Object Recognition by Parts

- Object recognition started with line segments.

    - Roberts recognized objects from line segments and junctions.

    - This led to systems that extracted linear features.

.

    - CAD-model-based vision works well for industrial.

- An “appearance-based approach” was first developed for face recognition and later generalized up to a point.

- The new interest operators have led to a new kind of recognition by “parts” that can handle a variety of objects that were previously difficult or impossible.

Object Class Recognition by Unsupervised Scale-Invariant Learning

R. Fergus, P. Perona, and A. Zisserman

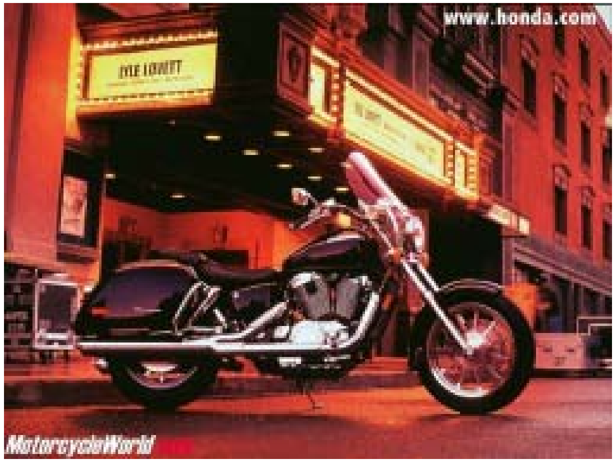
Oxford University and Caltech

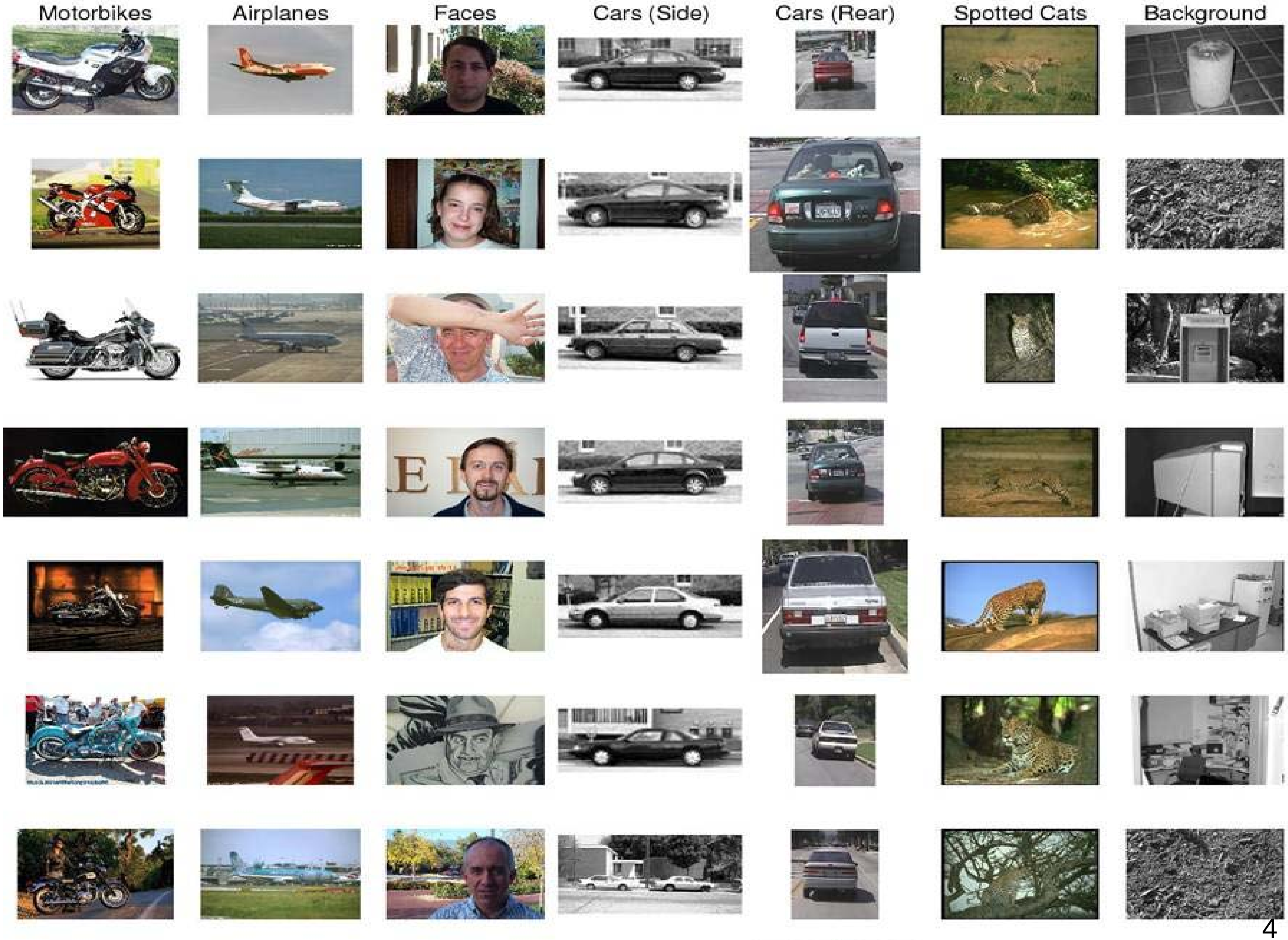
CVPR 2003

won the best student paper award

Goal:

- Enable Computers to Recognize Different Categories of Objects in Images.




Motorbikes
Airplanes
Faces
Cars (Side)
Cars (Rear)
Spotted Cats
Background

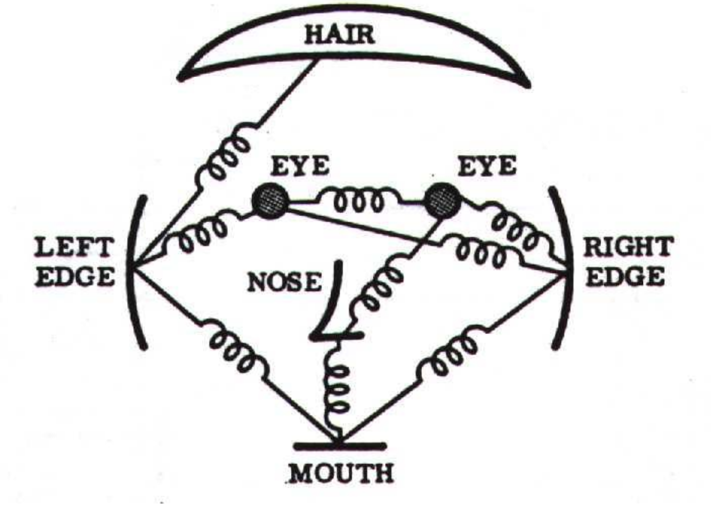
Approach

- An object is a random constellation of parts (from Burl, Weber and Perona, 1998).
- The parts are detected by an interest operator (Kadir's).
- The parts can be recognized by appearance.
- Objects may vary greatly in scale.
- The constellation of parts for a given object is learned from training images

Components

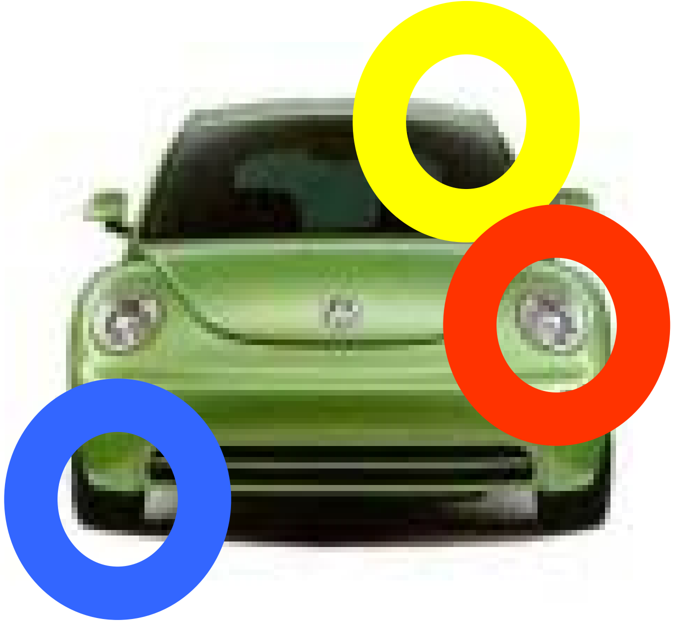
- Model
  - Generative Probabilistic Model including Location, Scale, and Appearance of Parts
- Learning
  - Estimate Parameters Via EM Algorithm
- Recognition
  - Evaluate Image Using Model and Threshold

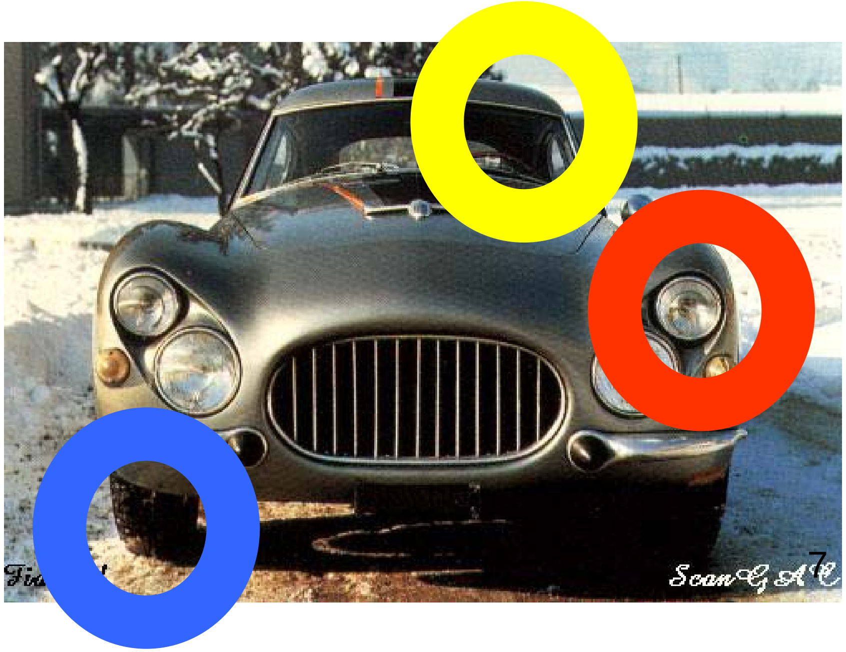
Model: Constellation Of Parts



Fischler & Elschlager, 1973

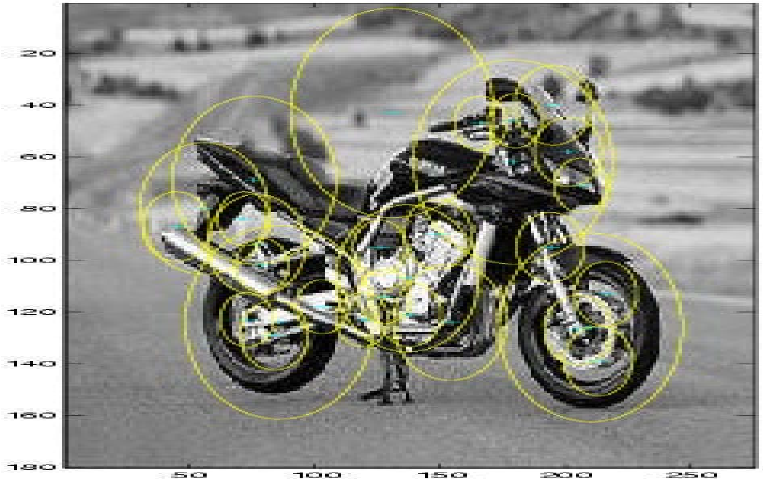
Yuille, □91
Brunelli & Poggio, □93
Lades, v.d. Malsburg et al. □93
Cootes, Lanitis, Taylor et al. □95
Amit & Geman, □95, □99
Perona et al. □95, □96, □98, □00

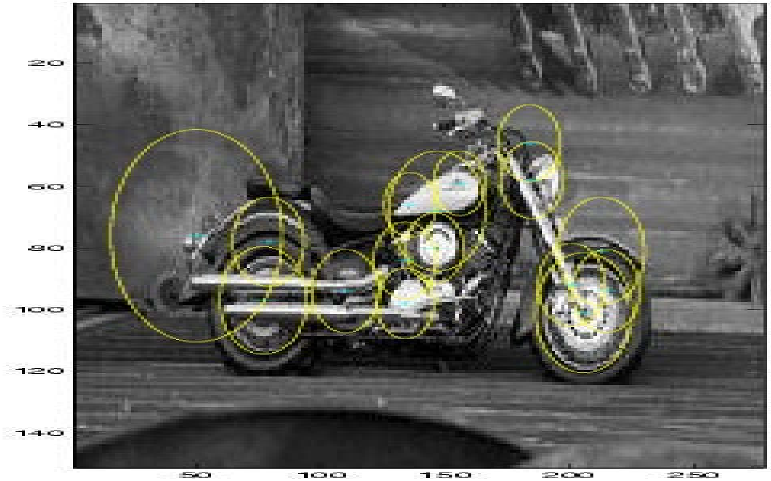


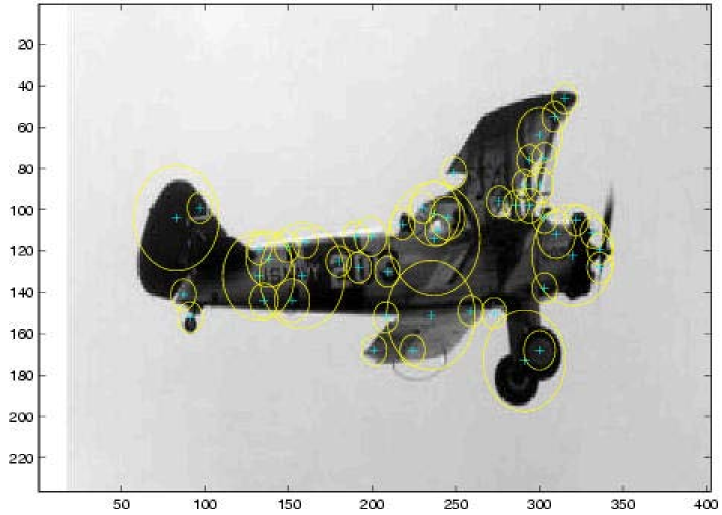


Parts Selected by Interest Operator

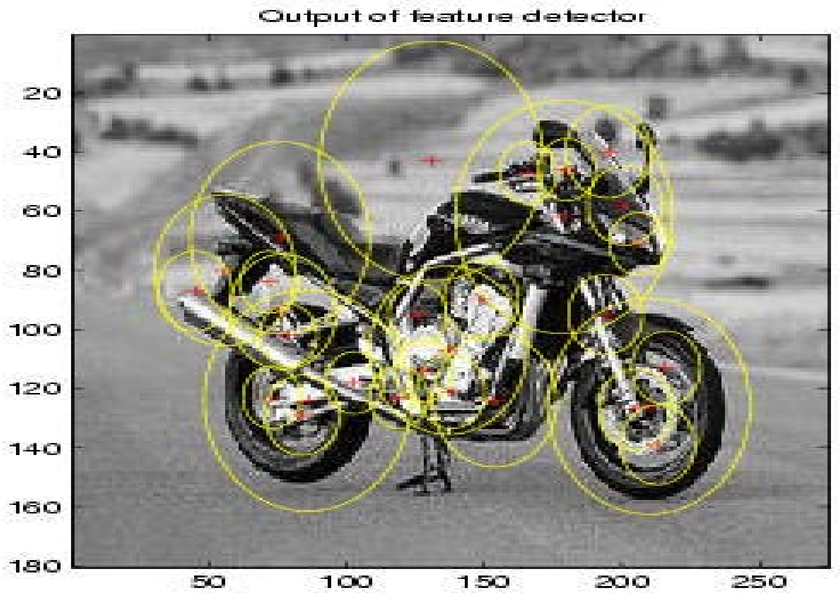
Kadir and Brady's Interest Operator.
Finds Maxima in Entropy Over Scale and Location

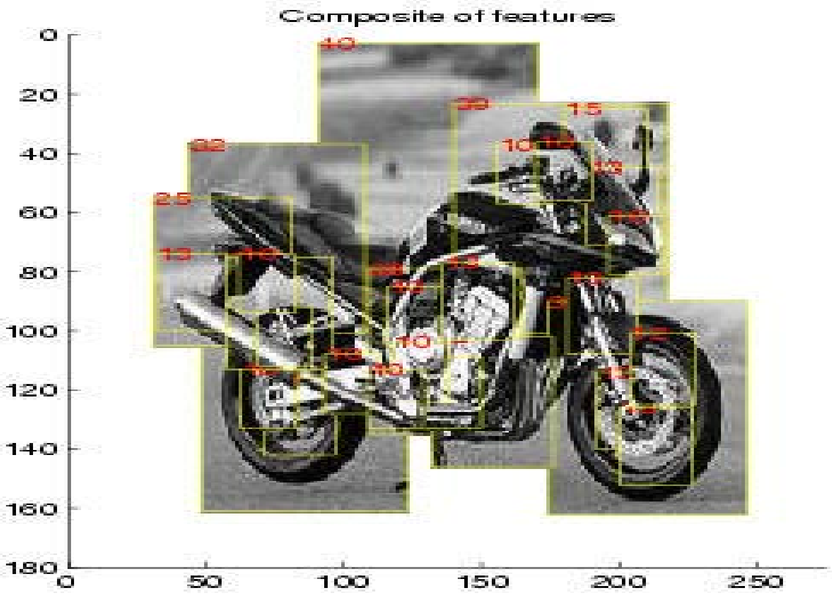


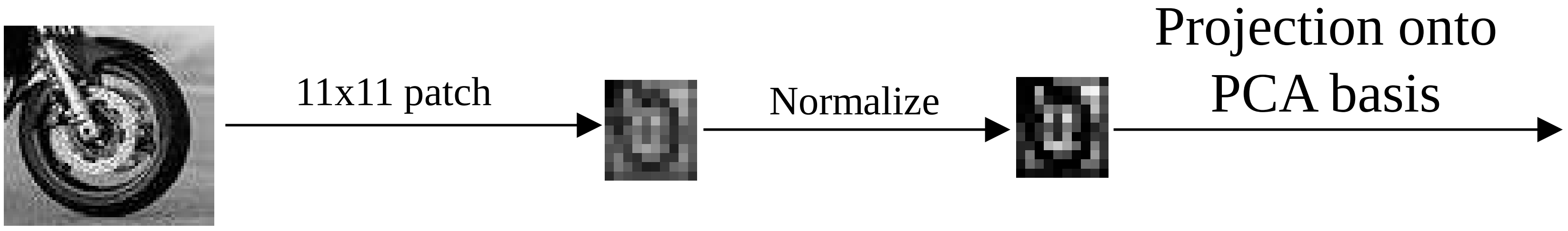




Representation of Appearance







$$\begin{pmatrix} c_1 \\ c_2 \\ \vdots \\ c_{15} \end{pmatrix}$$

121 dimensions was too big, so they used PCA to reduce to 10-15.

Learning a Model

- An object class is represented by a generative model with P parts and a set of parameters θ.

- Once the model has been learned, a decision procedure must determine if a new image contains an instance of the object class or not.

- Suppose the new image has N interesting features with locations X, scales S and appearances A.

Generative Probabilistic Model

Top-Down Formulation

Bayesian Decision Rule

$$
\begin{aligned}
R &= \frac{p(\text{Object}|\mathbf{X},\mathbf{S},\mathbf{A})}{p(\text{No object}|\mathbf{X},\mathbf{S},\mathbf{A})} \\
&= \frac{p(\mathbf{X},\mathbf{S},\mathbf{A}|\text{Object})\; p(\text{Object})}{p(\mathbf{X},\mathbf{S},\mathbf{A}|\text{No object})\; p(\text{No object})} \\
&\approx \frac{p(\mathbf{X},\mathbf{S},\mathbf{A}|\,\theta)\; p(\text{Object})}{p(\mathbf{X},\mathbf{S},\mathbf{A}|\theta_{bg})\; p(\text{No object})}
\end{aligned}
$$

$$
p(\mathbf{X},\mathbf{S},\mathbf{A}|\,\theta) = \sum_{\mathbf{h}\in H} p(\mathbf{X},\mathbf{S},\mathbf{A},\mathbf{h}|\,\theta) =
$$

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

R is the likelihood ratio.

θ is the maximum likelihood value of the parameters of the object and θ_{bg} of the background.

h is the hypothesis as to which P of the N features in the image are the object, implemented as a vector of length P with values from 0 to N indicating which image feature corresponds to each object feature.

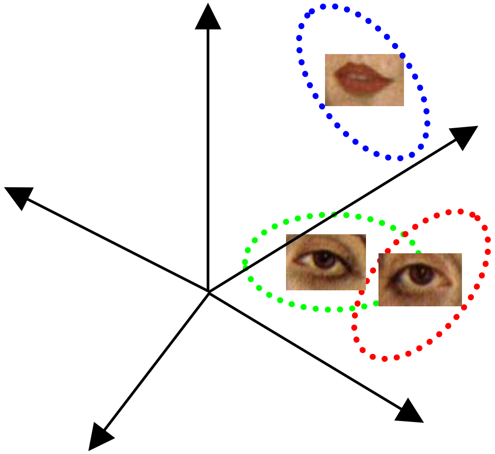
H is the set of all hypotheses; Its size is $O(N^P)$.

Appearance

The appearance (A) of each part p has a Gaussian density with mean c_p and covariance V_P.

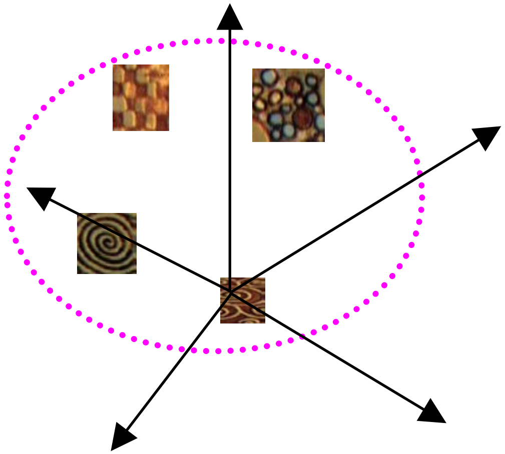
Background model has mean cbg and covariance Vbg.

Gaussian Part Appearance PDF



Object

Guausian Appearance PDF

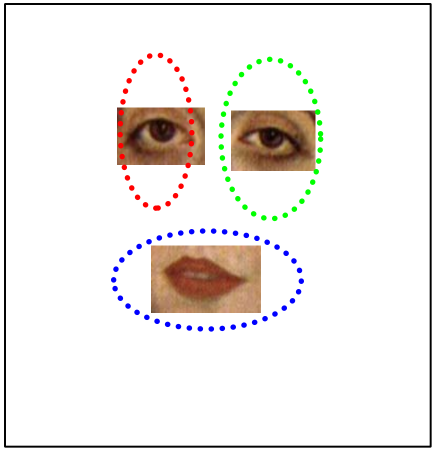


Background

Shape as Location

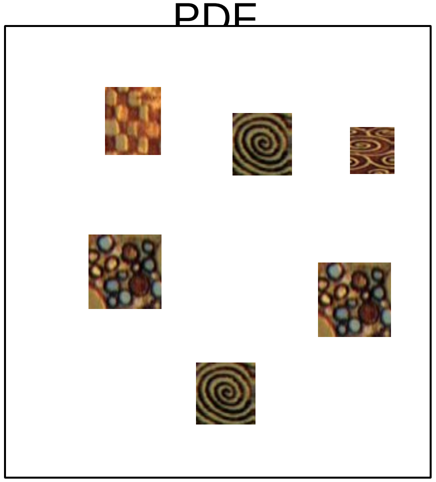
Object shape is represented by a joint Gaussian density of the locations (X) of features within a hypothesis transformed into a scale-invariant space.

Gaussian Shape PDF



Object

Uniform Shape PDF

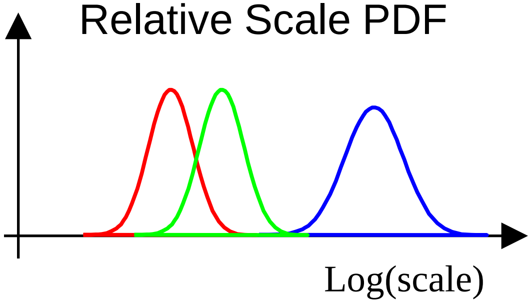


Background

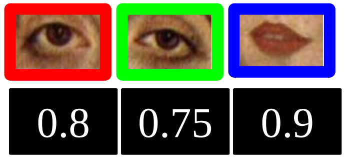
Scale

The relative scale of each part is modeled by a Gaussian density with mean t_p and covariance U_p.

Gaussian
Relative Scale PDF



Prob. of detection



Occlusion and Part Statistics

There are 3 terms used:

- First term: Poisson distribution (mean M) models the number of features in the background.

- Second term: (constant) 1/(number of combinations of f_t features out of a total of N_t)

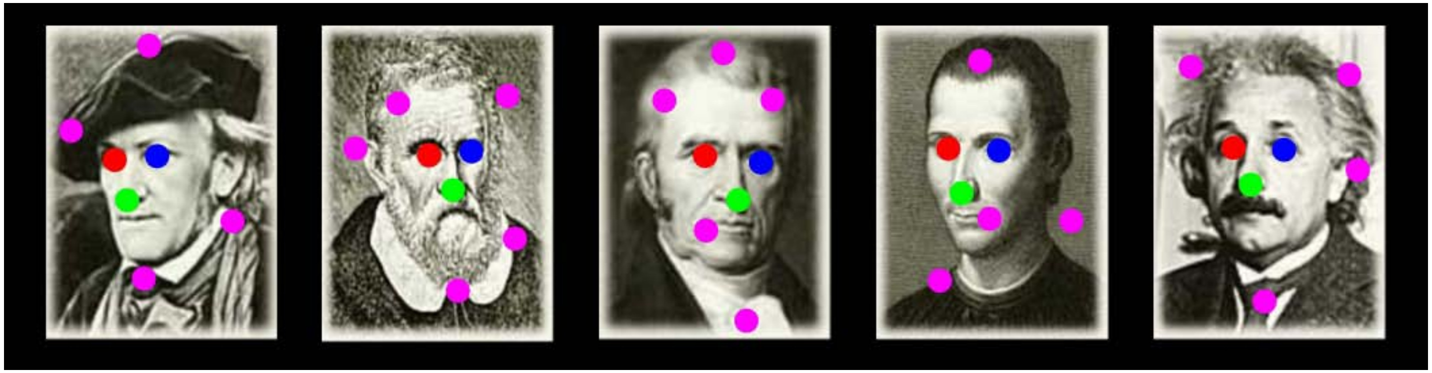
- Third term: gives probability for possible occlusion patterns.

Learning

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

$$\theta = \{\underbrace{\boldsymbol{\mu},\Sigma}_{\text{location}},\underbrace{\mathbf{c},V}_{\text{appearance}},\underbrace{M,p(\mathbf{d}|\theta)}_{\text{occlusion}},\underbrace{t,U}_{\text{scale}}\}$$

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



Recognition

Make This:

$$\begin{aligned} R &= \frac{p(\text{Object}|\mathbf{X},\mathbf{S},\mathbf{A})}{p(\text{No object}|\mathbf{X},\mathbf{S},\mathbf{A})} \\ &= \frac{p(\mathbf{X},\mathbf{S},\mathbf{A}|\text{Object})\;p(\text{Object})}{p(\mathbf{X},\mathbf{S},\mathbf{A}|\text{No object})\;p(\text{No object})} \\ &\approx \frac{p(\mathbf{X},\mathbf{S},\mathbf{A}|\,\theta)\;p(\text{Object})}{p(\mathbf{X},\mathbf{S},\mathbf{A}|\theta_{bg})\;p(\text{No object})} \end{aligned}$$

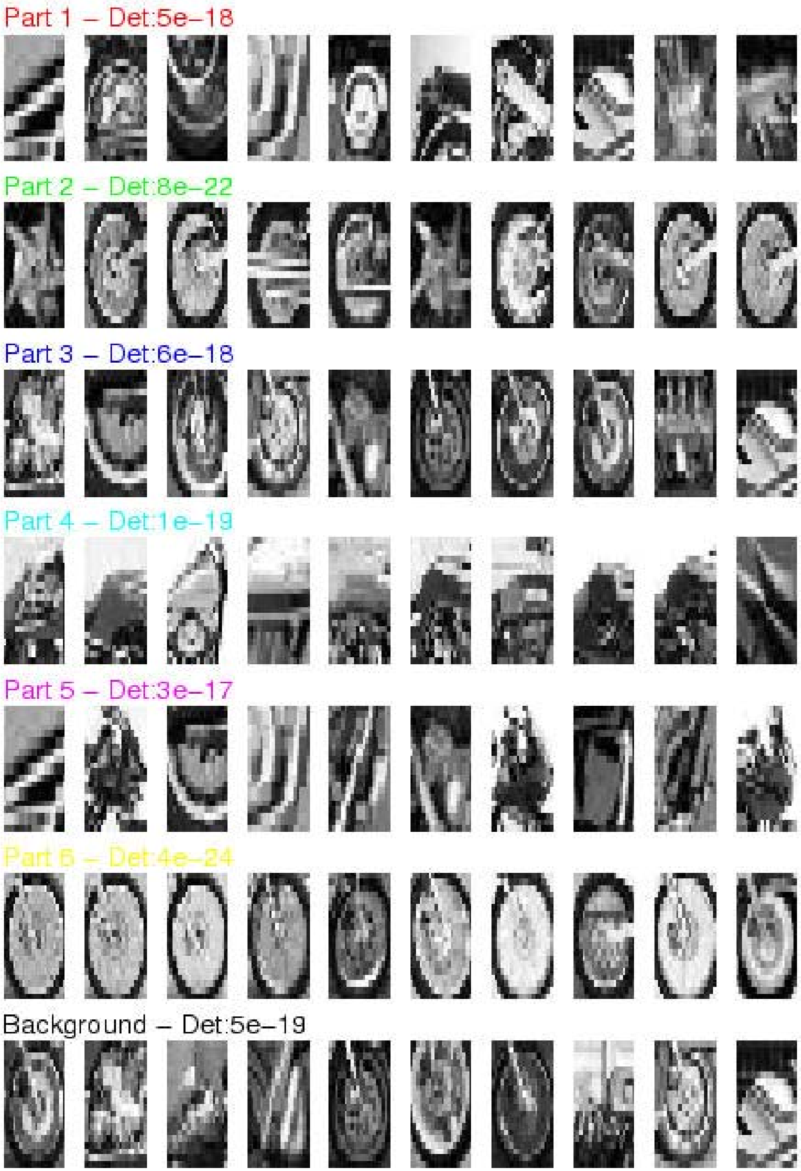
Greater Than Threshold

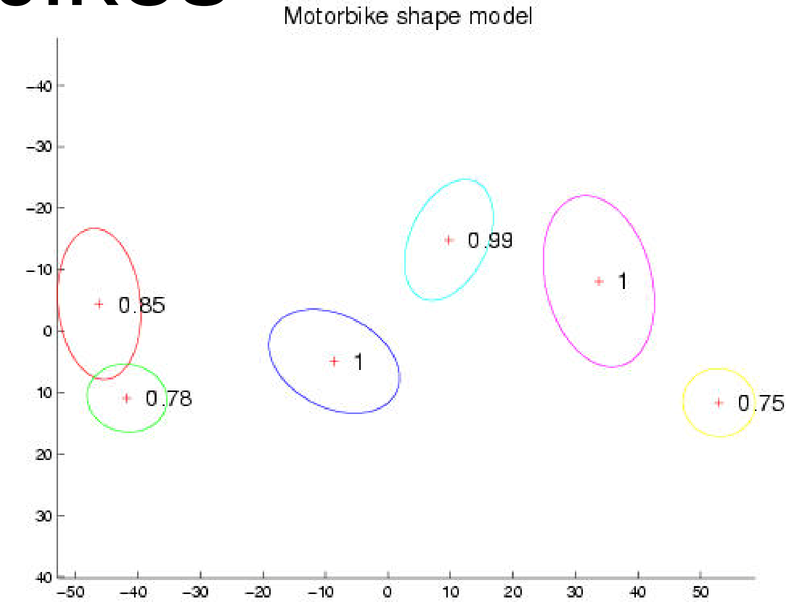
RESULTS

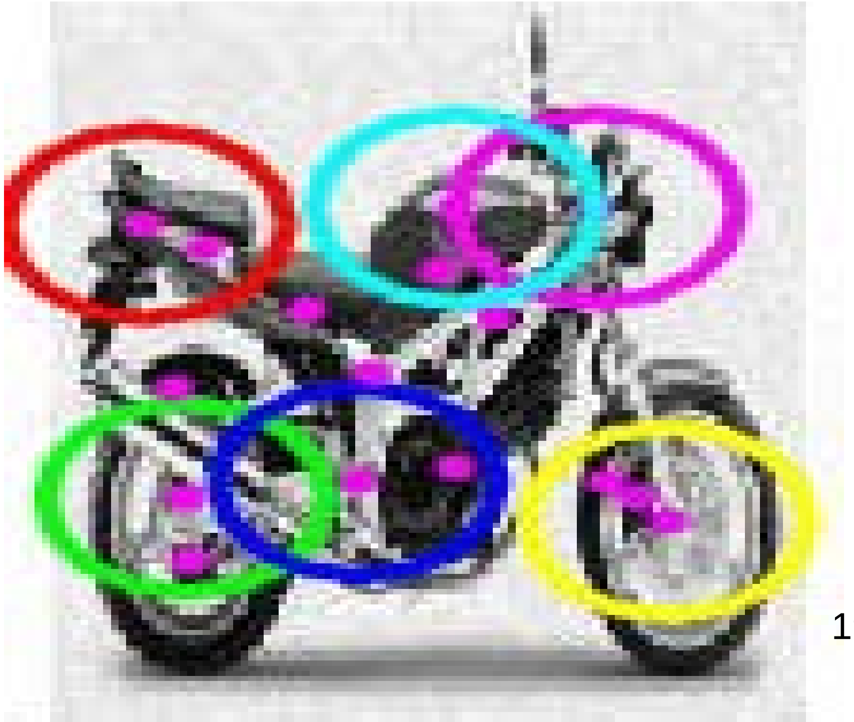
- Initially tested on the Caltech-4 data set
  - motorbikes
  - faces
  - airplanes
  - cars
- Now there is a much bigger data set: the Caltech-101 http://www.vision.caltech.edu/archive.html

Motorbikes

Equal error rate: 7.5%

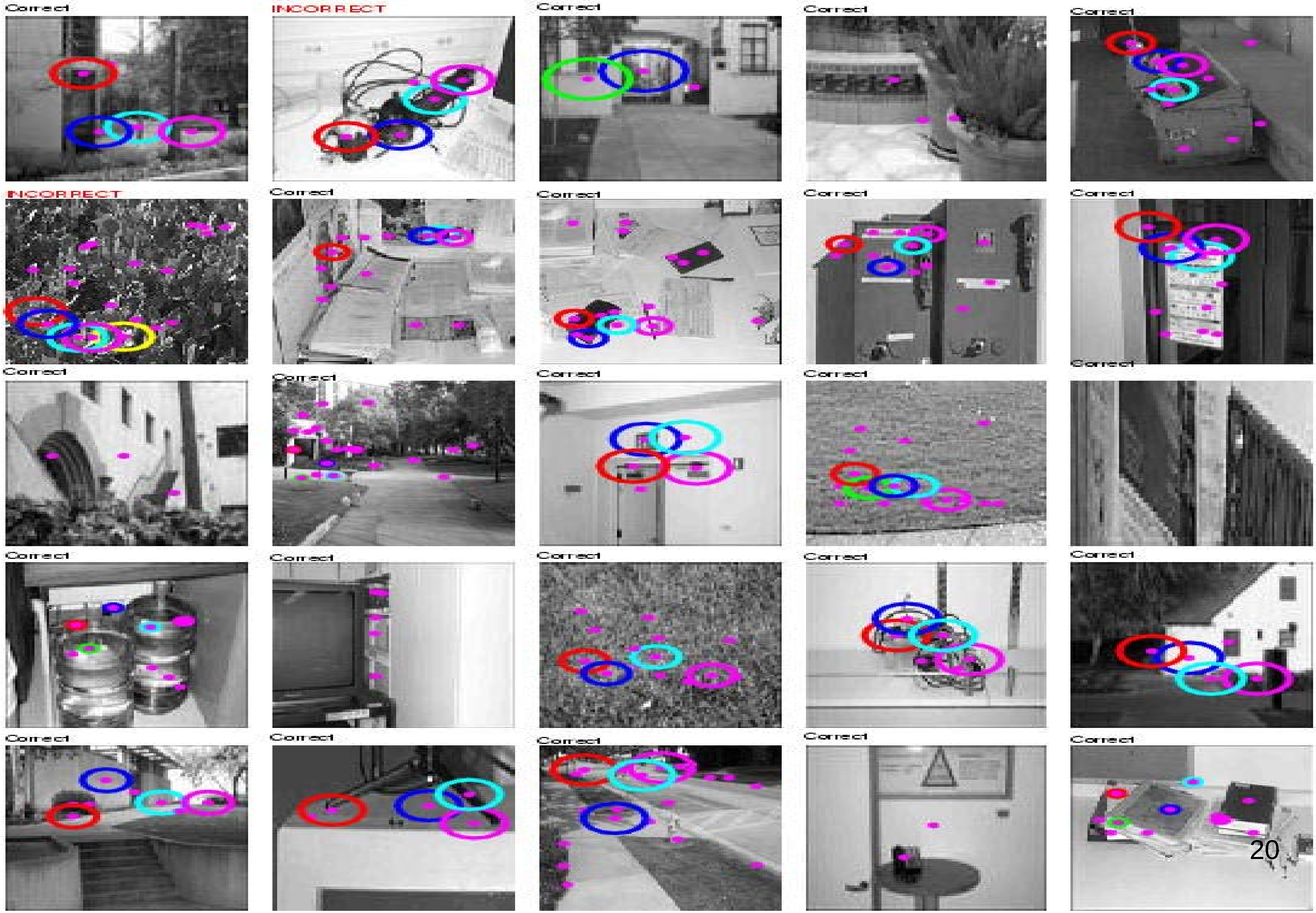






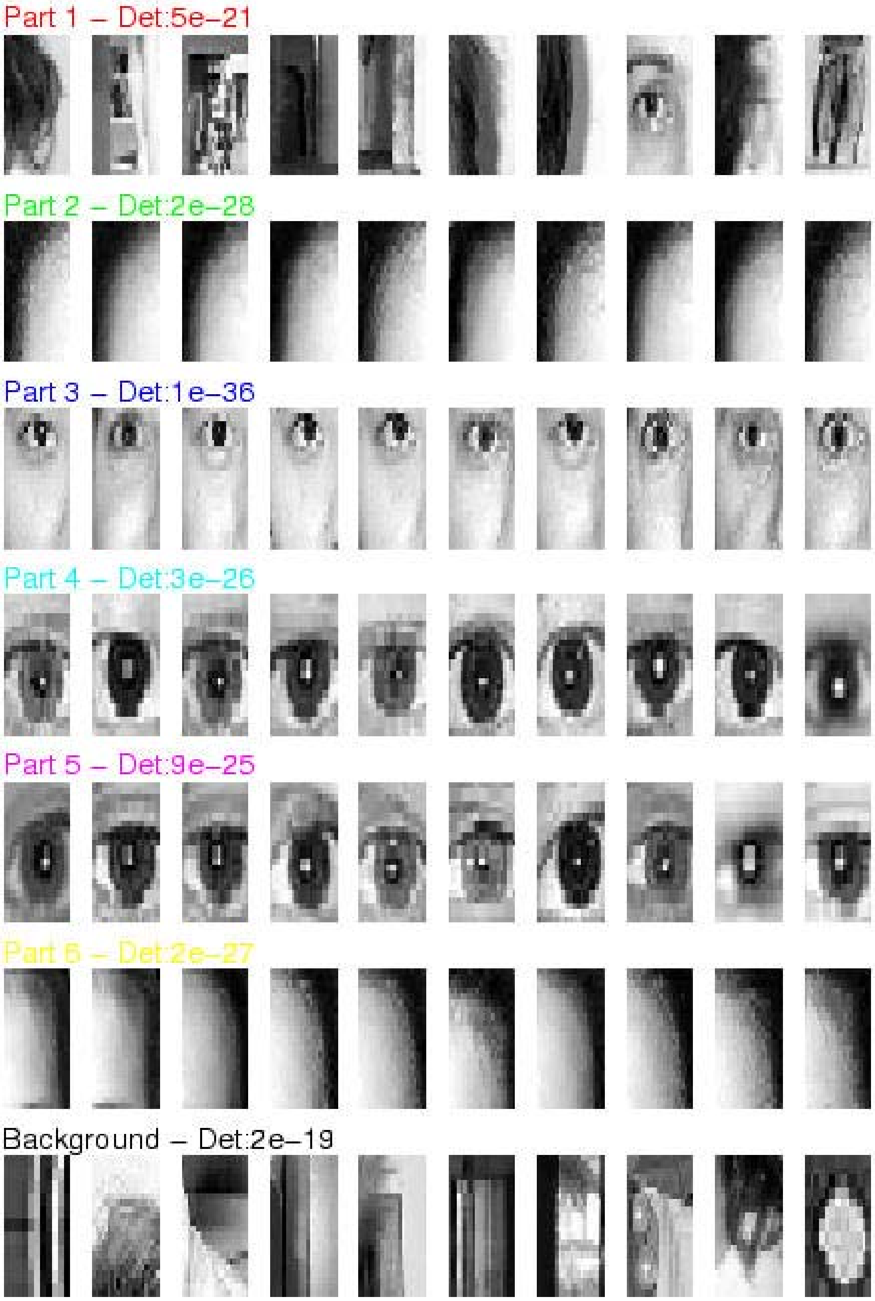
Background Images

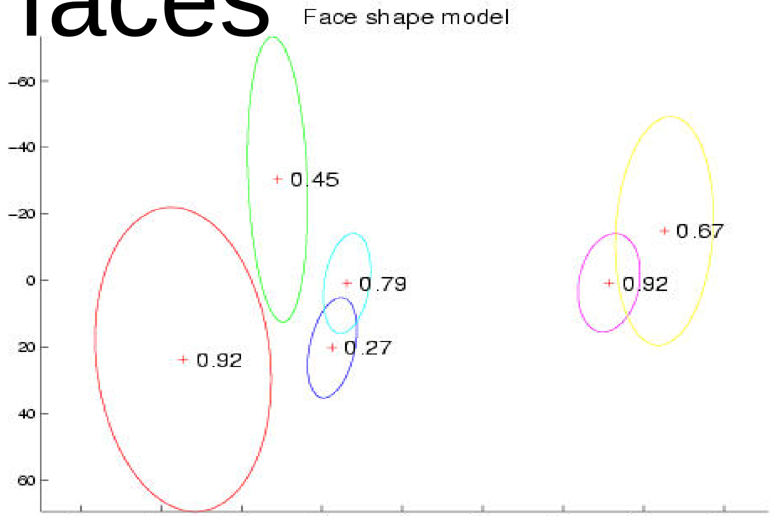
It learns that these are NOT motorbikes.

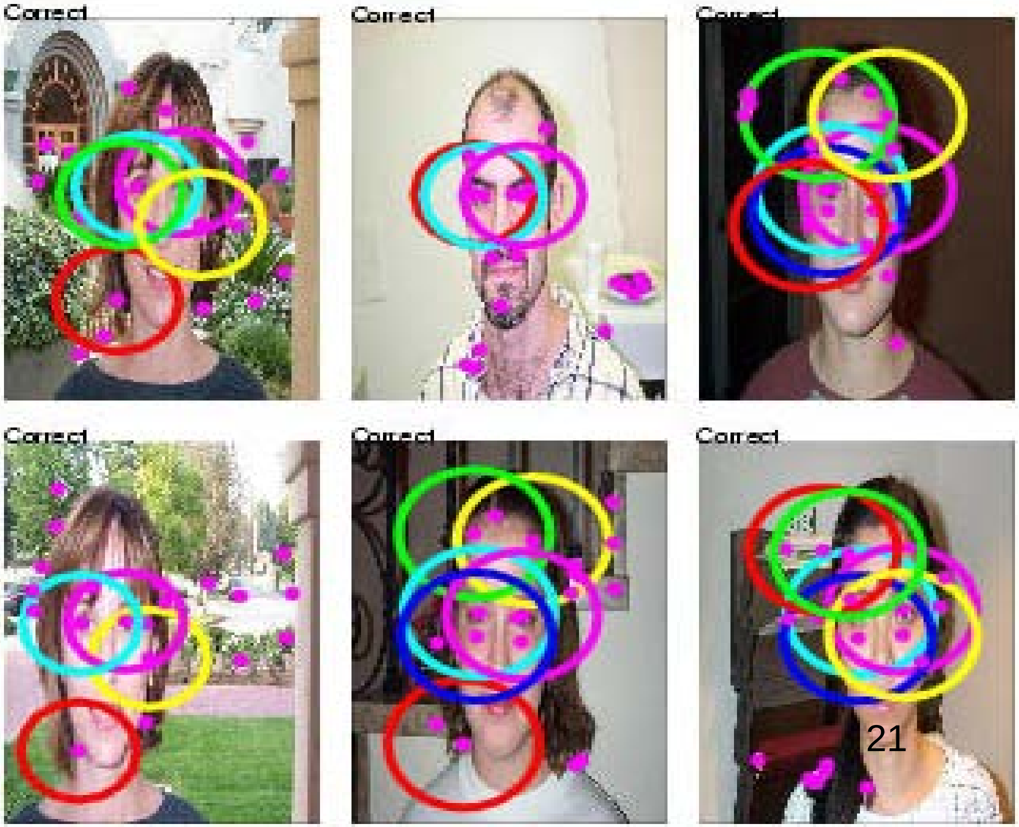


Frontal faces

Equal error rate: 4.6%

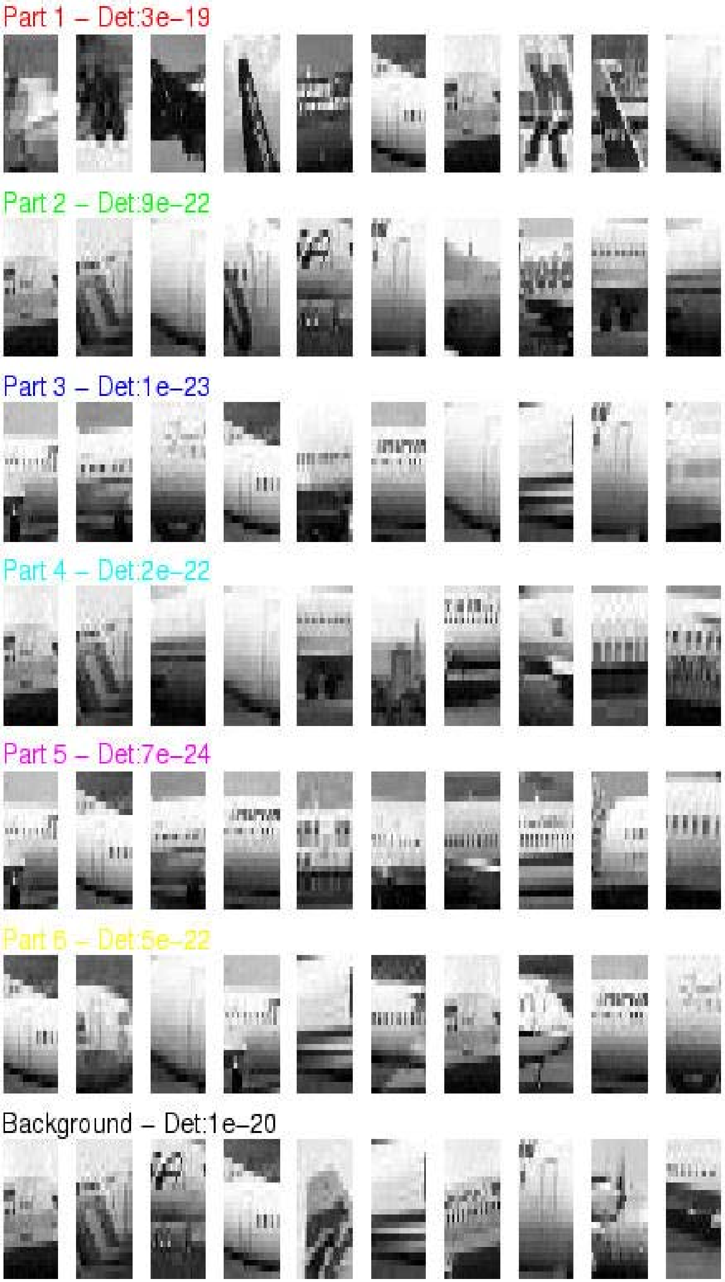


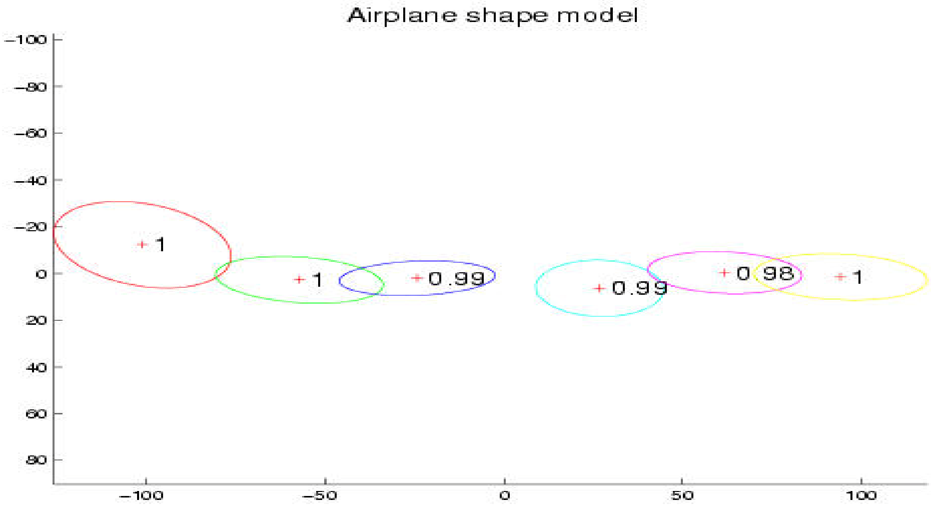




Equal error rate: 9.8%

Airplanes

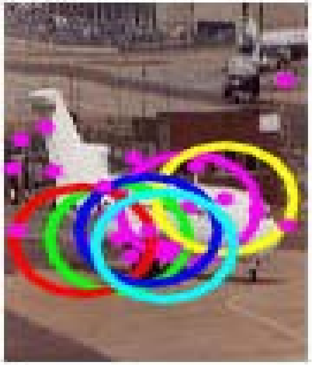




Correct

Correct

Correct



INCORRECT

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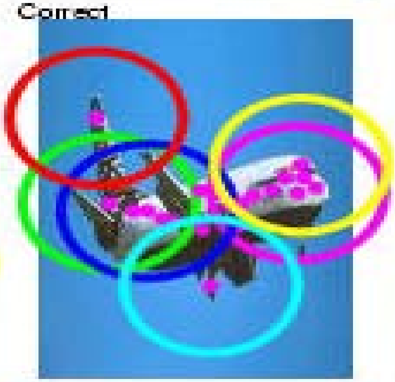

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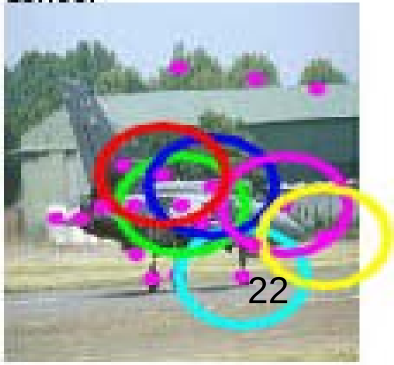
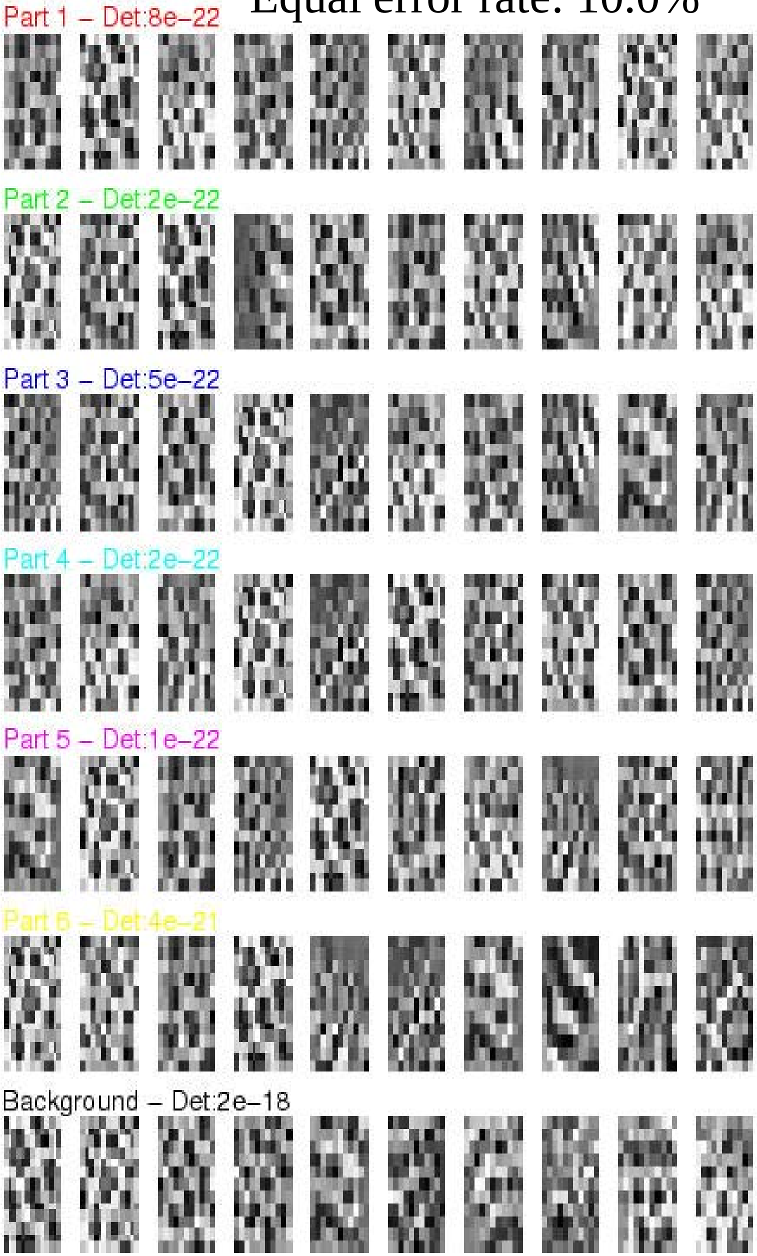
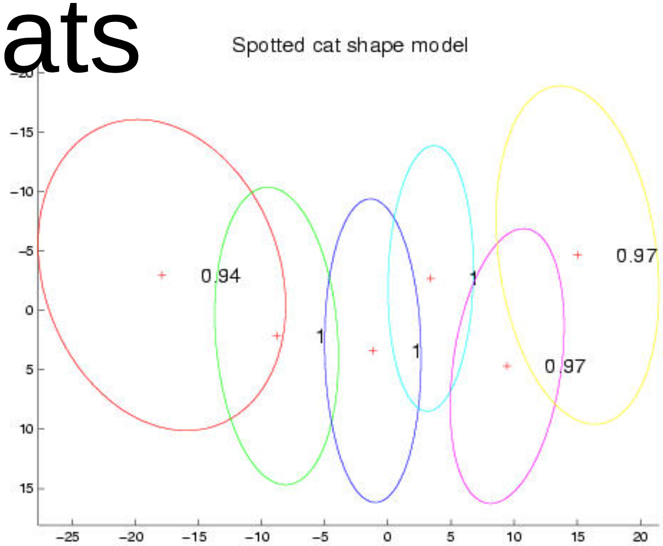


Scale-Invariant Cats

Equal error rate: 10.0%





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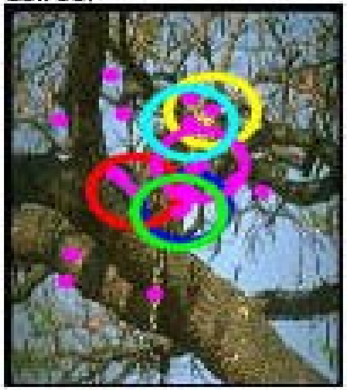

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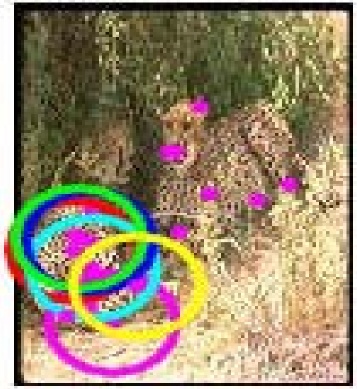

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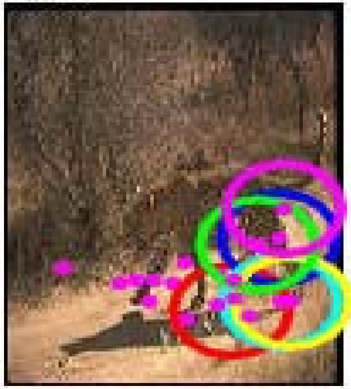

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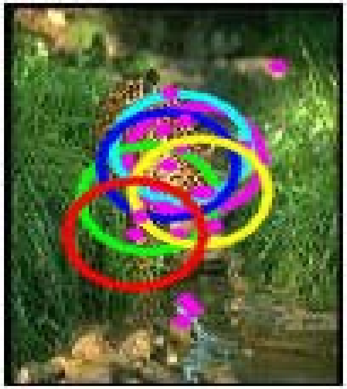

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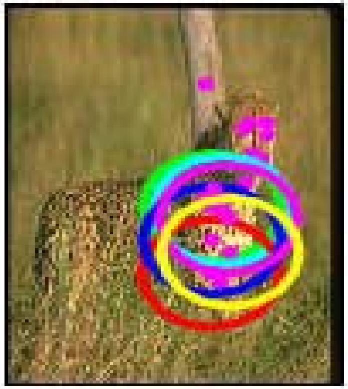

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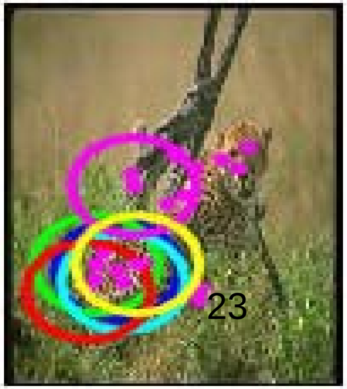
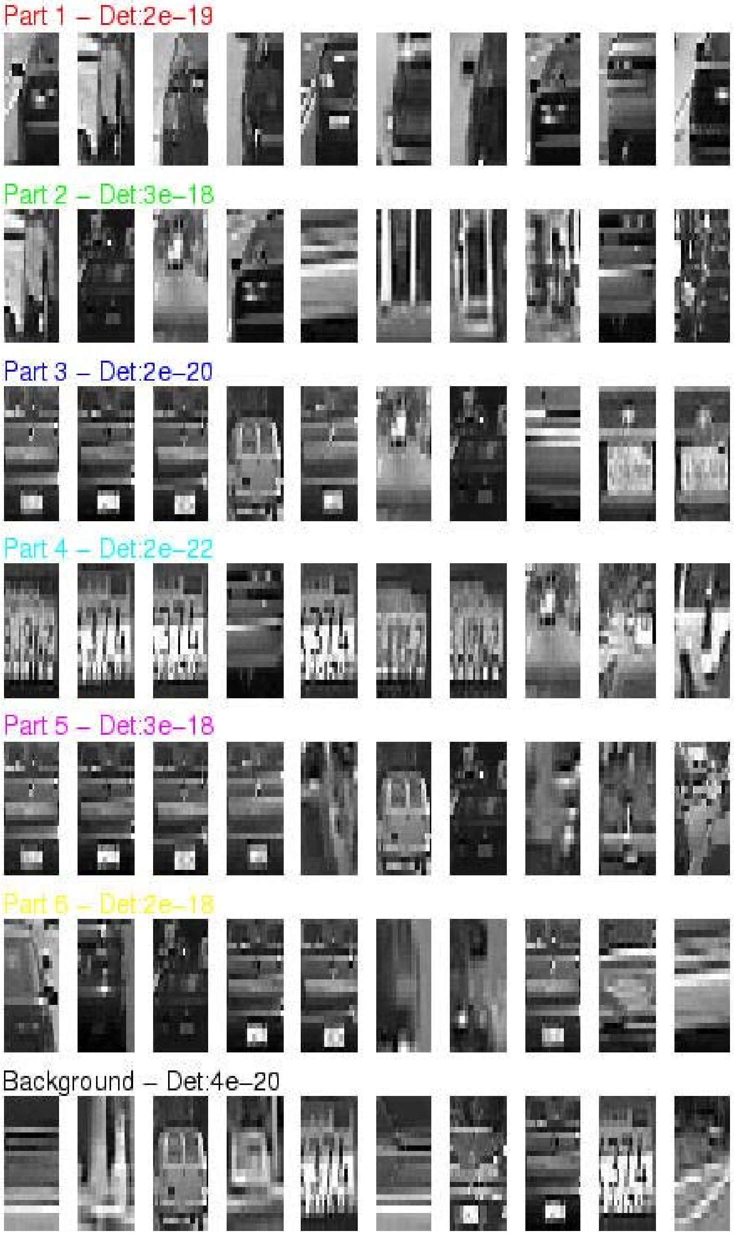
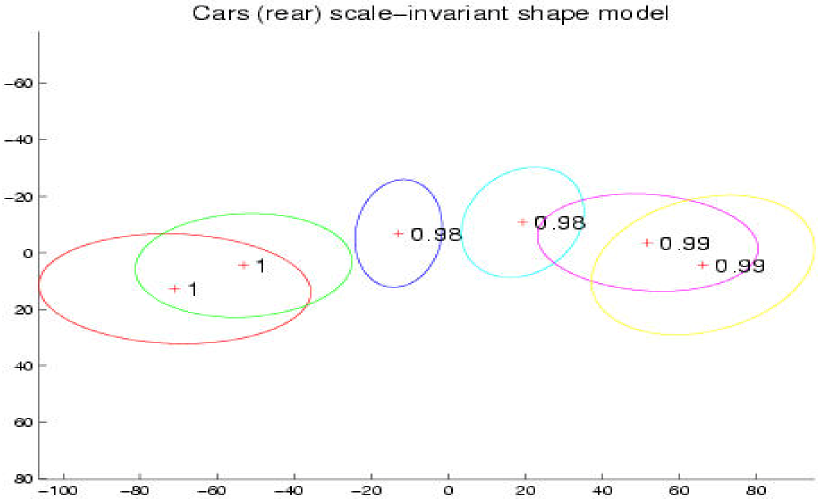
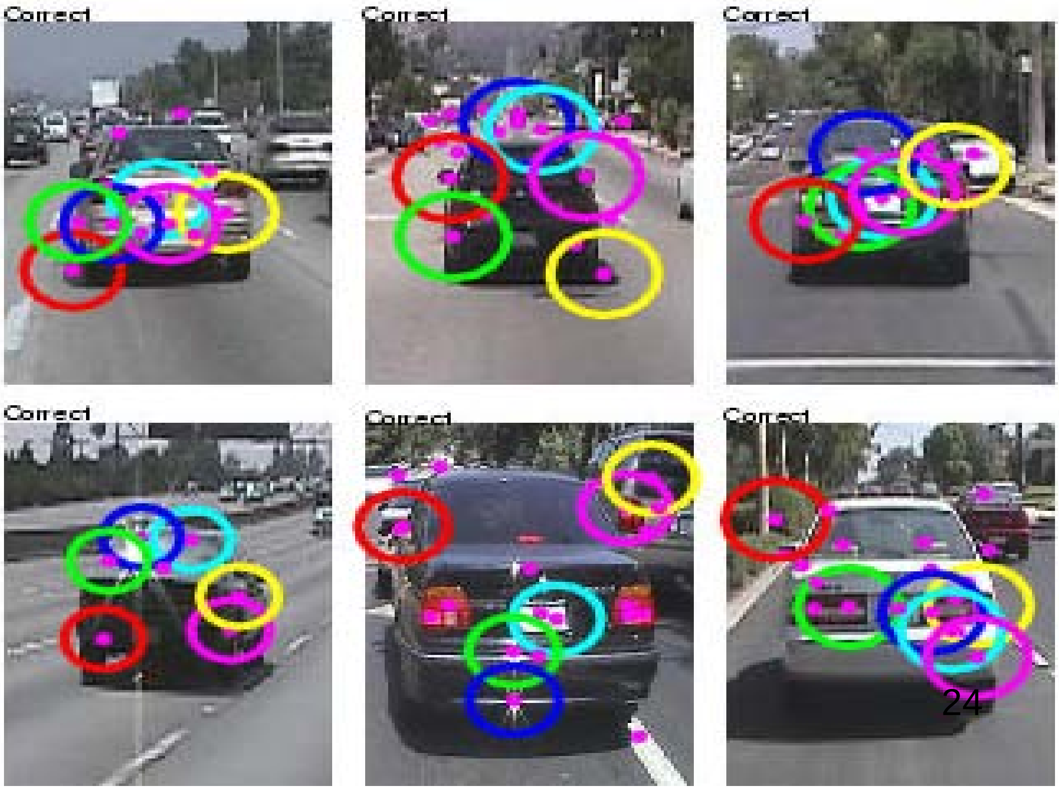


Scale-Invariant Cars

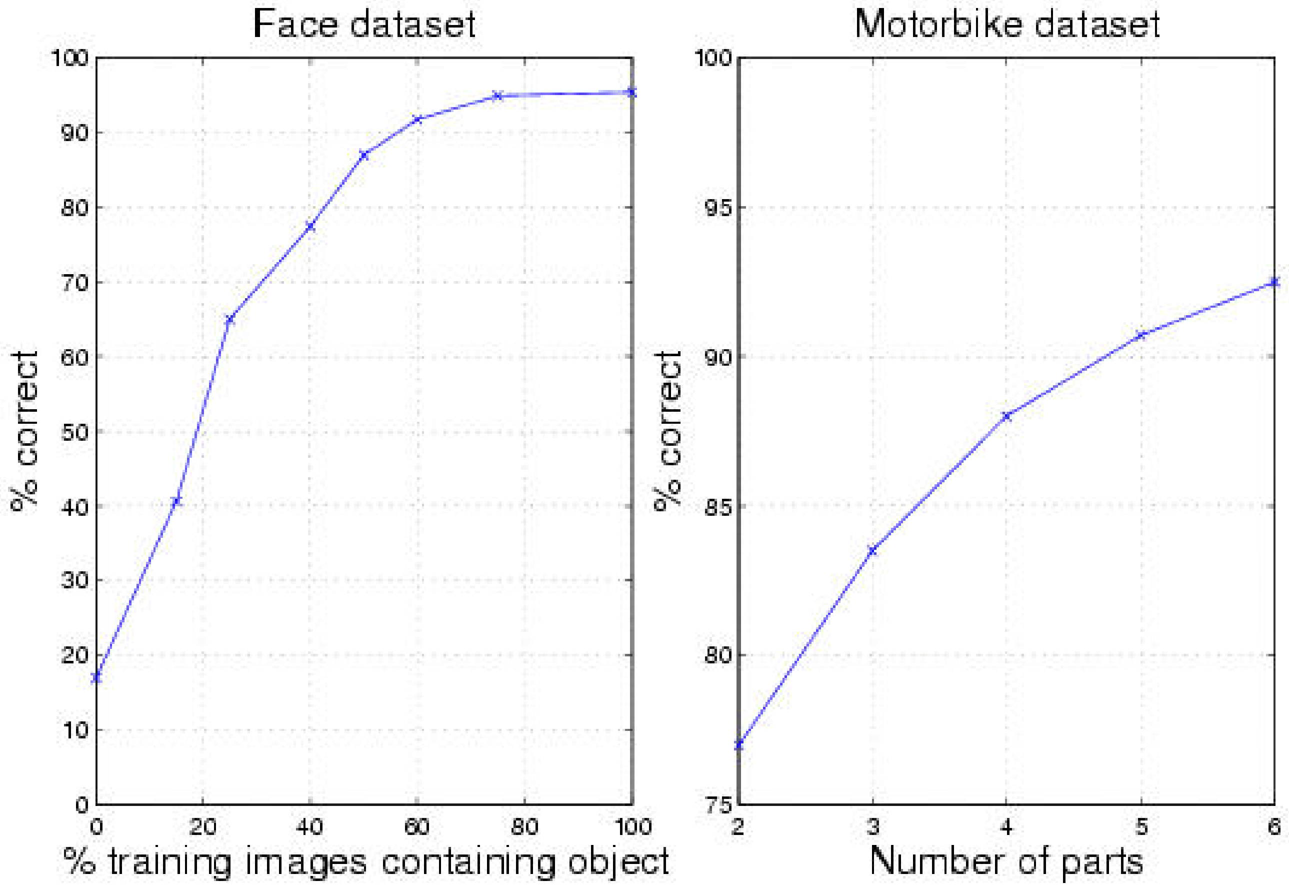
Equal error rate: 9.7%





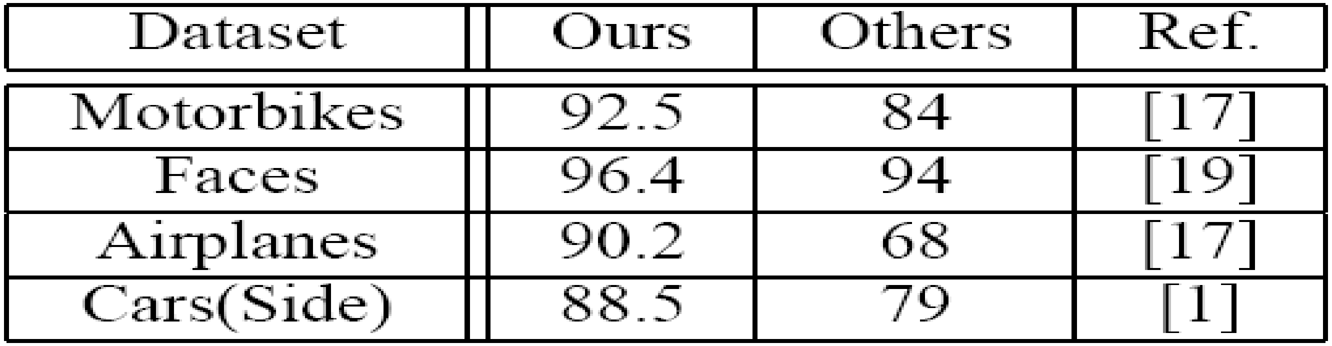


Robustness of Algorithm



Accuracy

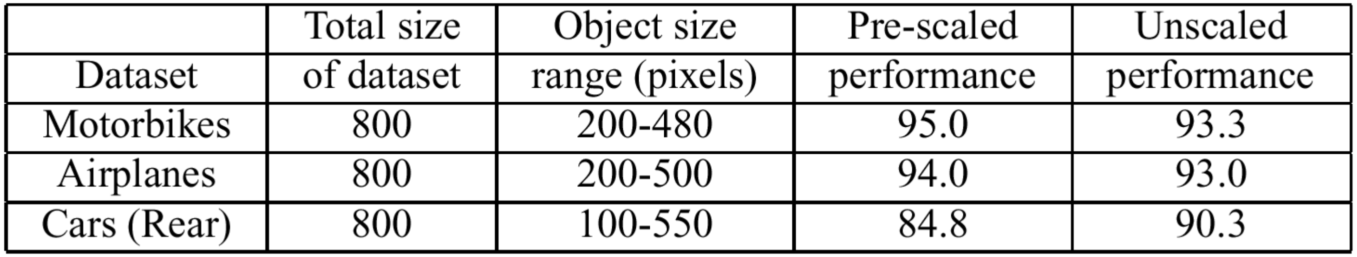
Initial Pre-Scaled Experiments



Dataset	Ours	Others	Ref.
Motorbikes	92.5	84	[17]
Faces	96.4	94	[19]
Airplanes	90.2	68	[17]
Cars(Side)	88.5	79	[1]

ROC equal error rates

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