Machine Listening for Music and Sound Analysis

Lecture 4 – Music Information Retrieval II

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https://machinelistening.github.io

Overview

- Pitch Detection
- Instrument Recognition
- Source Separation

Pitch Detection
Introduction

- Pitch
    - Perceptual sound attribute
    - Allows ordering from low to high in a frequency-related scale

Pitch Detection
Introduction

- Pitch
  - Perceptual sound attribute
  - Allows ordering from low to high in a frequency-related scale

- Two subtasks

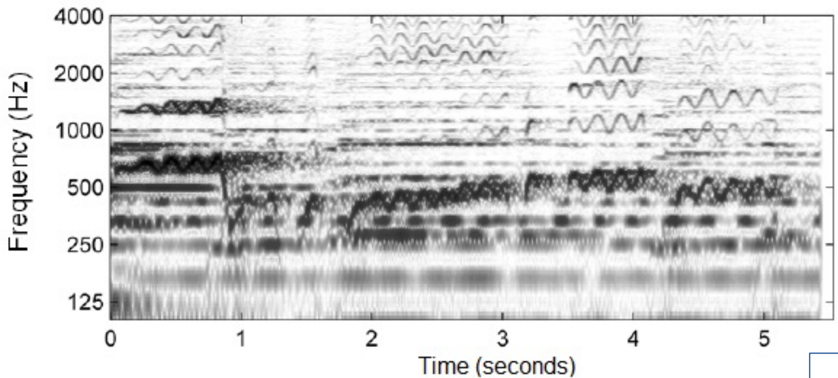


Fig. 1

Pitch Detection
Introduction

- Pitch
  - Perceptual sound attribute
  - Allows ordering from low to high in a frequency-related scale

- Two subtasks

1) Pitch detection

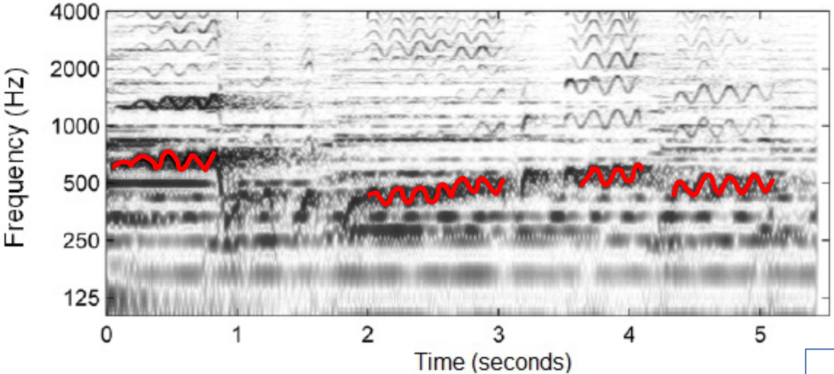


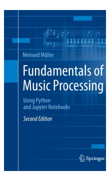
Fig. 1

Pitch Detection

Introduction

- Pitch
    - Perceptual sound attribute
    - Allows ordering from low to high in a frequency-related scale

- Two subtasks



FMP Notebooks

1) Pitch detection

2) Voicing detection

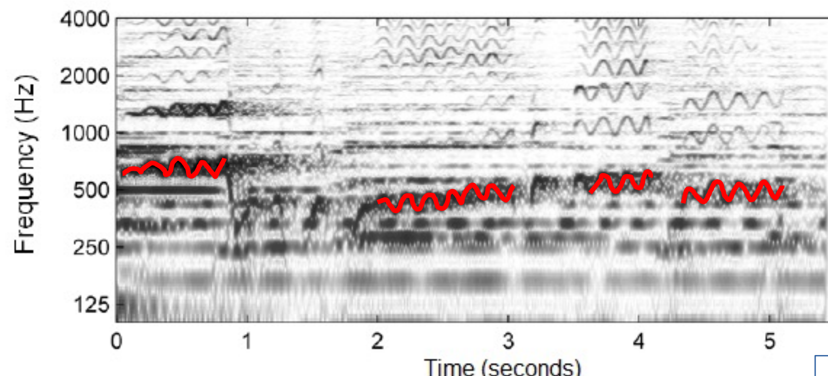


Fig. 1

Own

Pitch Detection
Application Scenarios

- Music Instrument Tuning
- Music Education
- Music Transcription
- Bird Recognition

Fig. 2

Fig. 3

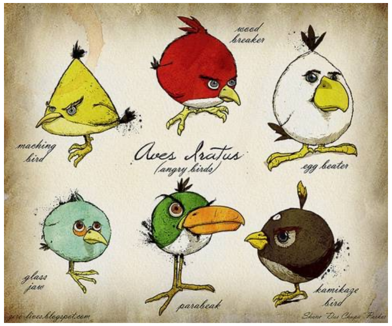


Fig. 4

Pitch Detection
Tasks

- Pitch detection of isolated monophonic instruments

Pitch Detection
Tasks

- Pitch detection of isolated monophonic instruments

- Predominant melody extraction in polyphonic music

Pitch Detection
Tasks

- Pitch detection of isolated monophonic instruments
- Predominant melody extraction in polyphonic music
- Polyphonic melody extraction

Increasing Difficulty

Pitch Detection
Traditional Methods

- MELODIA [Salamon & Gomez, 2012]
  - Melody Extraction from polyphonic audio
- Steps
  - Sinusoid Extraction
    - Equal loudness filter
    - STFT
    - Detection of predominant peaks
    - Frequency refinement via instantaneous frequency (IF)

Audio Signal

Sinusoid Extraction

Pitch Detection
Traditional Methods

- Salience Function
    - Harmonic summation
        - Sum over possibile harmonic frequencies

Audio Signal

Sinusoid Extraction

Salience Function

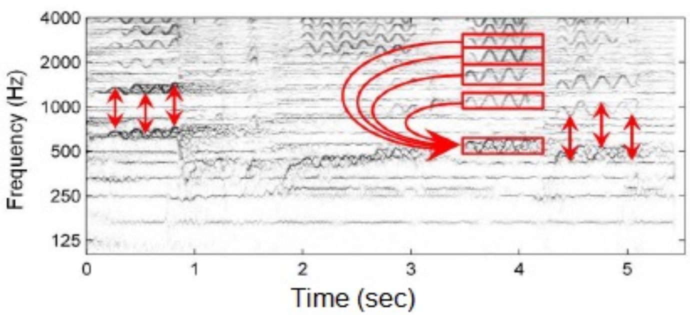


Fig. 5

Pitch Detection
Traditional Methods

- Salience Function
  - Harmonic summation
    - Sum over possibile harmonic frequencies
    - Frequencies → pitch candidates

Audio Signal

Sinusoid Extraction

Salience Function

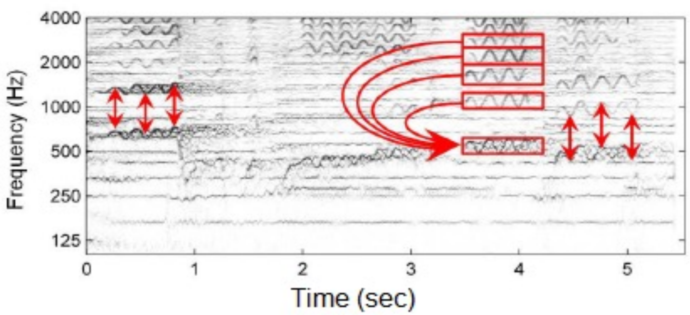
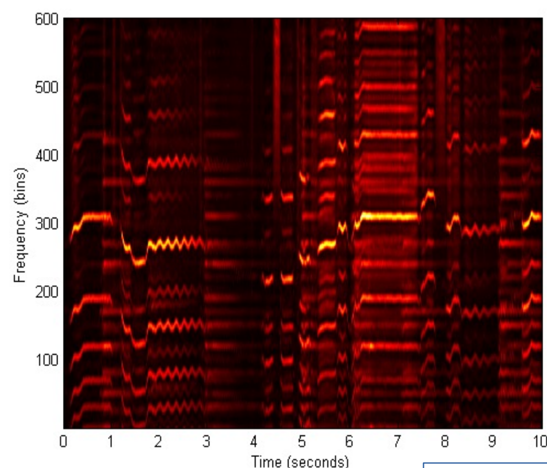


Fig. 5



Own

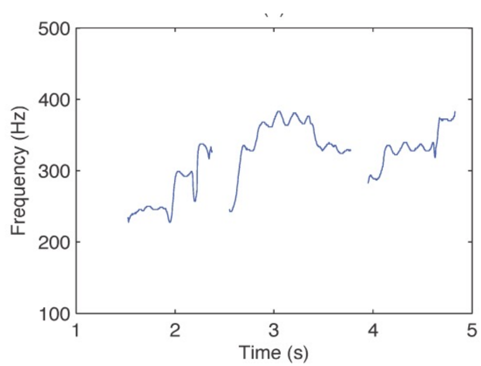
Pitch Detection
Traditional Methods

- Pitch contour creation
  - Auditory streaming cues → group peaks to continuous paths (pitch contours)

Audio Signal

Sinusoid Extraction

Salience Function



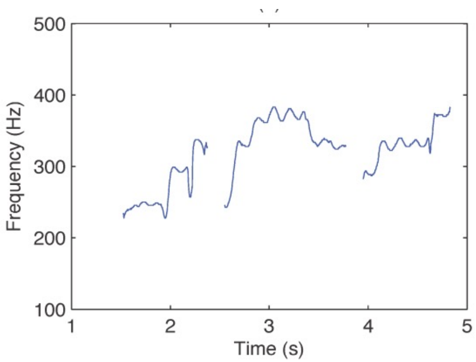
Pitch contour(s)

Pitch Contour Creation

Own

Pitch Detection
Traditional Methods

- Pitch contour creation & melody selection
  - Auditory streaming cues → group peaks to continuous paths (pitch contours)
  - Select melody contours using features (e.g. average pitch / salience, vibrato)



Own

Pitch contour(s)

Audio Signal

Sinusoid Extraction

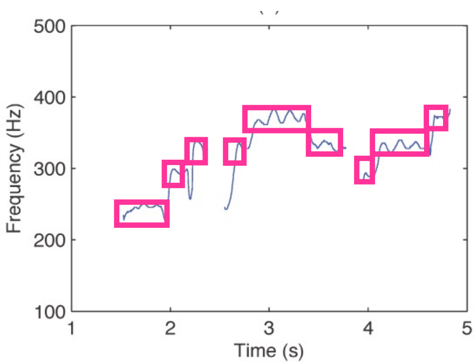
Salience Function

Pitch Contour Creation

Melody Selection

Pitch Detection
Traditional Methods

- Pitch contour creation & melody selection
  - Auditory streaming cues → group peaks to continuous paths (pitch contours)
  - Select melody contours using features (e.g. average pitch / salience, vibrato)
  - Note formation (one pitch value)



Own

Pitch contour(s)

↓

Note events

Audio Signal

Sinusoid Extraction

Salience Function

Pitch Contour Creation

Melody Selection

Pitch Detection
Traditional Methods (Melodia)

- Melodia plugin available for Sonic Visualiser

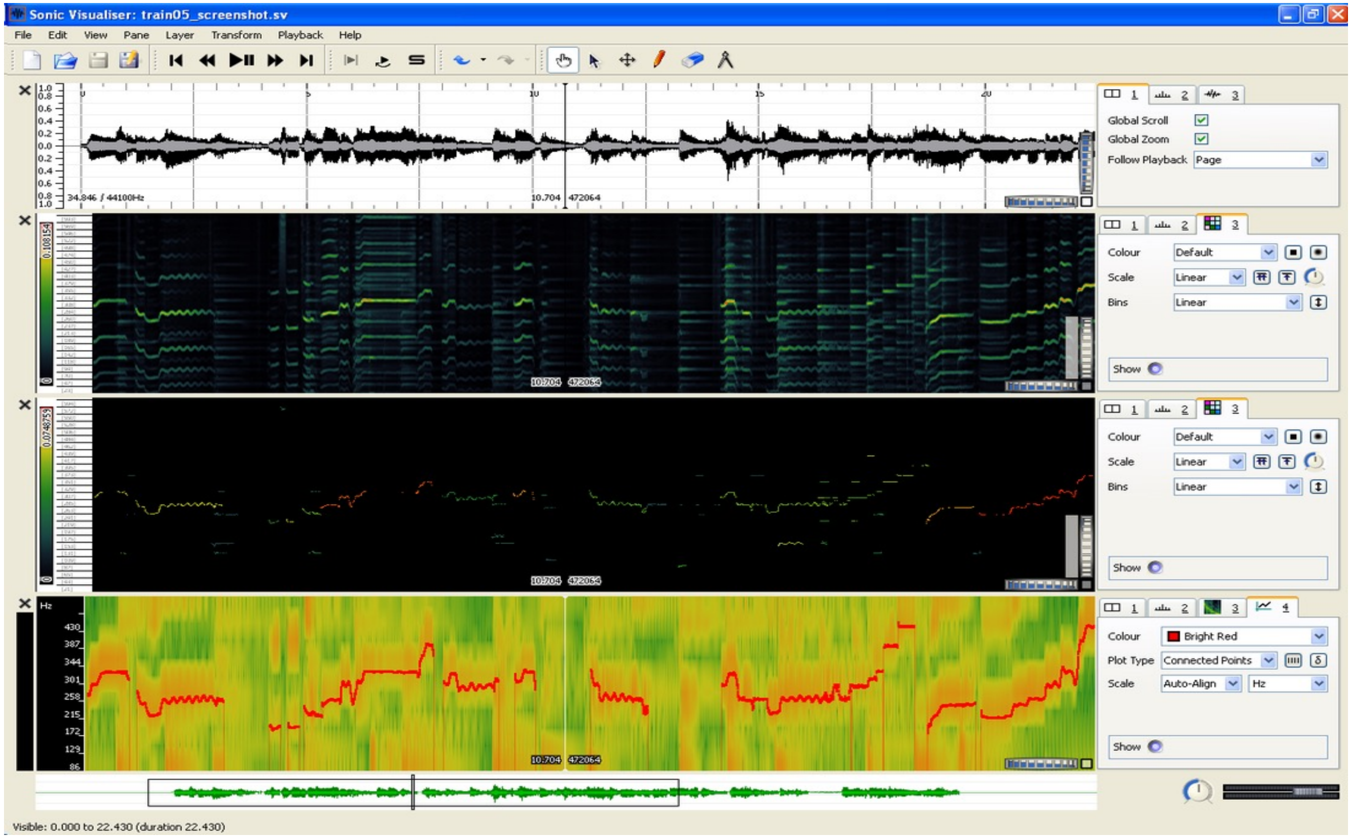


Fig. 6

Pitch Detection
Novel Methods

- CREPE (Convolutional Representation for Pitch Estimation) [Kim et al., 2018]
  - Monophonic pitch tracker

Fig. 7

Pitch Detection
Novel Methods

- CREPE (Convolutional Representation for Pitch Estimation) [Kim et al., 2018]
  - Monophonic pitch tracker
  - End-to-end modeling
    - Audio samples → pitch likelihoods
    - 20 cent resolution (5 pitch bins per semitones)

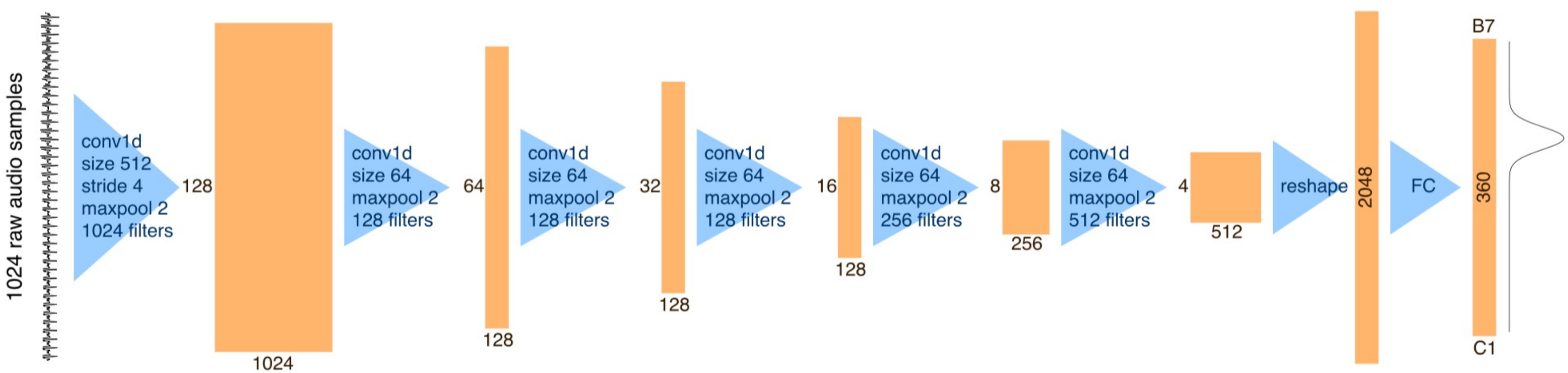
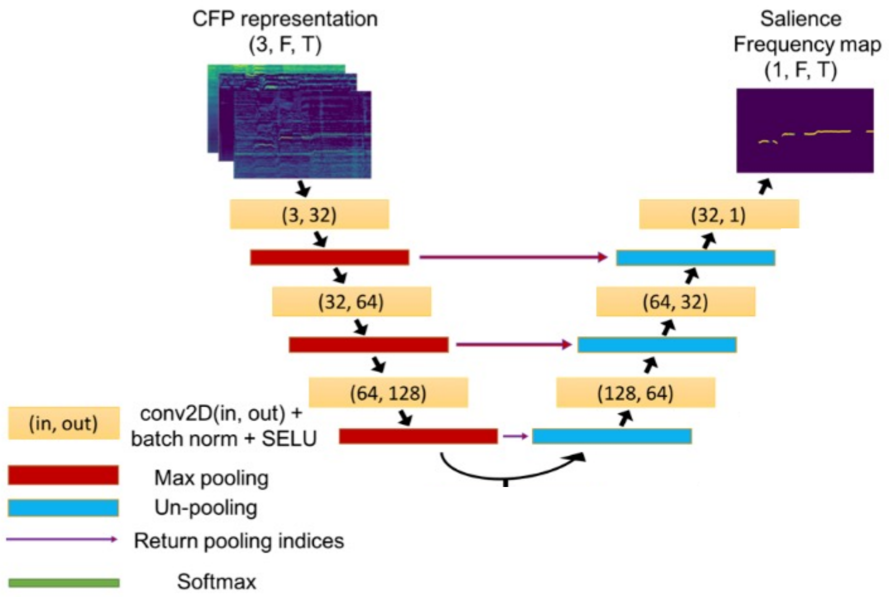


Fig. 7

Pitch Detection
Novel Methods

- Auto-encoder structure (U-Net) [Hsieh et al., 2019]
  - Time-frequency representations (2D) → pitch saliency map (2D)



Pitch Detection
Novel Methods

- Auto-encoder structure (U-Net) [Hsieh et al., 2019]
  - Time-frequency representations (2D) → pitch saliency map (2D)
  - (Bottleneck) embedding encodes pitch voicing (melody activity)

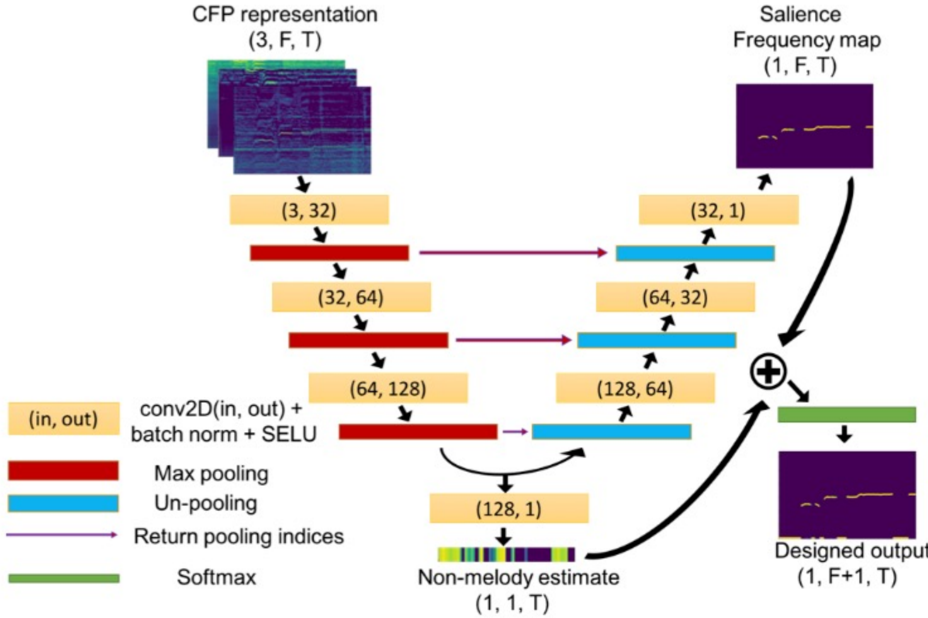


Fig. 8

Instrument Recognition
Introduction

- Music ensembles include multiple instruments
    - Sound production (string / wind / brass / drum instruments)
    - Instrument construction

Instrument Recognition
Introduction

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    - Instrument construction
- Overlapping sound sources (solo recording vs. orchestra)
    - Unison (same pitch)
    - Harmonic intervals (overtone overlap)
    - Rhythmic interconnection (note attacks overlap)

Instrument Recognition
Introduction

- Music ensembles include multiple instruments
    - Sound production (string / wind / brass / drum instruments)
    - Instrument construction
- Overlapping sound sources (solo recording vs. orchestra)
    - Unison (same pitch)
    - Harmonic intervals (overtone overlap)
    - Rhythmic interconnection (note attacks overlap)
- Classification on different taxonomy levels
    - Woodwind instruments → saxophone → tenor saxophone

Instrument Recognition
Tasks

- Sorted by increasing complexity/difficulty

    - Instrument recognition of isolated note recordings

Instrument Recognition
Tasks

- Sorted by increasing complexity/difficulty
    - Instrument recognition of isolated note recordings
    - Instrument recognition on isolated instrument tracks

Instrument Recognition

Tasks

- Sorted by increasing complexity/difficulty

    - Instrument recognition of isolated note recordings

    - Instrument recognition on isolated instrument tracks

    - Predominant instrument recognition in ensemble recordings

Instrument Recognition

Tasks

- Sorted by increasing complexity/difficulty
    - Instrument recognition of isolated note recordings
    - Instrument recognition on isolated instrument tracks
    - Predominant instrument recognition in ensemble recordings
    - Polyphonic instrument recognition (classify all instruments)

Increasing Difficulty

Instrument Recognition
Traditional Methods

- Multiple categories of audio features [Grasis et al., 2014]
  - Frame-level (e.g., spectral flux & flatness)
  - Overtone-level (e.g., modulation rate & frequency)
  - Note-event level (e.g., magnitude ratios of overtones)

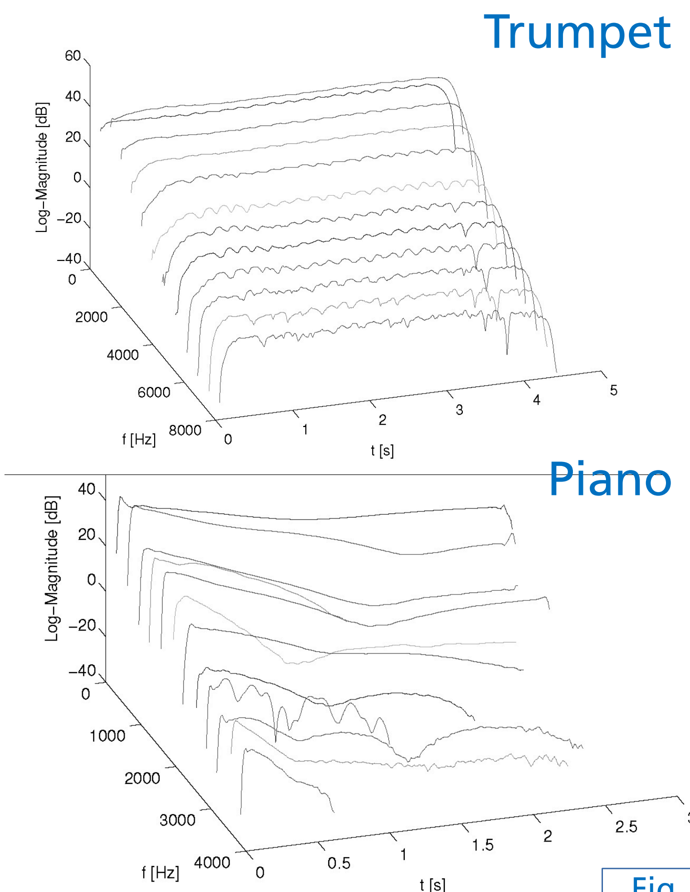


Fig. 9

Instrument Recognition
Traditional Methods

- Multiple categories of audio features [Grasis et al., 2014]
    - Frame-level (e.g., spectral flux & flatness)
    - Overtone-level (e.g., modulation rate & frequency)
    - Note-event level (e.g., magnitude ratios of overtones)
- Examples (trumpet / piano)
    - Partial envelops
    - Observe magnitude decay & modulation

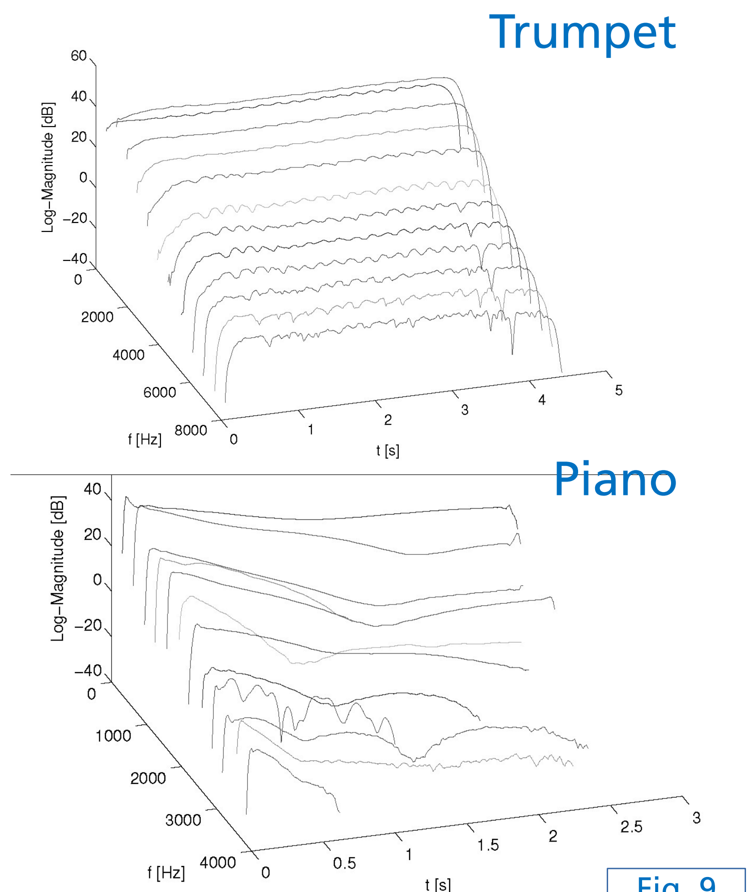


Fig. 9

Instrument Recognition
Novel Methods

- Mel spectrogram + CNN model [Han et al., 2017]
  - Front-end: Convolutional layers & pooling operations
  - Back-end: Dense classification layers

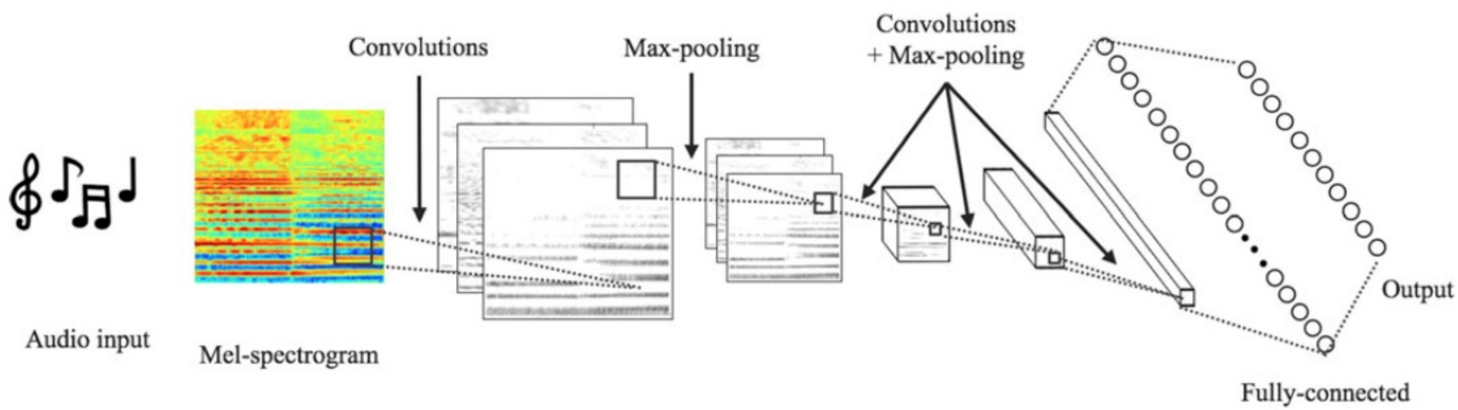


Fig. 10

Instrument Recognition
Novel Methods

- Separability of instrument classes in the feature space
    - Improves for deeper layers

Instrument Recognition
Novel Methods

- Separability of instrument classes in the feature space
  - Improves for deeper layers
- Example
  - 2D visualization of multi-dimensional feature space

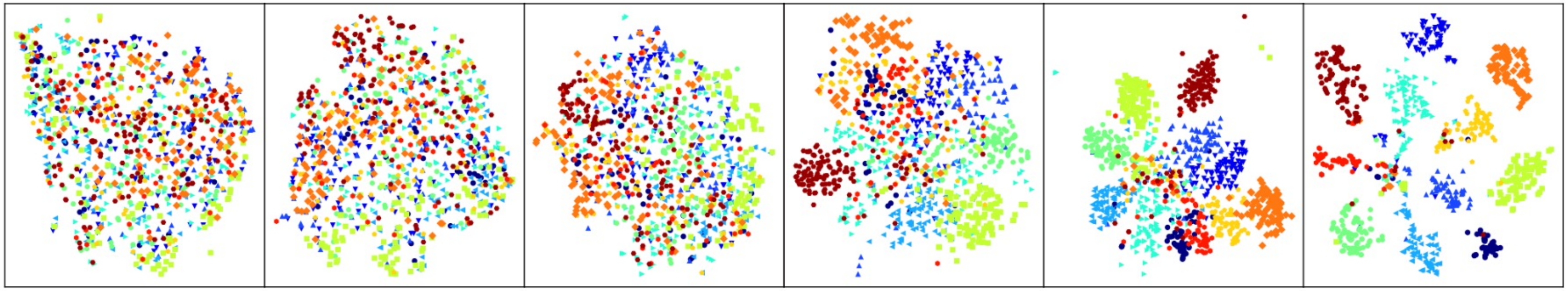


Fig. 11

Deeper layers

Instrument Recognition
Novel Methods

- Pitch-Informed Frame-level Instrument Recognition [Hung & Yang, 2018]

Instrument Recognition
Novel Methods

- Pitch-Informed Frame-level Instrument Recognition [Hung & Yang, 2018]
  - Combine two input branches
    - Spectral input features (CQT)
    - Pitch-activity (piano-roll)

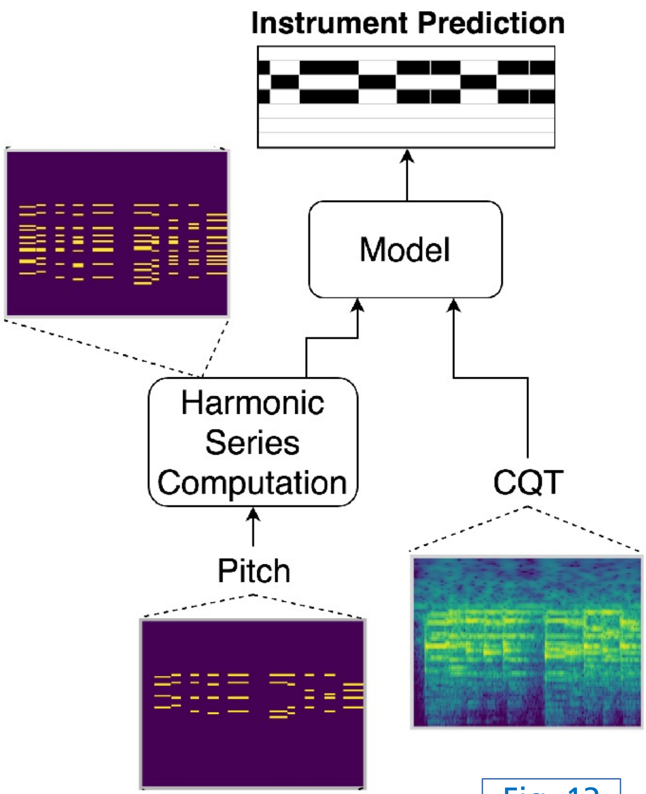


Fig. 12

Source Separation
Introduction

- Music recordings
  - Mixtures of different musical instruments (sources) playing simultaneously

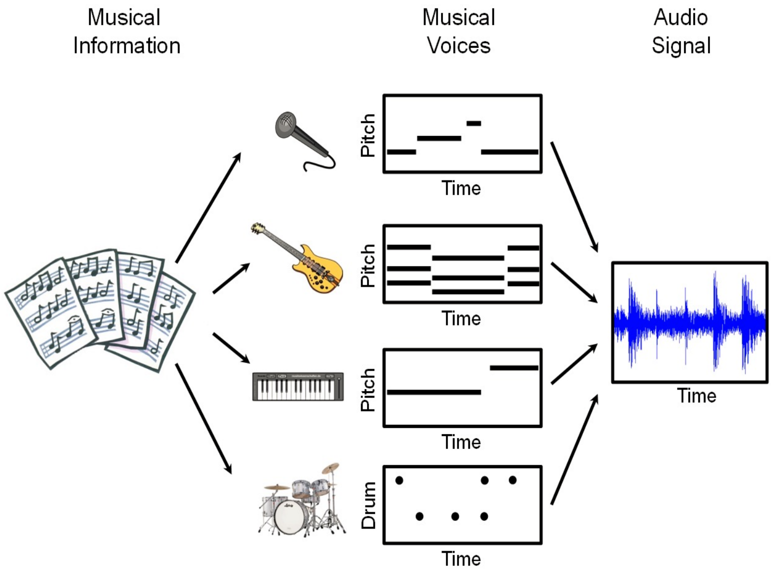


Fig. 18

Source Separation
Introduction

- Music recordings
  - Mixtures of different musical instruments (sources) playing simultaneously
- Sound Separation
  - Reverse engineering the audio mixing process
  - Output: 1 stem per instrument

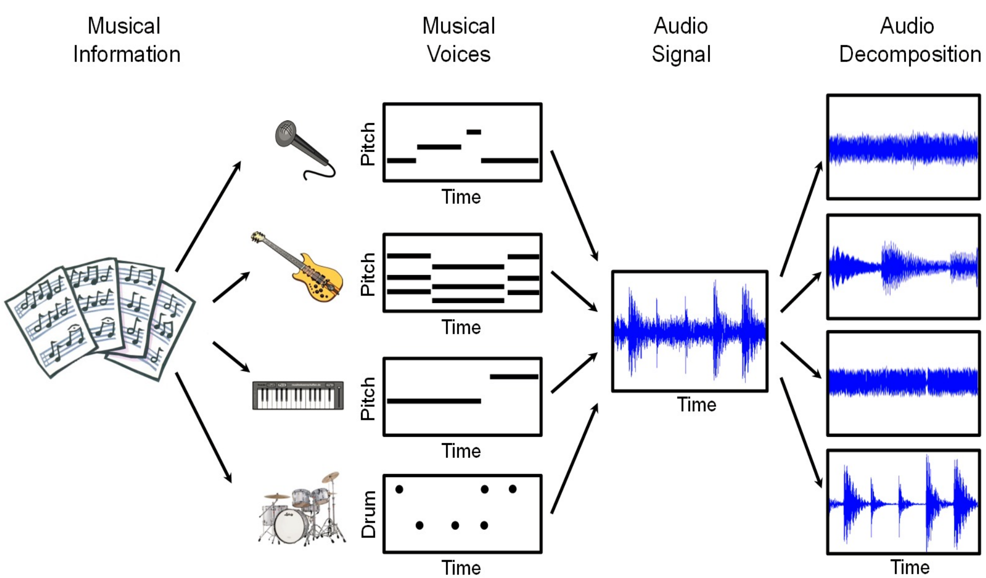


Fig. 18

Source Separation
Introduction

- Audio mix is influenced by
    - Instrument characteristics (timbre, note decay, …)

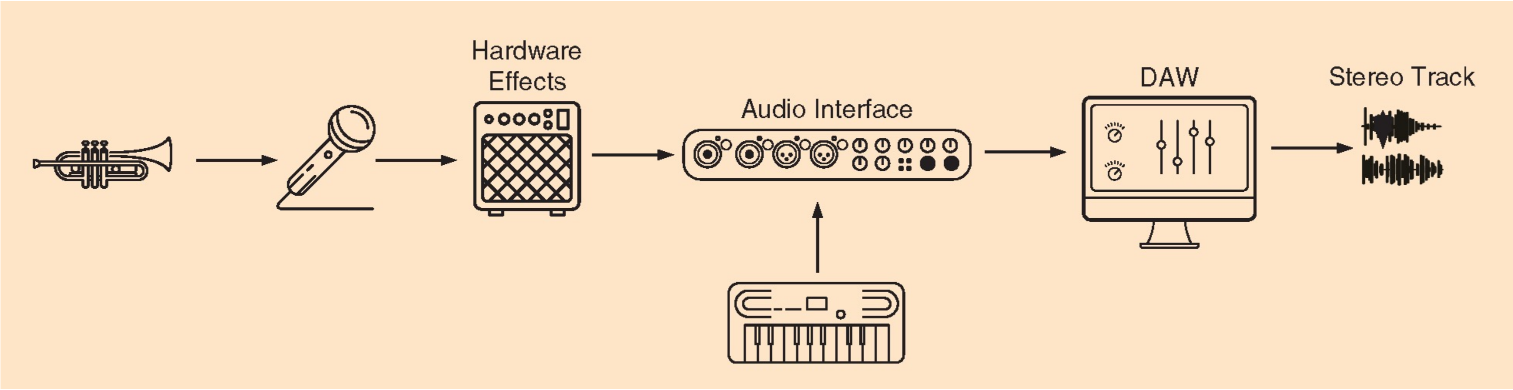


Fig. 13

Source Separation
Introduction

- Audio mix is influenced by
  - Instrument characteristics (timbre, note decay, …)
  - Musical performance (timing, dynamics, playing techniques, …)

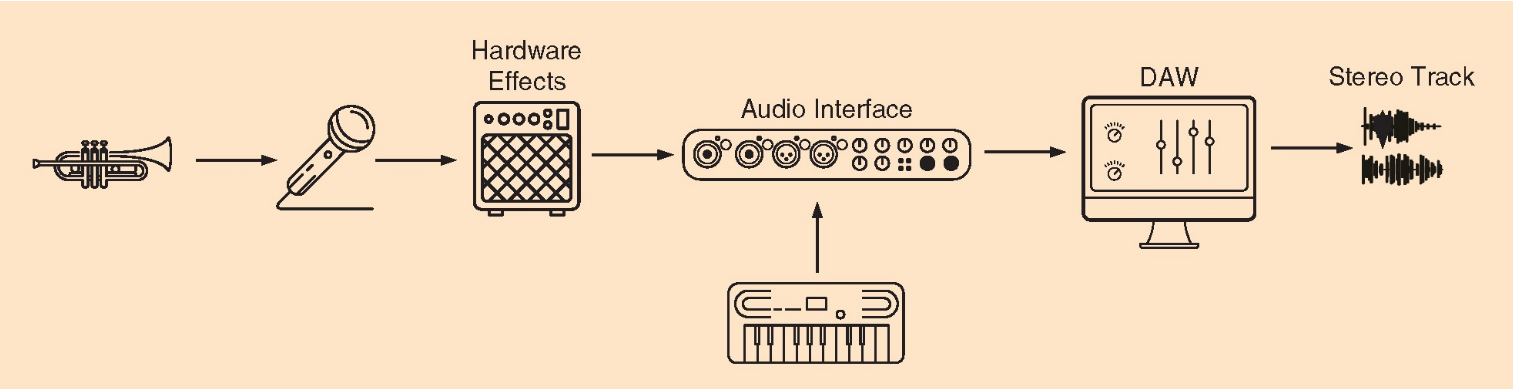


Fig. 13

Source Separation
Introduction

- Audio mix is influenced by
  - Instrument characteristics (timbre, note decay, …)
  - Musical performance (timing, dynamics, playing techniques, …)
  - Recording chain (microphones, room acoustics)

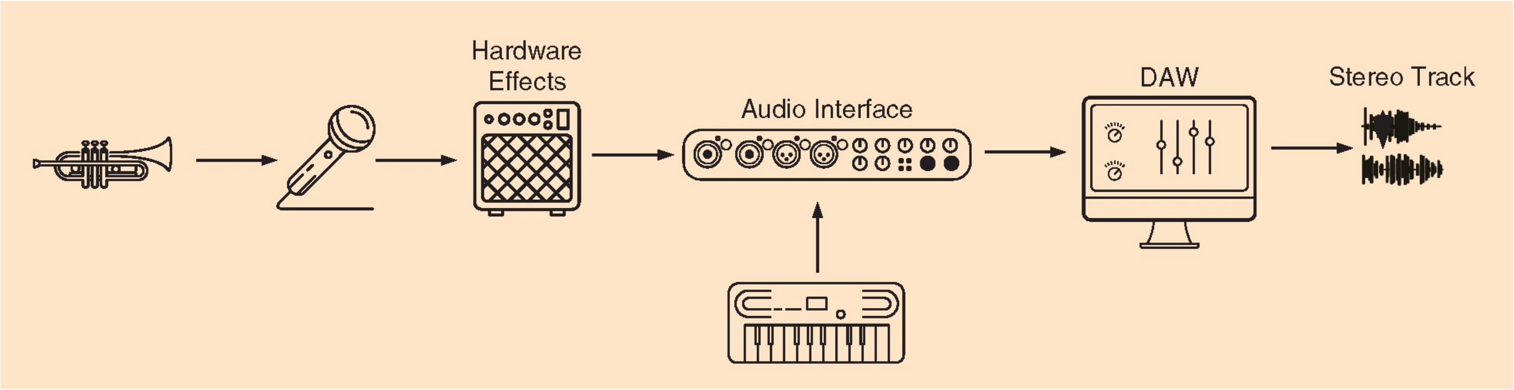


Fig. 13

Source Separation
Introduction

- Audio mix is influenced by
  - Instrument characteristics (timbre, note decay, …)
  - Musical performance (timing, dynamics, playing techniques, …)
  - Recording chain (microphones, room acoustics)
  - Post-processing (effects, mastering, DAW mix)

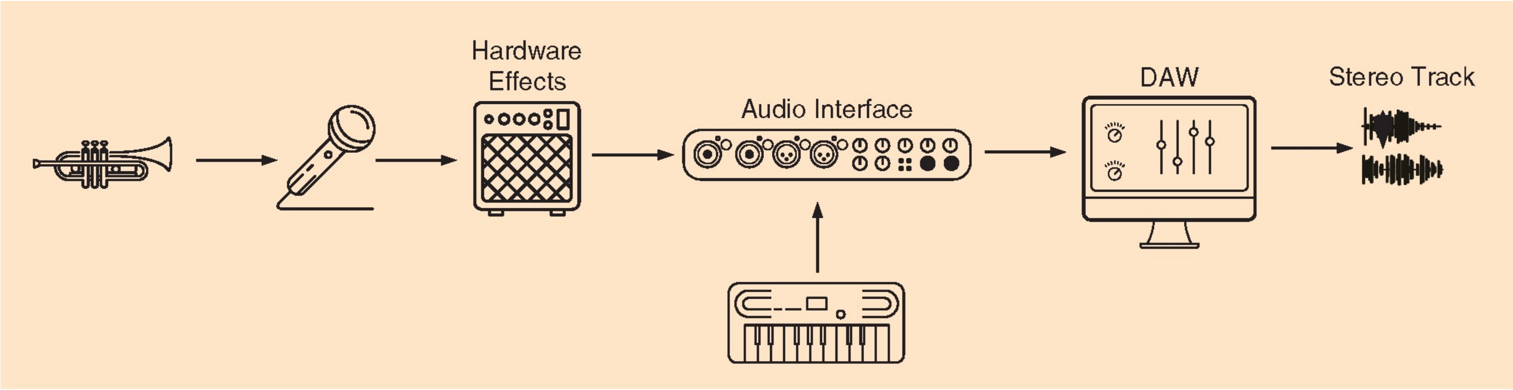


Fig. 13

Source Separation
Application Scenarios

- Audio remixing
- Audio upmixing
  - Mono $\rightarrow$ stereo
  - Stereo $\rightarrow$ 5.1

Source Separation
Application Scenarios

- Audio remixing
- Audio upmixing
    - Mono → stereo
    - Stereo → 5.1
- Music Analysis
    - Transcription, beat tracking, harmony analysis etc.
- Music Education
    - Solo / Backing track generation

Source Separation
Tasks

- Harmonic/percussive separation
    - H → stable harmonic components (fundamental frequency, overtones)
    - P → transient components (drum sounds, note attacks)

Source Separation
Tasks

- Harmonic/percussive separation
  - H $\rightarrow$ stable harmonic components (fundamental frequency, overtones)
  - P $\rightarrow$ transient components (drum sounds, note attacks)
- Solo/accompaniment separation
  - S $\rightarrow$ predominant melody instrument
  - A $\rightarrow$ accompanying instruments

Source Separation
Tasks

- Harmonic/percussive separation
    - H → stable harmonic components (fundamental frequency, overtones)
    - P → transient components (drum sounds, note attacks)
- Solo/accompaniment separation
    - S → predominant melody instrument
    - A → accompanying instruments
- Singing voice separation
    - S → singing voice (male / female)
    - A → band

Source Separation
Tasks

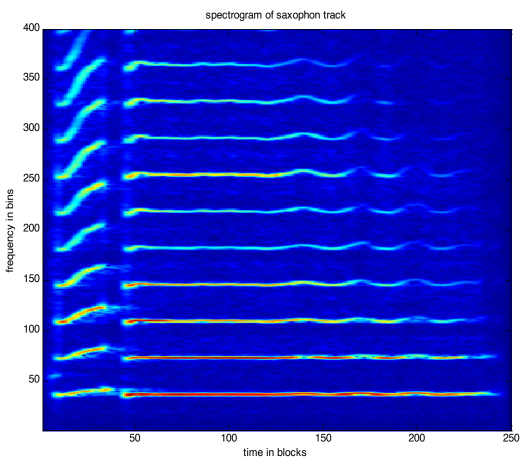
- Harmonic/percussive separation
  - H → stable harmonic components (fundamental frequency, overtones)
  - P → transient components (drum sounds, note attacks)
- Solo/accompaniment separation
  - S → predominant melody instrument
  - A → accompanying instruments
- Singing voice separation
  - S → singing voice (male / female)
  - A → band
- Separation of all sources

Source Separation
Traditional Approaches

- Harmonic/percussive (H/P) separation
  - Different spectral characteristics of harmonic and percussive signals

Source Separation
Traditional Approaches

- Harmonic/percussive (H/P) separation
  - Different spectral characteristics of harmonic and percussive signals

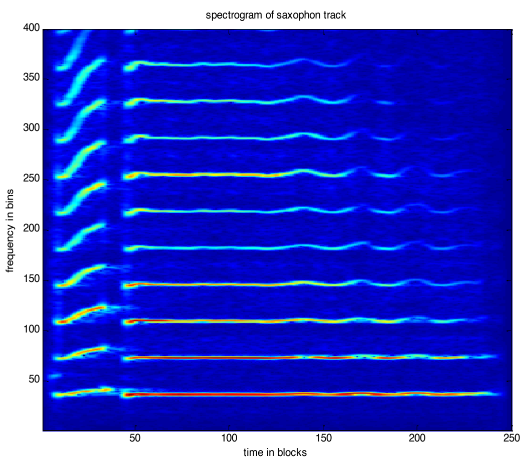


Own

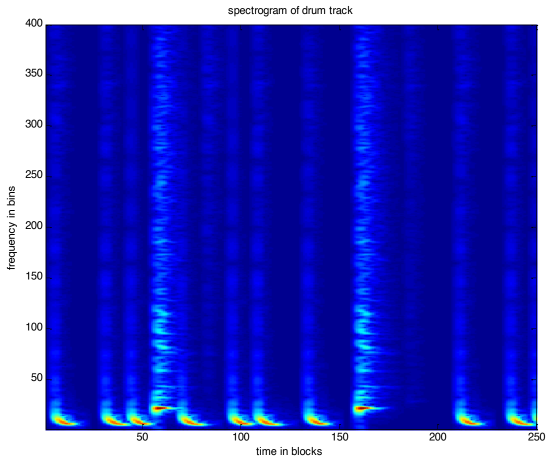
- Time-continuous (horizontal)
- Localized in frequency

Source Separation
Traditional Approaches

- Harmonic/percussive (H/P) separation
  - Different spectral characteristics of harmonic and percussive signals



Own

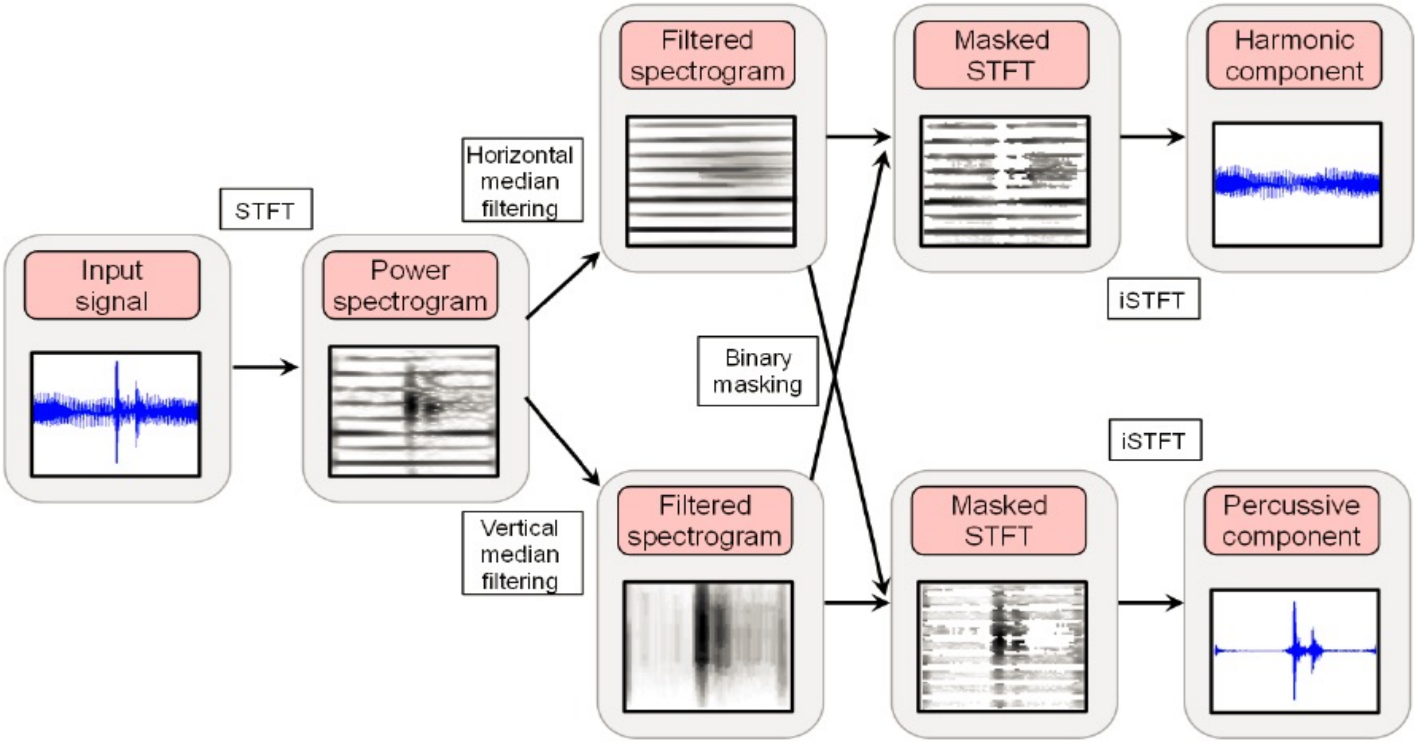


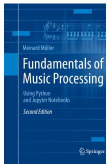
Own

- Time-continuous (horizontal)
- Localized in frequency

- Wide-band (vertical)
- Localized in time

Source Separation
Traditional Approaches





FMP Notebooks

Fig. 14

Source Separation
Traditional Approaches

- Phase-based H/P separation
  - Harmonic sources → phase change values are predictable
  - Percussive sources → unpredictable phase (noise-like characteristics)

Source Separation
Traditional Approaches

- Phase-based H/P separation
  - Harmonic sources → phase change values are predictable
  - Percussive sources → unpredictable phase (noise-like characteristics)
  - Instantaneous Frequency Distribution (IFD)
    - How does phase change over time?

$$\Phi(k,n) = \frac{1}{2\pi}\frac{d\phi(k,n)}{dn}$$

Unwrapped phase

Instantaeneous Frequency

k – Frequency bin

n – Time frame

Source Separation
Traditional Approaches

- Phase-based H/P separation
  - Harmonic mask → phase change within range / predictable?

$$H(k,n) = \begin{cases} 1 & \text{if } \Delta_{k_{Low}} < \Phi(k,n) < \Delta_{k_{High}} \\ 0 & \text{otherwise} \end{cases}$$

Source Separation
Traditional Approaches

- Phase-based H/P separation
  - Harmonic mask → phase change within range / predictable?

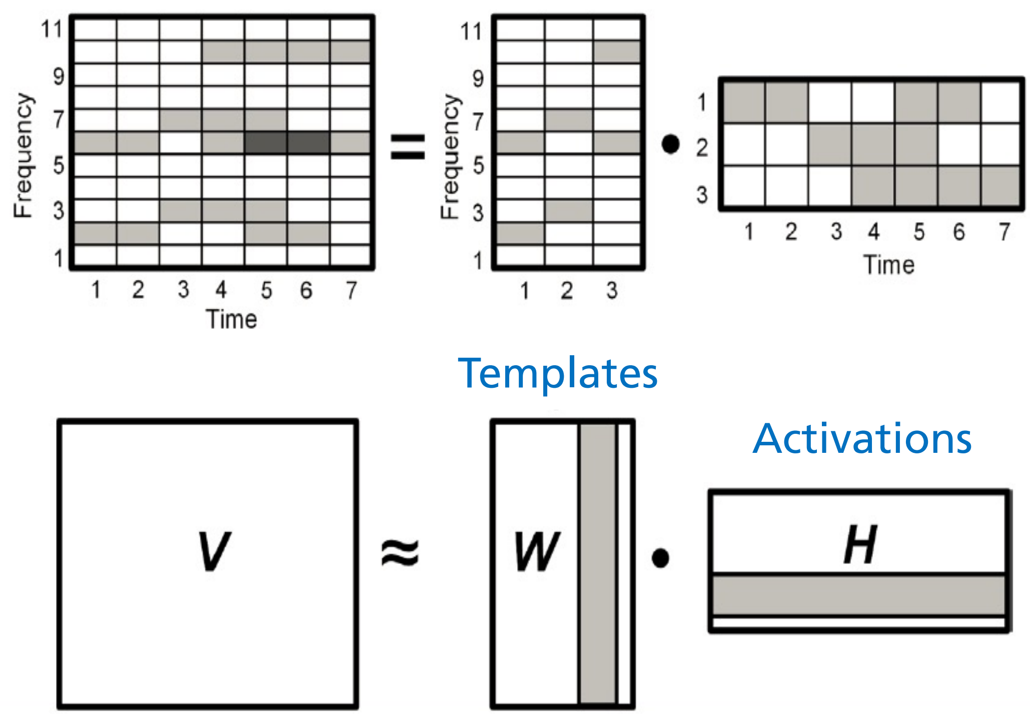
$$H(k,n) = \begin{cases} 1 & \text{if } \Delta_{k_{Low}} < \Phi(k,n) < \Delta_{k_{High}} \\ 0 & \text{otherwise} \end{cases}$$

  - Percussive mask

$$P(k,n) = 1 - H(k,n)$$

Source Separation
Traditional Approaches

- Non-Negative Matrix Factorization (NMF)
  - Factorize spectrogram V into set of components: $V \approx WH$



Source Separation
Traditional Approaches

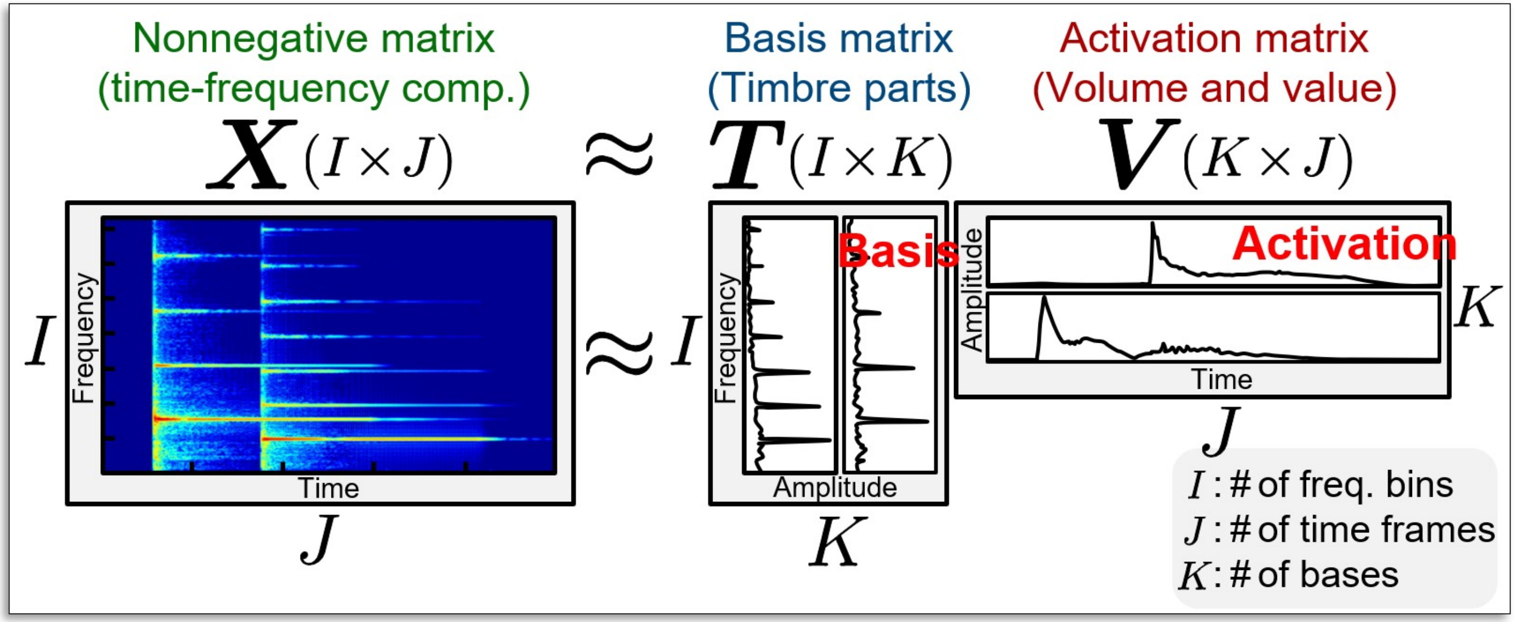


Fig. 19

Source Separation
Traditional Approaches

- Non-Negative Matrix Factorization (NMF)
  - Algorithm: $V \approx WH$
    - Randomly initialize W & H
    - Use update rules to alternately update W & H
      - Minimize cost function
    - Cost function examples
      - Euclidean distance

$$||A - B||^2 = \sum_{ij} (A_{ij} - B_{ij})^2$$

      - Kullback-Leibler divergence

$$D(A||B) = \sum_{ij} \left(A_{ij} \log \frac{A_{ij}}{B_{ij}} - A_{ij} + B_{ij} \right)$$

Source Separation
Novel Approaches

- U-Net based [Jannson et al., 2017]
  - Input → magnitude spectrogram (mix)
  - Output → 2 soft masks (voice / others)

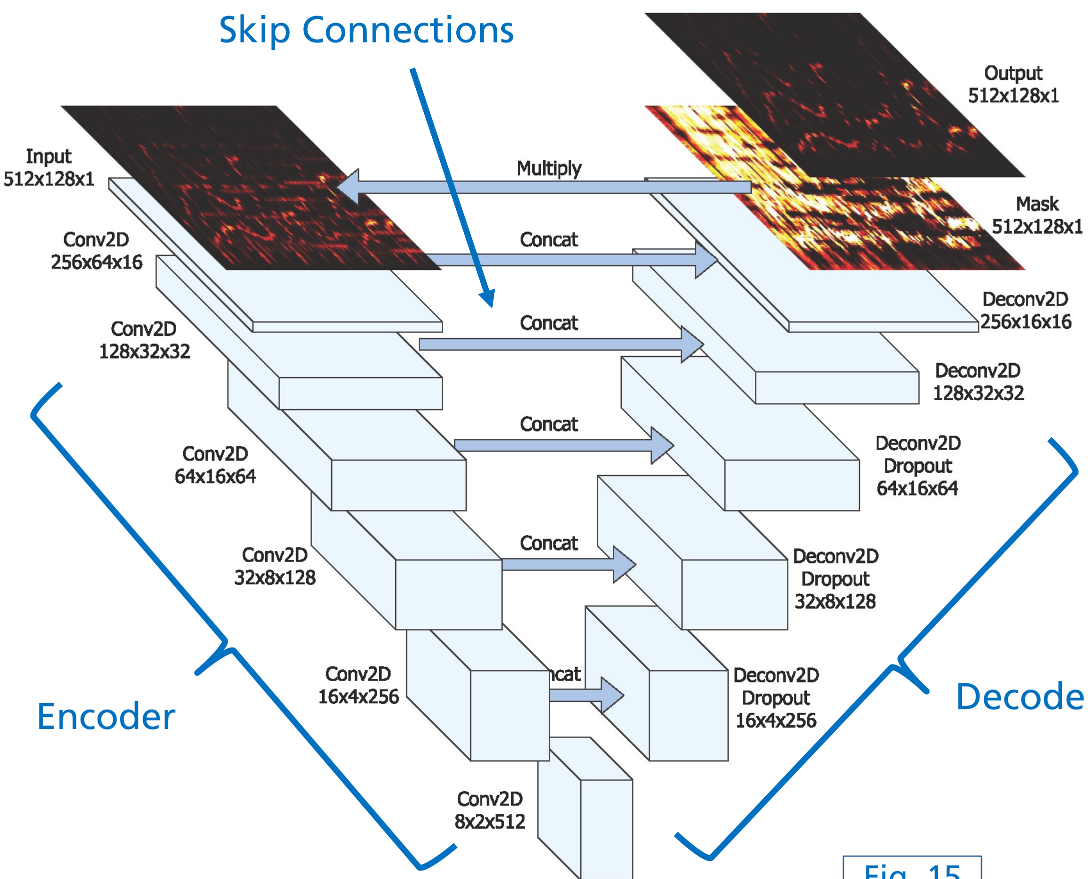


Fig. 15

Source Separation
Novel Approaches

- U-Net based [Jannson et al., 2017]
  - Input → magnitude spectrogram (mix)
  - Output → 2 soft masks (voice / others)
- Issue
  - Only magnitude of STFT is modeled
  - Still phase from the mixture is used

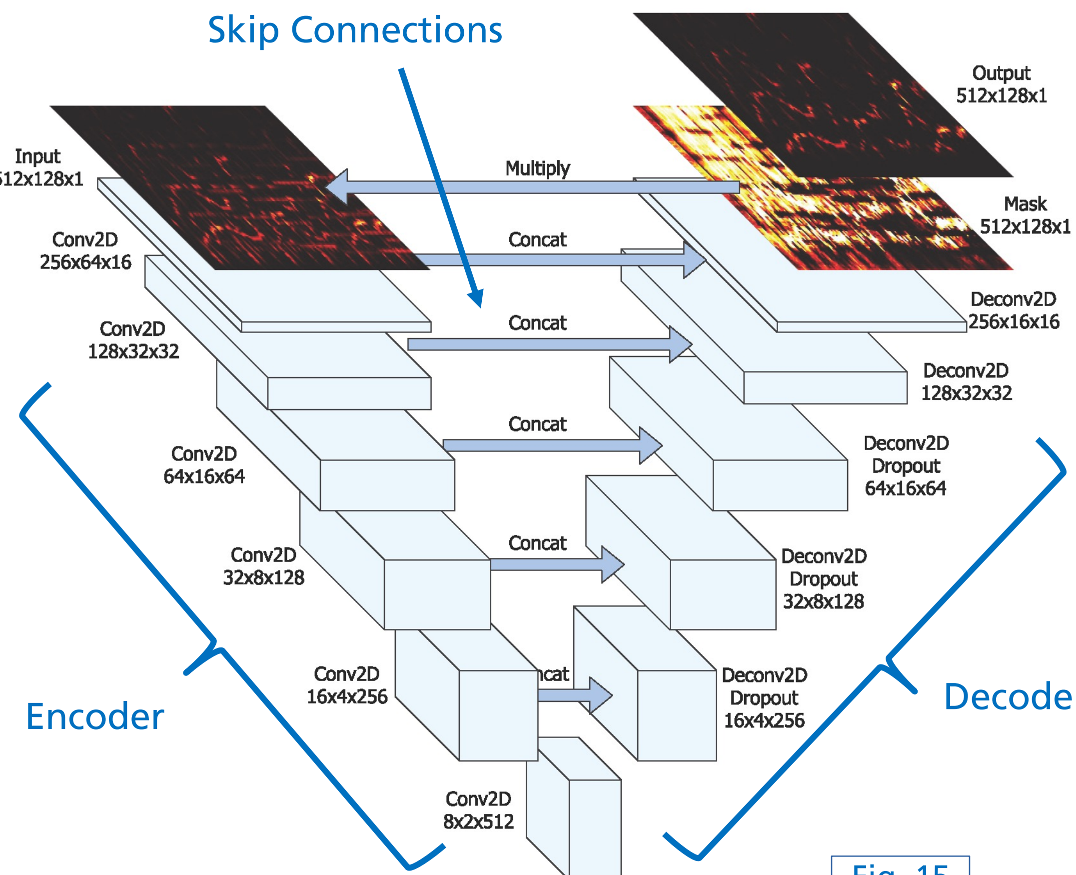


Fig. 15

Source Separation
Novel Approaches

- Spleeter [Hennequin et al., 2020]
  - Open-source version for MIR research

Source Separation
Novel Approaches

- Spleeter [Hennequin et al., 2020]
    - Open-source version for MIR research
    - 3 pre-trained models
        - 2 stems (vocals and accompaniments)
        - 4 stems (vocals, drums, bass, and other)
        - 5 stems (vocals, drums, bass, piano and other)

Spleeter Demo

Source Separation
Novel Approaches

- Conv-TasNet [Luo & Mesgarani, 2019]
  - Time-domain speech separation network (end-to-end)

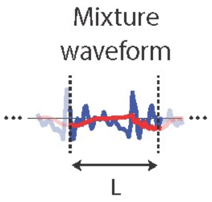


Fig. 16

Source Separation
Novel Approaches

- Conv-TasNet [Luo & Mesgarani, 2019]
  - Time-domain speech separation network (end-to-end)
  - Encoder → optimized representation for speaker separation

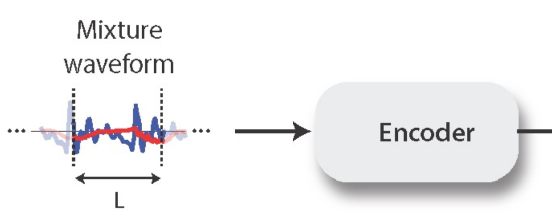


Fig. 16

Source Separation
Novel Approaches

- Conv-TasNet [Luo & Mesgarani, 2019]
  - Time-domain speech separation network (end-to-end)
  - Encoder → optimized representation for speaker separation
  - Seperation → masks (weighting functions)

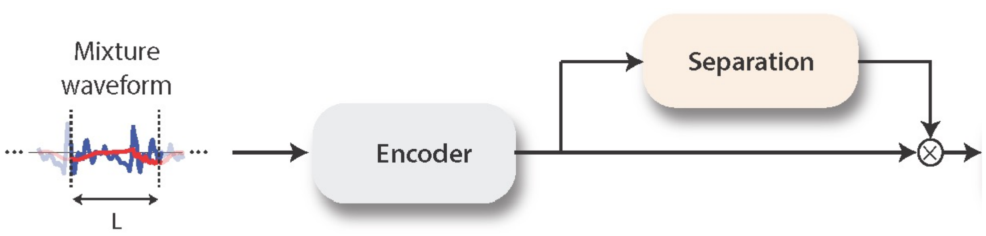


Fig. 16

Source Separation
Novel Approaches

- Conv-TasNet [Luo & Mesgarani, 2019]
  - Time-domain speech separation network (end-to-end)
  - Encoder → optimized representation for speaker separation
  - Seperation → masks (weighting functions)
  - Decoder → invert to waveforms

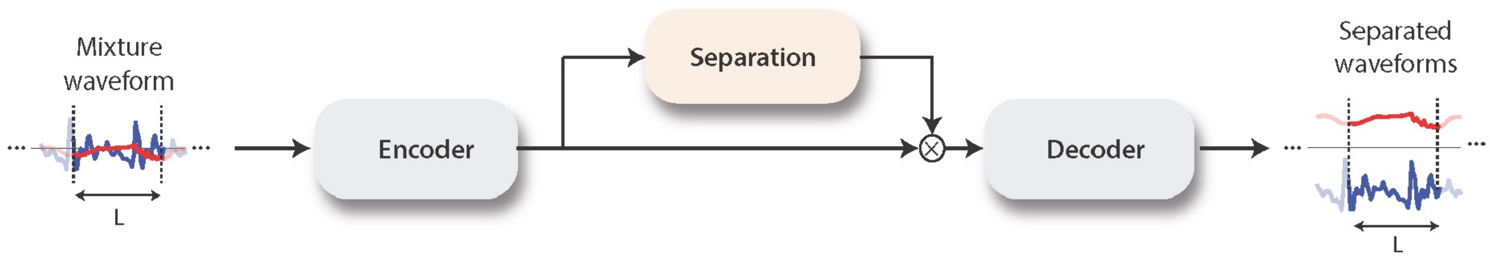


Fig. 16

Source Separation
Novel Approaches

- Conv-TasNet [Luo & Mesgarani, 2019]
  - Time-domain speech separation network (end-to-end)
  - Encoder → optimized representation for speaker separation
  - Seperation → masks (weighting functions)
  - Decoder → invert to waveforms
  - Temporal convolutional networks (TCN)
    - Stack of 1-D dilated convolutional blocks
    - Large receptive field → model long-term dependencies

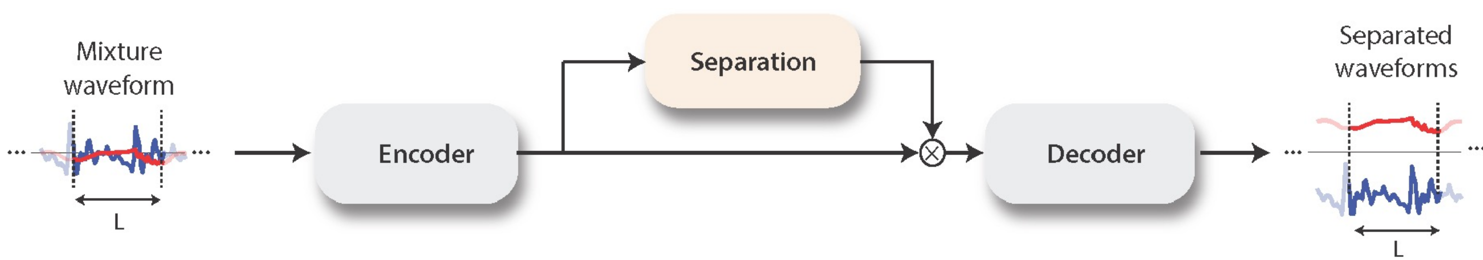


Fig. 16

Source Separation
Novel Approaches

- Conv-TasNet [Luo & Mesgarani, 2019]

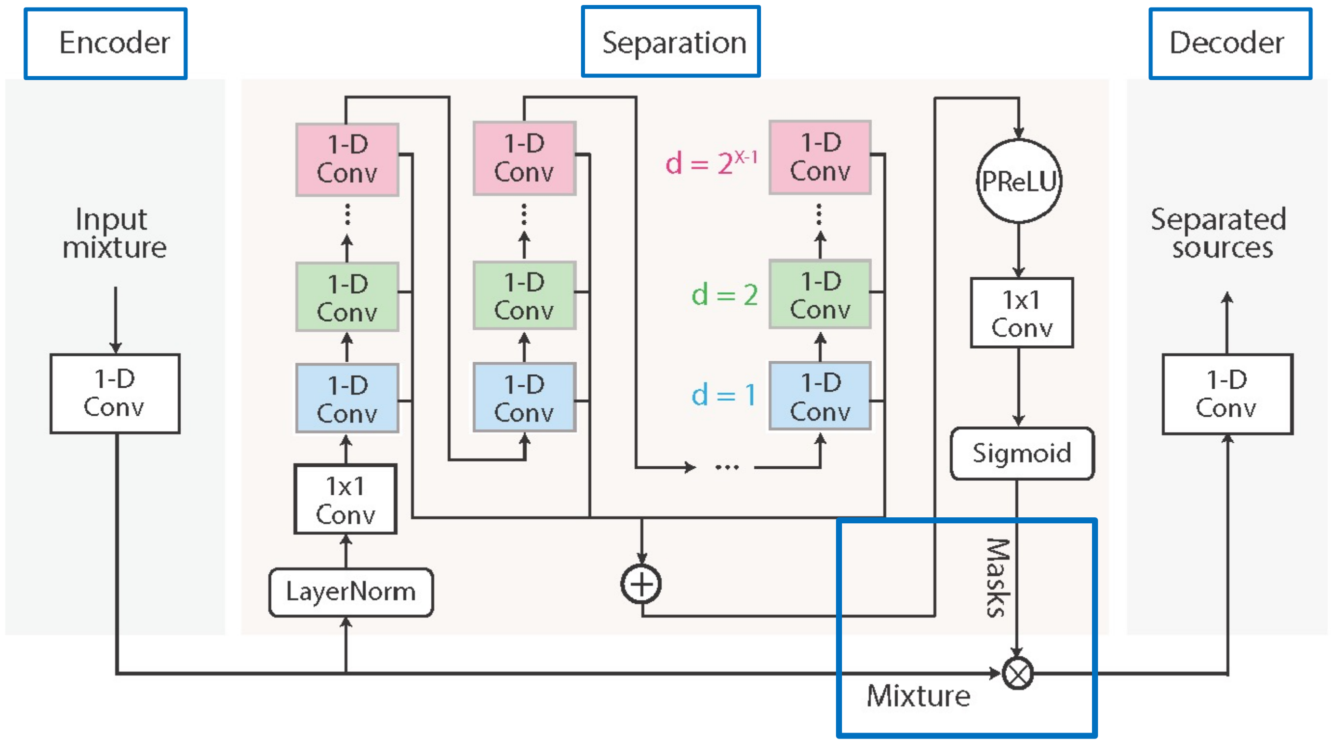


Fig. 17

Summary

- Case Studies
  - Pitch Detection
  - Instrument Recognition
  - Source Separation

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Images

Fig. 1: [Müller, 2021], p. 449, Fig. 8.15(b)

Fig. 2: http://www.guitaradventures.com/wp-content/uploads/Tuning-your-guitar.jpg

Fig. 3: https://cdn2.whatoplay.com/screenshots/2631slide-4.jpg

Fig. 4: https://cdn.androidcommunity.com/wp-content/uploads/2010/11/500x_angrybirdsdarwin.jpg

Fig. 5: [Müller, 2021], p. 449, Fig. 8.15(a)

Fig. 6: Sonic Visualiser: http://www.sonicvisualiser.org/ , Melodia plugin: http://mtg.upf.edu/technologies/melodia

Fig. 7: [Kim et al., 2018], p. 2, Fig. 1

Fig. 8: [Hsieh et al., 2019], p. 2, Fig. 2

Fig. 9: [Grasis et al., 2014], p. 6, Fig. 3

Fig. 10: [Han et al., 2017], p. 3, Fig. 1

Fig. 11: [Han et al., 2017], p. 9, Fig. 6

Fig. 12: [Hung & Yang, 2018], p. 4, Fig. 1

Fig. 13: [Cano et al., 2019], p. 3, Fig. 3

Fig. 14: [Müller, 2021], p. 425, Fig. 8.3

Images

Fig. 15: [Jansson, 2017], p. 3, Fig. 1

Fig. 16: [Luo & Mesgarani, 2019], p. 3, Fig. 1(A)

Fig. 17: [Luo & Mesgarani, 2019], p. 3, Fig. 1(B)

Fig. 18: [Müller, 2021], p. 422, Fig. 8.1

Fig. 19: http://d-kitamura.net/demo/defNMF/nmf_en.png

Sounds

AUD-1: Aislinn – Capclear (2013), https://freemusicarchive.org/music/Aislinn/Aislinn/10_-_Aislinn_-_Capclear

AUD-2: Aislinn – Fourteen Days (2013), https://freemusicarchive.org/music/Aislinn/Aislinn/11_-_Aislinn_-_Fourteen_days

AUD-3: Anonymous Choir – Amicus Meus (2009), https://freemusicarchive.org/music/Anonymous_Choir/Toms_Luis_de_Victorias_Amicus_Meus/Amicus_Meus

Thank you!

- Any questions?

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