

Learning with Music Signals: Technology Meets Education

Meinard Müller

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Jahrestreffen GIBU, Dagstuhl
03. April 2023

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

Meinard Müller: Research Group

Semantic Audio Processing

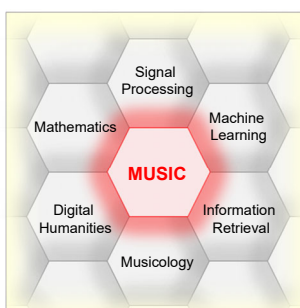
- Michael Krause
- Yigitcan Özer
- Simon Schwär
- Johannes Zeitler
- Peter Meier (external)
- Christof Weiß
- Sebastian Rosenzweig
- Frank Zalkow
- Christian Dittmar
- Stefan Balke
- Jonathan Driedger
- Thomas Prätzlich
- ...



Music Processing



Music Processing: A Multifaceted Research Area

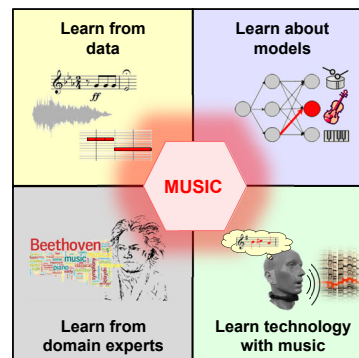


Music ...

- important part of our lives ...
- ... Spotify, Pandora, iTunes, ...
- interdisciplinary research
- intuitive entry point to education

Reinhard Koselleck-Projekt: LEARN

Learning with Music Signals: Technology Meets Education



- Machine learning for music signal processing
- Interpretable models and knowledge integration
- Music understanding and applications
- Interactive learning in engineering through music

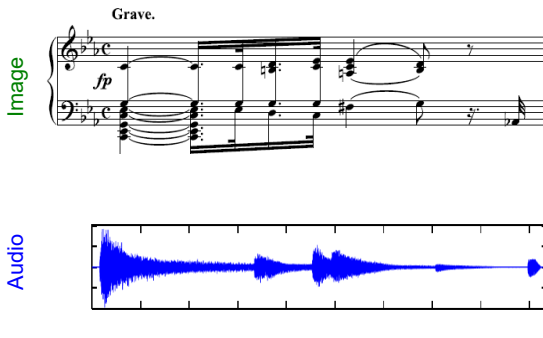
Multimodal Music Processing



Multimodal Music Processing

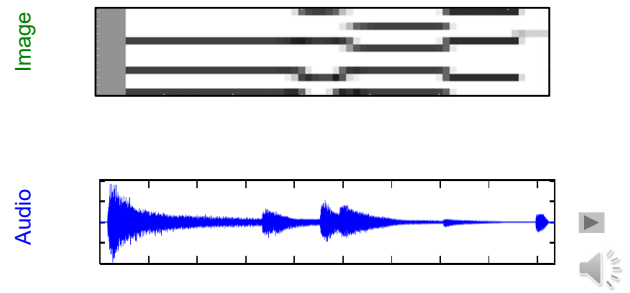


Multimodal Music Processing



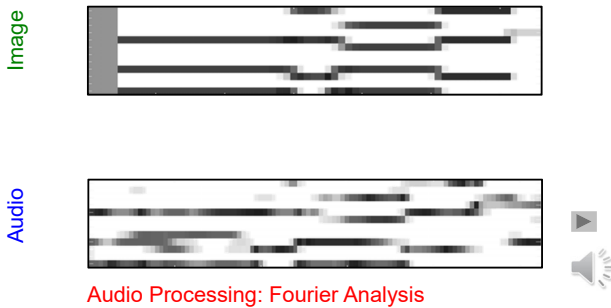
Multimodal Music Processing

Image Processing: Optical Music Recognition



Multimodal Music Processing

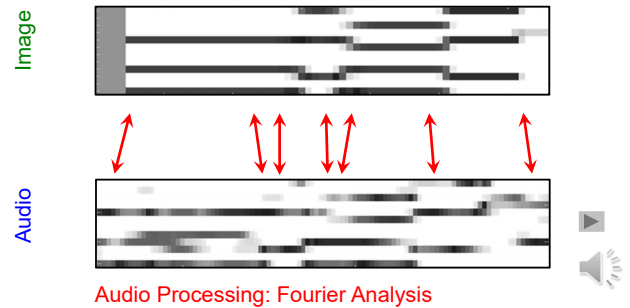
Image Processing: Optical Music Recognition



Audio Processing: Fourier Analysis

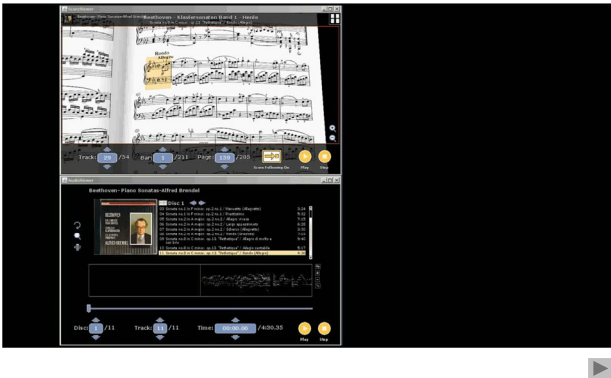
Multimodal Music Processing

Image Processing: Optical Music Recognition

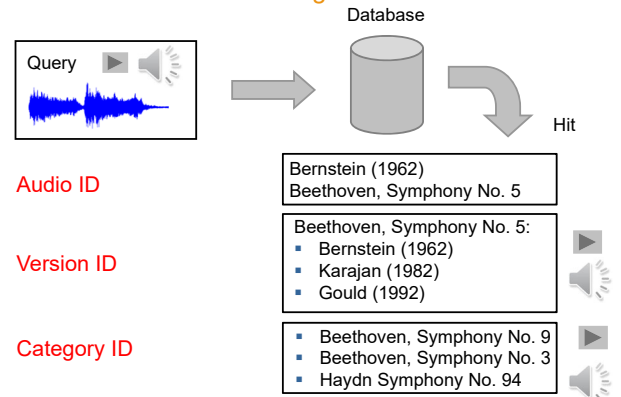


Audio Processing: Fourier Analysis

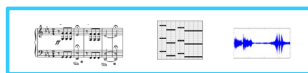
Multimodal Music Processing



Multimodal Music Processing



Multimodal Music Processing Modalities



Retrieval tasks:

Audio ID

Version ID

Category ID

Specificity

High specificity

Low specificity

Granularity

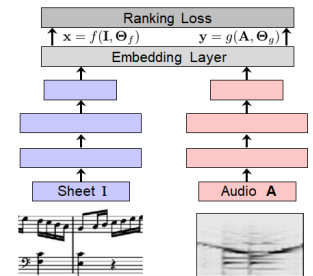
Fragment-based retrieval

Document-based retrieval

Reinhart Koselleck-Projekt: LEARN



- Representation learning
- Embedding techniques
- Weak annotations
- Loss functions
- ...



Computational Musicology

Cooperation:

- Rainer Kleinertz (Saarbrücken)
- Stephanie Klauk (Saarbrücken)
- Christof Weiß (Würzburg)



Objectives

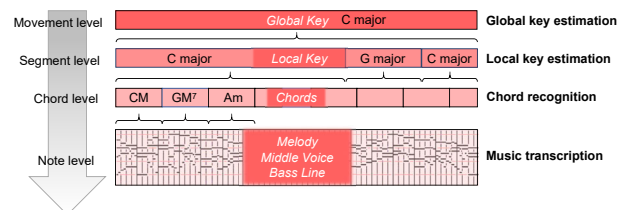
- Harmony-based structural analysis
- Beethoven Sonatas & Wagner's Ring
- Interdisciplinary dialogue

- Since 2014: DFG-funded project



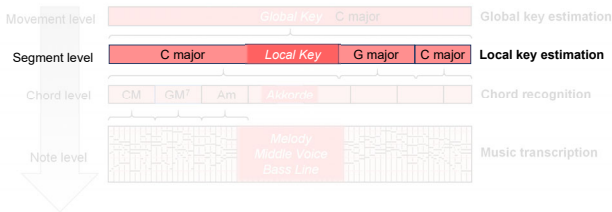
Computational Musicology: Harmony Analysis

- Different concepts
- Different temporal levels



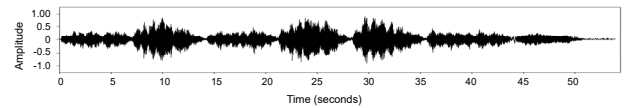
Computational Musicology: Harmony Analysis

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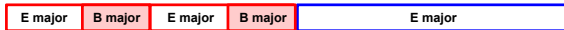
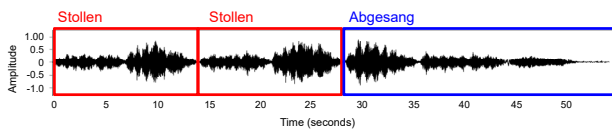
Local Key Estimation

Example: J.S. Bach, Choral "Durch Dein Gefängnis" (*Johannespassion*)



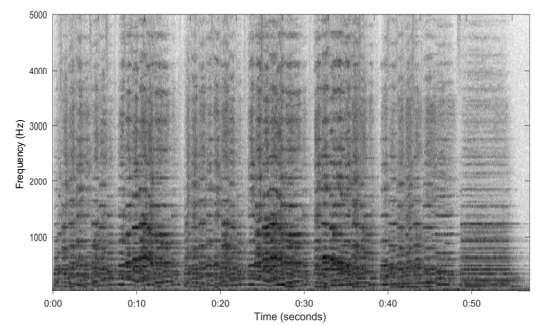
Local Key Estimation

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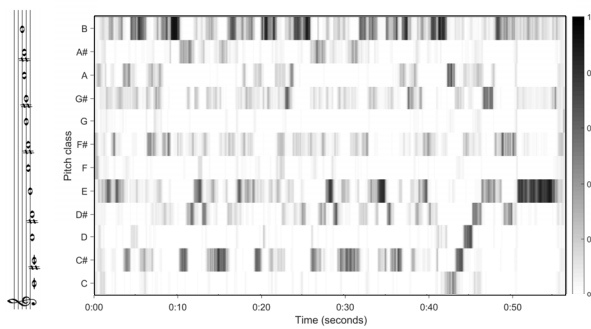
Local Key Estimation

Spectrogram



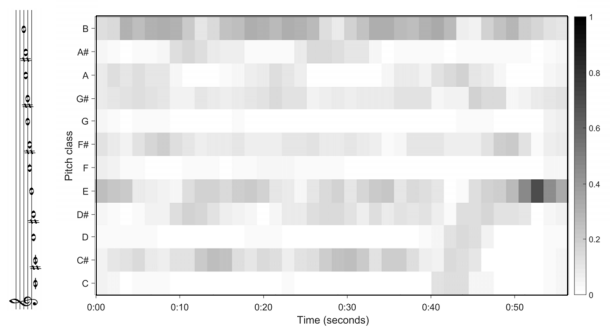
Local Key Estimation

Chromagram



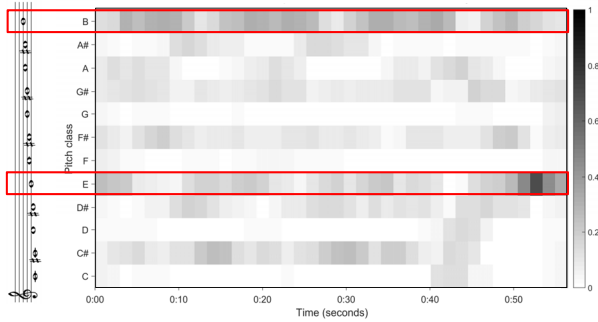
Local Key Estimation

Chromagram after smoothing



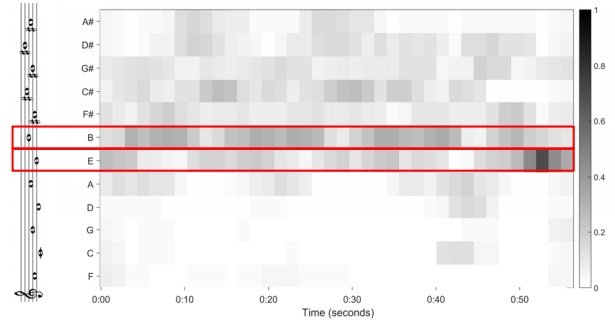
Local Key Estimation

Arrange pitch classes according to **perfect fifth series**



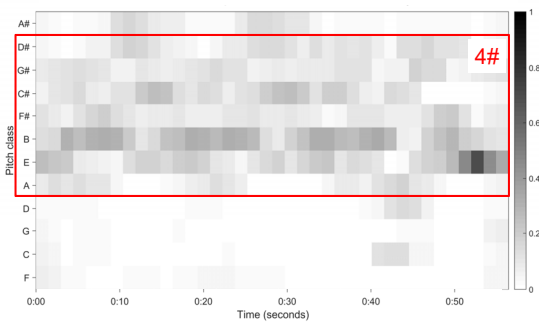
Local Key Estimation

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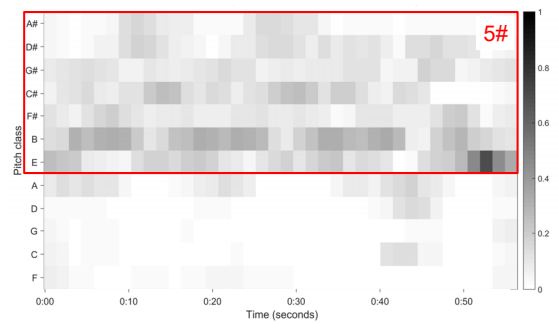
Local Key Estimation

Summarize pitch class content according to **diatonic scales**



Local Key Estimation

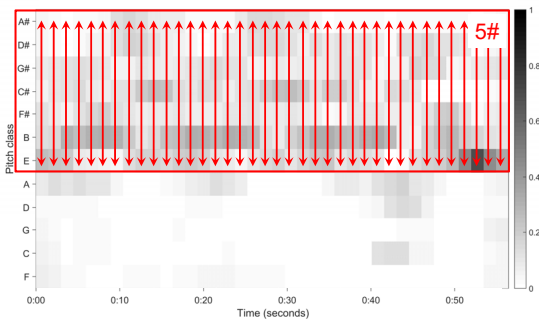
Summarize pitch class content according to **diatonic scales**



Local Key Estimation

Summarize pitch class content according to **diatonic scales**

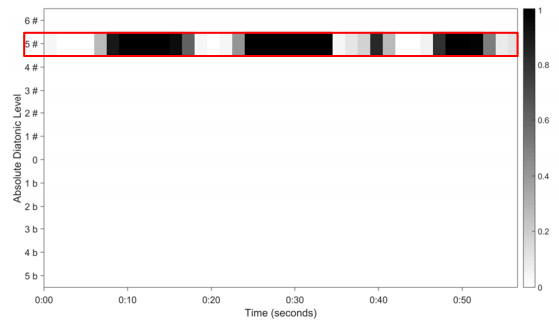
Multiply chroma values (in each column)



Local Key Estimation

Summarize pitch class content according to **diatonic scales**

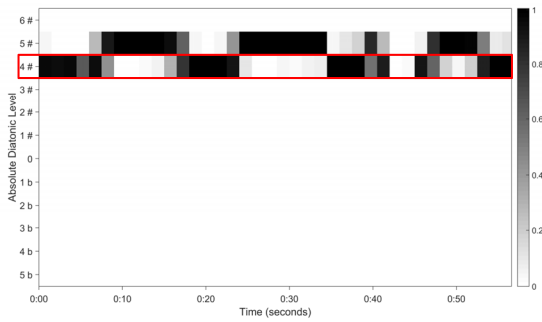
Multiply chroma values



Local Key Estimation

Summarize pitch class content according to **diatonic scales**

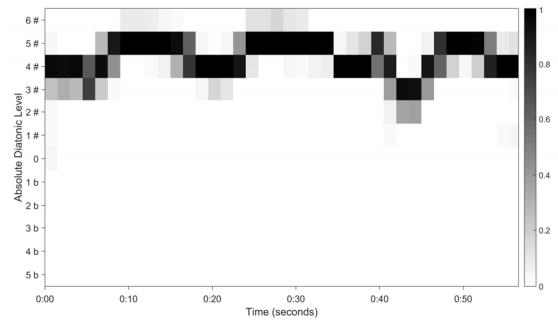
Multiply chroma values



Local Key Estimation

Summarize pitch class content according to **diatonic scales**

Multiply chroma values

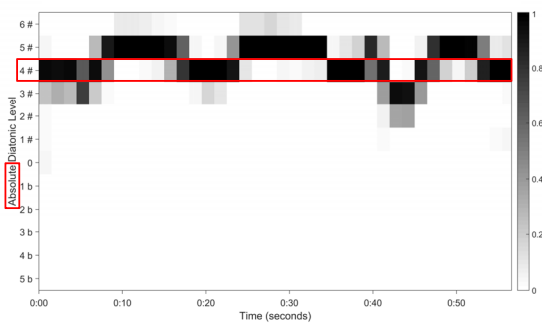


Local Key Estimation

Normalize representation relative to **global key**

4 #
(E major)

Absolute Diatonic Level

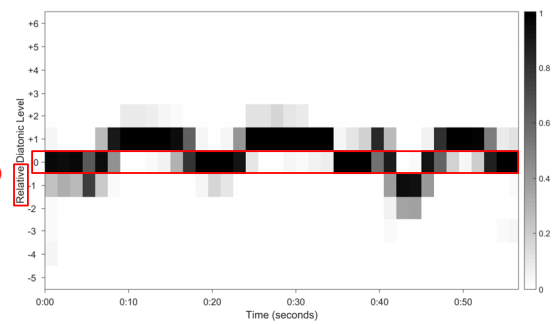


Local Key Estimation

Normalize representation relative to **global key**

4 #
(E major)

Relative Diatonic Level



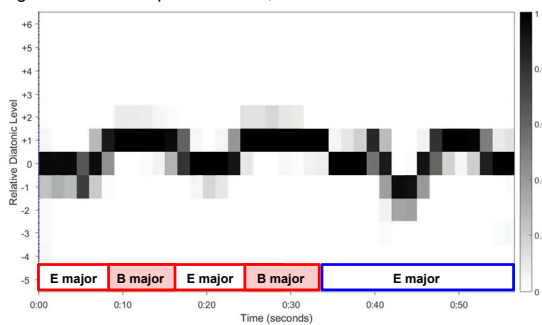
Local Key Estimation

J.S. Bach: Choral "Durch Dein Gefängnis" (*Johannespassion*)

Recording: Scholars Baroque Ensemble, Naxos 1994

4 #
(E major)

Relative Diatonic Level



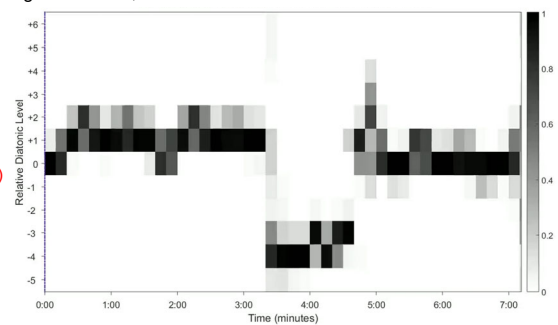
Local Key Estimation

L. v. Beethoven: Piano Sonata No. 10 (Op. 14 Nr. 2), 1. Allegro

Recording: Barenboim, EMI 1998

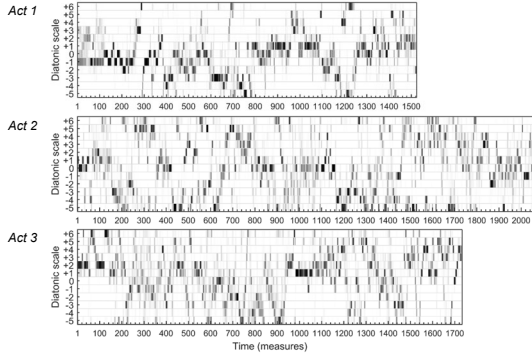
1 #
(G major)

Relative Diatonic Level



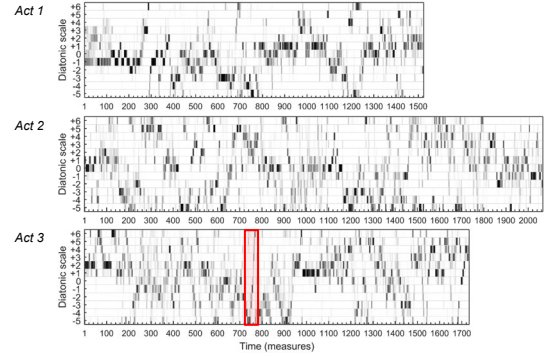
Local Key Estimation

R. Wagner: WWV 86 B (*Die Walküre*)



Local Key Estimation

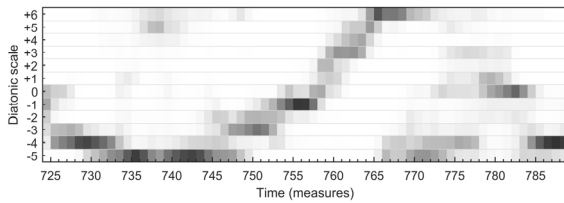
R. Wagner: WWV 86 B (*Die Walküre*)



Local Key Estimation

R. Wagner: WWV 86 B (*Die Walküre*)

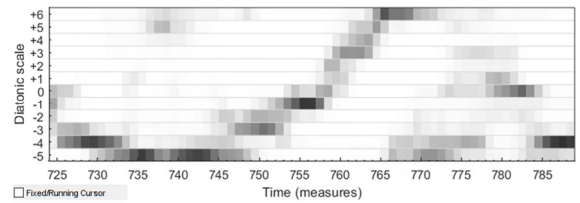
Act 3, measure 724–789 (*Wotan's punishment*)



Local Key Estimation

R. Wagner: WWV 86 B (*Die Walküre*)

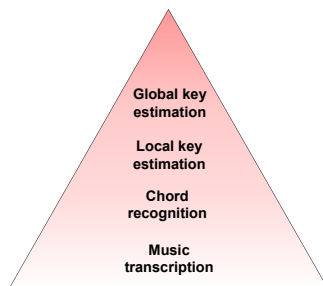
Act 3, measure 724–789 (*Wotan's punishment*)



Reinhart Koselleck-Projekt: LEARN

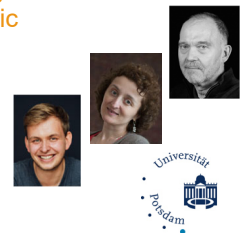


- Interpretability & explainability
- Knowledge integration
- Hybrid models
- Multitask learning
- Hierarchical approaches
- ...



Computational Ethnomusicology: Traditional Georgian Vocal Music

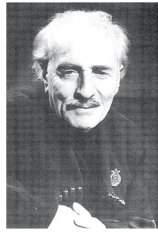
- Interdisciplinary research project
 - Prof. Dr. Frank Scherbaum (Potsdam)
 - Dr. Nana Mzhavanadze (Tbilisi)
 - Sebastian Rosenzweig (FAU)
- Objective: Tonal analysis
- 2018 – 2022: DFG-funded project



Traditional Georgian Vocal Music

Example: Erkomaishvili corpus

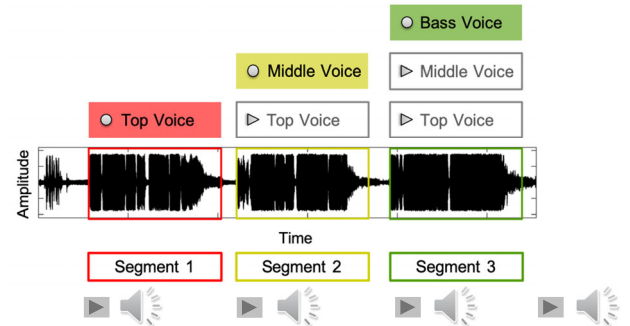
- Collection of traditional three-voice Georgian songs
- Performed by the former Georgian master chanter Artem Erkomaishvili (1887-1967)
- Recordings of 100 songs using tape recorders (1966)



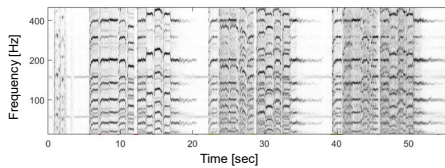
"Original masterpieces of Georgian musical thinking." (Shugliashvili, 2014)

Traditional Georgian Vocal Music

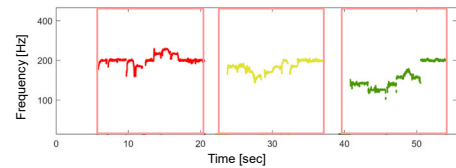
Example: Erkomaishvili corpus



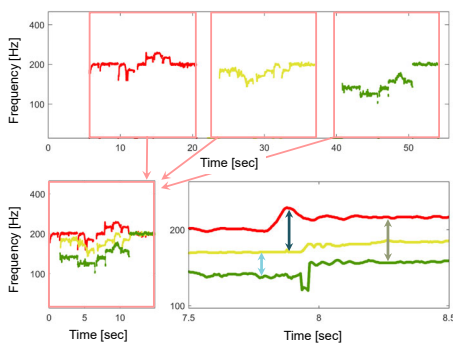
Traditional Georgian Vocal Music



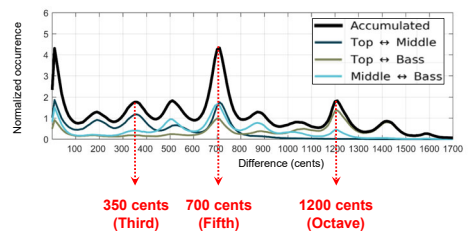
Traditional Georgian Vocal Music



Traditional Georgian Vocal Music



Traditional Georgian Vocal Music



- Peak at 350 cents (between minor and major third)
- Non-western temperament

Traditional Georgian Vocal Music

- Recordings from field expedition in 2016
- 216 performances
- Multitrack audio + video
 - Room, HSM, LRX
- Total duration: 6 h

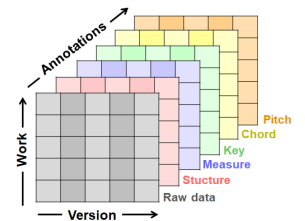


Room
Microphone

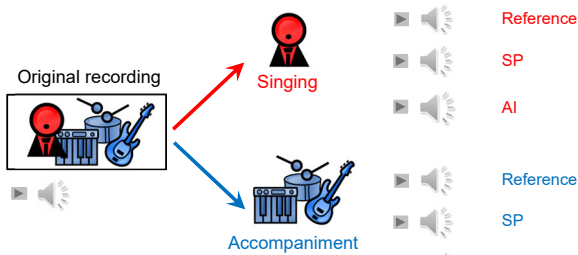
Reinhard Koselleck-Projekt: LEARN



- Non-standard datasets
 - Variety of music
 - Poor audio quality
 - Various sensor types
- Exploring DL models
 - Generalization
 - Overfitting
 - Data scarceness



Source Separation (Singing)



- Reference: Best possible result
- SP: Using traditional signal processing
- AI: Using data-driven approach

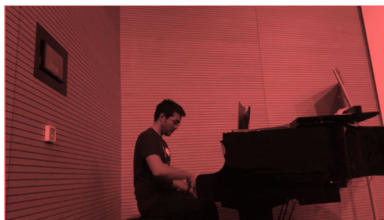
Source Separation (Piano Concerto)

- Yigitcan Özer
- PhD student in engineering
- Pianist



Source Separation (Piano Concerto)

- Yigitcan Özer
- PhD student in engineering
- Pianist



Only Piano!



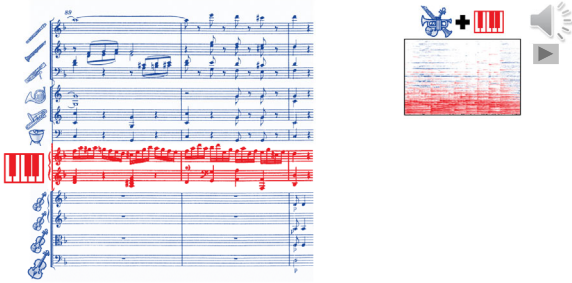
Where is the orchestra?



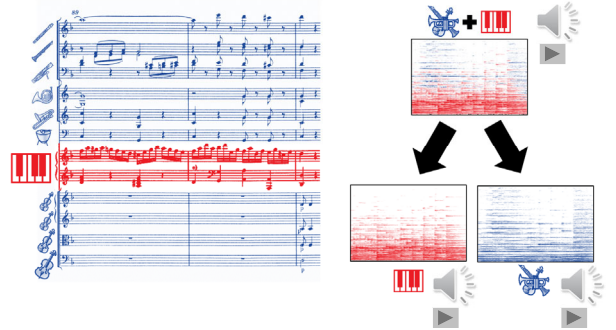
Source Separation (Piano Concerto)



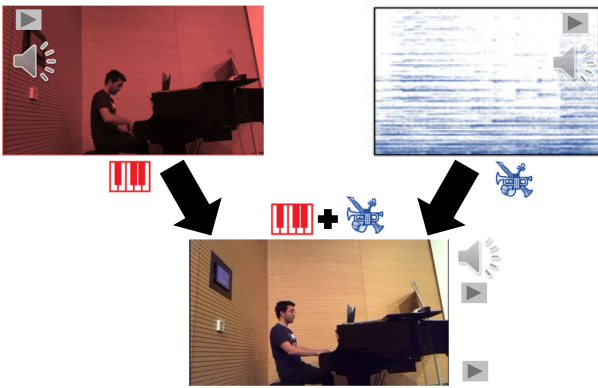
Source Separation (Piano Concerto)



Source Separation (Piano Concerto)

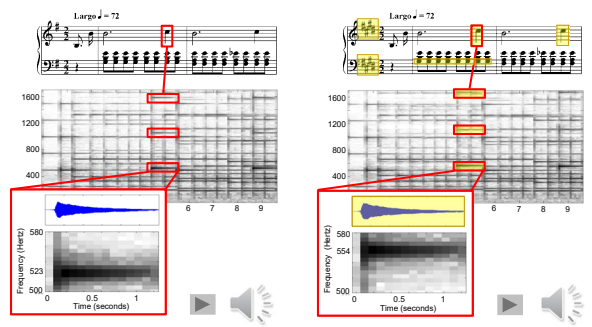


Source Separation (Piano Concerto)



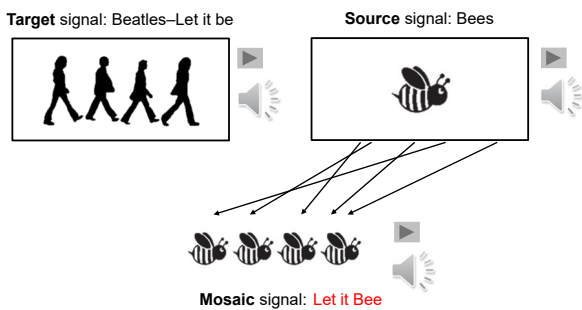
Source Separation

Score-informed audio editing



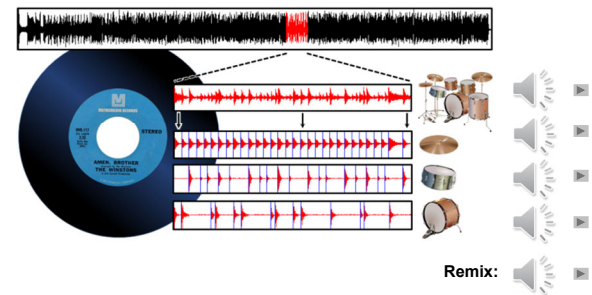
Source Separation

Audio mosaicing (style transfer)



Source Separation

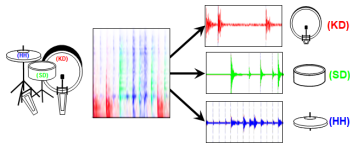
Informed Drum-Sound Decomposition



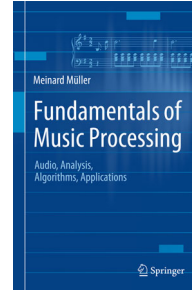
Reinhart Koselleck-Projekt: LEARN



- Reconstruction of sources
- Generative models
- Differentiable DSP
- Analysis by synthesis
- ...



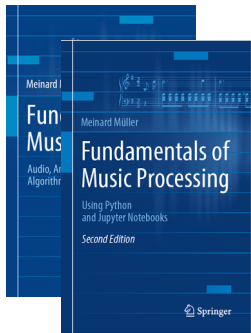
Fundamentals of Music Processing (FMP)



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

Accompanying website:
www.music-processing.de

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2nd edition
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Fundamentals of Music Processing
Using Python and Jupyter Notebooks
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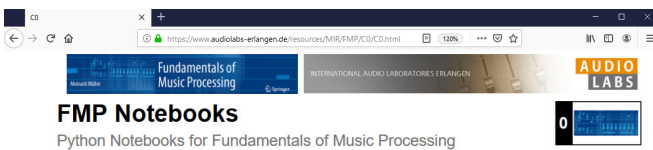
Fundamentals of Music Processing (FMP)

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

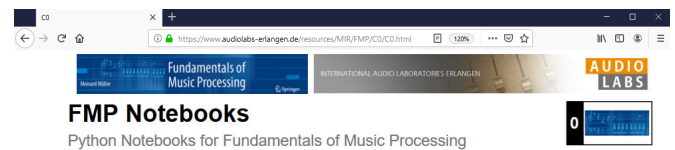
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<https://www.audiolabs-erlangen.de/FMP>

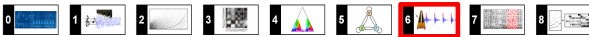


<https://www.audiolabs-erlangen.de/FMP>

Basics + 8 Chapters

<https://www.audiolabs-erlangen.de/resources/MIR/FMP/CE.html>
 Fundamentals of Music Processing
 INTERNATIONAL AUDIO LABORATORIES ERLANGEN
FMP Notebooks
 Python Notebooks for Fundamentals of Music Processing

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



Basics + 8 Chapters

Tempo and Beat Tracking

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 Fundamentals of Music Processing
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Tempo and Beat Tracking

<https://www.audiolabs-erlangen.de/resources/MIR/FMP/CE.html>
 Fundamentals of Music Processing
 INTERNATIONAL AUDIO LABORATORIES ERLANGEN
Tempo and Beat Tracking

Definition

We assume that we are given a discrete-time novelty function $\Delta : \mathbb{Z} \rightarrow \mathbb{1}$ indicate note onset candidates. The idea of Fourier analysis is to detect to in novelty curve by comparing it with windowed sinusoids. A high correlation of Δ with a windowed sinusoid indicates a periodicity of the sinus (given a suitable phase). This correlation (along with the phase) can be cc short-time Fourier transform. To this end, we fix a window function $w : \mathbb{Z}$ length centered at $n = 0$ (e.g., a sampled Hann window). Then, for a frequency parameter $\omega \in \mathbb{R}_{>0}$ and time parameter $n \in \mathbb{Z}$, the complex Fourier coefficient is defined by

$$\mathcal{F}(n, \omega) := \sum_{m \in \mathbb{Z}} \Delta(m) \bar{w}(m - n) \exp(-2\pi i \omega m).$$

<https://www.audiolabs-erlangen.de/resources/MIR/FMP/CE.html>
 Fundamentals of Music Processing
 INTERNATIONAL AUDIO LABORATORIES ERLANGEN
Tempo and Beat Tracking

Definition

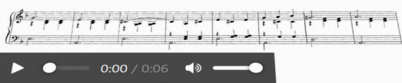
We assume that we are given a discrete-time novelty function $\Delta : \mathbb{Z} \rightarrow \mathbb{1}$ indicate note onset candidates. The idea of Fourier analysis is to detect to in novelty curve by comparing it with windowed sinusoids. A high correlation of Δ with a windowed sinusoid indicates a periodicity of the sinus (given a suitable phase). This correlation (along with the phase) can be cc short-time Fourier transform. To this end, we fix a window function $w : \mathbb{Z}$ length centered at $n = 0$ (e.g., a sampled Hann window). Then, for a frequency parameter $\omega \in \mathbb{R}_{>0}$ and time parameter $n \in \mathbb{Z}$, the complex Fourier coefficient is defined by

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 Fundamentals of Music Processing
 INTERNATIONAL AUDIO LABORATORIES ERLANGEN
Tempo and Beat Tracking

Example: Shostakovich

In the following example, we consider an excerpt of a recording of Dimitri Shostakovich's Suite for Variety Orchestra No. 1. The score version of the excerpt.

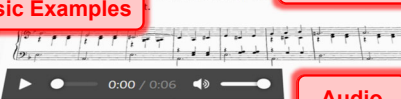


We start with a spectral-based novelty function resampled to F_n^Δ . Furthermore, we use a window size corresponding to 5 seconds (1

<https://www.audiolabs-erlangen.de/resources/MIR/FMP/CE.html>
 Fundamentals of Music Processing
 INTERNATIONAL AUDIO LABORATORIES ERLANGEN
Tempo and Beat Tracking

Example: Shostakovich

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Tempo and Beat Tracking

```

In [2]: def compute_sinusoid_optimal(c, tempo, n, Fs, N
        """Compute windowed sinusoid with optimal p
        Notebook: C6/C6S2_TempogramFourier.ipynb
        Args:
        c: Coefficient of tempogram (c=X(k,n))
        tempo: Tempo parameter corresponding to
        _coef_BPM(k))
        n: Frame parameter of c
        Fs: Sampling rate
        N: Window length
        H: Hop size
    
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Fundamentals of Music Processing

Tempo and Beat Tracking

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Python Code

Algorithms

Functions

Fundamentals of Music Processing

Tempo and Beat Tracking

Novelty function with detected peaks

PLP function with detected peaks

Fundamentals of Music Processing

Tempo and Beat Tracking

Novelty function with detected peaks

PLP function with detected peaks

Results

Visualization

Evaluation

Sonification

FMP Notebooks

Teaching

Understanding

Programming

Baselines

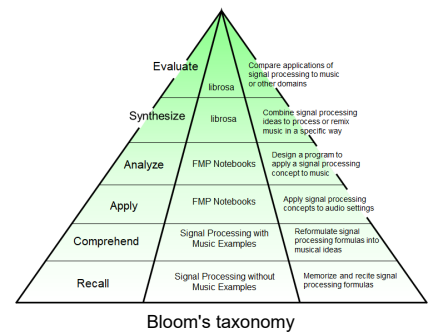
Research

Multimedia

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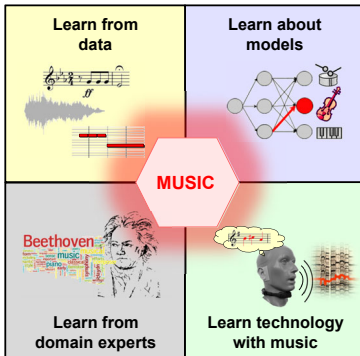


- Motivating examples
- Challenging domain
- Interdisciplinarity
- Structured learning
- ...



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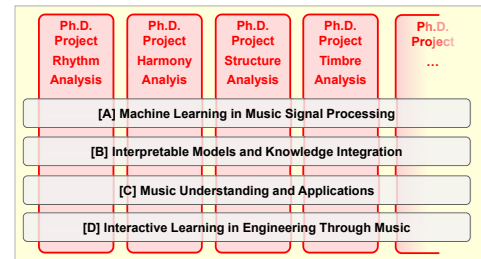
Learning with Music Signals: Technology Meets Education



- Machine learning for music signal processing
- Interpretable models and knowledge integration
- Music understanding and applications
- Interactive learning in engineering through music

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Learning with Music Signals: Technology Meets Education



References

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<https://joss.theoj.org/papers/10.21105/joss.03326>
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<https://www.mdpi.com/2624-6120/2/2/18>
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<https://zenodo.org/record/3527872#.YOHEQqzaUk>
- 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>