Machine Listening for Music and Sound Analysis

Lecture 3 – Music Information Retrieval

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https://machinelistening.github.io



Overview

- Music Information Retrieval
- Case Studies
 - Music Tagging
 - Pitch Detection
 - Tempo Estimation
 - Instrument Recognition



Introduction Examples

Examples:

Musical Instrument





Musical Genre / Tempo



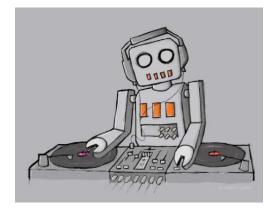




Introduction Motivation

- Large music collections
- Mobile device apps / instruments
- Music industry shifts almost completely to online products & services
- Growing market of music streaming services







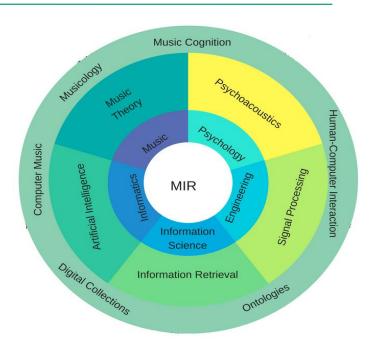
Introduction Typical Tasks

- What's that song again? Who's singing that?
 - Audio identification
- I want to learn that song on my instrument!
 - Automatic music transcription
- What songs are similar? How to generate a playlist?
 - Audio similarity search
- How to organize my music? Which genre / style?
 - Audio classification



Introduction MIR – Today

- Interdisciplinary research community since 2000
- ISMIR conference (International Society for Music Information Retrieval)
- Other conferences: ICASSP, DAFx, AES, ICMC, SMC, ...
- MIREX competition (Music Information Retrieval Evaluation eXchange)



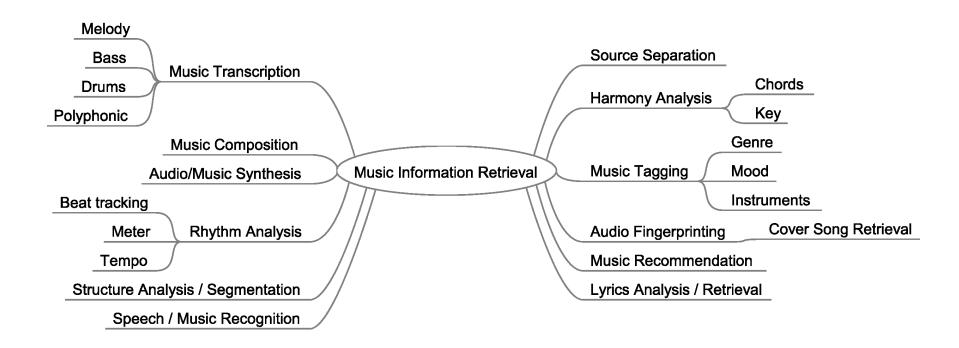


IntroductionResearch Landscape

- MIR @ Fraunhofer IDMT
 - Semantic music technologies (SMT) group
 - Staff + PhD / master / bachelor students + interns
- National / international research groups
 - International Audio Laboratories Erlangen, Germany
 - Centre for Digital Music, Queen Mary University, London, UK
 - Universitat Pompeu Fabra, Barcelona, Spain
 - Institute for music/acoustic research and coordination (IRCAM), Paris, France
 - USA, China, Taiwan etc.



Introduction MIR Tasks





Case Studies

- Music tagging → general classification tasks
- Pitch detection → melody
- Tempo estimation → rhythm
- Instrument recognition → timbre





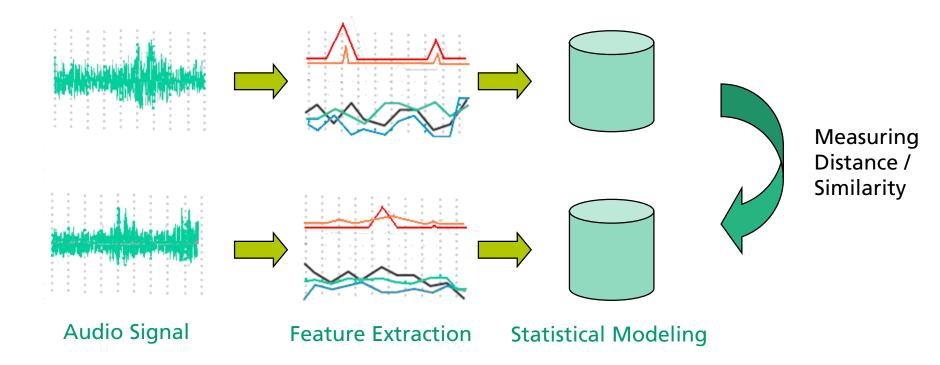
Music Tagging Introduction

- Tags
- Textual (objective / subjective) annotations of songs
- Examples
 - Instruments (drums, bass, guitar, vocals ...)
 - Genre (classical, electro, hip hop)
 - Mood (mellow, romantic, angry, happy)
 - Miscellaneous (noise, loud, ambient)
- Challenge
 - Music pieces change their characteristics over time
 - E.g.: trumpet plays only in the chorus



Music Tagging Traditional Approach

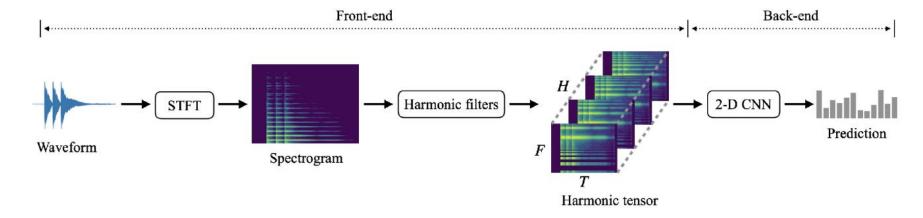
Typical processing pipeline





Music Tagging Novel Approaches

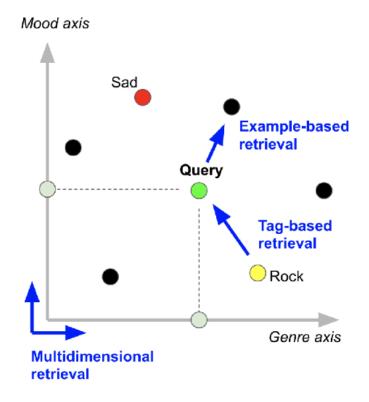
- Joint representation learning & classification using CNNs
 - Input: spectrograms (2D) or audio samples (1D end-to-end)
- Integrate musical knowledge in network design (e.g., filter shapes)





Music Tagging Novel Approaches

- Disentanglement learning
 - Multiple semantic concepts (e.g. genre, instrument, mood)
 - are learnt jointly
 - remain separable in the embedding space
 - Improves tagging (classification) and recommendation (similarity)





Pitch Detection Introduction

- Pitch
- (Subjective) psychoacoustic attribute of sound
- Allows ordering from low to high in a frequency-related scale
 - Pitch ≠ frequency!
- Two subtasks

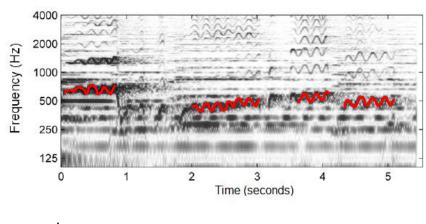


1) Pitch detection











Pitch Detection Application Scenarios

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







Pitch Detection

Tasks

- Sorted by increasing complexity/difficulty
 - Pitch detection of isolated monophonic instruments (extrumpet)







Predominant melody extraction in polyphonic music

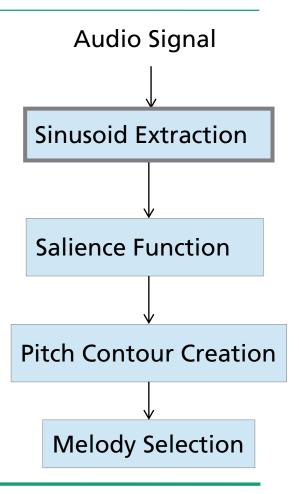


Polyphonic melody extraction



Pitch Detection Traditional Approach

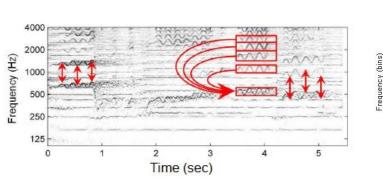
- Sinusoid Extraction
 - Equal loudness filter
 - STFT
 - Detection of predominant peaks
 - Frequency refinement via instantaneous frequency (IF)

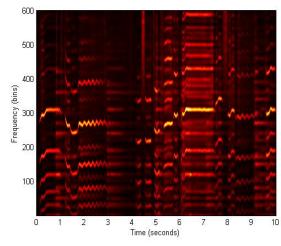


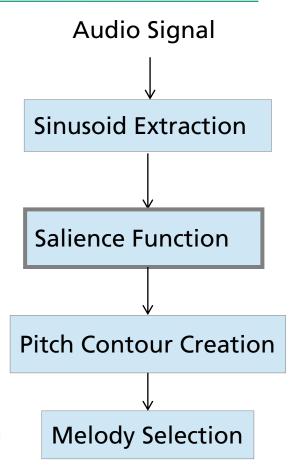


Pitch Detection Traditional Approach

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





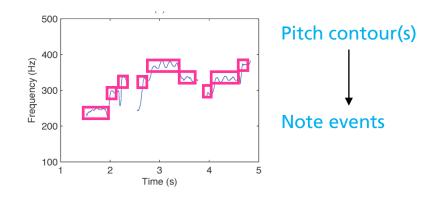


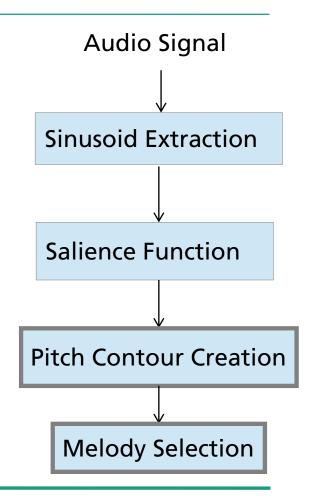




Pitch Detection Traditional Approach

- 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)

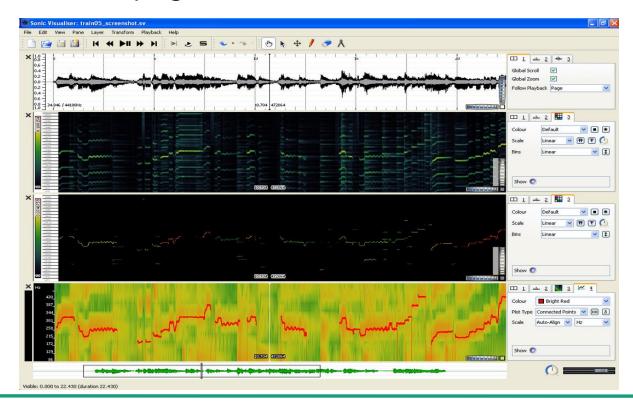






Pitch Detection Traditional Approach (Melodia)

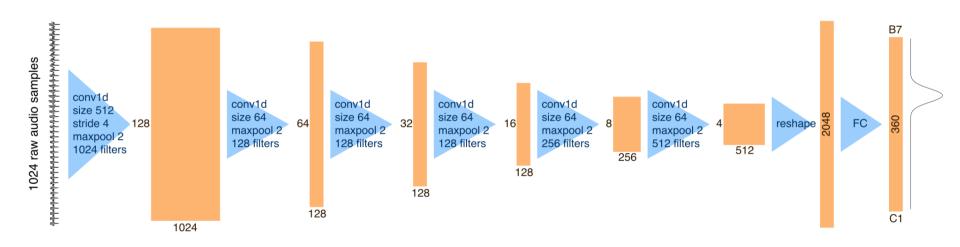
- Demo
- Melodia plugin for Sonic Visualiser





Pitch Detection Novel Approaches

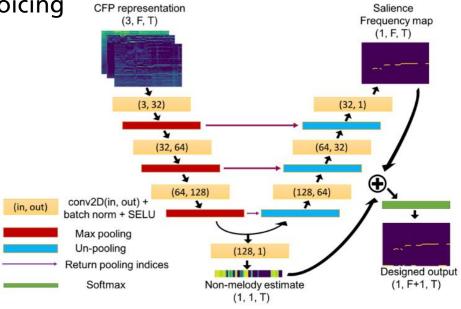
- CREPE (Convolutional Representation for Pitch Estimation)
 - Monophonic pitch tracker
 - End-to-end modeling
 - \blacksquare (Raw) audio samples (16 kHz) \rightarrow pitch likelihoods
 - 20 cent resolution (5 pitch bins per semitones)





Pitch Detection Novel Approaches

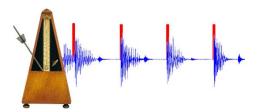
- Auto-encoder structure (U-Net)
 - Mapping from multiple time-frequency representations (2D) to pitch saliency map (2D)
 - Embedding encodes pitch voicing (melody activity)





Tempo Detection Introduction

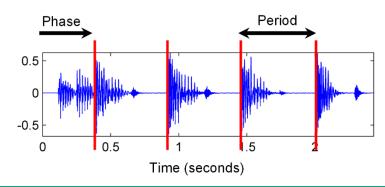
- Tempo [beats / minute]
 - Frequency with which humans tap along the beat



Beat tracking



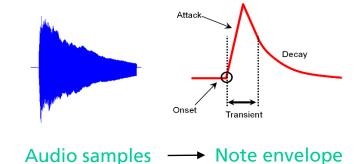
Estimating precise beat positions



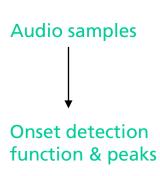


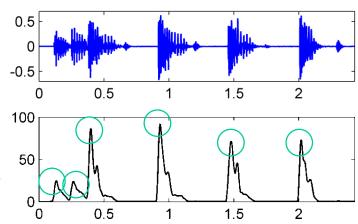
Tempo Detection Introduction

- Note onsets → note beginning times
 - Clearly defined for plucked string and percussion instruments
 - Ambiguous for wind & brass instruments



- Onset detection
 - Onset detection function
 - Peak picking



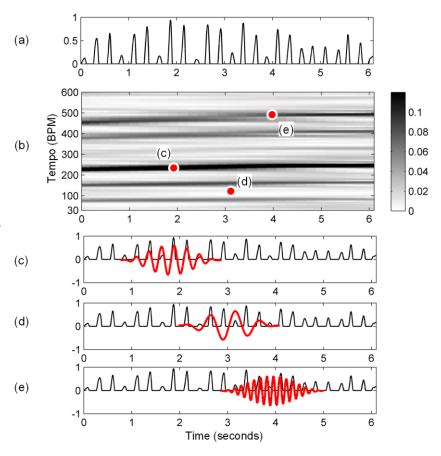




Tempo Detection Traditional Approach

- Predominant local pulse (PLP)
 - Correlation with local (windowed) periodic patterns
- Tempogram
 - Local likelihood of different tempo candidates
 - Allows to follow tempo changes (classical music)

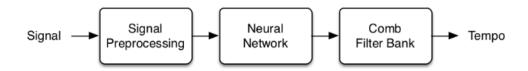




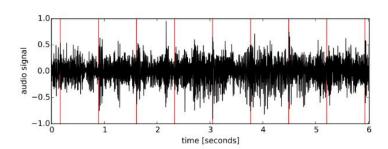


Tempo Detection Novel Approaches

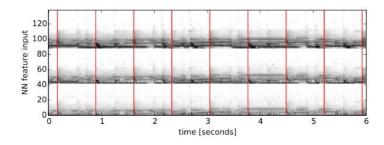
Approach



- Signal representation
 - Stacking of 3 STFT magnitude spectrograms (N=1024, 2048, 4096)
 - Log-amplitude & log-frequency



(a) Input audio signal

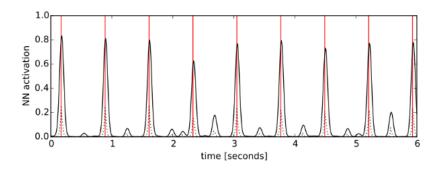


(b) Input to the neural network

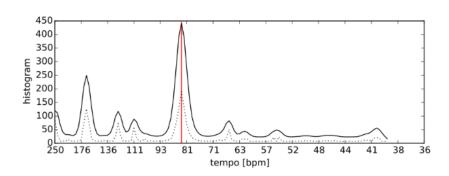


Tempo Detection Novel Approaches

- Neural Network
 - Recurrent (bi-directional LSTM) layer
 - Outputs beat activation function
- Comb filter bank
 - Multiple comb filters → detect periodicities
- Estimate tempo from histogram maximum



(c) Neural network output (beat activation function)

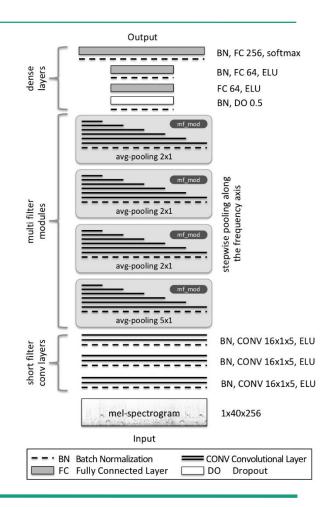


(f) Weighted histogram with summed maxima



Tempo Detection Novel Approaches

- Signal representation
 - Sample rate ~ 11 kHz, 40-band mel spectrogram
- Tempo estimation → classification (256 classes: 30 – 285 bpm)
- Neural Network
 - 3 layers (short filters) → onsets
 - 4 multi-filter modules (parallel conv layers) → compress along frequency & find periodicities
 - Dense layers → tempo classification





Instrument Recognition Introduction

- Music ensembles include multiple instruments
 - Sound production (string / wind / brass / drum instruments)
 - Unique timbre
- 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



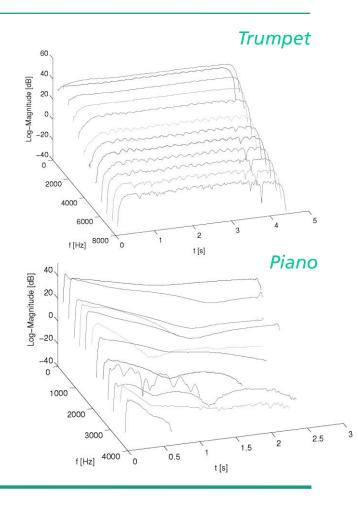
Instrument RecognitionTasks

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



Instrument Recognition Traditional Approach

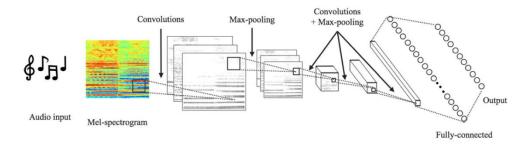
- Multiple categories of audio features
 - Per spectral frame
 - E.g. spectral flux & flatness
 - Per overtone / partial
 - E.g. modulation rate & frequency
 - Note-event level
 - Magnitude ratios of overtones
- Aggregation
 - Features (overtones)
 - Classification results (notes)





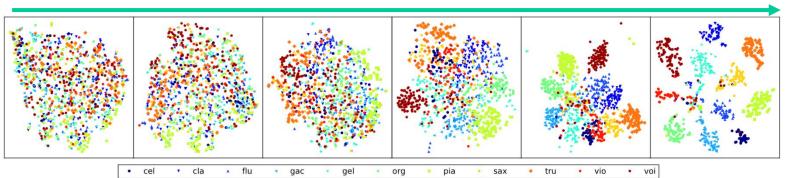
Instrument Recognition Novel Approaches

- Feature learning on mel spectrograms
- Convolutional layers & pooling & dense layers (classification)



Improving class separability in feature spaces

Deeper layers





Summary

- Music Information Retrieval
- Case Studies
 - Music Tagging
 - Pitch Detection
 - Tempo Estimation
 - Instrument Recognition
- Main trends
 - Adapt (data-driven) deep learning methods to audio domain
 - Incorporate music domain knowledge

