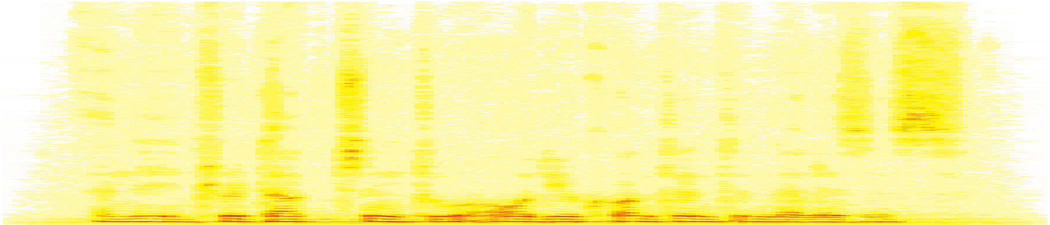
Introduction to Audio Content Analysis

Module 5.7: Musical Key Recognition

alexander lerch



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introduction

overview

corresponding textbook section

Chapter 5 — Tonal Analysis: pp. 88–94
Chapter 5 — Tonal Analysis: pp. 116–125

- **lecture content**
  - definition of musical key
  - pitch chroma feature
  - standard approach for key recognition
- **learning objectives**
  - explain the defining properties of a musical key
  - implement a simple pitch chroma feature extractor
  - describe and discuss a simple automatic key recognition system

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key
tonic & mode

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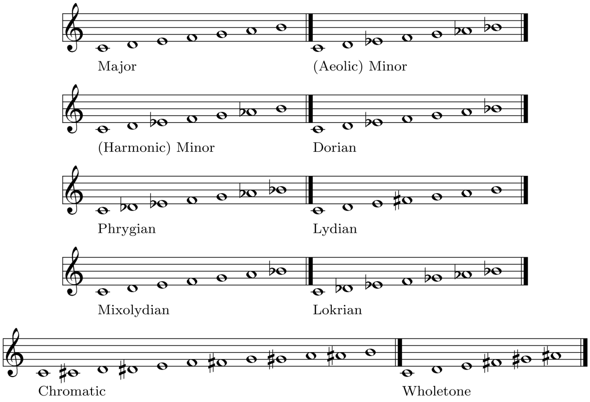
- **tonic**: first scale degree
  - most "important" pitch class
- **mode**: set of diatonic pitch relationships
  - Major: 2, 2, 1, 2, 2, 2, 1
  - Minor: 2, 1, 2, 2, 1, 2, 2



key

key & key signature 1/2

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- **key**:
  defined by *tonic* (root note) and *mode*
  - defines a set of pitch classes constructing both pitch and harmonic content
- **modulation** (local key changes):
  common in various styles, uncommon in others
- **key signature**:
  indicates current key with accidentals (score notation)

key

key & key signature 1/2

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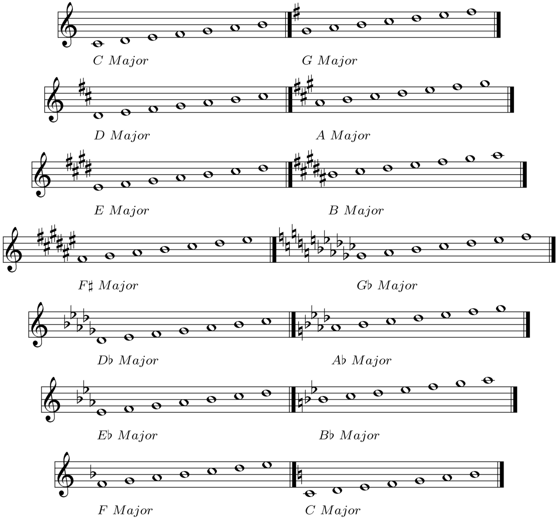
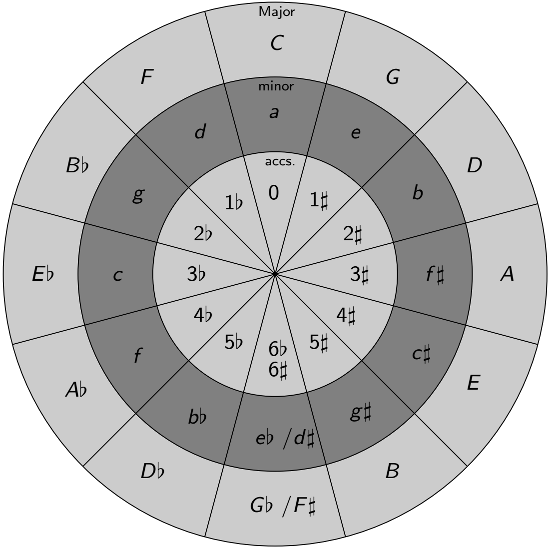
key

key & key signature 2/2



musical pitch

key: circle of fifths



pitch chroma
introduction

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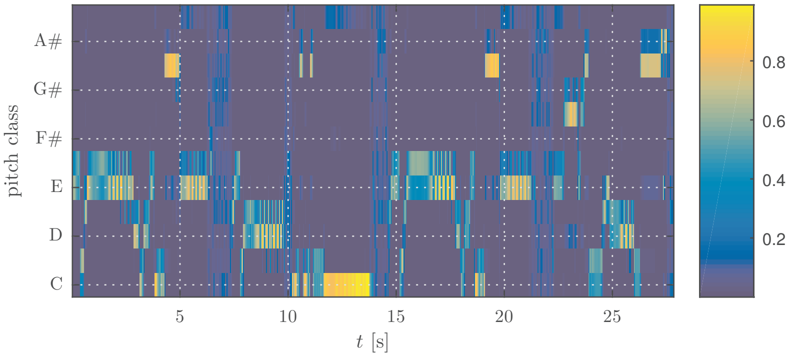
- pitch class distribution
- 12-dimensional vector



matlab source: matlab/displayPitchChroma.m

pitch chroma
introduction

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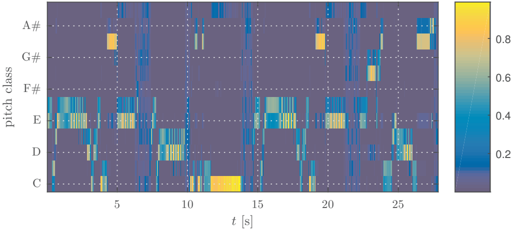

- **no** octave information
  - robust representation
  - no differentiation between unison and octave

pitch chroma

computation 1/2

1. divide spectral representation into **semi-tone bands**
2. compute **mean per band**

$$\mu(j,n) = \frac{1}{k_\mathrm{u}(j) - k_\mathrm{l}(j) + 1} \sum_{k=k_\mathrm{l}(j)}^{k_\mathrm{u}(j)} |X(k,n)|$$

3. sum/mean every 12th band

$$\begin{aligned}\nu(j\%12, n) &= \sum_{o=o_l}^{o_u} \mu(j,n),\\ \nu(n) &= \left[\nu(0,n), \nu(1,n), \nu(2,n), \ldots, \nu(10,n), \nu(11,n)\right]^\mathrm{T}\end{aligned}$$

pitch chroma

computation 1/2

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pitch chroma

computation 1/2

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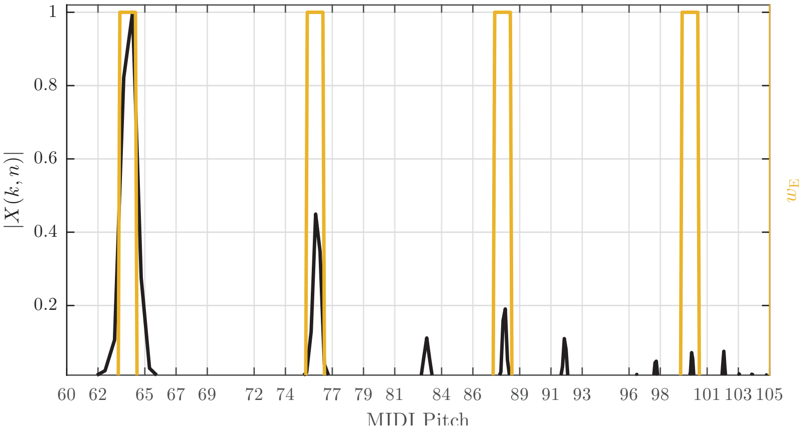
pitch chroma
computation 2/2

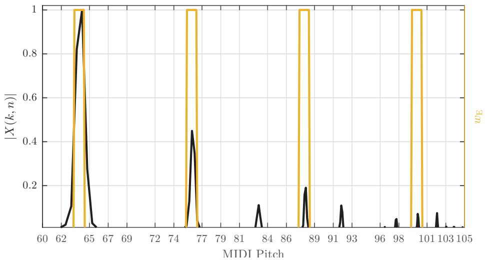


matlab source: matlab/displayPitchChromaGrouping.m

pitch chroma

computation: simple variants

- **STFT**:
  - *weighted* mean of bins (window function)
  - *tonalness preprocessing* (local maxima etc)



- sum of **filterbank** output energies
- **CQT**:
  - sum of bins/peaks
- beat-synchronous chroma

pitch chroma
computation: simple variants

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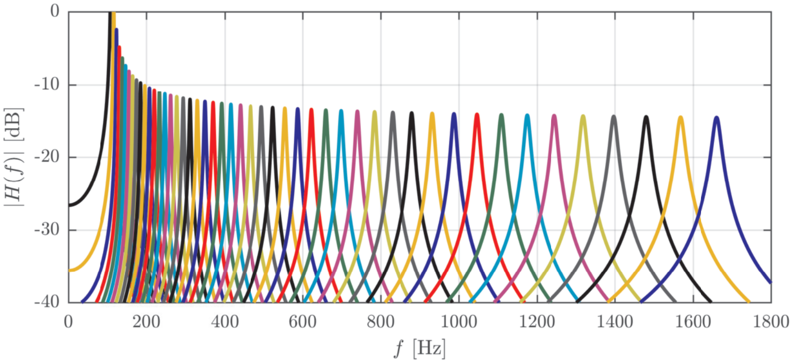

matlab source: matlab/displayResonanceFilterBank.m

pitch chroma
computation: simple variants

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pitch chroma

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pitch chroma
normalization

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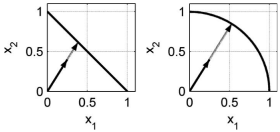
- pitch chroma as *distribution*:

$$\sum_{k=0}^{11} \nu(k,n) = 1$$



- pitch chroma as *vector*:

$$\sqrt{\sum_{k=0}^{11} \nu(k,n)^2} = 1$$

- other options:
  - e.g., short-term energy normalization (CENS)

pitch chroma
normalization

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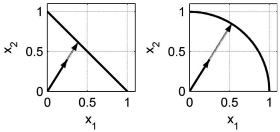

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pitch chroma
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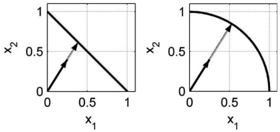

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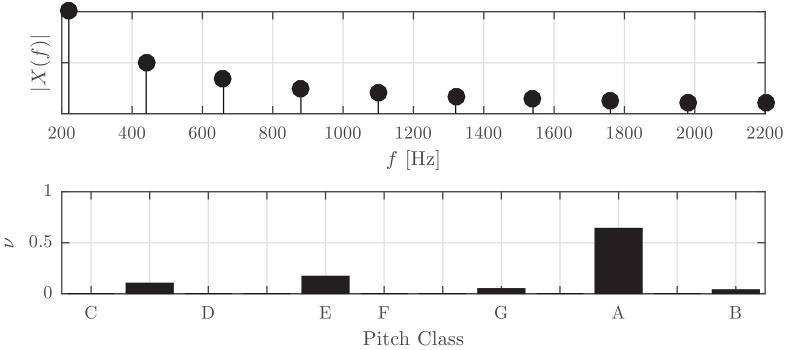
pitch chroma
problem 1: amplitude distortion

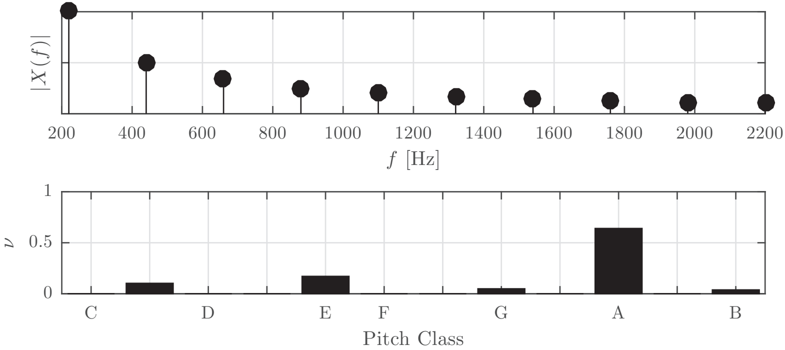


- every pitch contains not only fundamental but higher harmonics
  - ⇒ de-emphasize higher frequencies
  - ⇒ build amplitude model
  - ⇒ use multi-pitch detection system

matlab source: matlab/displayHarmonicsInPitchChroma.m

pitch chroma

problem 1: amplitude distortion



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pitch chroma

problem 2: frequency distortion

- higher harmonics are not "in-tune"

Harmonic	$\lvert\Delta C(f, f_T)\rvert$
$f = f_0$	0
$f = 2 \cdot f_0$	0
$f = 3 \cdot f_0$	1.955
$f = 4 \cdot f_0$	0
$f = 5 \cdot f_0$	13.6863
$f = 6 \cdot f_0$	1.955
$f = 7 \cdot f_0$	31.1741
$\mu_{\lvert\Delta C\rvert}$	6.9672

key detection
introduction

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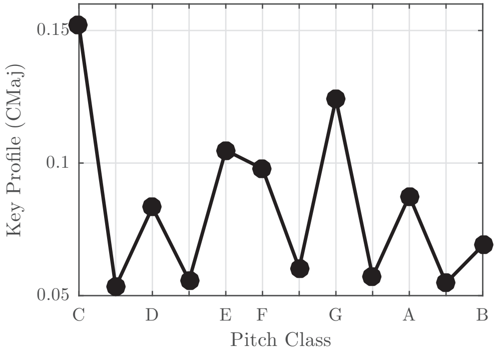
assumption:

- *pitch class distribution* is prototypical for key
    - tonic/root note is tonal center
    - tonal and harmonic relations define importance and occurrence of individual pitch classes
    - different root notes result in simple shift of distribution

key detection

processing steps of simple key detection

1. define reference distribution for specific keys
2. extract average pitch chroma from audio
3. compute distance between template and extracted chroma



matlab source: matlab/displayKrumhanslKeyProfile.m

key detection

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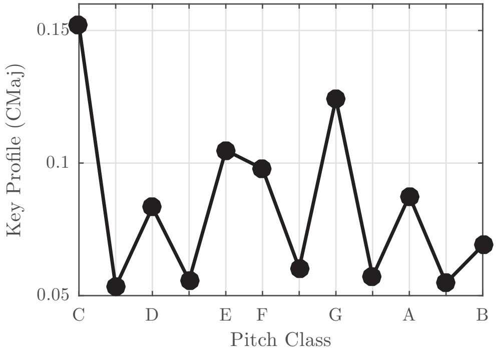

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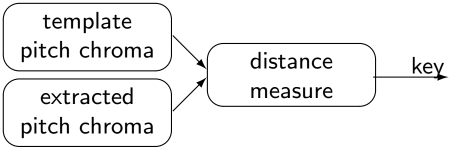
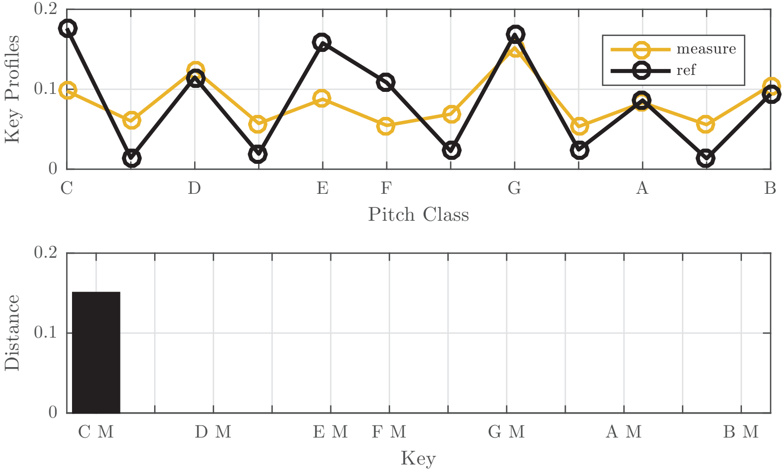


key detection

key template distance animation



matlab source: matlab/animateKeyDetection.m

key detection
key templates 1/2

- *Orthogonal* ν_o: root note is most salient component, other components negligible
  - same distance to all keys
  - no distinction between major and minor
- *Smoothed Orthogonal* ν_s: root note most salient, neighboring components less important
  - increasing key distance to tritone
  - no real distinction between major and minor
- *Diatonic* ν_d: all key-inherent pitches weighted equally
  - linear increasing key distance
- *Probe tone Ratings* ν_p: derived from perceptual tonal similarity
- *Extracted Key Profiles* ν_t: derived from real-world data

key detection

key templates 1/2

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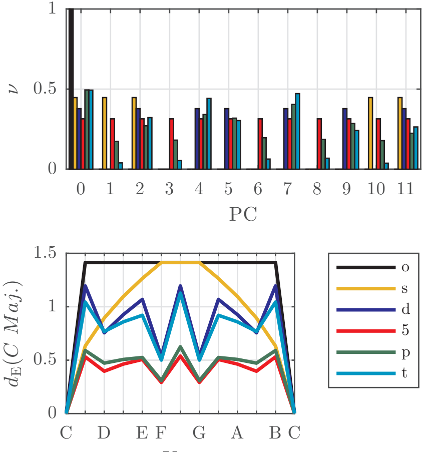
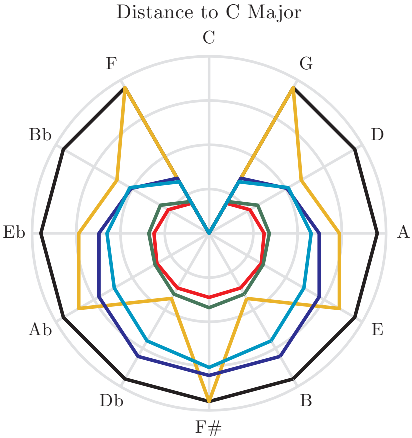
key detection

key templates 2/2





matlab source: matlab/displayKeyProfiles.m

key detection
variants

- **tonalness weight**:
  estimate the tonality/noisiness and weight instantaneous pitch chroma
- **multiple estimations**:
  split piece into regions and estimate key through majority
- **real-time key detection**:
  estimate in sliding window

key detection
variants

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key detection
results & typical errors

- typical errors: related keys
  - Dominant
  - Subdominant
  - Relative
  - Major/Minor

graph from[1]

[1] A. Lerch, "Ein Ansatz zur automatischen Erkennung der Tonart in Musikdateien," in *Proceedings of the VDT International Audio Convention (23. Tonmeistertagung)*, Leipzig, Nov. 2004.

summary
lecture content

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- **musical key**
  - set of pitch classes constructing pitched content
  - defined by *tonic* (important center) and *mode* (scale)
- **pitch chroma**
  - reduced 12-dimensional octave-independent pitch representation
  - relatively robust against timbre variation
- **automatic key recognition**
  - standard approach is template-based
  - extracted average pitch chroma is compared with predefined template
  - inverse distance measure indicates key likelihoods