Introduction to Audio Content Analysis

Module 10.1: Alignment — Dynamic Time Warping

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corresponding textbook section

Section 10.1

- **lecture content**
  - Dynamic Time Warping (DTW):
    synchronization of two sequences with similar content

- **learning objectives**
  - explain the standard DTW algorithm
  - discuss disadvantages of and modifications to the standard DTW algorithm
  - implement DTW

corresponding textbook section

Section 10.1

- **lecture content**
  - Dynamic Time Warping (DTW):
    synchronization of two sequences with similar content

- **learning objectives**
  - explain the standard DTW algorithm
  - discuss disadvantages of and modifications to the standard DTW algorithm
  - implement DTW

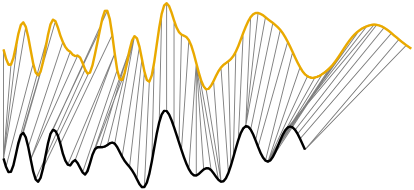
- **synchronize two sequences**
  - *similar* musical content
  - *different* tempo and timing

$$A(n_\mathrm{A}) \quad n_\mathrm{A} \in [0; \mathcal{N}_\mathrm{A} - 1]$$

$$B(n_\mathrm{B}) \quad n_\mathrm{B} \in [0; \mathcal{N}_\mathrm{B} - 1]$$

$\Rightarrow$ find alignment path

- minimizing pairwise distance between sequences
- covering whole sequence
- moving only forward in time



matlab source: plotSequenceAlignment.m

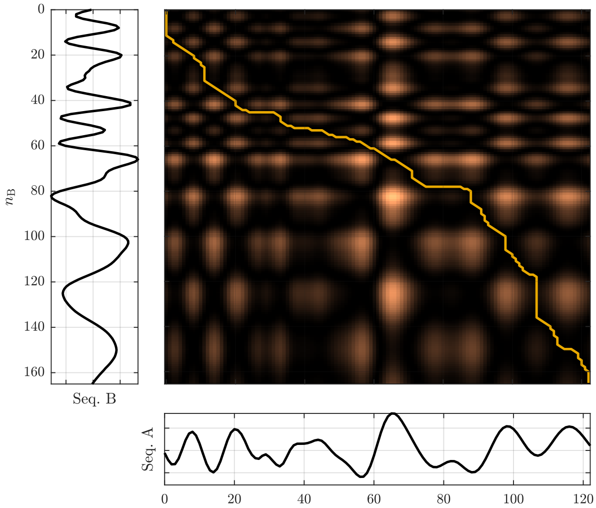
dynamic time warping
overview

- dynamic programming technique
- time is warped non-linearly to match sequences
- finds optimal match between two sequences given a cost function
- the overall cost indicates the overall distance between the sequences

dynamic time warping

processing steps

1. extract suitable **features**
   $\Rightarrow$ two series of feature vectors
2. compute **distance matrix** $\boldsymbol{D}_{\mathrm{AB}}(n_{\mathrm{A}}, n_{\mathrm{B}})$
3. compute **alignment path** $\boldsymbol{p}(n_{\mathrm{P}})$ with $n_{\mathrm{P}} \in [0; \mathcal{N}_{\mathrm{P}} - 1]$
   $\Rightarrow$ minimal *overall* distance
4. (align sequences using dynamic time stretching)

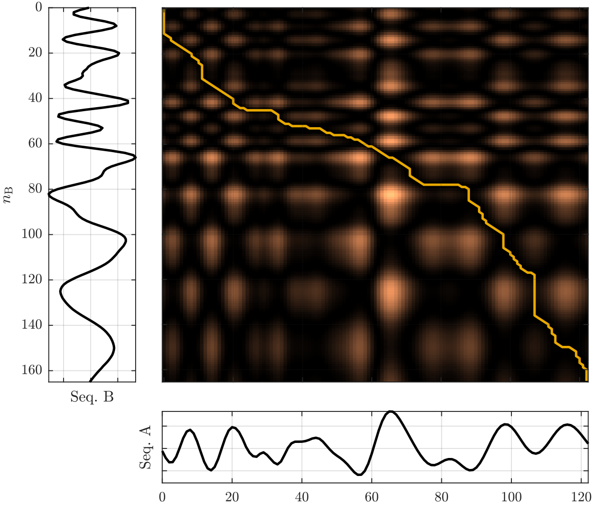


matlab source: plotDtwPath.m

dynamic time warping

distance matrix computation

- given 2 sequences of vectors, compute the distance between all pairs of observations
- compute distance matrix $\boldsymbol{D}_{\mathrm{AB}}(n_{\mathrm{A}}, n_{\mathrm{B}})$
  - example $\boldsymbol{D}_{\mathrm{AB}}(1, n_{\mathrm{B}})$ is the distance of the first vector in Seq. A to all vectors in Seq. B



matlab source: plotDtwPath.m

dynamic time warping

path properties 1/2

- **boundaries**: covers both A, B from beginning to end

$$\begin{aligned} \boldsymbol{p}(0) &= [0, 0] \\ \boldsymbol{p}(\mathcal{N}_\mathrm{P} - 1) &= [\mathcal{N}_\mathrm{A} - 1, \mathcal{N}_\mathrm{B} - 1] \end{aligned}$$

- **causality**: only forward movement

$$n_\mathrm{A}\big|_{\boldsymbol{p}(n_\mathrm{P})} \leq n_\mathrm{A}\big|_{\boldsymbol{p}(n_\mathrm{P}+1)}$$
$$n_\mathrm{B}\big|_{\boldsymbol{p}(n_\mathrm{P})} \leq n_\mathrm{B}\big|_{\boldsymbol{p}(n_\mathrm{P}+1)}$$

- **continuity**: no jumps

$$n_\mathrm{A}\big|_{\boldsymbol{p}(n_\mathrm{P}+1)} \leq (n_\mathrm{A} + 1)\big|_{\boldsymbol{p}(n_\mathrm{P})}$$
$$n_\mathrm{B}\big|_{\boldsymbol{p}(n_\mathrm{P}+1)} \leq (n_\mathrm{B} + 1)\big|_{\boldsymbol{p}(n_\mathrm{P})}$$

dynamic time warping
path properties 1/2

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dynamic time warping

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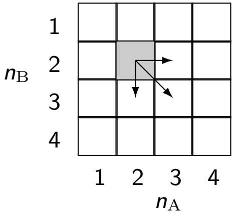
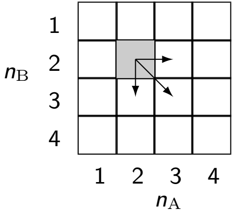
alignment
path properties 2/2



what is the minimum/maximum path length

alignment

path properties 2/2



what is the minimum/maximum path length

$$\mathcal{N}_{\mathrm{P,min}} = \max(\mathcal{N}_{\mathrm{A}}, \mathcal{N}_{\mathrm{B}})$$

$$\mathcal{N}_{\mathrm{P,max}} = \mathcal{N}_{\mathrm{A}} + \mathcal{N}_{\mathrm{B}} - 2$$

- every path has an *overall cost*

$$\mathfrak{C}_{\mathrm{AB}}(j) = \sum_{n_\mathrm{P}=0}^{\mathcal{N}_\mathrm{P}-1} \boldsymbol{D}\left(\boldsymbol{p}_j(n_\mathrm{P})\right)$$

- *optimal* path minimizes the overall cost

$$\mathfrak{C}_{\mathrm{AB},min} = \min_{\forall j}\left(\mathfrak{C}_{\mathrm{AB}}(j)\right)$$

$$j_{\mathrm{opt}} = \operatorname*{argmin}_{\forall j}\left(\mathfrak{C}_{\mathrm{AB}}(j)\right)$$

$\Rightarrow$ stay in the 'valleys' of distance matrix

how to determine the optimal path

- every path has an *overall cost*

$$\mathfrak{C}_{\mathrm{AB}}(j) = \sum_{n_{\mathrm{P}}=0}^{\mathcal{N}_{\mathrm{P}}-1} \boldsymbol{D}\left(\boldsymbol{p}_j(n_{\mathrm{P}})\right)$$

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$\Rightarrow$ stay in the 'valleys' of distance matrix

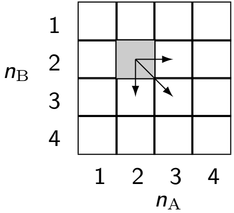
how to determine the optimal path

accumulated cost: *cost matrix*

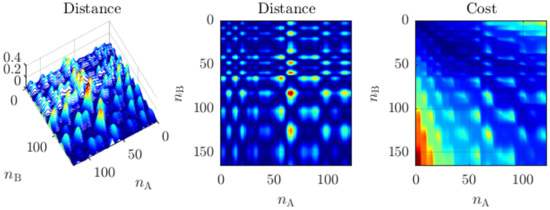
$$\mathbf{C}_{\mathrm{AB}}(n_\mathrm{A}, n_\mathrm{B}) = \mathbf{D}_{\mathrm{AB}}(n_\mathrm{A}, n_\mathrm{B}) + \min \begin{cases} \mathbf{C}_{\mathrm{AB}}(n_\mathrm{A} - 1, n_\mathrm{B} - 1) \\ \mathbf{C}_{\mathrm{AB}}(n_\mathrm{A} - 1, n_\mathrm{B}) \\ \mathbf{C}_{\mathrm{AB}}(n_\mathrm{A}, n_\mathrm{B} - 1) \end{cases}$$

- initialization

$$\mathbf{C}_{\mathrm{AB}}(0, 0) = \mathbf{D}_{\mathrm{AB}}(0, 0)$$



alignment
DTW: accumulated cost 2/2



matlab source: plotDtwCost.m

alignment
DTW: algorithm description 1/2

- **initialization**:

$$C_{\mathrm{AB}}(0,0) = D_{\mathrm{AB}}(0,0),\ C_{\mathrm{AB}}(n_{\mathrm{A}},-1) = \infty,\ C_{\mathrm{AB}}(-1,n_{\mathrm{B}}) = \infty$$

- **recursion**:

$$\begin{aligned}
C_{\mathrm{AB}}(n_{\mathrm{A}},n_{\mathrm{B}}) &= D_{\mathrm{AB}}(n_{\mathrm{A}},n_{\mathrm{B}}) + \min\begin{cases} C_{\mathrm{AB}}(n_{\mathrm{A}}-1,n_{\mathrm{B}}-1) \\ C_{\mathrm{AB}}(n_{\mathrm{A}}-1,n_{\mathrm{B}}) \\ C_{\mathrm{AB}}(n_{\mathrm{A}},n_{\mathrm{B}}-1) \end{cases} \\
j &= \operatorname{argmin}\begin{cases} C_{\mathrm{AB}}(n_{\mathrm{A}}-1,n_{\mathrm{B}}-1) \\ C_{\mathrm{AB}}(n_{\mathrm{A}}-1,n_{\mathrm{B}}) \\ C_{\mathrm{AB}}(n_{\mathrm{A}},n_{\mathrm{B}}-1) \end{cases} \\
\Delta p(n_{\mathrm{A}},n_{\mathrm{B}}) &= \begin{cases} [-1,-1] & \text{if } j=0 \\ [-1,0] & \text{if } j=1 \\ [0,-1] & \text{if } j=2 \end{cases}
\end{aligned}$$

alignment
DTW: algorithm description 1/2

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\end{aligned}$$

alignment
DTW: algorithm description 2/2

- **termination**:

$$n_\mathrm{A} = \mathcal{N}_\mathrm{A} - 1 \wedge n_\mathrm{B} = \mathcal{N}_\mathrm{B} - 1$$

- **path backtracking**:

$$\boldsymbol{p}(n_\mathrm{P}) = \boldsymbol{p}(n_\mathrm{P}+1) + \Delta\boldsymbol{p}\big(\boldsymbol{p}(n_\mathrm{P}+1)\big), \;\; n_\mathrm{P} = \mathcal{N}_\mathrm{P}-2, \mathcal{N}_\mathrm{P}-3, \ldots, 0$$

alignment
DTW: algorithm description 2/2

- **termination**:

$$n_\mathrm{A} = \mathcal{N}_\mathrm{A} - 1 \wedge n_\mathrm{B} = \mathcal{N}_\mathrm{B} - 1$$

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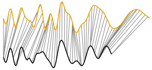
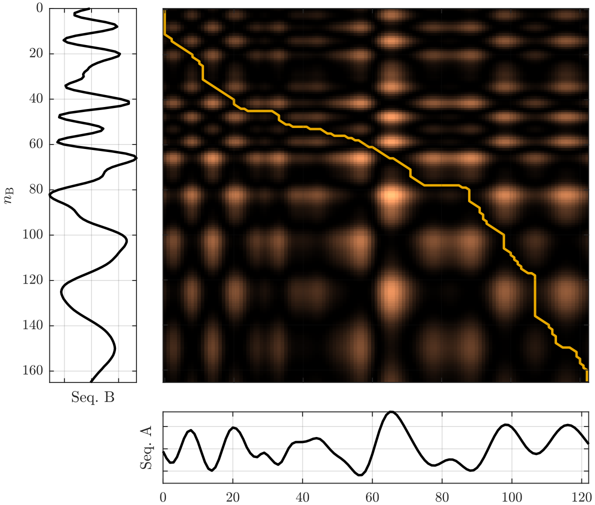
$$\boldsymbol{p}(n_\mathrm{P}) = \boldsymbol{p}(n_\mathrm{P}+1) + \Delta\boldsymbol{p}\big(\boldsymbol{p}(n_\mathrm{P}+1)\big),\ n_\mathrm{P} = \mathcal{N}_\mathrm{P} - 2, \mathcal{N}_\mathrm{P} - 3, \ldots, 0$$

dynamic time warping

DTW: example





matlab source: plotDtwPath.m

$$A = [1,\ 2,\ 3,\ 0],$$
$$B = [1,\ 0,\ 2,\ 3,\ 1],$$

compute distance matrix, cost matrix, and DTW path

$$\begin{aligned} A &= [1,\ 2,\ 3,\ 0], \\ B &= [1,\ 0,\ 2,\ 3,\ 1], \end{aligned}$$

compute distance matrix, cost matrix, and DTW path

$$\boldsymbol{D}_{\mathrm{AB}} = \begin{bmatrix} 0 & 1 & 2 & 1 \\ 1 & 2 & 3 & 0 \\ 1 & 0 & 1 & 2 \\ 2 & 1 & 0 & 3 \\ 0 & 1 & 2 & 1 \end{bmatrix}$$

$$
\begin{aligned}
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\qquad
\boldsymbol{C}_{\mathrm{AB}} = \begin{bmatrix} 0 & \leftarrow 1 & \leftarrow 3 & \leftarrow 4 \\ \uparrow 1 & \nwarrow 2 & \nwarrow 4 & \nwarrow 3 \\ \uparrow 2 & \nwarrow 1 & \leftarrow 2 & \leftarrow 4 \\ \uparrow 4 & \uparrow 2 & \nwarrow 1 & \leftarrow 4 \\ \uparrow 4 & \uparrow 3 & \uparrow 3 & \nwarrow 2 \end{bmatrix}
$$

dynamic time warping

example

$$A = [1,\ 2,\ 3,\ 0],$$
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compute distance matrix, cost matrix, and DTW path

$$\boldsymbol{D}_{\mathrm{AB}} = \begin{bmatrix} 0 & 1 & 2 & 1 \\ 1 & 2 & 3 & 0 \\ 1 & 0 & 1 & 2 \\ 2 & 1 & 0 & 3 \\ 0 & 1 & 2 & 1 \end{bmatrix} \qquad \boldsymbol{C}_{\mathrm{AB}} = \begin{bmatrix} 0 & \leftarrow 1 & \leftarrow 3 & \leftarrow 4 \\ \uparrow 1 & \nwarrow 2 & \nwarrow 4 & \nwarrow 3 \\ \uparrow 2 & \nwarrow 1 & \leftarrow 2 & \leftarrow 4 \\ \uparrow 4 & \uparrow 2 & \nwarrow 1 & \leftarrow 4 \\ \uparrow 4 & \uparrow 3 & \uparrow 3 & \nwarrow 2 \end{bmatrix}$$

- transition weights: favor specific path directions

$$\mathbf{C}_{\mathrm{AB}}(n_\mathrm{A}, n_\mathrm{B}) = \min \begin{cases} \mathbf{C}_{\mathrm{AB}}(n_\mathrm{A}-1, n_\mathrm{B}-1) & + \quad \lambda_\mathrm{d} \cdot \mathbf{D}_{\mathrm{AB}}(n_\mathrm{A}, n_\mathrm{B}) \\ \mathbf{C}_{\mathrm{AB}}(n_\mathrm{A}-1, n_\mathrm{B}) & + \quad \lambda_\mathrm{v} \cdot \mathbf{D}_{\mathrm{AB}}(n_\mathrm{A}, n_\mathrm{B}) \\ \mathbf{C}_{\mathrm{AB}}(n_\mathrm{A}, n_\mathrm{B}-1) & + \quad \lambda_\mathrm{h} \cdot \mathbf{D}_{\mathrm{AB}}(n_\mathrm{A}, n_\mathrm{B}) \end{cases}$$

- step types

- transition weights: favor specific path directions

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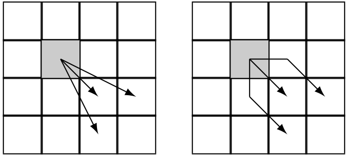

dynamic time warping

optimization

- **challenge**: distance matrix dimensions $\mathcal{N}_\mathrm{A} \cdot \mathcal{N}_\mathrm{B}$

$\Rightarrow$ DTW *inefficient* for long sequences

- high memory requirements
- large number of operations

optimizations:

1. maximum time and tempo deviation
2. sliding window
3. multi-scale DTW (several downsampled iterations)

dynamic time warping

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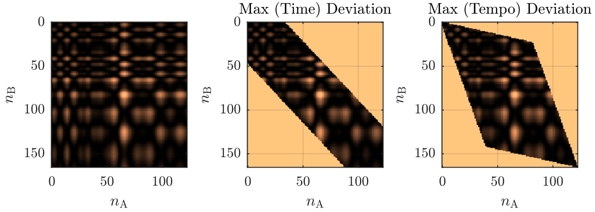

matlab source: plotDtwConstraints.m

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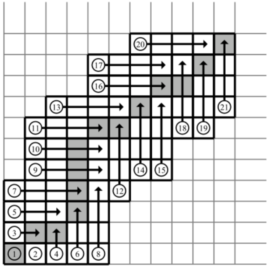

1

[1] S. Dixon and G. Widmer, "MATCH: A Music Alignment Tool Chest," in *Proceedings of the 6th International Conference on Music Information Retrieval (ISMIR)*, London, Sep. 2005.

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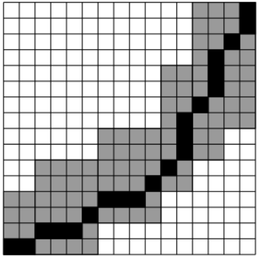

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1

[1] M. Müller, H. Mattes, and F. Kurth, "An Efficient Multiscale Approach to Audio Synchronization," in *Proceedings of the International Society for Music Information Retrieval Conference (ISMIR)*, Victoria, 2006.

dynamic time warping
DTW vs. Viterbi

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similarities and differences of DTW and the Viterbi algorithm

similarities and differences of DTW and the Viterbi algorithm

- **commonalities**
  - find path through matrix
  - maximizes overall probability/minimizes overall cost
  - based on dynamic programming principles
- **differences**
  - DTW has more constraints: start/end in corner, move only to neighbor
  - DTW is not usually parametrized by training data (transition probs, construction of distance/emission prob matrix)
  - Viterbi path length is predefined, DTW path length is not

summary
lecture content

- **dynamic time warping**
  - find globally optimal alignment path between two sequences

- **processing steps**
  1. compute distance matrix
  2. compute cost matrix
  3. back-track path