

Biometrics (CSE 40537/60537)

Lecture 6: Handwritten signatures recognition

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Fall 2014
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Lecture 6: Handwritten signatures recognition

What is a biometric handwritten signature?

Signature data capture

Signature data pre-processing

Feature extraction

Comparison of signatures

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Comparison of signatures

“Signature” by the American Heritage Dictionary

1. “One’s name as written by oneself”, or
2. “The act of signing one’s name”, or
3. “A distinctive mark, characteristic, or sound indicating identity”

Off-line vs. on-line signatures

1. Off-line signatures

- image on the paper, equivalent to a set of points on a plane:

$$S = \{(x, y) : x = x(t), y = y(t), t \in T\}$$

- order of signature points **is not registered**

Off-line vs. on-line signatures

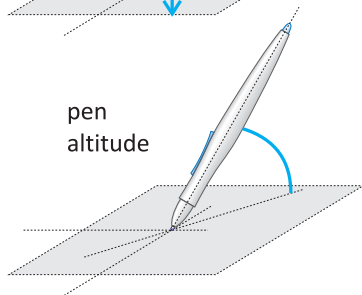
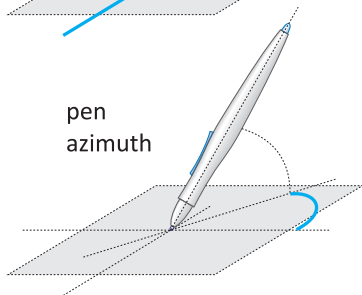
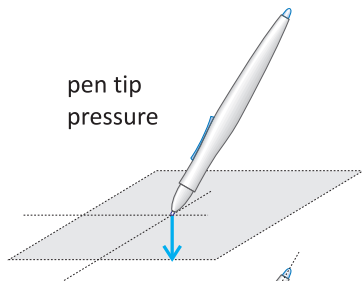
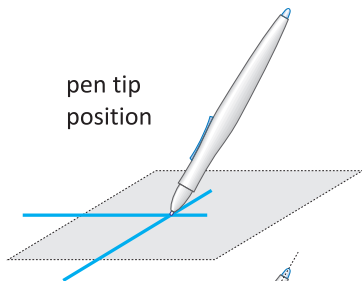
2. On-line signatures

- recording of the signing **process**
- observation of the complex, **dynamic system output** during time T of making the signature

$$s = s(t), t \in T$$

- various signature *components* can be used (i.e. the dimensionality of s varies), depending on the hardware capabilities; typical combinations:
 - 2D: position
 - 3D: position + pen tip pressure
 - 5D: position + pen tip pressure + pen orientation angles

Typical signature components



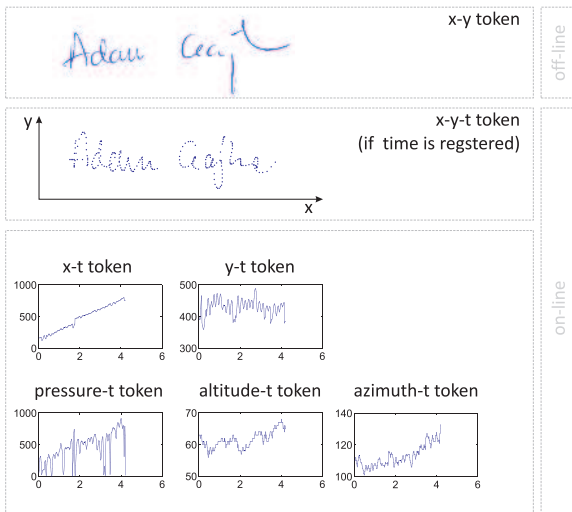
Signature vs. signature token

1. **Signature**: an abstract class of all possible signature tokens of a single person
 - examples of **different** signatures: initials, first and last name, just last name
2. **Signature token**: a particular instance of the signature
 - example: a curve in \mathbb{R}^6 when all five signature components are used (pen tip position, pen tip pressure and pen angles)

Signature vs. signature token

3. **Signature token graph**: any projection of the signature token onto a subspace formed by selected signature components
 - example: **x-y-t token** – projection of the token onto the position and time subspace
 - example: **p-t token** – a graph presenting the pen tip pressure as a function of time
 - example: **x-y token** – projection of the token onto a position plane (e.g. the paper); **no time-related information in x-y token**

Signature tokens



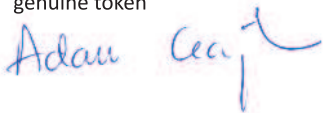
Signature forgeries

A – a genuine person, B – an attacker

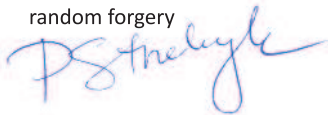
1. Random forgeries

- B has no information about a signature of A
- in practice: a different signature used in a forgery

genuine token

A handwritten signature in blue ink that reads "Adam Czajka". The signature is fluid and cursive, with a distinct loop at the end of the last name.

random forgery

A handwritten signature in blue ink that is a random forgery of the genuine signature. It appears as "PS Czajka" with a different, less fluid cursive style.

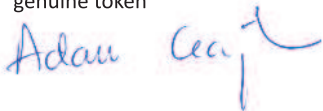
Signature forgeries

A – a genuine person, B – an attacker

2. Simple forgeries

- B knows elements of the signature of A (e.g. first name, or last name, or both)

genuine token

A handwritten signature in blue ink that reads "Adam Czajka". The letters are connected and fluid, with a distinct cursive style.

simple forgery

A handwritten signature in blue ink that reads "Adam Czajka". The letters are more blocky and less connected than the genuine token, appearing as a copy of the first name and last name.

random forgery

A handwritten signature in blue ink that reads "PS trelyk". The letters are highly stylized and do not match the original name, representing a random forgery.

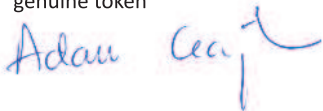
Signature forgeries

A – a genuine person, B – an attacker

3. Skilled forgeries

- B has an access to signature tokens made by A for training
- B can observe signature tokens of A when making a forgery
- B can observe how A makes the signature
- B can copy of A's signature token (carbon copy)

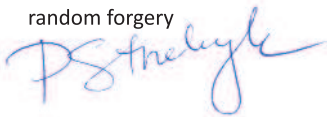
genuine token



simple forgery



random forgery



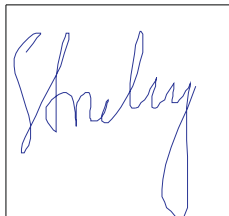
skilled forgery



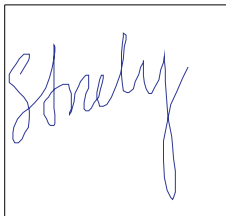
Signature forgeries

What we can see in off-line and on-line tokens?

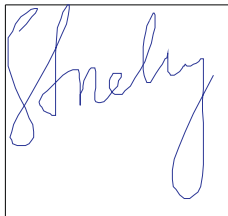
token 1



token 2

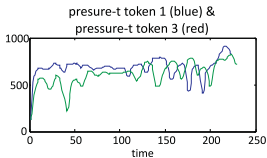
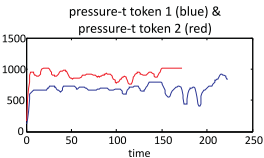
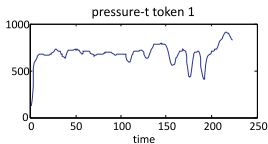
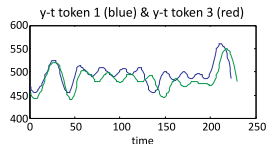
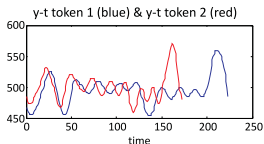
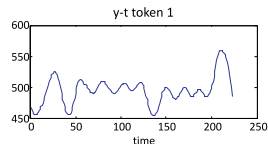
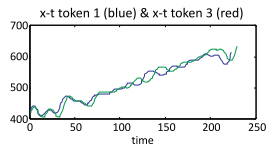
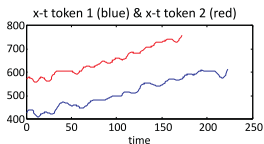
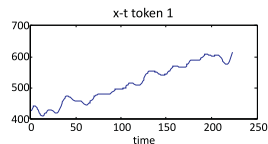


token 3



Signature forgeries

What we can see in off-line and on-line tokens?



Lecture 6: Handwritten signatures recognition

What is a biometric handwritten signature?

Signature data capture

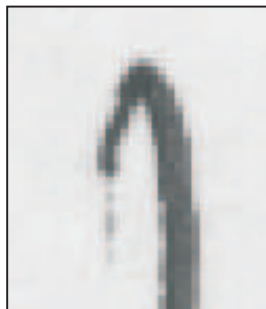
Signature data pre-processing

Feature extraction

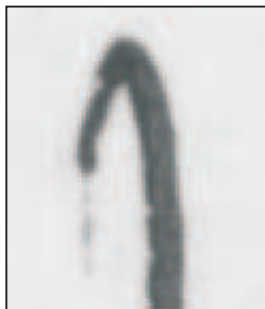
Comparison of signatures

Off-line signatures

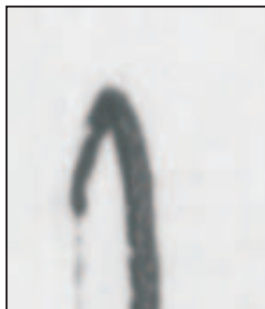
Scanning



300 dpi



600 dpi



1200 dpi

Scanning resolution impacts the recognition reliability.

On-line signatures

1. Use of general-purpose graphical tablets

- signature points registered in order as they appear (typical sampling rate: 100-200 Hz)
- allow to register other components apart from position (e.g. 2048 levels of the pen tip pressure)
- can measure the pen tip position when pen does not touch the tablet (even up to 2 cm above the tablet surface)



On-line signatures

2. Use of specialized biometric tablets

- implement additional elements important in biometric applications (e.g. embedded LCD panels)
- secure data transmission (cryptography)
- size adequate to biometric applications (signature does not require large tablets)
- good developer tools available (e.g. Software Development Kits for popular programming languages)



WACOM



Motion Touch



Topaz Systems

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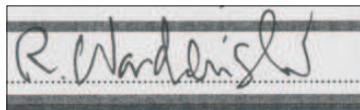
Off-line signatures

Segmentation

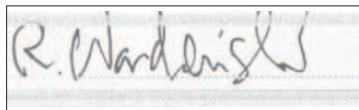
1. Signature extraction

- detection and localization (a)
- noise and background removal (b)
- depending on the matching algorithm:
generation of the binary (c) and skeletal (d) images

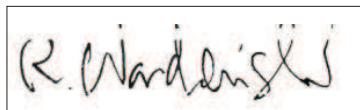
a)



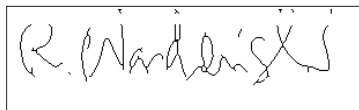
b)



c)



d)



Off-line signatures

Segmentation

2. Division into segments

- **homogenous**: use of a fixed mesh, e.g. rectangular or radial
 - simple but insensitive to signature deformations
 - requires careful alignment of signatures prior processing



Adam Czajka

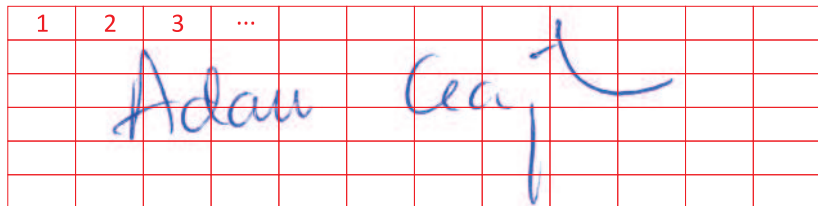
The image shows two handwritten signatures, 'Adam' and 'Czajka', in blue ink. Each signature is enclosed in a semi-transparent red rectangular bounding box. The 'Adam' signature is on the left, and the 'Czajka' signature is on the right. The 'Czajka' signature is more complex, with a long vertical stroke and a large loop at the top right.

Off-line signatures

Segmentation

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 - simple but insensitive to signature deformations
 - requires careful alignment of signatures prior processing

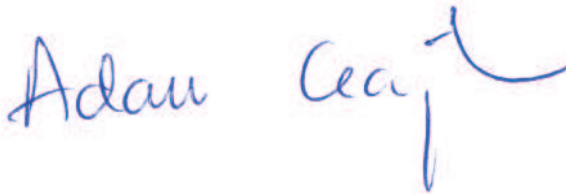


Off-line signatures

Segmentation

2. Division into segments

- **heterogeneous**: finding coherent signature elements (in a sense of selected quality metric), e.g. separate strokes, segments divided by moments when pen does not touch the paper, etc.



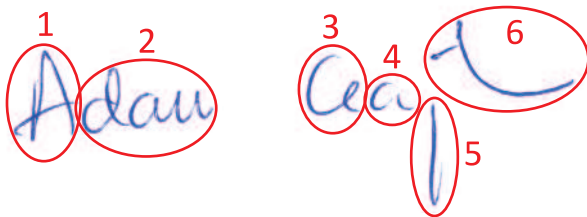
Adam Czajka

Off-line signatures

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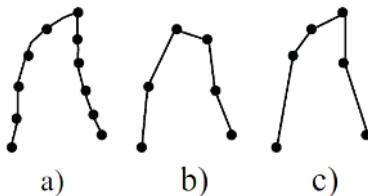


On-line signatures

Segmentation

1. Re-sampling

- **homogeneous**: skipping every k -th point (b)
- **heterogeneous**: skipping points with low curvature index (c)

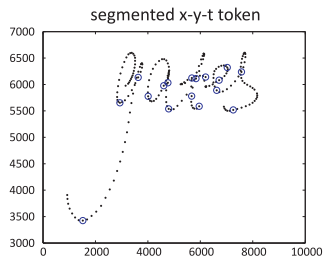
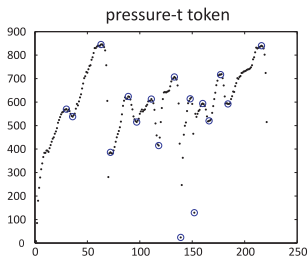


On-line signatures

Segmentation

2. Division into segments

- use of **static information**: pen-up moments, extreme points of single components (popular for the pen tip pressure)
- use of **dynamic information**: extreme points of the velocity or acceleration of the signature components



Example on-line signature segmentation using pen pressure information.
Sample originates from SVC 2004 dataset.

Lecture 6: Handwritten signatures recognition

What is a biometric handwritten signature?

Signature data capture

Signature data pre-processing

Feature extraction

Comparison of signatures

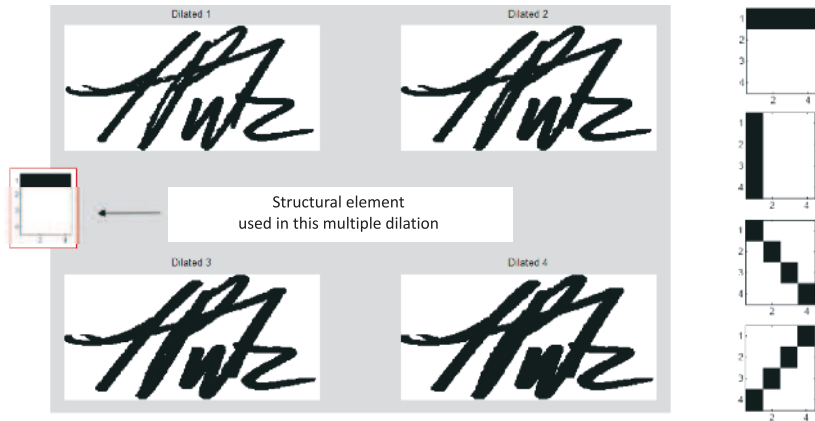
Off-line signatures

1. Global features

- geometrical properties of the signature silhouette
- number of loops
- number of intersections
- number of segments
- average line thickness
(should correspond to the pen tip pressure)
- properties of morphologically altered signature (e.g. multiple dilation with different structural elements): area, direction

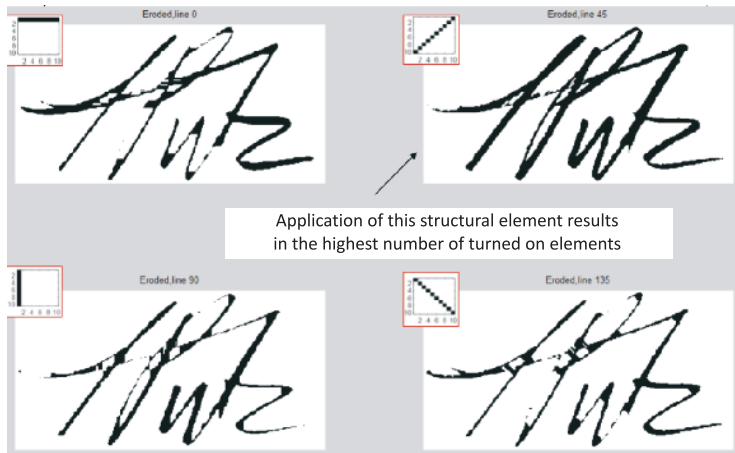
Off-line signatures

Example: multiple dilation with different structural elements



Off-line signatures

Example: multiple erosion to assess the signature direction



Off-line signatures

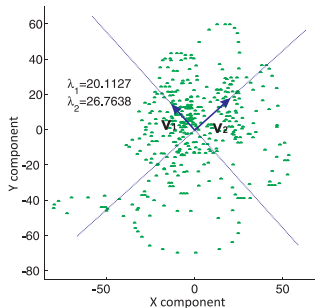
2. Local features

- selected global features (presented in point 1) but calculated within each signature segment
- local texture descriptors, e.g. LBP, Gabor-based features

On-line signatures

Global features [Pacut, Czajka, 2001]

1. Statistical moments



- For single components: mean (first raw moment), variance (second central moment), skewness (third central moment), kurtosis (fourth central moment)
- Mixed central moments, e.g. eigenvalues and eigenvectors of the covariance matrix

On-line signatures

Global features [Pacut, Czajka, 2001]

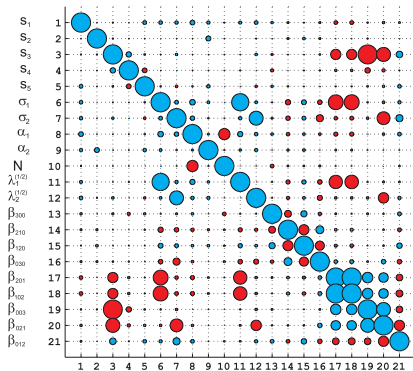
2. Length of the signature (number of points):
one of the most important features (!)
3. Linear trends of single components
4. Velocity and acceleration of the pen
5. Wavelet features and zero-crossing points after filtering of the signature components (building a 'signature code')

On-line signatures

Selection of global features

1. Elimination of **highly correlated features**
2. Selection of **most individual features** (e.g. use of Fisher ratio)

On the right: s – mean, σ – standard deviation, α – linear trend coefficient, β – third central moments, λ – eigenvalues of the x - y covariance matrix, N – length of the signature



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Comparison of signatures

Signature clustering in the space of global features

1. 'Visible' features

- **easy to be forged** by observing off-line signatures (i.e. x-y tokens on the paper)
- examples: mean and standard deviations of the position components (x,y)

2. 'Hidden' features

- **hard of impossible to be forged** when only the off-line signatures can be observed
- examples: velocity and acceleration of the pen (calculated for x, y or pressure), mean pen altitude, mean pen azimuth

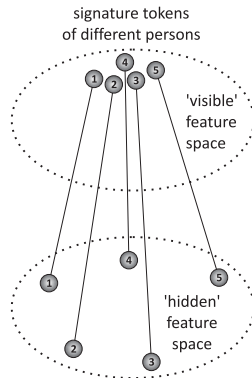
Signature clustering in the space of global features

3. Clustering in 'visible' feature space

- allows for grouping 'similar' tokens (in a sense of the image on a paper)

4. Classification in 'hidden' feature space

- allows for building classifiers that are robust for skilled forgeries



Classification of signatures

Popular approaches

1. Neural classifiers

- multilayer perceptron
- radial basis neural networks
- decision based on the winning neuron ('winner takes all')
- modification: use of the second-winning neuron output

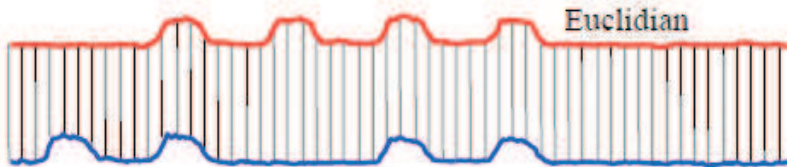
2. Support Vector Machine (SVM)

3. Classification variants

- single classifier for each signature
(appropriate approach in verification tasks)
- common classifier for clustered signatures
(e.g. clustering based on 'visible features')
- common classifier for all signatures
(appropriate approach in identification tasks)

Dynamic Time Warping

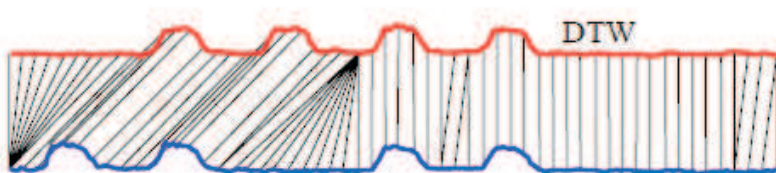
1. Linear (direct) assignment of two components



Source: http://www.markcorbyn.com/work/dissertation/chapter_2.php

Dynamic Time Warping

2. Nonlinear assignment of two components, with **time warping**



Source: http://www.markcorbyn.com/work/dissertation/chapter_2.php

Dynamic Time Warping

Continuous time case

1. DTW is used to compare functions r and g :

$$r = \{r(t), t \in \langle 1, T_r \rangle\} \quad \rightarrow \quad r(w^t(\ell)), \ell \in \langle 1, L_w \rangle$$

$$g = \{g(\tau), \tau \in \langle 1, T_g \rangle\} \quad \rightarrow \quad g(w^\tau(\ell)), \ell \in \langle 1, L_w \rangle$$

where $w^t, w^\tau \in \mathcal{W}$ are warping functions, \mathcal{W} is the family of warping functions and $L_w = \max(T_r, T_g)$

Dynamic Time Warping

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where $w^t, w^\tau \in \mathcal{W}$ are warping functions, \mathcal{W} is the family of warping functions and $L_w = \max(T_r, T_g)$

2. In general, r and g are curves in multidimensional space, hence they may represent single or multiple signature components

Dynamic Time Warping

Continuous time case

3. Example similarity metrics

$$\inf_{w^t, w^\tau \in \mathcal{W}} \int_1^{L_w} \|r(w^t(\ell)) - g(w^\tau(\ell))\|^2 d\ell$$

Dynamic Time Warping

Continuous time case

3. Example similarity metrics

$$\inf_{w^t, w^\tau \in \mathcal{W}} \int_1^{L_w} \|r(w^t(\ell)) - g(w^\tau(\ell))\|^2 d\ell$$

4. We often assume (for convenience) that time t in the reference template is **identical with 'ideal time'** ℓ , that is:

$$\inf_{w \in \mathcal{W}} \int_1^{T_r} \|r(t) - g(w(t))\|^2 dt$$

hence time of r is not warped, and time of g is warped by w

Dynamic Time Warping

Continuous time case

3. Example similarity metrics

$$\inf_{w^t, w^\tau \in \mathcal{W}} \int_1^{L_w} \|r(w^t(\ell)) - g(w^\tau(\ell))\|^2 d\ell$$

4. We often assume (for convenience) that time t in the reference template is **identical with 'ideal time'** ℓ , that is:

$$\inf_{w \in \mathcal{W}} \int_1^{T_r} \|r(t) - g(w(t))\|^2 dt$$

hence time of r is not warped, and time of g is warped by w

5. Time **should not be warped 'too much'**, that is:

$$w(t) \approx t, \quad \dot{w}(t) \approx 1$$

Dynamic Time Warping

Discrete time case

1. Discrete domain and values of the functions being compared

$$r = \{r(t), \quad t = 1, 2, \dots, M_r\}$$

$$g = \{g(\tau), \quad \tau = 1, 2, \dots, M_g\}$$

2. Warping functions represented by **warping paths**

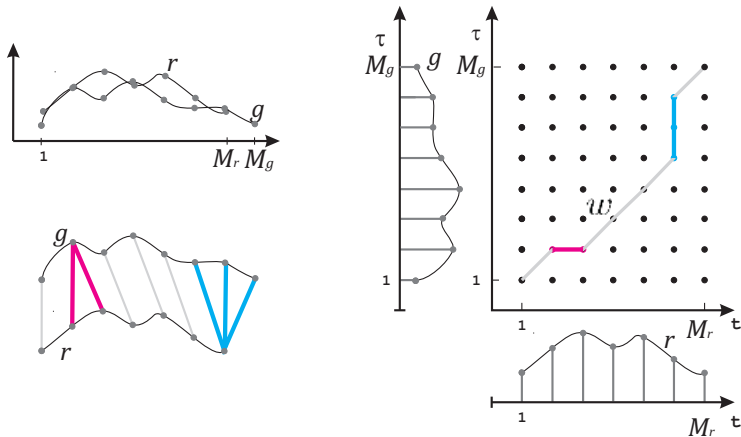
$$\mathbf{w}(\ell) = [w^t(\ell) \quad w^\tau(\ell)]^T; \quad \ell = 1, \dots, L_w$$

$$\text{where } w^t(\ell) \in \{1, \dots, M_r\}$$

$$w^\tau(\ell) \in \{1, \dots, M_g\}$$

Dynamic Time Warping

Discrete time case



Source: Joanna Putz-Leszczynska, Signature Verification – A Comprehensive Study Of The Hidden, International Journal of Applied Mathematics in Computer Science (to be published in 2014)

Dynamic Time Warping

Discrete time case

- 2a. Diagonal jumps in the warping path correspond to **identical time flow** in both signature tokens

Dynamic Time Warping

Discrete time case

- 2a. Diagonal jumps in the warping path correspond to **identical time flow** in both signature tokens
- 2b. Vertical or horizontal jumps in the warping path correspond to **time constriction or dilation** in one of the signature tokens

Dynamic Time Warping

Discrete time case

- 2a. Diagonal jumps in the warping path correspond to **identical time flow** in both signature tokens
- 2b. Vertical or horizontal jumps in the warping path correspond to **time constriction or dilation** in one of the signature tokens
- 2c. Warping paths meet the following conditions:
 - boundary: $w^t(1) = w^r(1) = 0$, $w^t(L_w) = M_r$, $w^r(L_w) = M_g$
i.e. warping paths connect $(1,1)$ with (M_r, M_g)

Dynamic Time Warping

Discrete time case

- 2a. Diagonal jumps in the warping path correspond to **identical time flow** in both signature tokens
- 2b. Vertical or horizontal jumps in the warping path correspond to **time constriction or dilation** in one of the signature tokens
- 2c. Warping paths meet the following conditions:
 - boundary: $w^t(1) = w^\tau(1) = 0$, $w^t(L_w) = M_r$, $w^\tau(L_w) = M_g$
i.e. warping paths connect (1,1) with (M_r, M_g)
 - monotonicity: $w^t(\ell + 1) \geq w^t(\ell)$, $w^\tau(\ell + 1) \geq w^\tau(\ell)$
i.e. we do not like to 'go back' in time

Dynamic Time Warping

Discrete time case

- 2a. Diagonal jumps in the warping path correspond to **identical time flow** in both signature tokens
- 2b. Vertical or horizontal jumps in the warping path correspond to **time constriction or dilation** in one of the signature tokens
- 2c. Warping paths meet the following conditions:
 - boundary: $w^t(1) = w^\tau(1) = 0$, $w^t(L_w) = M_r$, $w^\tau(L_w) = M_g$
i.e. warping paths connect (1,1) with (M_r, M_g)
 - monotonicity: $w^t(\ell + 1) \geq w^t(\ell)$, $w^\tau(\ell + 1) \geq w^\tau(\ell)$
i.e. we do not like to 'go back' in time
 - warping path length: $\max(M_r, M_g) \leq L_w \leq M_r + M_g - 1$

Dynamic Time Warping

Discrete time case

3. Local distance between points:

$$d(r(t), g(\tau)) = \|r(t) - g(\tau)\|^2$$

4. Distance along the entire warping path w :

$$\mathcal{D}(r, g, w) = \sum_{\ell=1}^{L_w} d(r(w^t(\ell)), g(w^\tau(\ell)))$$

Dynamic Time Warping

Discrete time case

5. Optimal warping path

$$\hat{\mathbf{w}}(r, g) = \arg \min_{\mathbf{w} \in \mathcal{W}_{r,g}} \mathcal{D}(r, g, \mathbf{w})$$

(provides the solution, i.e. how to warp the time to make two signature tokens as similar as possible, in a sense of $\mathcal{D}(r, g, \mathbf{w})$)

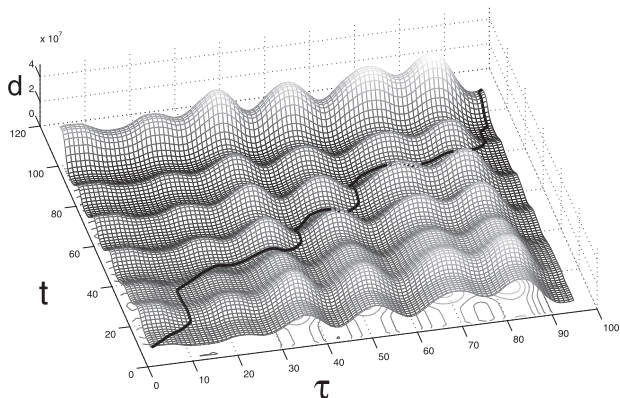
6. Minimum distance

$$\hat{\mathcal{D}}(r, g) = \mathcal{D}(r, g, \hat{\mathbf{w}}(r, g))$$

(provides the information about the quality of the optimal solution, i.e. what was the warping intensity; we use this distance in signature comparison)

Dynamic Time Warping

Discrete time case



Source: Joanna Putz-Leszczynska, Signature Verification – A Comprehensive Study Of The Hidden, International Journal of Applied Mathematics in Computer Science (to be published in 2014)

Dynamic Time Warping

Discrete time case

7. Use of dynamic programming to calculate optimal warping path and minimum global distance

- calculation of the global cost matrix \mathbf{D}

a) first row: $\mathbf{D}(1, j) = \sum_{k=1}^j d(r(1), g(k)); \quad j = \{1, \dots, M_r\}$

b) first column: $\mathbf{D}(i, 1) = \sum_{k=1}^i d(r(k), g(1)); \quad i = \{1, \dots, M_r\}$

- c) remaining elements:

$$\mathbf{D}(i, j) = \min\{\mathbf{D}(i-1; j-1), \mathbf{D}(i-1; j), \mathbf{D}(i; j-1)\} + d(r(i), g(j))$$

where $i = \{1, \dots, M_r\}$, $j = \{1, \dots, M_g\}$

- the last element is the minimum distance, that is:

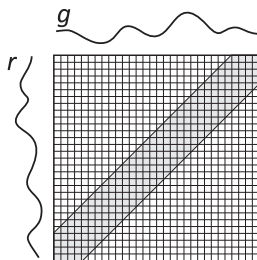
$$\hat{\mathcal{D}}(r, g) = \mathbf{D}(M_r, M_g)$$

- we go backwards, starting from (M_r, M_g) , to find the optimal warping path $\hat{\mathbf{w}}(r, g)$

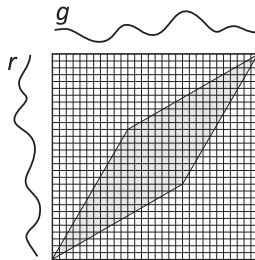
Dynamic Time Warping

Discrete time case

- Distance between signature tokens, i.e. the **matching score**
 - minimum global distance $\hat{D}(r, g) = \mathbf{D}(M_r, M_g)$, and/or
 - distance between signature tokens after applying optimal warping path
- Example boundaries **speeding up the calculations**



Sakoe-Chiba Band



Itakura Parallelogram

Thank you

