LECTURE 12: Active Shape Models and Oriented Active Shape Models

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Outline

• Shape Information
  – Representation
  – Simple processing (dilation + erosion)

• Shape Modeling
  – Active Shape Models (ASM)
  – Oriented Active Shape Models (OASM)
  – Application in anatomy recognition and segmentation
  – Comparison of ASM and OASM
Motivation

Most structures of clinical interest have a characteristic shape and anatomical location relative to other structures.

Brain image shows:
- Ventricles
- Caudate nucleus
- Lentiform nucleus
Heart model with large vessels
What is Shape?
What is Shape?

- **Shape is any connected set of points!**
What is Shape?

- **Shape** is any connected set of points!
Shape in Vision

- Several important imaging concepts are closely related to biologic principles: edge detection, Gabor filtering, artificial neural networks, high curvature points in shape perception, etc.
Shape in Vision

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• More than 50% of human brain is involved in visual information analysis (directly and indirectly).
Shape in Vision

• Several important imaging concepts are closely related to biologic principles: edge detection, Gabor filtering, artificial neural networks, high curvature points in shape perception, etc.
• More than 50% of human brain is involved in visual information analysis (directly and indirectly).
• Shape of the objects play a significant role in perception.
Example Applications for Shape Analysis

<table>
<thead>
<tr>
<th>NeuroScience</th>
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<tbody>
<tr>
<td>• Morphological taxonomy of neural cells</td>
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<tr>
<td>• Interplay between form and function</td>
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<tr>
<td>• Comparisons between cells of different cortical areas</td>
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<td>• Comparisons between cells of different species</td>
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<td>• …</td>
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<tr>
<th>Internet/Document Analysis</th>
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<tr>
<td>• Content-based information retrieval</td>
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<td>• Watermarking</td>
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<td>• Graphic design</td>
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<td>• WWW</td>
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<td>• Optical character recognition</td>
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<td>• Multimedia databases</td>
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<th>Visual Arts</th>
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<td>• Video restoration</td>
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<td>• Video tracking</td>
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<td>• Special effects</td>
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<td>• Games</td>
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<td>• Computer graphics</td>
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<td>• Image synthesis</td>
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<td>• Visualizations</td>
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<td>• …</td>
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<th>Imaging/Vision</th>
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<tr>
<td>• Pathology detection/classification (spiculated and spherical nodules)</td>
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<td>• 3D pose estimation</td>
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<tr>
<td>• Morphological operations</td>
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<td>• Anatomy modeling</td>
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<tr>
<td>• Segmentation</td>
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<td>• Registration</td>
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<td>• Volumetry</td>
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Other areas: medicine, biology, engineering, physics, agriculture, security…
Shape Representation – Contour based

- **Shape Representation**
  - **Contours**
  - **Regions**
  - **Transforms**

  - **Parametric Contour**
    - Vectors \((x(t), y(t))\)
    - Complex Signal \(u(t) = x(t) + jy(t)\)
    - Chain-Codes
    - Run-Depths

  - **Set of Contour Points**

  - **Curve Approximation**
    - Polygonal Approximation
    - Circle Arcs
    - Elliptical Arcs
    - Syntactic Primitives
    - Autoregressive Models
    - B-Splines
    - Snakes/Active Contours
    - Multiscale Primitives
Shape Representation – Region based

- Region Decomposition
  - Polygons
  - Voronoi / Delaunay
  - Quadtrees
  - Syntactic Primitives
  - Morphological Decomposition
  - Dendrograms

- Bounding Regions
  - Feret Box
  - Minimum Enclosing Rectangle
  - Convex Hull / Defficiency

- Internal Features
  - Skeletons
  - Shape Matrix
  - Distance Transform
  - Run-Length
Shape Representation – Transformation based

- **SHAPE REPRESENTATION**
  - **CONTOURS**
  - **REGIONS**
  - **TRANSFORMS**
    - **LINEAR TRANSFORMS**
      - **MONOSCALE**
        - Fourier
        - Karhunen-Loève
        - Sin
        - Cosine
        - Laplace
        - Z
      - **MULTISCALE**
        - Short-Time Fourier Transform
        - Haar
        - Wavelets
        - Gabor
        - Scale-Space
    - **NONLINEAR TRANSFORMS**
      - Hough
      - Time-Frequency Distributions
      - Cohen Classes
      - Wigner-Ville
      - Mathematical Morphology

Typical Transform Domain Descriptors
- Transform Coefficients
- Transform Measures (e.g. Energy)
- Transform Statistics
Shape Processing: Dilation

• Morphological operations are often done with a structural element “s” and a binary image “f”.
• Different structuring elements define different outputs for the same processed shape.
• Dilation is used to expand or dilate the shapes in an input image.

1. Shaded area -> effected area from dilation
2. Structural element has a reference point
3. Boundary is tracked
1. Shaded area (both internal and external of the object) is effected region by dilation.
2. Depending on the size of the structural element, holes can be diminished/eliminated (left)
3. Concave regions narrower than size of structural element are filled up (right).

The result of image dilation is the set of image pixels where the intersection between structuring element and object is not empty.

It is often used for noise reduction in shapes, gap and hole filling, etc.
Dilation: Example

Structuring element \(g\), centered at \(o\).

\[
 g = \begin{bmatrix}
 0 & 1 & 0 \\
 1 & 1 & 1 \\
 0 & 1 & 0 \\
\end{bmatrix}
\]

Binary image (f)
Dilation: Example

Structuring element (g), centered at o.

Binary image (f)
Dilation: Example

Input Binary image (f)

Output Binary image (f)
Shape Processing: Erosion

- Opposite of dilation
- Practically it is used for object separation
Opening & Closing

• Please read
  – Morphological grayscale reconstruction in image analysis: applications and efficient algorithms by L. Vincent, IEEE TIP 1993.
Shape Models

- **Point distribution, Active Shape**, Active Appearance models (Cootes & Taylor)
- Fourier Snakes (Szekely)
- Active Contours (Blake)
- Parametrically-deformable models (Staib & Duncan)
- ...
Shape Models

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Active Shape Models can be used to help interpret new images by finding the parameters which best match an instance of the model to the image.
The shape of an organ can be characterized as being a transformed version of some template.
Active Shape Model (T. Cootes et al., 1995)

- Representation of Shapes
  - Point Distribution Model (PDM)
  - Represent a shape instance by a judiciously chosen set of points (features), each of which is a $k$-dim vector. $N$ feature points are stacked into a long vector of length $kn$:

$$q = [p_1, \ldots, p_n]^T$$

where

$$p_i = (x_i, y_i), \text{ for } i = 1, \ldots, n$$
Active Shape Model – Landmark Representation

Landmarks on VB (vertebrae), DXA
Active Shape Model – How to?

(1) Build a statistical boundary shape model that consists of a **mean shape** and its allowable **variations**.

(2) Use the model to **recognize** the boundary in the given scene.

(3) Use the model to **fit to the information in the scene**. The resulting model is considered to be the boundary delineation.
(1) Mean Shape

• Model is constructed via a set of landmarks or homologous points.

• Align the shapes after landmarking corresponding points
  – The Procrustes Algorithm is used to that the sum of instances to the mean of each shape is minimized! Why?

\[ \sum_{i=1,\ldots,M} (q_i - \bar{q})^2 \]

• The mean shape and allowable variations are determined from a set of N training shapes
(1) Mean Shape

Landmark Selection
(1) Mean Shape – Alignment Step

Shape Alignment

Before

After
(1) Mean Shape

1. Compute the mean of the data

\[ \bar{q} = \frac{1}{M} \sum_{i=1}^{M} q_i \]
(1) Mean Shape

1. Compute the mean of the data
\[
\bar{q} = \frac{1}{M} \sum_{i=1}^{M} q_i
\]

2. Compute the covariance of the data
\[
S = \frac{1}{M - 1} \sum_i (q_i - \bar{q})(q_i - \bar{q})^T
\]
(1) Mean Shape

1. Compute the mean of the data

\[ \bar{q} = \frac{1}{M} \sum_{i=1}^{M} q_i \]

2. Compute the covariance of the data

\[ S = \frac{1}{M-1} \sum_{i} (q_i - \bar{q})(q_i - \bar{q})^T \]

3. Compute the eigenvectors \( u_i \) and eigenvalues \( \lambda_i \) of the covariance matrix, sorted in decreasing order of eigenvalue size

4. Remove the small eigenvalues, retaining “most” (eg 98%) of the variation

Choose \( t \) so that \[ \sum_{i=1}^{t} \lambda_i \geq 0.98 \sum_{i=1}^{M} \lambda_i \]
**Mean Shape – Model Variation**

- We now **approximate** any instance of the shape, including the training instances, by projecting onto the first $t$ eigenvectors:

  $$ q = \bar{q} + \sum_{i=1}^{t} b_i u_i $$

- The weight vector $b$ is identified as the characteristic of this instance of the shape:

  $$ b = [b_1, \ldots, b_t]^T $$

- Varying the weights $b_i$ enables us to explore the allowable variations in the shape!
Variation in Shape Model

+2 standard deviations
+1 standard deviations
Mean Outline
-1 standard deviation
-2 standard deviations

Credit:
Inst. of Medical Sciences
Univ. of Aberdeen
(1) Mean Shape – Example Modes

Shape instances generated (talus bone of foot):

mean -2 std  mean  mean+2 std
(1) Mean Shape – Example Brain Structures

\[ b_1 = -2\sigma_1 \]

Mean Shape

\[ b_1 = +2\sigma_1 \]
(1) Mean Shape – Example Modes

Shape instances generated (talus bone of foot):

\[-3\sqrt{\lambda_1} \leq b_1 \leq 3\sqrt{\lambda_1} \quad -3\sqrt{\lambda_2} \leq b_2 \leq 3\sqrt{\lambda_2}\]
(2) Placing the model – ASM Search

• (0) Specify mean shape location.

• (1) Along line segments orthogonal to current shape, determine intensity profile.

• (2) Reposition landmark along line to match boundary information.

• (3) Subject landmarks to model constraints. If convergence, stop. Else go to (1).
(2) Placing the model – ASM Search

\begin{align*}
&(X_i, Y_i) \\
\text{Need to search for local match} \\
\text{For each point:} \\
\text{- strongest edge} \\
\text{- correlation} \\
\text{- statistical model of profile}
\end{align*}
Deeper in ASM Search

Model boundary

Model point \((X, Y)\)

Interpolate at these points

\[(X, Y) + i(s_n n_x, s_n n_y)\]

\(i = \ldots -2, -1, 0, 1, 2, \ldots\)

Take steps of length \(s_n\) along \((n_x, n_y)\)

Select point along profile at strongest edge

\[\frac{dg(x)}{dx} = 0.5(g(x+1) - g(x-1))\]
Finding the model pose & parameters

- Suppose we have identified a set of points $Y$ in the image. Evidently, we can seek to minimize the squared distance:

$$|Y - T(\bar{q} + \sum_{i=1}^{t} b_i u_i)|^2$$

**Algorithm**

1. Initialize $b=0$
2. Generate initial model instance $q = (\bar{q} + \sum_{i=1}^{t} b_i u_i)$
3. Find $T$ that best aligns $q$ to $Y$ (e.g., similarity transform)
4. Invert pose parameters, to project $y = T^{-1}(Y)$ into model frame
5. Update the model parameters: $b = U^T(y - \bar{q})$, $U = [u_1|u_1|...u_t]$
6. Repeat from step 2 until convergence
Example Application: Knee Cartilage quantification - MRI
Ex: MR Brain structure segmentation
ASM Summary

Pros:
- Shape prior helps overcoming segmentation errors
- Fast optimization
- Can handle interior/exterior dynamics

Cons:
- Optimization gets trapped in local minima
- Re-initialization is problematic

Possible improvements:
Learn and apply specific motion priors for different actions
ASM - Problems

True boundary

ASM result
ASM Problems

10 points

2D landmarking

How about 3D?

Time consuming!
Correspondence Issue!

20 points

Talus 1

Liver 1
Alternative solutions for landmarking

- Based on image registration
- Based on MDL (min description length) and optimization techniques
- Based on shape characteristics of the objects
ASM Problems – Initialization Sensitivity
Oriented Active Shape Models (OASM)

Overview of Approach

(1) Selecting landmarks.
(2) Building models. \{ \text{training} \}
(3) Creating boundary cost function.
(4) Coarse level recognition. ⇐
(5) Fine level recognition & delineation – 2LDP. ⇐
(5) Fine level recognition & delineation – 2LDP

- Construct a graph to set up synergy between recgn. and deln.
- Automate recognition.
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- Construct a graph to set up synergy between recognition and delineation.
- Automate recognition.
OASM – Recognition (model placement)

Coarse level recognition

- At each location in a coarse grid, evaluate the total boundary cost (from Live Wire) via $2LDP$ by placing the mean shape at that point.
- Select that location for which this total cost is the minimum.
OASM – Recognition (model placement)
OASM - Segmentation

Automatic recognition

Final segmentation
Comparison with ASM

ASM  n=36

OASM  n=20
Comparison with ASM

ASM  n=28  

OASM  n=28
Comparison with ASM

ASM

OASM
Comparison with ASM

ASM

OASM
Comparison with ASM
Comparison with ASM

ASM

OASM
Active Appearance Model

• PLEASE READ THE FOLLOWING PAPER
Summary

• Shape
  – Shape representation (landmark based)

• ASM
  – Model placement, ASM search (optimization)

• OASM
  – Orientedness – Cost function
  – Less number of landmarks
  – Improved results
Slide Credits and References

- **Credits to:** Jayaram K. Udupa of Univ. of Penn., MIPG
- Bagci’s CV Course 2015 Fall.
- TF. Cootes et al. ASM and their training and applications, 1995.
- K.D. Toennies, Guide to Medical Image Analysis,
- Shape Analysis in Medical Image Analysis, Springer.
- Handbook of Biomedical Imaging, Paragios, Duncan, Ayache.