



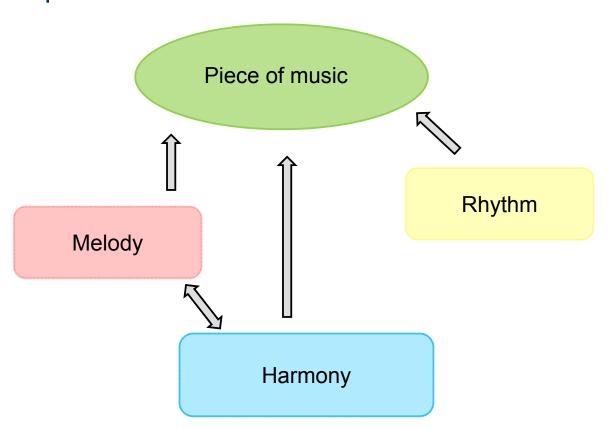
Lecture **Music Processing**

Chord Recognition

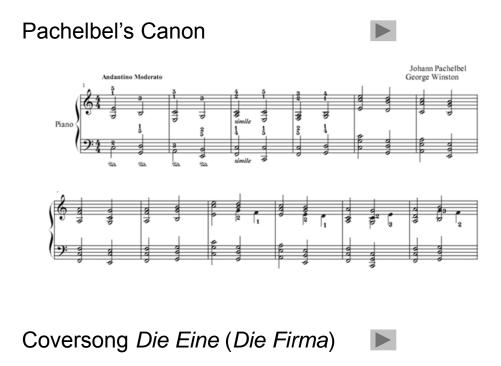
Meinard Müller

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Aspects of Music



Harmony: The Basis of Music



Musical Chords

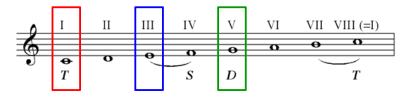
- Combination of three or more tones which sound simultaneously
- Chord classes
 - Triads including major, minor, diminished, augmented chords
 - Many other more complex chords such as seventh chords
- Here: focus on major and minor triads

Musical Chords

The C major chord



Derived from the C major scale



C ---- the root

E ---- the (major) third

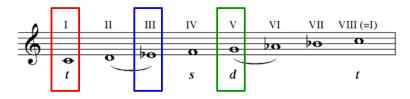
G ---- the fifth

Musical Chords

The C minor chord



Derived from the C minor scale



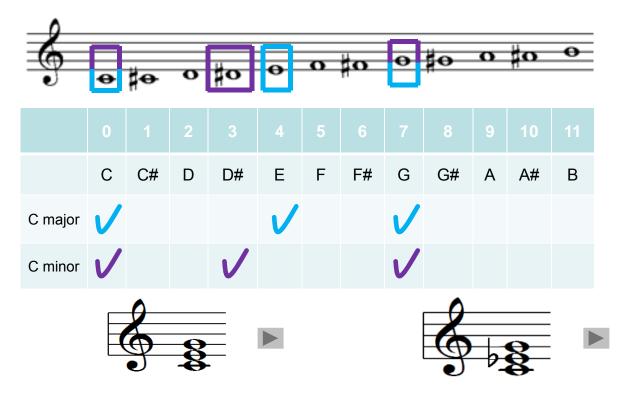
C ---- the root

Eb ---- the (minor) third

G ---- the fifth

Musical Chords

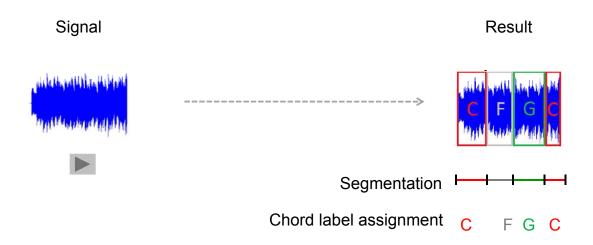
Structure of the 24 major/minor chords



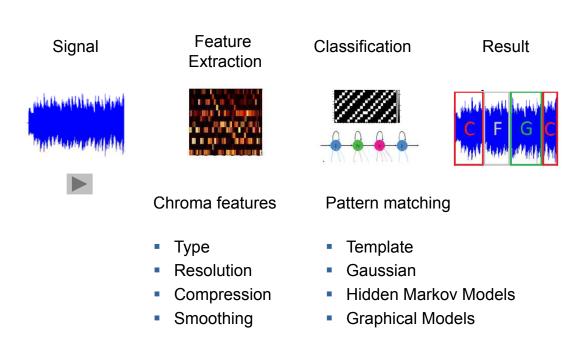
Chord Recognition

- Development of automatic methods for the harmonic analysis of audio data
- Applications in the field of music information retrieval:
 - music segmentation
 - cover song identification
 - audio matching
 - music structure analysis
 - **–** ...

Chord Recognition



Chord Recognition



Chord Recognition

Given: Audio file

Output: Segmentation and chord labeling



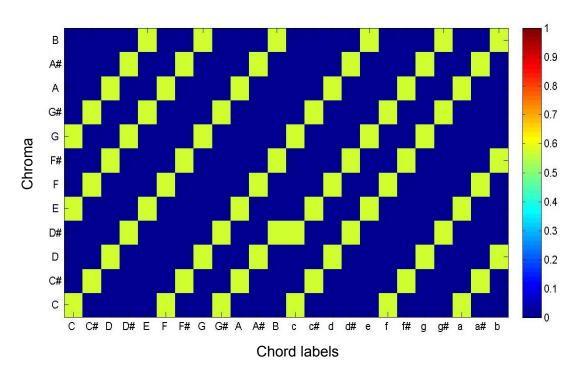
Baseline Method for Chord Recognition

Chord templates 24 major/minor chords

	C major	C# major	D major	D# major	 C minor	C# minor	
В	0	0	0	0	 0	0	
A#	0	0	0	1	 0	0	
Α	0	0	1	0	 0	0	
G#	0	1	0	0	 0	1	
G	1	0	0	1	 1	0	
F#	0	0	1	0	 0	0	
F	0	1	0	0	 0	0	
E	1	0	0	0	 0	1	
D#	0	0	0	1	 1	0	
D	0	0	1	0	 0	0	
C#	0	1	0	0	 0	1	
С	1	0	0	0	 1	0	

Baseline Method for Chord Recognition

Chord templates 24 major/minor chords



Baseline Method for Chord Recognition

24 chord templates (12 major, 12 minor)

Chroma feature extraction (framewise)

Baseline Method for Chord Recognition

24 chord templates (12 major, 12 minor)

Chroma feature extraction (framewise)



Compute for each frame the distance of the feature vector to the 24 templates

Baseline Method for Chord Recognition

24 chord templates (12 major, 12 minor)

Chroma feature extraction (framewise)



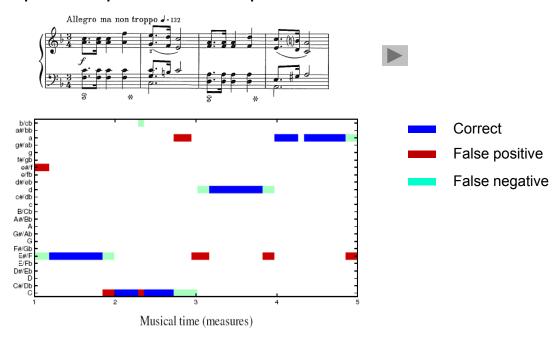
Compute for each frame the distance of the feature vector to the 24 templates



Selected chord according to template with minimal distance to respective feature vector

Problem: Transitions between subsequent chord

Example: Chopin Mazurka Op. 68 No.3



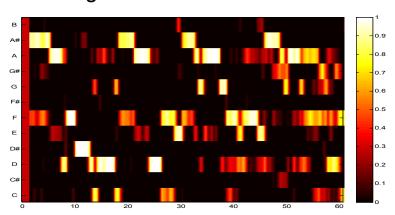
Problems in Chord Recognition

Problem: Monphonic musical passages

Example: Excerpt of Wagner's Meistersinger



Chromagram



Problem: Frame-wise chord analysis may not be meaningful

Example: Bach: Prelude C major, BWV 846

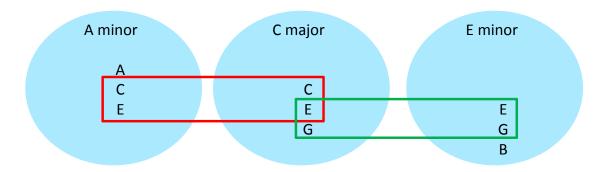


Problem: Broken chords

→ Measure-wise chord analysis necessary

Problems in Chord Recognition

Problem: Ambiguity of chords



Problem: Reduction to the 24 major/minor chords makes the recognition of more complex chords difficult/impossible!

Example: Prelude C major, BWV 846, mm.19-25



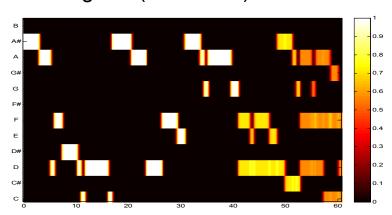
Problems in Chord Recognition

Problem: Tuning problems

Example: Excerpt of Wagner's Meistersinger



Chromagram (from MIDI)



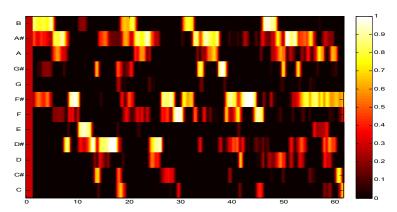
Problem: Tuning problems

Example: Excerpt of Wagner's Meistersinger





Chromagram (from MIDI)



Problem:

Audio is tuned more than half a semi-tone upwards

Problems in Chord Recognition

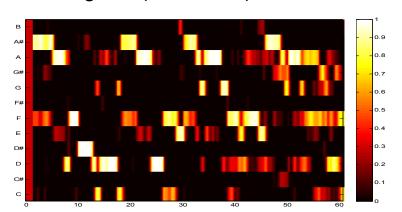
Problem: Tuning problems

Example: Excerpt of Wagner's Meistersinger





Chromagram (from MIDI)



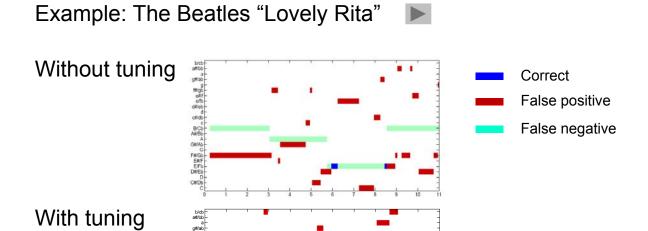
Problem:

Audio is tuned more than half a semi-tone upwards

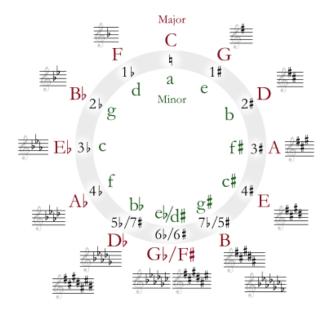
Solution:

Adjust frequency binning when computing pitch features.

Problem: Tuning problems

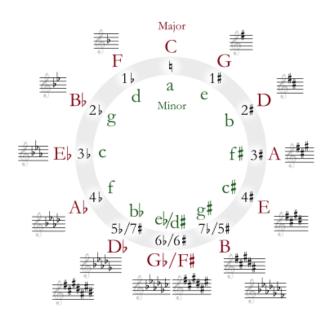


Key Relations: Circle of Fifths



From http://en.wikipedia.org/wiki/Circle_of_fifths

Key Relations: Circle of Fifths



Observation:
For tonality reasons,
some chord progressions
are more likely than
others.

Idea:

Usage of Hidden Markov Models (HMMs) to model chord dependencies

From http://en.wikipedia.org/wiki/Circle_of_fifths

Markov Models

Description of certain stochastic processes



Andrei Markov (Wikipedia)

Markov Models

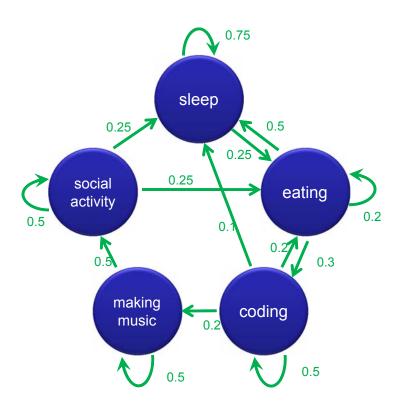
Description of certain stochastic processes



Andrei Markov (Wikipedia)

- Processes over discrete time
- Sequence of random variables X1, X2, ...
- Process has to follow Markov property:
 - no "memory", only current state "known"
 - " future " depends only on "present", not on "past"
 - $-P(X_{n+1}=x\mid X_n=y)=P(X_{n+1}=x\mid X_n=y,\ X_{n-1}=y_2,\ \ldots)$

Hidden Markov Models



$$G = (S,E,P)$$

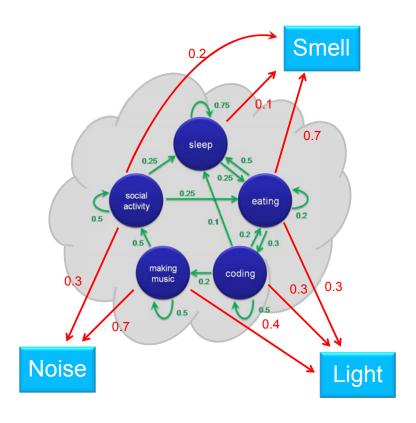
S: States

E: Transitions

P: Transition probabilities

Note: For each state, the sum of outgoing transition probabilities is equal to one.

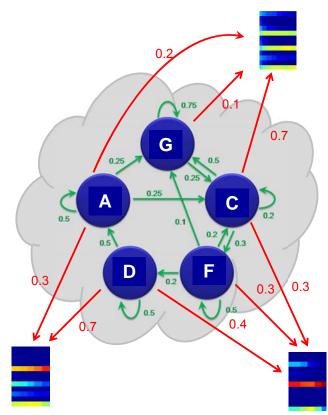
[Radu Curticapean]



- G = (S,P,V,B)
- S: States
- P: Transition probabilities
- V: Observations
- B: Emission probabilities

[Radu Curticapean]

Hidden Markov Models



- G = (S,P,V,B)
- S: States
- P: Transition probabilities
- V: Observations
- B: Emission probabilities

G = (S,P,V,B)

24 major/minor chords

S: States

Probabilities for having a transition from one chord to another chord

P: Transition probabilities

Chroma vectors

V: Observations

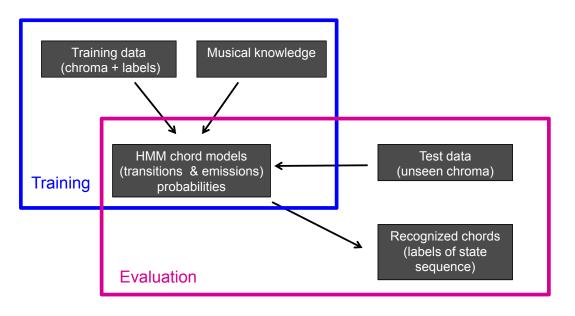
Probability for a chord model to produce a chorma distribution

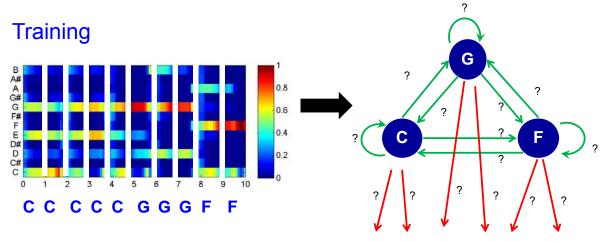
B: Emission probabilities

Hidden Markov Models

Two computational problems

- 1. Training: learn model parameters (Baum-Welch Algorithm)
- 2. Evaluation: find optimal state sequence (Viterbi Algorithm)





Input:

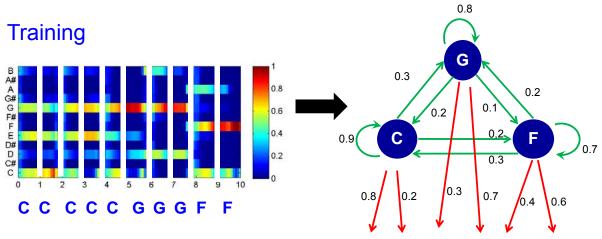
Sequence of features (observations)
Corresponding ground truth chord labels

Output:

Emission probabilities

Transition probabilities

Hidden Markov Models



Input:

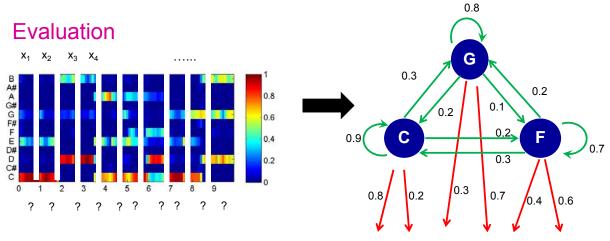
Sequence of features (observations)

Corresponding ground truth chord labels

Output:

Emission probabilities

Transition probabilities



Input:

Sequence of features Emission probabilities Transition probabilities

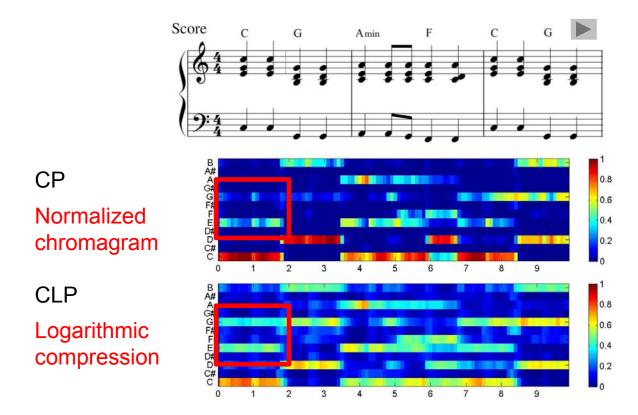
Output:

Optimal state sequence (estimated chord progression)

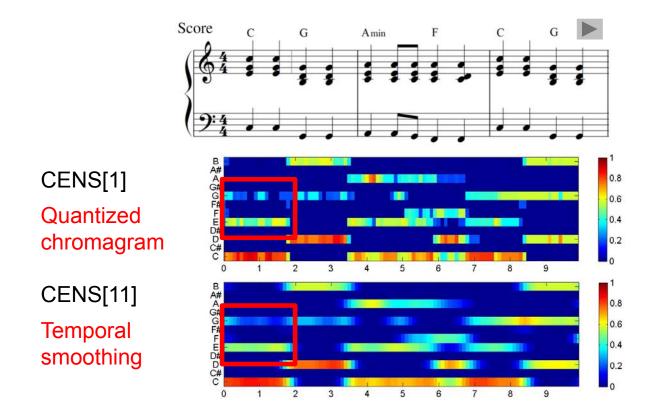
Hidden Markov Models 8.0 **Evaluation** X_1 X_2 X_3 X_4 G 0.3 0.2 0.8 0.2 0.9 0.4 0.3 0.3 0.7 CCGGFFFFCC Input: Sequence of features Emission probabilities Transition probabilities CC GGF FFFC C

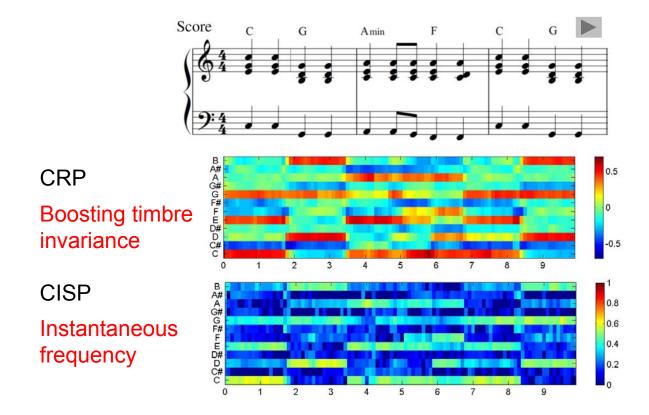
Output:

Optimal state sequence (estimated chord progression)

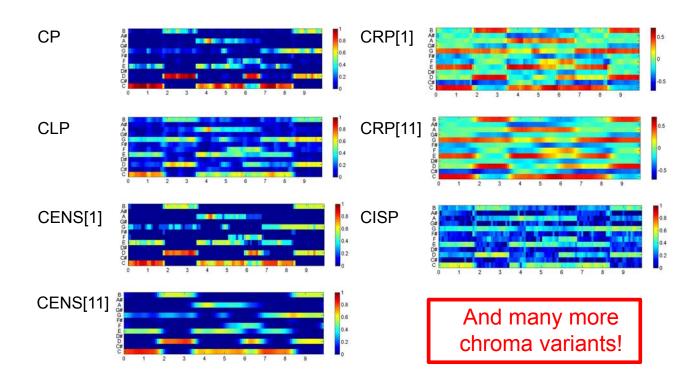


Importance of Chroma Feature Variant





Importance of Chroma Feature Variant

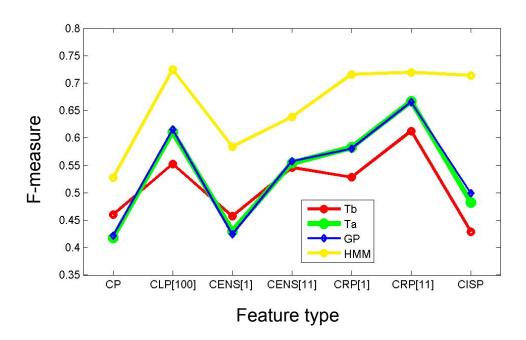


Experiment

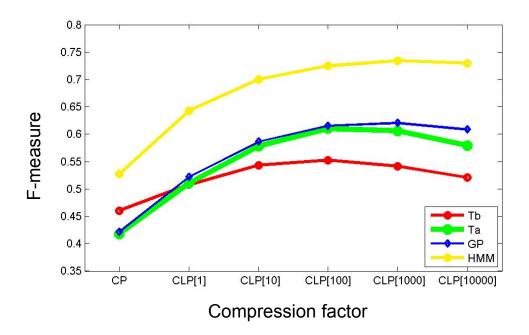
- Beatles dataset
- Three-fold cross validation
- Measurement: F-measure
- Framewise evaluation, each frame = 100 ms
- 12 major and 12 minor triads

Importance of Chroma Feature Variant

Dependency on feature type

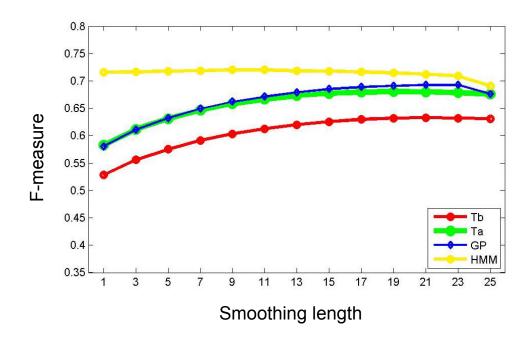


Dependency on logarithmic compression



Importance of Chroma Feature Variant

Dependency on smoothing (using CRP features)

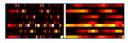


Chroma Toolbox

Chroma Toolbox: Pitch, Chroma, CENS, CRP









Croma Toolbox
Feature description
MATLAB Code
References
Links
MPI Informatik
Bonn University

roma Toolhox: Pitch. Chroma. CENS. CRP

The Chroma Toolbox has been developed by Meinard Müller and his collaborates from the research group headed by Michael Clausen. It contains MATLAB implementations for extracting various types of novel pitch-based and chroma-based audio features. The MATLAB implementations provided on this website are free for use in non-commercial research projects worldwide. If you publish results obtained using these implementations, please cite the references below, [1], [2], [3], [4].

Description of Pitch, Chroma, CENS, CRP feature

Chroma-based audio features have turned out to be a powerful tool for various analysis tasks in Music Information Retrieval including task such as chord labeling, music summarization, structure analysis, music synchronization and audio alignment. A 12-dimensional chroma feature encodes the short-time energy distribution of the underlying music signals over the twelve chroma bands, which correspond to the twelve traditional pitch classes of the equal-tempered scale encoded by the attributes C,C#,D,D#,...,B. Such features strongly correlate to the harmonic progression of the music signal, often prominent in Western music. By identifying spectral components that differ by a musical octave, chroma features possess a significant degree of robustness to changes in timbre and instrumentation.

- Freely available Matlab toolbox
- Feature types: Pitch, Chroma, CENS, CRP
- http://www.mpi-inf.mpg.de/resources/MIR/chromatoolbox/

Cross-Version Analysis

General Procedure

- Conduct analysis for multiple versions of the same object
- Relate the versions (using a reference)
- Compare analysis results accross different versions
- Look for consistencies and inconsistencies

Harmonic analysis

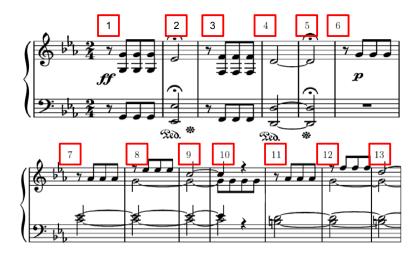
Different music recordings

Same piece of music

Music synchronization

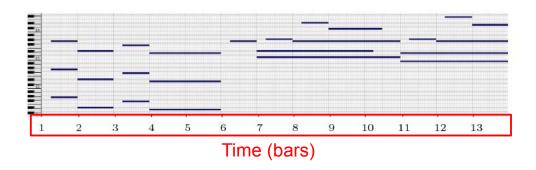
Musical score

Barwise Synchronization



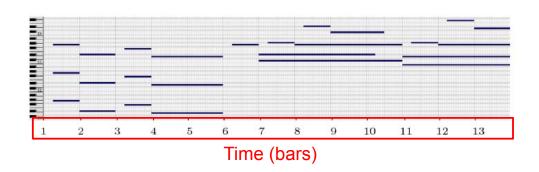
Barwise Synchronization

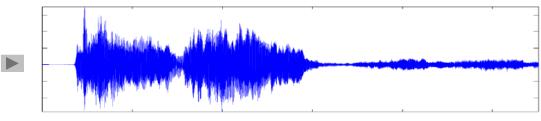
MIDI representation with bar information



Barwise Synchronization

MIDI representation with bar information

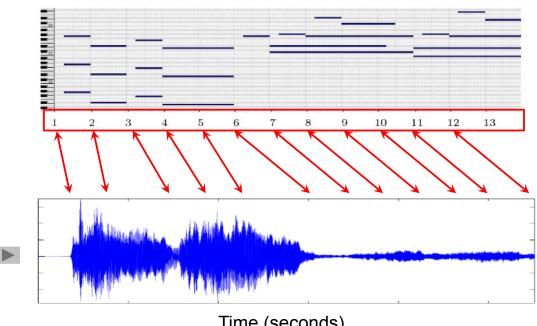




Time (seconds)

Barwise Synchronization

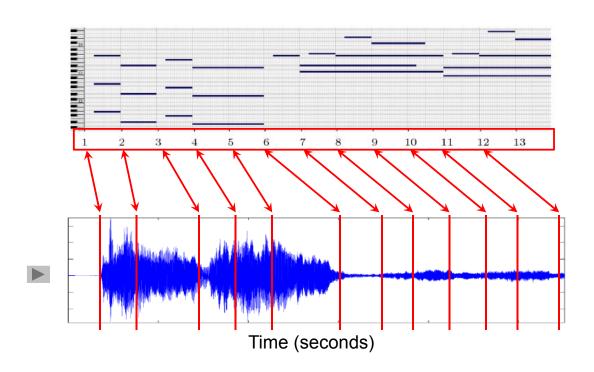
Music synchronization



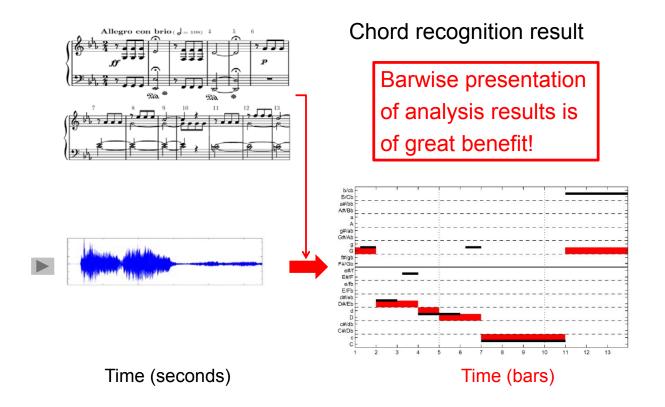
Time (seconds)

Barwise Synchronization

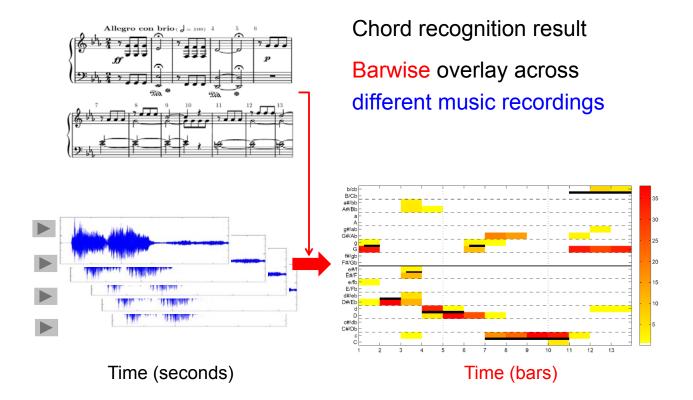
Transfer bar information to audio domain



Cross-Version Harmonic Analysis



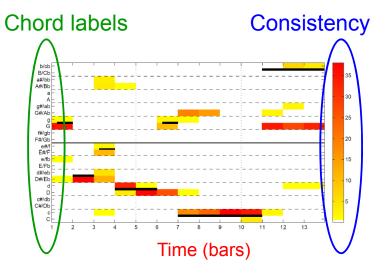
Cross-Version Harmonic Analysis



Cross-Version Harmonic Analysis



Cross-version chord recognition result



Cross-Version Harmonic Analysis



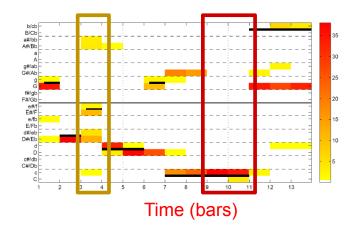
Cross-version chord recognition result

Highly consistent:

C-minor

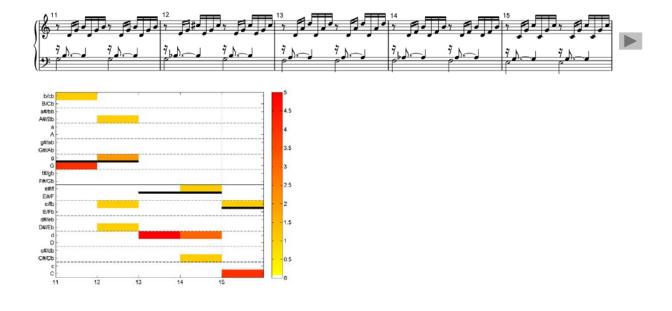
Inconsistent:

F-minor, F-major, E^b -major ... ???



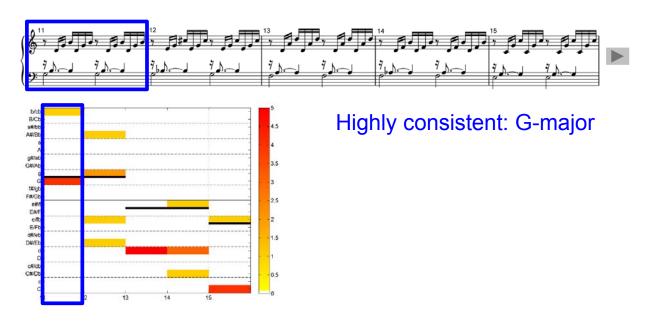
Cross-Version Visualization

Example: Bach's Prelude BWV 846 in C major (bars 11-15)



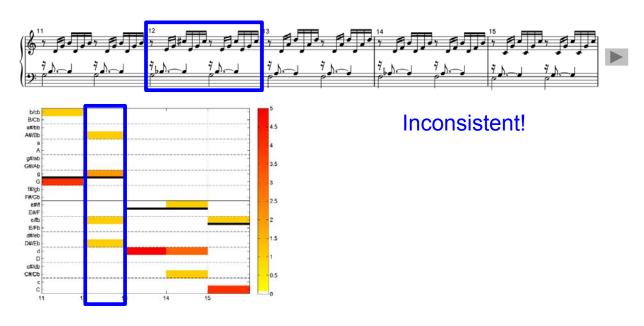
Cross-Version Visualization

Example: Bach's Prelude BWV 846 in C major (bars 11-15)



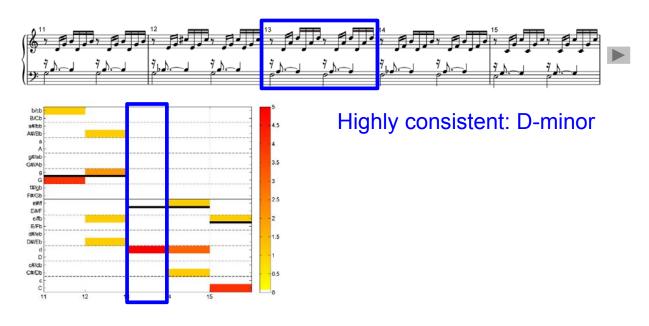
Cross-Version Visualization

Example: Bach's Prelude BWV 846 in C major (bars 11-15)



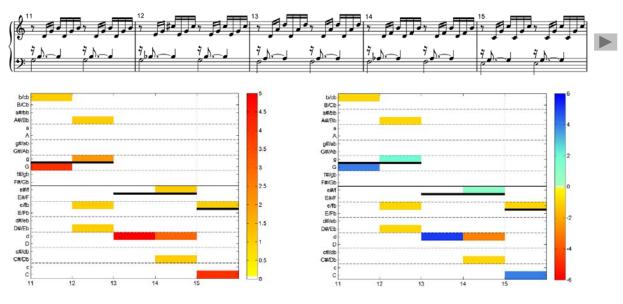
Cross-Version Visualization

Example: Bach's Prelude BWV 846 in C major (bars 11-15)



Cross-Version Visualization

Example: Bach's Prelude BWV 846 in C major (bars 11-15)

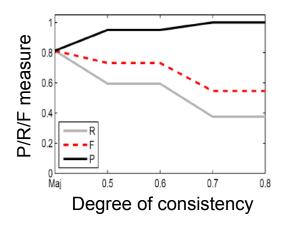


Ground-truth visualization

Convenient tool for manual error analysis and evaluation

Quantitative Evaluation

Example: Bach's Prelude BWV 846



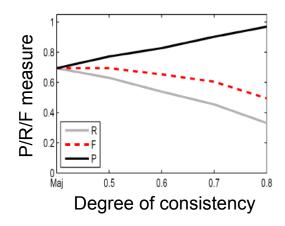
F-measures for individual recordings:

Min: 0.44 Max: 0.87 Mean: 0.70

- Consistent regions tend to be classified correctly
- Precision high
- Recall not too bad
- → Indication of harmonically stable, well-defined tonal centers

Quantitative Evaluation

Example: Beethoven's Fifth



F-measures for individual recordings:

Min: 0.53 Max: 0.83 Mean: 0.60

- Consistent regions tend to be classified correctly
- Precision high
- Recall not too bad
- → Indication of harmonically stable, well-defined tonal centers

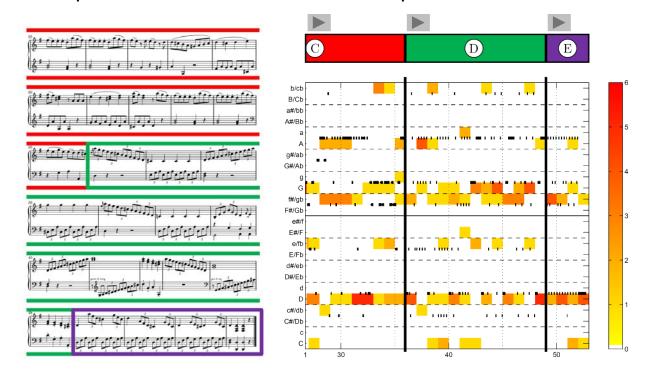
Application: Exploring Harmonic Structures

Example: Beethoven's Piano Sonata Op. 49 No. 2



Application: Exploring Harmonic Structures

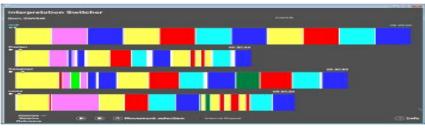
Example: Beethoven's Piano Sonata Op. 49 No. 2



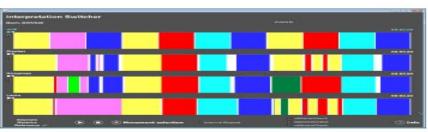
Interface: Interpretation Switcher

Chord annotations for four versions

Absolute mode



Reference mode



Simultaneous comparison of different version-dependent analysis results (here: chord labels)

Conclusions & Future Work

- Importance of feature design step
- Cross-version framework
 - Harmonic analysis
 - Tempo analysis
 - Structure analysis
- Musically meaningful timeline in bars → very convenient!
- Stabilization of analysis results
 - Consistencies seem to have musical meaning
 - Which meaning? Tonal centers?
- Towards interdisciplinary research (MIR + musicology)
 - Visualization as meanigful tool in musicology?
 - Helpful for analyis of harmonic relations across entire music corpora?

Literature

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 Proc. International Computer Music Conference (ICMC), pages 464–467, Beijing, 1999.
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