Machine Listening for Music and Sound Analysis

Lecture 1 – Audio Representations

Dr.-Ing. Jakob Abeßer

Fraunhofer IDMT

Jakob.abesser@idmt.fraunhofer.de

https://www.machinelistening.de

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Learning Objectives

- Sound categories
- Music representations
- Audio representations
- Audio signal decomposition
- Audio features

Sound Categories
Environmental Sounds

- Sound sources
  - Animals, climate, humans, machines
- Sound characteristics
  - Structured or unstructured, stationary or non-stationary, repetitive or without any predictable nature
- Sound duration
  - From very short (gun shot, door knock, shouts) to very long and almost stationary (running machines, wind, rain)

AUD-1

Fig. 1

Fig. 2

Fig. 3

Sound Categories
Music Signals

- Sound sources
  - Music instruments
    - Sound production mechanisms (brass, wind, string, percussive)
  - Singing Voice
- Sound characteristics
  - Mostly well structured along
    - Frequency (pitch, overtone relationships, harmony)
    - Time (onset, rhythm, structure)

AUD-2

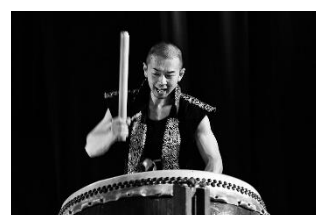


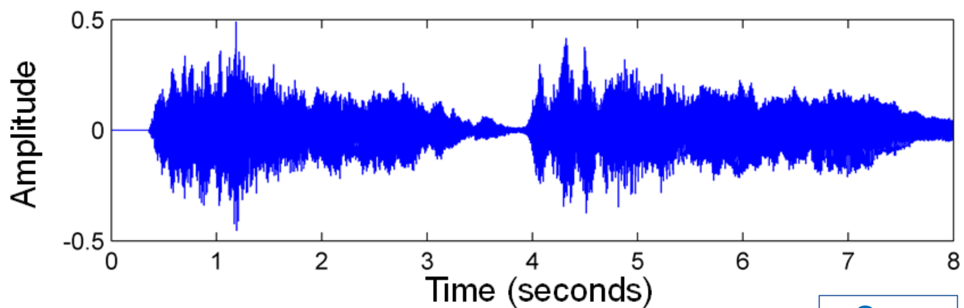
Fig. 4

Fig. 5

Fig. 6

Music Representations
Recording & Notation

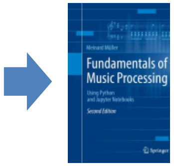
- Music recording (waveform)



Own

- Music notation (score)

Fig. 7



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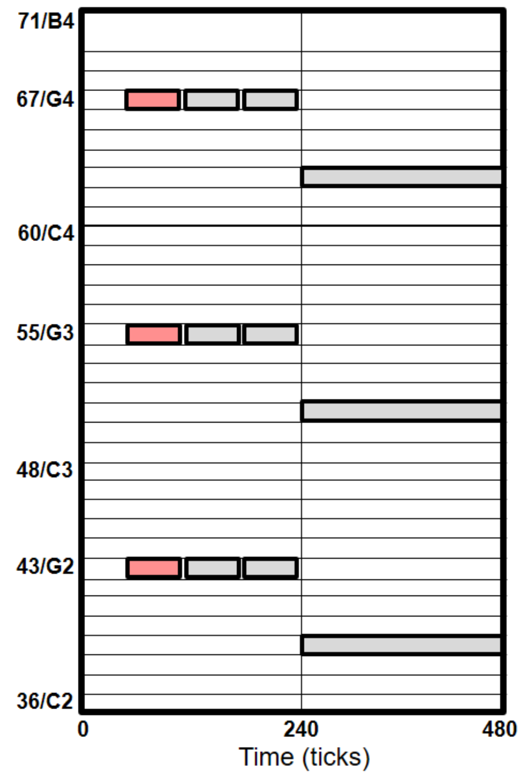
Music Representations
MIDI

- Sequence of note events (MIDI)

Time (Ticks)	Message	Channel	Note Number	Velocity
60	NOTE ON	1	67	100
0	NOTE ON	1	55	100
0	NOTE ON	2	43	100
55	NOTE OFF	1	67	0
0	NOTE OFF	1	55	0
0	NOTE OFF	2	43	0
5	NOTE ON	1	67	100
0	NOTE ON	1	55	100
0	NOTE ON	2	43	100
55	NOTE OFF	1	67	0
0	NOTE OFF	1	55	0
0	NOTE OFF	2	43	0
5	NOTE ON	1	67	100
0	NOTE ON	1	55	100
0	NOTE ON	2	43	100
55	NOTE OFF	1	67	0
0	NOTE OFF	1	55	0
0	NOTE OFF	2	43	0
5	NOTE ON	1	63	100
0	NOTE ON	2	51	100
0	NOTE ON	2	39	100
240	NOTE OFF	1	63	0
0	NOTE OFF	2	51	0
0	NOTE OFF	2	39	0



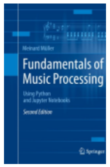


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Fig. 8

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Music Representations
MusicXML

- Textual description of note events (MusicXML)

```
<note>
  <pitch>
    <step>E</step>
    <alter>-1</alter>
    <octave>4</octave>
  </pitch>
  <duration>2</duration>
  <type>half</type>
</note>
```

Fig. 9

Audio Representations
Short-term Fourier Transform (STFT)

- Discrete Short-Term Fourier Transform (STFT)

$$X(m,k) = \sum_{n=0}^{N-1} x(n + mH)w(n)e^{-2\pi ikn/N}$$

  - Instead of full signal, short (overlapping) windowed segments are used
  - Fixed frequency resolution & linearly-spaced frequency axis
  - Trade-off between
    - Frequency resolution
    - Time resolution

Audio Representations
Short-term Fourier Transform (STFT)

- Example: Sinusoid signal, two frequencies

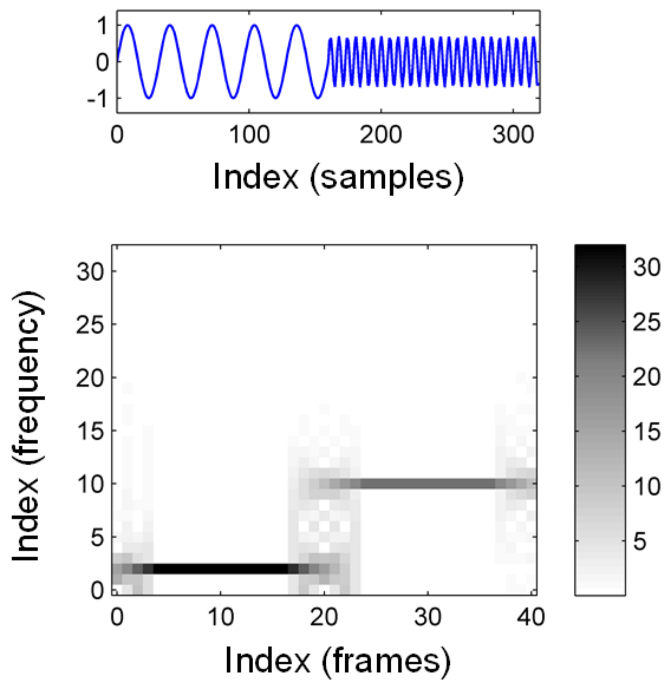
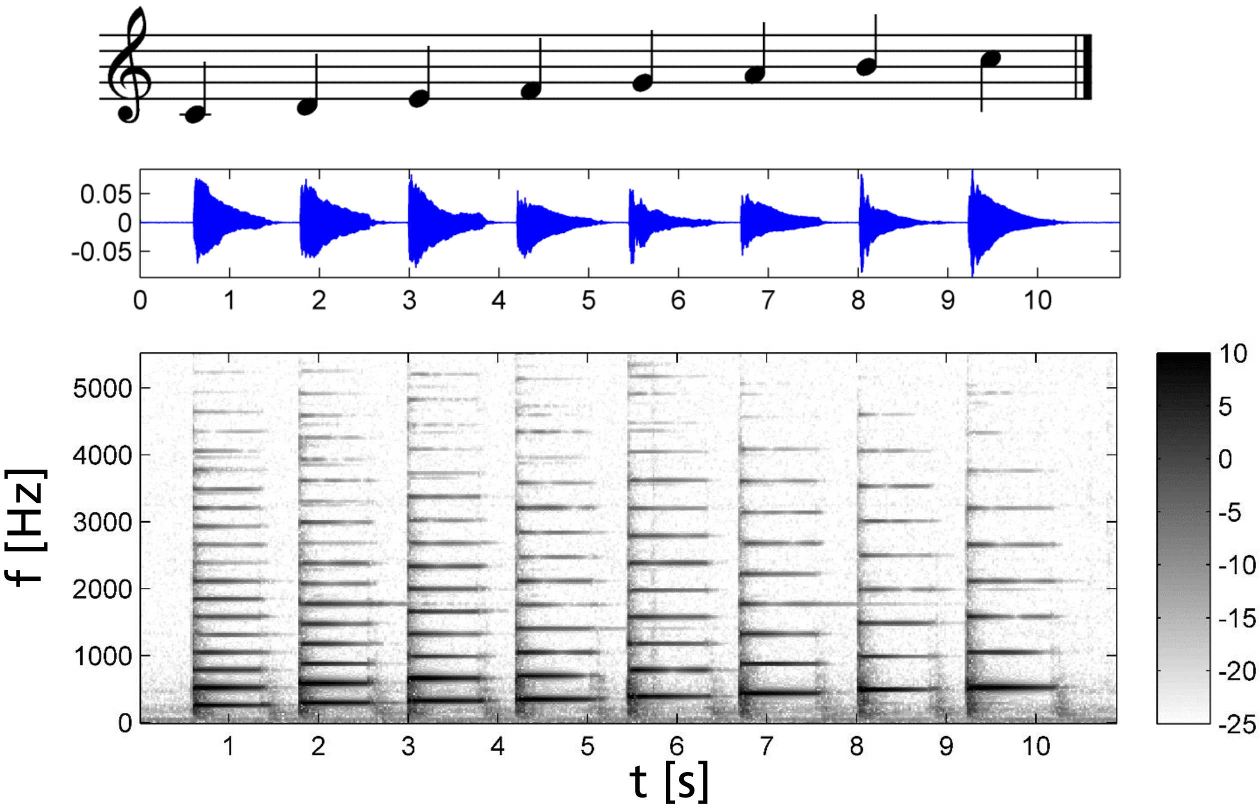


Fig. 10

Audio Representations
Short-term Fourier Transform (STFT)

- Example: C major scale, fundamental frequencies (f0) & overtones



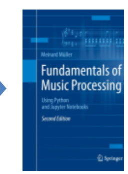


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Fig. 11

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Audio Representations
Constant-Q Transform (CQT)

- Bank of filters with geometrically spaced center frequencies

$$f_k = f_0 \cdot 2^{k/b}$$

k - Filter index

b - Number of filters per octave

- Filter bandwidth (for adjacent filters)

$$\Delta_k = f_{k+1} - f_k = f_k \left(2^{\frac{1}{b}} - 1\right)$$

  - Increasing time resolution towards higher frequencies
  - Resembles human auditory perception

Audio Representations
Constant-Q Transform (CQT)

- Constant frequency-to-resolution ratio

$$Q = \frac{f_k}{\Delta_k} = \frac{1}{2^{\frac{1}{b}-1}}$$

- Correspondence to musical note frequencies

$$f_m[\mathrm{Hz}] = 440 \cdot 2^{\frac{m-69}{12}}$$

m: MIDI pitch

A4 (440 Hz): reference pitch

Audio Representations
Constant-Q Transform (CQT)

- Example signal (speech)
  - CQT (top)
  - STFT (bottom)

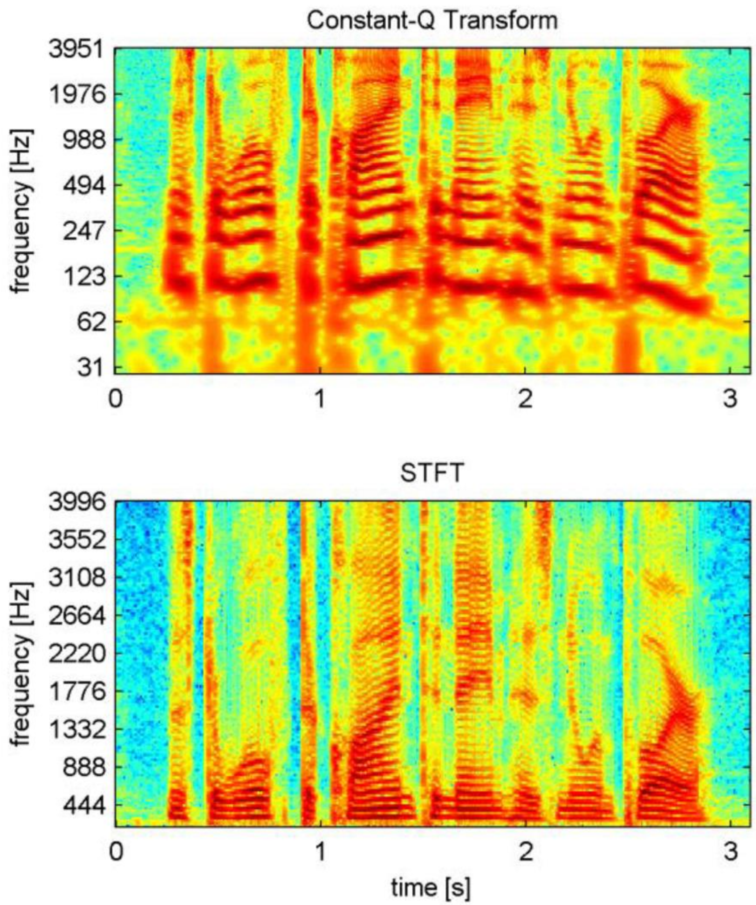


Fig. 12

Audio Representations
Mel Spectrogram

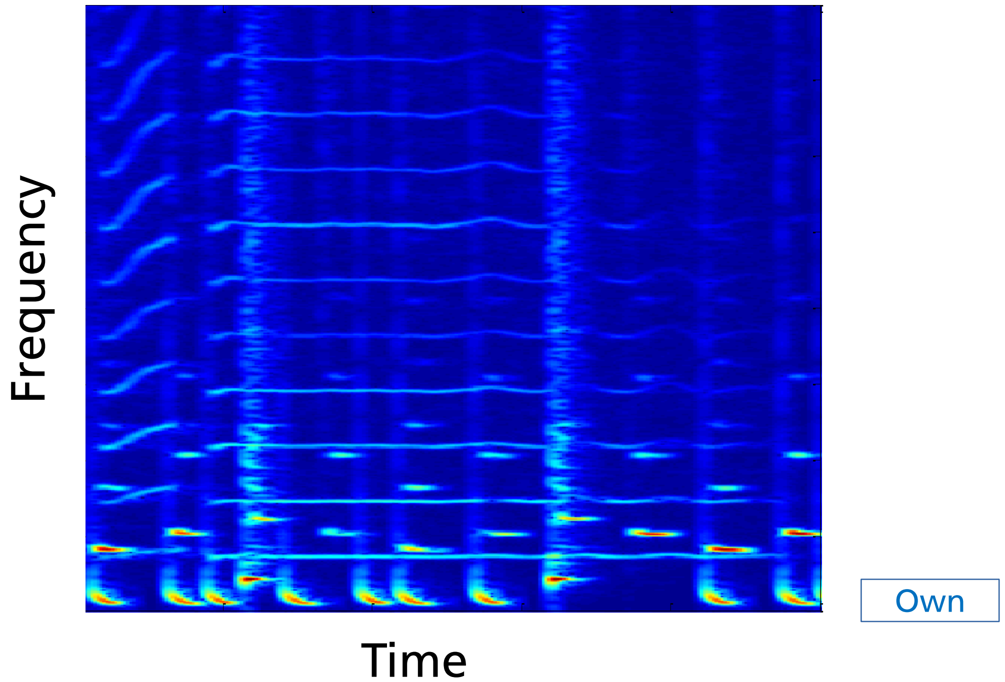
- Mel frequency scale (Stevens et al., 1937)

$$f[\mathrm{Mel}] = 2595 \cdot \log_{10}(1 + \frac{f[\mathrm{Hz}]}{700})$$

  - Describes perceived pitch of sinusoidal frequencies
- Mel spectrogram
  - Time-frequency representation sampled around
    - Equally spaced times
    - Frequency points along the mel-scale

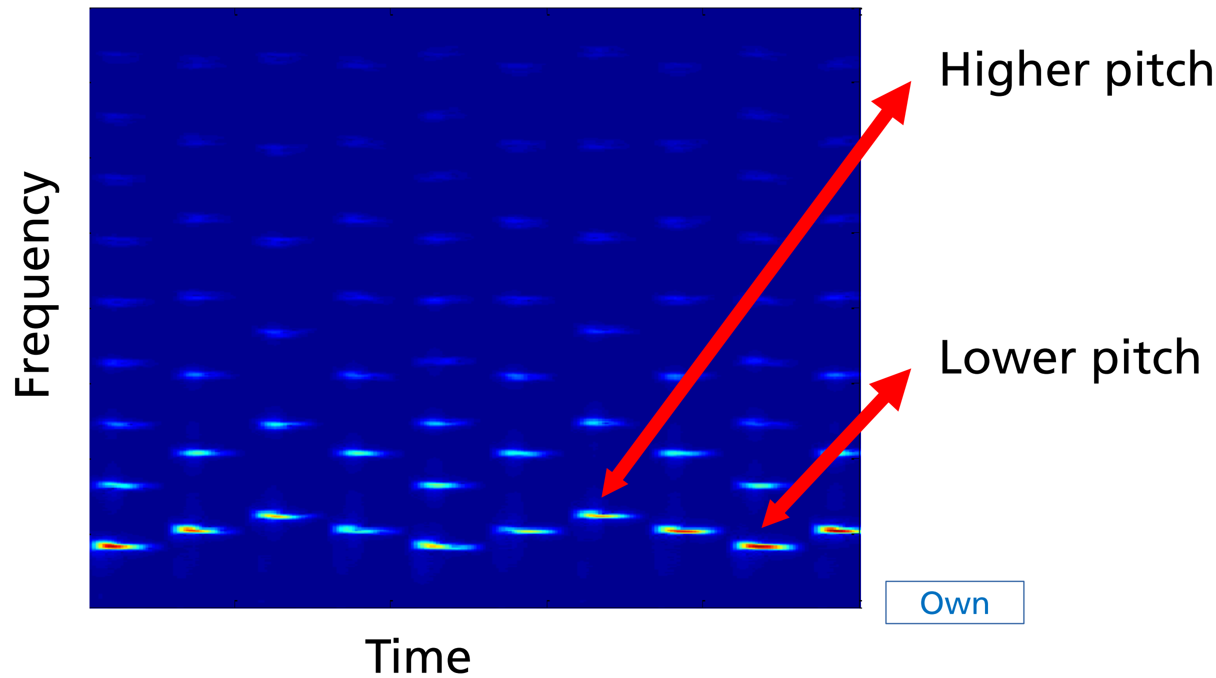
Audio Signal Decomposition
Music mixtures

- Instrument mixture (spectrogram)
  - Bass + melody (saxophone) + drums



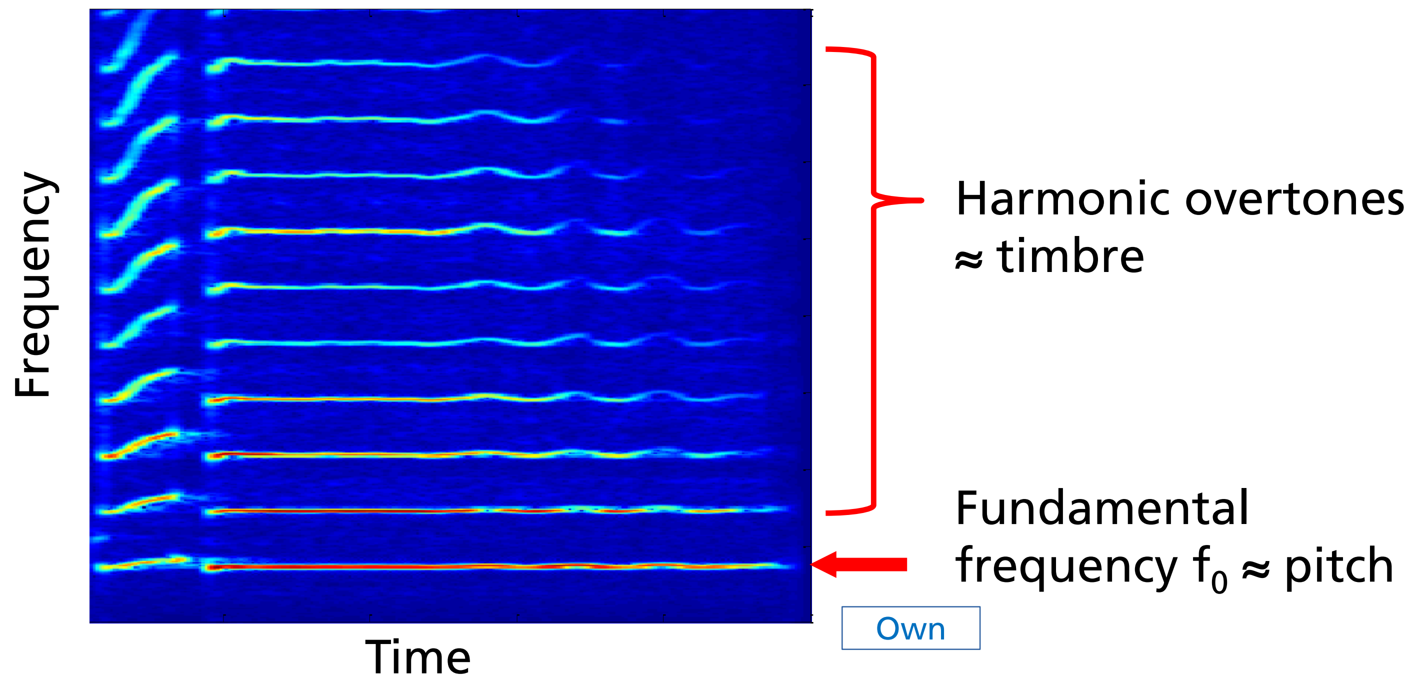
Audio Signal Decomposition
Music mixtures

- Bass
  - Harmonic structure, stable tones



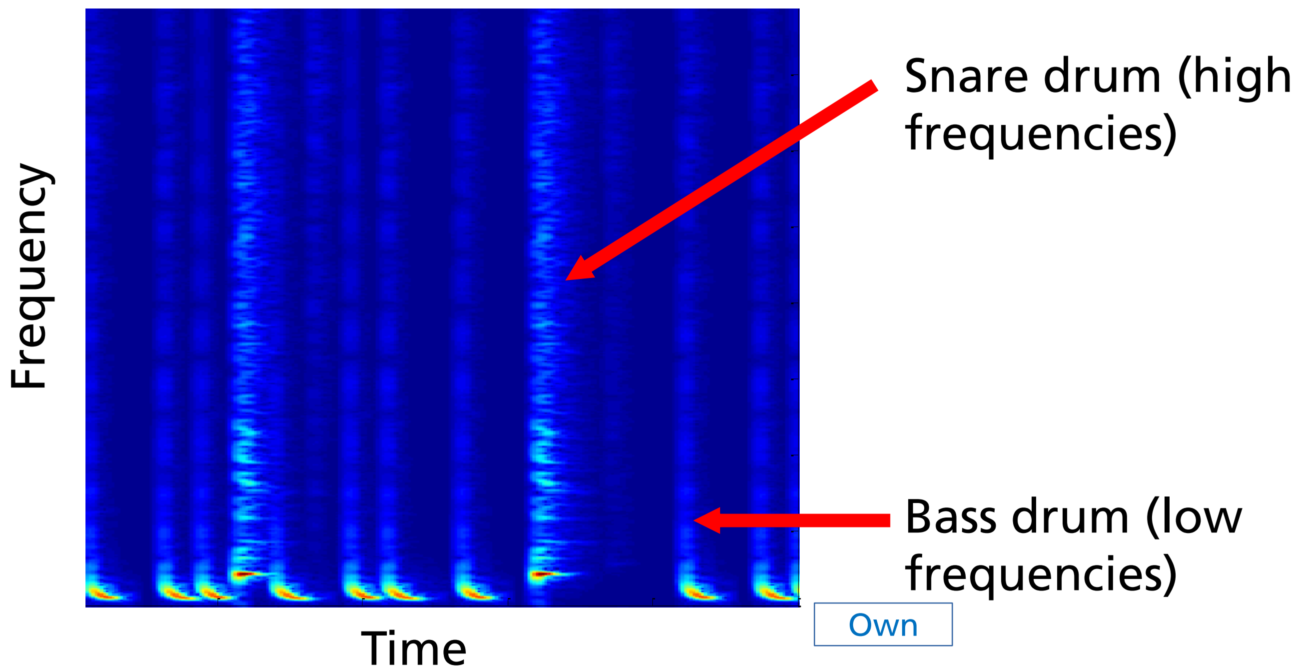
Audio Signal Decomposition
Music mixtures

- Melody (saxophone)
  - Harmonic components (melody)



Audio Signal Decomposition
Music mixtures

- Drums
    - Percussive components (noise-like, inharmonic spectra)



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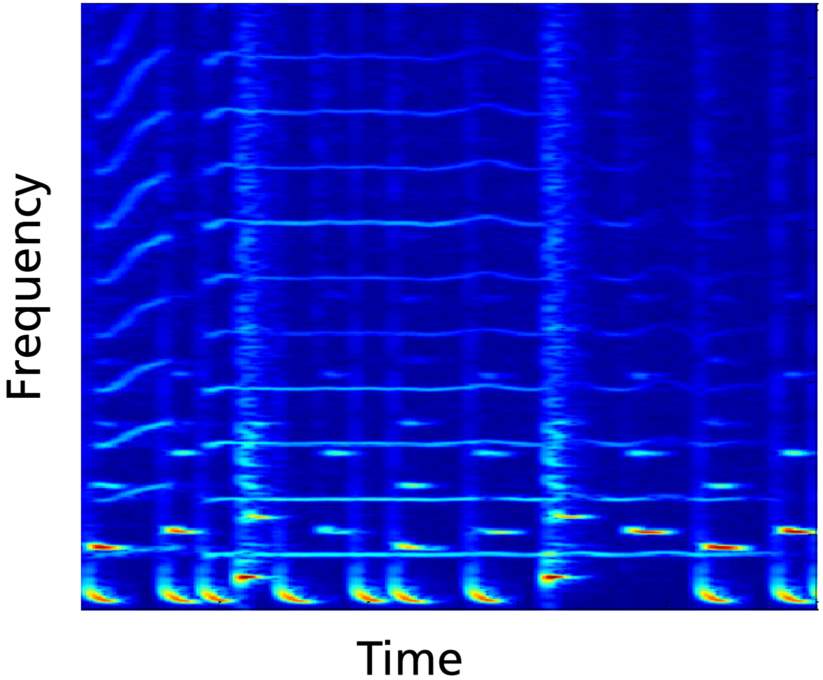
Audio Signal Decomposition
Music mixtures

- Instrument mixture (magnitude STFT)
    - All components add up



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Audio Features
Motivation

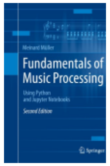
- Compact representation of audio signal for machine learning applications
- Capture different properties at different semantic levels
  - Timbre – perceived sound, instrumentation
  - Rhythm – tempo, meter
  - Melody/Tonality – pitches, harmonies
  - Structure – repetitions, novelty, homogeneous segments

Audio Features
Categorization

	Timbre	Rhythm	Tonality
Low-Level (Q~10 ms)	- Zero Crossing Rate (ZCR) - Linear Predictive Coding (LPC) - Spectral Centroid / Spectral Flatness		
Mid-Level (Q ~ 2.5s)	- Mel-Frequency Cepstral Coefficients (MFCC) - Octave-Based Spectral Contrast (OSC) - Loudness	- Tempogram - Log-Lag Autocorrelation (ACF)	- Chromagram - Enhanced Pitch Class Profiles (EPCP)
High-Level	- Instrumentation	- Tempo - Time Signature - Rhythm Patterns	- Key - Scales - Chords

Audio Features
Timbre

- Timbre
  - Timbre distinguishes musical sounds that have the same pitch (fundamental frequency) and loudness
  - Affected by different acoustic phenomena such as
    - Spectral structure / envelope of overtones
    - Noise-like components
    - Formants (speech)
    - Inharmonicity (non-integer relationship between partials)
    - Variations over time: frequency (vibrato) or loudness (tremolo)



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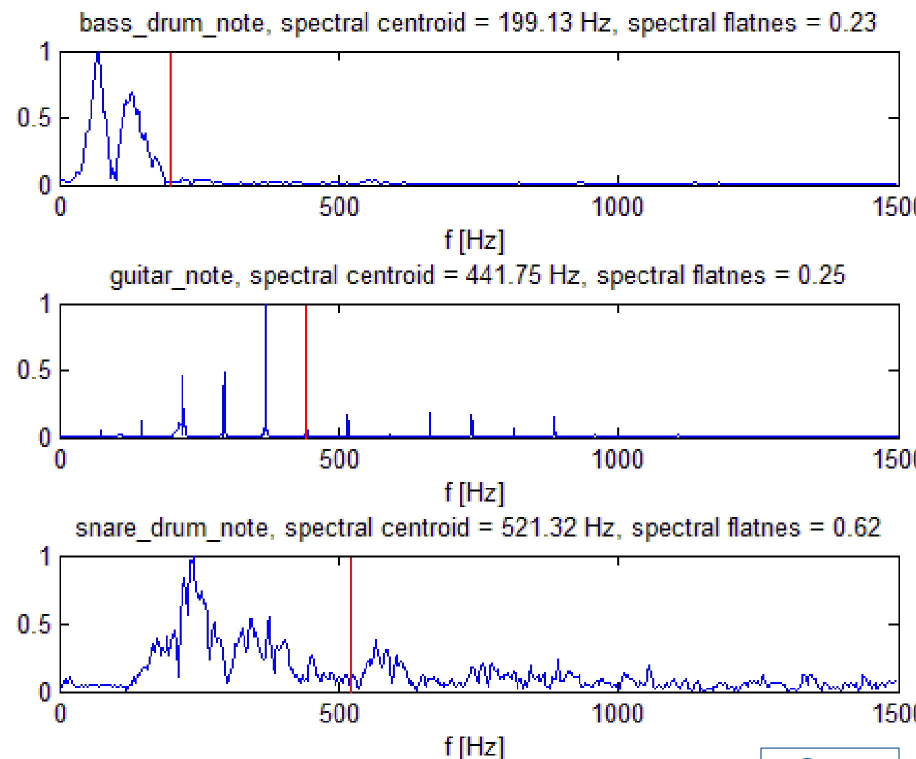
Audio Features
Timbre

- Timbre
    - When looking at musical instruments, we need to consider
        - Instrument’s construction
        - Sound production principles
            - Membranophones, chordophones, aerophones, electrophones
        - Human performance
            - Playing techniques, expressivity, dynamics, style

- How to design features to quantify these acoustic phenomena?

Audio Features
Timbre Low-level Audio Features

- Spectral Centroid (SC):
  - Center of mass in the magnitude spectrogram
  - Low-pitched vs. high-pitched sounds
- Spectral Flatness Measure (SFM)
  - Harmonic sounds (sparse energy distribution)
  - Percussive sounds (wideband energy distribution)



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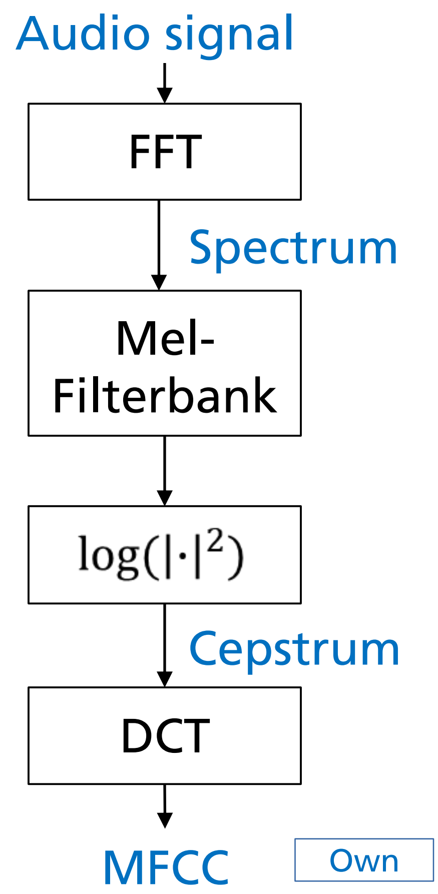
Audio Features
Timbre Mid-level Audio Features: MFCC

- Convolutive excitation * filter model
  - Excitation: vibration of vocal folds
  - Filter: resonance of the vocal tract
- FFT magnitude spectrum
  - Multiplicative excitation · filter model
- Logarithm of magnitude spectrum
  - Additive excitation + filter model
- Discrete Cosine Transform (DCT)
  - First coefficients allow for a compact description of the spectral envelope shape



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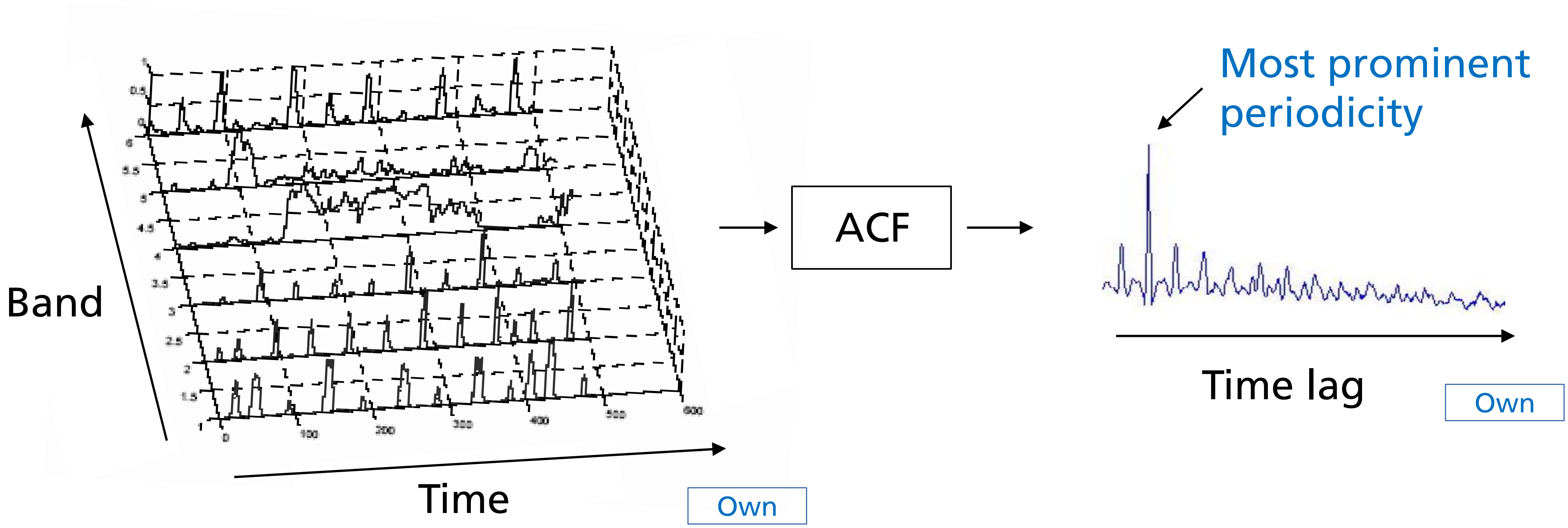
Audio Features
Rhythmic Mid-level Audio Features

- Rhythmic properties are important for audio classification
- Audio Spectral Energy (ASE)
    - Analyze energy slopes in different frequency bands
    - Find periodicities via auto-correlation function (ACF)



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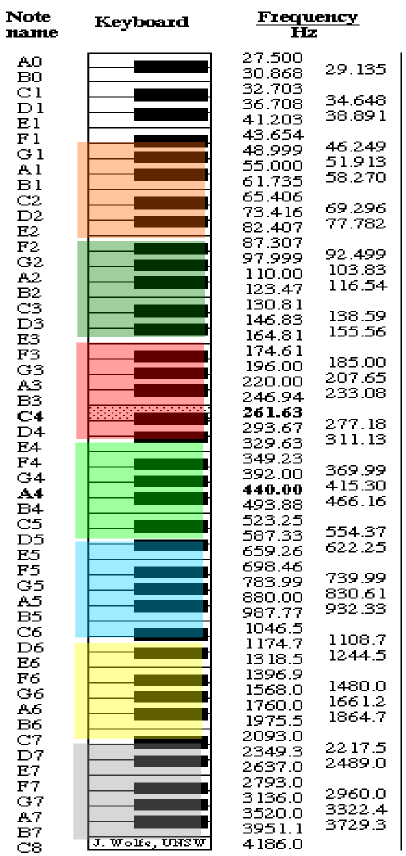
Audio Features

Tonal Mid-level Audio Features: Chromagram



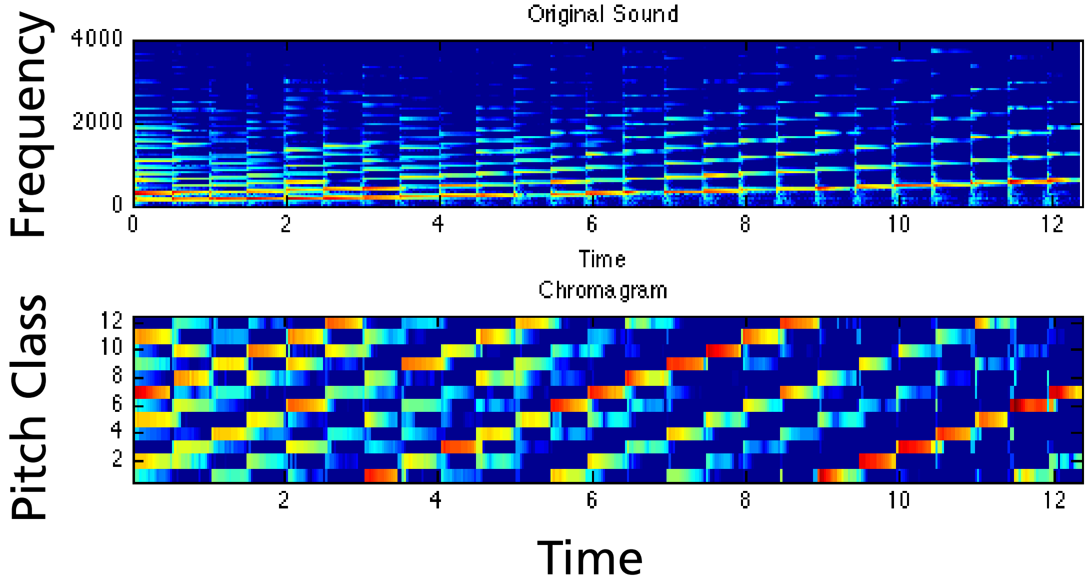


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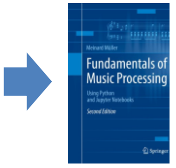
Fig. 13



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Summary

- Sound categories
- Music representations
- Audio representations
- Audio signal decomposition
- Audio features

References

Müller, M. (2021). *Fundamentals of Music Processing - Using Python and Jupyter Notebooks* (2nd ed.). Springer.

Shi, Z., Lin, H., Liu, L., Liu, R., & Han, J. (2019). Is CQT More Suitable for Monaural Speech Separation than STFT? An Empirical Study. *ArXiv Preprint ArXiv:1902.00631*.

Images

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Fig. 7: [Müller, 2021], p. 2, Fig. 1.1

Fig. 8: [Müller, 2021], p. 14, Fig. 1.13

Fig. 9: [Müller, 2021], p. 17, Fig. 1.15

Fig. 10: [Müller, 2021], p. 56, Fig. 2.9

Fig. 11: [Müller, 2021], p. 57, Fig. 2.10

Fig. 12: [Shi, 2019], p. 3, Fig. 2

Fig. 13: https://newt.phys.unsw.edu.au/jw/graphics/notes.GIF

Sounds

AUD-1: Medley: https://freesound.org/people/InspectorJ/sounds/416529, https://freesound.org/people/prometheus888/sounds/458461, https://freesound.org/people/MrAuralization/sounds/317361

AUD-2: Medley: https://freesound.org/people/whatsanickname4u/sounds/127337, https://freesound.org/people/jcveliz/sounds/92002, https://freesound.org/people/klankbeeld/sounds/192691

Thank you!

- Any questions?

Dr.-Ing. Jakob Abeßer

Fraunhofer IDMT

Jakob.abesser@idmt.fraunhofer.de

https://www.machinelistening.de

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