

Introduction to Audio Content Analysis

module 10.2: audio-to-audio & audio-to-score alignment

alexander lerch

introduction overview



corresponding textbook section

sections 10.2 & 10.3

lecture content

- Audio-to-Audio alignment
 - use cases
 - features
 - distance measures
 - ► typical accuracy
- Audio-to-Score alignment

learning objectives

- elaborate on possible use cases for audio-to-audio alignment
- give examples for features and distance measures for alignment
- discuss differences between audio-to-audio and audio-to-score alignment



introduction overview



corresponding textbook section

sections 10.2 & 10.3

lecture content

- Audio-to-Audio alignment
 - use cases
 - features
 - distance measures
 - ► typical accuracy
- Audio-to-Score alignment

learning objectives

- elaborate on possible use cases for audio-to-audio alignment
- give examples for features and distance measures for alignment
- discuss differences between audio-to-audio and audio-to-score alignment



audio-to-audio alignment introduction



objective

• align two sequences of audio

use cases

- quick browsing for certain parts in recordings
- timing adjustment (backing vocals, loops, . . .)
- automated dubbing
- musicological analysis (relative timing of several performances)

processing steps

- extract suitable features
- compute distance matrix
- compute alignment path

audio-to-audio alignment introduction



objective

align two sequences of audio

use cases

- quick browsing for certain parts in recordings
- timing adjustment (backing vocals, loops, . . .)
- automated dubbing
- musicological analysis (relative timing of several performances)

processing steps

- extract suitable features
- compute distance matrix
- compute alignment path

audio-to-audio alignment introduction



objective

align two sequences of audio

use cases

- quick browsing for certain parts in recordings
- timing adjustment (backing vocals, loops, ...)
- automated dubbing
- musicological analysis (relative timing of several performances)

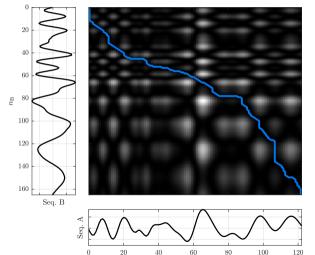
processing steps

- extract suitable features
- compute distance matrix
- compute alignment path

audio-to-audio alignment alignment path computation

Georgia Center for Music Tech Technology

prerequisite:Module 10.1 — DynamicTime Warping



Georgia Center for Music

use case examples

- quick browsing find the same part across files
- ⇒ use pitch based features
- timing adjustment backing vocals to lead vocals
 - ⇒ use *intensity based* features
- automated dubbing same speaker several recordings
 - ⇒ use *intensity based* and *timbre based* features

feature categories

- intensity: energy, onset probability. . . .
- tonal: pitch chroma. . . .
- timbral: MFCCs, spectral shape, . . .

Georgia Center for Music

audio-to-audio alignment features

use case examples

- quick browsing find the same part across files
 - ⇒ use pitch based features
- timing adjustment backing vocals to lead vocals
 - ⇒ use *intensity based* features
- automated dubbing same speaker several recordings
 - ⇒ use *intensity based* and *timbre based* features

feature categories

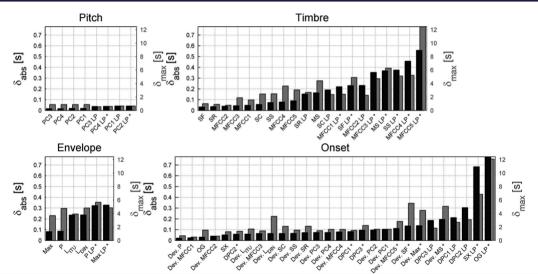
- **intensity**: energy, onset probability, . . .
- tonal: pitch chroma, ...
- timbral: MFCCs, spectral shape, ...

plot from¹

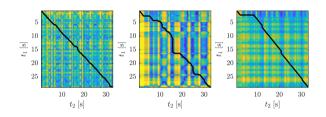
H. Kirchhoff and A. Lerch. "Evaluation of Features for Audio-to-Audio Alignment," Journal of New Music Research, vol. 40, no. 1, pp. 27–41,

audio-to-audio alignment features





audio-to-audio alignment feature-dependency of results



features (left to right): pitch chroma, RMS, MFCCs

Georgia | Center for Music

typical distance measures

$$ullet$$
 Euclidean distance: $d_{
m E}(s) = \sqrt{\sum\limits_{j=0}^{11} \left(
u_{
m e}(j) -
u_{
m t,s}(j)
ight)^2}$

$$ullet$$
 Manhattan distance: $d_{
m M}(s) = \sum\limits_{j=0}^{11} \left|
u_{
m e}(j) -
u_{
m t,s}(j)
ight|$

• Cosine distance:
$$d_{\mathrm{C}}(s) = 1 - \left(\frac{\sum\limits_{j=0}^{11} \nu_{\mathrm{e}}(j) \cdot \nu_{\mathrm{t,s}}(j)}{\sqrt{\sum\limits_{j=0}^{11} \nu_{\mathrm{e}}(j)^2} \sqrt{\cdot \sum\limits_{j=0}^{11} \nu_{\mathrm{t,s}}(j)^2}}\right)$$
• Kullback-Leibler divergence: $d_{\mathrm{KL}}(s) = \sum\limits_{j=0}^{11} \nu_{\mathrm{e}}(j) \cdot \log\left(\frac{\nu_{\mathrm{e}}(j)}{\nu_{\mathrm{t,s}}(j)}\right)$

• Kullback-Leibler divergence:
$$d_{\mathrm{KL}}(s) = \sum\limits_{j=0}^{11}
u_{\mathrm{e}}(j) \cdot \log \left(rac{
u_{\mathrm{e}}(j)}{
u_{\mathrm{t,s}}(j)}
ight)$$

data-driven approach: train classifier with 2-class problem¹

Georgia | Center for Music

typical distance measures

- ullet Euclidean distance: $d_{
 m E}(s) = \sqrt{\sum\limits_{j=0}^{11} \left(
 u_{
 m e}(j)
 u_{
 m t,s}(j)
 ight)^2}$
- ullet Manhattan distance: $d_{
 m M}(s) = \sum\limits_{i=0}^{11} \left|
 u_{
 m e}(j)
 u_{
 m t,s}(j)
 ight|$

• Cosine distance:
$$d_{\mathrm{C}}(s) = 1 - \left(\frac{\sum\limits_{j=0}^{11} \nu_{\mathrm{e}}(j) \cdot \nu_{\mathrm{t,s}}(j)}{\sqrt{\sum\limits_{j=0}^{11} \nu_{\mathrm{e}}(j)^2} \sqrt{\cdot \sum\limits_{j=0}^{11} \nu_{\mathrm{t,s}}(j)^2}} \right)$$

• Kullback-Leibler divergence: $d_{\mathrm{KL}}(s) = \sum\limits_{i=1}^{11} \nu_{\mathrm{e}}(j) \cdot \log\left(\frac{\nu_{\mathrm{e}}(j)}{\nu_{\mathrm{t,s}}(j)}\right)$

data-driven approach: train classifier with 2-class problem¹

Georgia | Center for Music

- typical distance measures
 - ullet Euclidean distance: $d_{
 m E}(s) = \sqrt{\sum\limits_{j=0}^{11} \left(
 u_{
 m e}(j)
 u_{
 m t,s}(j)
 ight)^2}$

 - $\begin{array}{l} \bullet \quad \textit{Manhattan distance:} \quad d_{\mathrm{M}}(s) = \sum\limits_{j=0}^{11} \left| \nu_{\mathrm{e}}(j) \nu_{\mathrm{t,s}}(j) \right| \\ \bullet \quad \textit{Cosine distance:} \quad d_{\mathrm{C}}(s) = 1 \left(\frac{\sum\limits_{j=0}^{11} \nu_{\mathrm{e}}(j) \cdot \nu_{\mathrm{t,s}}(j)}{\sqrt{\sum\limits_{j=0}^{11} \nu_{\mathrm{e}}(j)^2} \sqrt{\cdot \sum\limits_{j=0}^{11} \nu_{\mathrm{t,s}}(j)^2}} \right) \end{array}$
 - Kullback-Leibler divergence: $d_{\mathrm{KL}}(s) = \sum_{i=1}^{11} \nu_{\mathrm{e}}(j) \cdot \log \left(\frac{\nu_{\mathrm{e}}(j)}{\nu_{\mathrm{t,s}}(j)} \right)$
- data-driven approach: train classifier with 2-class problem¹

audio-to-audio alignment compute distance matrix — distance measures

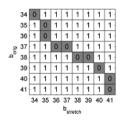
Georgia | Center for Music

- typical distance measures
 - ullet Euclidean distance: $d_{
 m E}(s) = \sqrt{\sum\limits_{j=0}^{11} \left(
 u_{
 m e}(j)
 u_{
 m t,s}(j)
 ight)^2}$
 - ullet Manhattan distance: $d_{
 m M}(s) = \sum\limits_{j=0}^{11} \left|
 u_{
 m e}(j)
 u_{
 m t,s}(j)
 ight|$
 - ullet Cosine distance: $d_{\mathrm{C}}(s)=1-\left(rac{\sum\limits_{j=0}^{11}
 u_{\mathrm{e}}(j)\cdot
 u_{\mathrm{t,s}}(j)}{\sqrt{\sum\limits_{i=0}^{11}
 u_{\mathrm{e}}(j)^2}\sqrt{\cdot\sum\limits_{i=0}^{11}
 u_{\mathrm{t,s}}(j)^2}}
 ight)$
 - Kullback-Leibler divergence: $d_{\mathrm{KL}}(s) = \sum_{i=1}^{11} \nu_{\mathrm{e}}(j) \cdot \log \left(\frac{\nu_{\mathrm{e}}(j)}{\nu_{\mathrm{t,s}}(j)} \right)$
- data-driven approach: train classifier with 2-class problem¹

audio-to-audio alignment compute distance matrix — distance measures

Georgia Center for Music Tech Technology

- typical distance measures
- data-driven approach: train classifier with 2-class problem¹

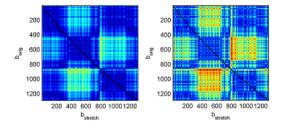


¹H. Kirchhoff and A. Lerch, "Evaluation of Features for Audio-to-Audio Alignment," *Journal of New Music Research*, vol. 40, no. 1, pp. 27–41, 2011. DOI: 10.1080/09298215.2010.529917.

audio-to-audio alignment compute distance matrix — distance measures

Georgia Center for Music Tech Technology

- typical distance measures
- data-driven approach: train classifier with 2-class problem¹

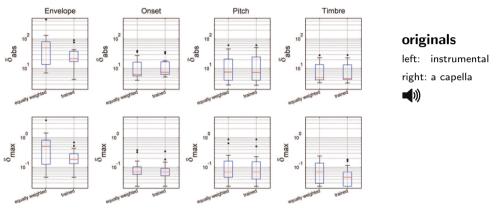


¹H. Kirchhoff and A. Lerch, "Evaluation of Features for Audio-to-Audio Alignment," Journal of New Music Research, vol. 40, no. 1, pp. 27–41,

A2A 000000

audio-to-audio alignment typical results





synced



²H. Kirchhoff and A. Lerch, "Evaluation of Features for Audio-to-Audio Alignment," Journal of New Music Research, vol. 40, no. 1, pp. 27-1, 2011, DOI: 10.1080/09298215.2010.529917.

audio-to-score alignment



objective

• align an audio sequence with a score sequence

use cases

- score viewer
- music education
- retrieve matching score/audio via cost function
- musicological analysis

processing steps

see audio-to-audio alignment

audio-to-score alignment



objective

• align an audio sequence with a score sequence

use cases

- score viewer
- music education
- retrieve matching score/audio via cost function
- musicological analysis

processing steps

see audio-to-audio alignment

audio-to-score alignment



objective

align an audio sequence with a score sequence

use cases

- score viewer
- music education
- retrieve matching score/audio via cost function
- musicological analysis

processing steps

see audio-to-audio alignment

audio-to-score alignment challenges



features from different domains

- score contains no timbre info
- score cannot be expected to contain no loudness info
- score has no clear "time axis"
- \Rightarrow two prototypical for distance/similarity calculation
 - approach 1: convert score into audio-like representation
 - ► MIDI-to-audio
 - use model synthesize
 - approach 2: convert audio into score-like representation
 - audio-to-MIDI
 - pitch chroma
 - event-based segmentation

audio-to-score alignment challenges



- features from different domains
 - score contains no timbre info
 - score cannot be expected to contain no loudness info
 - score has no clear "time axis"
- ⇒ two prototypical for distance/similarity calculation
 - approach 1: convert score into audio-like representation
 - ► MIDI-to-audio
 - use model synthesize
 - approach 2: convert audio into score-like representation
 - audio-to-MIDI
 - pitch chroma
 - event-based segmentation

goal: compare two sequences of time stamps

- evaluation challenges
 - pauses/rests, and long held notes: what is the reference path?
 - noise in the begin and end of the recording
 - data not easily available
 - synthesized
 - piano sensors
 - pseudo-ground truth with time stretching
 - automatic annotation with quality assurance

- goal: compare two sequences of time stamps
- evaluation challenges
 - pauses/rests, and long held notes: what is the reference path?
 - noise in the begin and end of the recording
 - data not easily available
 - synthesized
 - piano sensors
 - pseudo-ground truth with time stretching
 - automatic annotation with quality assurance

alignment evaluation metrics



■ audio-to-score

- missed note rate
- misalign rate
- piece completion
- average absolute deviation
- variance of deviation

■ audio-to-audio

- mean deviation
- mean absolute deviation
- maximum deviation
- relative number of matching path points

summary lecture content



■ audio-to-audio alignment

- 1 extract features
- 2 create distance matrix with suitable distance measure
- 3 use DTW to find alignment path
- 4 (use time-stretching to actually align the sequences)

audio-to-score alignment

- 1 extract usually pitch-based features
- 2 distance measure
- 3 use DTW, HMM, etc to extract alignment path

