Shape Alignment
Shape context & Geometric Blur

CSE399b Spring 2007
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Many Slides Taken From Alex Berg
Object Category Recognition
Deformable Template Matching with Exemplars for Recognition

- Use exemplars as deformable templates
- Find a correspondence between the query image and each template
Deformable Template Matching with Exemplars for Recognition

- Use exemplars as deformable templates
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Query Image

Database of Templates

Best matching template is a helicopter
D’Arcy Thompson: On Growth and Form, 1917 studied transformations between shapes of organisms
Evaluate correspondence based on:

- **Similarity of appearance** near feature points
- **Similarity in configuration** of the feature points
Correspondence for Deformable Template Matching

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Correspondence for Deformable Template Matching

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Correspondence Result
Interpolated Correspondence Using Thin Plate Splines
Step 1: feature correspondence

Goal: high precision (low miss rate), low false positive (false alarm)

Method: use many features, and add geometric context

Features: Shape Context, Geometric Blur
Detect edges, and subsample edge nodes
Shape Context

Count the number of points inside each bin, e.g.:

Count = 4

\[ \vdots \]

Count = 10

Φ Compact representation of distribution of points relative to each point
Shape contexts are histograms.
Properties of Shape Context

1) Invariant under translation and scale
2) Can be made invariant to rotation by using local tangent orientation frame
3) Tolerant to small affine distortion
   Log–polar bins make spatial blur proportional to r

Cf. Spin Images (Johnson & Hebert) – range image registration
Matching point features using Shape Context

Compute matching costs using Chi Squared distance:

\[ C_{ij} = \frac{1}{2} \sum_{k=1}^{K} \frac{[h_i(k) - h_j(k)]^2}{h_i(k) + h_j(k)} \]

Recover correspondences by solving linear assignment problem with costs \( C_{ij} \)
Global match between all feature point can be done using Hungarian Bipartite graph matching method.
Example: similar and different shapes
Find best match for the shape context at only a few random points and add up cost

\[
\text{dist}(S_{\text{query}}, S_i) = \sum_{j=1}^{r} \chi^2 (SC^j_{\text{query}}, SC^*_i)
\]

\[
SC^*_i = \arg \min_u \chi^2 (SC^j_{\text{query}}, SC^u_i)
\]
But if we want to use color and texture features?
Paul Debevec 1992

CS283 Course Project,
“A Neural Network for Facial Feature Location”
Geometric Blur
(Local Appearance Descriptor)

Berg & Malik '01

Compute sparse channels from image
Extract a patch in each channel
Geometric Blur
(Local Appearance Descriptor)\textsuperscript{Berg & Malik '01}

- Compute sparse channels from image
- Extract a patch in each channel
- Apply spatially varying blur
- Descriptor is robust to small affine distortions
Geometric blur vs. Gaussian Blur

Geometric Blur is a spatially variant convolution:

\[ G_I(x) = \int_y I(x - y)K_x(y)dy \]

\[ K_x(y) = f(\alpha|x| + \beta)G_{\alpha|x|+\beta}(y), \]
Geometric blur vs. Gaussian Blur

How to compute it fast:

1) compute gaussian blur at different scale across the entire image
2) for each feature point, pick up blurred image at different scale depends on the radial distance to the feature point
Geometric Blur (Local Appearance Descriptor)

Compute sparse channels from image

Extract a patch in each channel

Apply spatially varying blur and sub-sample

Descriptor is robust to small affine distortions

Berg & Malik '01
Geometric Blur
(Local Appearance Similarity)
Are Features Enough?

Color indicates similarity using Geometric Blur Descriptor

Not Quite...
Linear Assignment
(e.g. Hungarian)
STEP 2: Enforce Geometric Configuration

• Evaluate correspondence based on:
  • Similarity of appearance near feature points
  • Similarity in configuration of the feature points
Idea: Thin-Plate Spline Function to "regularize" the geometrical transformation

From a shape to another: TPS transformations

The goal is to find $f_x, f_y : \mathbb{R}^2 \mapsto \mathbb{R}^2$ such as:

$$\begin{cases}
\forall i \ f_x(x_i, y_i) = x'_i \\
f_x = \arg \min_g \left\{ I_g = \int \int_{\mathbb{R}^2} \left( \frac{\partial^2 g}{\partial x^2} \right)^2 + \left( \frac{\partial^2 g}{\partial x \partial y} \right)^2 + \left( \frac{\partial^2 g}{\partial y^2} \right)^2 \right\} \\
f_x(x, y) = v + v_xx + v_yy + \sum_{i=1}^{n} w_i U \left( \| (x_i, y_i) - (x, y) \| \right)
\end{cases}$$

where $U(r) = r^2 \log r^2$, and with the same conditions on $f_y$. 
From a shape to another: TPS transformations

Model  Target
Overall Shape Matching Steps:

1) Compute interesting points on image A and B. This could be edges, or corners. Any stable features would do.
2) Extract Shape Context or Geometric Blur features on both images.
3) Run Hungarian matching to compute point-wise correspondence between A and B.
4) Compute Thin-plate spline (TPS) mapping between A and B.
5) Warp image A using TPS computed in 4), and repeat step 1-4.
• **MNIST 60 000:**
  - linear: 12.0%
  - 40 PCA+ quad: 3.3%
  - 1000 RBF +linear: 3.6%
  - K-NN: 5%
  - K-NN (deskewed): 2.4%
  - K-NN (tangent dist.): 1.1%
  - SVM: 1.1%
  - LeNet 5: 0.95%

• **MNIST 600 000**
  (distortions):
  - LeNet 5: 0.8%
  - SVM: 0.8%
  - Boosted LeNet 4: 0.7%

• **MNIST 20 000:**
  - K-NN, Shape Context matching: 0.63%
Correspondence Examples (Shape Matching)
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