

# Beethoven, Bach, und Billionen Bytes

## Musik trifft Informatik

**Meinard Müller**  
International Audio Laboratories Erlangen

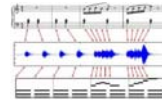
Informatik-Kolloquium  
Universität Bamberg  
23. Oktober 2014



# Meinard Müller



- 2007 Habilitation, Bonn
- 2007 MPI Informatik, Saarbrücken  
Senior Researcher  
Music Processing & Motion Processing

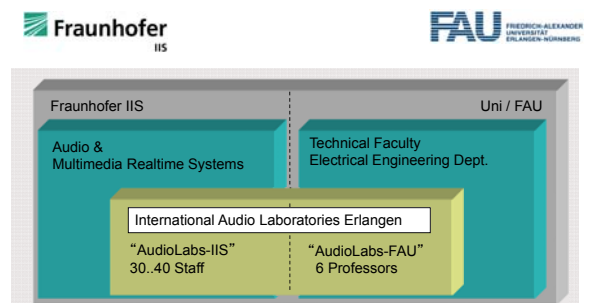


- 2012 W3-Proffur, AudioLabs Erlangen  
Semantic Audio Processing

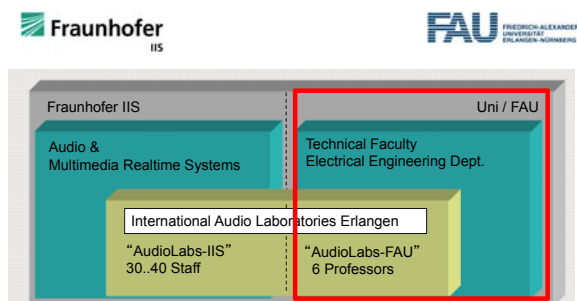
# International Audio Laboratories Erlangen



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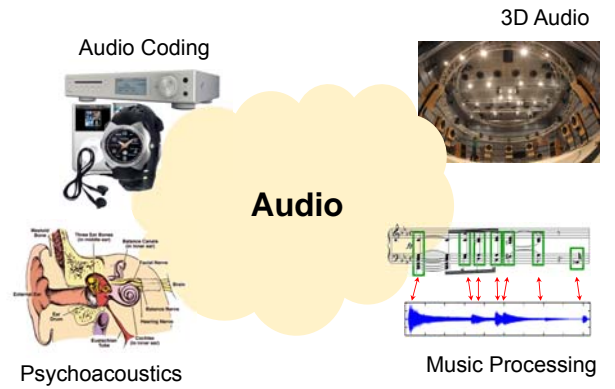
# International Audio Laboratories Erlangen



## International Audio Laboratories Erlangen

Audio

## International Audio Laboratories Erlangen

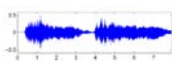


## Music Representations

Sheet Music (Image)



CD / MP3 (Audio)



MusicXML (Text)



Dance / Motion (Mocap)



Music

MIDI



Singing / Voice (Audio)



Music Film (Video)



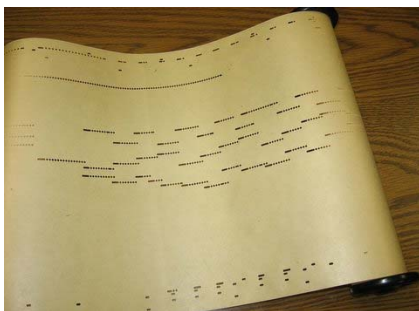
Music Literature (Text)



## Research Goals

- Music Information Retrieval (MIR) → ISMIR
- Analysis of music signals (harmonic, melodic, rhythmic, motivic aspects)
- Design of musically relevant audio features
- Tools for multimodal search and interaction

## Piano Roll Representation

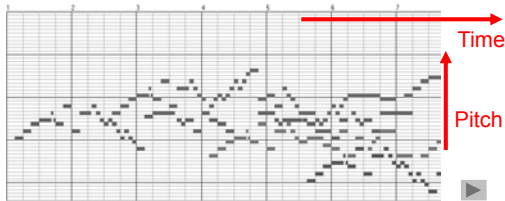


## Player Piano (1900)



## Piano Roll Representation (MIDI)

J.S. Bach, C-Major Fuge  
(Well Tempered Piano, BWV 846)

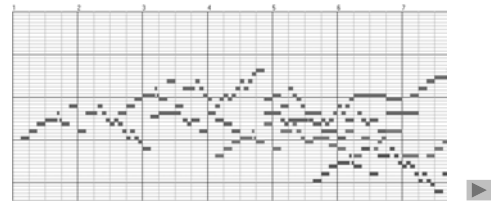


## Piano Roll Representation (MIDI)

Query:



Goal: Find all occurrences of the query



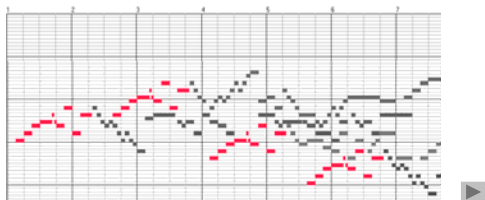
## Piano Roll Representation (MIDI)

Query:



Goal: Find all occurrences of the query

Matches:



## Audio Data

Various interpretations – Beethoven's Fifth



Bernstein



Karajan



Scherbakov (piano)



MIDI (piano)



## Audio Data (Memory Requirements)

1 Bit	=	1: on, 0: off
1 Byte	=	8 Bits
1 Kilobyte (KB)	=	1 Thousand Bytes
1 Megabyte (MB)	=	1 Million Bytes
1 Gigabyte (GB)	=	1 <b>Billion Bytes</b>
1 Terabyte (TB)	=	1000 Billion Bytes

Two audio CDs	>	1 <b>Billion Bytes</b>
1000 audio CDs	=	<b>Billions of Bytes</b>
12.000 MIDI files	<	350 MB

## Music Synchronization: Audio-Audio

Beethoven's Fifth

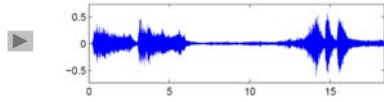


## Music Synchronization: Audio-Audio

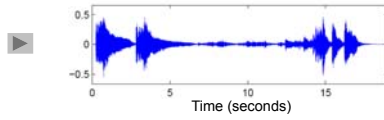
Beethoven's Fifth



Orchester (Karajan)



Piano (Scherbakov)



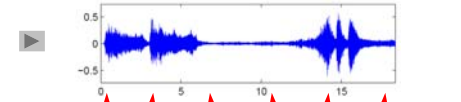
Time (seconds)

## Music Synchronization: Audio-Audio

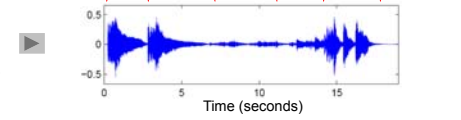
Beethoven's Fifth



Orchester (Karajan)



Piano (Scherbakov)

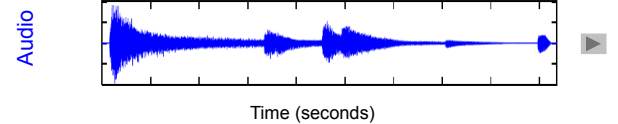


Time (seconds)

## Application: Interpretation Switcher

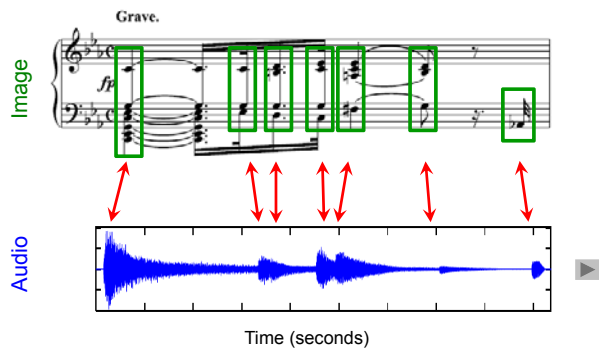


## Music Synchronization: Image-Audio



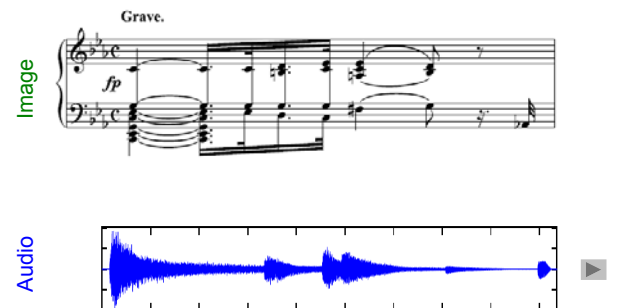
Time (seconds)

## Music Synchronization: Image-Audio



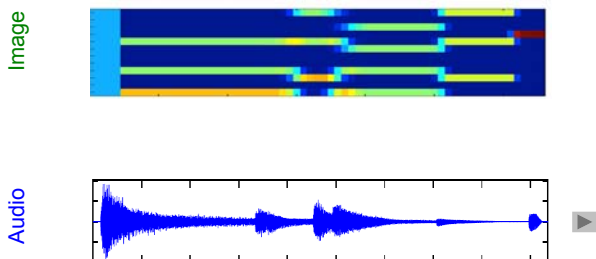
Time (seconds)

## How to make the data comparable?



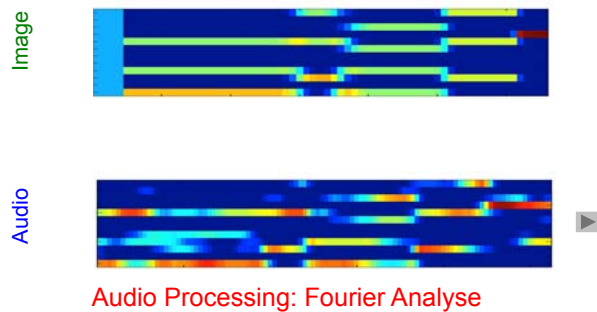
## How to make the data comparable?

### Image Processing: Optical Music Recognition



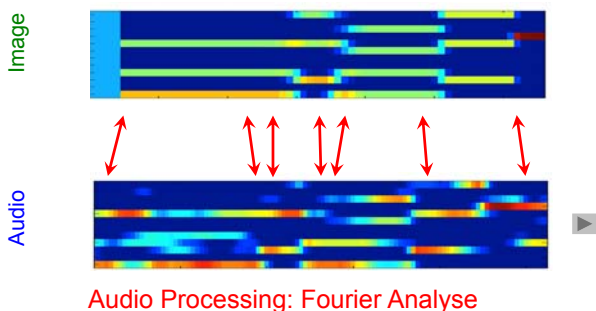
## How to make the data comparable?

### Image Processing: Optical Music Recognition

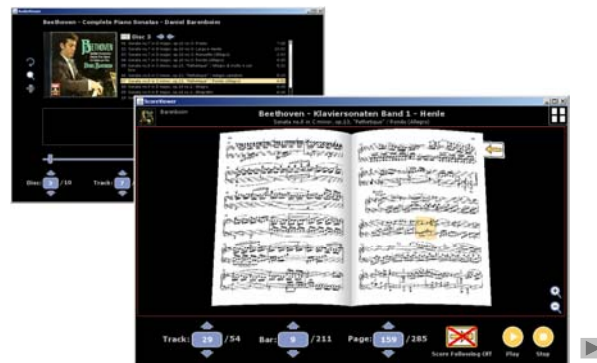


## How to make the data comparable?

### Image Processing: Optical Music Recognition



## Application: Score Viewer



## Feature Representation

**General goal:** Convert an audio recording into a mid-level representation that captures certain musical properties while suppressing other properties.

- Timbre / Instrumentation
- Tempo / Rhythm
- Pitch / Harmony

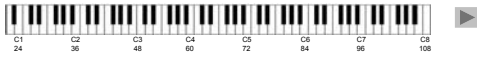
## Feature Representation

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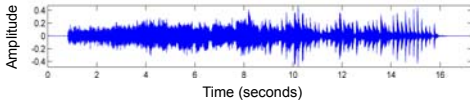
- Timbre / Instrumentation
- Tempo / Rhythm
- Pitch / Harmony

## Feature Representation

Example: Chromatic scale

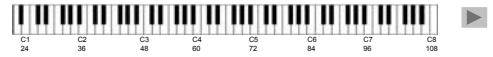


Waveform

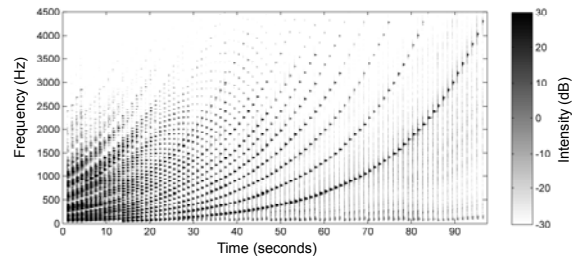


## Feature Representation

Example: Chromatic scale

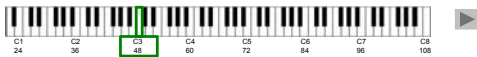


Spectrogram

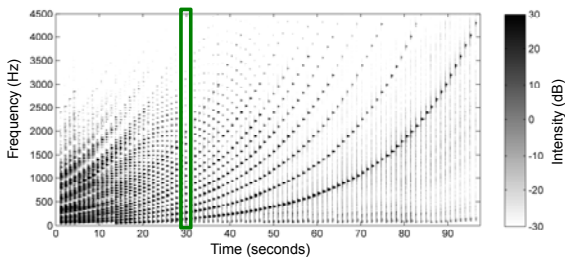


## Feature Representation

Example: Chromatic scale

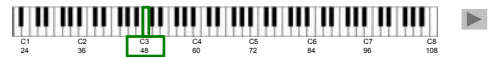


Spectrogram

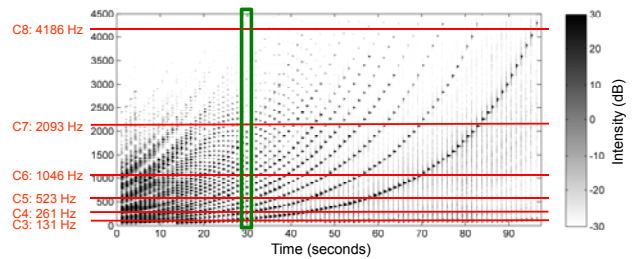


## Feature Representation

Example: Chromatic scale

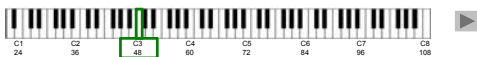


Spectrogram

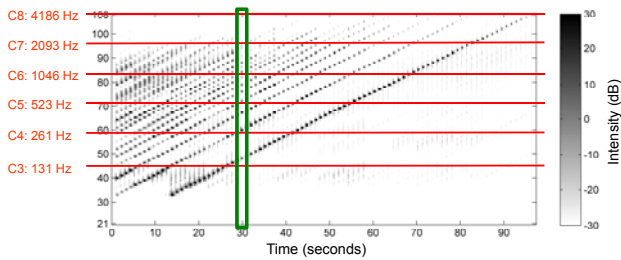


## Feature Representation

Example: Chromatic scale

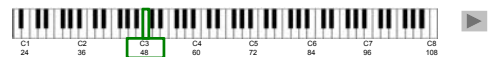


Log-frequency spectrogram

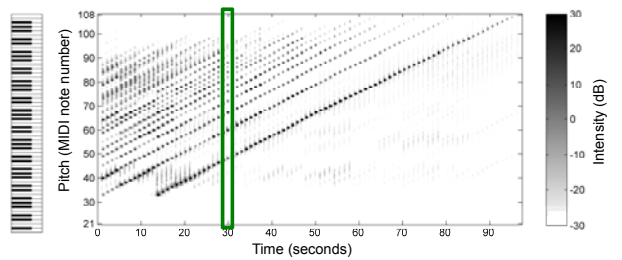


## Feature Representation

Example: Chromatic scale

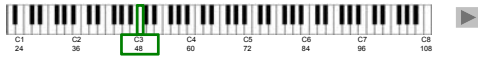


Log-frequency spectrogram

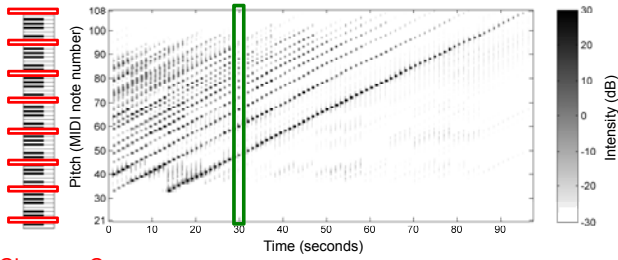


## Feature Representation

Example: Chromatic scale



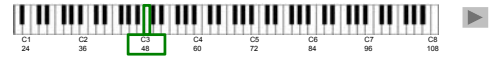
Log-frequency spectrogram



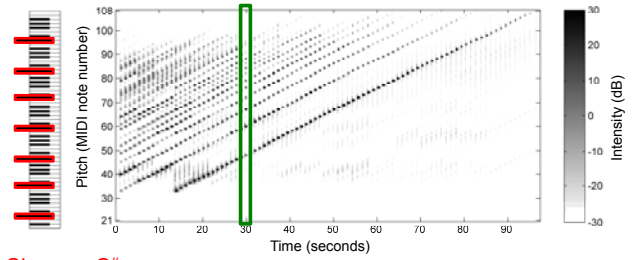
Chroma C

## Feature Representation

Example: Chromatic scale



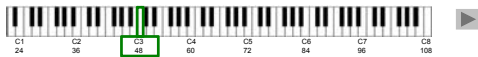
Log-frequency spectrogram



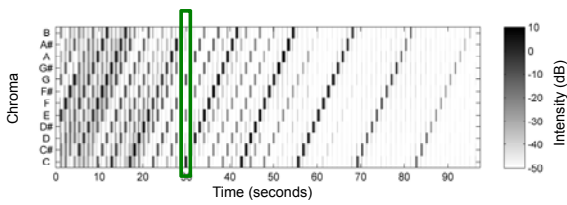
Chroma C#

## Feature Representation

Example: Chromatic scale



Chroma representation



## Why is Music Processing Challenging?

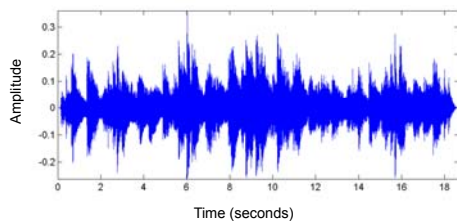
Example: Chopin, Mazurka Op. 63 No. 3



## Why is Music Processing Challenging?

Example: Chopin, Mazurka Op. 63 No. 3

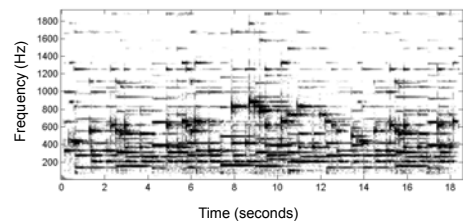
- Waveform



## Why is Music Processing Challenging?

Example: Chopin, Mazurka Op. 63 No. 3

- Waveform / Spectrogram



## Why is Music Processing Challenging?

**Example:** Chopin, Mazurka Op. 63 No. 3 ▶

- Waveform / Spectrogram
- Performance
  - Tempo
  - Dynamics
  - Note deviations
  - Sustain pedal

## Why is Music Processing Challenging?

**Example:** Chopin, Mazurka Op. 63 No. 3 ▶

- Waveform / Spectrogram

- Performance
  - Tempo
  - Dynamics
  - Note deviations
  - Sustain pedal



- Polyphony

- █ Main Melody
- █ Additional melody line
- █ Accompaniment

## Source Separation

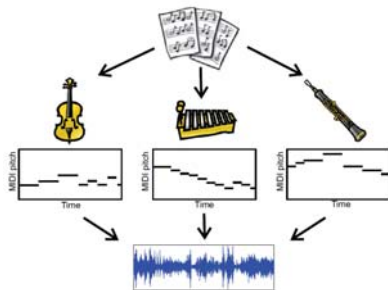
- Decomposition of audio stream into different sound sources
- Central task in digital signal processing
- “Cocktail party effect”
- Sources are often assumed to be statistically independent
- This is often not the case in music

**Strategy:** Exploit additional information (e.g. musical score) to support the separation process

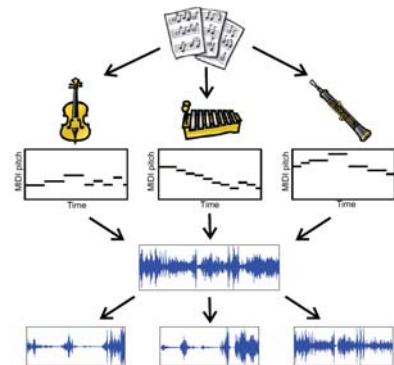
## Score-Informed Source Separation



## Score-Informed Source Separation



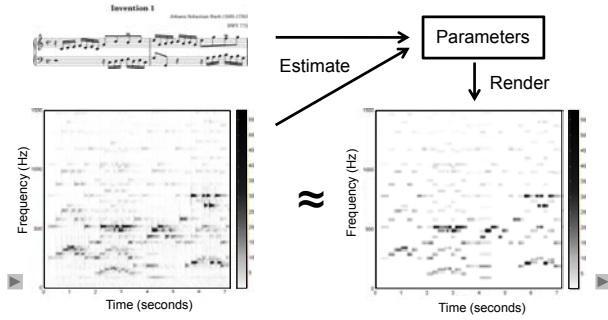
## Score-Informed Source Separation



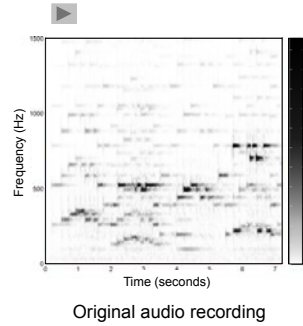


## Score-Informed Source Separation

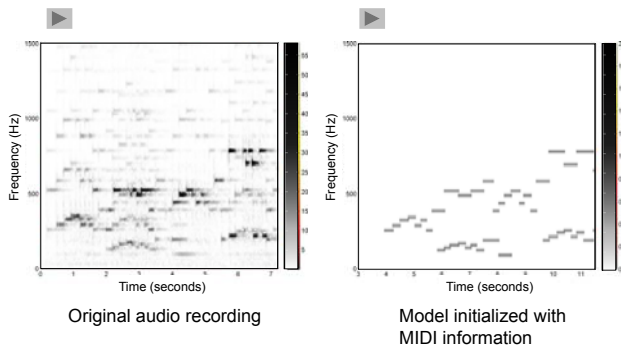
**Goal:** Approximate spectrogram using a parametric model exploiting availability of score information



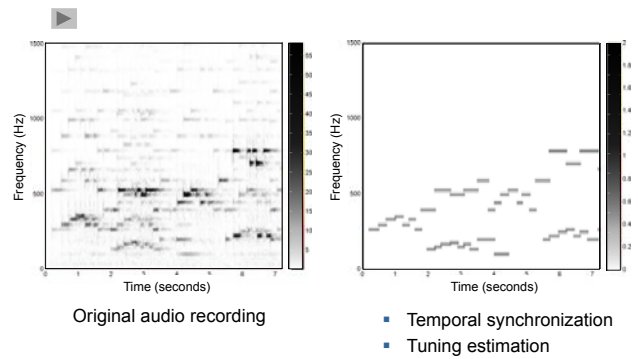
## Score-Informed Source Separation



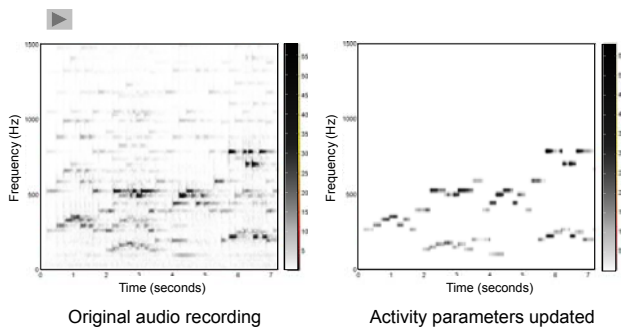
## Score-Informed Source Separation



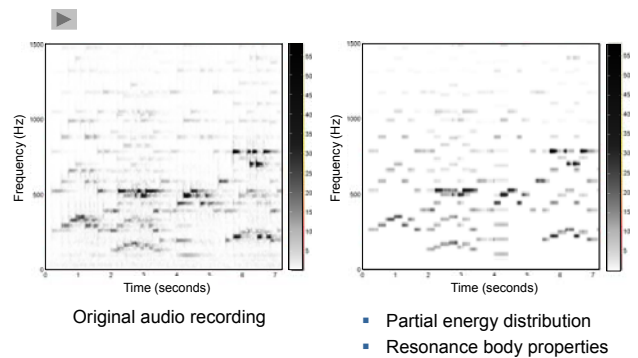
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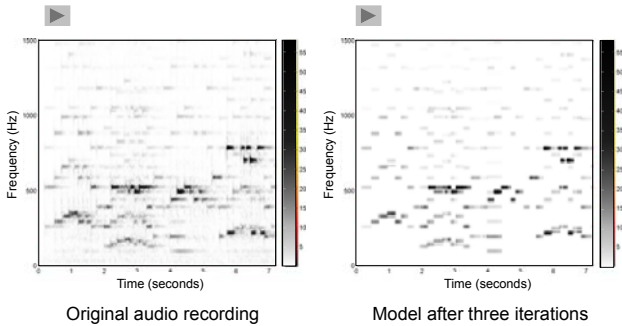
## Score-Informed Source Separation



## Score-Informed Source Separation



## Score-Informed Source Separation



**Note: Each note specified by the score parameterizes a portion of the spectrogram**

## Score-Informed Source Separation

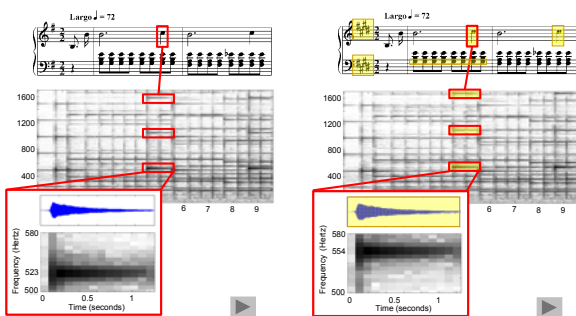
Experimental results for separating left and right hands for piano recordings:



Composer	Piece	Database	Results			
			L	R	Eq	Org
Bach	BWV 875, Prelude	SMD	▶▶▶▶	▶▶▶▶	▶▶▶▶	▶▶▶▶
Chopin	Op. 28, No. 15	SMD	▶▶▶▶	▶▶▶▶	▶▶▶▶	▶▶▶▶
Chopin	Op. 64, No. 1	European Archive	▶▶▶▶	▶▶▶▶	▶▶▶▶	▶▶▶▶

## Score-Informed Source Separation

Audio editing



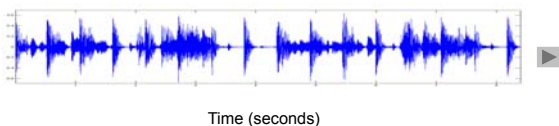
## Tempo Estimation and Beat Tracking

Basic task: "Tapping the foot when listening to music"

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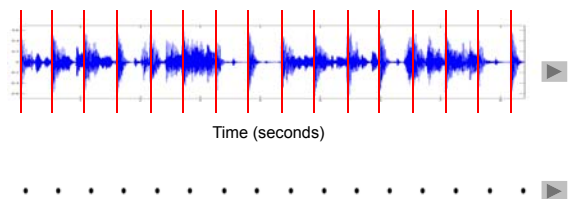
Example: Queen – Another One Bites The Dust



## Tempo Estimation and Beat Tracking

Basic task: "Tapping the foot when listening to music"

Example: Queen – Another One Bites The Dust



## Tempo Estimation and Beat Tracking

Example: Happy Birthday to you

Pulse level: **Measure**

Two staves of music for 'Happy Birthday to you'. The top staff is the vocal line and the bottom is the piano accompaniment. Red arrows point to the beginning of each measure in the vocal line.

## Tempo Estimation and Beat Tracking

Example: Happy Birthday to you

Pulse level: **Tactus (beat)**

Two staves of music for 'Happy Birthday to you'. Red arrows point to the onset of every note in the vocal line.

## Tempo Estimation and Beat Tracking

Example: Happy Birthday to you

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

Two staves of music for 'Happy Birthday to you'. Red arrows point to every eighth note in the vocal line.

## Tempo Estimation and Beat Tracking

Example: Chopin – Mazurka Op. 68-3

Pulse level: Quarter note

Tempo: ???

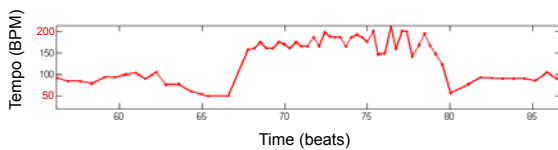
## Tempo Estimation and Beat Tracking

Example: Chopin – Mazurka Op. 68-3

Pulse level: Quarter note

Tempo: **50-200 BPM**

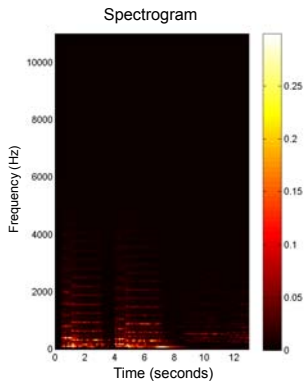
Tempo curve



## Tempo Estimation and Beat Tracking

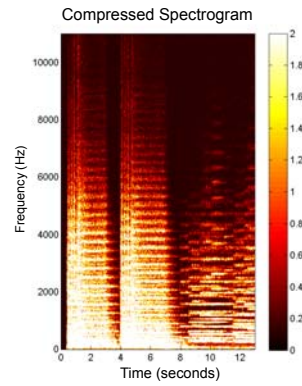
- Which temporal level?
- Local tempo deviations
- Sparse information (e.g., only note onsets available)
- Vague information (e.g., extracted note onsets corrupt)

## Tempo Estimation and Beat Tracking



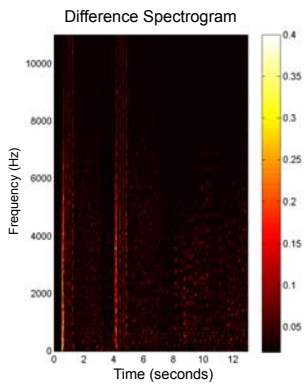
- Steps:**
1. Spectrogram

## Tempo Estimation and Beat Tracking



- Steps:**
1. Spectrogram
  2. Log Compression

## Tempo Estimation and Beat Tracking

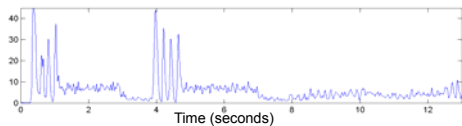


- Steps:**
1. Spectrogram
  2. Log Compression
  3. Differentiation

## Tempo Estimation and Beat Tracking

- Steps:**
1. Spectrogram
  2. Log Compression
  3. Differentiation
  4. Accumulation

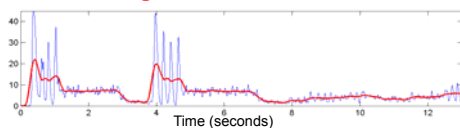
### Novelty Curve



## Tempo Estimation and Beat Tracking

- Steps:**
1. Spectrogram
  2. Log Compression
  3. Differentiation
  4. Accumulation

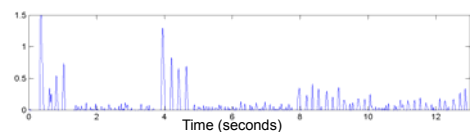
### Novelty Curve Local Average



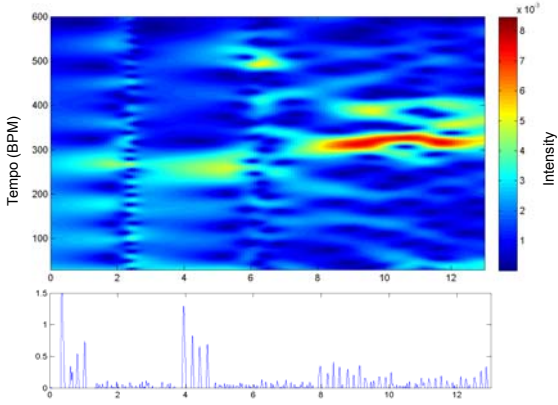
## Tempo Estimation and Beat Tracking

- Steps:**
1. Spectrogram
  2. Log Compression
  3. Differentiation
  4. Accumulation
  5. Normalization

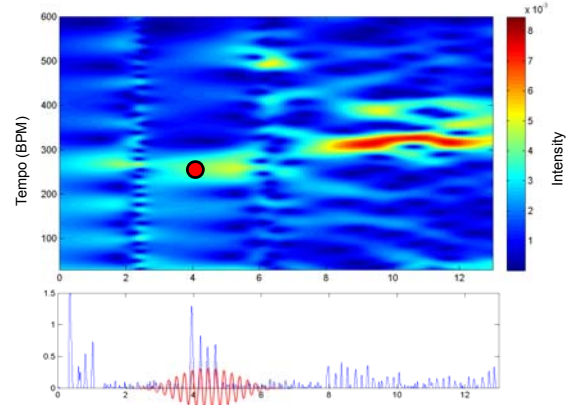
### Novelty Curve



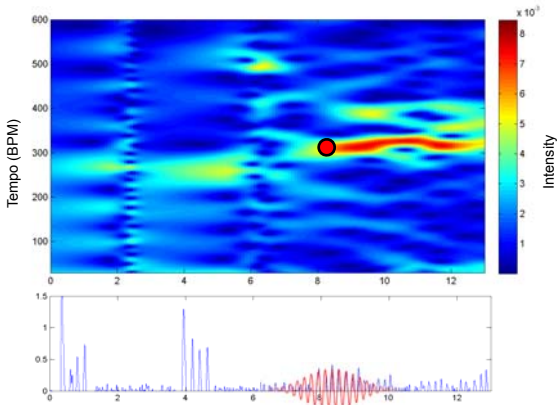
### Tempo Estimation and Beat Tracking



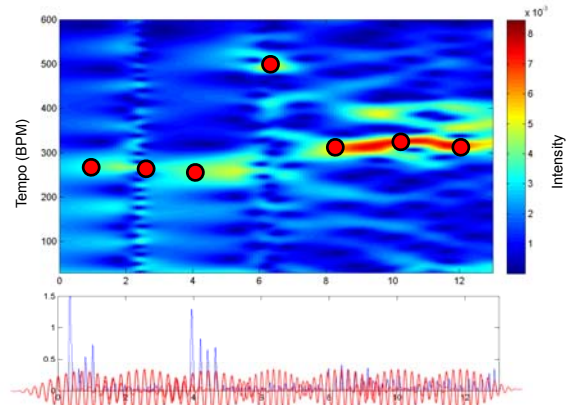
### Tempo Estimation and Beat Tracking



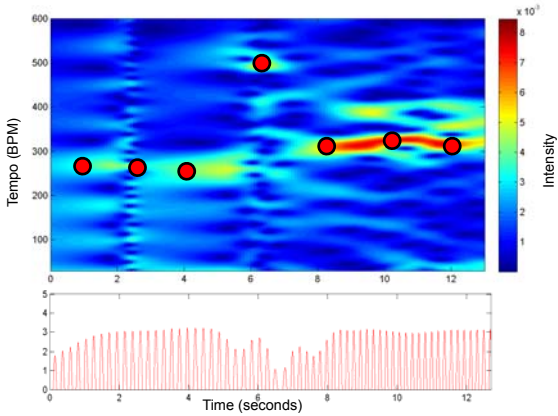
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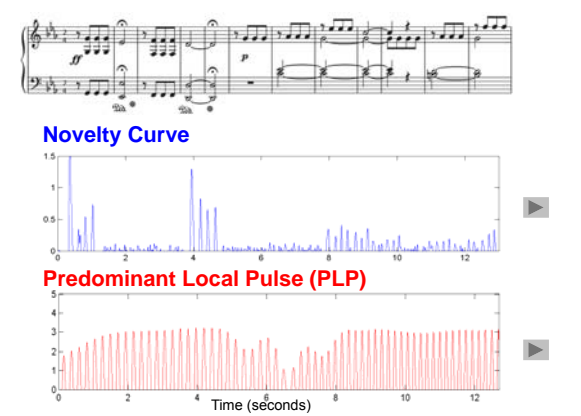
### Tempo Estimation and Beat Tracking



### Tempo Estimation and Beat Tracking



### Tempo Estimation and Beat Tracking



## Information Retrieval



Audio-ID

Bernstein (1962)  
Beethoven, Symphony No. 5

Version-ID

Beethoven, Symphony No. 5:  
▪ Bernstein (1962)  
▪ Karajan (1982)  
▪ Gould (1992)

Category-ID

▪ Beethoven, Symphony No. 9  
▪ Beethoven, Symphony No. 3  
▪ Haydn Symphony No. 94

## Information Retrieval

Musiksynchronisation

Audio-ID

Version-ID

Category-ID

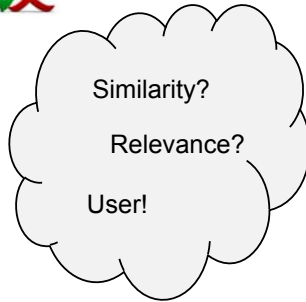
## Information Retrieval

Musiksynchronisation

Audio-ID

Version-ID

Category-ID



## Motivic Similarity



Beethoven's Fifth (1st Mov.)

## Motivic Similarity



Beethoven's Fifth (1st Mov.)

Beethoven's Fifth (3rd Mov.)

## Motivic Similarity



Beethoven's Fifth (1st Mov.)

Beethoven's Fifth (3rd Mov.)

Beethoven's Appassionata

## Motivic Similarity

Var. 4: Vivace



## Motivic Similarity



## Music Processing

### Computer Science

Information Retrieval  
Pattern Matching  
Multimedia  
User Interfaces



### Humanities

Music Analysis  
Performance Analysis  
Music Education

### EEL

Signal Processing  
Audio Processing  
Computational Acoustics  
Sensors

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## Projekte & Kooperationen

- DFG-Projekt: **METRUM**  
Mehrschichtige Analyse und Strukturierung von Musiksignalen  
Kooperation: Michael Clausen  
Laufzeit: 2011-2015
- BMBF-Projekt: **Freischütz Digital**  
Freischütz Digital – Paradigmatische Umsetzung eines genuin digitalen Editionskonzepts  
Kooperation: Joachim Veit, Thomas Betzwieser, Gerd Szwillus  
Laufzeit: 2012-2015
- DFG-Projekt: **SIAMUS**  
Notentext-Informierte Audioparametrisierung von Musiksignalen  
Laufzeit: 2014-2017
- Projekt **Musikwissenschaften**  
Computergestützte Analyse harmonischer Strukturen  
Kooperation: Rainer Kleinertz  
Laufzeit: 2015-2018

## Selected Publications (Music Processing)

- M. Müller, N. Jiang, P. Grosche (2013):  
**A robust fitness measure for capturing repetitions in music recordings with applications to audio thumbnailing.**  
IEEE Trans. on Audio, Speech & Language Processing, Vol. 21, No. 3, pp. 531-543.
- M. Müller, P.W. Ellis, A. Klapuri, G. Richard (2011):  
**Signal Processing for Music Analysis.**  
IEEE Journal of Selected Topics in Signal Processing, Vol. 5, No. 6, pp. 1088-1110.
- P. Grosche and M. Müller (2011):  
**Extracting Predominant Local Pulse Information from Music Recordings.**  
IEEE Trans. on Audio, Speech & Language Processing, Vol. 19, No. 6, pp. 1688-1701.
- M. Müller and S. Ewert (2010):  
**Towards Timbre-Invariant Audio Features for Harmony-Based Music.**  
IEEE Trans. on Audio, Speech & Language Processing, Vol. 18, No. 3, pp. 649-662.
- F. Kurth, M. Müller (2008):  
**Efficient Index-Based Audio Matching.**  
IEEE Trans. Audio, Speech & Language Processing, Vol. 16, No. 2, 382-395.
- M. Müller (2007):  
**Information Retrieval for Music and Motion.**  
Monograph, Springer, 318 pages