Machine Listening for Music and Sound Analysis

Lecture 1 – Audio Representations

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https://www.machinelistening.de

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

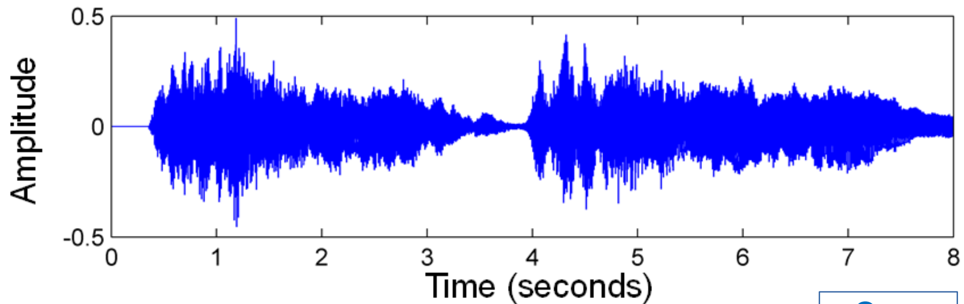
Fig. 4

Fig. 5

Fig. 6

Music Representations
Recording & Notation

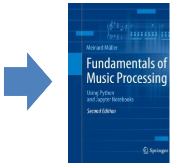
- Music recording (waveform)



Own

- Music notation (score)

Fig. 7

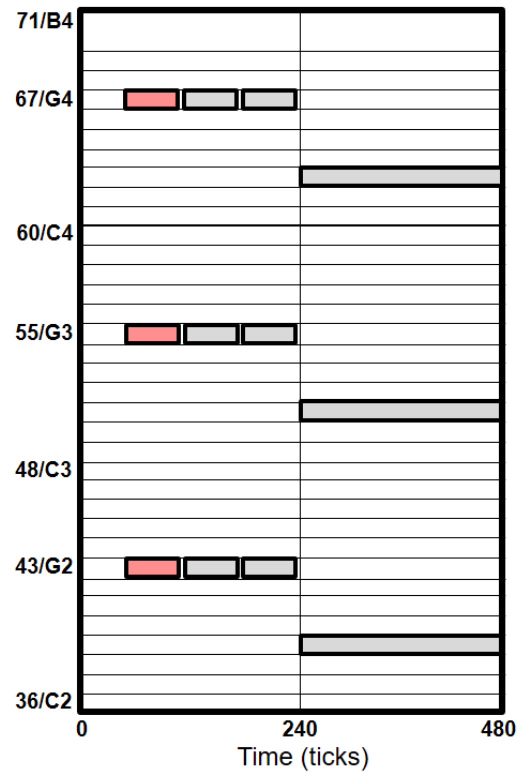


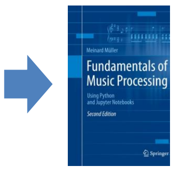
FMP Notebooks

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





FMP Notebooks

Fig. 8

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)
  - Windowed analysis of audio signals

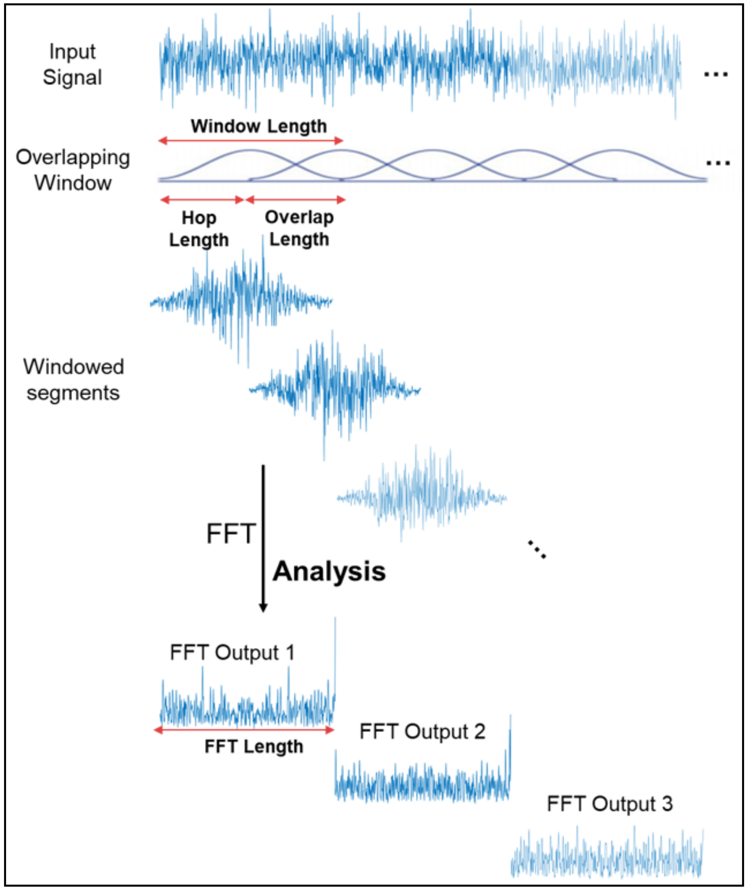


Fig. 9.5

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

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
  - Linearly-spaced frequency axis
  - Trade-off between
    - Frequency resolution
    - Time resolution

Audio Representations
Short-term Fourier Transform (STFT)

- Example: Sinusoid signal, two frequencies

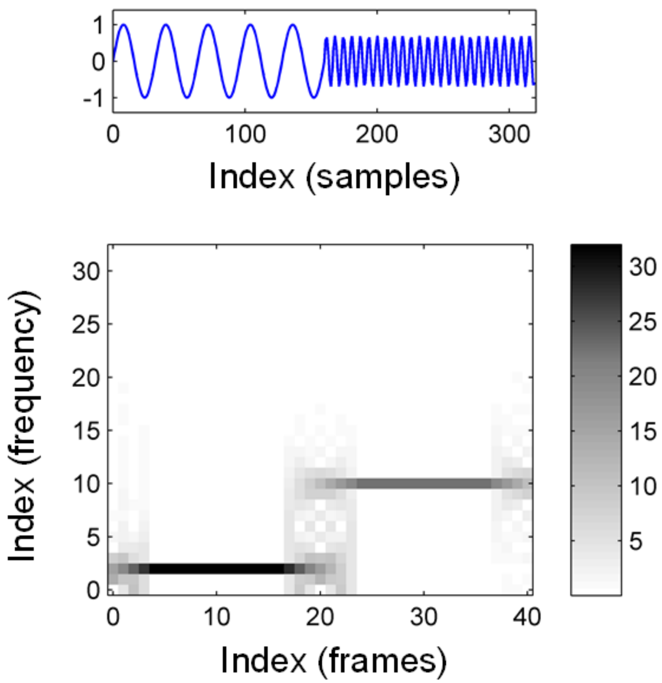


Fig. 10

Audio Representations
Short-term Fourier Transform (STFT)

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

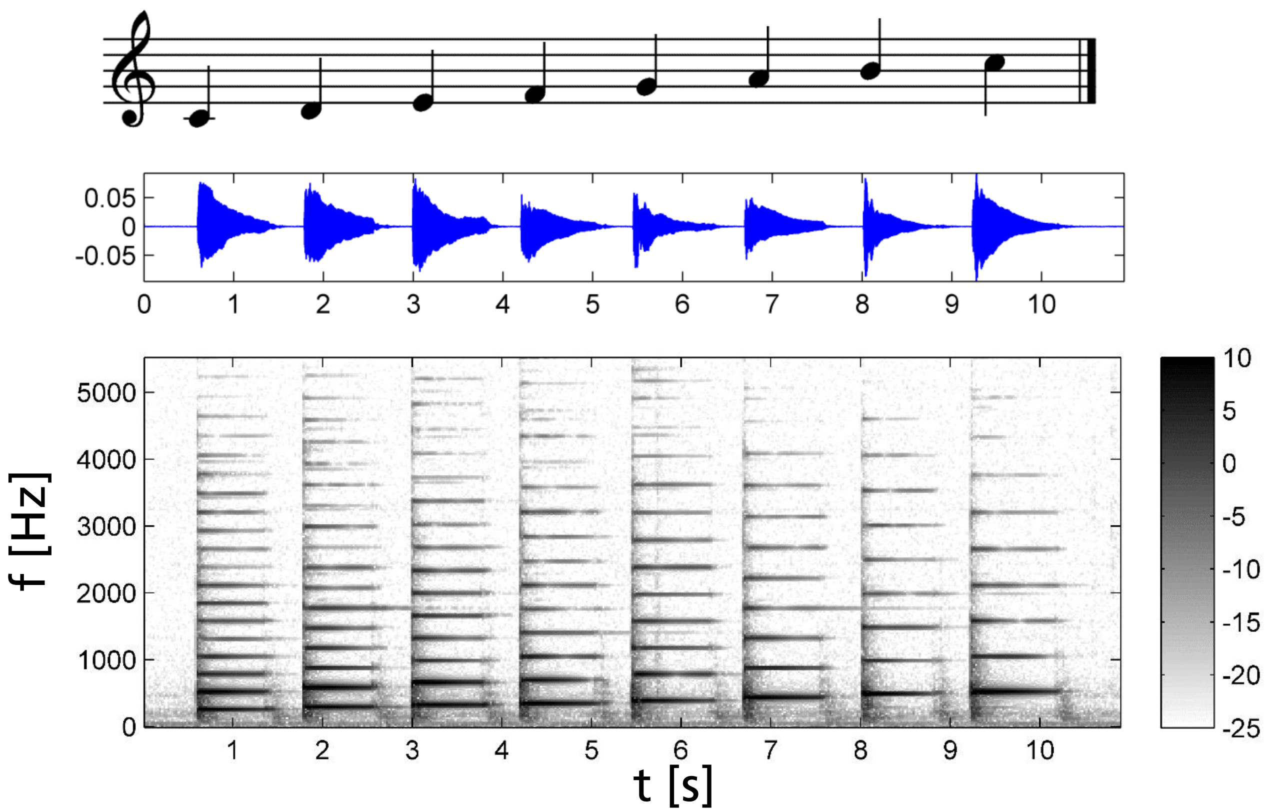


Fig. 11

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

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

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

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)

- STFT (linearly-spaced frequencies)
- CQT (logarithmically-spaced, closer to human auditory perception)
  - Variable number of frequency bins per octave
  - Increasing time resolution towards higher frequencies

Audio Representations
Constant-Q Transform (CQT)

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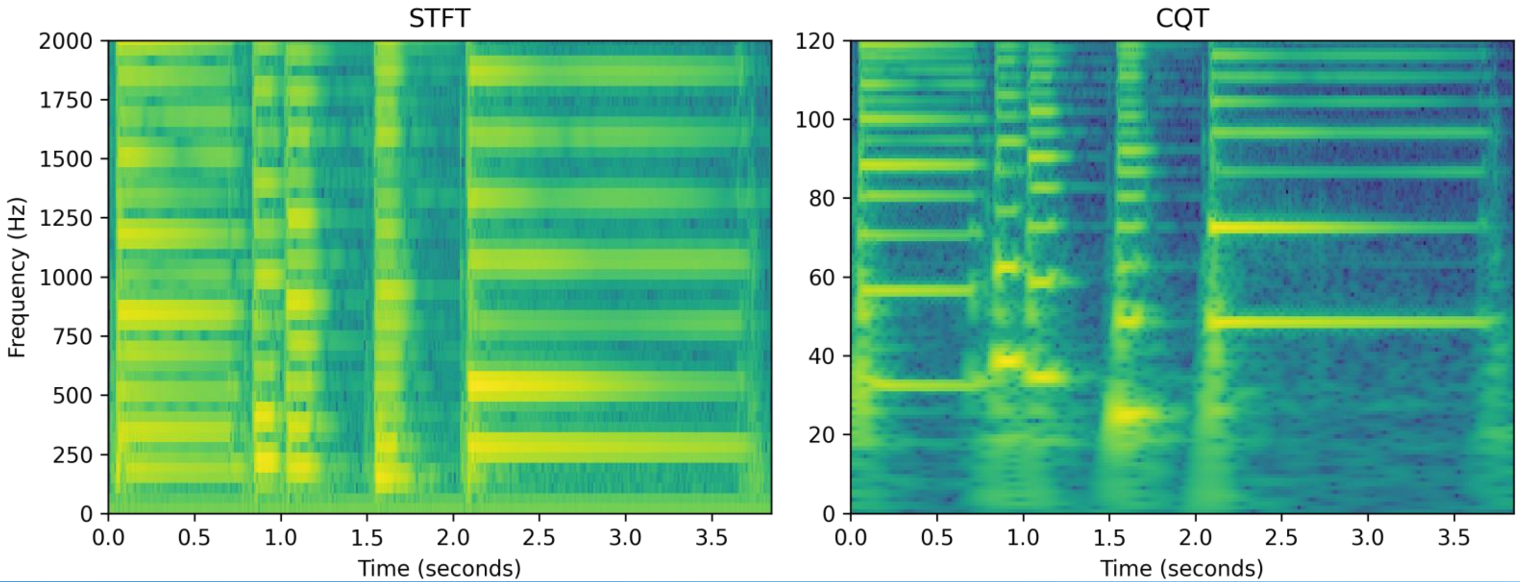
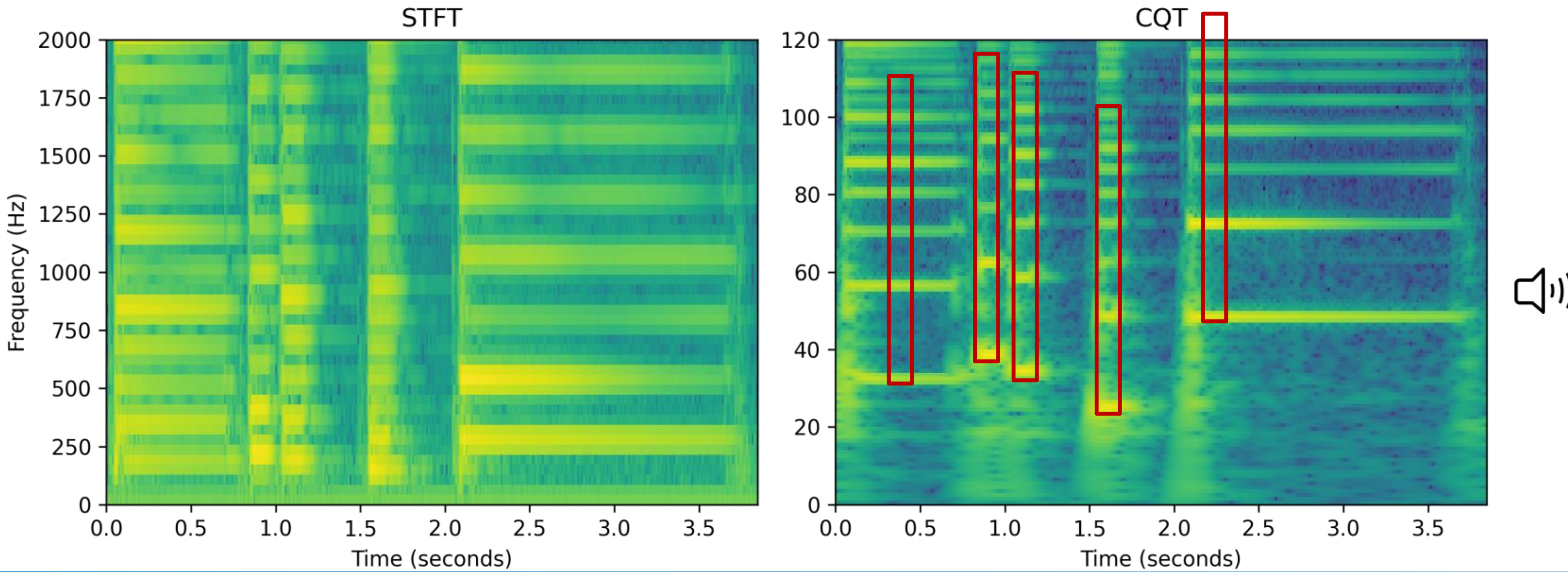
  - Variable number of frequency bins per octave
  - Increasing time resolution towards higher frequencies



Audio 1

Audio Representations
Constant-Q Transform (CQT)

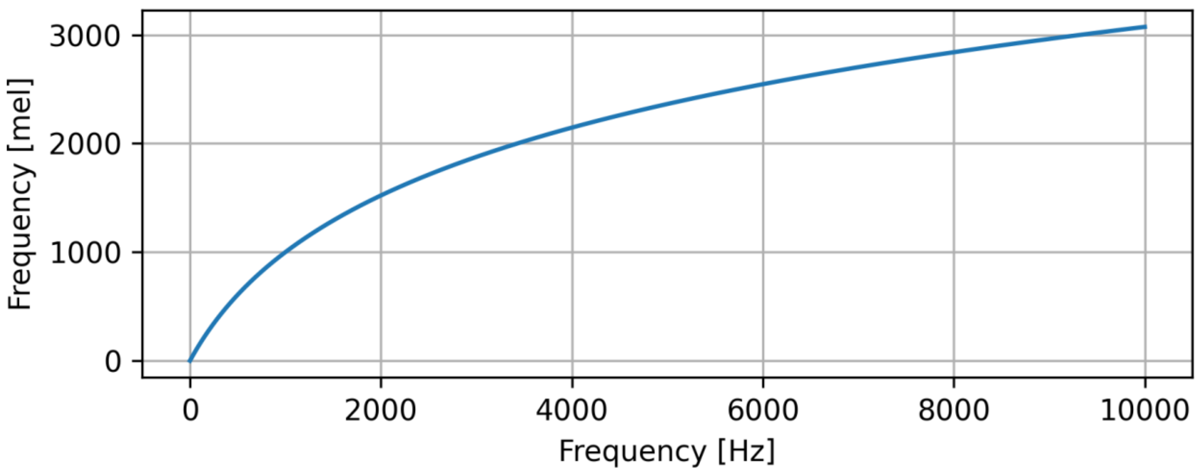
- Suitable for music transcription
- Partials have a constant frequency pattern
  - Vertically shifted
  - Pitch-independent



Audio 1

Audio Representations
Mel Spectrogram

- Logarithmic frequency mapping (human pitch perception)
  - $f[\text{mel}] = 2595 \cdot \log_{10}\left(1 + \frac{f[\text{Hz}]}{700}\right)$

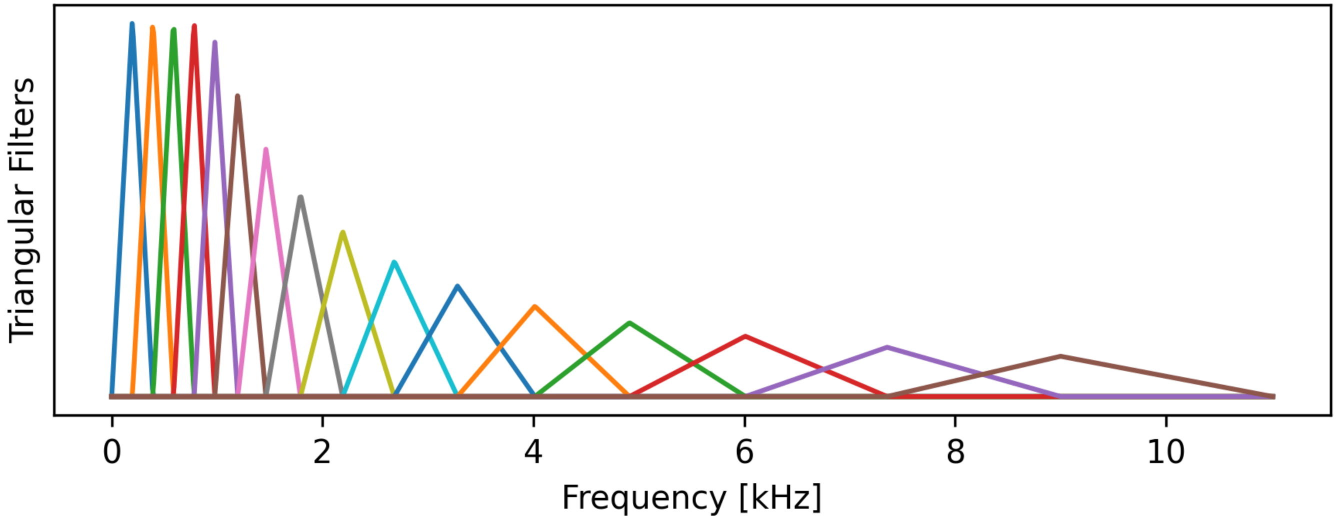


Audio Representations
Mel Spectrogram

- Mapping from STFT magnitude spectrogram to Mel spectrogram
  - Triangular filterbank + Matrix multiplication

Audio Representations
Mel Spectrogram

- Mapping from STFT magnitude spectrogram to Mel spectrogram
  - Triangular filterbank + Matrix multiplication
- Example: 16 mel bands, $f_s = 22.05\ \mathrm{kHz}$



Audio Representations
Mel Spectrogram

- More efficient representation (fewer frequency bands)
- Still captures perceptually relevant information

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Mel Spectrogram

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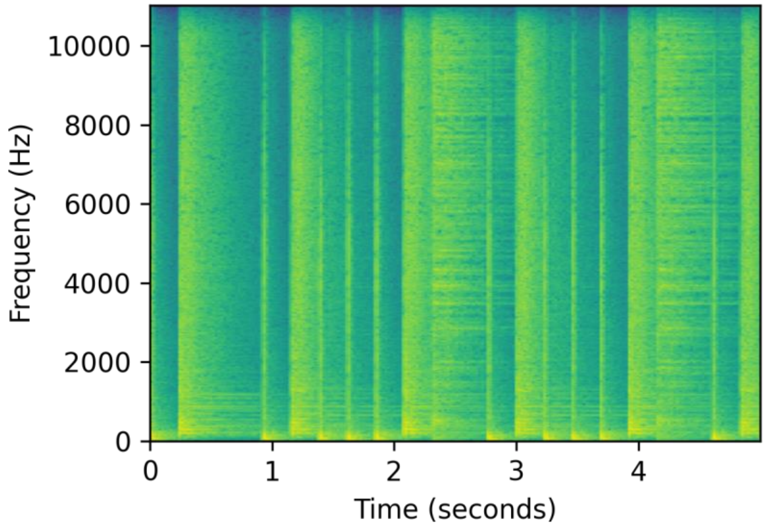
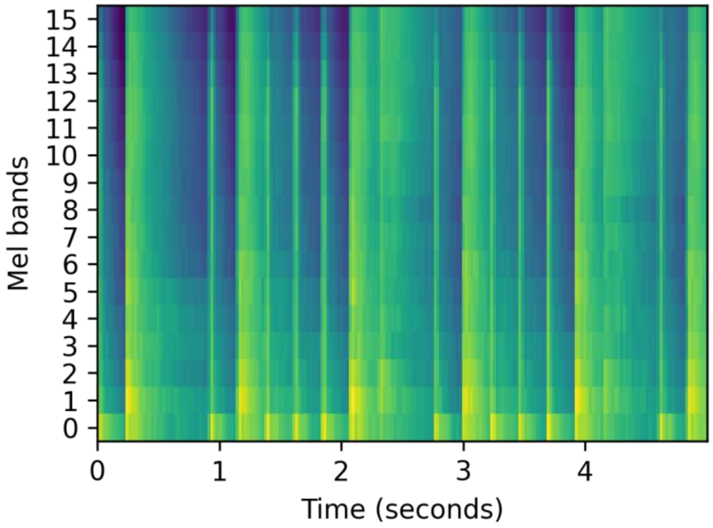
STFT



Mel Spectrogram

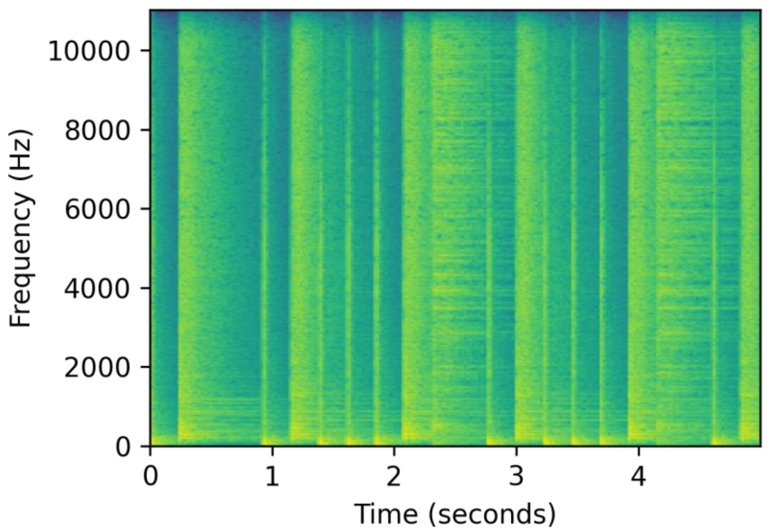


Audio 3

Audio Representations
Mel Spectrogram

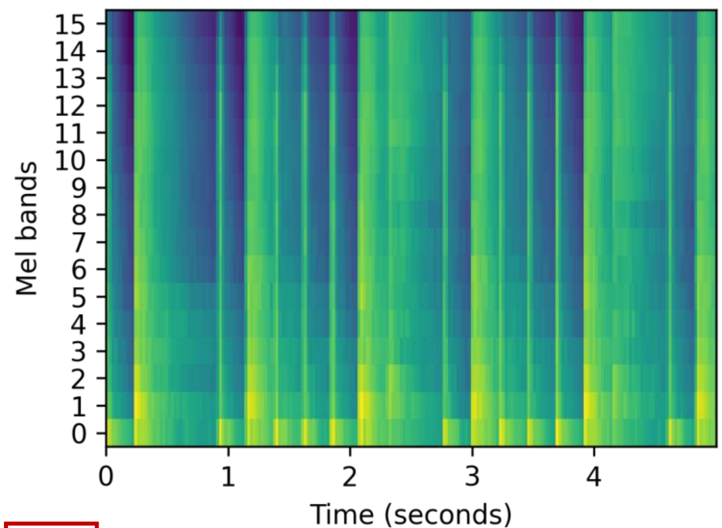
- More efficient representation (fewer frequency bands)
- Still captures perceptually relevant information

STFT



(513 frequency bands)

Mel Spectrogram

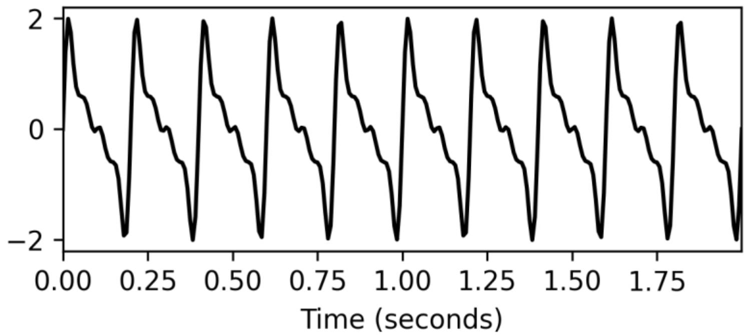


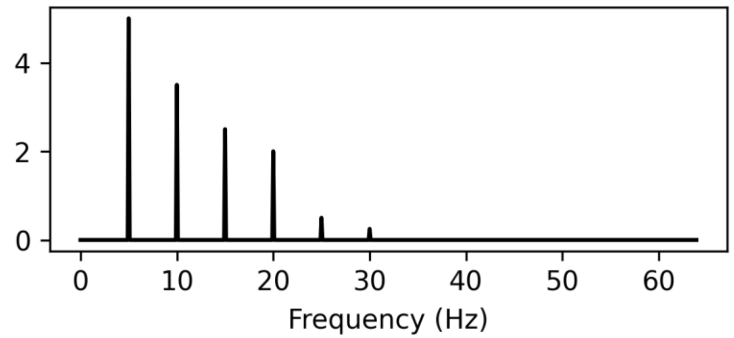
(16 mel bands)

Compression by 96.9 %

Audio Signal Decomposition
Periodic Signals

- Periodic signals:
  - Sum of pure tones (partials)
    - Fundamental frequency f_0
    - Harmonics f_k (approx. integer multiples of f_0):
      - $f_k \approx (k+1) \cdot f_0$





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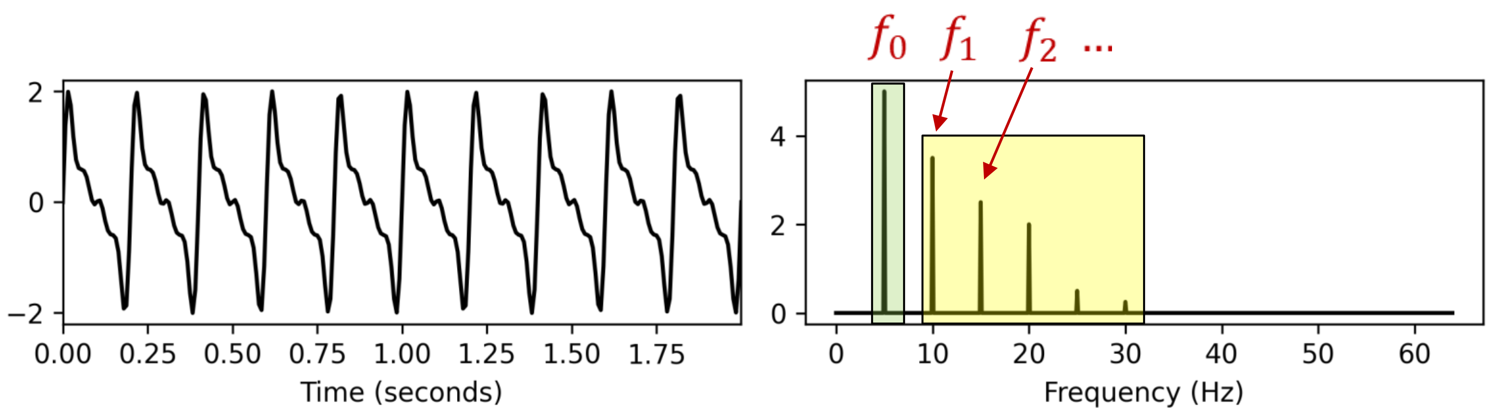


Audio Signal Decomposition
Pitch

- Perceptual property (sort sounds from low to high pitch)
- Closely related to frequency
    - $f = 440 \cdot 2^{\frac{p-69}{12}}$ [Hz]

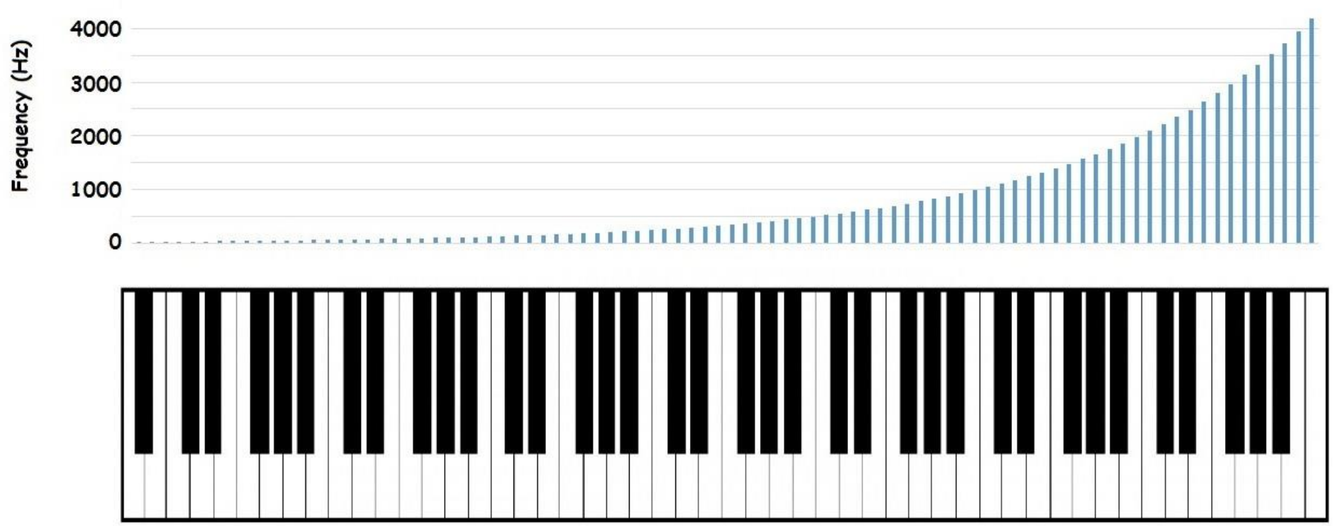


Fig. 2.5

Audio Signal Decomposition
Frequency Modulation

- Techniques
  - Glissando – continuous transition between note pitches
  - Vibrato – periodic frequency modulation

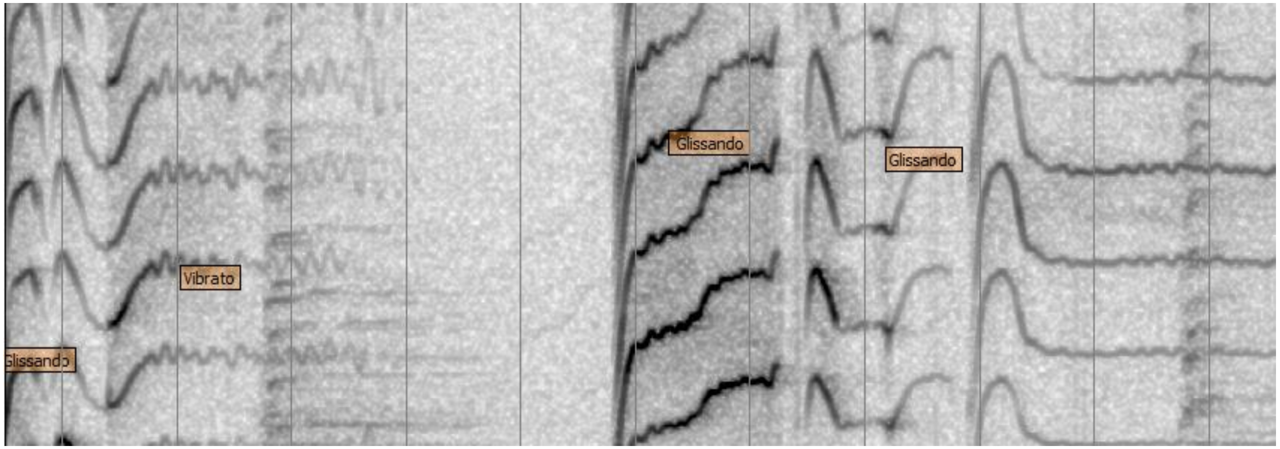


Fig. 2.6

Spectrogram example (frequency x time)

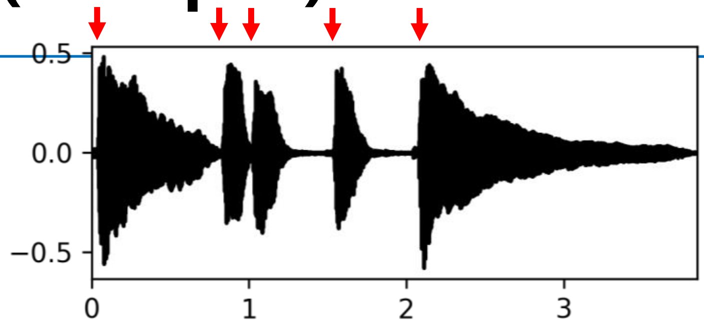
Audio Signal Decomposition
Transients

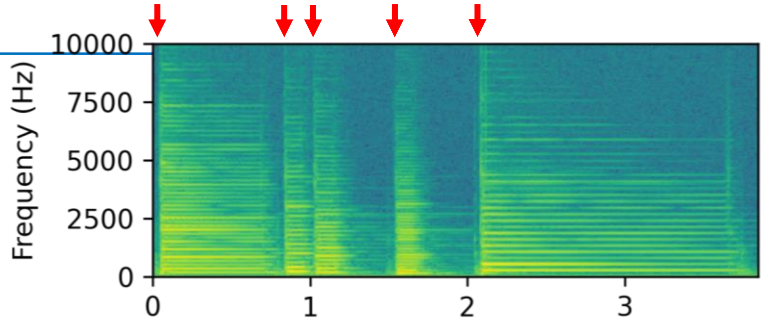
- Sound characteristics
    - High amplitude
    - Short duration
    - Wide-band signal
        - Energy distributed over large frequency range
          (not just a few frequencies)

Audio Signal Decomposition

Transients (Examples)

- String instruments
  Audio 1



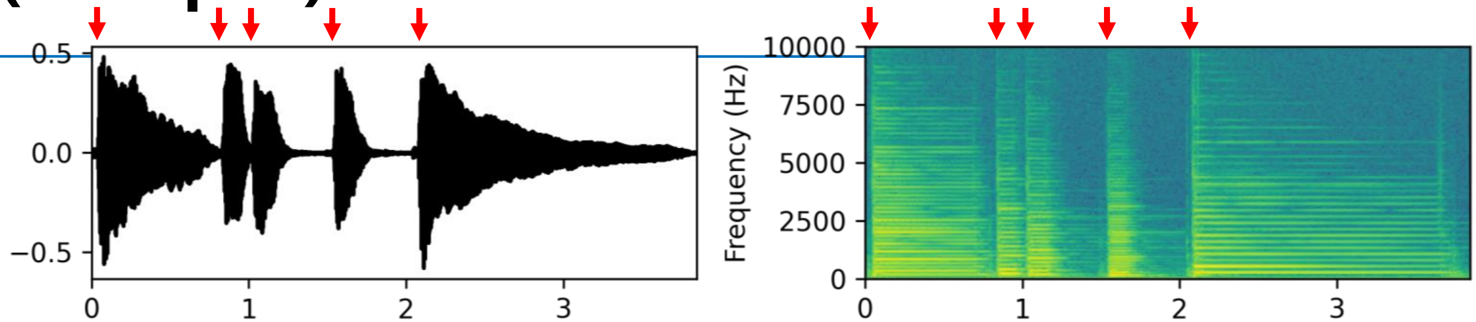


Audio Signal Decomposition

Transients (Examples)

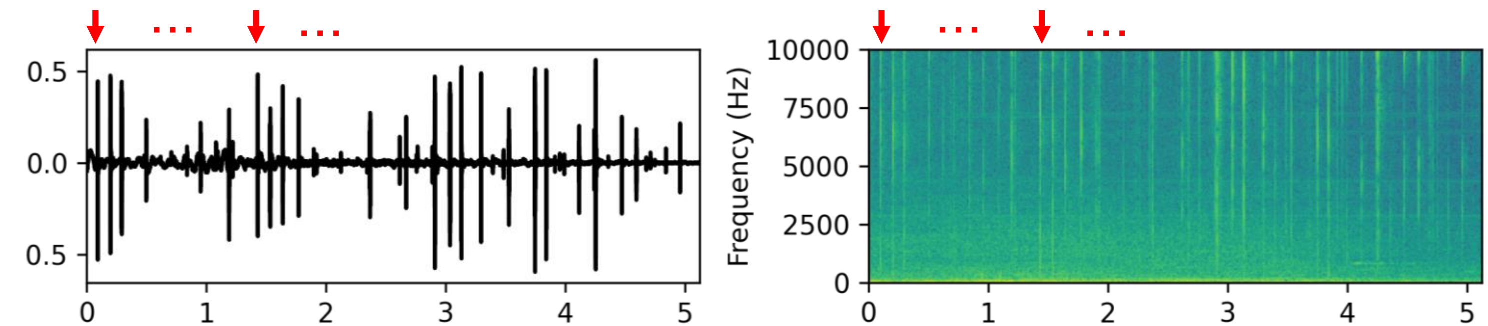
- String instruments

  Audio 1



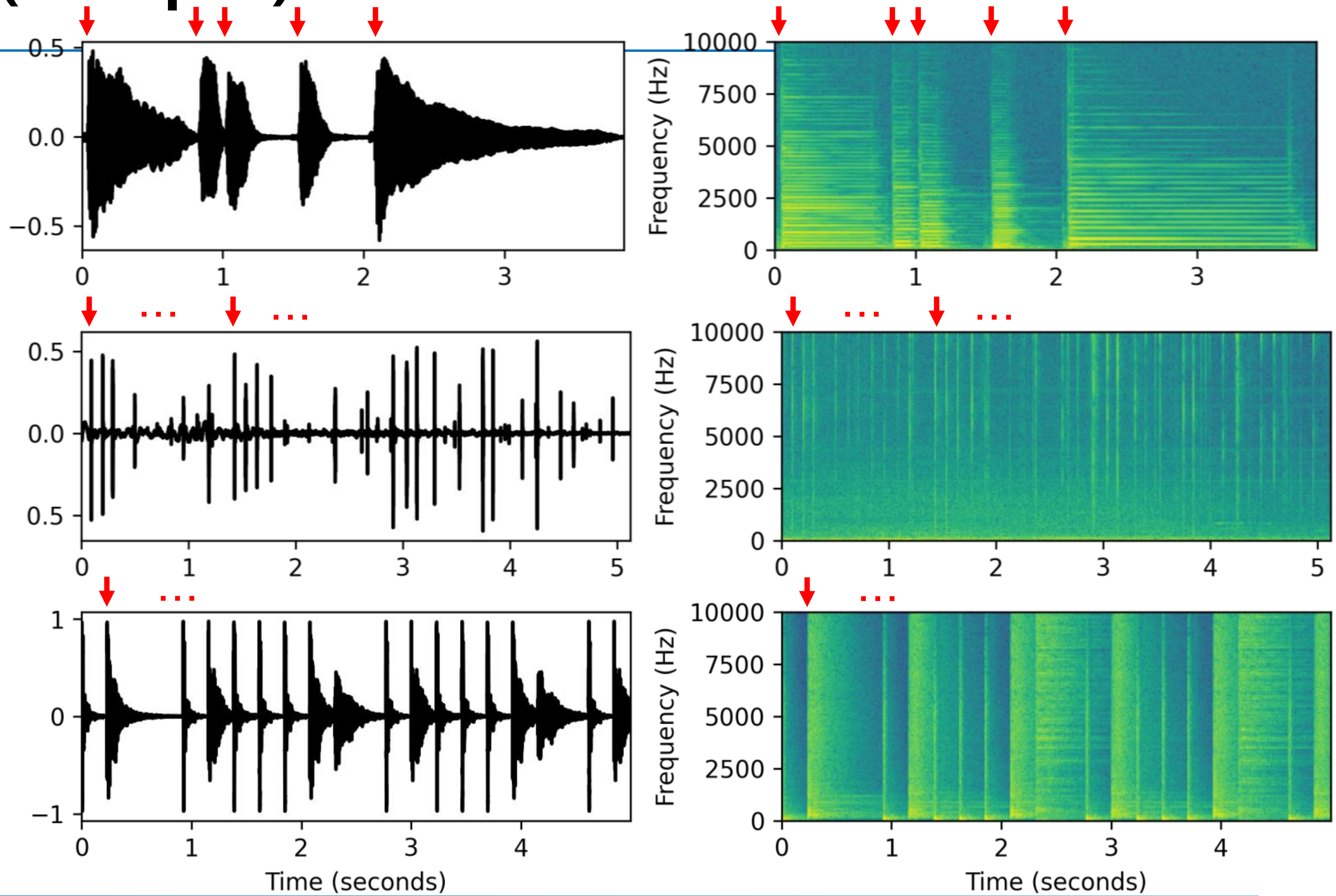
- Bat vocalizations

  Audio 2



Audio Signal Decomposition
Transients (Examples)

- String instruments
  Audio 1
- Bat vocalizations
  Audio 2
- Drum instruments
  Audio 3

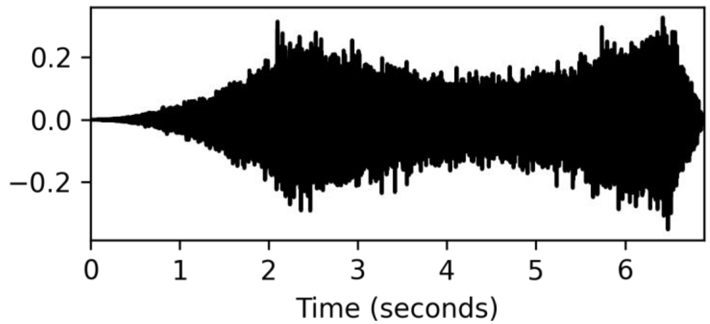


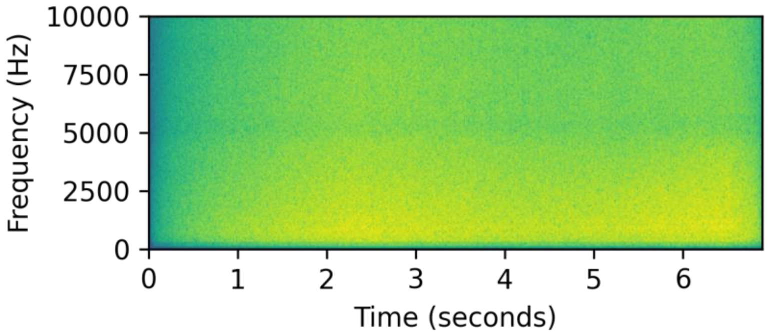
Audio Signal Decomposition
Noise

- Sound characteristics
    - Non-periodic, texture-like
    - Random fluctuations of air pressure

Audio Signal Decomposition
Noise

- Sound characteristics
  - Non-periodic, texture-like
  - Random fluctuations of air pressure
- Examples
  - Consonants (speech)
  - Wind (random aerodynamic turbulences)
  - Waves (ocean) Audio 4





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
Timbre

- Timbre
  - Timbre distinguishes musical sounds that have the same pitch (fundamental frequency) and loudness

Audio Features
Timbre

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  - 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

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)

FMP Notebooks

Audio Features
Timbre

- Timbre
    - When looking at musical instruments, we need to consider
        - Instrument’s construction

Audio Features
Timbre

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  - When looking at musical instruments, we need to consider
    - Instrument's construction
    - Sound production principles
      - Membranophones, chordophones, aerophones, electrophones

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

Audio Features

Temporal Envelope

- Smooth curve outlining the signal extreme points
- ADSR envelope model (also used for audio synthesis)
    - Attack, Decay, Sustain, Release

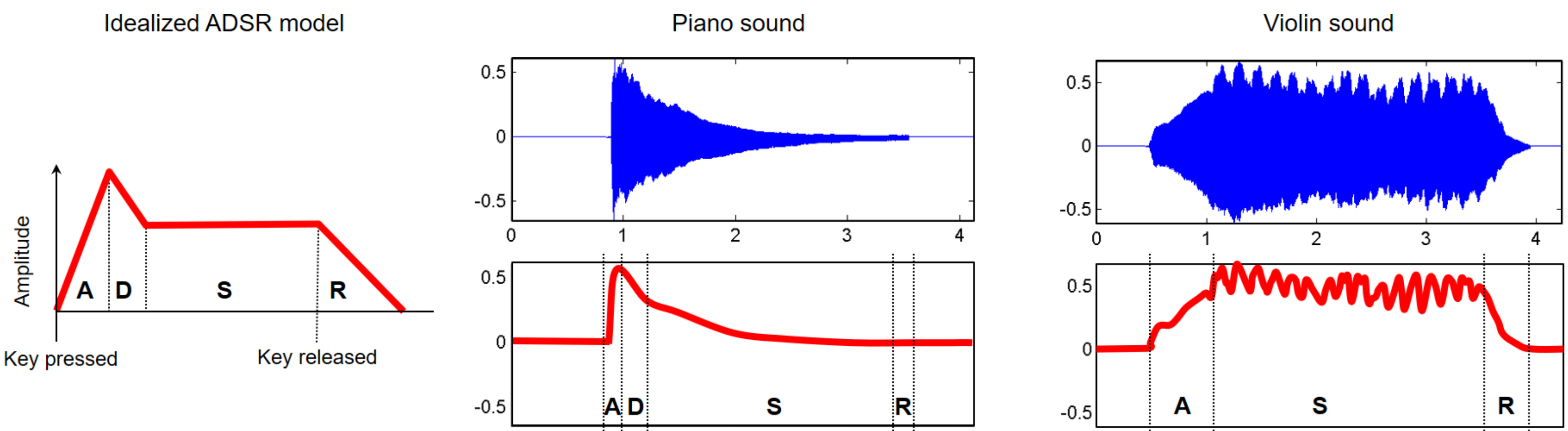
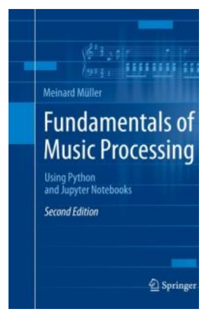


Figure 1.22b and Figure 1.23 from [Müller, FMP, Springer 2015]

Fig. 2.7

Audio Features
Temporal Envelope

- Tremolo
    - Periodic amplitude modulation
    - Often coincides with frequency modulation (vibrato)
    - Examples: instrument sounds



FMP Notebooks

Fig. 2.7

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

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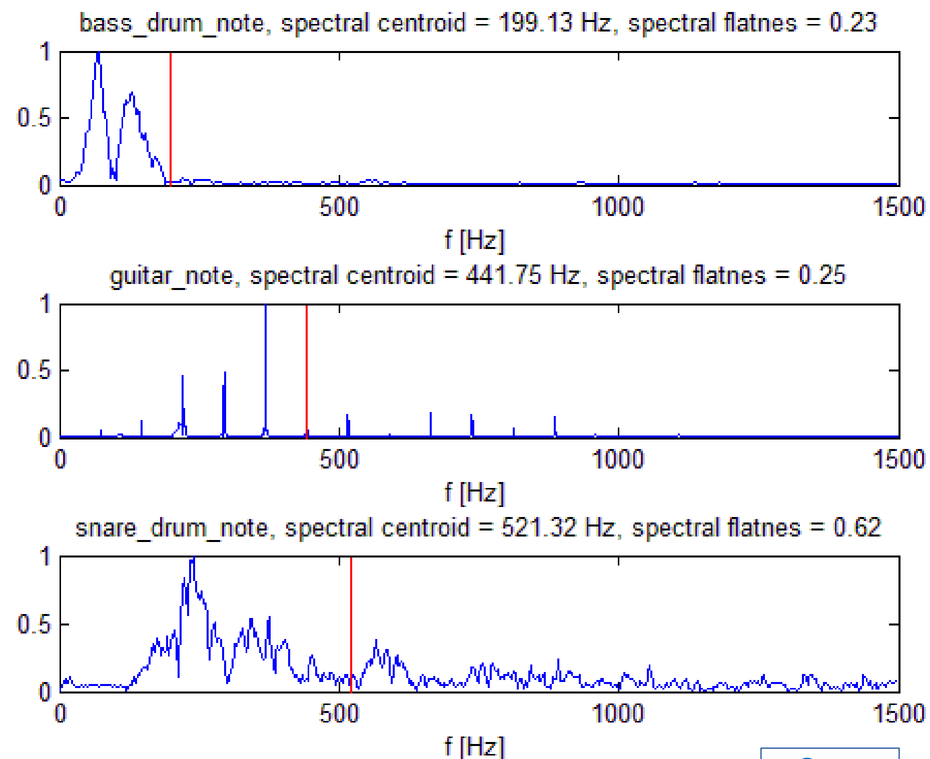
Audio Features
Timbre Low-level Audio Features

- Spectral Centroid (SC):
    - Center of mass in the magnitude spectrogram
    - Low-pitched vs. high-pitched sounds

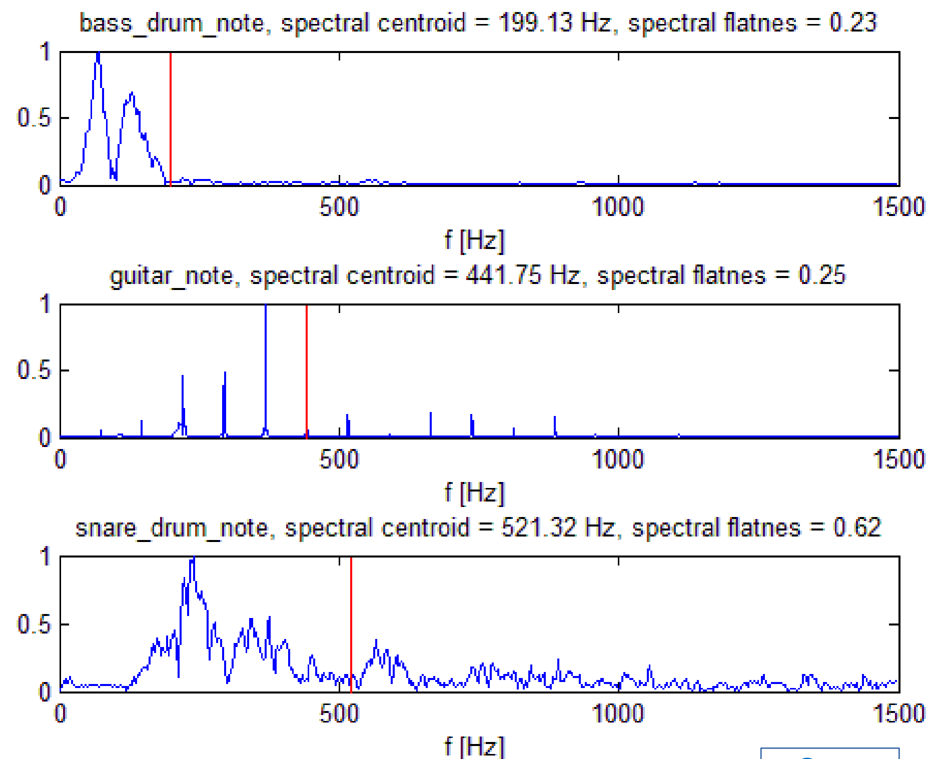


Own

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)



Own

Audio Features
Mel-Frequency Cepstral Coefficients (MFCC)

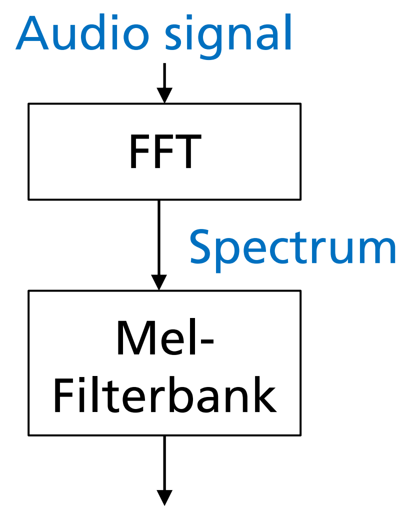
- Convolutive excitation * filter model
    - Excitation: vibration of vocal folds
    - Filter: resonance of the vocal tract

Audio signal

Own

Audio Features
Mel-Frequency Cepstral Coefficients (MFCC)

- Convolutive excitation * filter model
  - Excitation: vibration of vocal folds
  - Filter: resonance of the vocal tract
- FFT magnitude spectrum
  - Multiplicative excitation · filter model



Own

Audio Features
Mel-Frequency Cepstral Coefficients (MFCC)

- Convolutive excitation * filter model
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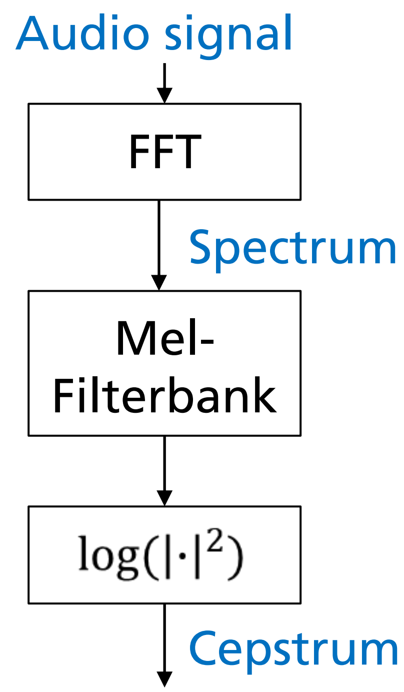
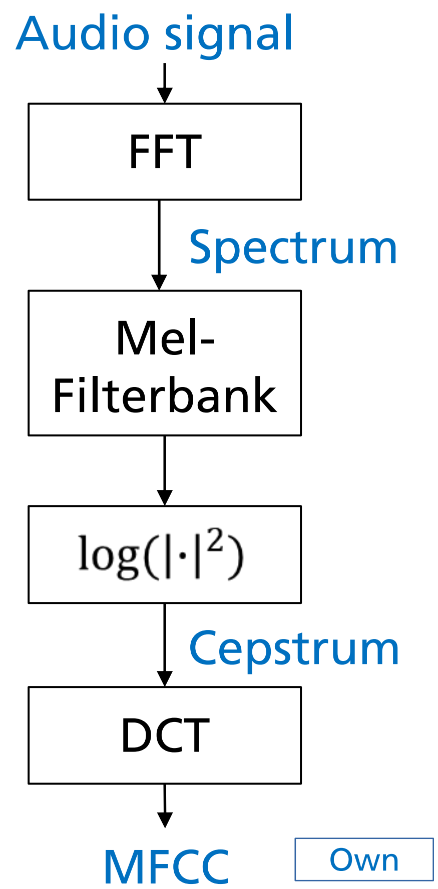
    - Filter: resonance of the vocal tract
- FFT magnitude spectrum
    - Multiplicative excitation · filter model
- Logarithm of magnitude spectrum
    - Additive excitation + filter model



Own

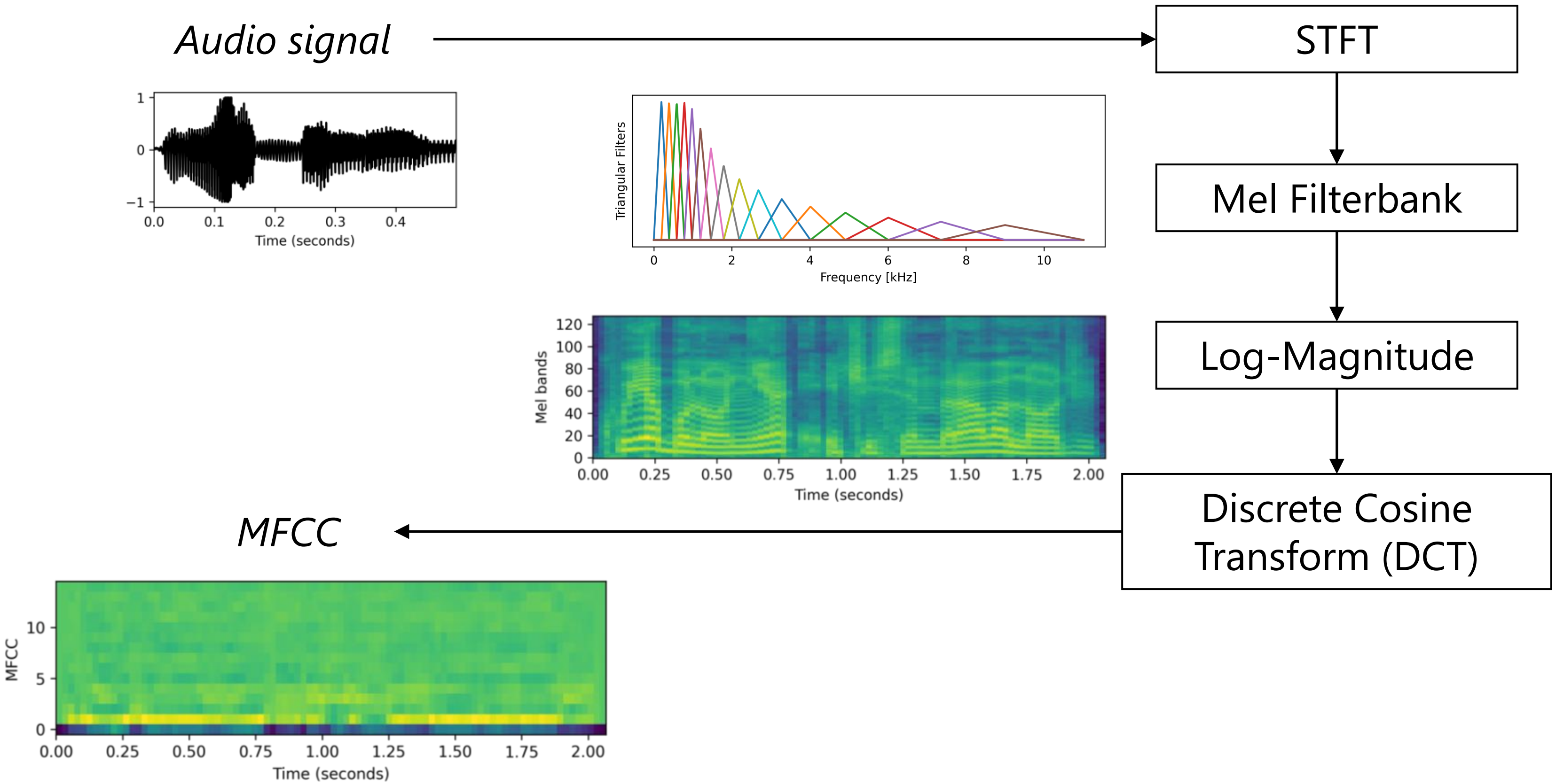
Audio Features
Mel-Frequency Cepstral Coefficients (MFCC)

- 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



Audio Features
Mel-Frequency Cepstral Coefficients (MFCC)

- Compact representation of spectral envelope



Audio Processing
Chroma Features

- Human pitch perception is periodic
- 2 pitches one octave apart are perceived as similar

Audio Processing
Chroma Features

- Human pitch perception is periodic
- 2 pitches one octave apart are perceived as similar
- Pitch = chroma + tone height
    - Chroma: C, C#, D, D#, ..., B (12)
    - Tone height: Octave number

Figure 3.3a from [Müller, FMP, Springer 2015]

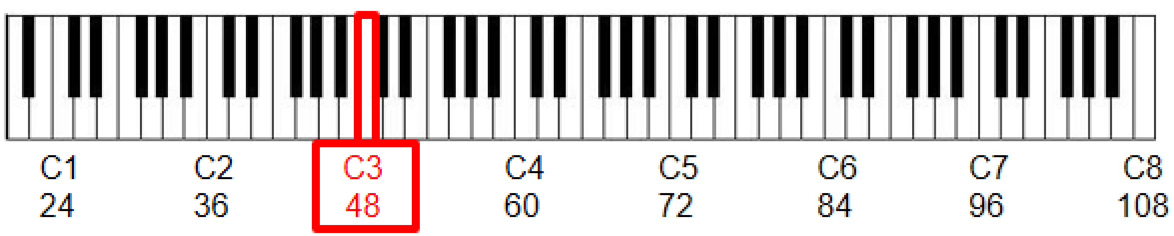
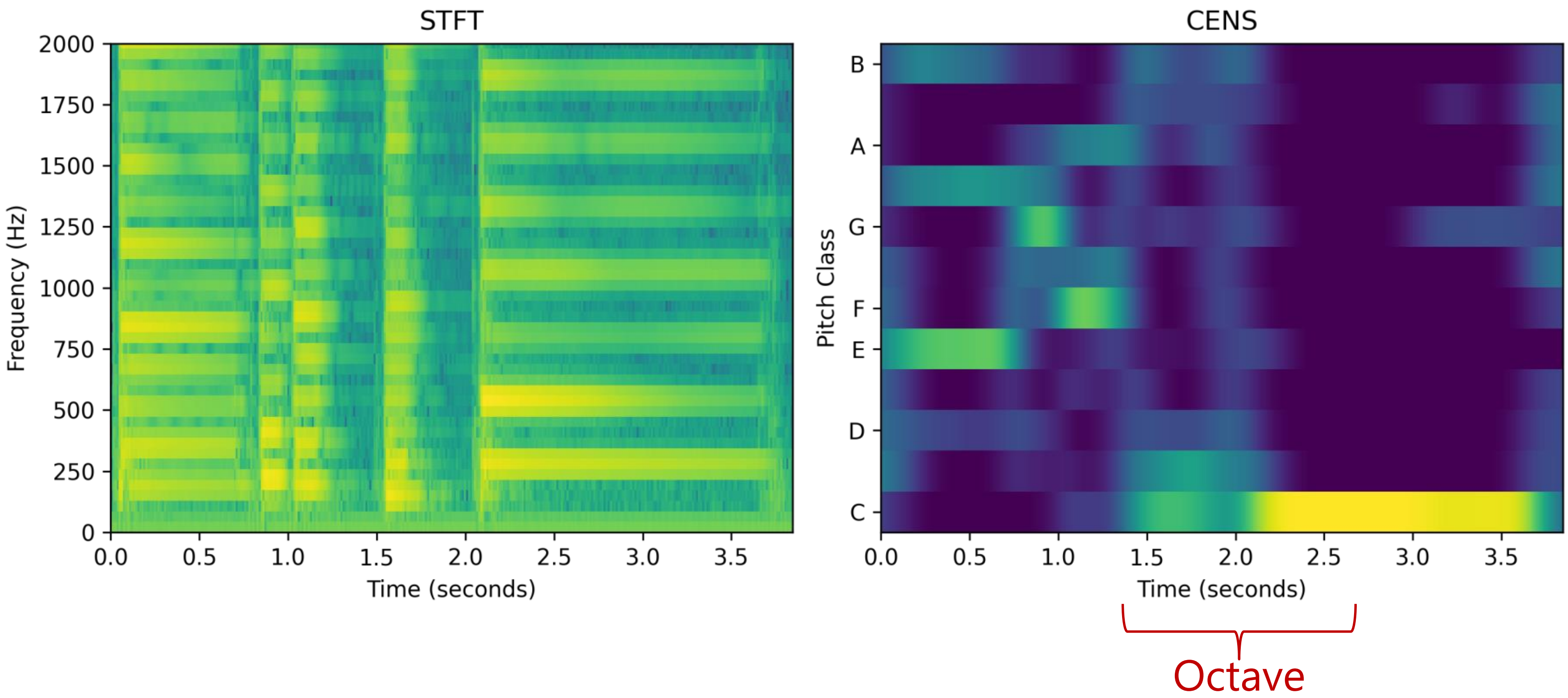


Fig. 2.8

Audio Processing
Chroma Features

- Example Audio 1



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

Fig. 1: https://ccsearch-dev.creativecommons.org/photos/39451123-ee45-4ec3-ad8d-b42d856bca06

Fig. 2: https://ccsearch-dev.creativecommons.org/photos/c69d3b07-76bd-43e2-a44e-8742edc8447a

Fig. 2.8: [Müller, 2015]: Fundamentals of Music Processing (FMP), Springer, 2015, Fig. 3.3a

Fig. 3: https://ccsearch-dev.creativecommons.org/photos/ab3062ab-fe0f-420d-b93d-7451db166b4e

Fig. 4: https://ccsearch-dev.creativecommons.org/photos/a27a7541-45f5-4176-91a4-e2cb70eea266

Fig. 5: https://ccsearch-dev.creativecommons.org/photos/79d466c1-cfa6-417e-9832-34438678bf5d

Fig. 6: https://ccsearch-dev.creativecommons.org/photos/269394a4-5803-47fd-abaa-57ef92735e24

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. 9.5: https://www.mathworks.com/help/dsp/ref/stft_output.png

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

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

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

[Audio 1] https://freesound.org/people/xserra/sounds/196765/

[Audio 2] https://freesound.org/people/IliasFlou/sounds/498058/ (~0:00 – 0:05)

[Audio 3] https://freesound.org/people/danlucaz/sounds/517860/ (~0:00 – 0:05)

[Audio 4] https://freesound.org/people/IENBA/sounds/489398/ (~0:00 – 0:07)

Thank you!

- Any questions?

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