Introduction to Audio Content Analysis

Module 10.2: Audio-to-Audio & Audio-to-Score Alignment

alexander lerch



introduction overview

corresponding textbook section

Section 10.2

Section 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

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Section 10.3

■ lecture content

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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

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use cases

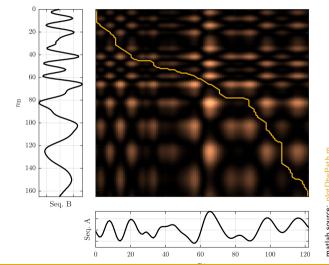
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audio-to-audio alignment alignment path computation

prerequisite:Module 10.1 — DynamicTime Warping



■ 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

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

■ 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

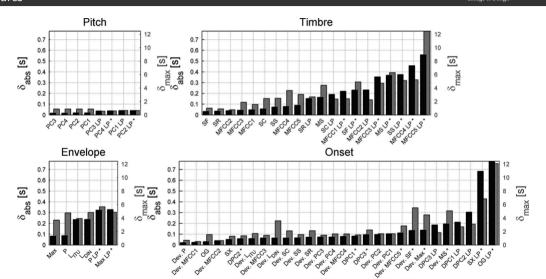
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audio-to-audio alignment



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typical distance measures

- ullet Euclidean distance: $d_{
 m E}({\sf s}) = \sqrt{\sum\limits_{j=0}^{11} ig(
 u_{
 m e}(j)
 u_{
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- ullet Manhattan distance: $d_{
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- 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: $d_{\mathrm{KL}}(s) = \sum\limits_{j=0}^{11} \nu_{\mathrm{e}}(j) \cdot \log\left(\frac{\nu_{\mathrm{e}}(j)}{\nu_{\mathrm{t,s}}(j)}\right)$

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

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

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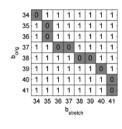
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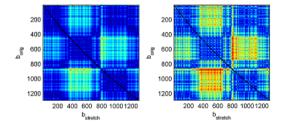
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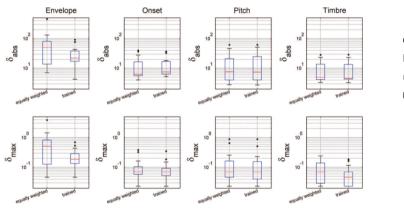
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audio-to-audio alignment typical results





originals synced

left: instrumental right: a capella





²H. Kirchhoff and A. Lerch, "Evaluation of Features for Audio-to-Audio Alignment," *Journal of New Music Research*, vol. 40, no. 1, pp. 27-11, 2011, pp. 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

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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

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■ 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



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alignment evaluation metrics

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audio-to-score

- missed not 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

■ 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

