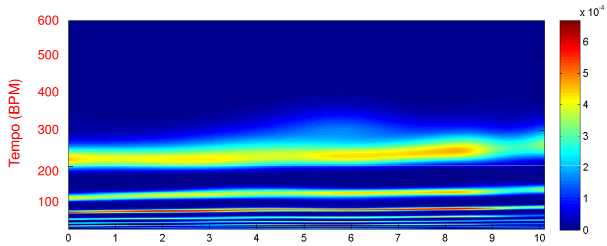
[Peeters 2007]



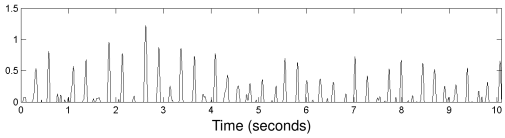
Time – Lag is not musically meaningful

Autocorrelation-Tempogram

[Peeters 2007]



Rescaled to linear tempo axis: Tempogram



Autocorrelation-Tempogram

[Peeters 2007]

- Autocorrelation $\mathcal{A}(t,\ell) = \sum_{n\in\mathbb{Z}} \Delta(n)\Delta(n+\ell)\cdot W(n-t)$

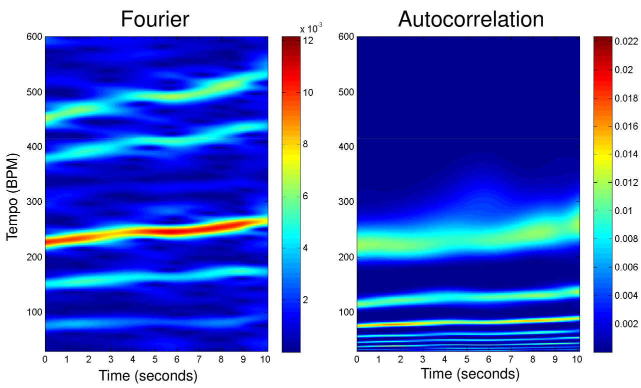
  window function $W:\mathbb{Z}\to\mathbb{R}$ centered at $t=0$ $\quad \ell\in[0:N]$

- Autocorrelation tempogram

$$\mathcal{T}^{\mathrm{A}}(t,\tau)=\mathcal{A}(t,60/\tau)$$

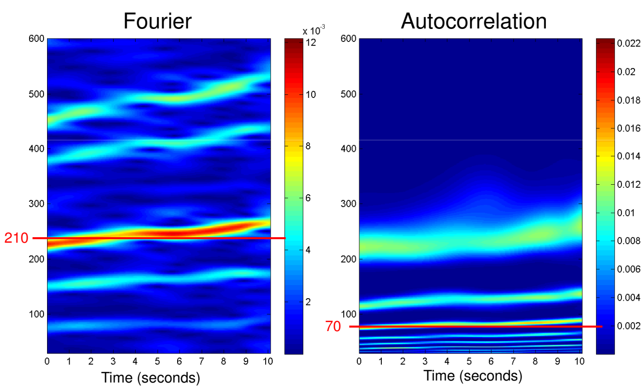
Tempograms

[Peeters 2007]



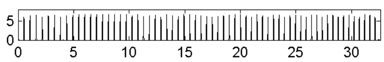
Tempograms

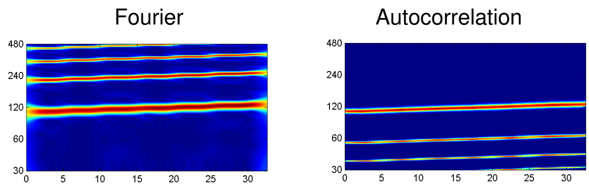
[Peeters 2007]



Tempograms

[Peeters 2007]





Tempogram

[Peeters 2007]

Time-tempo representations that encode the local tempo of the piece over time

Fourier

- Compare the novelty curve with templates consisting of sinusoidal kernels each representing a specific tempo
- Reveals periodic sequences of peaks
- Emphasizes harmonics, i.e. multiples of the tempo:
  Tatum - Level

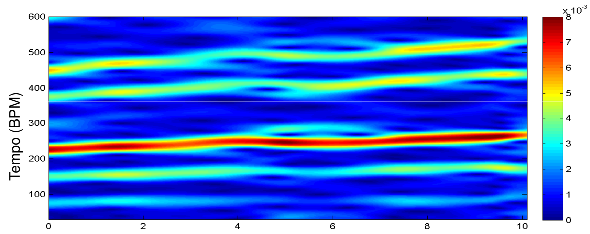
Autocorrelation

- Compare the novelty curve with time-shifted copies of itself
- Reveals periodic self-similarities
- Emphasizes subharmonics, i.e. fractions of the tempo:
  Measure - Level

Tempo Estimation

[Peeters 2007]

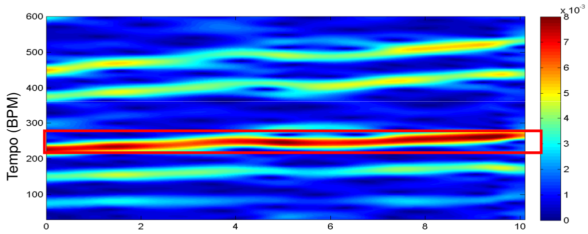
- Extract musically meaningful tempo from tempograms



Tempo Estimation

[Peeters 2007]

- Extract musically meaningful tempo from tempograms

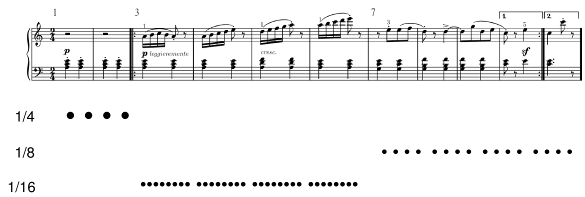


- Local maximum of tempogram is correct in many cases

Tempo Estimation

[GroscheMueller 2009]

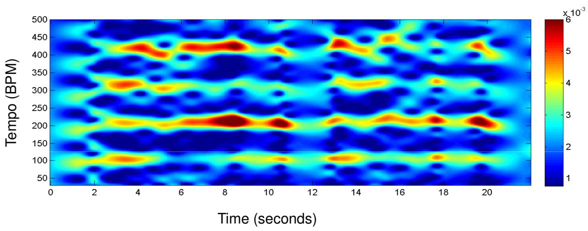
Piano Etude Op. 100 No. 2 by Burgmüller



What if the pulse level is changing?

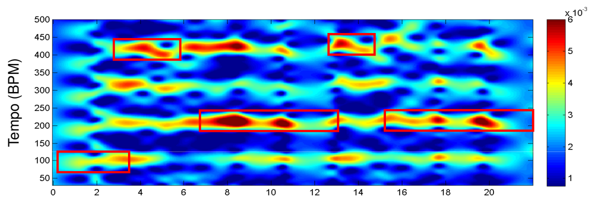
Tempo Estimation

[GroscheMueller 2009]



Tempo Estimation

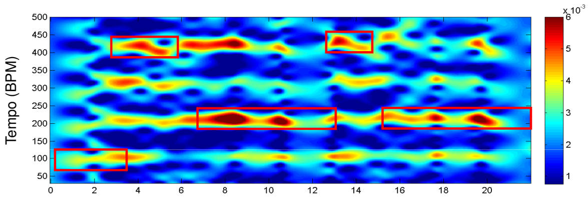
[GroscheMueller 2009]



Switching of predominant pulse level

Tempo Estimation

[GroscheMueller 2009]

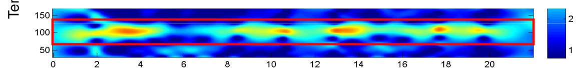


Switching of predominant pulse level

We can restrict the analysis to certain pulse levels

Tempo Estimation

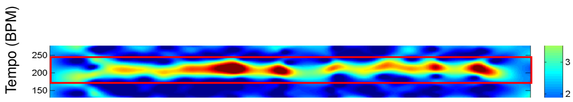
[GroscheMueller 2009]



Prior knowledge: 1/4 **note pulse level**

Tempo Estimation

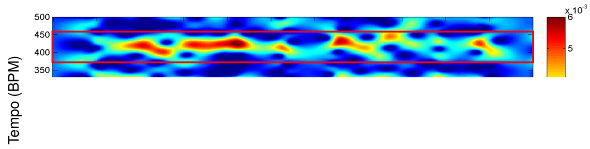
[GroscheMueller 2009]



Prior knowledge: 1/8 **note pulse level**

Tempo Estimation

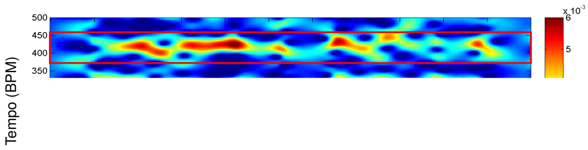
[GroscheMueller 2009]



Prior knowledge: 1/16 **note pulse level**

Tempo Estimation

[GroscheMueller 2009]

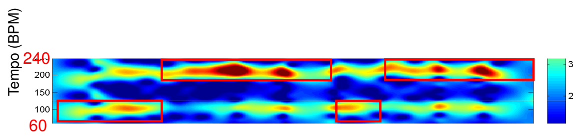


Prior knowledge: 1/16 **note pulse level**

Without prior knowledge?

Tempo Estimation

[Peeters 2007]

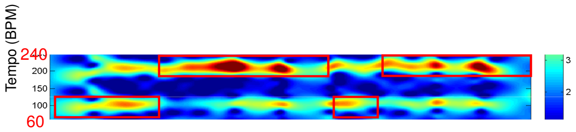


Restrict the tempo to a certain range:

For most pieces the tempo will be in the range of 60 to 240 BPM (close to the human heartbeat ~120 BPM)

Tempo Estimation

[Peeters 2007]

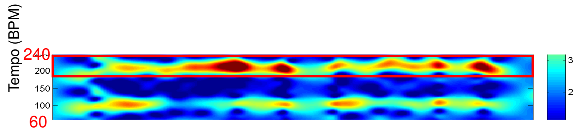


Prevent pulse level changes:

Assuming smooth tempo changes: the tempo of a piece will not change abruptly
Compute a tempo curve that constrains the local tempo estimates to a single pulse level

Tempo Estimation

[Peeters 2007]



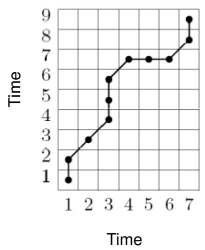
Prevent pulse level changes:

Assuming smooth tempo changes: the tempo of a piece will not change abruptly
Compute a tempo curve that constrains the local tempo estimates to a single pulse level and finds the best sequence of local tempi

Tempo Estimation

[Peeters 2007]

DTW:

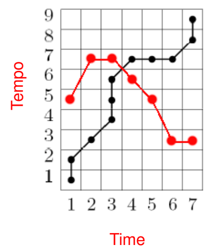


- Boundary conditions:
  find path from (1,1) to (M,N)
- Monotonicity:
  monotone in both axes
- Step size condition:
  from (n,m) only to (n+1,m), (n, m+1) or (n+1, m+1)

Tempo Estimation

[Peeters 2007]

Tempocurve determination:



- Boundary conditions:
  find path from (1,.) to (M,.)
- Monotonicity:
  monotone in time axis
- Step size condition:
  depending on allowed tempo change

Overview

Tasks

1. Note onset detection
2. Tempo estimation
3. Beat tracking

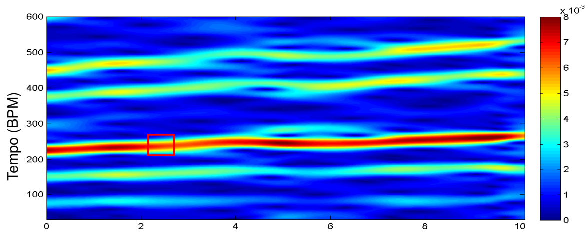
Beat Tracking

[GroscheMueller 2009]

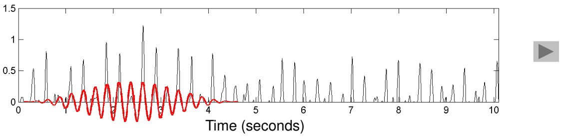
- Given the tempo, find the best sequence of beats
- Complex Fourier tempogram contains magnitude and phase information
- The magnitude encodes how well the novelty curve resonates with a periodicity kernel of a tempo
- The phase aligns the periodicity kernels with the peaks of the novelty curve

Beat Tracking

[GroscheMueller 2009]

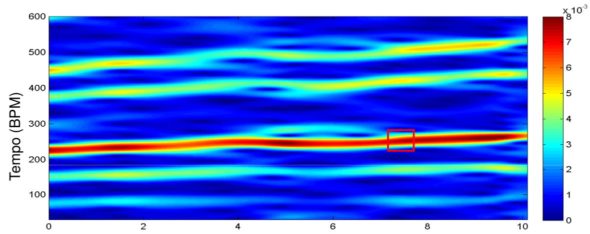


Complex Fourier tempogram

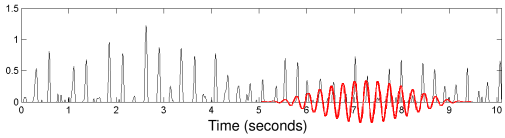


Beat Tracking

[GroscheMueller 2009]

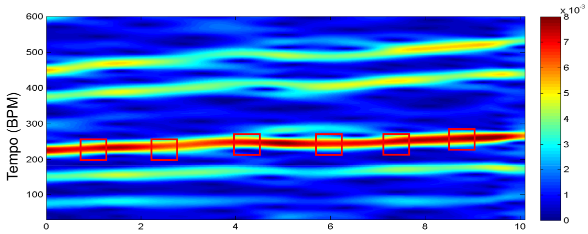


Locally aligned periodicity kernel

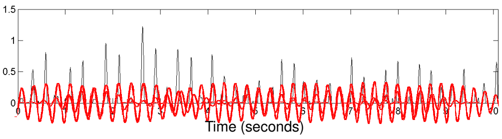


Beat Tracking

[GroscheMueller 2009]

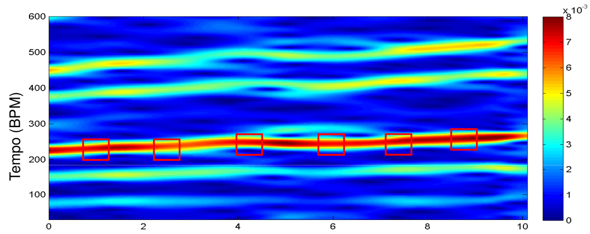


Overlap-add accumulation of all kernels

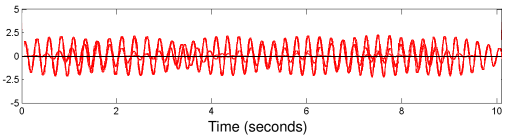


Beat Tracking

[GroscheMueller 2009]

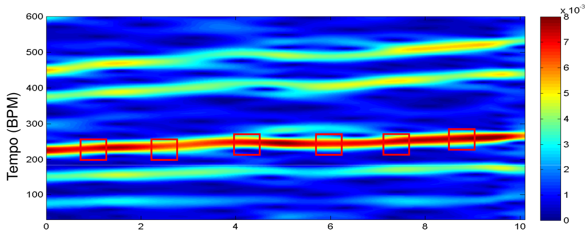


Overlap-add accumulation of all kernels

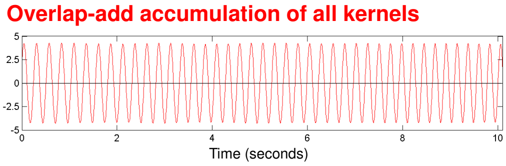


Beat Tracking

[GroscheMueller 2009]

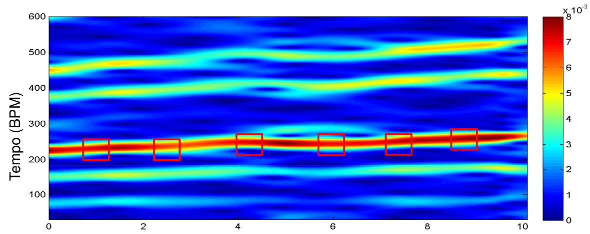


Overlap-add accumulation of all kernels

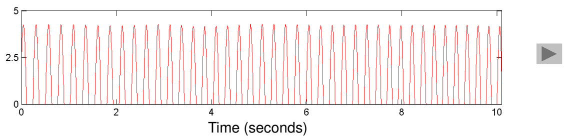


Beat Tracking

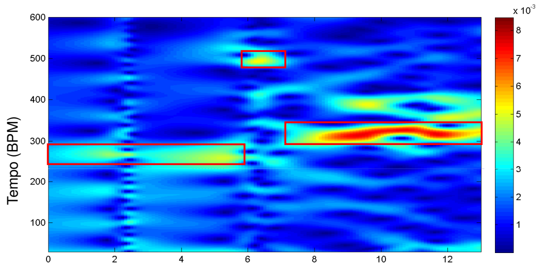
[GroscheMueller 2009]



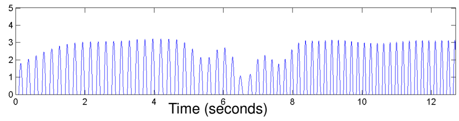
Halfwave rectification



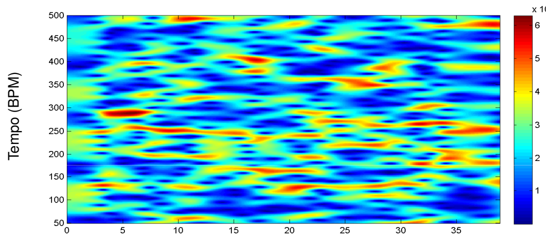
Beat Tracking



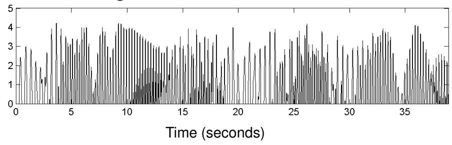
Beethoven – Symphony No. 5



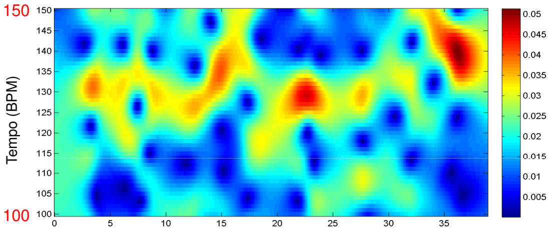
Beat Tracking



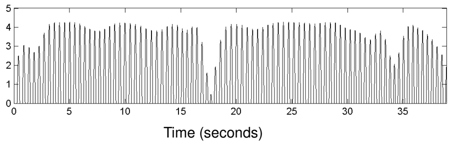
Borodin – String Quartet No. 2



Beat Tracking

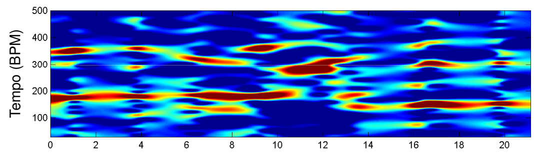


Borodin – String Quartet No. 2



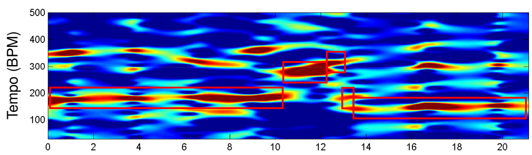
Beat Tracking

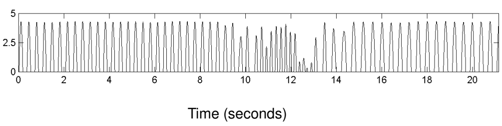
Brahms Hungarian Dance No. 5



Beat Tracking

Brahms Hungarian Dance No. 5





Beat Tracking

[GroscheMueller 2009]

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

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

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

References

[GroscheMueller 2009]
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Computing predominant local periodicity information in music recordings.
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Template-based estimation of time-varying tempo
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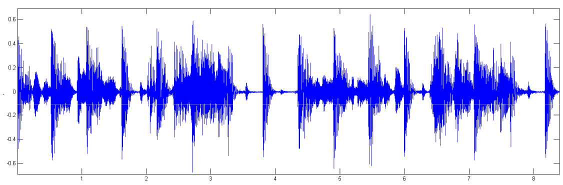
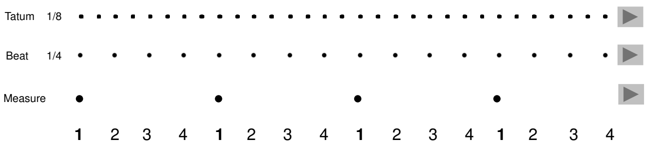
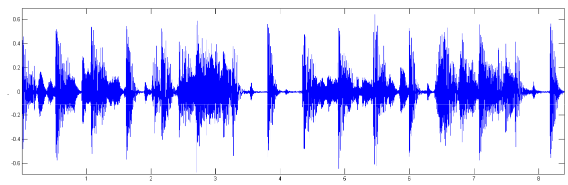
J. P. Bello , L. Daudet, S. Abdallah, C. Duxbury, M. Davies, M. B. and Sandler
A tutorial on onset detection in music signals.
IEEE Transactions on Speech and Audio Processing, 2005.

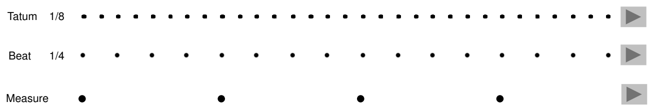
Introduction



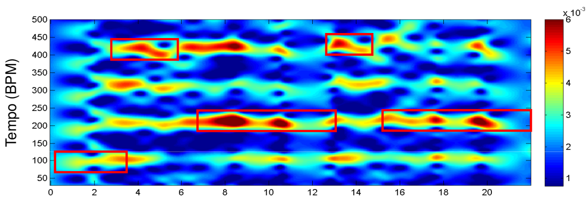


Introduction

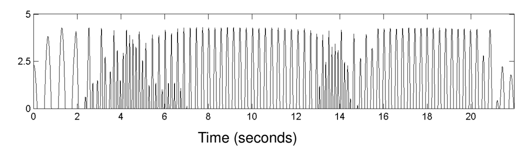




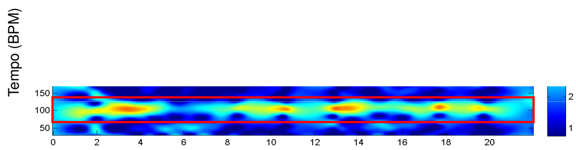
Beat Tracking



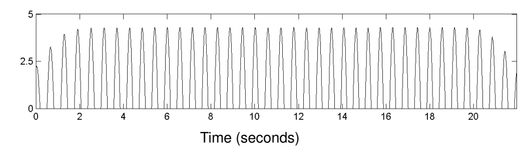
Switching of predominant pulse level



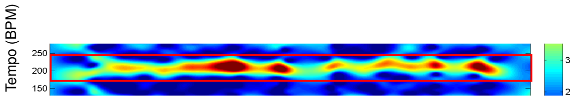
Beat Tracking



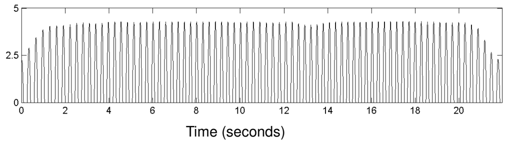
1/4 note pulse level



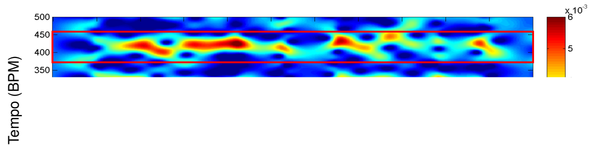
Beat Tracking



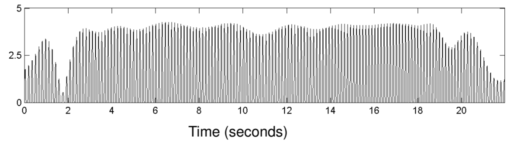
1/8 note pulse level



Beat Tracking



1/16 note pulse level



Beat Tracking

- Queen – Another One Bites The Dust
- Shostakovich – 2nd Waltz
- Beethoven – Symphony No. 5
- Borodin – String Quartet No. 2

Examples: Strong or weak rhythm?

- Queen – Another One Bites The Dust
- Shostakovich – 2nd Waltz
- Beethoven – Pathetique
- Beethoven – Symphony No. 5
- Borodin – String Quartet No. 2