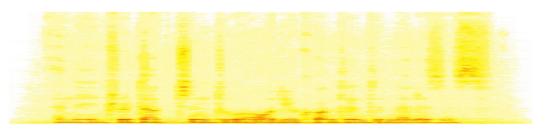
Module 7.1: Audio-to-Audio & Audio-to-Score Alignment

alexander lerch





introduction

overview



corresponding textbook section

Chapter 7: Alignment (pp. 146–150)

- 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



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corresponding textbook section

Chapter 7: Alignment (pp. 146-150)

lecture content

- Audio-to-Audio alignment
 - use cases
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audio-to-audio alignment introduction



objective

align two sequences of audio

a lise cases

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

processing steps

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

audio-to-audio alignment introduction



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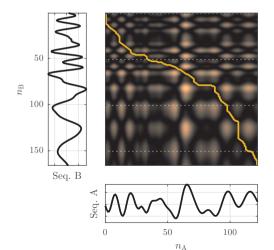
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audio-to-audio alignment alignment path computation

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→ prerequisite: Module 7.0—Dynamic Time 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,

overview

use case examples

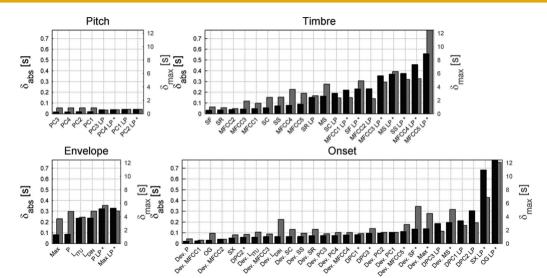
- quick browsing find the same part across files
 - ⇒ use pitch based features
- **timing adjustment** backing vocals to lead vocals
 - ⇒ use *intensity based* features
- automated dubbing same speaker several recordings
 - ⇒ use *intensity based* and *timbre based* features

feature categories

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

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compute distance matrix — distance measures

- typical distance measures
 - ullet Euclidean distance: $d_{
 m E}(s) = \sqrt{\sum\limits_{j=0}^{11} ig(
 u_{
 m e}(j)
 u_{
 m t,s}(j)ig)^2}$
 - 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_{i=0}^{11}
 u_{\mathrm{e}}(j) \cdot \log\left(rac{
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- data-driven approach: train classifier with 2-class problem

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- compute distance matrix distance measures
 - typical distance measures

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

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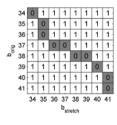
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audio-to-audio alignment

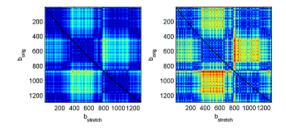
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- compute distance matrix distance measures
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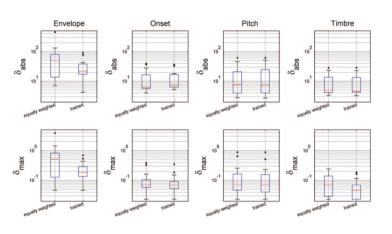
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audio-to-audio alignment typical results





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. 27–41,

audio-to-score alignment



objective

align an audio sequence with a score sequence

use cases

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

processing steps

see audio-to-audio alignment

audio-to-score alignment



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audio-to-score alignment challenges



- features from **different domains** (no timbre and proper loudness information in the score)
 - approach 1: convert score into audio-like representation
 - MIDI-to-audio
 - use model for harmonics and ADSR
 - approach 2: convert audio into score-like representation
 - audio-to-MIDI
 - pitch chroma
 - event-based segmentation
- pauses and rests
 - DTW algorithm has no graceful way of dealing with pauses

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audio-to-audio alignment

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

audio-to-score alignment

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

