Region Descriptors

- Reading: 8.3.1
- A descriptor is a number or set of numbers that describes some property of a shape
- Can't usually reconstruct the shape, but can be used to distinguish shapes
- Examples:
  - Area
  - Perimeter
  - Compactness
  - Eccentricity
  - Euler Number (count components and holes)
- Practical considerations:
  - Inside or outside borders?
  - 4- vs. 8-connected perimeters?
  - Complicated regions?

From Brian Morse, Computer Vision I, http://morse.cs.byu.edu/650/home/index.php

Compactness

$$compactness = \frac{(region\_border\_length)^2}{area} \qquad (6.40)$$

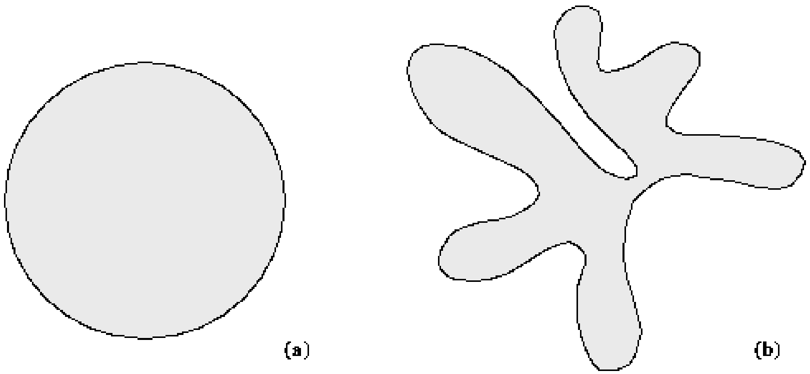


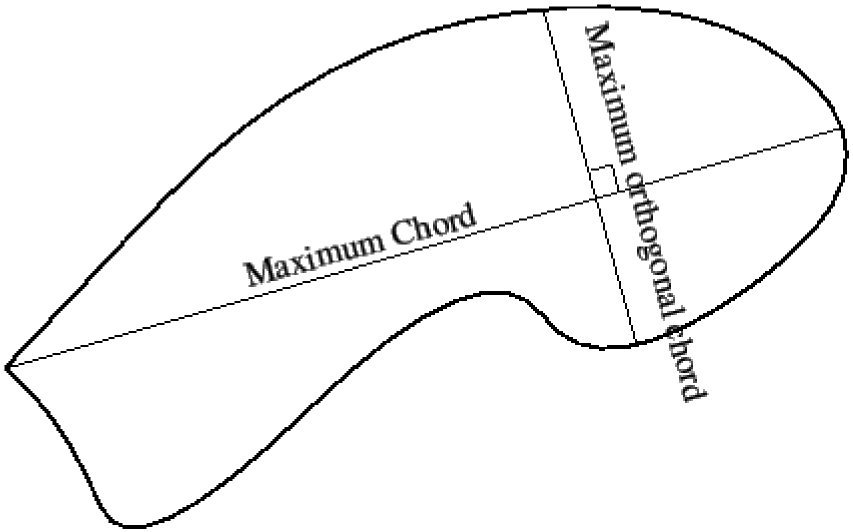
Figure 6.25 *Compactness: (a) Compact, (b) non-compact.*

The compactness measure is independent of linear transformations if the outer boundary is measured

Most compact shape: the circle : 4π compactness

Eccentricity

- The ratio of the longest chord compared to the chord perpendicular to it;
- measure of how non-circular a shape is



Rectangularity

http://www.mobileye.com/

Elongation

Can be measured as the ratio between the length and width of the region bounding rectangle

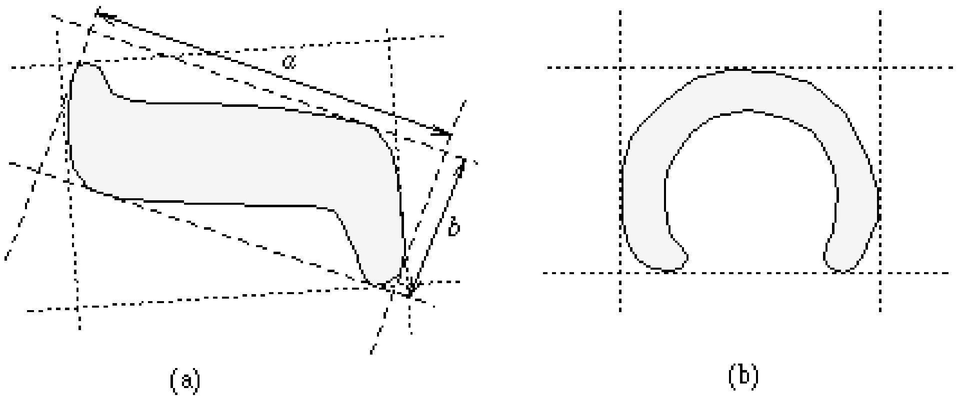


Figure 6.24 *Elongatedness: (a) Bounding rectangle gives acceptable results, (b) bounding rectangle cannot represent elongatedness.*

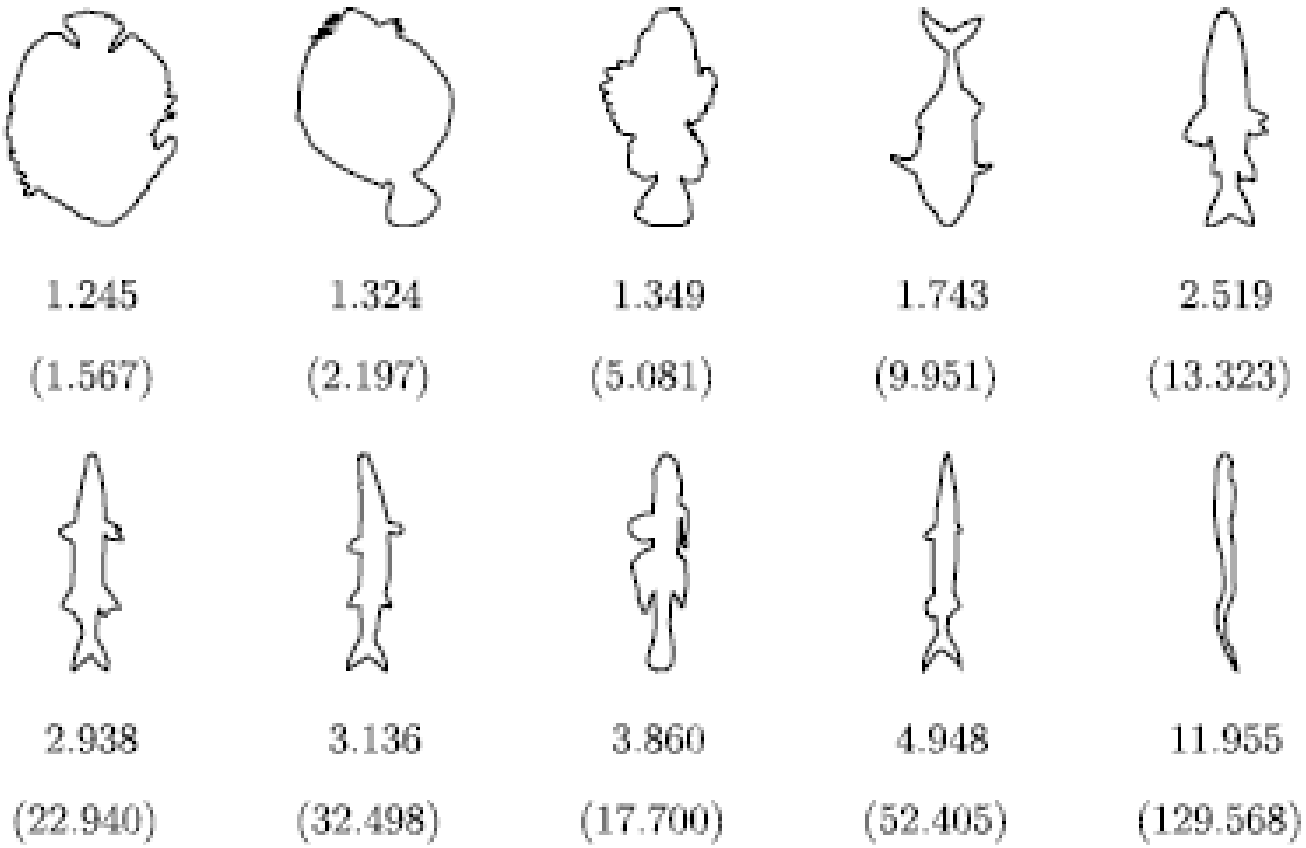
This measure can not be used in curved regions!

Elongation (morphological measure)

$$\text{Elongation} = \frac{\text{Area}}{(2d)^2}$$

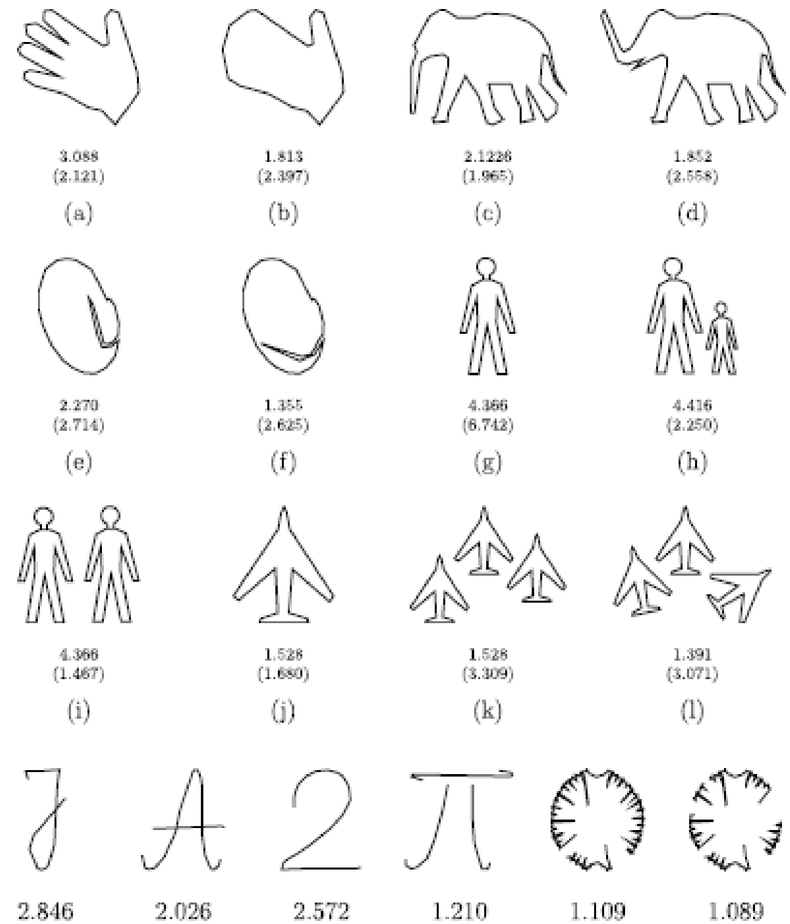
where d is the maximum number of erosions before the shape disappears (half the width of the object)

Examples of shapes that can be described via elongation (1)



Examples of shapes that can be described via elongation (2)

Stojmenovic, Žunic (2008)
Measuring elongation from shape boundary



Concavities

- Read section 8.3.3
- Differences between object and its convex hull are holes or concavities.
- For complex shapes: We can build a hierarchical representation of concavities (concavity tree)

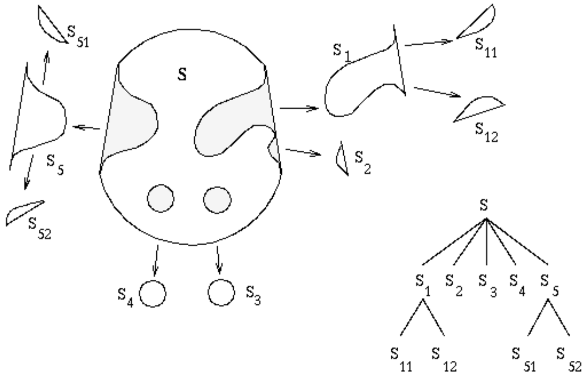
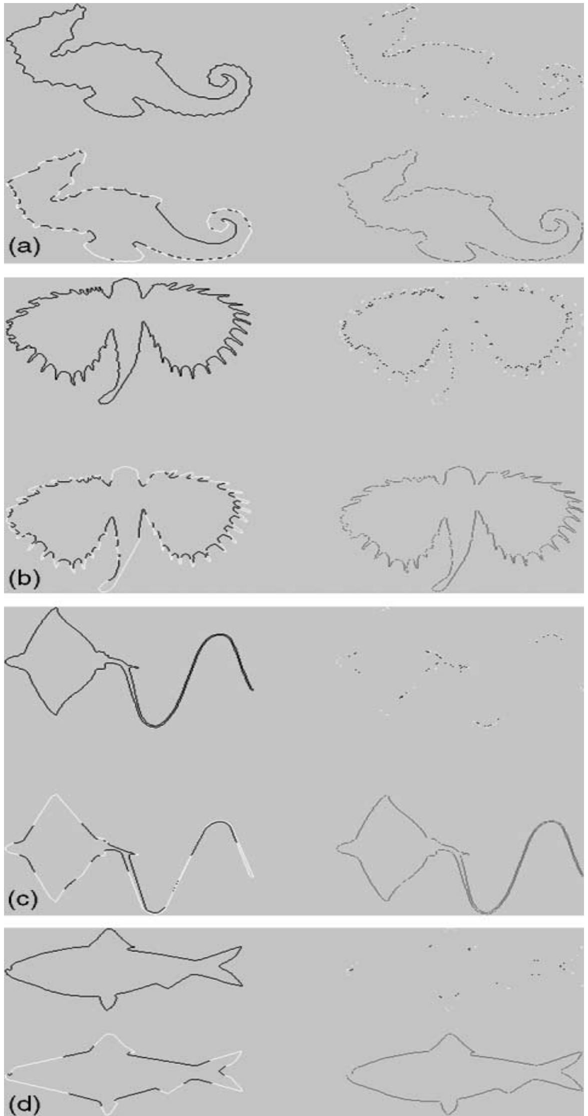


Figure 6.30 *Concavity tree construction: (a) Convex hull and concave residua, (b) concavity tree.*

Contour partitioning via concavity analysis

Cronin, “Visualizing concave and convex partitioning of 2D contours”, Pattern Recognition Letters, 2003.



Statistical region descriptors: moments

- Read section 8.3.2
- Region moment representations interpret a normalized gray level image function as a probability density of a 2D random variable.
- Properties of this random variable can be described using statistical characteristics - **moments**.
- Assuming that non-zero pixel values represent regions, moments can be used for binary or gray level region description.

$$m_{pq} = \sum_{i=-\infty}^{\infty} \sum_{j=-\infty}^{\infty} i^p j^q f(i,j) \qquad (6.42)$$

- where i,j are the region point co-ordinates (pixel co-ordinates in digitized images).

Moments

- Represent a global description of a shape layout
- Combine area, compactness, irregularity, and higher order descriptions together
- Associated with statistical pattern recognition
- Not able to handle shape occlusion

Central moments

- The n-th central moment for probability density function f:

$$\mu_n = \int_{-\infty}^{\infty} (x-\mu)^n \; f(x) \; dx$$

- Or for arbitrary discrete functions:

$$\mu_n = \sum_{x=1}^{N} (x-\mu)^n f(x)$$

- First two central moments:

$$\mu_0 = \text{Area}$$

$$\mu_1 = 0$$

Higher order moments

Mean	μ	$=$	m_1 / m_0
Variance	σ^2	$=$	μ_2 / m_0
Skew			μ_3 / m_0
Kertosis			μ_4 / m_0

For Skewness : Darker and glossier surfaces tend to be more positively skewed than lighter and matte surfaces. Skewness can be used for making judgements about image surfaces.

In digital image processing kurtosis / kertosis values are interpreted in combination with noise and resolution measurement. High kurtosis values should go hand in hand with low noise and low resolution.

Central and normalized bidimensional moments

$$\mu_{pq} = \sum_{x=1}^{M} \sum_{y=1}^{N} (x - \overline{x})^p (y - \overline{y})^q P_{xy}$$

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}^{\gamma}}$$

$$\gamma = \frac{p+q}{2} + 1 \qquad \forall (p+q) \geq 2$$

Symmetry analysis with moments

(a) (b)

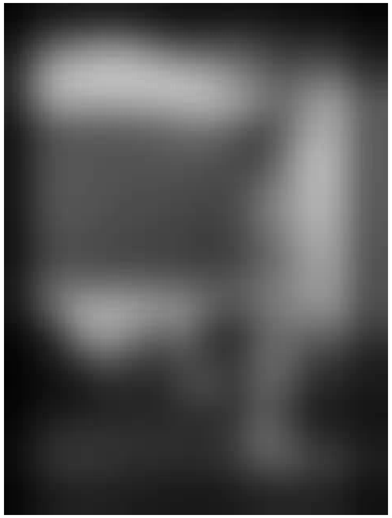
Figure 1.5: Axes of symmetry for typed characters.

Table 1.1: Typed characters η_{pq} values indicating symmetry.

Character	η_{11}	η_{20}	η_{02}	η_{21}	η_{12}	η_{30}	η_{03}
M	0	+	+	-	0	0	-
C	0	+	+	0	+	+	0

Example of shape descriptors applied to motion analysis

Bobick and Davis “The recognition of human movement using temporal templates”, IEEE Transactions on Pattern Analysis and Machine Intelligence, March 2001.

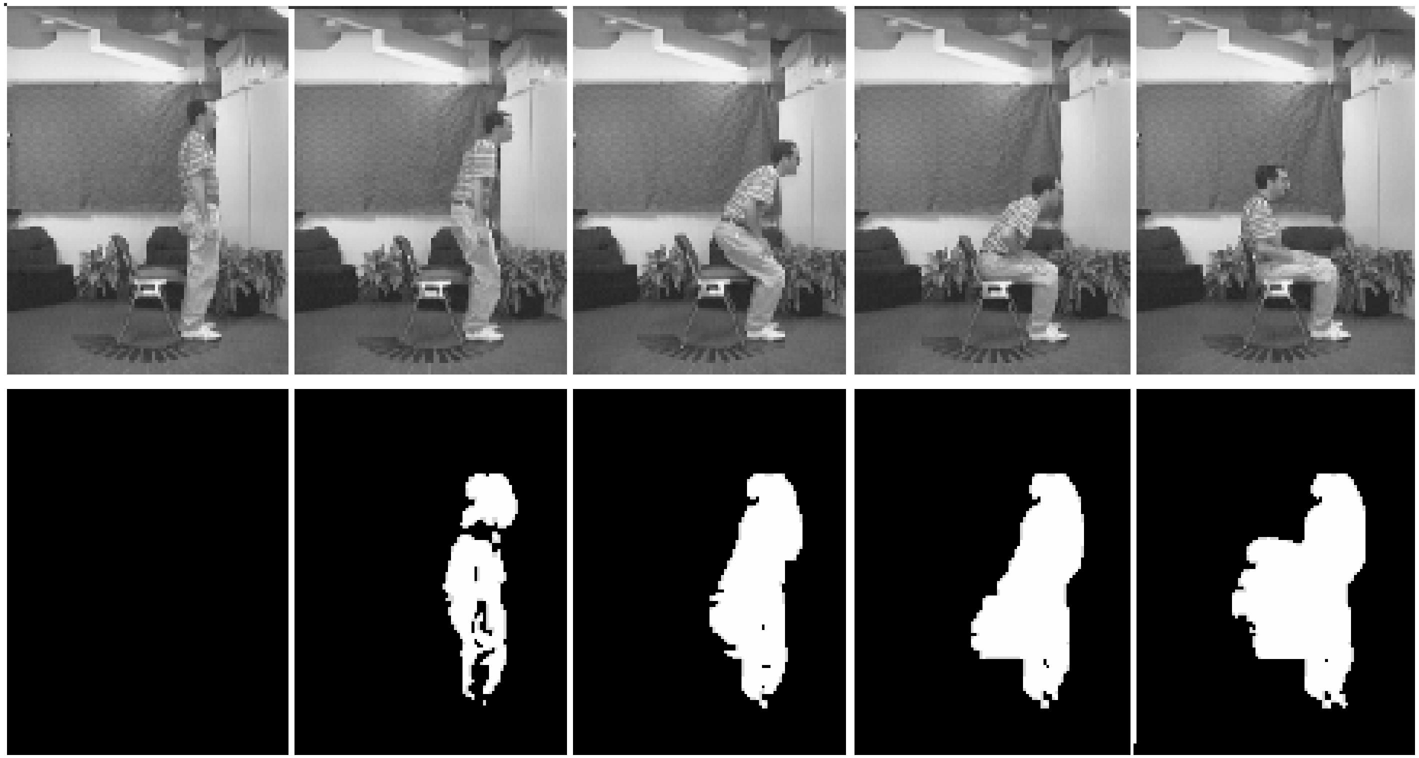


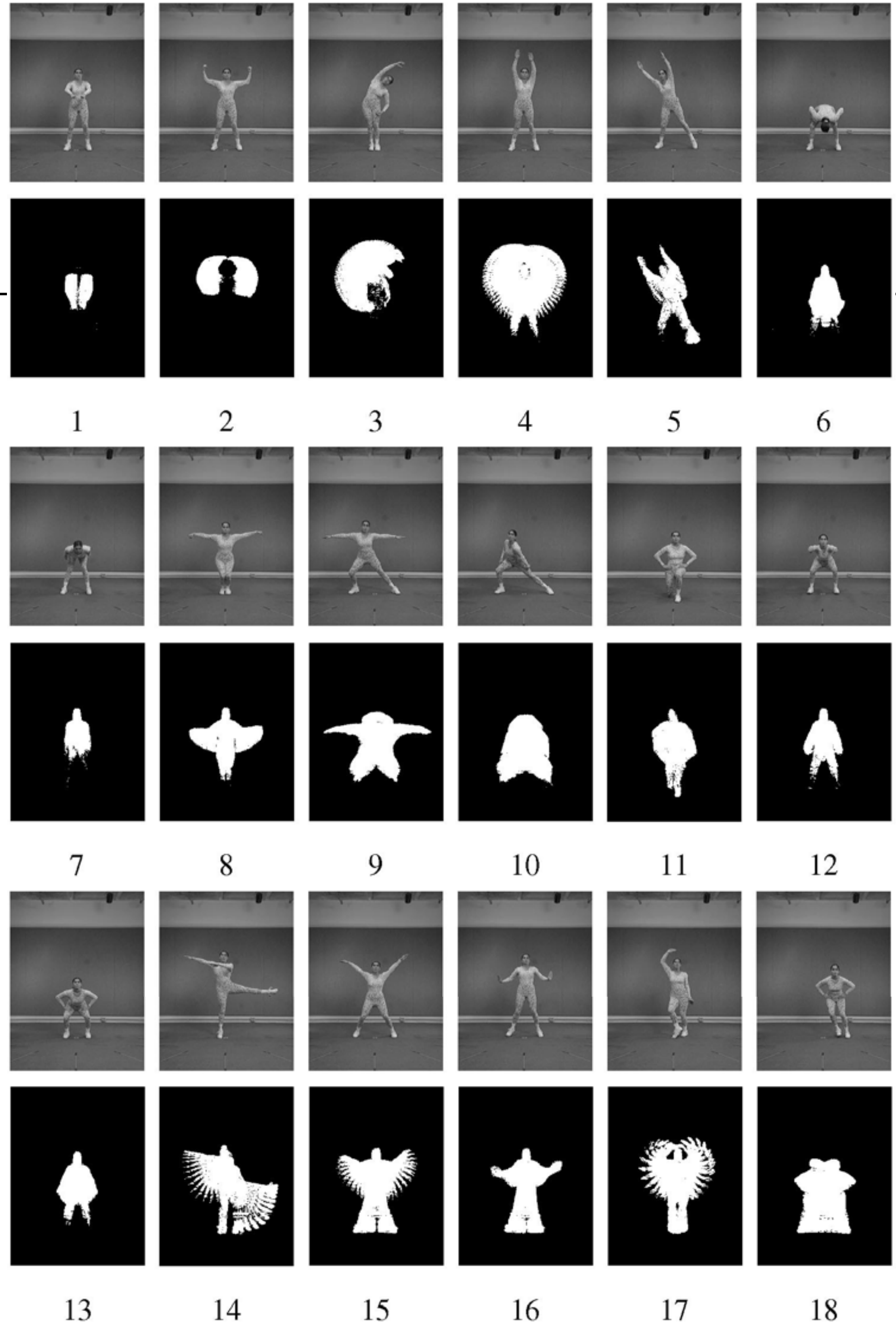
Main ideas:

- analyzing the shape of motion leads to action recognition
- the shape of motion is considered separately from the shape of the object in motion (here, a human silhouette)

Motion energy image (MEI)

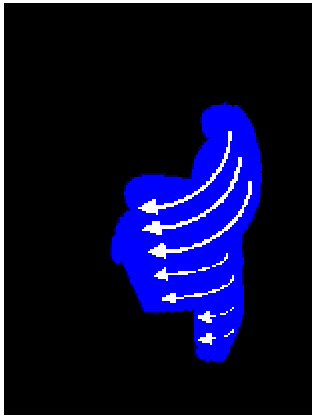
- a representation of the spatial distribution of motion ('where')

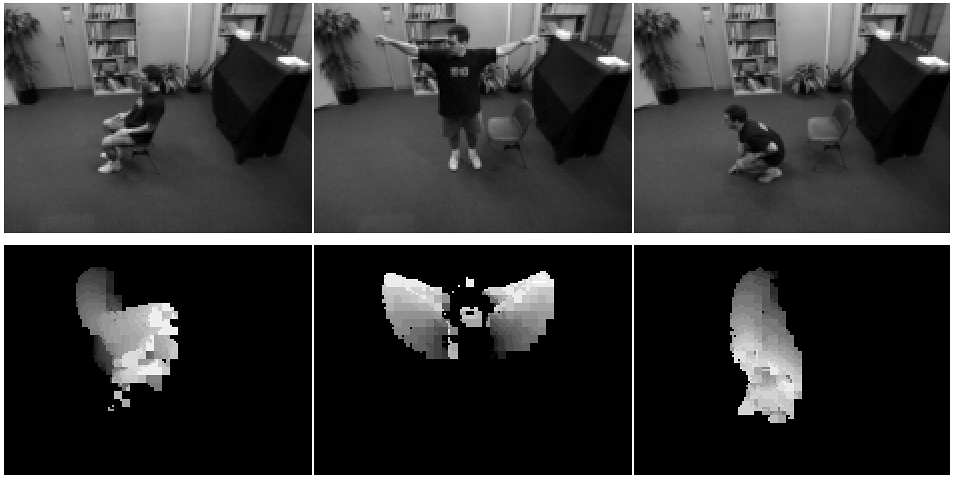


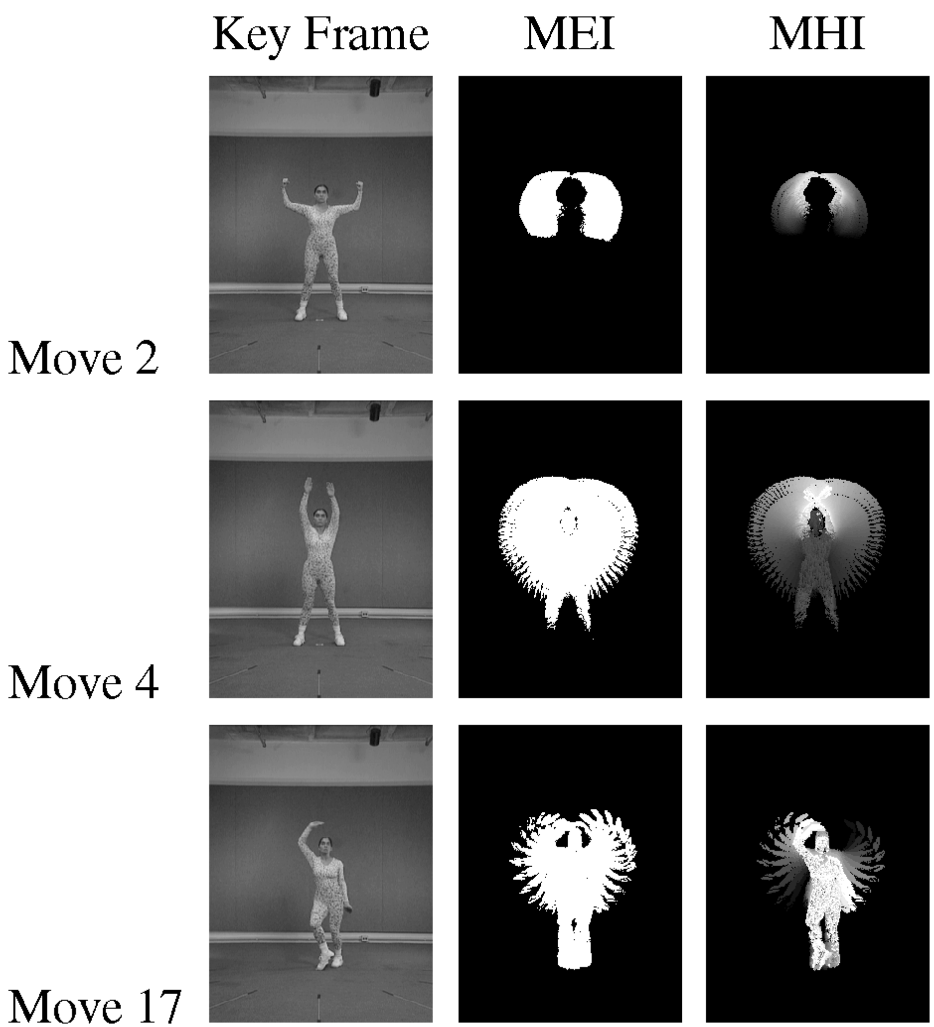

1 2 3 4 5 6
7 8 9 10 11 12
13 14 15 16 17 18

Motion History Image (MHI)

- Describes how the motion evolves over a predefined length of time
- pixel intensity is a function of the motion history at that location, where brighter values correspond to more recent motion.






Key Frame
MEI
MHI
Move 2
Move 4
Move 17

How are these two templates described?

- 7 Hu moments are computed for each motion template/view; the Hu moments are invariant to rotation/scale/translation

$$
\begin{aligned}
I_1 &= \eta_{20} + \eta_{02} \\
I_2 &= (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2 \\
I_3 &= (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2 \\
I_4 &= (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \\
I_5 &= (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + (3\eta_{21} \\
&\quad -\eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \\
I_6 &= (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2 \\
&\quad +4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03})]
\end{aligned}
$$

$$
\begin{aligned}
I_7 &= (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} \\
&\quad +\eta_{03})^2] + (\eta_{30} - 3\eta_{12})(\eta_{21} + \eta_{03})[3(\eta_{30} \\
&\quad +\eta_{12})^2 - (\eta_{21} + \eta_{03})^2]
\end{aligned}
$$

Hu moments

- A compact set of descriptors invariant to image scaling, rotation, and translation

$$
\begin{aligned}
I_1 &= \eta_{20} + \eta_{02} \\
I_2 &= (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2 \\
I_3 &= (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2 \\
I_4 &= (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \\
I_5 &= (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + (3\eta_{21} \\
&\quad - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \\
I_6 &= (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2 \\
&\quad + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03})] \\
I_7 &= (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} \\
&\quad + \eta_{03})^2] + (\eta_{30} - 3\eta_{12})(\eta_{21} + \eta_{03})[3(\eta_{30} \\
&\quad + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]
\end{aligned}
$$