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Basic Algorithms for Digital Image Analysis: a course

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http://visual.ipan.sztaki.hu

Lecture 6: Template Matching and Feature Detection

- Template matching
  - Similarity and dissimilarity measures
  - Interior matching versus contour matching
  - Invariance
  - Distortion-tolerant matching
  - Stable matching
  - Fast implementations
- Types of local image features
  - Edges
  - Lines
  - Corners
  - Blobs

Interior matching versus contour matching

template

0	0	0
1	1	1
0	0	0

input image

0	0	0
1	1	1
0	0	0

output of CC

1	2	3	2	1

output of NCC

1.0	1.4	1.7	1.4	1.0

1	1	1
1	1	1
1	1	1

1	2	3	2	1
1	2	3	2	1
1	2	3	2	1

1.0	1.2	1.0
	1.0	
1.0	1.2	1.0

0	1	0
0	1	0
0	1	0

1	1	1
1	1	1
1	1	1

1	1	1
1	0	1
1	1	1

1	2	3	2	1
1	1	2	1	1
1	2	3	2	1

1.2	1.3	1.2
1.2	1.3	1.2

Numerical examples of matching by unnormalised (CC) and normalised (NCC) cross-correlations. In output, values below 1 are set to 0 and not shown.

Observation in the numerical example: The perfect match value (1.7) is not much better than the near misses in position and shape.

- The match is not sharp.

Matching of the outlines yields sharper matches:

input image

1	1	1
1	1	1
1	1	1

template

0	0	0	0	0
0	1	1	1	0
0	1	1	1	0
0	1	1	1	0
0	0	0	0	0

output of NCC

		1.2		
	1.3	2.0	1.3	
1.2	2.0	3.0	2.0	1.2
	1.3	2.0	1.3	
		1.2		

input image

1	1	1
1	0	1
1	1	1

template

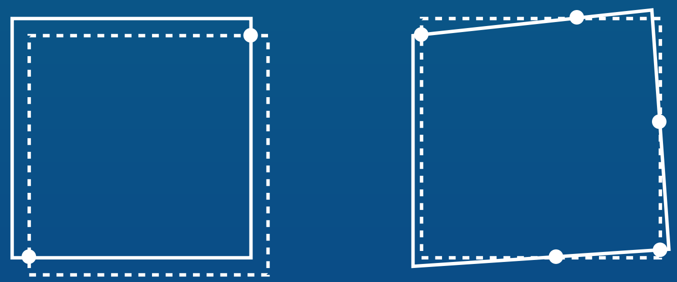
0	0	0	0	0
0	1	1	1	0
0	1	0	1	0
0	1	1	1	0
0	0	0	0	0

output of NCC

		1.3		
		1.4		
1.3	1.4	2.8	1.4	1.3
		1.4		
		1.3		

Trade-off between localisation accuracy and reliability of matching

- Matching the contours: faster, yields sharp matches, but sensitive to distortions;
- Matching the interior: slower and less sharp, but more robust.



Contours matching versus interior matching. Template: Dashed rectangle. Object: Solid line. Circles: Overlapping points of contours.

- Left: Small shift of template results in drastic decrease of contour overlap and negligible descrease of area overlap.

  $\Rightarrow$ Contour matching is sharper.

- Right: Distortion of pattern has a similar effect.

  $\Rightarrow$ Contour matching is less robust.

Critical issues in template matching

- Sensitivity to changes in size and rotation
- Sensitivity to pattern distortion
  - For example, because of varying viewing angle
- 'Noisy' matches: Unexpected configurations may occur that produce high matching values
- Heavy computational load

Handling variations in size and orientation

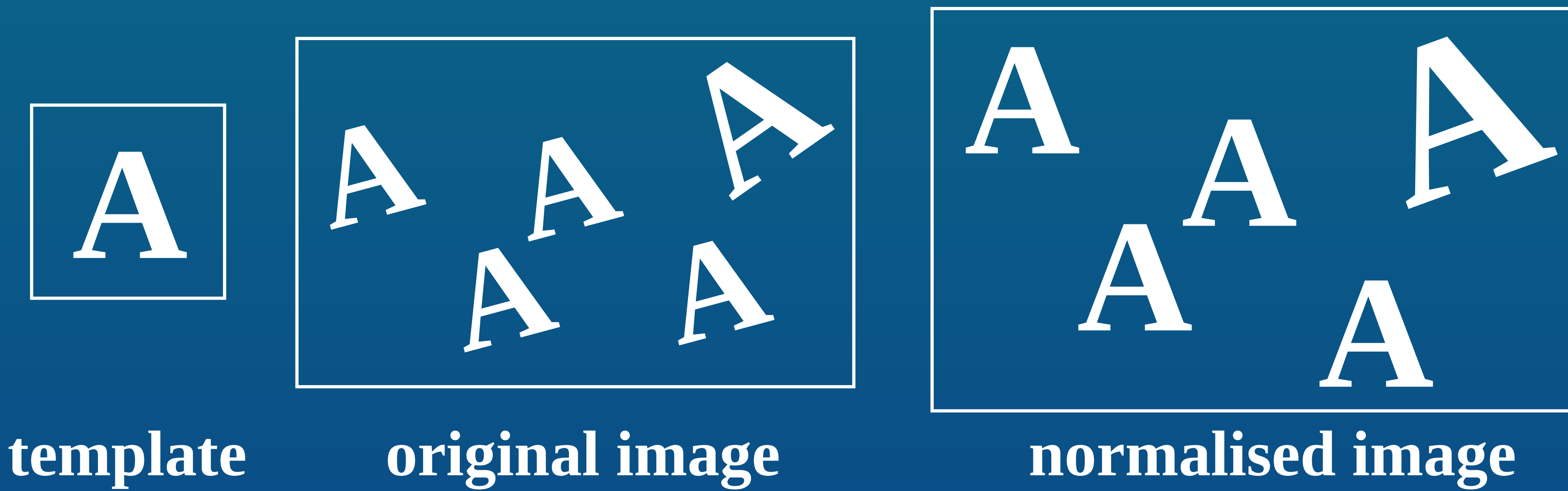
Options:

- Normalisation: Transform image to standard size and orientation
  - Works only if there is no size or orientation variation within the image
  - Requires definition of orientation

- Adaptivity: Spatially scale and rotate the template in each position, select the best matching scale and rotation
  - Very slow if number of scales and rotations is large

  $\Rightarrow$ Used only for small number of scales and rotations

- Alternative solution: Use scale and rotation invariant description
  - Compare descriptions instead of patterns



Normalising an image for size and orientation.

- The letter **A** in the top right corner differs in size and orientation.

$\Rightarrow$ This letter will not match.

- The other four letters will match.

- How to define image orientation?

Distortion-tolerant matching

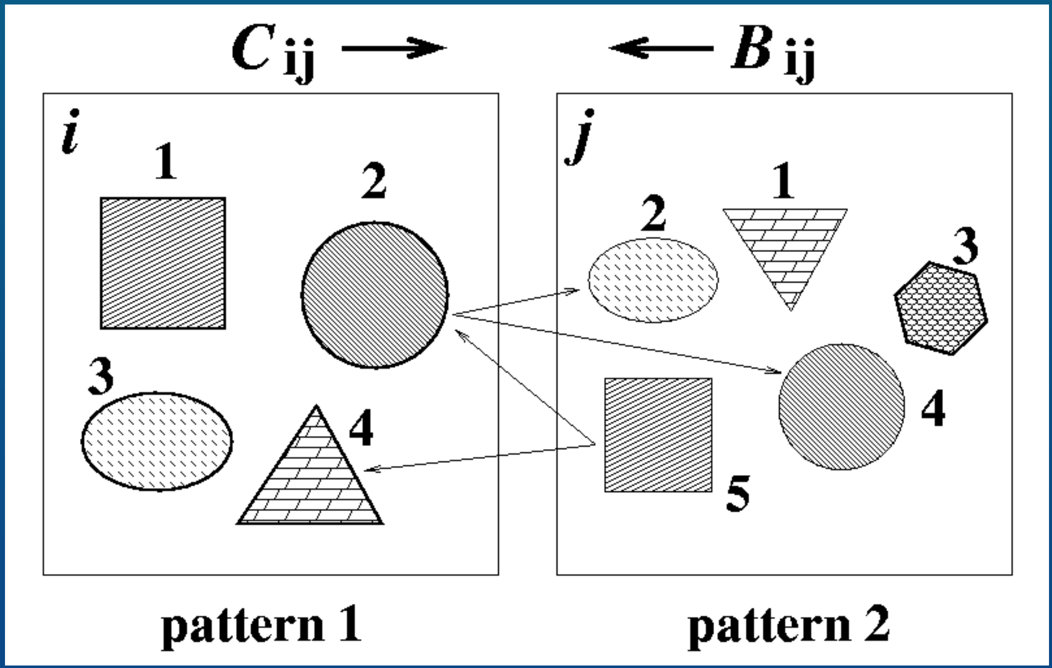
Use flexible templates composed of spatially connected subtemplates with flexible links ('springs').

- The springs allow for a moderate spatial variation of the template.
  - A cost function is introduced to penalise large variations

  $\Rightarrow$ The larger the variation the larger the penalty
- Works well when the subtemplates are characteristic enough for reliable matching.

Representing a face template as a set of flexibly connected subtemplates.

Matching segmented patterns



Matching two patterns by segmenting them into regions.

- Segment patterns into regions and find correspondences by comparing region properties.
  - A distance measure between properties of regions should be defined.
- This solution works well when the segmentation is reliable.

Algorithm 1: Stable Matching of Two Images

1. Compute distance matrix D_{ij}; i: i^{th} region of image 1, j: j^{th} region of image 2.

2. Calculate forward matching matrix C_{ij}: $C_{ij} = 1$ if $D_{ij} < D_{ik}$ for all $k \neq j$; otherwise, $C_{ij} = 0$.

3. Calculate backward matching matrix B_{ij}: $B_{ij} = 1$ if $D_{ij} < D_{kj}$ for all $k \neq i$; otherwise, $B_{ij} = 0$.

4. Match regions i and j if $C_{ij} B_{ij} = 1$.

5. Remove established correspondences from D_{ij}.

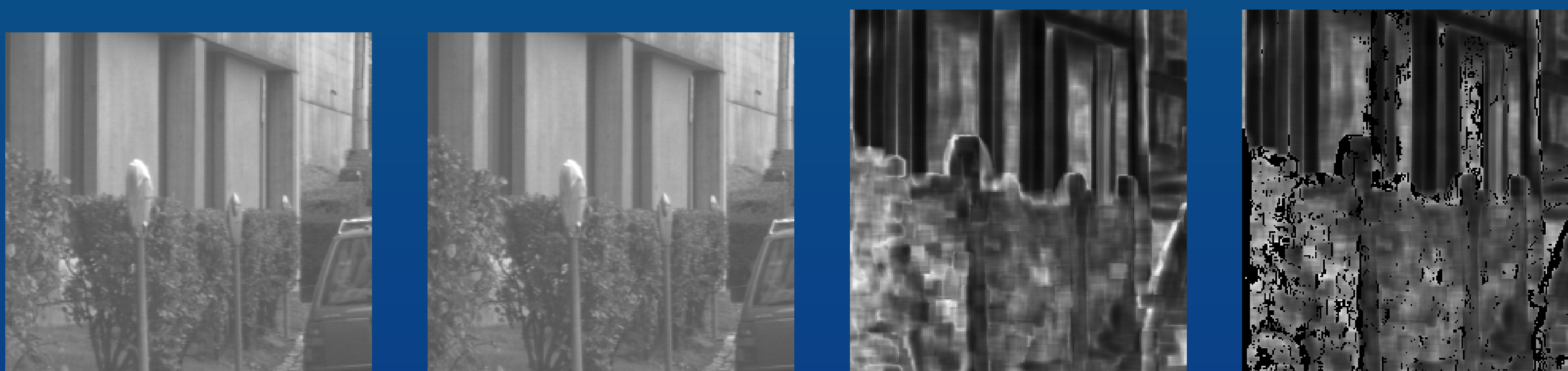
6. Iterate until no further matching is possible.

Comments to the Stable Matching algorithm:

- The backward matching (steps 2–4) is a consistency check.

  $\Rightarrow$ This is a standard way to discard noisy (unreliable or erroneous) matches

- The iterative procedure is based on an algorithm for the Stable Marriage Problem.



left image | right image | original ME | consistent ME

Matching a stereo pair in presence of occlusion. ME is the matching error.
The consistency check removes wrong matches due to occlusion.

Fast impementations of matching

- Work with local features of images and templates rather that the patterns themselves
  - For example: Edges, contours
  - Useful for sparse and reliable features
  - Caution: Remember sensitivity to distortions!

- For large templates ($> 13 \times 13$ pixels), use implementation of cross-correlation via Fast Fourier Transform (FFT):

$$f \otimes w = IFFT\Big[FFT\big[f(x,y)\big]^* \cdot FFT\big[w(x,y)\big]\Big],$$

where $IFFT$ is the inverse FFT and X^* is the complex conjugate of X.

  - Needs $O(N^2 \log N)$ operations for $N \times N$ images
  - Straightforward implementation needs $O(N^4)$ operations

Another solution: Use a fast procedure to

1. Select match candidates and reject mismatches rapidly, then
2. Test the selected candidates

Options for fast selection and rejection:

- Use a coarsely spaced grid of template positions, then rectify the candidates.
  - This is a coarse-to-fine sampling method for the cross-correlation function
  - It works if peaks of cross-correlation are smooth and broad (no spikes).
- Compute simple properties of template and image region. Reject region if its properties differ from properties of the template.
- Use subtemplates to reject a mismatch rapidly when a subtemplate does not match.
- If a cumulative measure of mismatch is used, reject a candidate when the mismatch exceeds a preset threshold.

Image features

Basic image features.

Types of local image features considered in this course:

- Edges – More detail
- Lines – Less detail
- Corners – Less detail
- Blobs – No details

Edges and blobs

An image edge is a drastic change of intensity across object contour.

- Image edges do not necessarily coincide with physical edges
  - Image edges are intensity discontinuities
  - Physical edges are surface discontinuities
  - Example: Edges of shadows are not surface discontinuities
- Importance of intensity edges: Human eye detects them ‘in hardware’, at the initial level of visual processing.

A blob is a compact image region of approximately constant intensity.

- Blobs are elementary patterns used to build more sophisticared patterns.
  - Example: Eyes in a face model
- Blob detectors exist, but they are less frequently used than edge and corner detectors.

Lines

A line is a narrow, elongated image region of approximately constant width and intensity.

- Formally, a line can be viewed as two parallel sequences of edges.
  - In practice, a thin line is rarely detected like that

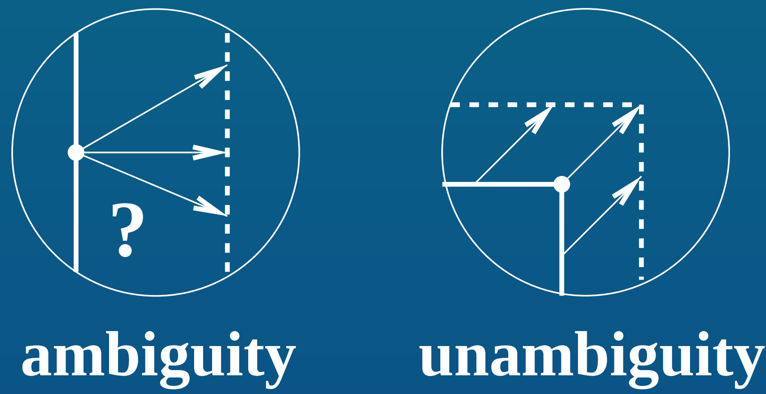
- Blurred lines and other linear objects may have different cross-sections.
  - Example: Roof-shaped.

- Two different operations are often called line detection:
  - Line filtering (enhancement), detecting pieces of lines. This is a local operation similar to edge detection.
  - Detecting lines (curves) of a given shape. This is a global operation, whose typical example is the Hough transform.

Corners

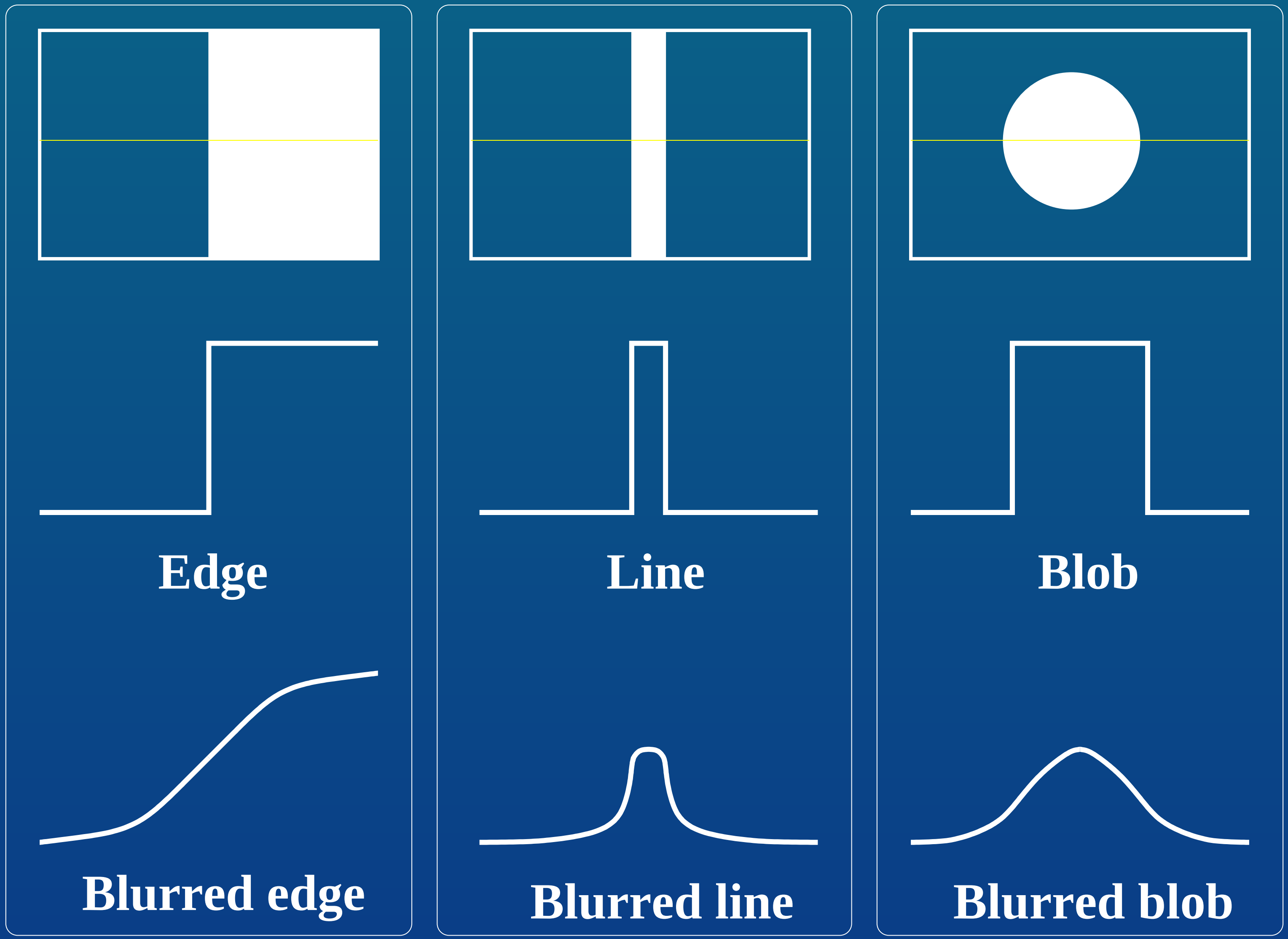
A corner is a sharp turn of a contour.

- Corners are used in shape analysis and motion analysis
- Corners and other points of high curvature are dominant in human perception of 2D shapes
  - Shapes can be approximately reconstructed from their dominant points
- Two different operations but related operations are called corner detection:
  - Detection of corners in digital curves
    $\Rightarrow$ This assumes extracted contours
  - Detection of corners in greyscale images
    $\Rightarrow$ This does not assume extracted contours



The aperture problem and the use of corners in motion analysis. The displacement vectors are ambiguous at an edge, but unambiguous at a corner.

The Attneave's Cat. The original smooth shape has been restored based on a small number of high curvature points. The cat is easy to recognise.



Three image features and their intensity profiles along the indicated lines.