INTERNATIONAL AUDIO LABORATORIES ERLANGEN
A joint institution of Fraunhofer IIS and Universität Erlangen-Nürnberg

AUDIO LABS

An Introduction to Music Information Retrieval

Meinard Müller

International Audio Laboratories Erlangen
meinard.mueller@audiolabs-erlangen.de

Guest Lecture
Central Conservatory of Music (CCOM)
Beijing, March 2023

FAU Friedrich-Alexander-Universität Erlangen-Nürnberg

Fraunhofer IIS

Meinard Müller

- Mathematics (Diplom/Master, 1997)
  Computer Science (PhD, 2001)
  Information Retrieval (Habilitation, 2007)
- Senior Researcher (2007-2012)
- Professor Semantic Audio Processing (since 2012)
- Former President of the International Society for Music Information Retrieval (MIR)
- IEEE Fellow for contributions to Music Signal Processing

universitätbonn
mpii max planck institut informatik
FAU
ISMIR
IEEE

Meinard Müller: Research Group

Semantic Audio Processing

- Michael Krause
- Yigitcan Özer
- Simon Schwär
- Johannes Zeitler
- Peter Meier (external)

- Christof Weiß
- Sebastian Rosenzweig
- Frank Zalkow
- Christian Dittmar
- Stefan Balke
- Jonathan Driedger
- Thomas Prätzlich
- …

International Audio Laboratories Erlangen

Fraunhofer IIS

- Fraunhofer Institute for Integrated Circuits IIS
- Largest Fraunhofer institute with ≈ 1000 members
- Applied research for sensor, audio, and media technology

mp3

AUDIO LABS

FAU Friedrich-Alexander Universität Erlangen-Nürnberg

- Friedrich-Alexander Universität Erlangen-Nürnberg (FAU)
- One of Germany's largest universities with ≈ 40,000 students
- Strong Technical Faculty

International Audio Laboratories Erlangen

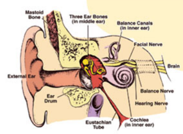
Audio

International Audio Laboratories Erlangen

Audio

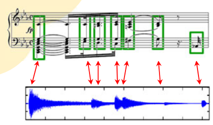
Audio Coding

3D Audio



Psychoacoustics

Internet of Things

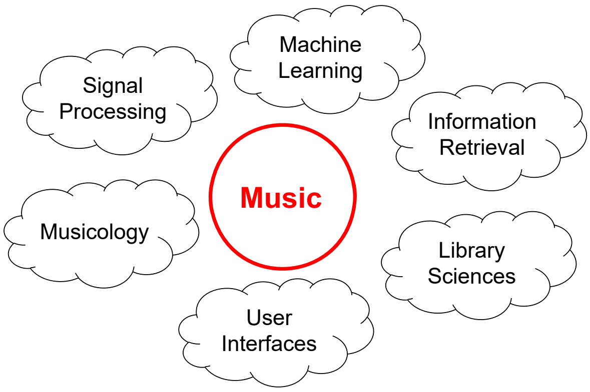


Music Processing

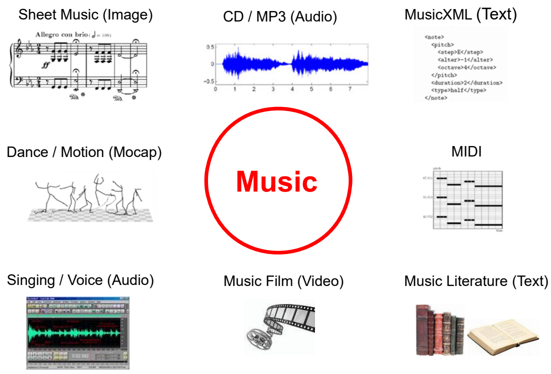
AudioLabs – FAU

- Prof. Dr. Jürgen Herre
  Audio Coding
- Prof. Dr. Bernd Edler
  Audio Signal Analysis
- Prof. Dr. Meinard Müller
  Semantic Audio Processing
- Prof. Dr. Emanuël Habets
  Spatial Audio Signal Processing
- Prof. Dr. Nils Peters
  Audio Signal Processing
- Dr. Stefan Turowski
  Coordinator AudioLabs-FAU

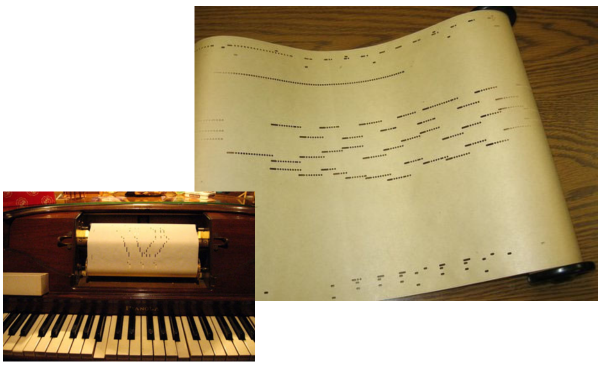
Music Information Retrieval (MIR)



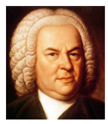
Music Information Retrieval (MIR)



Piano Roll Representation (1900)

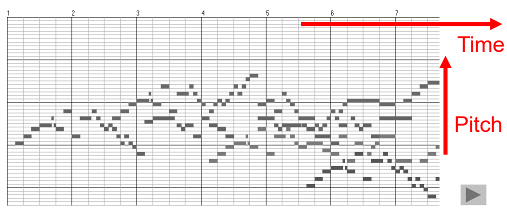


Piano Roll Representation

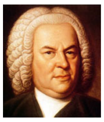


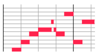
J.S. Bach, C-Major Fuge

(Well Tempered Piano, BWV 846)

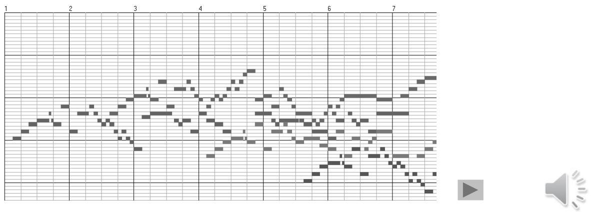


Piano Roll Representation

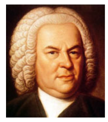


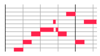
Query: 

Goal: Find all occurrences of the query



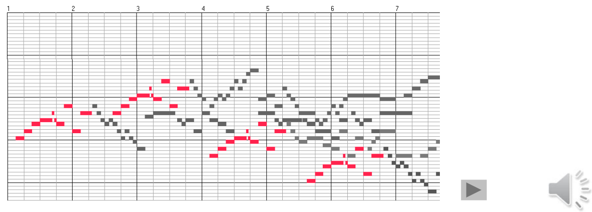
Piano Roll Representation



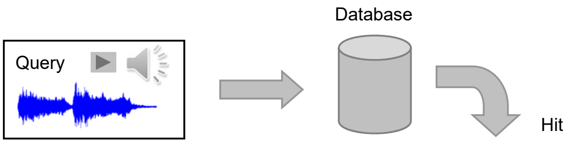
Query: 

Goal: Find all occurrences of the query

Matches:



Music Retrieval



Audio ID

Bernstein (1962) Beethoven, Symphony No. 5

Version ID

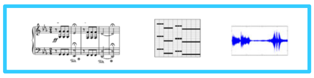
Beethoven, Symphony No. 5:
- Bernstein (1962)
- Karajan (1982)
- Gould (1992)

Category ID

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

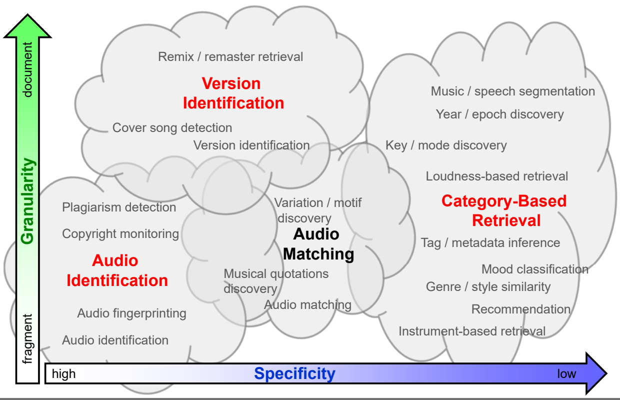
Music Retrieval

Modalities



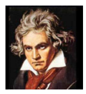
Retrieval tasks:	Specificity	Granularity
Audio ID	High specificity	Fragment-based retrieval
Version ID	↕	↕
Category ID	Low specificity	Document-based retrieval

Music Retrieval



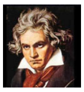
Music Synchronization: Audio-Audio

Beethoven's Fifth

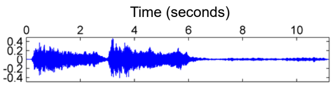


Music Synchronization: Audio-Audio

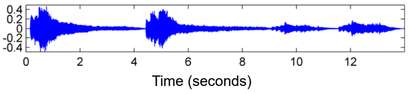
Beethoven's Fifth



Karajan (Orchester)

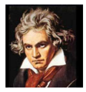


Gould (Piano)



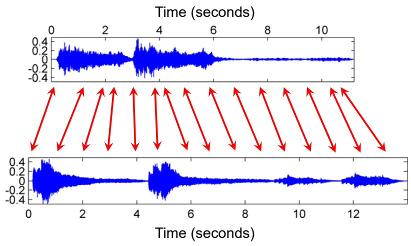
Music Synchronization: Audio-Audio

Beethoven's Fifth

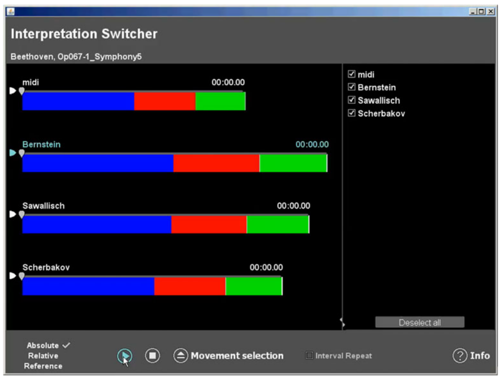


Karajan (Orchester)

Gould (Piano)



Application: Interpretation Switcher



Music Synchronization: Audio-Audio

Task

Given: Two different audio recordings (two versions) of the same underlying piece of music.

Goal: Find for each position in one audio recording the musically corresponding position in the other audio recording.

Music Synchronization: Audio-Audio

Traditional Engineering Approach:

1.) Feature extraction

- Robust to variations (e.g., instrumentation, timbre, dynamics)
- Discriminative (e.g., capturing harmonic, melodic, tonal aspects)

➡ **Chroma features**

2.) Temporal alignment

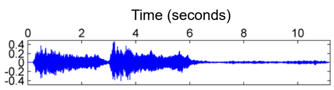
- Capturing local and global tempo variations
- Trade-off: Robustness vs. accuracy
- Efficiency

➡ **Dynamic time warping (DTW)**

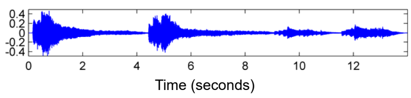
Music Synchronization: Audio-Audio

Beethoven's Fifth

Karajan (Orchester)



Gould (Piano)

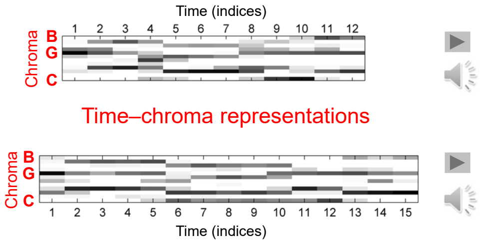


Music Synchronization: Audio-Audio

Beethoven's Fifth

Karajan (Orchester)

Gould (Piano)

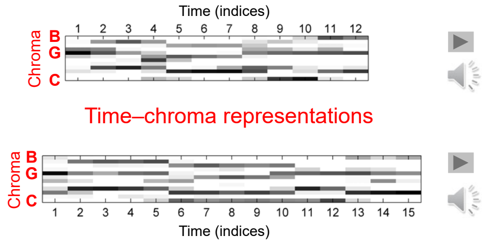


Music Synchronization: Audio-Audio

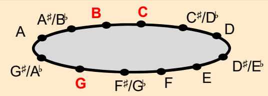
Beethoven's Fifth

Karajan (Orchester)

Gould (Piano)



Chromatic circle

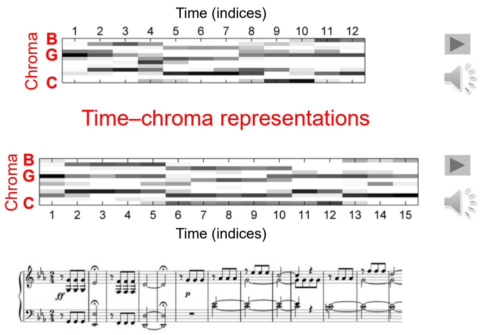


Music Synchronization: Audio-Audio

Beethoven's Fifth

Karajan (Orchester)

Gould (Piano)

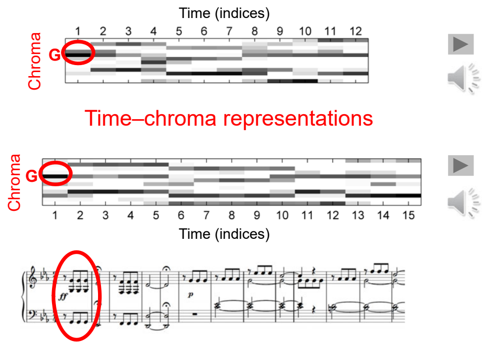


Music Synchronization: Audio-Audio

Beethoven's Fifth

Karajan (Orchester)

Gould (Piano)

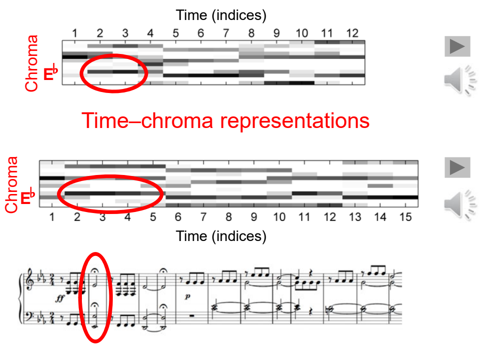


Music Synchronization: Audio-Audio

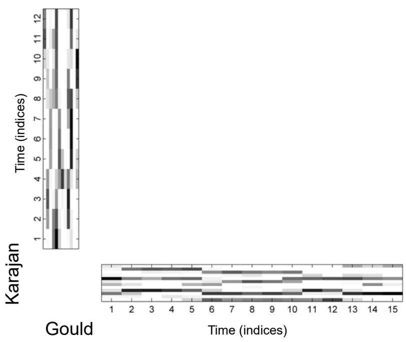
Beethoven's Fifth

Karajan (Orchester)

Gould (Piano)

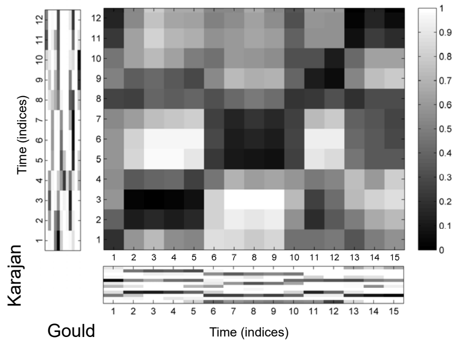


Music Synchronization: Audio-Audio



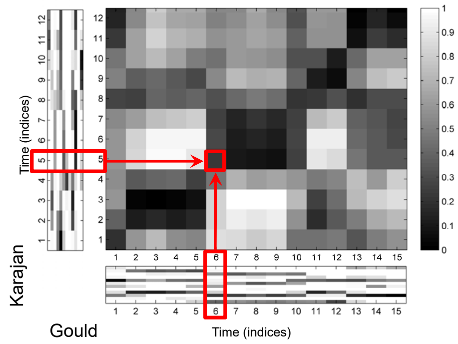
Music Synchronization: Audio-Audio

Cost matrix



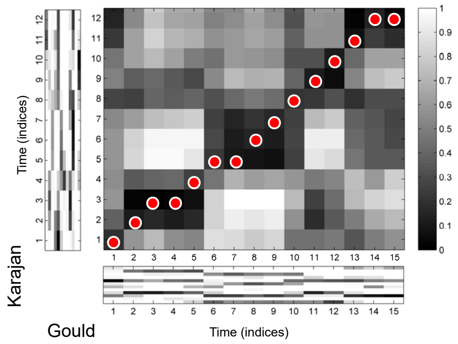
Music Synchronization: Audio-Audio

Cost matrix



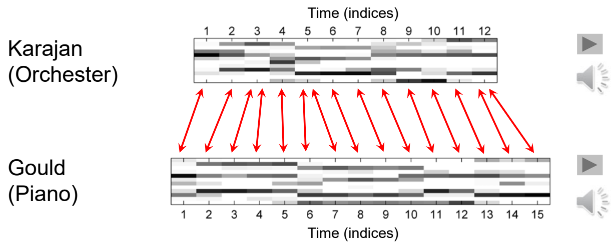
Music Synchronization: Audio-Audio

Cost-minimizing warping path



Music Synchronization: Audio-Audio

Cost-minimizing warping path = Optimal alignment



Music Synchronization: Audio-Audio

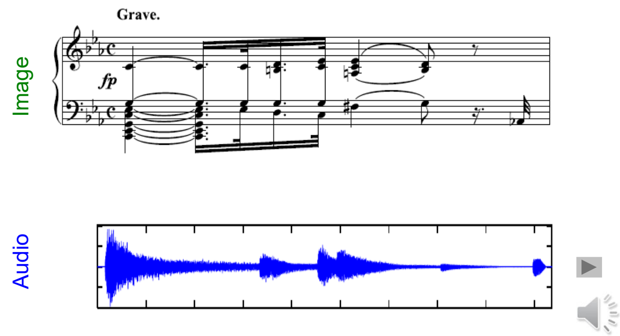
Deep Learning Approaches

- Learn audio features from data
  - Should be able to achieve high alignment accuracy
  - Should be robust to performance variations
  - Musical relevance?
- Alignment problem
  - Pre-aligned data for training
  - Part of loss function → differentiability?

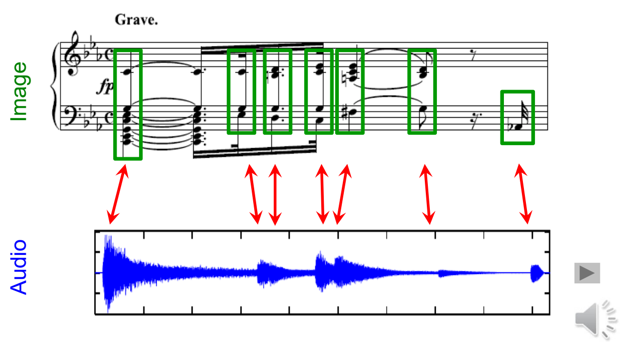
CTC-Loss
Graves et al.: Connectionist Temporal Classification: Labelling Unsegmented Sequence Data with Recurrent Neural Networks. ICML, 2006

Soft-DTW
Cuturi, Blondel: Soft-DTW: A Differentiable Loss Function for Time-Series. ICML, 2017

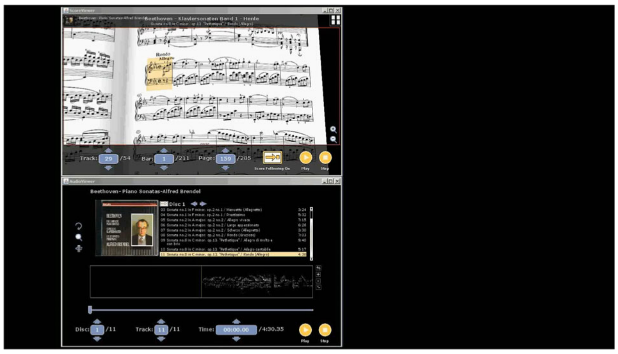
Music Synchronization: Image-Audio



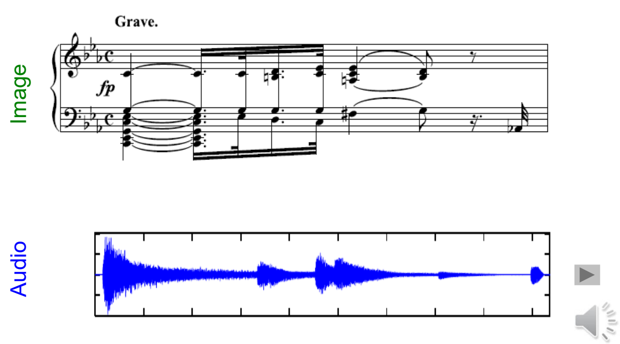
Music Synchronization: Image-Audio



Application: Score Viewer

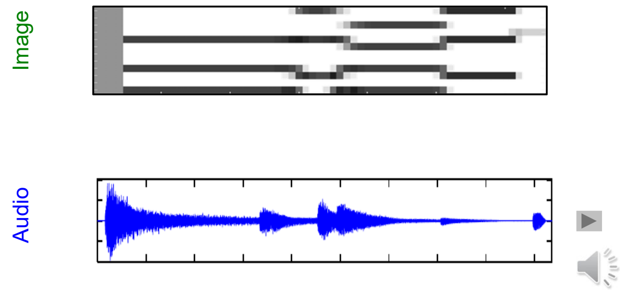


Music Synchronization: Image-Audio



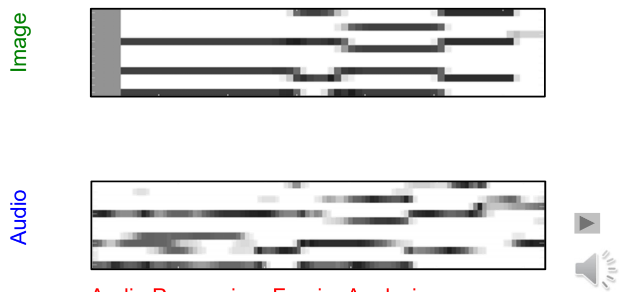
Music Synchronization: Image-Audio

Image Processing: Optical Music Recognition



Music Synchronization: Image-Audio

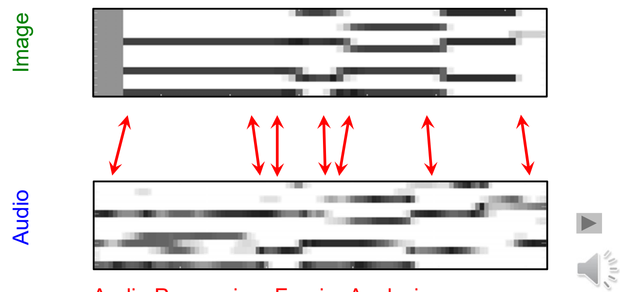
Image Processing: Optical Music Recognition



Audio Processing: Fourier Analysis

Music Synchronization: Image-Audio

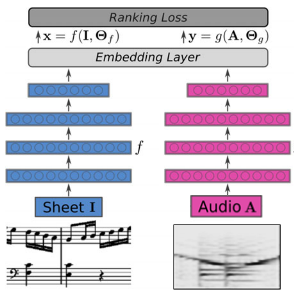
Image Processing: Optical Music Recognition



Audio Processing: Fourier Analysis

Music Synchronization: Image-Audio

Deep Learning Approach



- Deep learning
- Embedding techniques
- Triplet loss
- …

Cross-Modal Retrieval
Dorfer et al.: End-to-End Cross-Modality Retrieval with CCA Projections and Pairwise Ranking Loss. International Journal of Multimedia Information Retrieval, 2018.

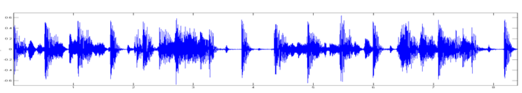
Music Processing

Coarse/Relative Level	Fine/Absolute Level
What do different versions or instances have in common?	What are the characteristics of a specific version or instance?
Provide coarse description: What makes up a piece of music?	Capture nuances and subtleties: What makes music come alive?
Identify despite of differences	Identify the differences
Example tasks: **Music Retrieval** **Genre Classification** **Global Tempo Estimation**	Example tasks: **Music Transcription** **Performance Analysis** **Local Tempo Estimation**

Tempo Estimation and Beat Tracking

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

Example: Queen – Another One Bites The Dust

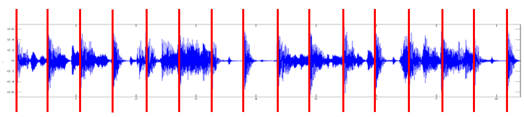


Time (seconds)

Tempo Estimation and Beat Tracking

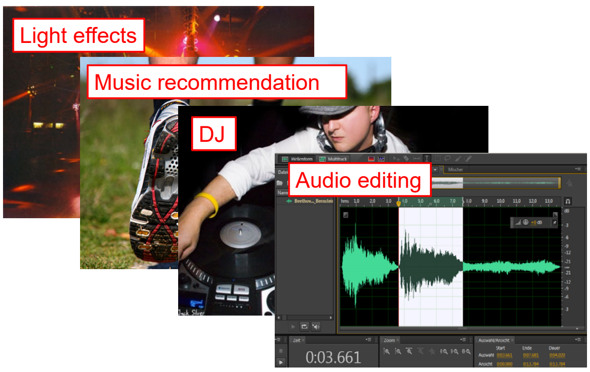
Basic task: "Tapping the foot when listening to music"

Example: Queen – Another One Bites The Dust



Time (seconds)

Tempo Estimation and Beat Tracking



Tempo Estimation and Beat Tracking

Example: Chopin – Mazurka Op. 68-3

Pulse level: Quarter note

Tempo: ???

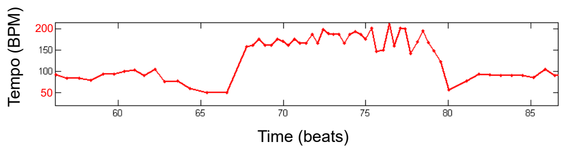
Tempo Estimation and Beat Tracking

Example: Chopin – Mazurka Op. 68-3

Pulse level: Quarter note

Tempo: 50-200 BPM

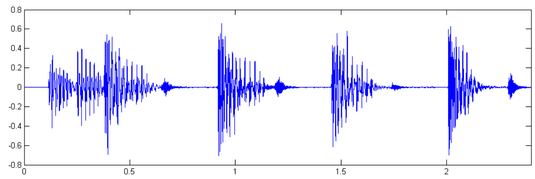
Tempo curve



Tempo Estimation and Beat Tracking

Tasks

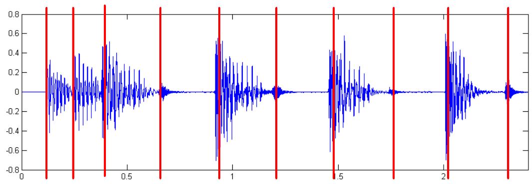
- Onset detection
- Beat tracking
- Tempo estimation



Tempo Estimation and Beat Tracking

Tasks

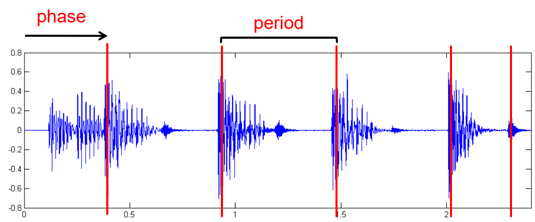
- Onset detection
- Beat tracking
- Tempo estimation



Tempo Estimation and Beat Tracking

Tasks

- Onset detection
- Beat tracking
- Tempo estimation



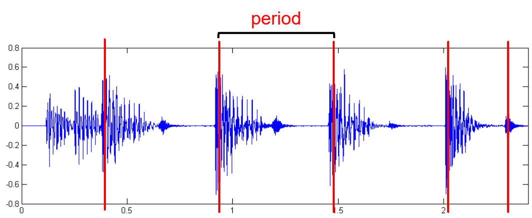
Tempo Estimation and Beat Tracking

Tasks

- Onset detection
- Beat tracking
- Tempo estimation

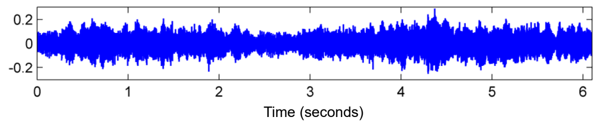
Tempo := 60 / period

Beats per minute (BPM)



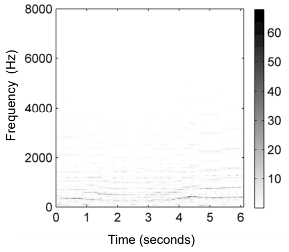
Onset Detection (Spectral Flux)

Audio recording



Onset Detection (Spectral Flux)

Magnitude spectrogram $|X|$

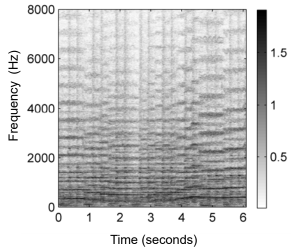


Steps:

1. Spectrogram

Onset Detection (Spectral Flux)

Compressed spectrogram Y

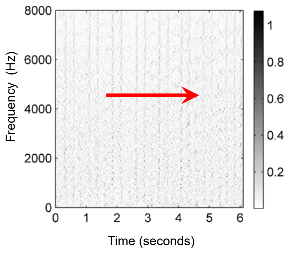


Steps:

1. Spectrogram
2. Logarithmic compression

Onset Detection (Spectral Flux)

Spectral difference

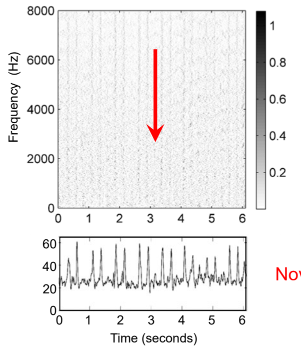


Steps:

1. Spectrogram
2. Logarithmic compression
3. Differentiation &
half wave rectification

Onset Detection (Spectral Flux)

Spectral difference



Novelty curve

Steps:

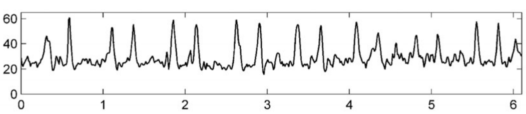
1. Spectrogram
2. Logarithmic compression
3. Differentiation &
half wave rectification
4. Accumulation

Onset Detection (Spectral Flux)

Steps:

1. Spectrogram
2. Logarithmic compression
3. Differentiation &
half wave rectification
4. Accumulation

Novelty function



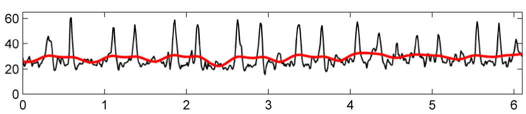
Onset Detection (Spectral Flux)

Steps:

1. Spectrogram
2. Logarithmic compression
3. Differentiation &
half wave rectification
4. Accumulation
5. Normalization

Novelty function

Substraction of local average

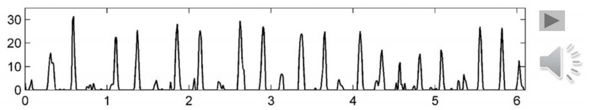


Onset Detection (Spectral Flux)

Steps:

1. Spectrogram
2. Logarithmic compression
3. Differentiation & half wave rectification
4. Accumulation
5. Normalization

Normalized novelty function



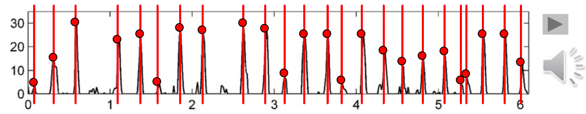
Onset Detection (Spectral Flux)

Steps:

1. Spectrogram
2. Logarithmic compression
3. Differentiation & half wave rectification
4. Accumulation
5. Normalization

Normalized novelty function

Peak positions indicate beat candidates



Onset Detection (Spectral Flux)

Deep Learning

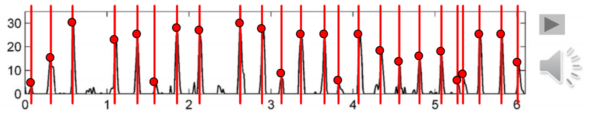
1. Input representation
2. Sigmoid activation
3. Convolution & rectified linear unit (ReLU)
4. Pooling
5. Convolution & ReLU

Steps:

1. Spectrogram
2. Logarithmic compression
3. Differentiation & half wave rectification
4. Accumulation
5. Normalization

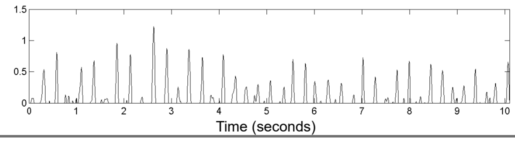
Normalized novelty function

Peak positions indicate beat candidates



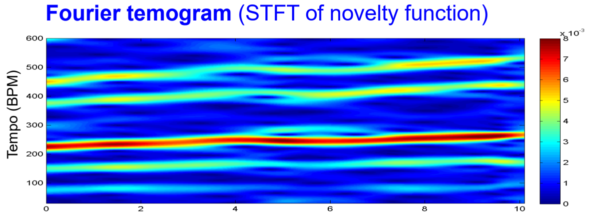
Local Pulse and Tempo Tracking

Normalized novelty function

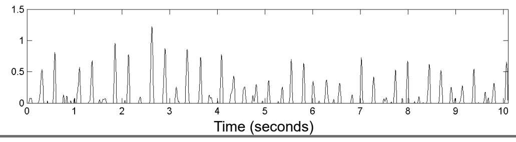


Local Pulse and Tempo Tracking

Fourier temogram (STFT of novelty function)

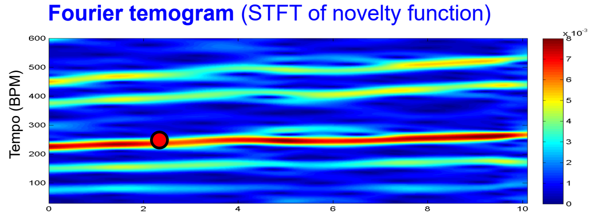


Normalized novelty function

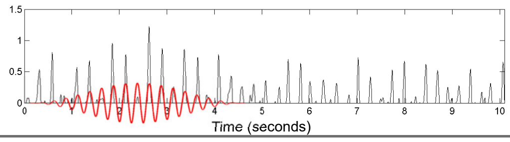


Local Pulse and Tempo Tracking

Fourier temogram (STFT of novelty function)

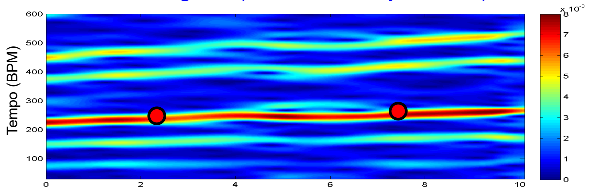


Optimizing local periodicity kernel

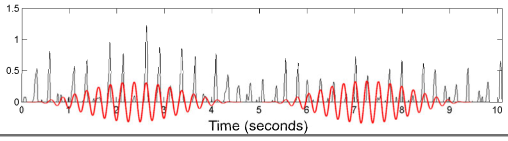


Local Pulse and Tempo Tracking

Fourier temogram (STFT of novelty function)

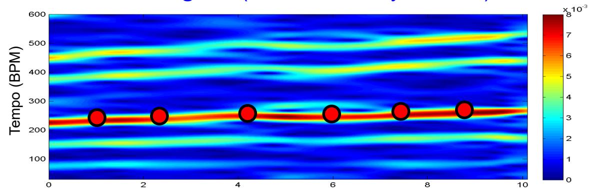


Optimizing local periodicity kernel

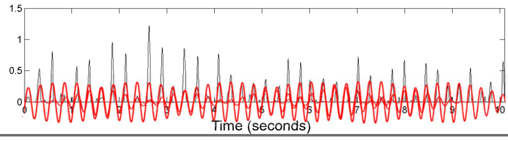


Local Pulse and Tempo Tracking

Fourier temogram (STFT of novelty function)

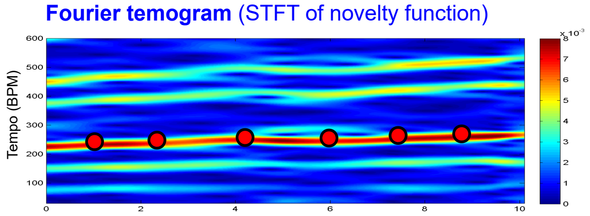


Optimizing local periodicity kernel

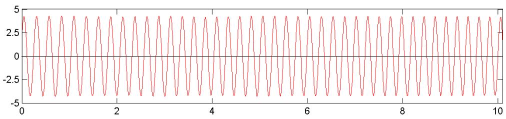


Local Pulse and Tempo Tracking

Fourier temogram (STFT of novelty function)

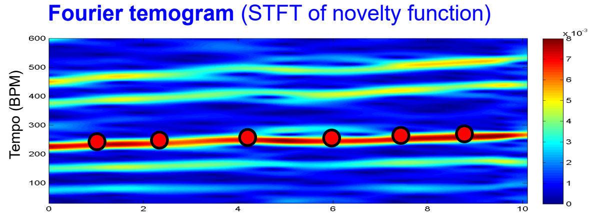


Accumulation of kernels

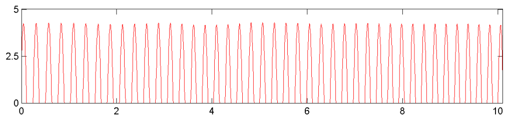


Local Pulse and Tempo Tracking

Fourier temogram (STFT of novelty function)



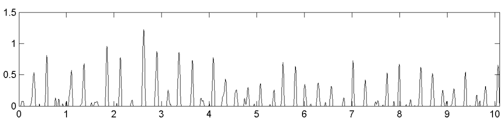
Halfwave rectification



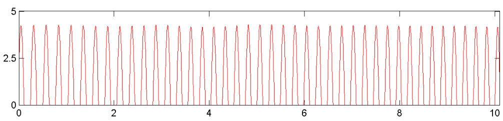
Local Pulse and Tempo Tracking

Pulse Tracking
Grosche, Müller: Extracting Predominant Local Pulse Information from Music Recordings. IEEE TASLP 19(6), 2011.

Novelty Curve



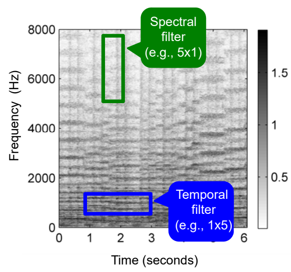
Predominant Local Pulse (PLP)



Local Pulse and Tempo Tracking

Deep Learning Approach

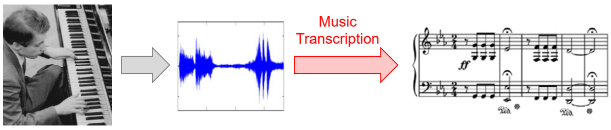
- End-to-end approach
  - Input: Short audio snippets
  - Output: Tempo value
- DL architecture inspired by traditional engineering
  - Layers and activation functions
  - Shape of convolutional kernels



Tempo Estimation
Schreiber, Müller: A Single-Step Approach to Musical Tempo Estimation Using a Convolutional Neural Network, ISMIR, 2018.

Automatic Music Transcription

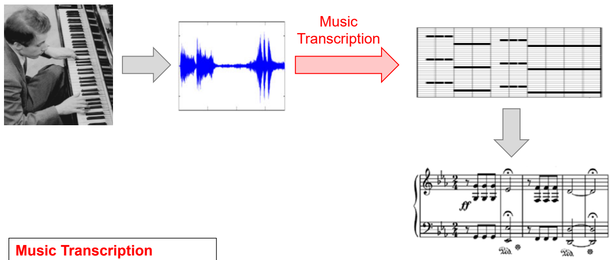
Task: Convert a music recording into sheet music



Music Transcription
Benetos et al.: Automatic Music Transcription: An Overview. IEEE Signal Processing Magazine 36(1), 2019.

Automatic Music Transcription

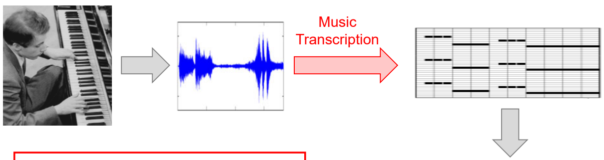
Task: Convert a music recording into sheet music
(or another symbolic music representation)



Music Transcription
Benetos et al.: Automatic Music Transcription: An Overview. IEEE Signal Processing Magazine 36(1), 2019.

Automatic Music Transcription

Task: Convert a music recording into sheet music
(or another symbolic music representation)



Multitask Learning for estimating
- pitches,
- note onsets & offsets,
- beat & measure positions,
- musical voices & instrumentation,
- pedalling, dynamics, …

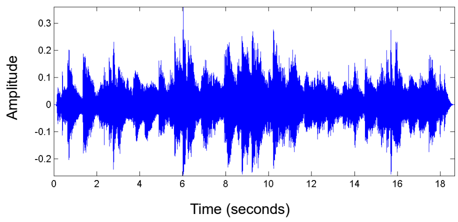
Why is Music Processing Challenging?

Example: Chopin, Mazurka Op. 63 No. 3

Why is Music Processing Challenging?

Example: Chopin, Mazurka Op. 63 No. 3

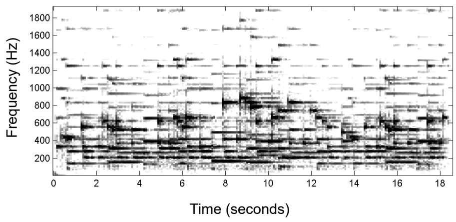
- Waveform



Why is Music Processing Challenging?

Example: Chopin, Mazurka Op. 63 No. 3

- Waveform / Spectrogram



Why is Music Processing Challenging?

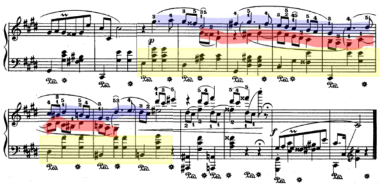
Example: Chopin, Mazurka Op. 63 No. 3

- 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

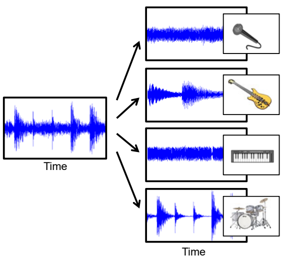
- Decomposition of audio stream into different sound sources
- Central task in digital signal processing
- “Cocktail party effect”

Source Separation

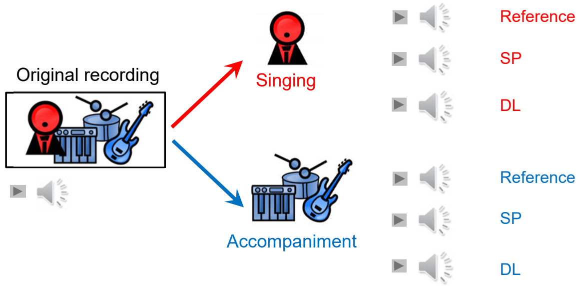
- Decomposition of audio stream into different sound sources
- Central task in digital signal processing
- “Cocktail party effect”
- Several input signals
- Sources are assumed to be statistically independent

Source Separation (Music)

- Main melody, accompaniment, drum track
- Instrumental voices
- Individual note events
- Only mono or stereo
- Sources are often highly dependent



Source Separation (Singing Voice)

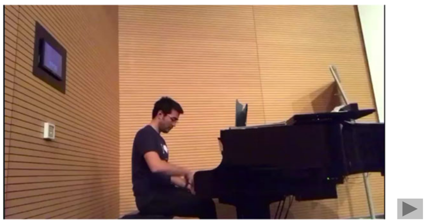


DL-Based Source Separation
Stöter, Uhlich Luitkus, Mitsufuji: Open-Unmix – A Reference Implementation for Music Source Separation. JOSS, 2019.

- Reference: Best possible result
- SP: Traditional signal processing
- DL: Deep Learning

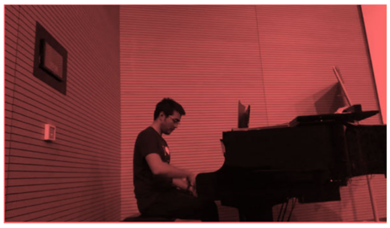
Source Separation (Piano Concerto)

- Yigitcan Özer
- PhD student in engineering
- Pianist



Source Separation (Piano Concerto)

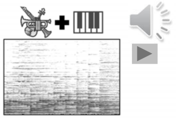
- Yigitcan Özer
- PhD student in engineering
- Pianist



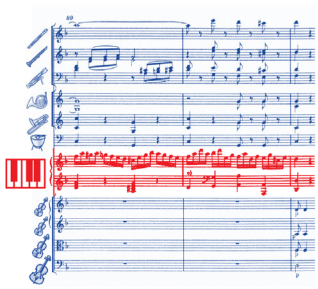
Only Piano!

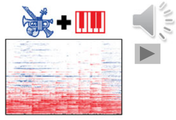
Where is the orchestra?

Source Separation (Piano Concerto)

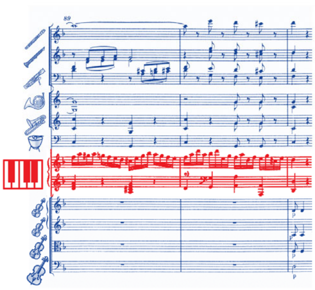


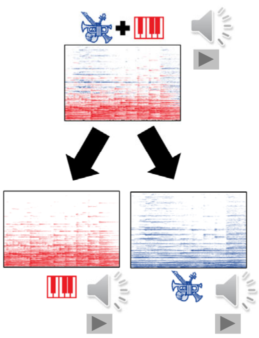
Source Separation (Piano Concerto)



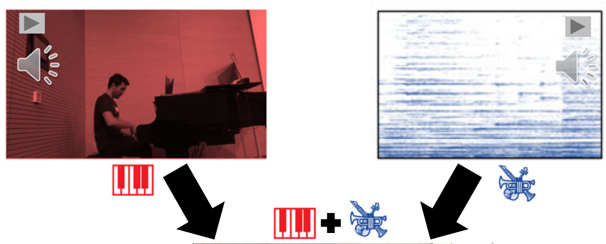


Source Separation (Piano Concerto)

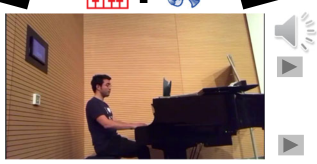




Source Separation (Piano Concerto)



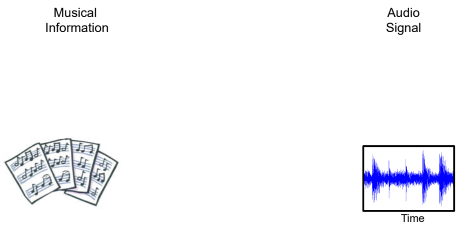
Piano Source Separation
Özer, Müller: Source Separation of Piano Concertos with Test-Time Adaptation, ISMIR, 2022.



Score-Informed Source Separation

Prior Knowledge
Ewert, Pardo, Müller, Plumbley:
Score-Informed Source Separation for Musical Audio Recordings.
IEEE SPM 31(3), 2014.

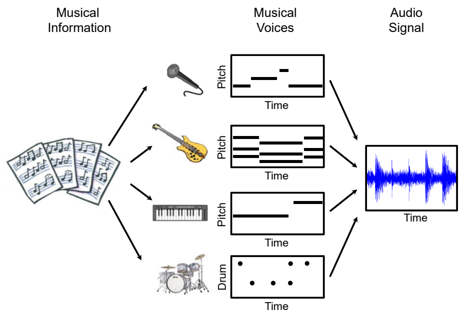
Exploit musical score to support decomposition process



Score-Informed Source Separation

Prior Knowledge
Ewert, Pardo, Müller, Plumbley:
Score-Informed Source Separation for Musical Audio Recordings.
IEEE SPM 31(3), 2014.

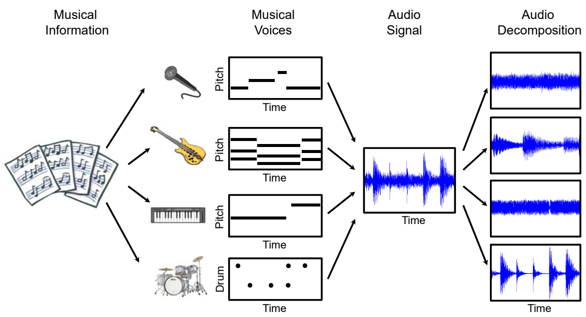
Exploit musical score to support decomposition process



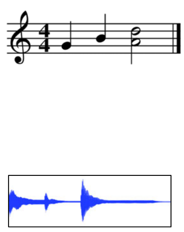
Score-Informed Source Separation

Prior Knowledge
Ewert, Pardo, Müller, Plumbley:
Score-Informed Source Separation for Musical Audio Recordings.
IEEE SPM 31(3), 2014.

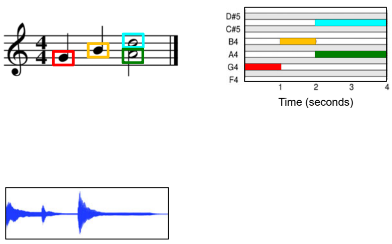
Exploit musical score to support decomposition process



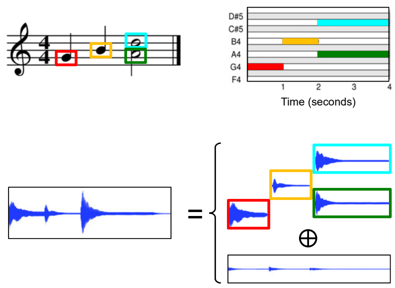
Score-Informed Audio Decomposition



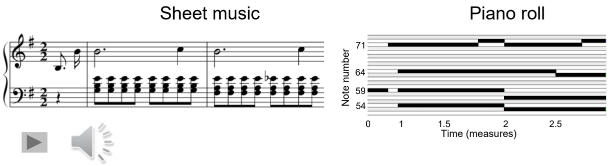
Score-Informed Audio Decomposition



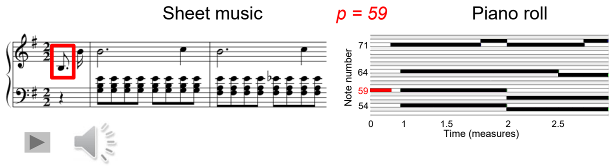
Score-Informed Audio Decomposition



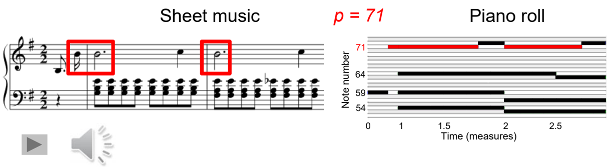
Score-Informed Audio Decomposition



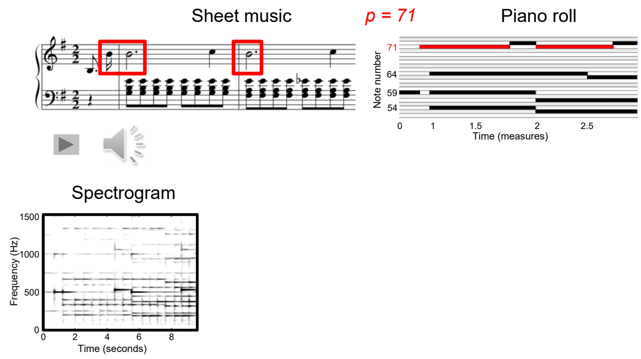
Score-Informed Audio Decomposition



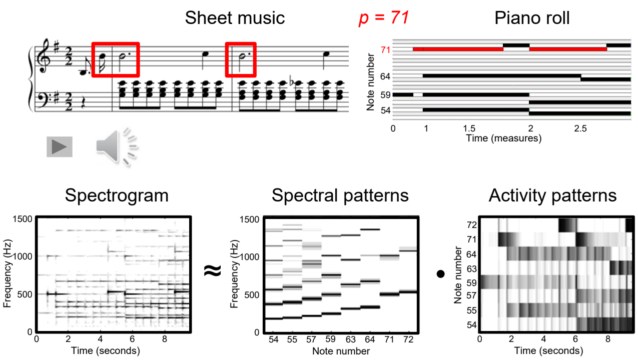
Score-Informed Audio Decomposition



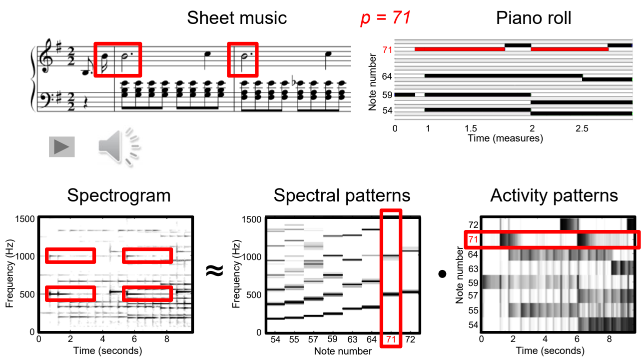
Score-Informed Audio Decomposition



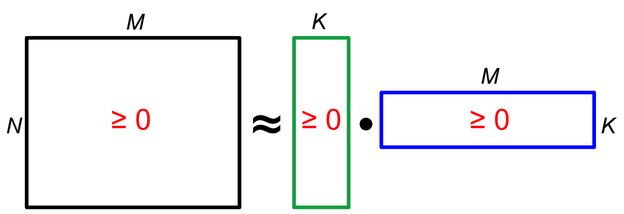
Score-Informed Audio Decomposition



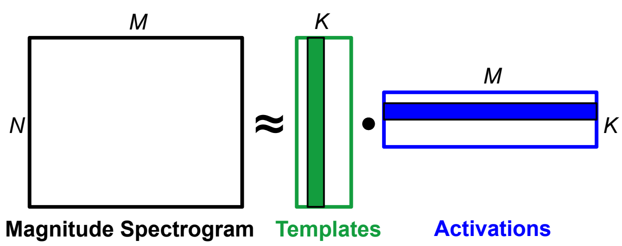
Score-Informed Audio Decomposition



NMF (Nonnegative Matrix Factorization)



NMF (Nonnegative Matrix Factorization)

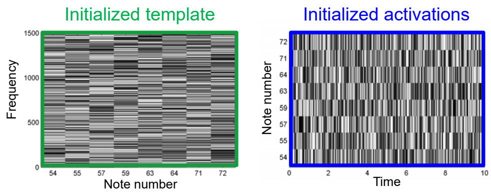


Templates: **Pitch + Timbre** **"How does it sound"**

Activations: **Onset time + Duration** **"When does it sound"**

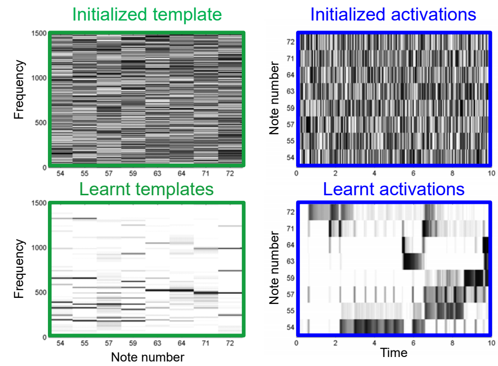
NMF-Decomposition

Random initialization



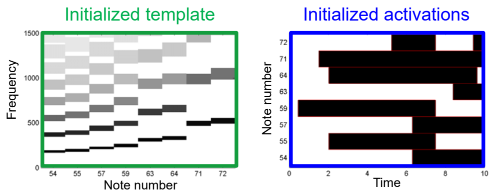
NMF-Decomposition

Random initialization → No semantic meaning



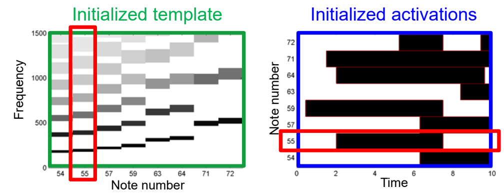
NMF-Decomposition

Constrained initialization



NMF-Decomposition

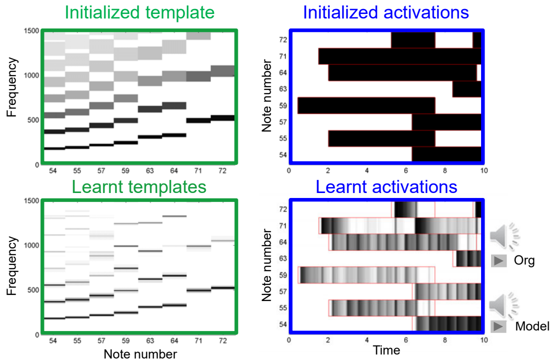
Constrained initialization



Template constraint for p=55 Activation constraint for p=55

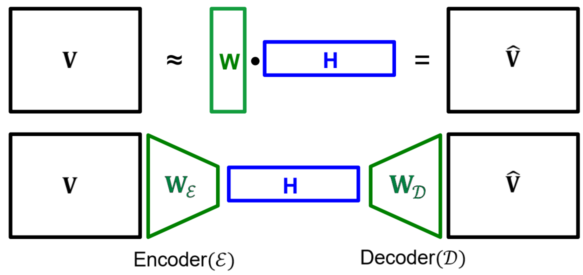
NMF-Decomposition

Constrained initialization → NMF as refinement



NMF-Decomposition

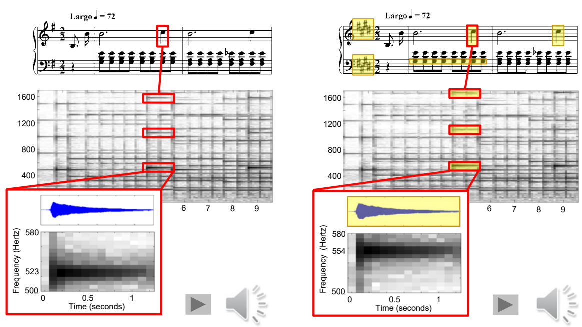
Simulation of NMF via Autoencoder



NMF as Autoencoder
Smaragdis, Venkataramani: A Neural Network Alternative to Non-Negative Audio Models. ICASSP, 2017.

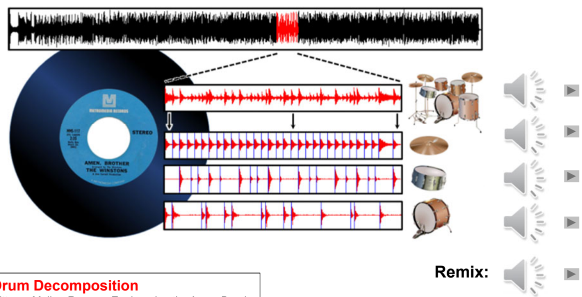
Constraint Autoencoders
Ewert, Sandler: Structured dropout for weak label and multi-instance learning and its application to score-informed source separation. ICASSP, 2017

Score-Informed Audio Decomposition



Score-Informed Audio Decomposition

Informed Drum-Sound Decomposition



Drum Decomposition
Dittmar, Müller: Reverse Engineering the Amen Break – Score-Informed Separation and Restoration Applied to Drum Recordings. IEEE/ACM TASLP 24(9), 2016.

Score-Informed Audio Decomposition

Major challenge: Reconstructed sound events often have artifacts

Approaches:

- Resynthesize certain sound components
- Differentiable Digital Signal Processing (DDSP) combines classical DSP and deep learning
- Generative adversarial networks may help to reduce the artifacts

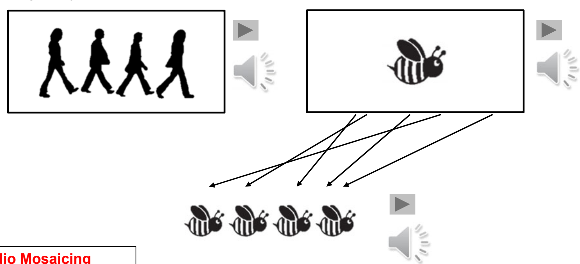
DDSP
Engel et al.: DDSP: Differentiable Digital Signal Processing. ICLR, 2020.

Score-Informed Audio Decomposition

Audio mosaicing (style transfer)

Target signal: Beatles–Let it be

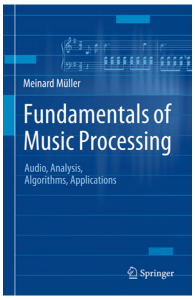
Source signal: Bees



Mosaic signal: Let it Bee

Audio Mosaicing
Driedger, Prätzlich, Müller: Let It Bee – Towards NMF-Inspired Audio Mosaicing. ISMIR, 2015.

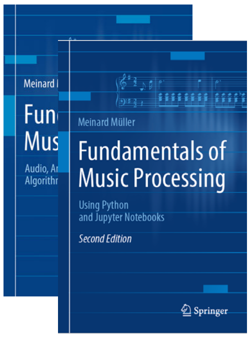
Fundamentals of Music Processing (FMP)



Meinard Müller
Fundamentals of Music Processing
Audio, Analysis, Algorithms, Applications
Springer, 2015

Accompanying website:
www.music-processing.de

Fundamentals of Music Processing (FMP)



Meinard Müller
Fundamentals of Music Processing
Audio, Analysis, Algorithms, Applications
Springer, 2015

Accompanying website:
www.music-processing.de

2nd edition
Meinard Müller
Fundamentals of Music Processing
Using Python and Jupyter Notebooks
Springer, 2021

Fundamentals of Music Processing (FMP)

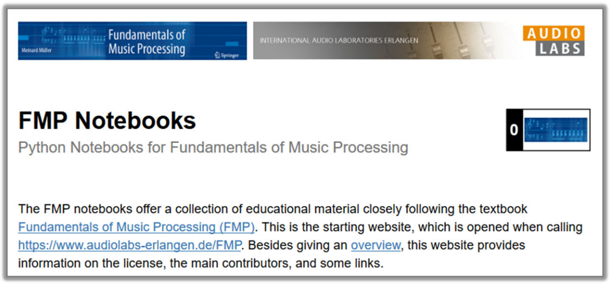
Chapter		Music Processing Scenario
1		Music Representations
2		Fourier Analysis of Signals
3		Music Synchronization
4		Music Structure Analysis
5		Chord Recognition
6		Tempo and Beat Tracking
7		Content-Based Audio Retrieval
8		Musically Informed Audio Decomposition

Meinard Müller
Fundamentals of Music Processing
Audio, Analysis, Algorithms, Applications
Springer, 2015

Accompanying website:
www.music-processing.de

2nd edition
Meinard Müller
Fundamentals of Music Processing
Using Python and Jupyter Notebooks
Springer, 2021

FMP Notebooks: Education & Research



https://www.audiolabs-erlangen.de/FMP

References (FMP Textbook & Notebooks)

- Meinard Müller: Fundamentals of Music Processing – Using Python and Jupyter Notebooks. 2nd Edition, Springer, 2021.
  https://www.springer.com/gp/book/9783030698072
- Meinard Müller and Frank Zalkow: libfmp: A Python Package for Fundamentals of Music Processing. Journal of Open Source Software (JOSS), 6(63): 1–5, 2021.
  https://joss.theoj.org/papers/10.21105/joss.03326
- Meinard Müller: An Educational Guide Through the FMP Notebooks for Teaching and Learning Fundamentals of Music Processing. Signals, 2(2): 245–285, 2021.
  https://www.mdpi.com/2624-6120/2/2/18
- Meinard Müller and Frank Zalkow: FMP Notebooks: Educational Material for Teaching and Learning Fundamentals of Music Processing. Proc. International Society for Music Information Retrieval Conference (ISMIR): 573–580, 2019.
  https://zenodo.org/record/3527872#.YOhEQOgzaUk
- Meinard Müller, Brian McFee, and Katherine Kinnaird: Interactive Learning of Signal Processing Through Music: Making Fourier Analysis Concrete for Students. IEEE Signal Processing Magazine, 38(3): 73–84, 2021.
  https://ieeexplore.ieee.org/document/9418542

Resources (Group Meinard Müller)

- FMP Notebooks:
  https://www.audiolabs-erlangen.de/FMP
- libfmp:
  https://github.com/meinardmueller/libfmp
- synctoolbox:
  https://github.com/meinardmueller/synctoolbox
- libtsm:
  https://github.com/meinardmueller/libtsm
- Preparation Course Python (PCP) Notebooks:
  https://www.audiolabs-erlangen.de/resources/MIR/PCP/PCP.html
  https://github.com/meinardmueller/PCP

Resources

- librosa:
  https://librosa.org/
- madmom:
  https://github.com/CPJKU/madmom
- Essentia Python tutorial:
  https://essentia.upf.edu/essentia_python_tutorial.html
- mirdata:
  https://github.com/mir-dataset-loaders/mirdata
- open-unmix:
  https://github.com/sigsep/open-unmix-pytorch
- Open Source Tools & Data for Music Source Separation:
  https://source-separation.github.io/tutorial/landing.html