



Introduction to **Audio Content Analysis**

module 7.6: chord detection

alexander lerch

introduction

overview

corresponding textbook section

section 7.6

■ lecture content

- musical chords and harmony
- baseline chord detection
- Hidden Markov Models (HMMs) and the Viterbi algorithm

■ learning objectives

- name basic chords and describe the concept of chord inversions
- discuss commonalities and differences between chord & key detection
- discuss the usefulness of HMMs for chord detection
- explain the Viterbi algorithm with an example



introduction

overview

corresponding textbook section

section 7.6

■ lecture content

- musical chords and harmony
- baseline chord detection
- Hidden Markov Models (HMMs) and the Viterbi algorithm

■ learning objectives

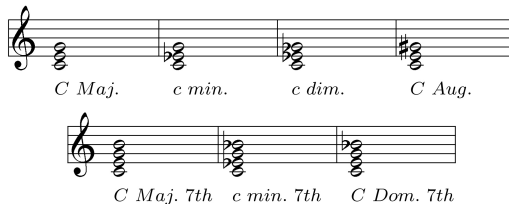
- name basic chords and describe the concept of chord inversions
- discuss commonalities and differences between chord & key detection
- discuss the usefulness of HMMs for chord detection
- explain the Viterbi algorithm with an example



musical pitch

chords

- simultaneous use of several pitches \Rightarrow **chords**
- usually constructed of (major/minor) thirds

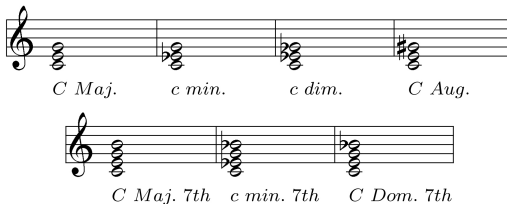


- note:
 - chord type independent of pitch doubling, pitch order
 - same label for keys and chords

musical pitch

chords

- simultaneous use of several pitches \Rightarrow **chords**
- usually constructed of (major/minor) thirds

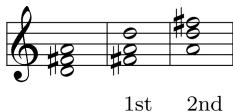


- note:
 - chord type independent of pitch doubling, pitch order
 - same label for keys and chords

musical pitch

chord inversion

- most common: root note is lowest note
- otherwise: chord inversion



musical pitch

harmony

- key and tonal context define chord's *harmonic function*
- examples:
 - **tonic:**
chord on 1st scale degree (tonal center)
 - **dominant:**
chord on 5th scale degree (often moves to tonic)
 - **subdominant:**
chord on 4th scale degree
 - ...

chord detection

introduction: key vs. chord detection

■ commonalities

- chords are octave independent \Rightarrow pitch chroma sufficient
- process flow: pitch chroma extraction + classification

■ differences

- time frame for pitch chroma calculation
- templates
- number of templates/chords
- many results per song (time series)

chord detection

introduction: key vs. chord detection

■ commonalities

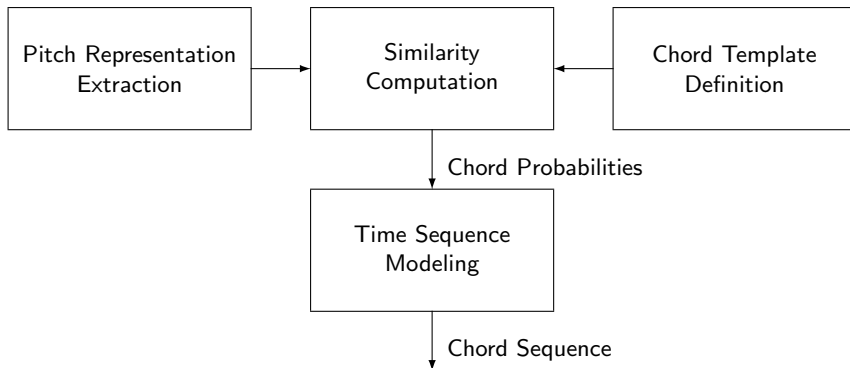
- chords are octave independent \Rightarrow pitch chroma sufficient
- process flow: pitch chroma extraction + classification

■ differences

- time frame for pitch chroma calculation
- templates
- number of templates/chords
- many results per song (time series)

chord detection

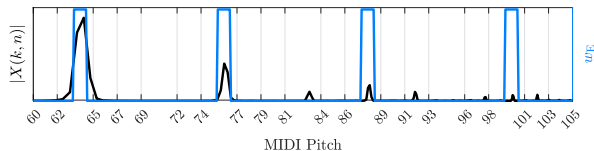
introduction: overview



pitch chroma

introduction

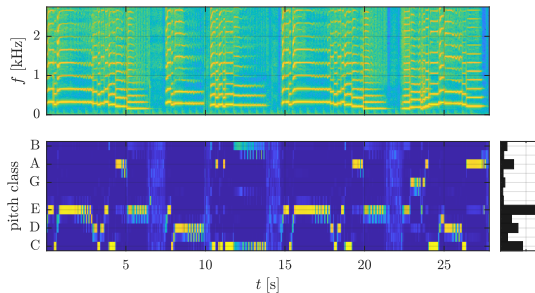
- pitch class distribution: 12-dimensional vector
- map all pitch class bands in all octaves to one



pitch chroma

introduction

- pitch class distribution: 12-dimensional vector
- map all pitch class bands in all octaves to one



pitch chroma

introduction

- pitch class distribution: 12-dimensional vector
- map all pitch class bands in all octaves to one

pitch chroma properties

- **no** octave information
 - no differentiation between prime and octave
 - no info on inversion
- robust, timbre-independent representation

chord detection

chord template

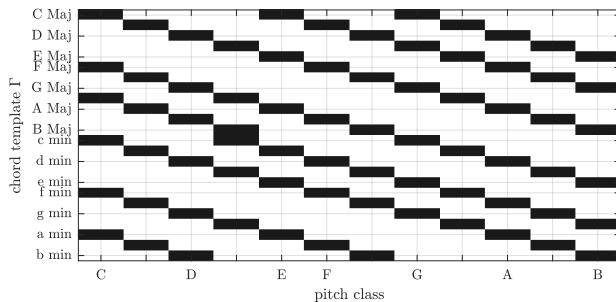
■ compare extracted pitch chroma with template

- simplest possible template and distance: linear transformation
example — C major:

$$\Gamma(0, j) = [1/3, 0, 0, 0, 1/3, 0, 0, 1/3,$$

⇒ instantaneous chord likelihood:

$$\psi(c, n) = \sum_{j=0}^{11} \Gamma(c, j) \cdot \nu(j, n)$$



chord detection

chord progression 1/2

apply **musical knowledge** to increase the result's robustness and accuracy:

- probabilities for different chord progressions (similar to key modulations), e.g.
 - cadences: I-IV-V-I
 - sequences: circle progression

⇒ model for *chord progression probabilities*

1 *analytical model* based on music theory

- circle of fifths (!?)
- key profile correlation (!?)

2 *empirical model* based on data

- annotate audio
- symbolic score

chord detection

chord progression 1/2

apply **musical knowledge** to increase the result's robustness and accuracy:

- probabilities for different chord progressions (similar to key modulations), e.g.
 - cadences: I-IV-V-I
 - sequences: circle progression

⇒ model for *chord progression probabilities*

1 *analytical model* based on music theory

- circle of fifths (!?)
- key profile correlation (!?)

2 *empirical model* based on data

- annotate audio
- symbolic score

chord detection

chord progression 1/2

apply **musical knowledge** to increase the result's robustness and accuracy:

- probabilities for different chord progressions (similar to key modulations), e.g.
 - cadences: I-IV-V-I
 - sequences: circle progression

⇒ model for *chord progression probabilities*

1 *analytical model* based on music theory

- circle of fifths (!?)
- key profile correlation (!?)

2 *empirical model* based on data

- annotate audio
- symbolic score

chord detection

chord progression 2/2

what properties do chord progression probabilities depend on



chord detection

chord progression 2/2

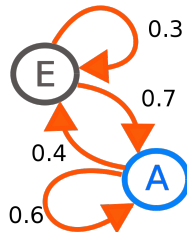


what properties do chord progression probabilities depend on

- musical key
- larger musical context (model order)
- style
- tempo/length??

chord detection

markov chain



- two possible states E, A
- transition probabilities to other state(s) and to self
- sum of transition probabilities equals 1

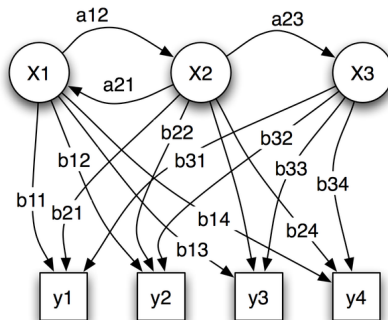
chord detection

hidden markov model: variables

- **states:**
unknown/hidden
- **transition probability:**
probability of transitioning from one state to the other
- **observations:**
measureable time series
- **emission probability:**
probability of an observation given a state
- **start probability:**
probability of the initial state

chord detection

hidden markov model: variables



- X : states
- y : possible observations
- a : state transition probabilities
- b : emission probabilities

chord detection

hidden markov model: example (WP) 1/2

■ scenario

- doctor diagnoses fever by how patients feel
- patient may feel normal, dizzy, or cold
- patient visits multiple days in a row

what are the states and observations in this case



chord detection

hidden markov model: example (WP) 1/2

■ scenario

- doctor diagnoses fever by how patients feel
- patient may feel normal, dizzy, or cold
- patient visits multiple days in a row

what are the states and observations in this case

■ states

- *healthy*
- *fever*

■ observations:

- *normal*
- *cold*
- *dizzy*



chord detection

hidden markov model: example (WP) 2/2

■ start probabilities (initial state assumption)

- *healthy*: 0.6
- *fever*: 0.4

■ emission probabilities (prob of obs given state)

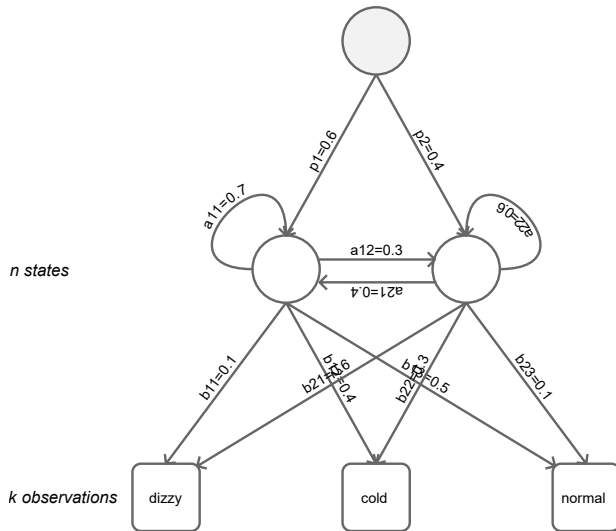
- *healthy*: normal 0.5, cold 0.4, dizzy 0.1
- *fever*: : normal 0.1, cold 0.3, dizzy 0.6

■ transition probabilities

- *healthy*: healthy 0.7, fever 0.3
- *fever*: : healthy 0.4, fever 0.6

chord detection

hidden markov model: example (WP) 2/2



start probabilities $\sum_n p_n = 1$

transition probabilities $\sum_n a_{1,n} = 1$

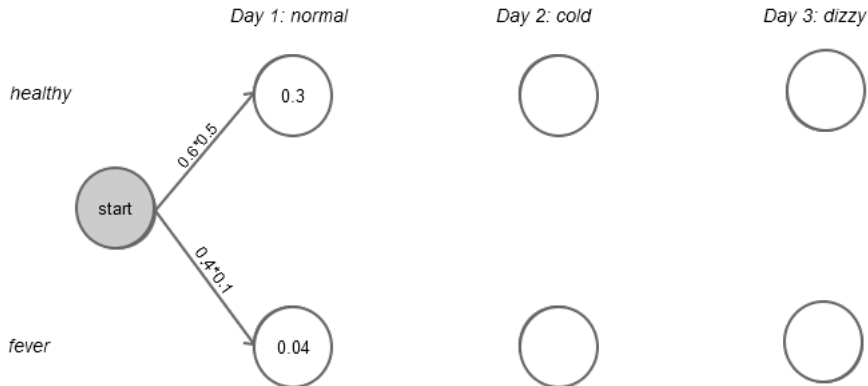
emission probabilities $\sum_k b_{1,k} = 1$

chord detection

hidden markov model: example (WP) 2/2

three observations:

day 1 *normal* → day 2 *cold* → day 3 *dizzy*

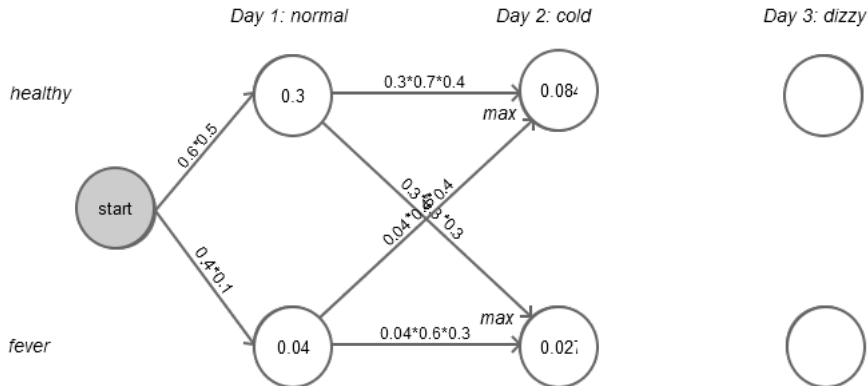


chord detection

hidden markov model: example (WP) 2/2

three observations:

day 1 *normal* → day 2 *cold* → day 3 *dizzy*

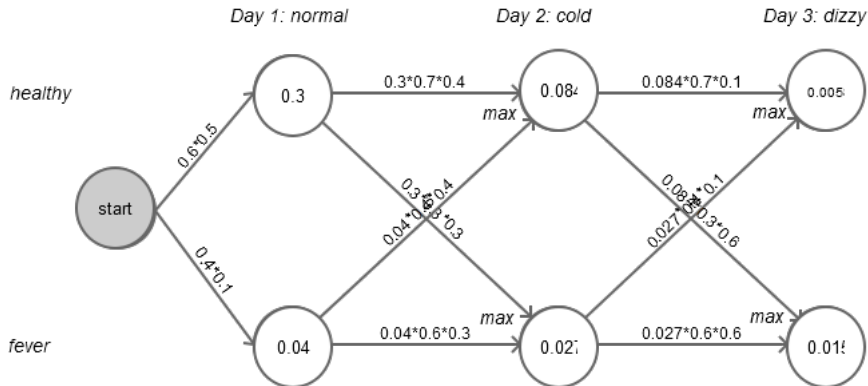


chord detection

hidden markov model: example (WP) 2/2

three observations:

day 1 *normal* → day 2 *cold* → day 3 *dizzy*

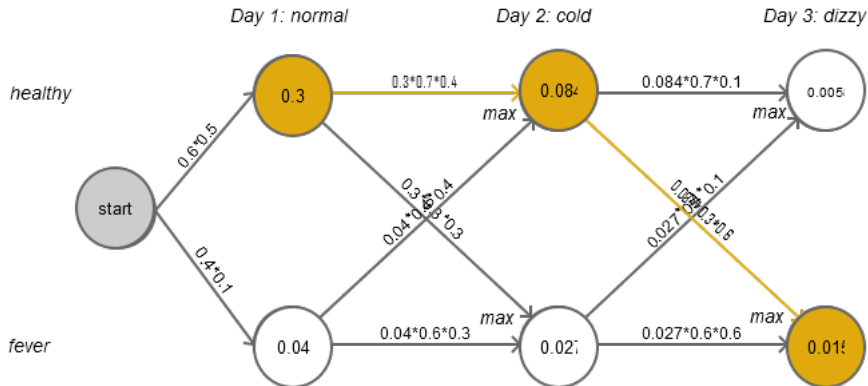


chord detection

hidden markov model: example (WP) 2/2

three observations:

day 1 *normal* → day 2 *cold* → day 3 *dizzy*



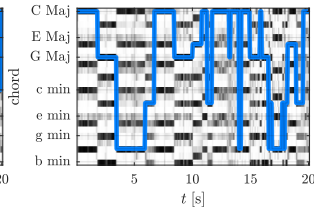
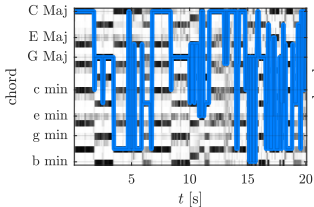
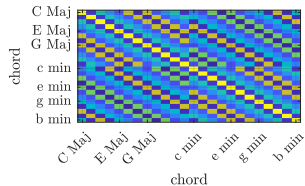
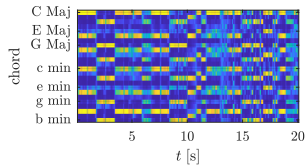
chord detection

HMMs for chord detection

- states \rightarrow chords
- observations \rightarrow pitch chroma
- emission probability \rightarrow trained with pitch chroma
- transition probability \rightarrow trained from dataset
- start probability \rightarrow chord statistics (style dependent?)

chord detection

chord detection example



summary

lecture content

■ chords

- combination of three or more pitches
- usually stacked thirds
- can be inverted

■ chord detection

- processing steps
 - ▶ pitch chroma extraction
 - ▶ template matching
 - ▶ chord transition model

■ Viterbi algorithm

- find globally optimal path through state space
- estimate state sequence with
 - ▶ emission probabilities
 - ▶ transition probabilities

