EECS 442 – Computer vision

Object Recognition

- Intro
- Recognition of 3D objects
  - Recognition of object categories:
    - Bag of world models
    - Part based models
    - 3D object categorization
    - Faces

Segments of this lectures are courtesy of Prof A. Torralba, R. Fergus and F. Li

“Recognizing and Learning Object Categories: Year 2007”
Challenges: intra-class variation
Usual Challenges:

Variability due to:

• View point
• Illumination
• Occlusions
Problem with bag-of-words

• All have equal probability for bag-of-words methods

• Location information is important
Part Based Representation

• Object as set of parts

• Model:
  – Relative locations between parts
  – Appearance of part

Figure from [Fischler & Elschlager 73]
History of Parts and Structure approaches

- Fischler & Elschlager 1973
- Yuille ‘91
- Brunelli & Poggio ‘93
- Lades, v.d. Malsburg et al. ‘93
- Cootes, Lanitis, Taylor et al. ‘95
- Amit & Geman ‘95, ‘99
- Ullman et al. 02
- Felzenszwalb & Huttenlocher ’00, ‘04
- Crandall & Huttenlocher ’05, ’06
- Leibe & Schiele ’03, ’04
- Many papers since 2000
Deformations
Presence / Absence of Features

www.corbis.com
Background clutter
Sparse representation

+ Computationally tractable ($10^5$ pixels $\rightarrow$ $10^1$ -- $10^2$ parts)
+ Generative representation of class
+ Avoid modeling global variability

- Throw away most image information
- Parts need to be distinctive to separate from other classes
Different connectivity structures

- a) Constellation [13]
- b) Star shape [9, 14]
- c) k-fan (k = 2) [9]
- d) Tree [12]
- e) Bag of features [10, 21]
- f) Hierarchy [4]
- g) Sparse flexible model

from Sparse Flexible Models of Local Features
Gustavo Carneiro and David Lowe, ECCV 2006
Hierarchical representations

• Pixels $\rightarrow$ Pixel groupings $\rightarrow$ Parts $\rightarrow$ Object

• Multi-scale approach increases number of low-level features

- Amit and Geman ‘98
- Bouchard & Triggs ‘05
Hierarchical representations

- Pixels $\rightarrow$ Pixel groupings $\rightarrow$ Parts $\rightarrow$ Object

- Multi-scale approach increases number of low-level features

- Amit and Geman ‘98
- Bouchard & Triggs ‘05

Images from [Amit98, Bouchard05]
Hierarchical representations

- Pixels $\rightarrow$ Pixel groupings $\rightarrow$ Parts $\rightarrow$ Object

- Multi-scale approach increases number of low-level features

  - Amit and Geman ‘98
  - Bouchard & Triggs ‘05

Images from [Amit98,Bouchard05]
Some class-specific graphs

• Articulated motion
  – People
  – Animals

• Special parameterisations
  – Limb angles

Images from [Kumar, Torr and Zisserman 05, Felzenszwalb & Huttenlocher 05]
Stochastic Grammar of Images

S.C. Zhu et al. and D. Mumford
animal head instantiated by tiger head

animal head instantiated by bear head

e.g. discontinuities, gradient

e.g. linelets, curvelets, T-junctions

e.g. contours, intermediate objects

e.g. animals, trees, rocks

e.g. discontinuities, gradient
Two approaches

• Generative part-based models (constellation models) (explicit shape models)

• Implicit shape models
Generative part-based models

E.g. Gaussian distribution (parameters of model, \( \mu \) and \( \Sigma \))

- Burl et al. ‘96
- R. Fergus, P. Perona and A. Zisserman, ‘03
Learn appearance & shape

[appearance first, then shape]

Weber et al. ‘00

Preselected Parts (≈100)
[Code book]
Recall: Object categorization: the statistical viewpoint

\[
\frac{p(\text{zebra} \mid \text{image})}{p(\text{no zebra} \mid \text{image})} = \frac{p(\text{image} \mid \text{zebra})}{p(\text{image} \mid \text{no zebra})} \cdot \frac{p(\text{zebra})}{p(\text{no zebra})}
\]

- Posterior ratio
- Likelihood ratio
- Prior ratio

- Discriminative methods model posterior
- Generative methods model likelihood and prior
Probabilistic model

\[ P(\text{image} \mid \text{object}) = P(\text{appearance, shape} \mid \text{object}) \]

Candidate parts (features)

Credit slide: S. Lazebnik
Probabilistic model

\[ P(\text{image} \mid \text{object}) = P(\text{appearance, shape} \mid \text{object}) \]
Probabilistic model

\[ P(\text{image} | \text{object}) = P(\text{appearance, shape} | \text{object}) \]

\[ P(\text{appearance} | h, \text{object}) p(\text{shape} | h, \text{object}) p(h | \text{object}) \]

\[ h: \text{ assignment of features to parts} \]

Introduce variable \( h \) to regulate feature assignment

Credit slide: S. Lazebnik
Probabilistic model

\[ P(\text{image} \mid \text{object}) = P(\text{appearance, shape} \mid \text{object}) \]

\[ P(\text{appearance} \mid h, \text{object}) p(\text{shape} \mid h, \text{object}) p(h \mid \text{object}) \]

High-dimensional appearance (feature) space

Distribution over patch descriptors

Credit slide: S. Lazebnik
Probabilistic model

\[ P(\text{image} \mid \text{object}) = P(\text{appearance, shape} \mid \text{object}) \]

\[ P(\text{appearance} \mid h, \text{object}) p(\text{shape} \mid h, \text{object}) p(h \mid \text{object}) \]

Credit slide: S. Lazebnik
Recognition

1. Run part detectors exhaustively over image

2. Try different combinations of detections in model
   - Allow detections to be missing (occlusion)

3. Pick hypothesis which maximizes:
   \[
   p(\text{Data} \mid \text{Object}, \text{Hyp}) \frac{p(\text{Data} \mid \text{Clutter}, \text{Hyp})}{p(\text{Data} \mid \text{Clutter}, \text{Hyp})}
   \]

4. If ratio is above threshold then, instance detected
Learning Models `Manually`

- Obtain set of training images
- Choose parts
- Label parts by hand, train detectors
- Learn model from labeled parts
(Semi) Unsupervised learning

- Know if image contains object or not
- But no segmentation of object or manual selection of features
• Highly textured neighborhoods are selected automatically
• produces 100-1000 patterns per image
Appearance Learning procedure

"Pattern Space" (100+ dimensions)
Appearance Learning procedure

100-1000 images  ~100 detectors
Shape Learning procedure

• Find regions & their location & appearance

• Initialize model parameters \( \theta = [\mu, \Sigma] \)

• Use EM and iterate to convergence:
  - E-step: Use current \( \theta \) to compute assignments
  - M-step: Given assignments, update model parameters \( \theta = [\mu, \Sigma] \)

• Trying to maximize likelihood – consistency in shape & appearance
Example scheme, using EM for maximum likelihood learning

1. Current estimate of $\theta$

2. Assign probabilities to constellations

3. Use probabilities as weights to re-estimate parameters. Example: $\mu$

new estimate of $\mu$
Learned face model

Pre-selected Parts

Test Error: 6% (4 Parts)

Parts in Model

Model Foreground pdf

Sample Detection
Background images
Results: Motorbikes and airplanes
Results: Motorbikes and airplanes
Two approaches

• Generative part-based models
  (constellation models)
  (explicit shape models)

• Implicit shape models
Implicit shape models

• Visual codebook is used to index votes for object position

training image

visual codeword with displacement vectors

B. Leibe, A. Leonardis, and B. Schiele, Combined Object Categorization and Segmentation with an Implicit Shape Model, ECCV Workshop on Statistical Learning in Computer Vision 2004

Credit slide: S. Lazebnik
Implicit shape models: Training

1. Build codebook of patches around extracted interest points using clustering
Implicit shape models: Training

1. Build codebook of patches around extracted interest points using clustering
2. Map the patch around each interest point to closest codebook entry

Credit slide: S. Lazebnik
Implicit shape models: Training

1. Build codebook of patches around extracted interest points using clustering
2. Map the patch around each interest point to closest codebook entry
3. For each codebook entry, store all positions it was found, relative to object center [center is given]

Credit slide: S. Lazebnik
Implicit shape models: Testing

1. Given test image, extract patches, match to codebook entry
2. Cast votes for possible positions of object center
3. Search for maxima in voting space
4. Extract weighted segmentation mask based on stored masks for the codebook occurrences
Implicit shape models

- Visual codebook is used to index votes for object position [Cast votes for possible positions of object center]

test image

Search for maxima in voting space
Summary: Part based models

• Generative part-based models
  – Pro: very nice conceptually
  – Pro: semi-supervised!
  – Con: combinatorial hypothesis search problem

• Implicit shape models
  – Pro: can localize object, maintain translation and possibly scale invariance
  – Con: need supervised training data (known object positions and possibly segmentation masks)
Object Recognition

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  • Recognition of object categories:
    • Bag of world models
    • Part based models
    • 3D object categorization
    • Faces
3D Object Categorization

- Weber et al. ‘00
- Schneiderman et al. ‘01
- Capel et al. ‘02
- Johnson & Herbert ‘99
- Bronstein et al. ‘03
- Ruiz-Correa et al. ‘03
- Funkhouser et al. ‘03
- Bart et al. ‘04
- Thomas et al. ‘06
- Kushal, et al., ‘07
- Savarese et al., 07, 08
- Chiu et al. ‘07
- Hoiem, et al., ‘07
- Yan, et al. ‘07
Single view object categorization

• Leung et al. ’99
• Weber et al. ’00
• Ullman et al. ’02
• Fergus et al. ’03
• Torralba et al. ’03
• Felzenszwalb & Huttenlocher ’03
• Fei-Fei et al. ’04
• Leibe et al. ’04
• Kumar & Hebert ’04
• Sivic et al. ’05
• Shotton et al. ’05
• Grauman et al. ’05
• Sudderth et al. ’05
• Torralba et al. ’05
• Lazebnik et al. ’06
• Todorovic et al. ’06
• Bosh et al. ’07
• Vedaldi & Soatto ’08
Single 3D object recognition

- Ballard, ’81
- Grimson & L.-Perez, ’87
- Lowe, ’87
- Zhang et al.’95
- Ullman & Barsi, ’91
- Rothwell ’92
- Linderberg, ’94
- Murase & Nayar ’94
- Schmid & Mohr, ’96
- Schiele & Crowley, ’96
- Lowe, ’99
- Jacob & Barsi, ’99
- Rothganger et al., ’04
- Ferrari et al., ’05
- Brown & Lowe ‘05
- Snavely et al ’06
- Yin & Collins, ’07
3D Object Categorization

Additional challenges

- how to model 3D shape variability?

- How to model texture (appearance) variability?
3D Object Categorization

Mixture of 2D single view models

- Weber et al. ‘00
- Schneiderman et al. ‘01
- Bart et al. ‘04

Full 3D models

- Bronstein et al., ‘03
- Ruiz-Correa et al. ‘03
- Funkhouser et al. ‘03
- Capel et al. ‘02
- Johnson & Herbert ‘99

Multi-view models

- Chiu et al. ‘07
- Hoiem, et al., ‘07
- Yan, et al. ‘07

- Thomas et al. ‘06
- Kushal, et al., ‘07
- Savarese et al., 07, 08
Mixture of single-view 2D models

- Weber et al. ‘00
- Schneiderman et al. ‘01
Multiple views

- **Mixture of 2-D models**
  - Weber, Welling and Perona CVPR ’00

![Component 1](image1)

![Component 2](image2)

**Orientation Tuning**

% Correct

angle in degrees

Frontal

Profile
Mixture of single-view 2D models

Single view models are independent
• No information is shared
• No sense of correspondences of parts under 3D transformations

- Weber et al. ‘00
- Schneiderman et al. ‘01

3D Category model
3D Object Categorization

Mixture of 2D single view models

- Weber et al. ‘00
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- Bart et al. ‘04

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Multi-view models

- Thomas et al. ‘06
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- Savarese et al, 07, 08
Multi-view models

- Thomas et al. ‘06
- Kushal, et al., ‘07
- Savarese et al, 07, 08

Sparse set of interest points or parts of the objects are linked across views.
Combining multi-views and ISM models

Representation

[Thomas et al. ’06]
Combining multi-views and ISM models

Representation

Set of *region-tracks* connecting model views
Each track is composed of image regions of a single physical surface patch along the model views in which it is visible.

[Thomas et al. ’06]
[Ferrari et al. ’04, ’06]
[Leibe et al. ’04]
Combining multi-views and ISM models

[Thomas et al. ’06]

1. Features are extracted from the image ... and matched to all the codebooks of the different ISMs.
2. Votes are cast in the Hough spaces of each ISM separately
3. Initial hypotheses are detected as local density maxima in these spaces.
Combining multi-views and ISM models

Recognition

[Thomas et al. ’06]

4. Augment the Hough spaces of each selected working view by inserting additional votes from codebook matches in other views [vote transferring]

- Qi is not being matched to Ot in the test image.
- However, Qj is linked to Qi to another view via activation link;
- Since Qi is matched to Ot, an additional vote is added.
- This is vote transferring
Combining multi-views and ISM models

Results

[Thomas et al. ’06]
Combining multi-views and ISM models

Results

[Thomas et al. ’06]
3D Object Categorization

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- Chiu et al. ‘07
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- Savarese et al, 07, 08
Flexible models of object categories by PSMs

Representation

PSMs = dense, locally rigid assemblies of texture patches

- PSMs are learned by matching repeating patterns of features across training images of each object class

[Kushal et al. '06]

[Lazebnick et al. '04]
Flexible models of object categories by PSMs

Representation

PSM graph = MRF model the joint probability distribution of the variables $A_u$ associated with all PSMs in an object model

$A_{ul}$

$A_{ul}$ = the random variable associated with the affine deformation corresponding to PSM $u$

This transformation represents the affine deformation of the PSM from its base image to its matched location
Flexible models of object categories by PSMs

[Kushal et al. '06]

Recognition

Most likely explanation of the scene:

\[ E^* = \arg \max_{E \in \mathcal{P}(D)} P(E|D) = \arg \max_{E \in \mathcal{P}(D)} p(E, D). \]

\[ p(E, D) = \text{probability that an explanation } E \text{ generates the matches } D \text{ in the image} \]

\[ E = \{O_1, O_2, \ldots, O_k, B\} \]

\[ D = \text{set of all the PSM matches detected in the test image} \]

\[ O_i = \text{subset of } D \text{ corresponding to instance number } i \text{ of the object in the image} \]
Flexible models of object categories by PSMs

Results

PASCAL VOC Challenge 2005 Cars Test 1 dataset

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>AP</th>
</tr>
</thead>
<tbody>
<tr>
<td>PSM graph</td>
<td>0.628</td>
</tr>
<tr>
<td>Dalal &amp; Triggs [2]</td>
<td>0.613</td>
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<tr>
<td>Voting+MS</td>
<td>0.590</td>
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<td>Fritz et al. [11]</td>
<td>0.489</td>
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<tr>
<td>Garcia &amp; Duffner [6]</td>
<td>0.353</td>
</tr>
</tbody>
</table>

No geometric model
Flexible models of object categories by PSMs

Results

[Kushal et al. ’06]
3D Object Categorization

Mixture of 2D single view models

- Weber et al. ‘00
- Schneiderman et al. ‘01

Full 3D models

- Bronstein et al, ‘03
- Ruiz-Correa et al. ‘03,
- Funkhouser et al ‘03
- Capel et al ‘02
- Johnson & Herbert ‘99

- Chiu et al. ‘07
- Hoiem, et al., ‘07
- Yan, et al. ‘07

Multi-view models

- Thomas et al. ‘06
- Kushal, et al., ‘07
- Savarese et al, 07, 08
Linkage structure of canonical parts

- Canonical parts
- Linkage structure via weak geometry

Savarese & Fei-Fei, ‘07, ‘08
Canonical parts

A stable and compact representation across multiple views!
Canonical parts

How to learn canonical parts?
Canonical parts

Unlabeled mix of images
\[ \pi : I^h \rightarrow \{ P_1^h, P_2^h, P_3^h, O^h \} \]
\[ \tau : I^k \rightarrow \{ P_1^k, P_2^k, P_3^k, O^k \} \]

- Match candidates based on appearance
- Use RANSAC on H & F to filter best matches & partition matched features into matched parts
- Output: matched parts related by H

Alternative methods

[Ref: Lazebnick et al '04]
[Ref: Ferrari et al '04]
Canonical parts

Property:
1. A canonical part is a stable point in the manifold if physical part is planar
2. The stable point can be reached by descending the gradient $\nabla$

$$\|\nabla\|_{ij} \approx (\lambda_1^i \lambda_2^i - 1)$$
(Pair-wise fore-shortening)
Linkage structure

\[ \mathcal{H}_{2,1} = \begin{pmatrix} H_{2,1} & t_{2,1} \\ 0 & 1 \end{pmatrix} \]
Category Model

\[
\text{Cost} = \sum_{h,k \in L} \sum_{i,j \in L} G(i, j, h, k) \delta_{ij} \delta_{hk} + \sum_{i,j \in L} A(i, j) \delta_{ij}
\]

\[
\sum_{j \in L} \delta_{ij} = 1 \quad \forall \ i
\]

\[
\delta_i = \{0, 1\}
\]

IQP problem
NP-complete \( \rightarrow O(N^2) \)

Maciel & Costeira ‘03
Berg et al ‘05
Leordeanu & Hebert ‘05
Deformable Template Matching

Berg, Berg and Malik CVPR 2005

- Formulate problem as Integer Quadratic Programming
- $O(N^p)$ in general
- Use approximations that allow $p=50$ and $N=2550$ in <2 secs
Category Model

\[ P_j = \frac{1}{N} \sum_{k}^{N} P_j^k \]
$H_{i,j} = \begin{pmatrix} 1 & t_{i,j} \\ 0 & 1 \end{pmatrix}$

$H_{i,j} = \begin{pmatrix} H_{i,j} & t_{i,j} \\ 0 & 1 \end{pmatrix}$

Category Model

Canonical view

2D constellation model!
Recognition

Algorithm
1. Find hypotheses of canonical parts consistent with a given pose
Recognition

Algorithm
1. Find hypotheses of canonical parts consistent with a given pose
2. Infer position and pose of other canonical parts
Recognition

Algorithm

1. Find hypotheses of canonical parts consistent with a given pose
2. Infer position and pose of other canonical parts
Recognition

Algorithm

1. Find hypotheses of canonical parts consistent with a given pose
2. Infer position and pose of other canonical parts
3. Optimize over $A$, $G$ and $s$ to find best combination of hypothesis

$$\text{Cost} = \sum_{h,k \in L} \sum_{i,j \in L} G(i,j,h,k) \delta_{ij} \delta_{hk} + \sum_{i,j \in L} A(i,j) \delta_{ij}$$
Examples

Category: iron
Azimuth = 135°
Zenith = 60°
Distance = medium
Classification accuracy

Average Perf. = 75.7%

<table>
<thead>
<tr>
<th></th>
<th>c</th>
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<th>i</th>
<th>m</th>
<th>s</th>
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<td>.07</td>
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<tr>
<td>car</td>
<td>.04</td>
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<td>.12</td>
<td>.04</td>
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</tbody>
</table>
Failure example

Category: shoe
Azimuth = 225°
Zenith = 30°
Distance = close
Linkage structure of canonical parts

Results

Savarese & Fei-Fei, ’07, ’08

Motorbike database from the PASCAL visual object classes challenge
# Conclusions

<table>
<thead>
<tr>
<th></th>
<th>Single view</th>
<th>Thomas et al.</th>
<th>Kushal et al.</th>
<th>Savarese &amp; Fei-Fei</th>
</tr>
</thead>
<tbody>
<tr>
<td>View point invariant</td>
<td>X</td>
<td>√</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>No supervision</td>
<td>√</td>
<td>X</td>
<td>X → √ category, instance, views</td>
<td>X → √ category</td>
</tr>
<tr>
<td># Categories</td>
<td>~100</td>
<td>2</td>
<td>1</td>
<td>8</td>
</tr>
<tr>
<td>Share information across views</td>
<td>X</td>
<td>√</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>View synthesis</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X → √</td>
</tr>
<tr>
<td>Sampling density</td>
<td>N.A.</td>
<td>X</td>
<td>X → √ category, views</td>
<td>X → √</td>
</tr>
</tbody>
</table>
EECS 442 – Computer vision

Next lecture

Pool: Faces recognition or Motion analysis/Tracking?
Spatial pyramid representation

- Extension of a bag of features
- Locally orderless representation at several levels of resolution

Lazebnik, Schmid & Ponce (CVPR 2006)
Spatial pyramid representation

- Extension of a bag of features
- Locally orderless representation at several levels of resolution

Lazebnik, Schmid & Ponce (CVPR 2006)
Spatial pyramid representation

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- Locally orderless representation at several levels of resolution

Lazebnik, Schmid & Ponce (CVPR 2006)
## Scene category dataset

### Multi-class classification results
(100 training images per class)

<table>
<thead>
<tr>
<th>Level</th>
<th>Weak features (vocabulary size: 16)</th>
<th>Strong features (vocabulary size: 200)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Single-level</td>
<td>Pyramid</td>
</tr>
<tr>
<td>0 (1 × 1)</td>
<td>45.3 ± 0.5</td>
<td></td>
</tr>
<tr>
<td>1 (2 × 2)</td>
<td>53.6 ± 0.3</td>
<td>56.2 ± 0.6</td>
</tr>
<tr>
<td>2 (4 × 4)</td>
<td>61.7 ± 0.6</td>
<td>64.7 ± 0.7</td>
</tr>
<tr>
<td>3 (8 × 8)</td>
<td>63.3 ± 0.8</td>
<td>66.8 ± 0.6</td>
</tr>
</tbody>
</table>
## Caltech101 dataset


### Multi-class classification results (30 training images per class)

<table>
<thead>
<tr>
<th>Level</th>
<th>Weak features (16)</th>
<th>Strong features (200)</th>
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<td>Pyramid</td>
</tr>
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<td>15.5 ±0.9</td>
<td>32.8 ±1.3</td>
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<td>31.4 ±1.2</td>
<td>49.3 ±1.4</td>
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<td>47.2 ±1.1</td>
<td>54.0 ±1.1</td>
</tr>
<tr>
<td>3</td>
<td>52.2 ±0.8</td>
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