#### Object Class Recognition by Unsupervised Scale-Invariant Learning

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### Goal:

 Enable Computers to Recognize Different Categories of Objects in Images.









# Components

- Model
  - Generative Probabilistic Model
  - Location, Scale, and Appearance
- Learning
  - Estimate Parameters Via EM
- Recognition

- Evaluate Image Using Model and Threshold

#### Model: Constellation Of Parts



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 Perona et al. 95, 96, 98, 00





#### Parts Selected by Interest Operator

Kadir and Brady's Interest Operator. Finds Maxima in Entropy Over Scale and Location





#### **Representation of Appearance**



#### **Generative Probabilistic Model**

Start with Recognition:

$$R = \frac{p(\text{Object}|\mathbf{X}, \mathbf{S}, \mathbf{A})}{p(\text{No object}|\mathbf{X}, \mathbf{S}, \mathbf{A})}$$
  
= 
$$\frac{p(\mathbf{X}, \mathbf{S}, \mathbf{A}|\text{Object}) p(\text{Object})}{p(\mathbf{X}, \mathbf{S}, \mathbf{A}|\text{No object}) p(\text{No object})}$$
  
$$\approx \frac{p(\mathbf{X}, \mathbf{S}, \mathbf{A}|\boldsymbol{\theta}) p(\text{Object})}{p(\mathbf{X}, \mathbf{S}, \mathbf{A}|\boldsymbol{\theta}_{bg}) p(\text{No object})}$$

$$\begin{split} p(\mathbf{X},\mathbf{S},\mathbf{A}|\,\theta) &= \sum_{\mathbf{h}\in H} p(\mathbf{X},\mathbf{S},\mathbf{A},\mathbf{h}|\,\theta) = \\ \sum_{\mathbf{h}\in H} \underbrace{p(\mathbf{A}|\mathbf{X},\mathbf{S},\mathbf{h},\theta)}_{Appearance} \underbrace{p(\mathbf{X}|\mathbf{S},\mathbf{h},\theta)}_{Shape} \underbrace{p(\mathbf{S}|\mathbf{h},\theta)}_{Rel.\ Scale\ Other} \underbrace{p(\mathbf{h}|\theta)}_{Other} \end{split}$$

#### Appearance

$$\frac{p(\mathbf{A}|\mathbf{X}, \mathbf{S}, \mathbf{h}, \theta)}{p(\mathbf{A}|\mathbf{X}, \mathbf{S}, \mathbf{h}, \theta_{bg})} = \prod_{p=1}^{P} \left( \frac{\mathbf{G}(\mathbf{A}(h_p)|\mathbf{c}_p, V_p)}{\mathbf{G}(\mathbf{A}(h_p)|\mathbf{c}_{bg}, V_{bg})} \right)^{d_p}$$

Gaussian Part Appearance PDF





# Shape

$$\frac{p(\mathbf{X}|\mathbf{S}, \mathbf{h}, \theta)}{p(\mathbf{X}|\mathbf{S}, \mathbf{h}, \theta_{bg})} = G(\mathbf{X}(\mathbf{h})|\boldsymbol{\mu}, \boldsymbol{\Sigma}) \, \alpha^{f}$$

Gaussian Shape PDF







## Scale

$$\frac{p(\mathbf{S}|\mathbf{h}, \theta)}{p(\mathbf{S}|\mathbf{h}, \theta_{bg})} = \prod_{p=1}^{P} \mathbf{G}(\mathbf{S}(h_p)|t_p, U_p)^{d_p} r^f$$



Prob. of detection





Poission PDF On # Detections

### **Occlusion and Part Statistics**

$$\frac{p(\mathbf{h}|\theta)}{p(\mathbf{h}|\theta_{bg})} = \frac{p_{Poiss}(n|M)}{p_{Poiss}(N|M)} \, \frac{1}{{}^nC_r(N,f)} \, p(\mathbf{d}|\theta)$$

# Learning

- Train Model Parameters Using EM:
  - Optimize Parameters
  - Optimize Assignments
  - Repeat Until Convergence

$$\boldsymbol{\theta} = \{\boldsymbol{\mu}, \boldsymbol{\Sigma}, \mathbf{c}, \boldsymbol{V}, \boldsymbol{M}, p(\mathbf{d}|\boldsymbol{\theta}), t, \boldsymbol{U}\}$$

$$\hat{\theta}_{ML} = \mathop{arg\,max}\limits_{\theta} \, p(\mathbf{X}, \mathbf{S}, \mathbf{A} | \, \theta)$$



## Recognition

Make This:

$$R = \frac{p(\text{Object}|\mathbf{X}, \mathbf{S}, \mathbf{A})}{p(\text{No object}|\mathbf{X}, \mathbf{S}, \mathbf{A})}$$
  
= 
$$\frac{p(\mathbf{X}, \mathbf{S}, \mathbf{A}|\text{Object}) p(\text{Object})}{p(\mathbf{X}, \mathbf{S}, \mathbf{A}|\text{No object}) p(\text{No object})}$$
  
$$\approx \frac{p(\mathbf{X}, \mathbf{S}, \mathbf{A}|\boldsymbol{\theta}) p(\text{Object})}{p(\mathbf{X}, \mathbf{S}, \mathbf{A}|\boldsymbol{\theta}_{bg}) p(\text{No object})}$$

Greater Than Threshold

### RESULTS



#### **Background Images**

#### Correct

OPPE



Contec



Correct



Correct









Contec



Correct





Correct



Correct





Correct





Correct





Correct











Correct



#### Equal error rate: 9.8%

#### Airplanes



1022

#### Scale-Invariant Cats

Spotted cat shape model

![](_page_19_Figure_2.jpeg)

![](_page_19_Figure_3.jpeg)

![](_page_19_Picture_4.jpeg)

Correct

![](_page_19_Picture_6.jpeg)

Correct

![](_page_19_Picture_8.jpeg)

#### Equal error rate: S. Cale-Invariant cars

![](_page_20_Figure_1.jpeg)

80

#### **Robustness of Algorithm**

![](_page_21_Figure_1.jpeg)

#### **ROC** equal error rates

#### Pre-Scaled Data (Identical Settings):

|              |            |                     |            | Model |           |              |
|--------------|------------|---------------------|------------|-------|-----------|--------------|
|              | Total size | $\sim$ Object width |            |       |           |              |
| Dataset      | of dataset | (pixels)            | Motorbikes | Faces | Airplanes | Spotted Cats |
| Motorbikes   | 800        | 200                 | 92.5       | 50    | 51        | 56           |
| Faces        | 435        | 300                 | 33         | 96.4  | 32        | 32           |
| Airplanes    | 800        | 300                 | 64         | 63    | 90.2      | 53           |
| Spotted Cats | 200        | 80                  | 48         | 44    | 51        | 90.0         |

#### Scale-Invariant Learning and Recognition:

|             | Total size | Object size    | Pre-scaled  | Unscaled    |
|-------------|------------|----------------|-------------|-------------|
| Dataset     | of dataset | range (pixels) | performance | performance |
| Motorbikes  | 800        | 200-480        | 95.0        | 93.3        |
| Airplanes   | 800        | 200-500        | 94.0        | 93.0        |
| Cars (Rear) | 800        | 100-550        | 84.8        | 90.3        |

#### **Scale-Invariant Cars**

![](_page_23_Figure_1.jpeg)

### The End

![](_page_24_Picture_1.jpeg)

![](_page_25_Figure_0.jpeg)

![](_page_25_Figure_1.jpeg)