## Introduction to Audio Content Analysis

Module 7.5: Musical Key Recognition

alexander lerch



# introduction overview

### corresponding textbook section

#### Section 7.5

#### **■** 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



### corresponding textbook section

#### Section 7.5

#### **■** lecture content

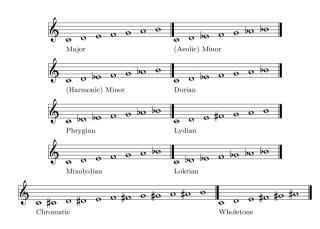
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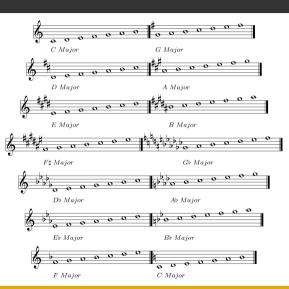
- tonic: first scale degree
  - most "important" pitch class
- **mode**: set of diatonic pitch relationships
  - Major: 2, 2, 1, 2, 2, 2, 1
  - Minor: 2, 1, 2, 2, 1, 2, 2



- key:
  - 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

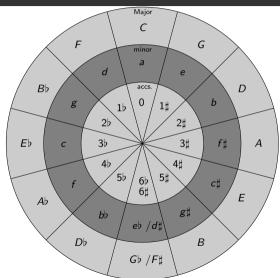
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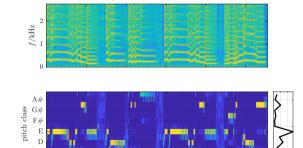


# musical pitch key: circle of fifths

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- pitch class distribution
- 12-dimensional vector
- no octave information
  - robust representation
  - no differentiation between unison and octave
- **(**(



15

t/s

20

10

### 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

$$\nu(j\%12, n) = \sum_{o=o_l}^{o_u} \mu(j, n),$$

$$\nu(n) = [\nu(0, n), \nu(1, n), \nu(2, n), \dots, \nu(10, n), \nu(11, n)]^{\mathrm{T}}$$

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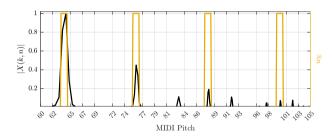
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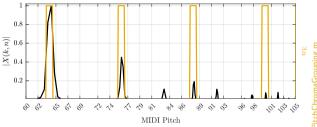
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computation: simple variants

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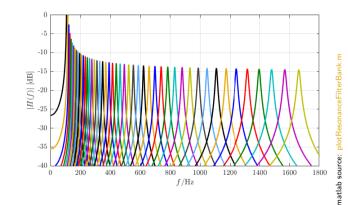
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- tonalness preprocessing (local maxima etc)
- sum of filterbank output energies
- CQT:
  - sum of bins/peaks
- beat-synchronous chroma



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### pitch chroma normalization

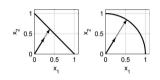
■ pitch chroma as *distribution*:

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

■ pitch chroma as *vector*:

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

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



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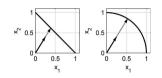
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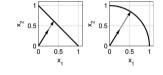


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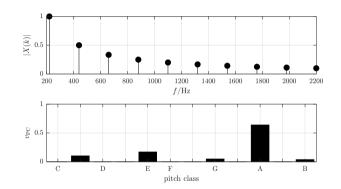
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## pitch chroma problem 1: amplitude distortion

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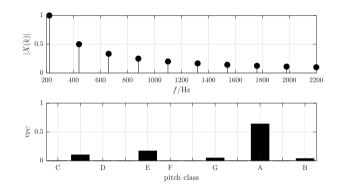


- every pitch contains not only fundamental but higher harmonics
  - ⇒ de-emphasize higher frequencies
  - $\Rightarrow$  build amplitude model
  - ⇒ use multi-pitch detection system

problem 1: amplitude distortion

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### pitch chroma problem 2: frequency distortion

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■ higher harmonics are not "in-tune"

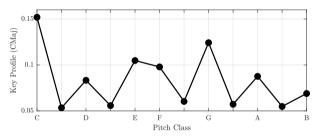
Harmonic	$ \Delta C(f, f_T) $
$f = f_0$	0
$f=2\cdot f_0$	0
$f=3\cdot f_0$	1.955
$f = 4 \cdot f_0$	0
$f = 5 \cdot f_0$	13.6863
$f = 6 \cdot f_0$	1.955
$f = 7 \cdot f_0$	31.1741
$\mu_{ \Delta C }$	6.9672

# key detection introduction

#### 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

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

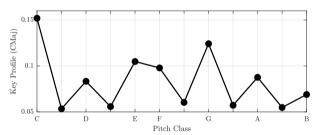


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## kev detection

processing steps of simple key detection

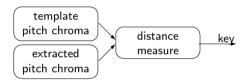
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# key detection processing steps of simple key detection

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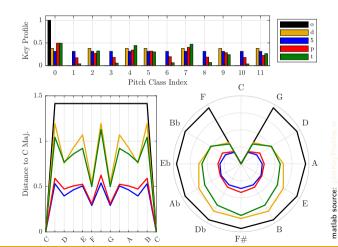
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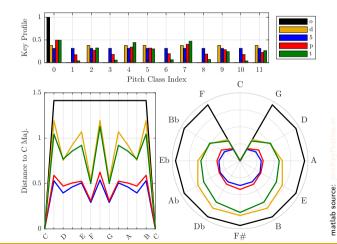
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- Orthogonal  $\nu_0$ : root note is most salient component, other components negligible
  - same distance to all keys



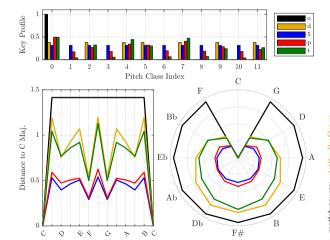
# key detection key templates

- Orthogonal  $\nu_0$ : root note is most salient component, other components negligible
  - same distance to all keys
  - no major/minor distinction
- Diatonic ν<sub>d</sub>: all key-inherent pitches weighted equally
   linear increasing key dist
- Probe tone Ratings  $\nu_p$ :
  derived from perceptual tonal similarity
- Extracted Key Profiles ν<sub>t</sub>: derived from real-world data



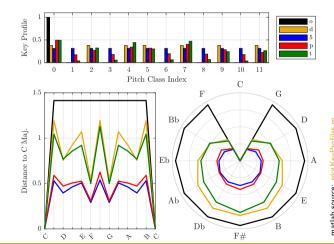
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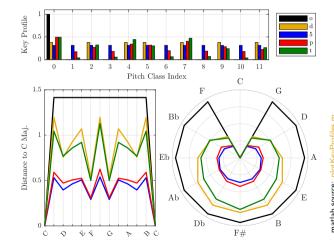
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- tonalness weight:
  estimate the tonality/noisiness and weight instantaneous pitch chroma
- multiple estimations: split piece into regions and estimate key through majority
- real-time key detection: estimate in sliding window

## key detection

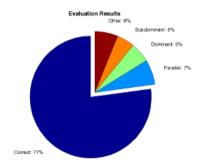
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## key detection results & typical errors

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



graph from<sup>1</sup>

<sup>&</sup>lt;sup>1</sup>A. Lerch, "Ein Ansatz zur automatischen Erkennung der Tonart in Musikdateien," in *Proceedings of the VDT International Audio Convention* (23. Tonmeistertagung), Leipzig, Nov. 2004.

#### 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

