Trainable visual models for object class recognition

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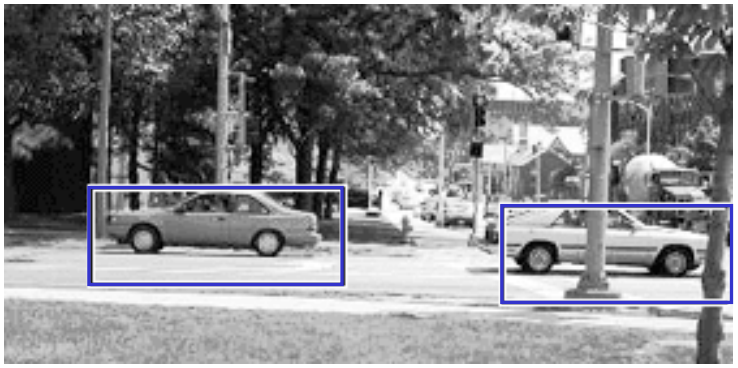
Slides from: Rob Fergus, Dan Huttenlocher, Bastian Leibe, Shimon Ullman

Objectives

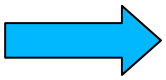
- Recognition of visual object classes
- (semi) Unsupervised learning

Recognition

- Identify class (car, face, airplane etc)
- Determine approximate localization
  - multiple instances in a single image



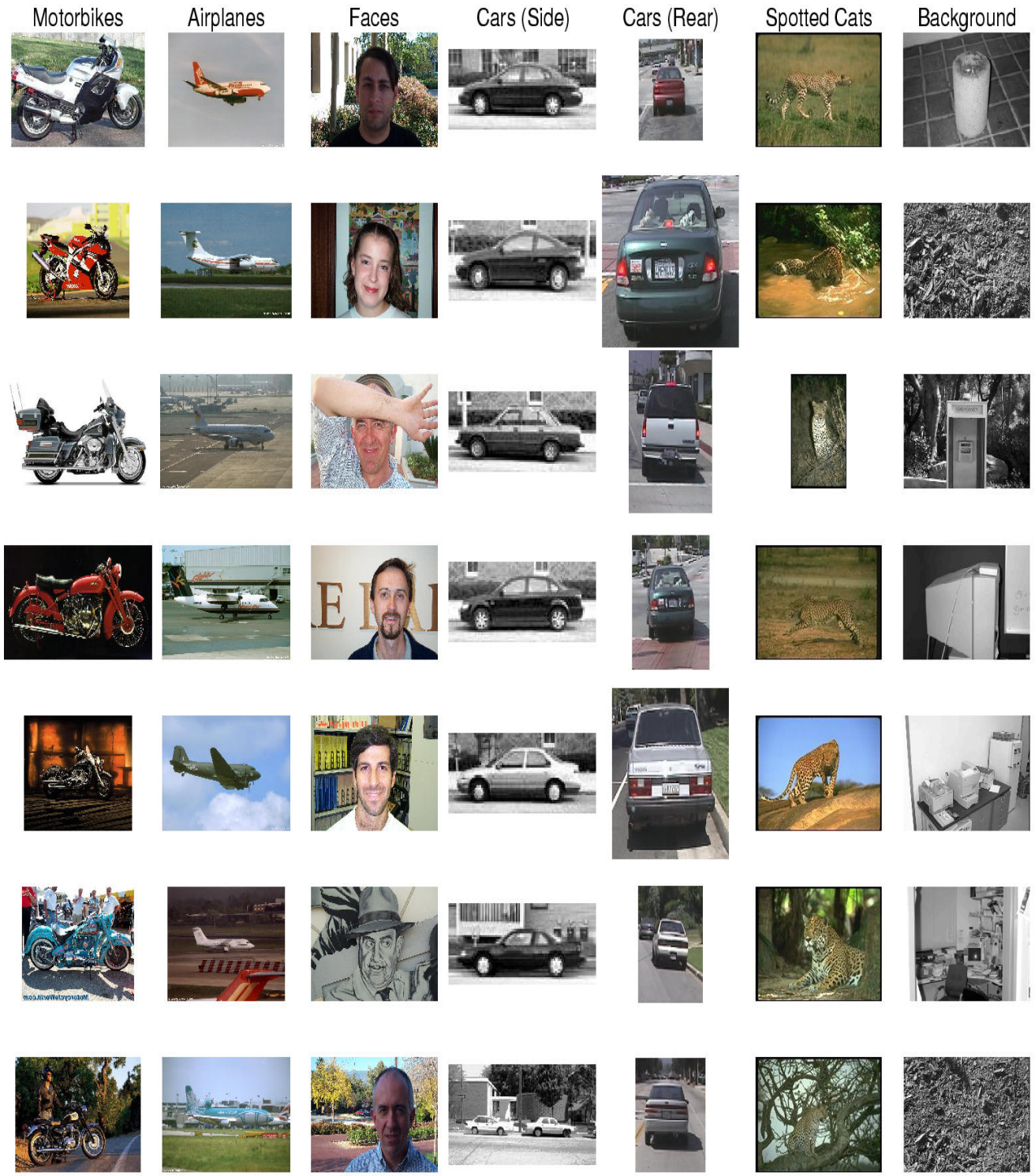
- But not a perfect segmentation



(Semi) Unsupervised learning

- Know if image contains object or not
- But no segmentation of object or manual selection of features

Some object classes

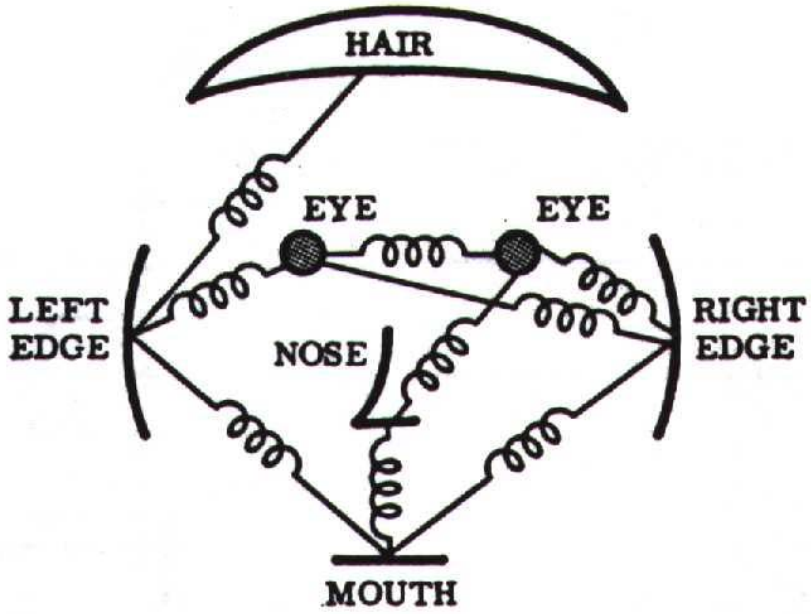


Difficulties:

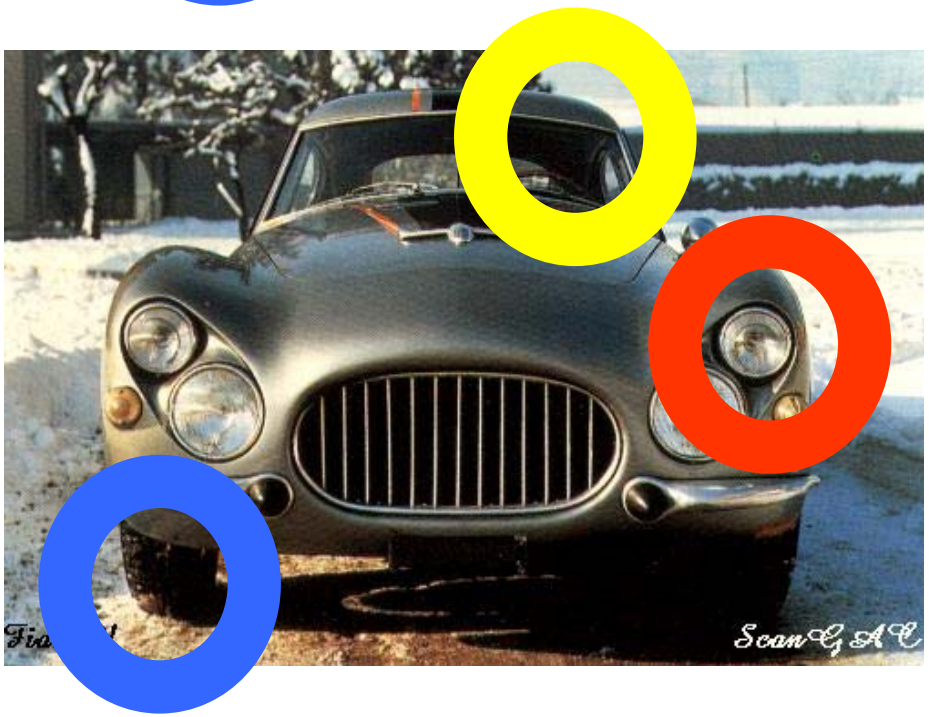
- Visual aspects
- Size variation
- Background clutter
- Partial occlusion
- Intra-class variation

Class of model: Pictorial Structure

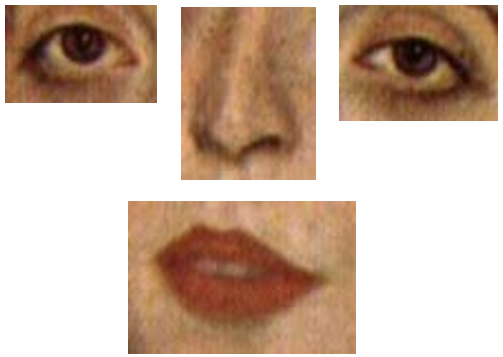
- Fischler & Elschlager 1973
- Model has two components:
  1. parts (2D image fragments)
  2. structure (configuration of parts)
- Why this class of model?



Representation: Parts and Structure



Deformations



A

B

C

D

Presence / Absence of Features

occlusion

Main issues:

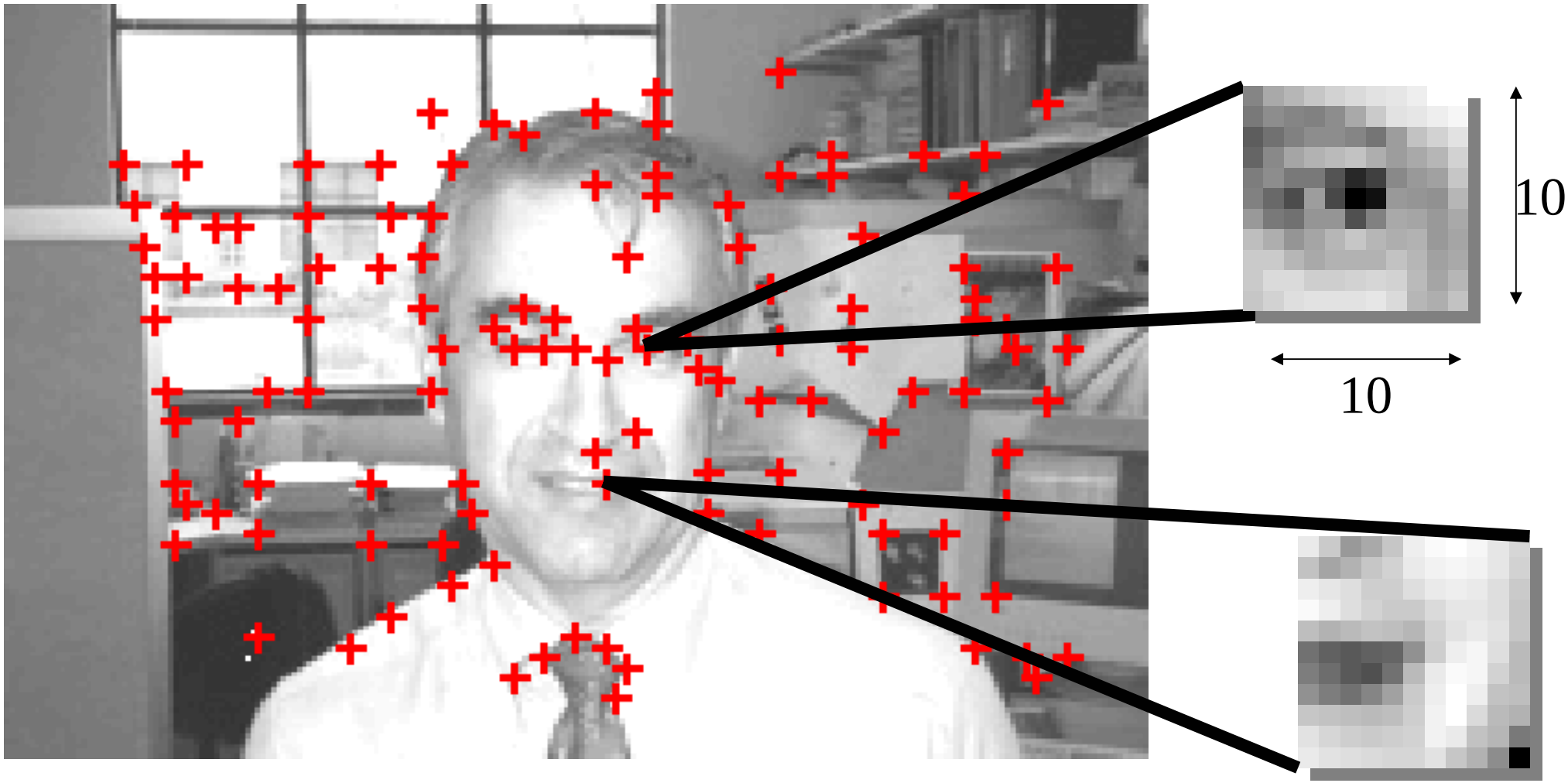
- Parts
  - appearance, shape
- Structure
  - model (e.g. implicit or explicit)
- Model learning
  - from training data
- Model fitting (recognition)
  - complexity

Outline

1. Models that learn parts, then add structure
    - Weber, Welling & Perona, Leibe & Schiele, Agarwal & Roth, Borenstein & Ullman
2. Models for which the structure is primary
    - Felzenszwalb & Huttenlocher, Ramanan & Forsyth
3. Models that learn parts and structure simultaneously
    - Fergus, Perona & Zisserman
4. Summary and open challenges
    - Pascal Challenge: 101 Visual Object Classes

1. Models that learn parts, then add structure

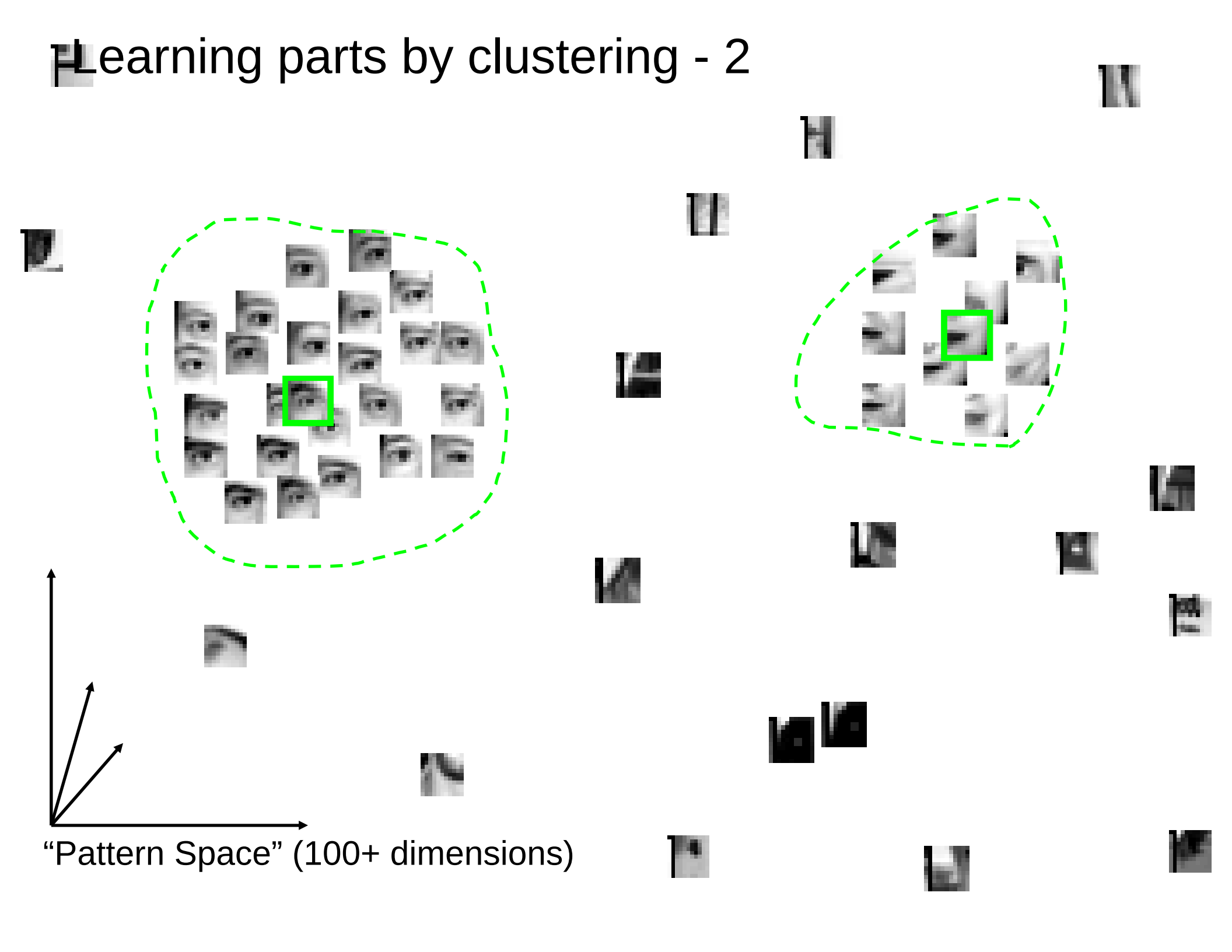
Learning parts by clustering - 1



- Interest point features: textured neighborhoods are selected
- produces 100-1000 regions per image

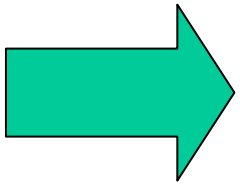
Weber, Welling & Perona 2000

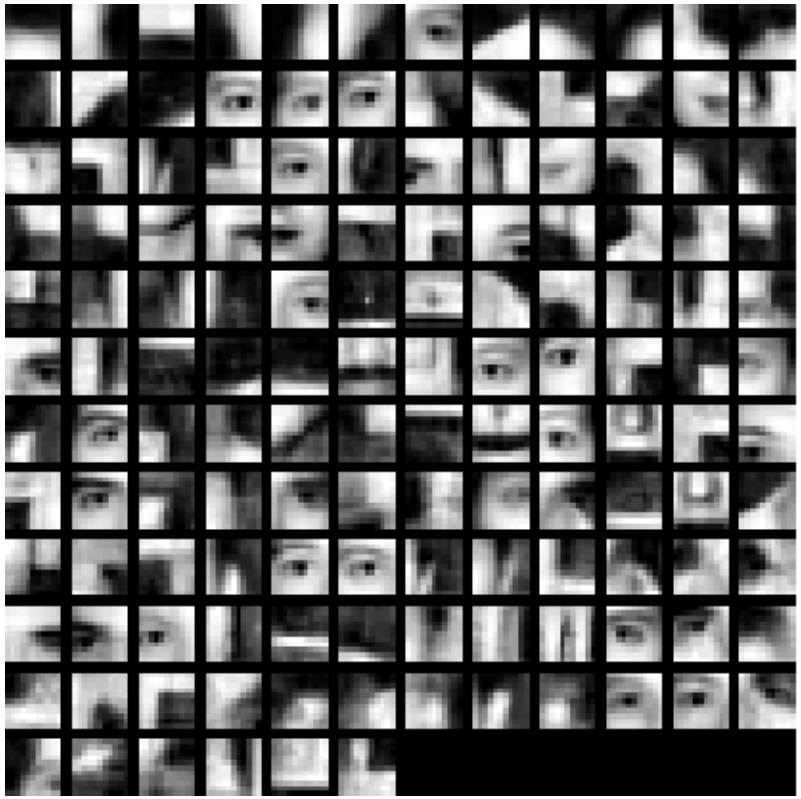
Learning parts by clustering - 2



“Pattern Space” (100+ dimensions)

Learning parts by clustering - 3



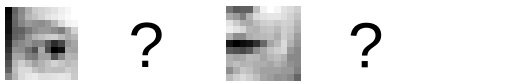


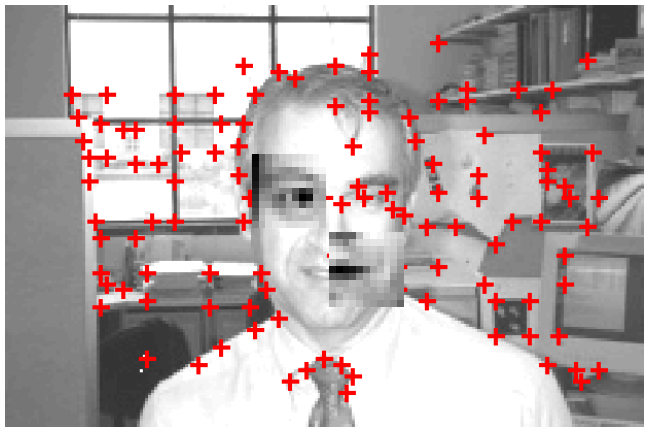
100-1000 images

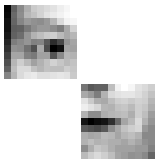
~100 parts

Detecting part positions

- Detect interest point features
- Correlate parts with regions around detected points
- Candidate parts:
  - Best match at each interest point, or
  - Set of parts above similarity threshold

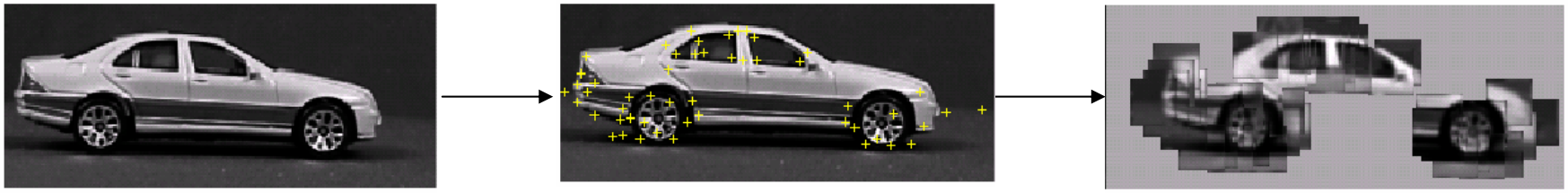




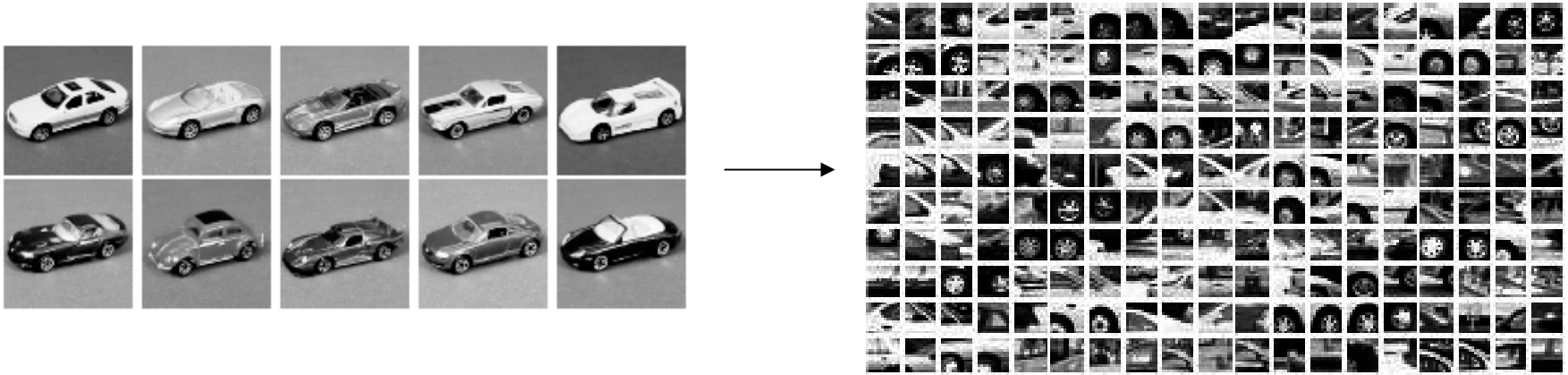


Leibe & Schiele 2003/2004

- Extraction of local object patches
  - Interest Points (Harris detector)



- Example: training set of 160 car images
  - 16 views of 10 cars
  - results in 8'269 training patches



Visual Vocabulary (Codebook Entries)

- Visual Clustering procedure
  - agglomerative clustering: most similar clusters are merged (t > 0.7)

$$similarity(C_1, C_2) = \frac{\sum_{p \in C_1, q \in C_2} NGC(p,q)}{|C_1| \times |C_2|} > t$$

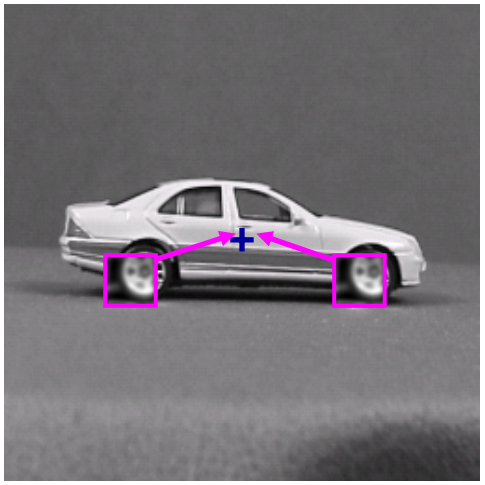
$$NGC(p,q) = \frac{\sum_i (p_i - \overline{p_i})(q_i - \overline{q_i})}{\sqrt{\sum_i (p_i - \overline{p_i})^2 \sum_i (q_i - \overline{q_i})^2}}$$

- Examples (from 2519 codebook entries)
  - visual similarity preserved
  - wheel parts, window corners, fenders, ...

Visual Object Categorization

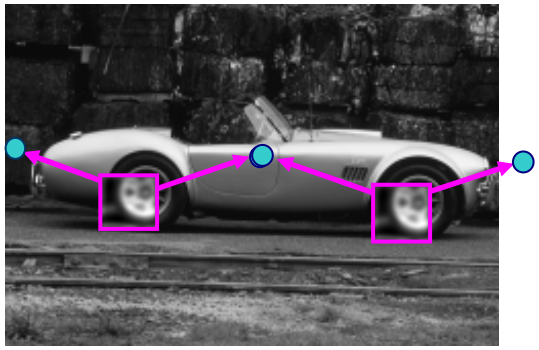
Structure: Generalized Hough Transform

- **Learning:** For every cluster, store possible "occurrences"



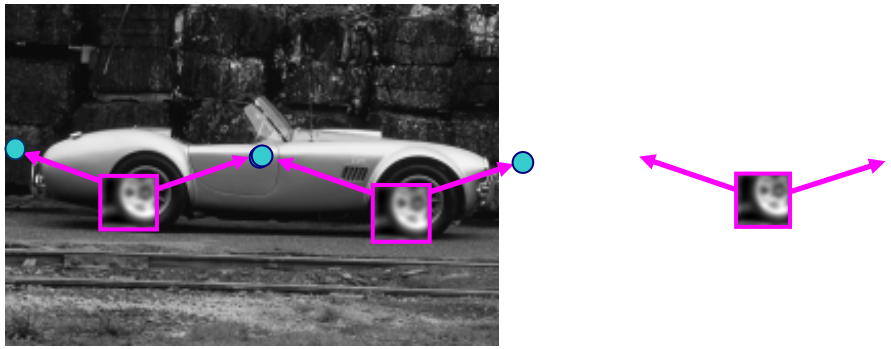
  - Object Identity
  - Pose
  - Relative position

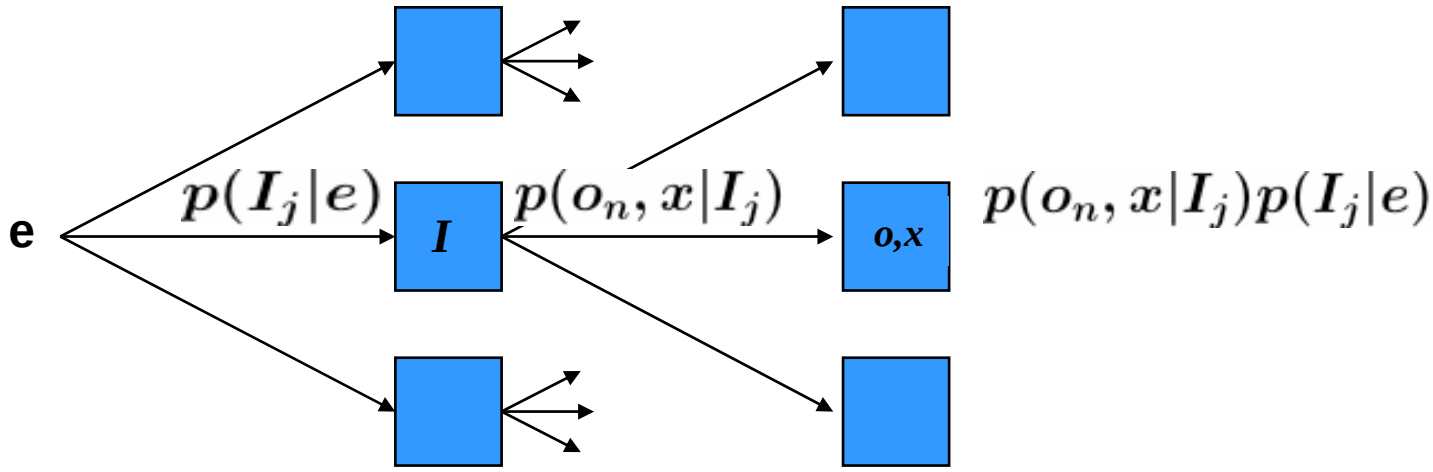
- **Recognition:** For new image, let the matched patches vote for possible object positions



Probabilistic Formulation

- 'Probabilistic Voting'

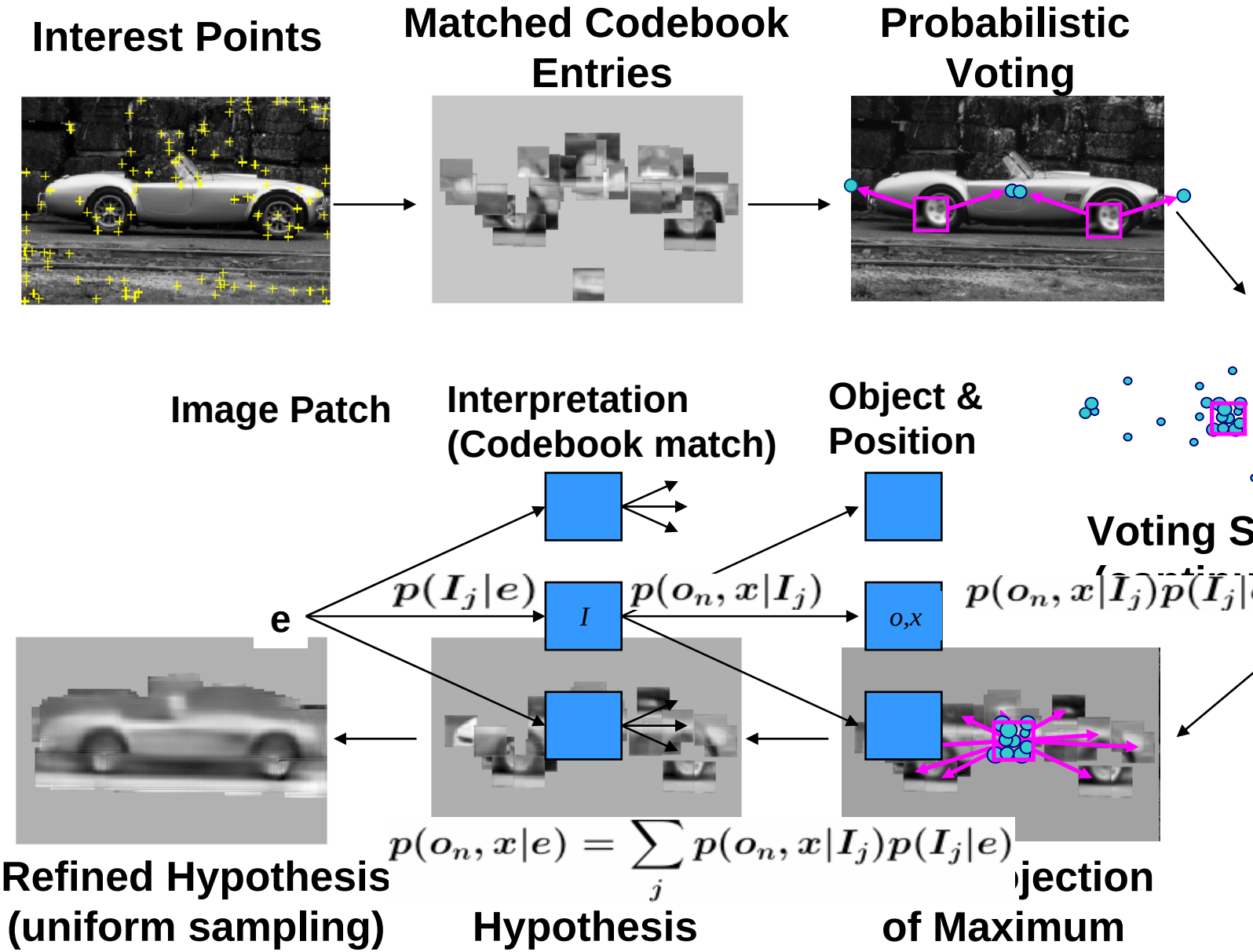




$$p(o_n, x|e) = \sum_j p(o_n, x|I_j)p(I_j|e)$$

Learn probabilities from positive and negative examples

Object Categorization Procedure

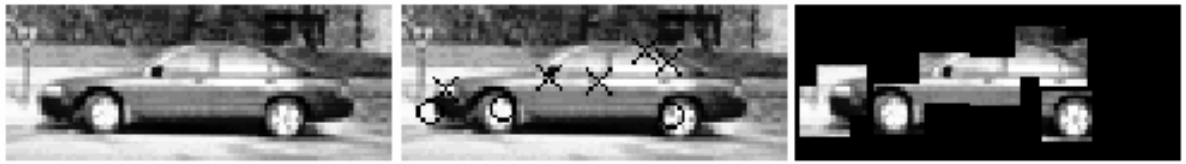


Detection Results

- Qualitative Performance
  - Recognizes different kinds of cars
  - Robust to clutter, occlusion, low contrast, noise

Agarwal & Roth 2002

- Interest points detected

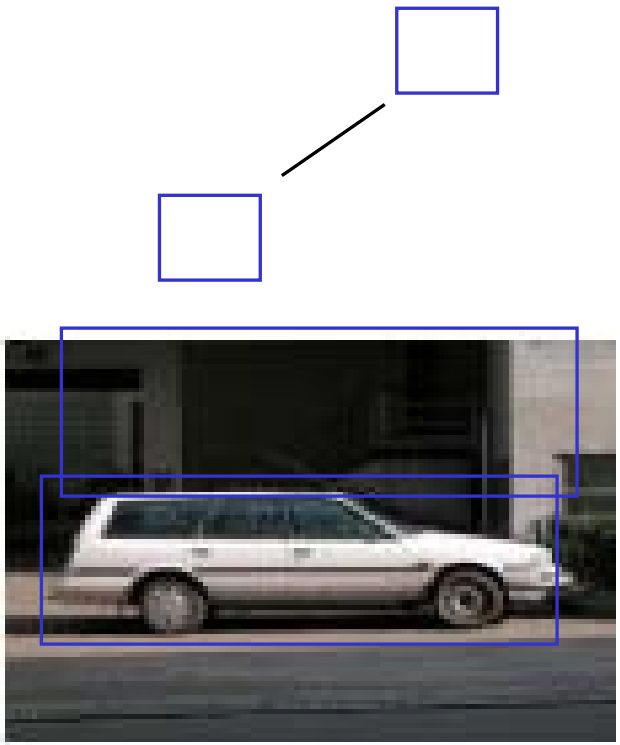


- Extracted fragments from training images

- Clustered Fragments (Dictionary) – 270 parts

Learning: Structure

- Representation: binary feature vector
- Feature vector components
  - Part present/absent (270)
  - Pair wise relation between parts (20 of these for each pair)



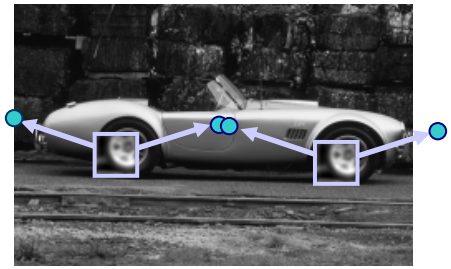
Coarse representation of:

- angles (4 bins)
- distance (5 bins)

Use sliding window to measure feature vectors from positive and negative examples

Recognition

- Detect parts
- Apply sliding window
- Linear classifier on feature vector for window
- Use SNoW (Sparse network of Winnows)
    - suited to very large, very sparse vectors



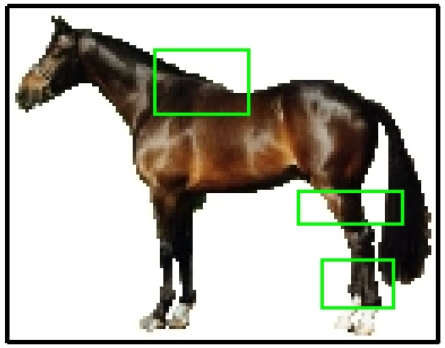
Comparison with Leibe & Schiele

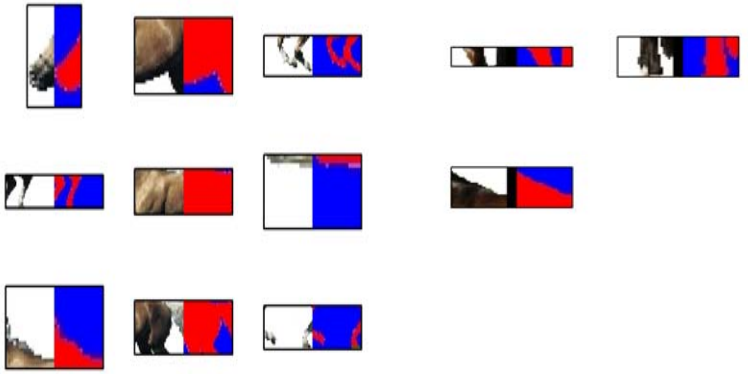
Agarawal & Roth:

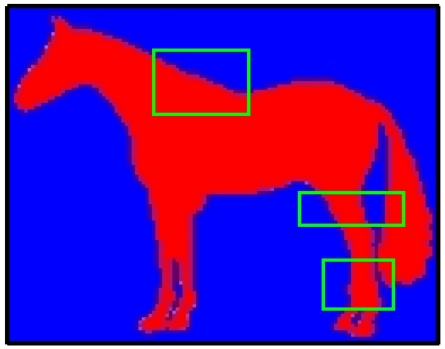
- looser geometric relations
- more tolerant of structure deformation

Borenstein & Ullman 2002

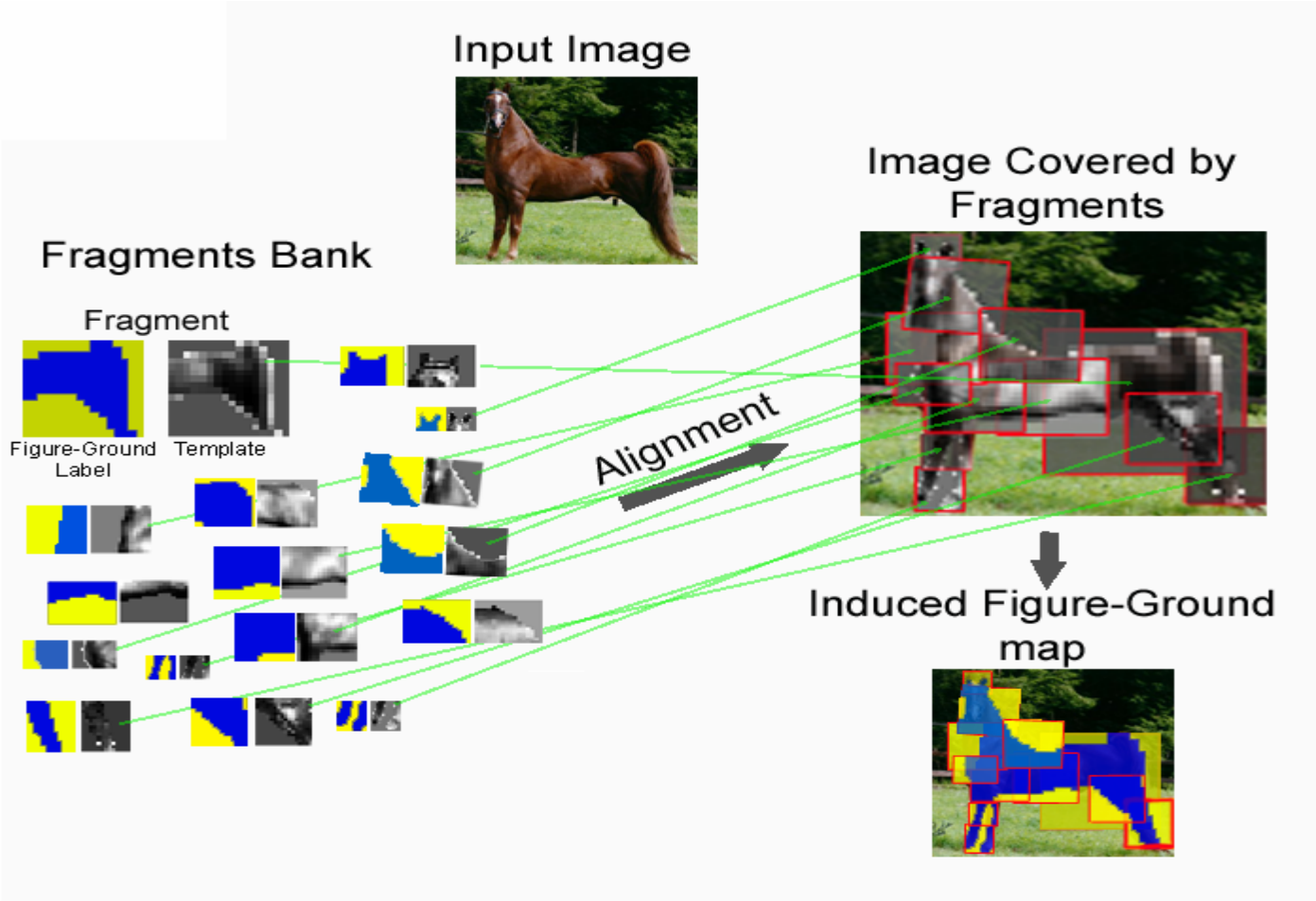
- Training
- Learn fragments from segmented images





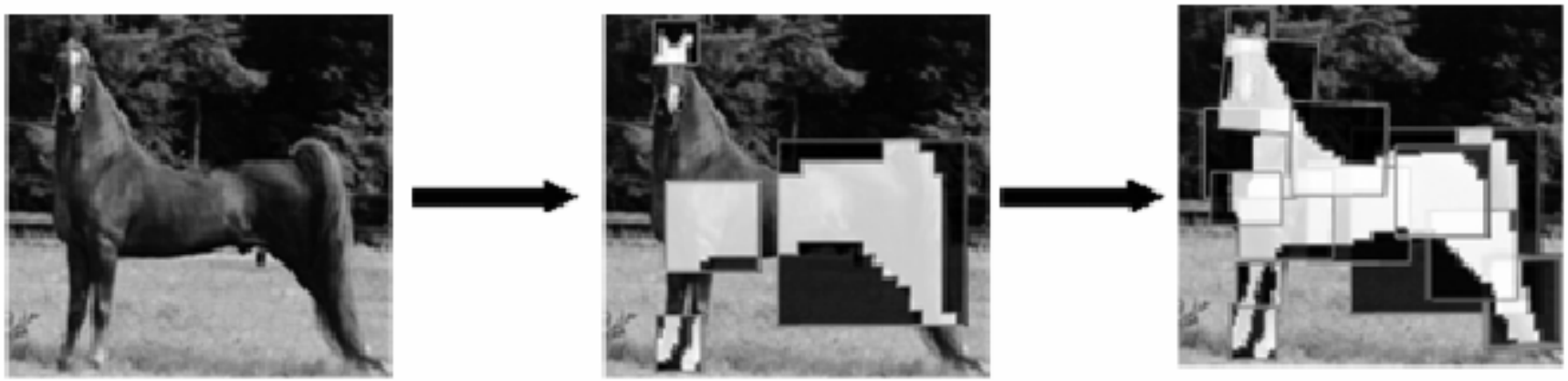


Class-based Recognition/Segmentation



Structure: jigsaw puzzle approach

1. Part matches image
2. Overlap of parts agree on foreground/background
3. Greedy algorithm for fitting



Comparison with Leibe & Schiele, Agarwal & Roth

Borenstein & Ullman:

• geometric constraints too loose

• often gets stuck on background regions

Summary

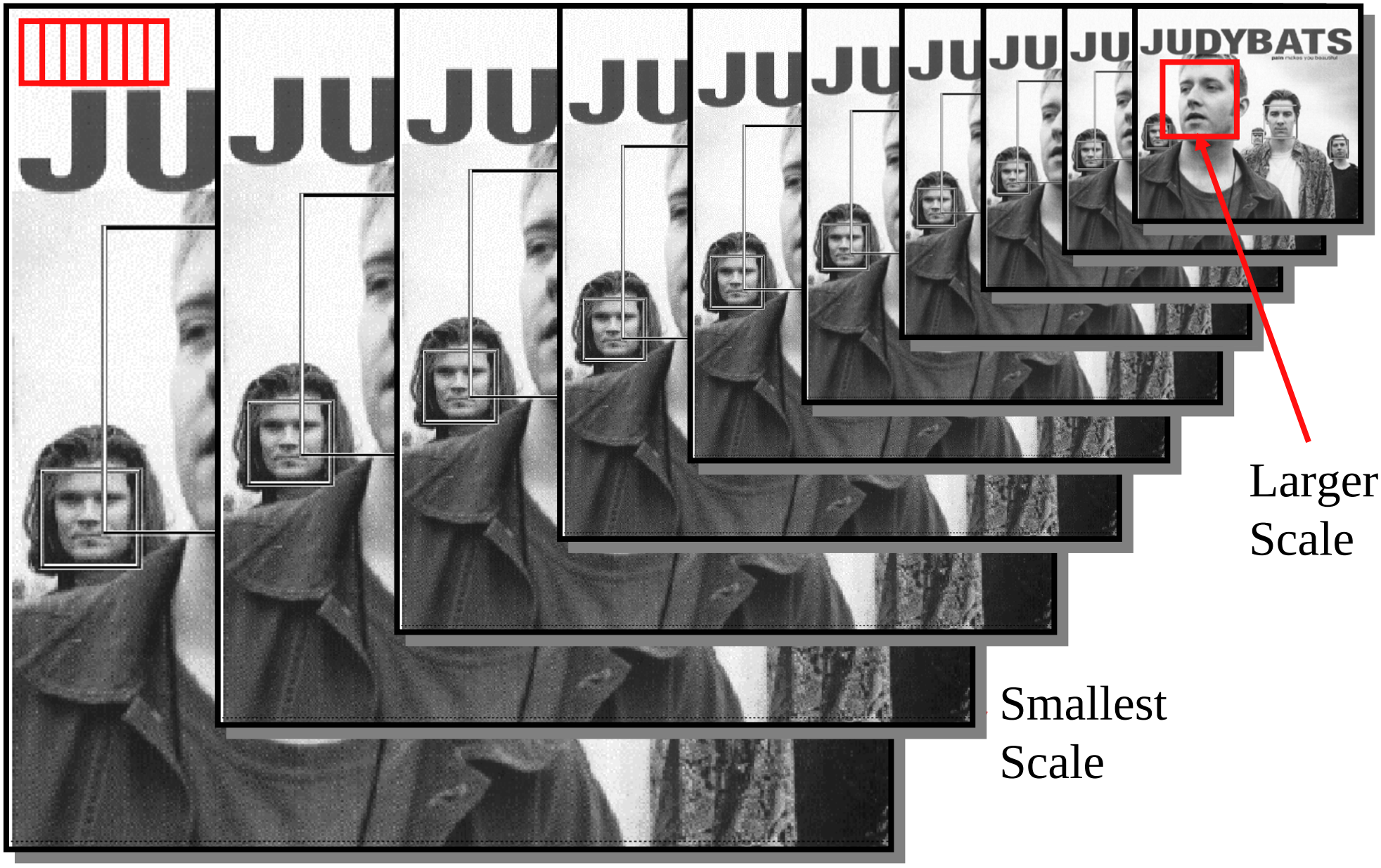
	Parts	Structure
Leibe & Schiele	Cluster from positive examples	Vote on centroid
Agarwal & Roth	Cluster from positive examples	Linear classifier on parts and relations between pairs
Borenstein & Ullman	MI to select fragments from positive & negative examples	Jigsaw like overlap of fragments

So far …..

- Recognize class instances under image translation
- Implicit structure model
- No inter-part articulation
- Only single visual aspect

Extend to image scale change and rotation by exhaustive search over scale and orientation

Search over scale



2. Models for which the structure model is primary

New ideas

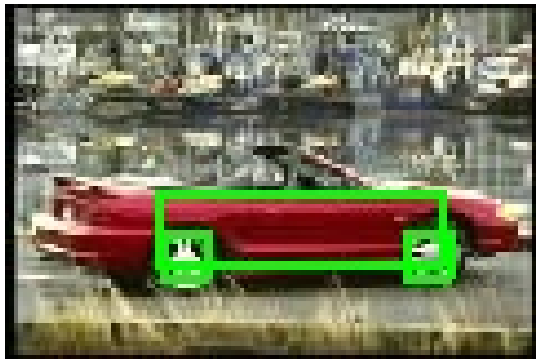
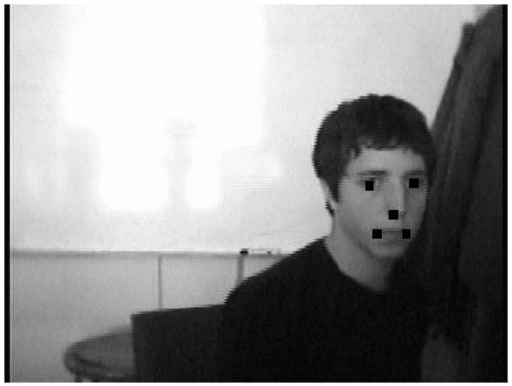
- Explicit structure model
- Articulated structure

Pictorial Structure Models for Object Recognition

Felzenszwalb & Huttenlocher 2000

Goal

- Detect and localize multi-part objects at arbitrary locations in a scene
  - Generic object models such as person or car
  - Allow for articulated objects
  - Combine 2D geometry and appearance
  - Provide efficient and practical algorithms

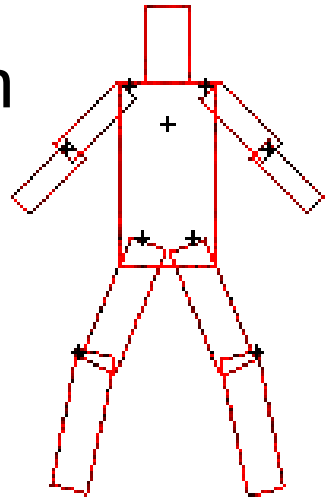

Matching Pictorial Structures

- Simultaneous use of appearance and spatial information

- Minimize an energy (or cost) function that reflects both
  - Appearance: how well each part matches at given location
  - Configuration: degree to which model is deformed in placing the parts at chosen locations

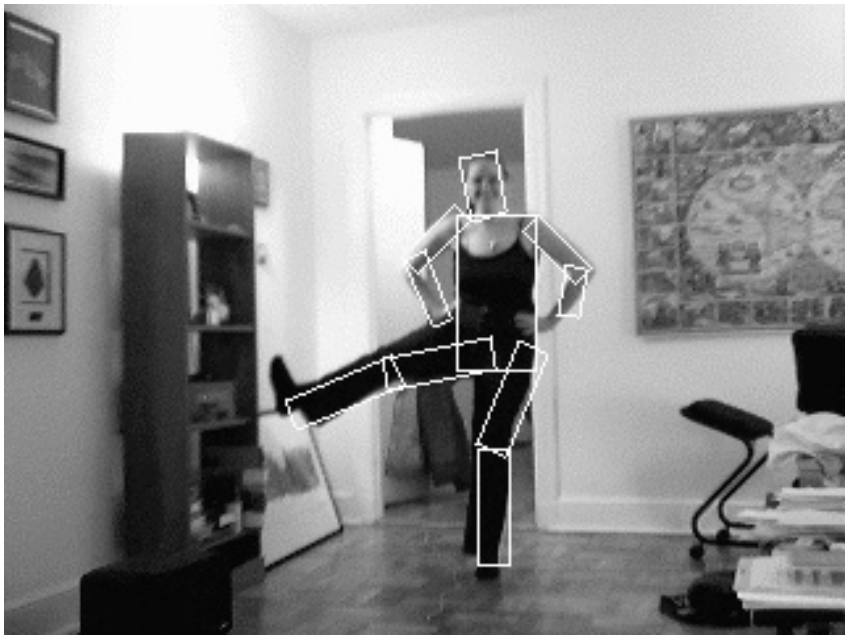
Example: Generic Person Model

- Each part represented as rectangle
  - Fixed width, varying length, uniform colour
  - Learn average and variation
    - Connections approximate revolute joints
  - Joint location, relative part position, orientation, foreshortening - Gaussian
  - Estimate average and variation
- Learned 10 part model
  - All parameters learned
    - Including “joint locations”
  - Shown at ideal configuration (mean locations)



Learning

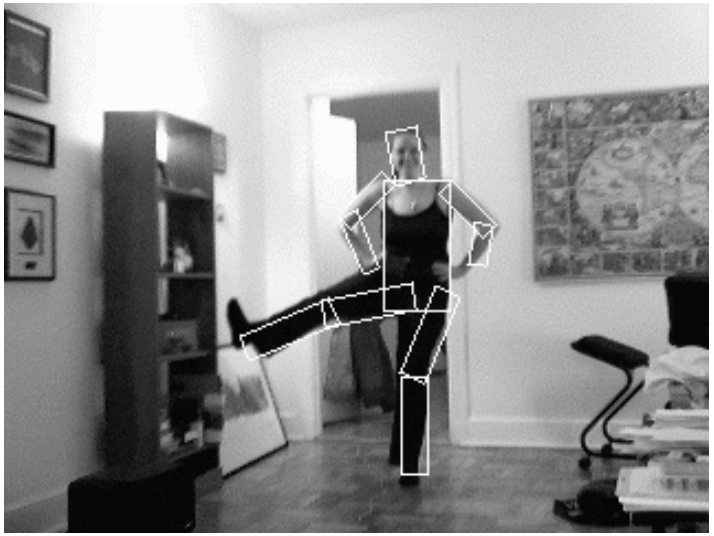
- Manual identification of rectangular parts in a set of training images hypotheses
- Learn relative position (x & y), relative angle, relative foreshortening

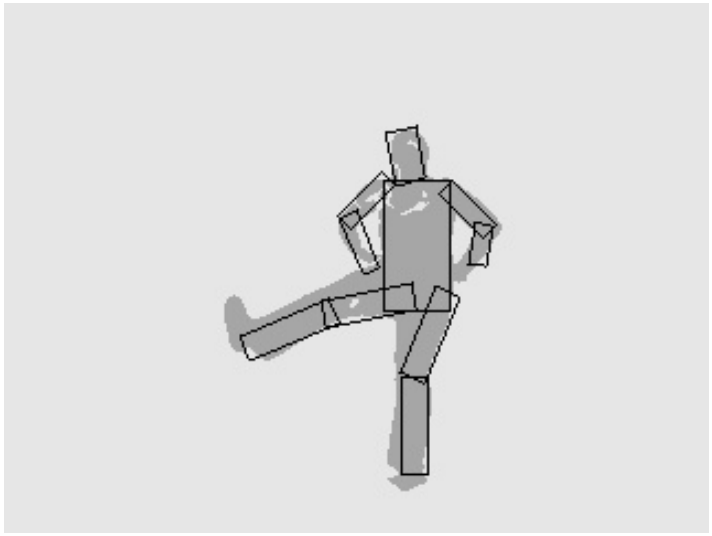


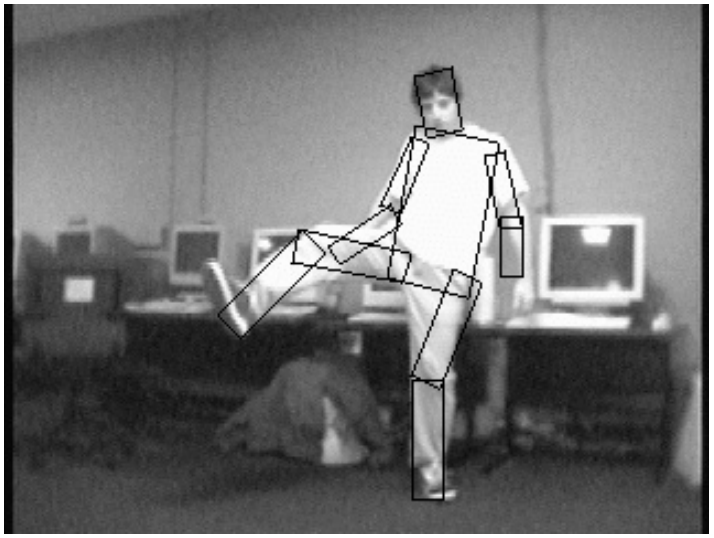
Recognition

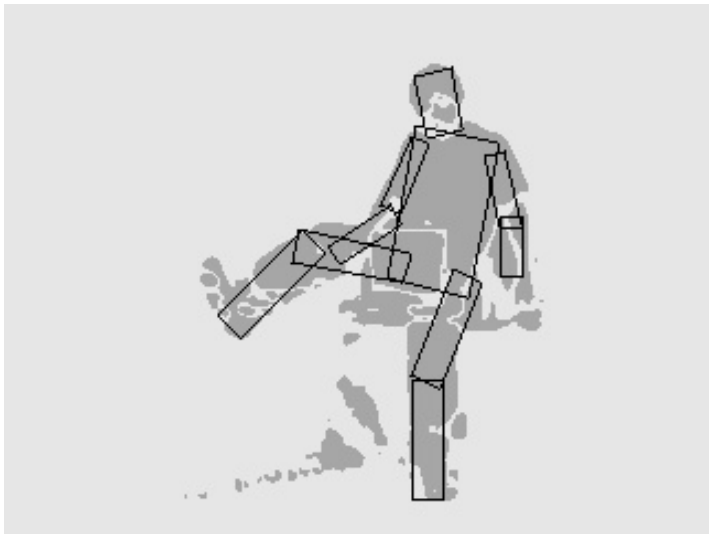
- Given model Θ and image I, seek "good" configuration(s) L
  - Maximum a posteriori (MAP) estimate
    - Highest probability (lowest energy) configuration L
    - $L^* = \text{argmax}_L \; p(L|I,\Theta)$
- Brute force solutions intractable
  - With p parts and s possible discrete locations per part, $O(s^p)$
- If model is a tree then complexity reduces to O(ps)

Example: Recognizing People



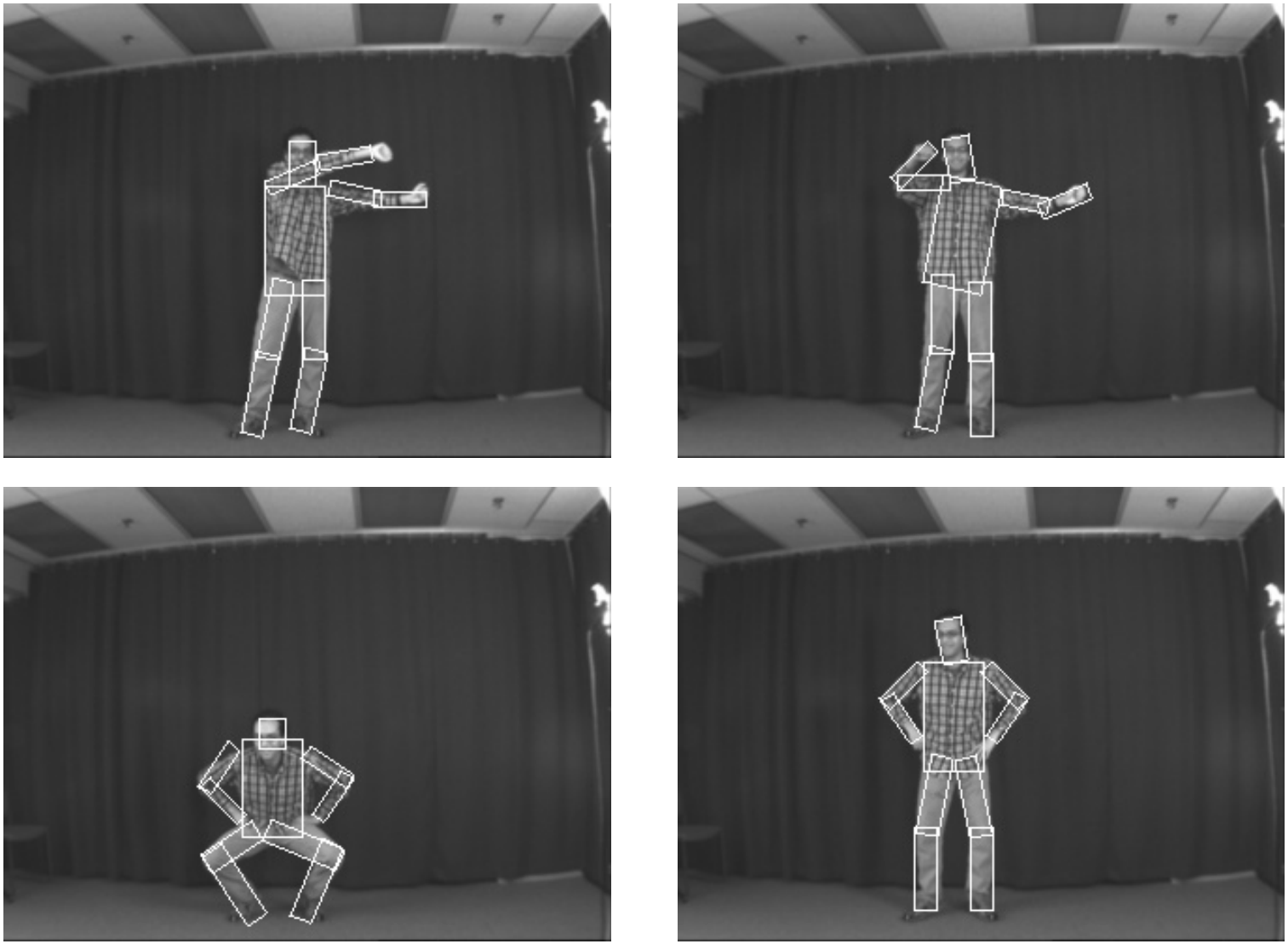




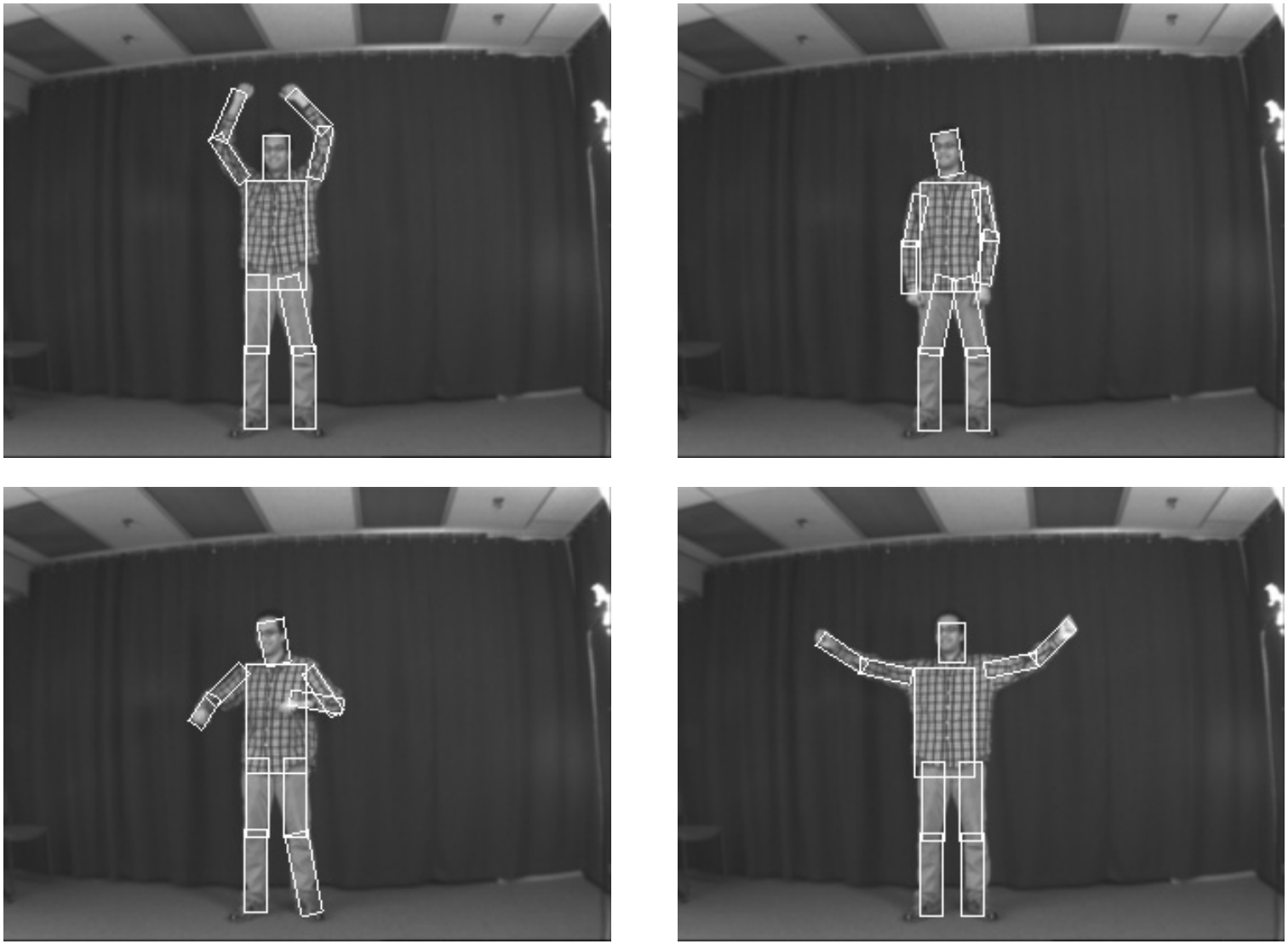


NB: requires background subtraction

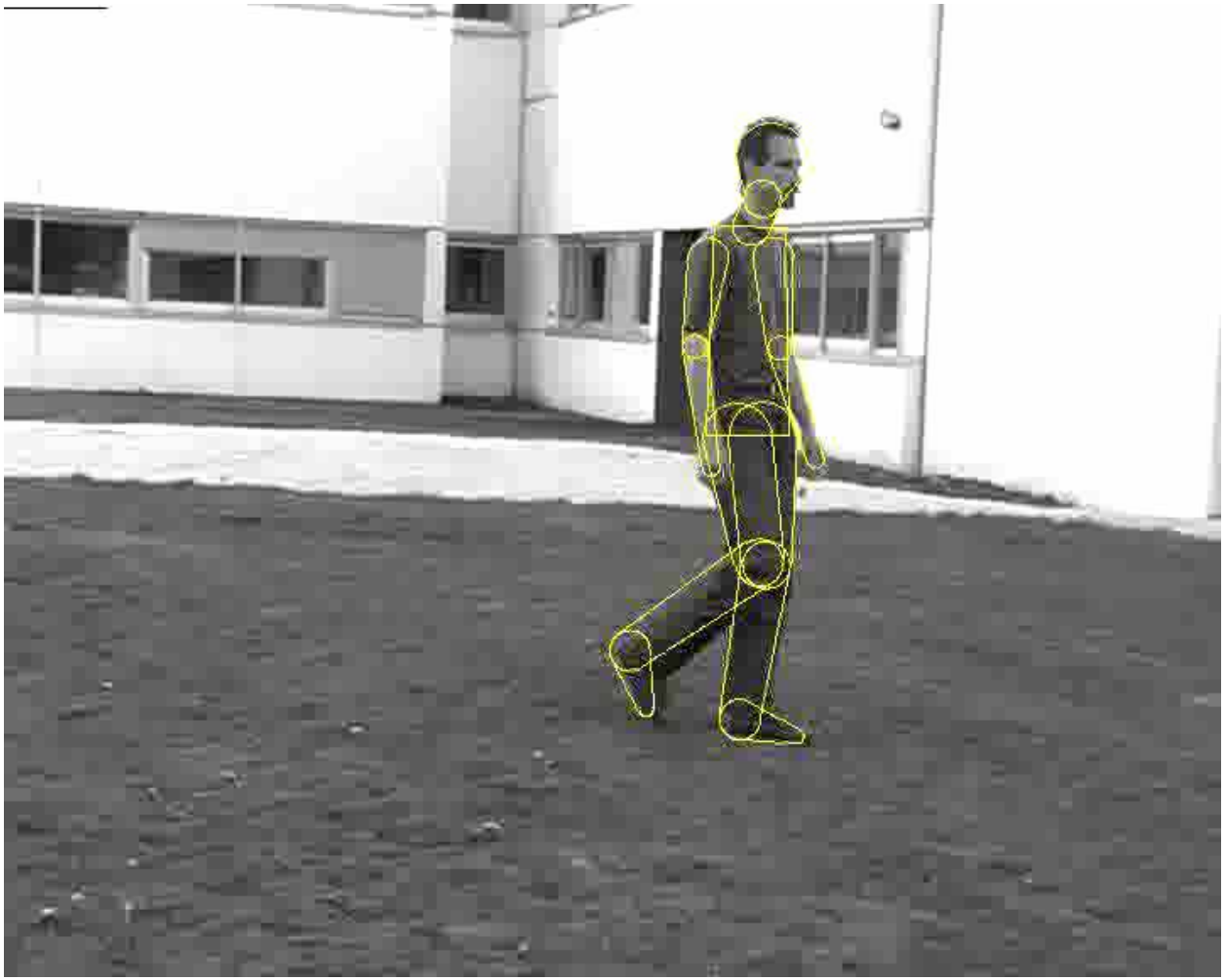
Variety of Poses



Variety of Poses



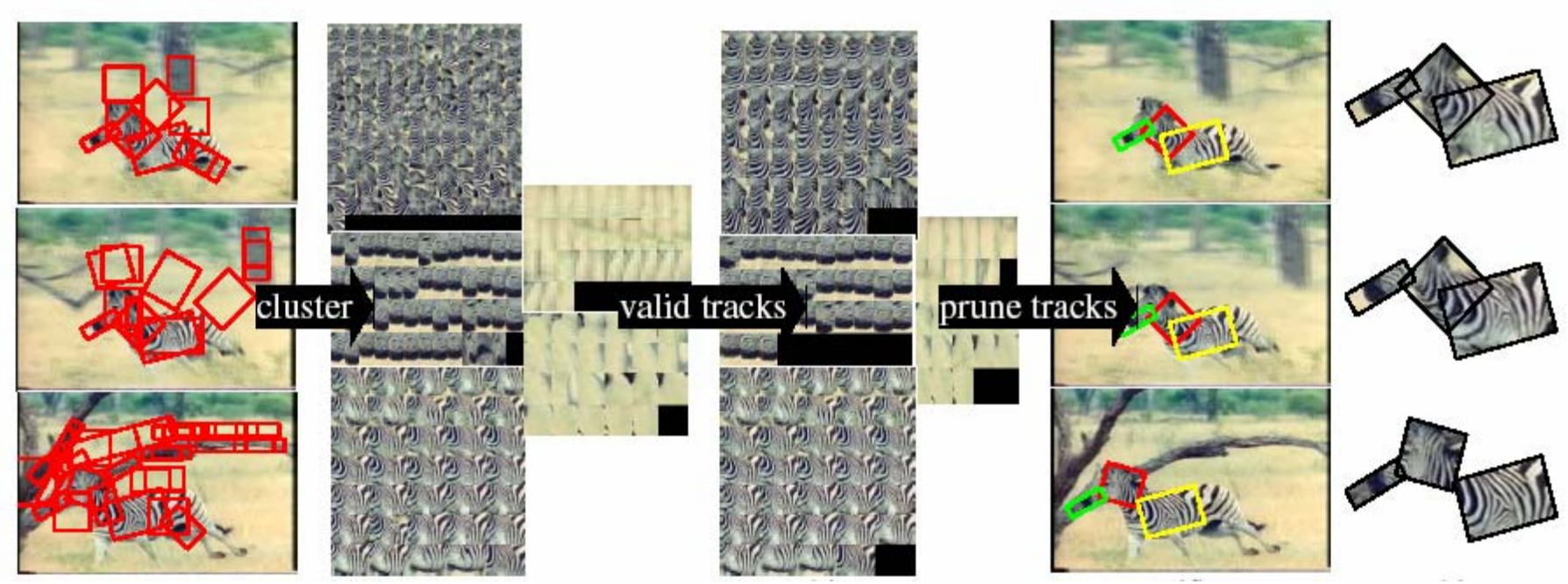
Pictorial structures for tracking



Learning articulated pictorial structures using temporal coherence

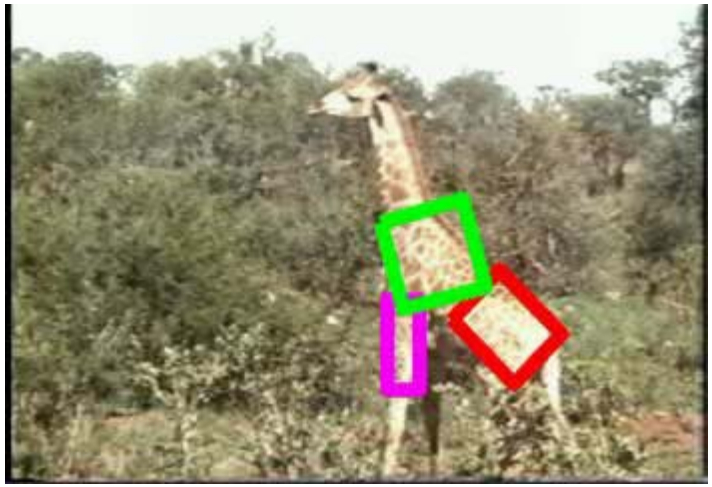
Ramanan & Forsyth 2003

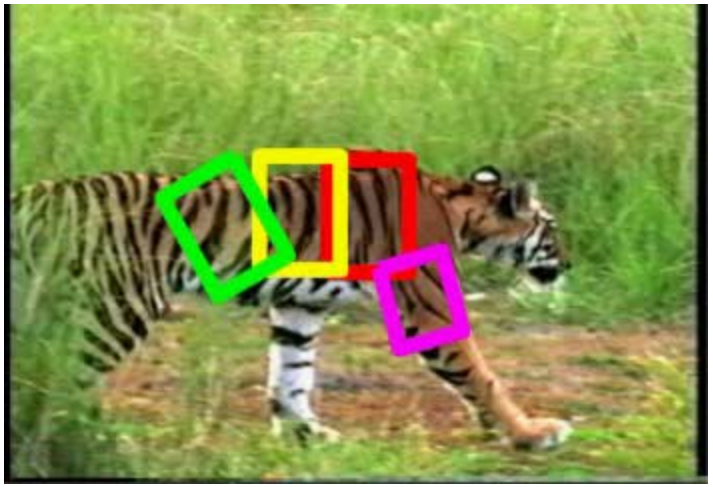
- Parts detected as parallel lines of contrast



- Parts are clustered together.
- Stationary clusters are rejected.

Results





3. Models that learn parts and structure simultaneously

New ideas

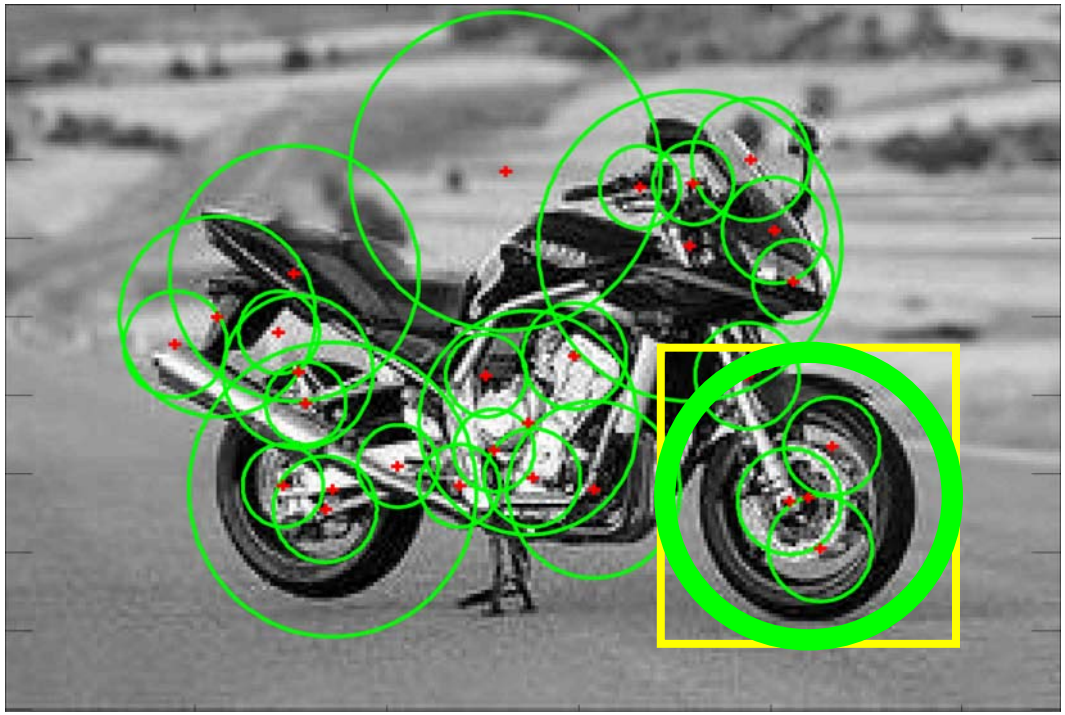
- Explicit structure model – Joint Gaussian over all part positions
  - dates back to Weber, Welling & Perona 2000 and earlier
- Part detector determines position *and* scale
- Heterogeneous parts
- Simultaneous learning of parts and structure

Constellation model of Fergus, Perona & Zisserman 2003

Detect region for candidate parts

Use salient region operator (Kadir & Brady 01)

Representation of regions



- Find regions within image

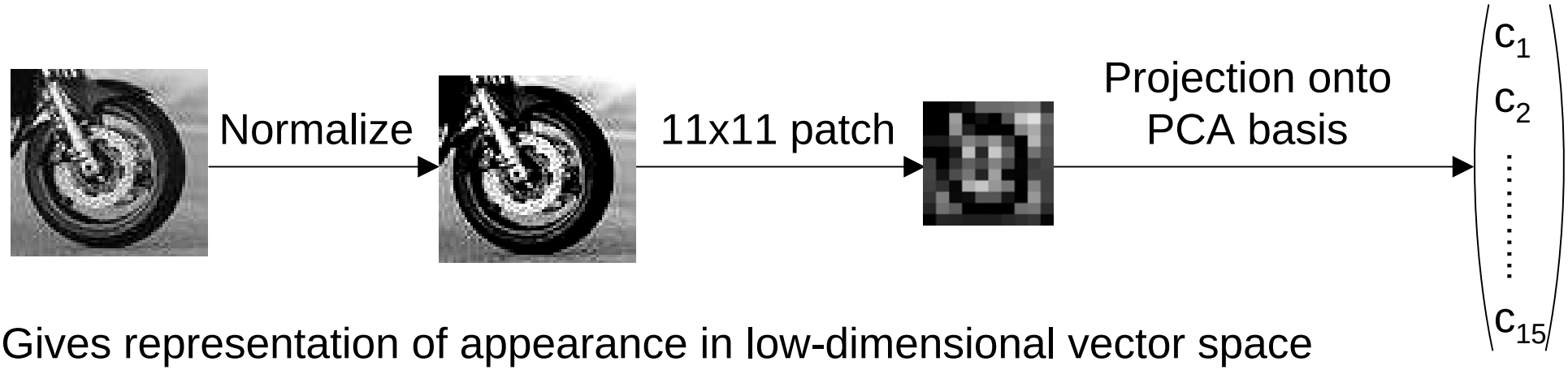
Location

(x,y) coords. of region centre

Scale

Radius of region (pixels)

Appearance (monochrome)

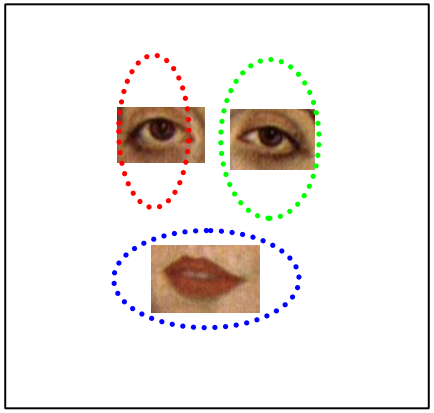


Gives representation of appearance in low-dimensional vector space

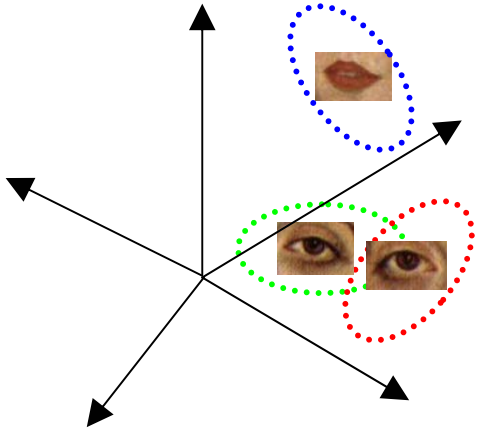
Generative probabilistic model

Foreground model

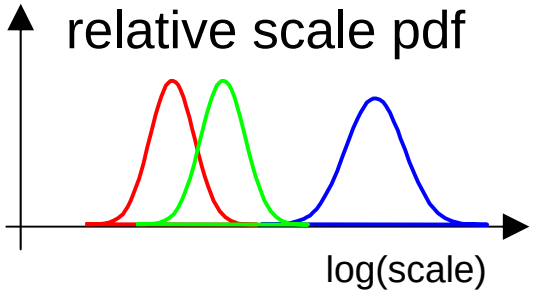
Gaussian shape pdf



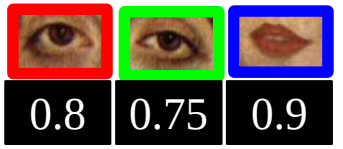
Gaussian part appearance pdf



Gaussian
relative scale pdf

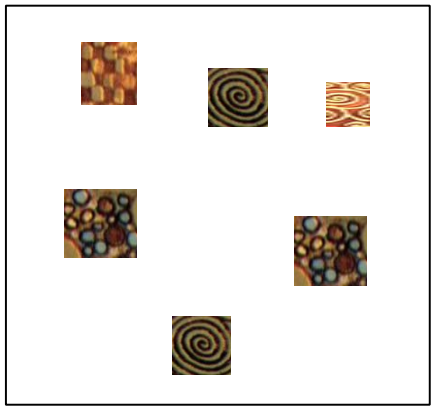


Prob. of detection

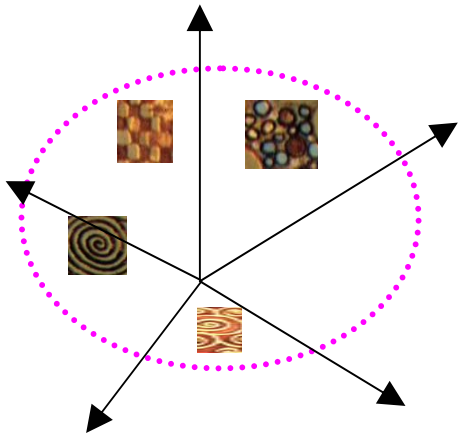


Clutter model

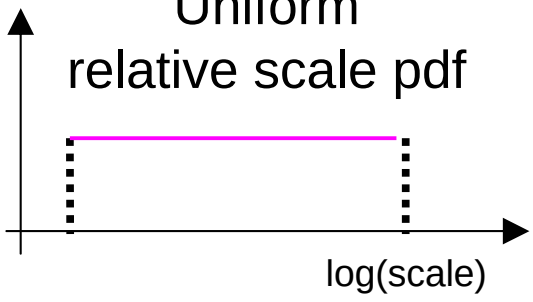
Uniform shape pdf



Gaussian background
appearance pdf



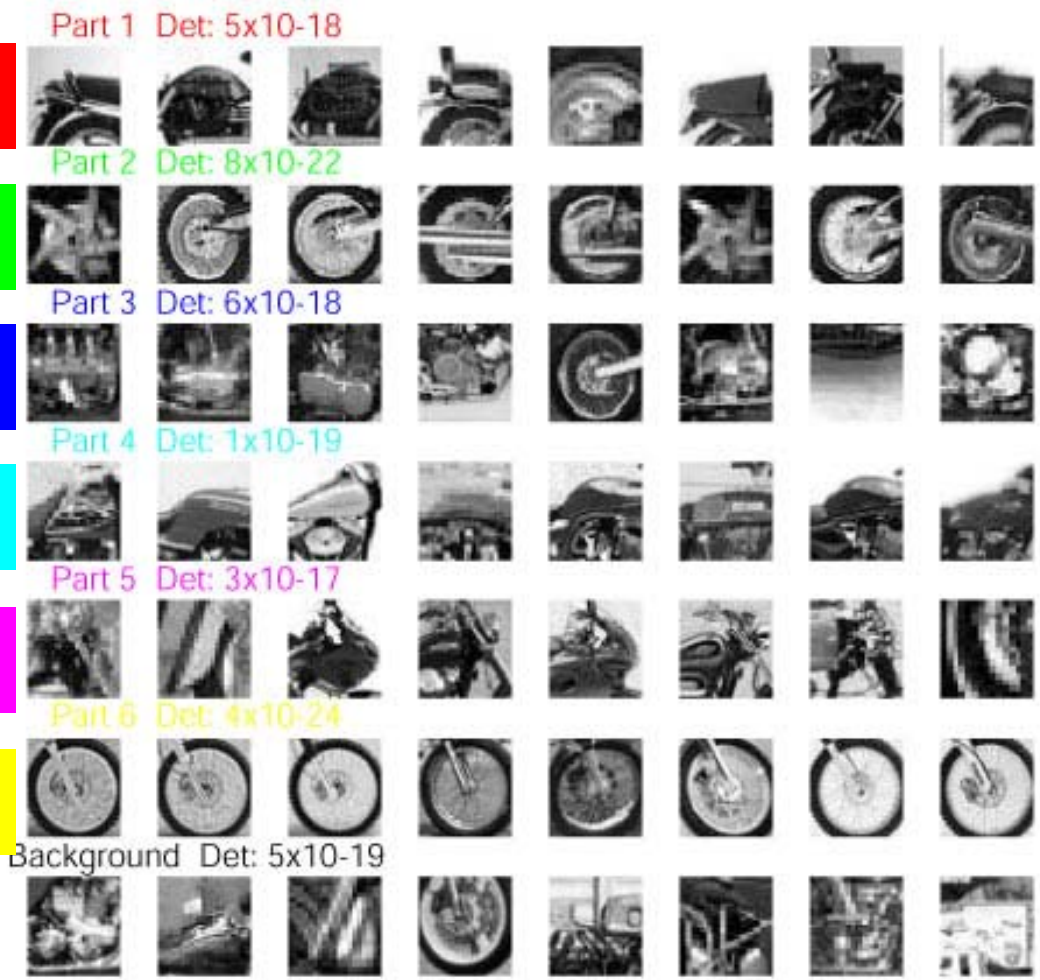
Uniform
relative scale pdf

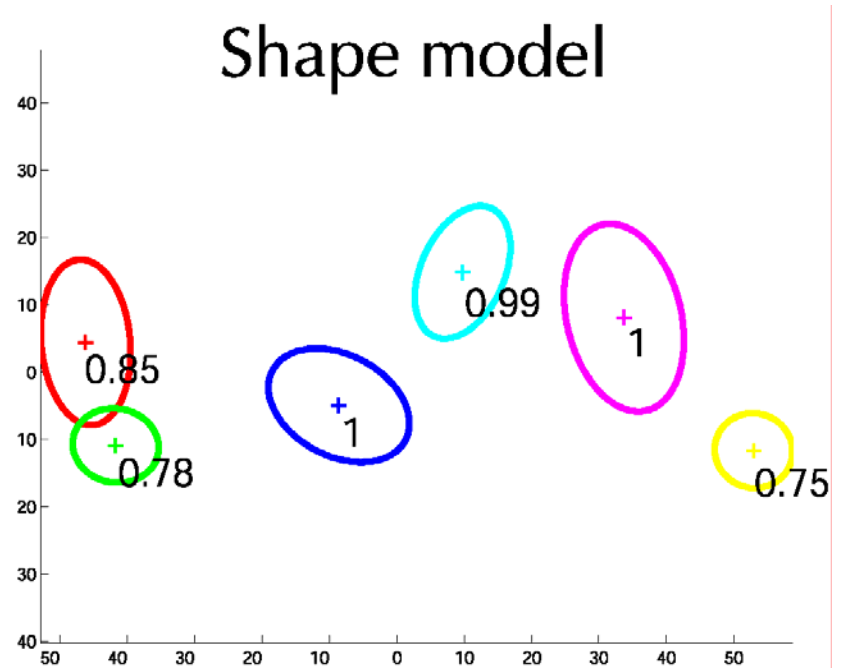


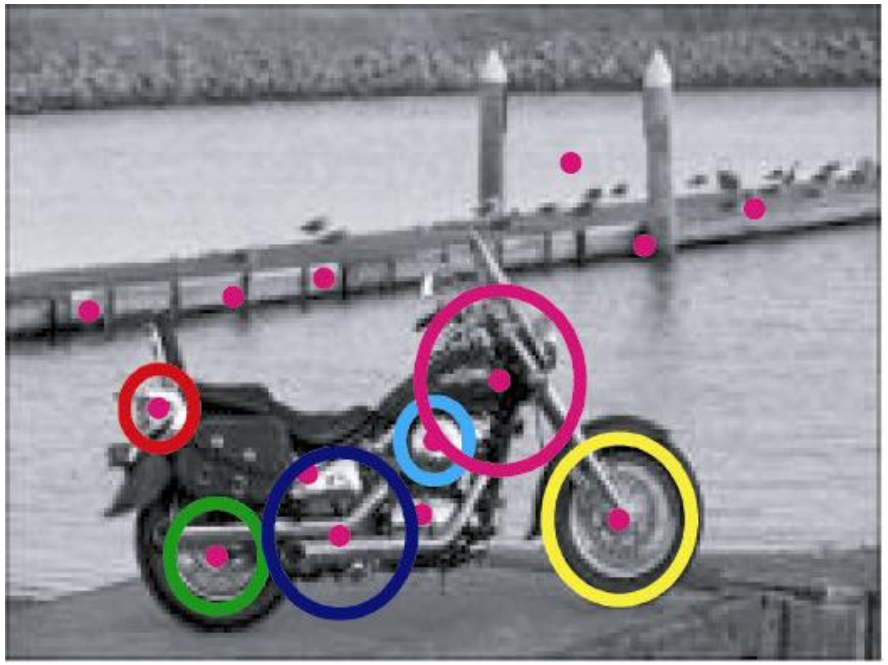
Poission pdf on #
detections

Example – Learnt Motorbike Model

Samples from appearance model







Learning

- Task: Estimation of model parameters
- Chicken and Egg type problem, since we initially know neither:
  - Model parameters
  - Assignment of regions to foreground / background
- Let the assignments be a hidden variable and use EM algorithm to learn them and the model parameters

Learning procedure

- Find regions & their location, scale & appearance

  over all training, compute PCA

- Initialize model parameters

- Use EM and iterate to convergence:

  E-step: Compute assignments for which regions are foreground / background

  M-step: Update model parameters

- Trying to maximize likelihood – consistency in shape & appearance

Recognition

- Detect regions in target image
- Evaluate the likelihood of the model (a search over assignments of parts to features)
- Threshold on the likelihood ratio

Experiments

Experimental procedure

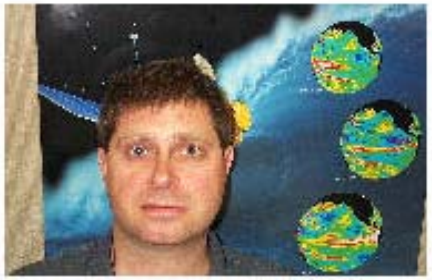
Cal Tech Datasets

Training
- 50% images
- No identifcation of object within image

Motorbikes

Airplanes

Frontal Faces



Testing
- 50% images
- Simple object present/absent test

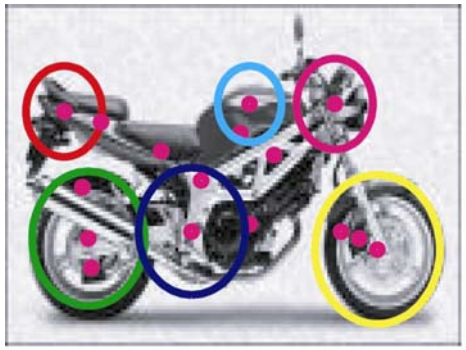
Cars (Side)

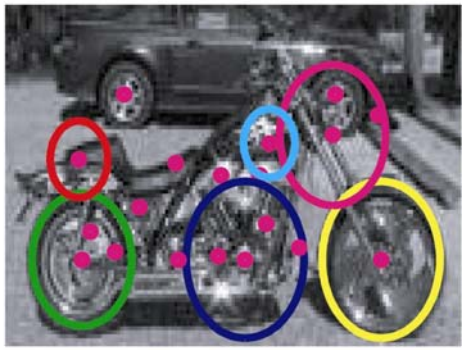
Cars (Rear)

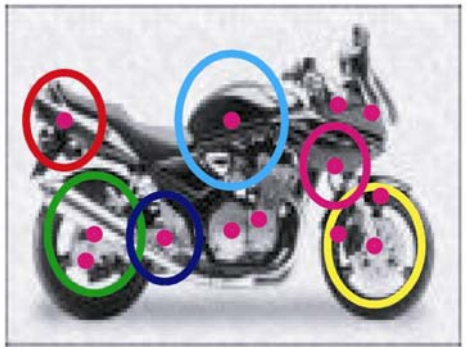
Spotted cats

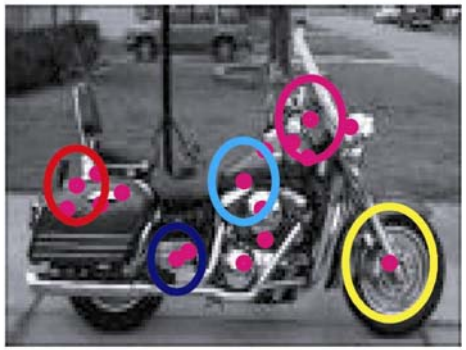
Between 200 and 800 images in each dataset
Objects between 100 and 550 pixels in width

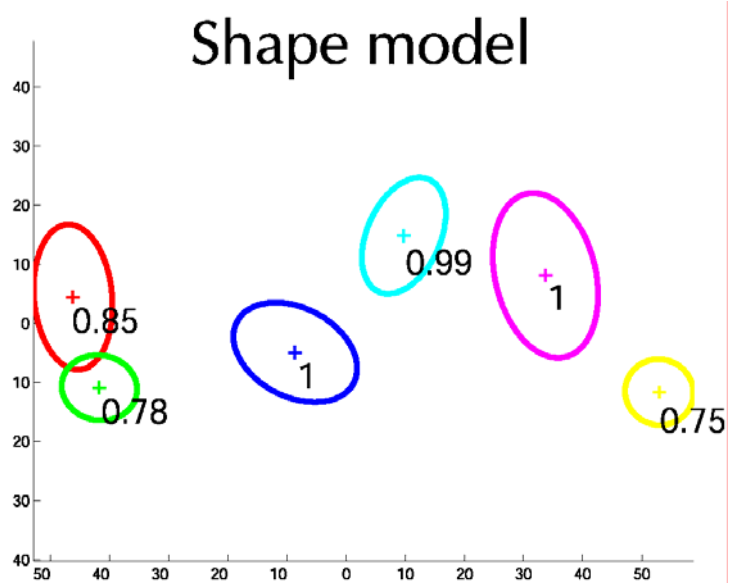
Recognized Motorbikes

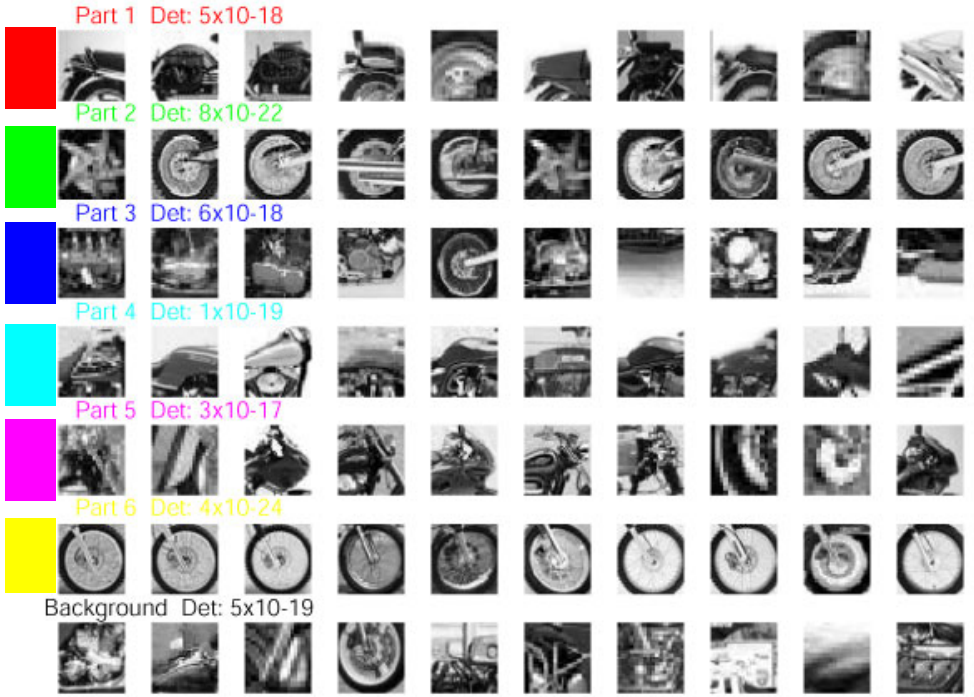








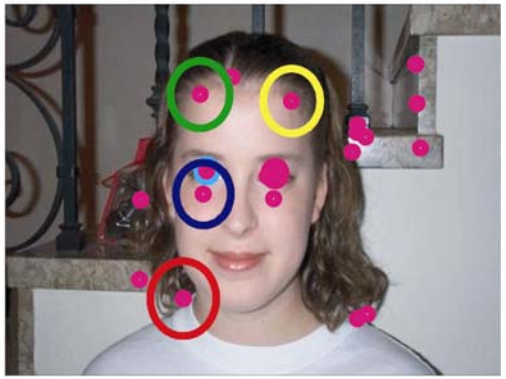


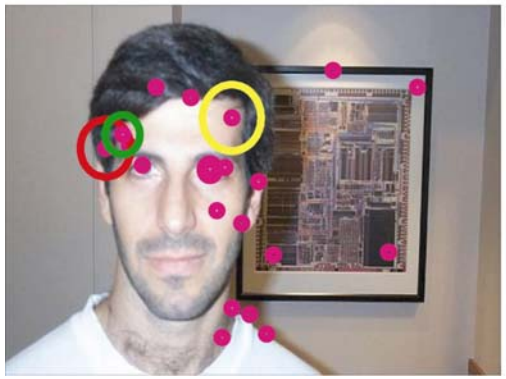


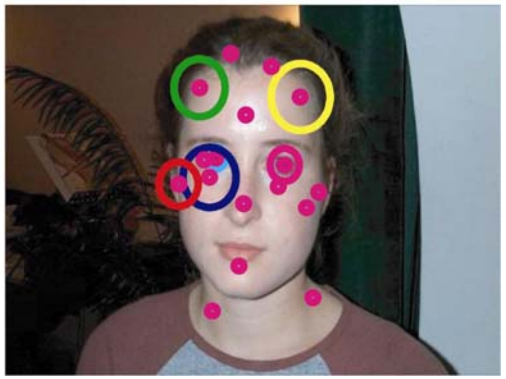
position of object determined

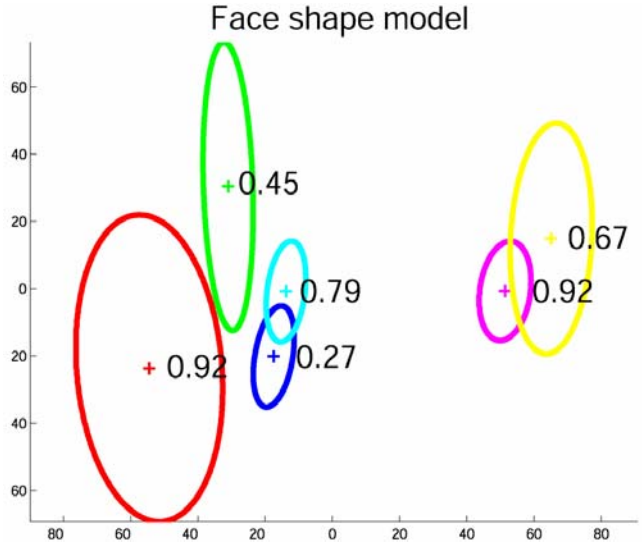
Background images evaluated with motorbike model

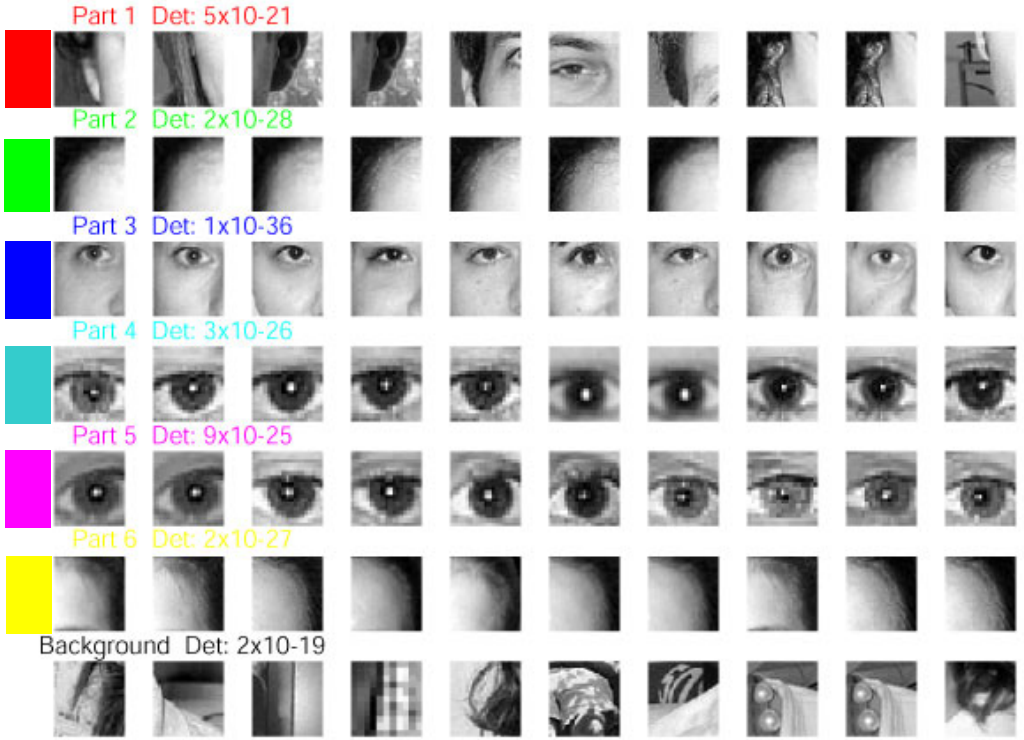
Frontal faces



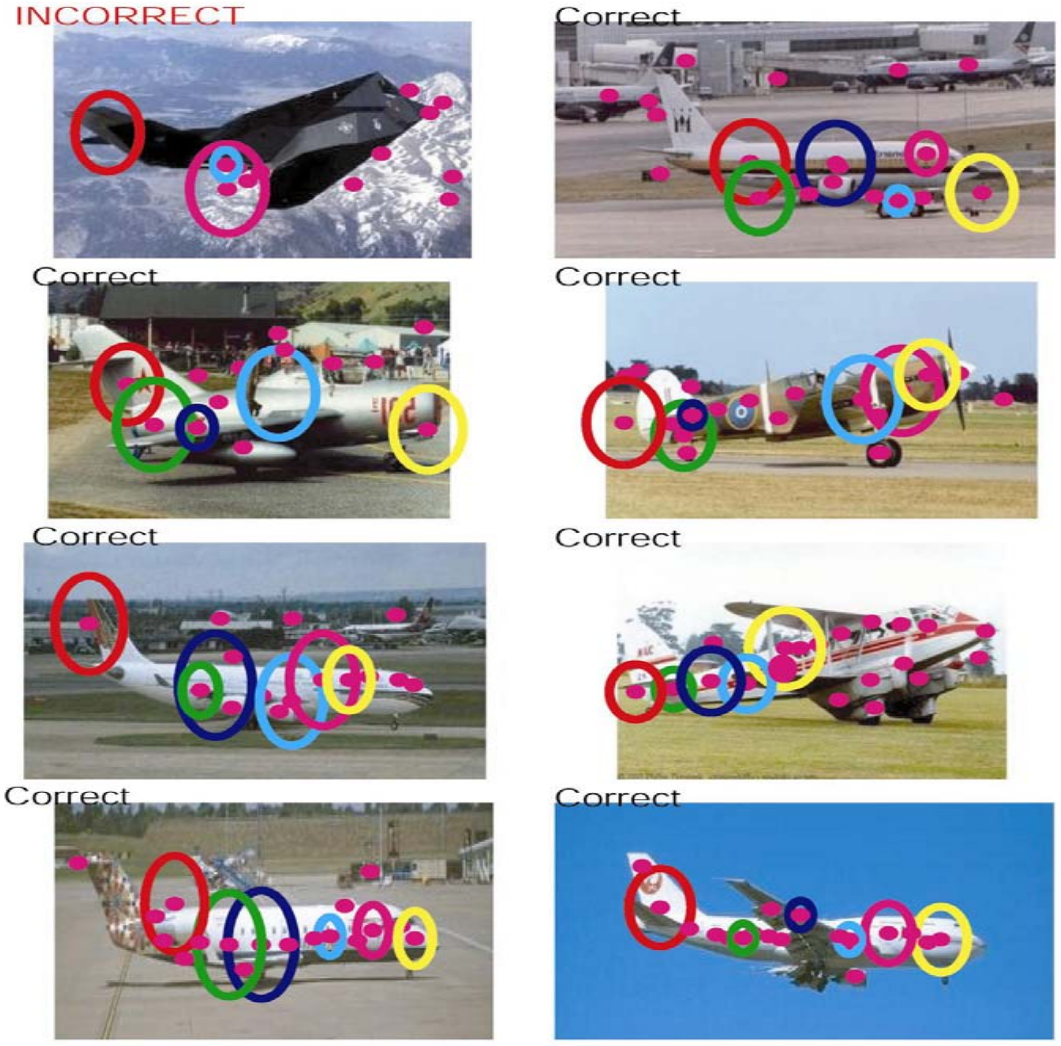


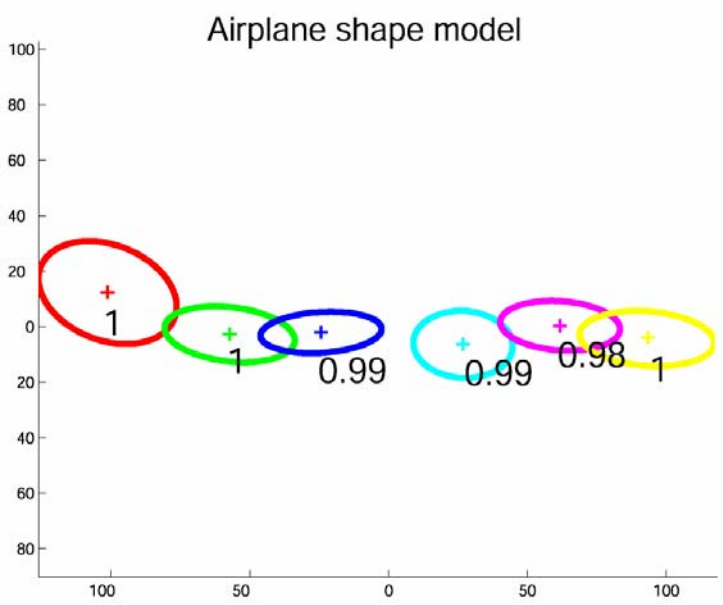


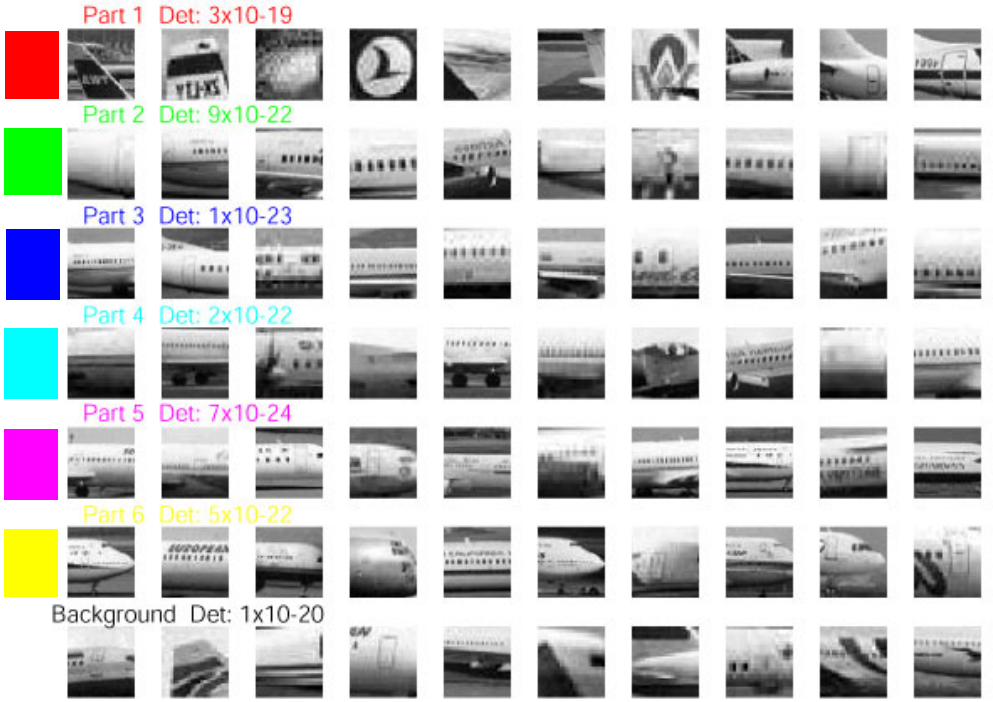




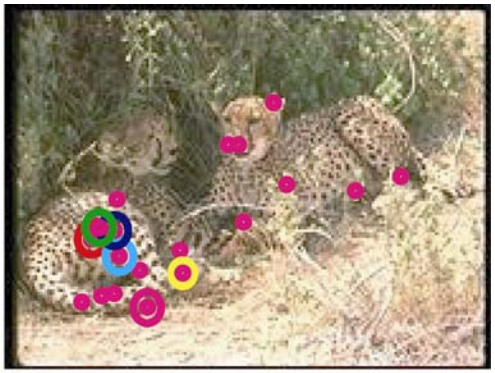
Airplanes

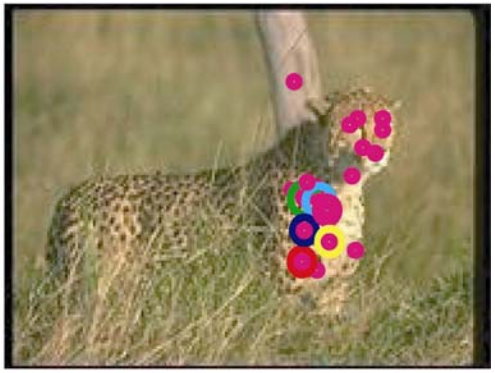

INCORRECT
Correct
Correct
Correct
Correct
Correct
Correct
Correct

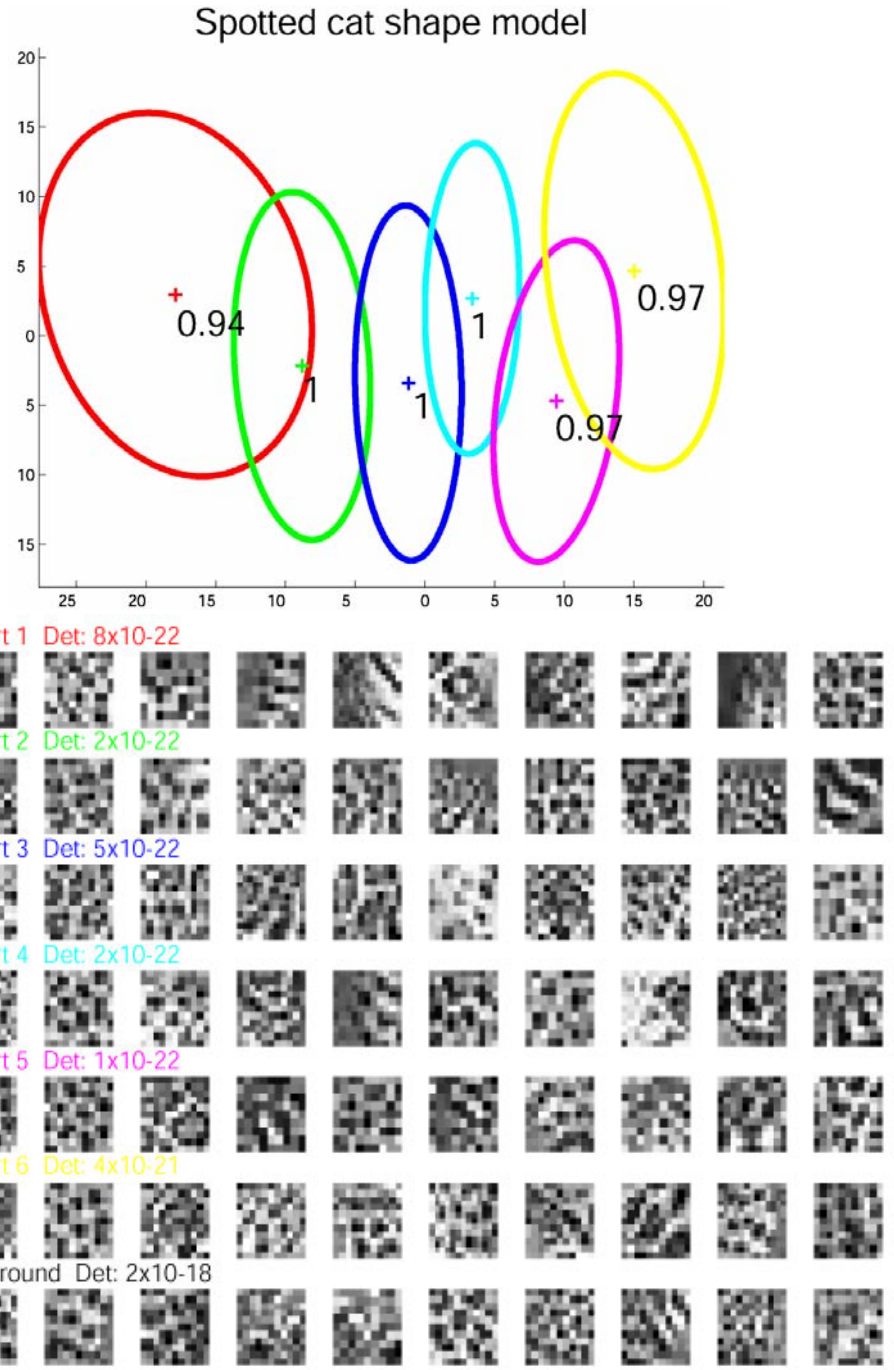

Airplane shape model
100
80
60
40
20
0
20
40
60
80
100
50
0
50
100
1
1
0.99
0.99
0.98
1


Part 1 Det: 3x10-19
Part 2 Det: 9x10-22
Part 3 Det: 1x10-23
Part 4 Det: 2x10-22
Part 5 Det: 7x10-24
Part 6 Det: 5x10-22
Background Det: 1x10-20

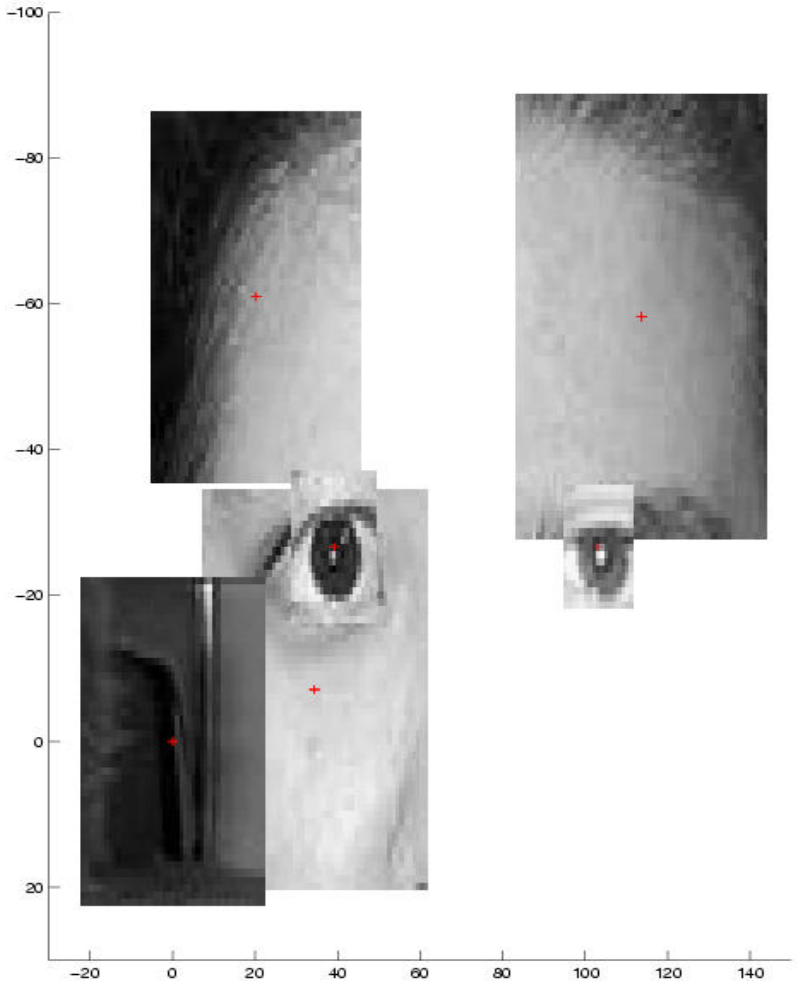
Spotted cats

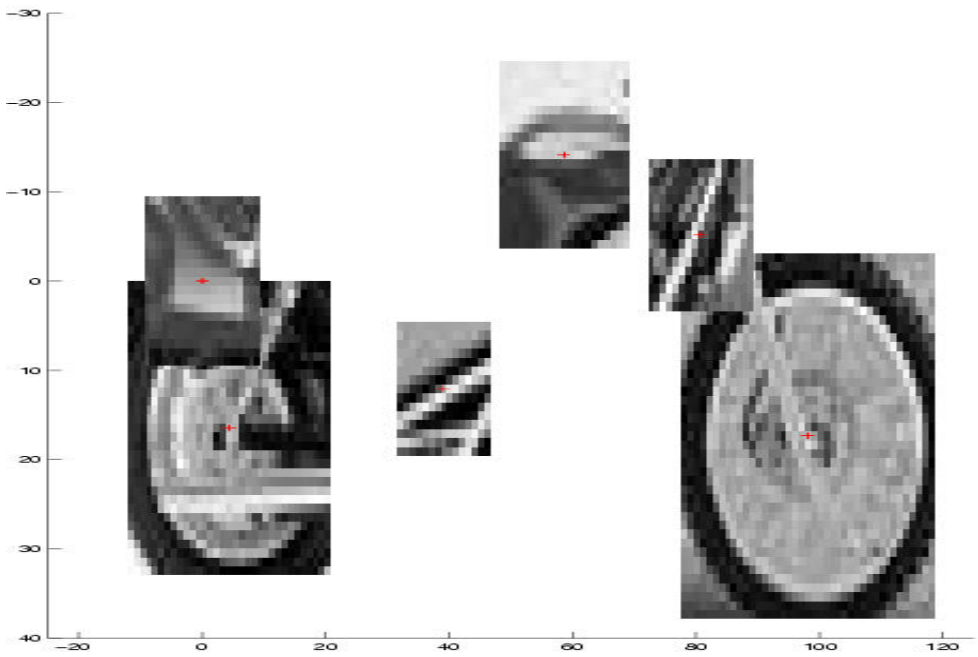




Sampling from models



Faces

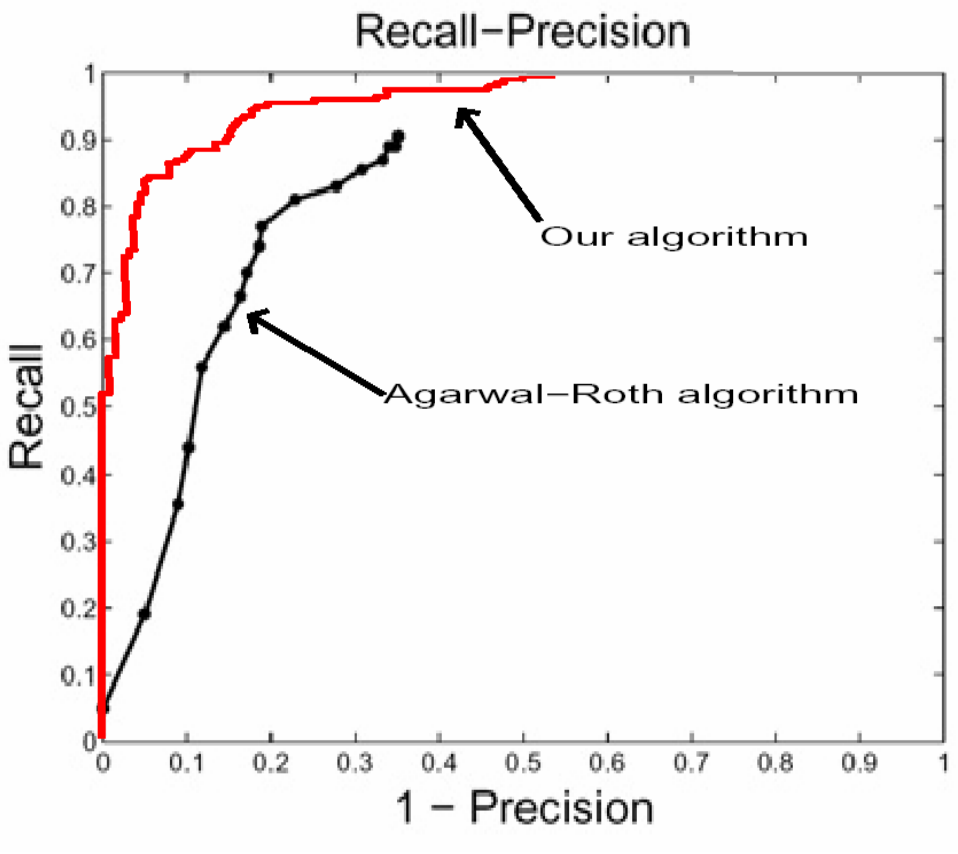


Motorbikes

Comparison to other methods

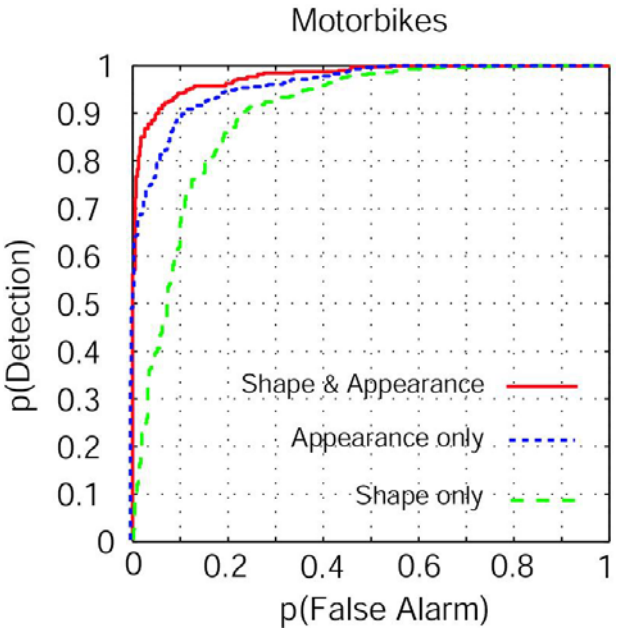
Dataset	Ours	Others	
Motorbikes	7.5	16.0	Weber et al. [ECCV ‘00]
Faces	4.6	6.0	Weber
Airplanes	9.8	32.0	Weber
Cars (Side)	11.5	21.0	Agarwal Roth [ECCV ’02]

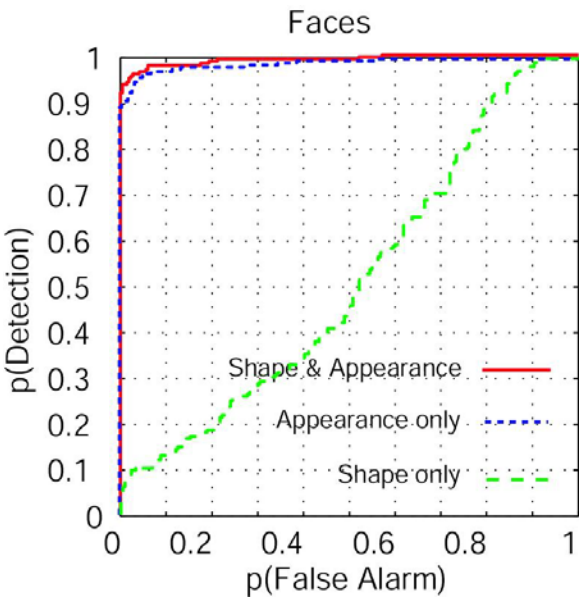
% equal error rate

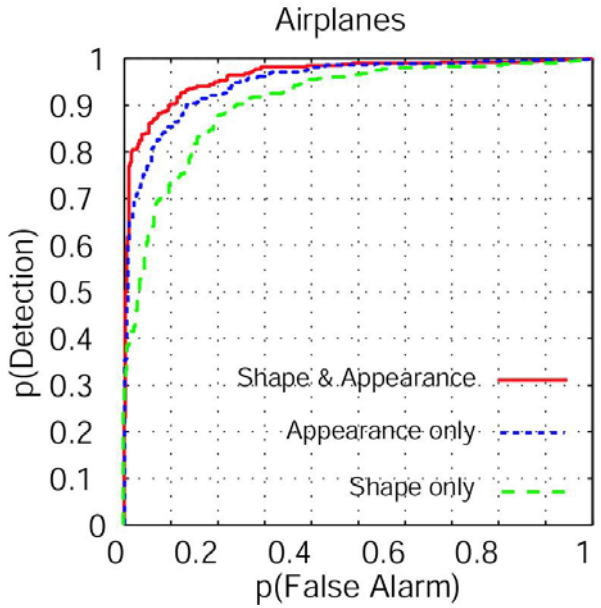


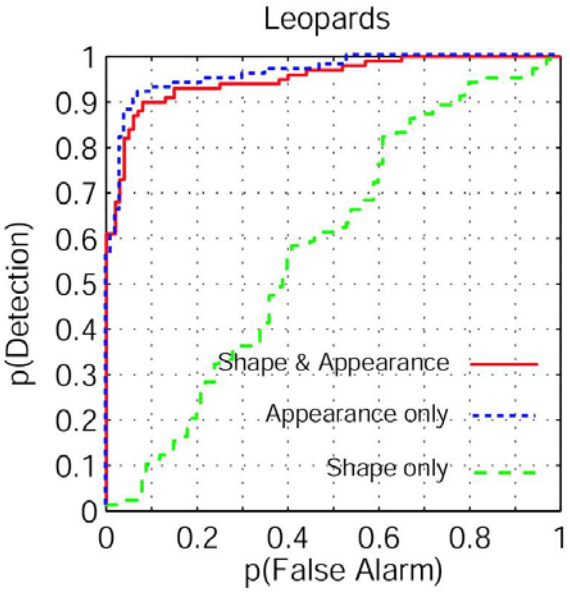
“Brain damaged” Constellation model

- Learn on full model, but for recognition use only parts or structure probability term







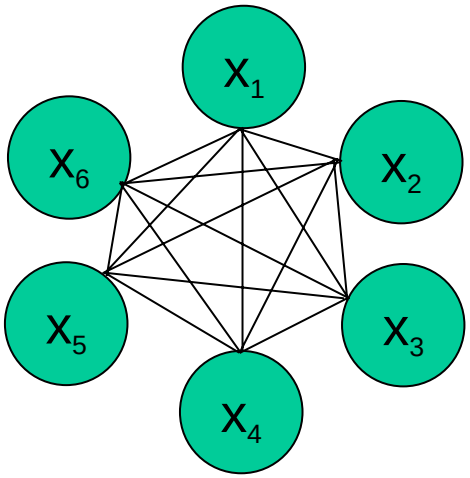


Constellation Model Generalization 1:

Conditionally independent model

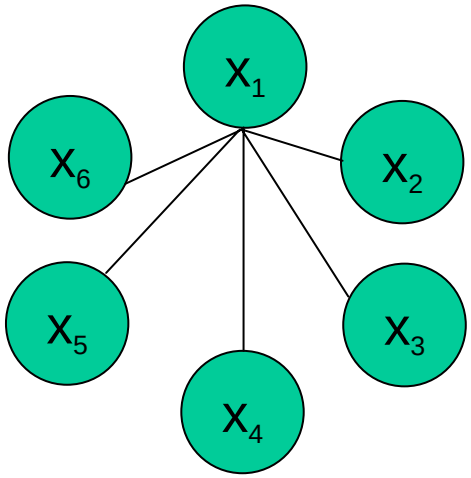
Shape model

Fully connected model



$O(N^P)$

"Star" model



$O(NP)$

+ Handle more detections per frame (N) - was ~25/image now 100's/image

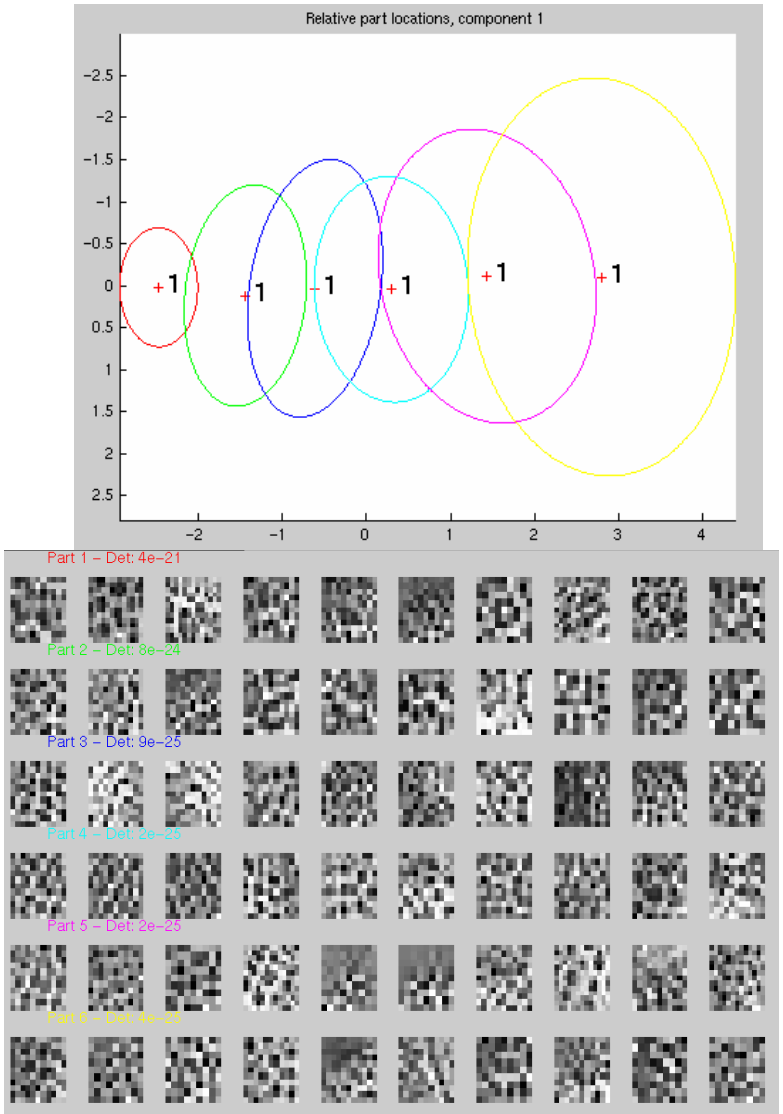
+ Handle more parts in model (P) - was 6, now 10-20

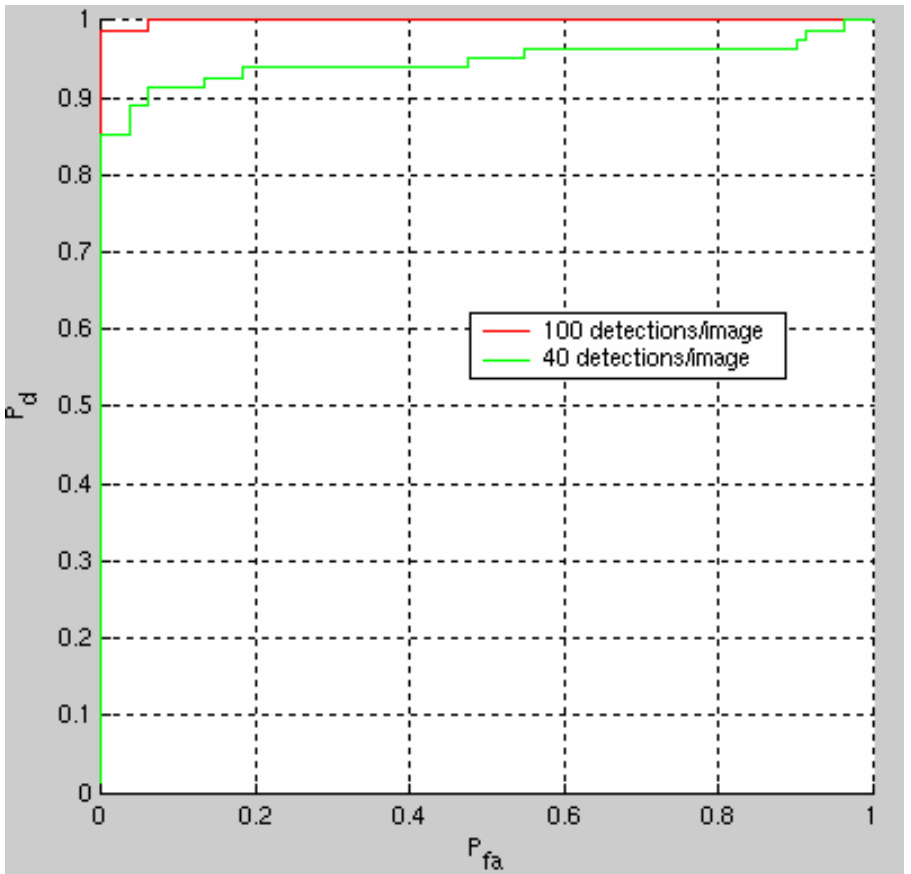
- Looser model: lack of inter-part covariance

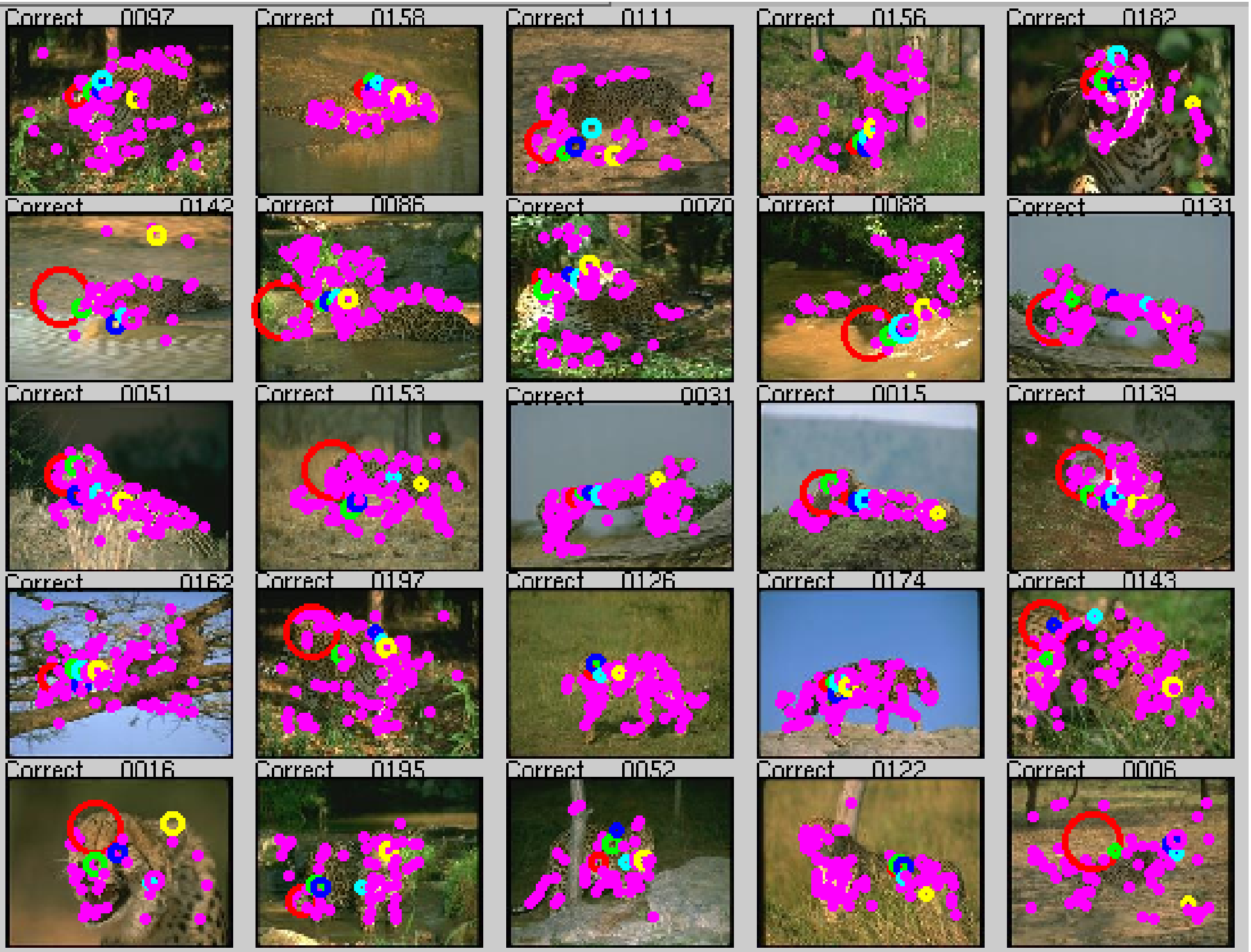
- Anchor point cannot be occluded

Spotted Cats

- 6 part model
- Using average of 100 detections/frame






Correct 0097
Correct 0158
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Correct 0182
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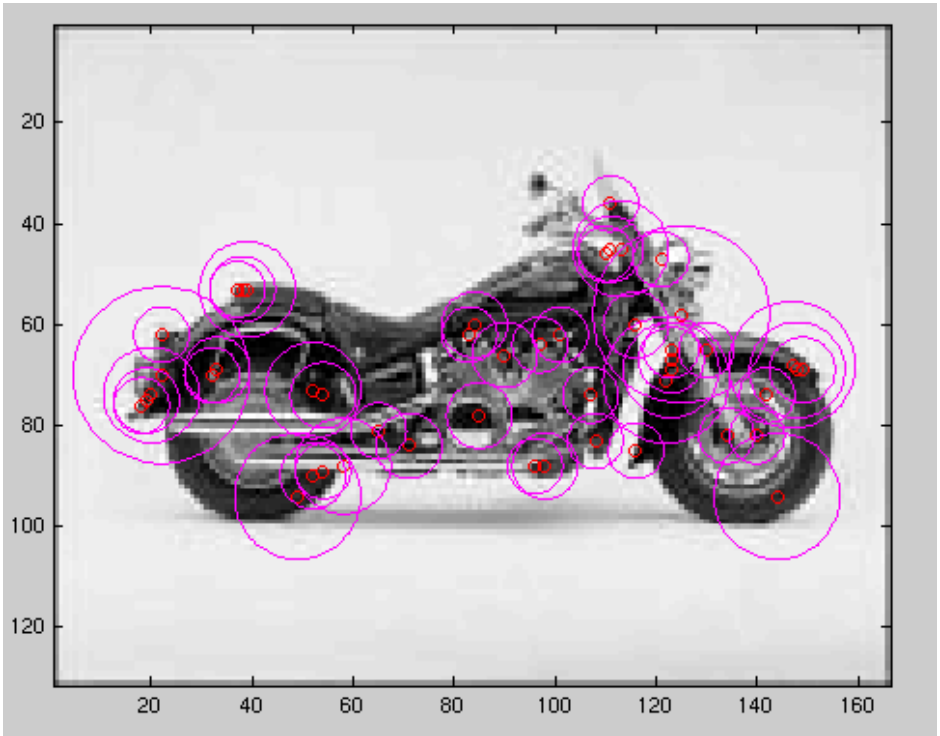
Correct 0015
Correct 0139
Correct 0162
Correct 0197
Correct 0126
Correct 0174
Correct 0143
Correct 0018
Correct 0195
Correct 0052
Correct 0122
Correct 0006

Constellation Model Generalization 2:

Heterogeneous parts

Variety of feature types

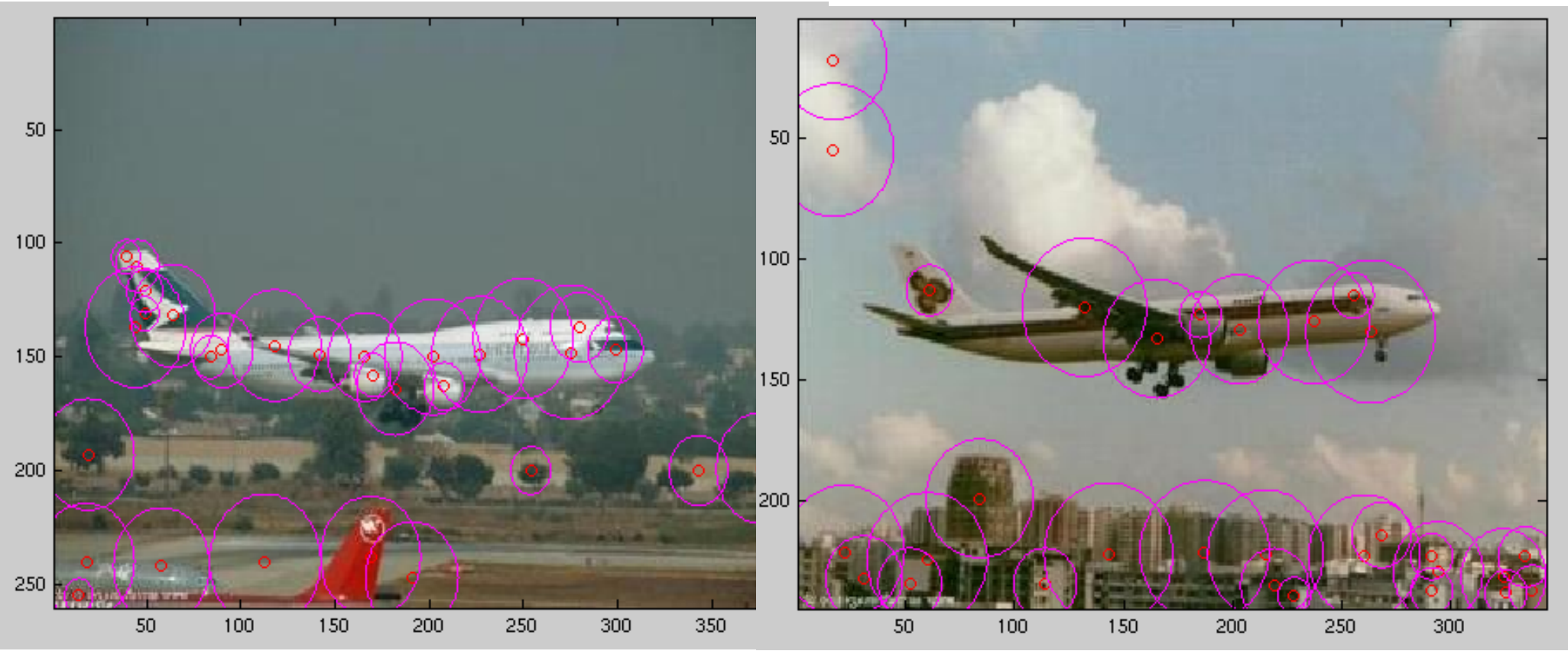
- So far patch features using Kadir & Brady regions
- Other region operators (Multiscale Harris, Lowe etc.)
- Curve feature to capture outline of object
- Heterogeneous object models



Multiscale Harris interest point

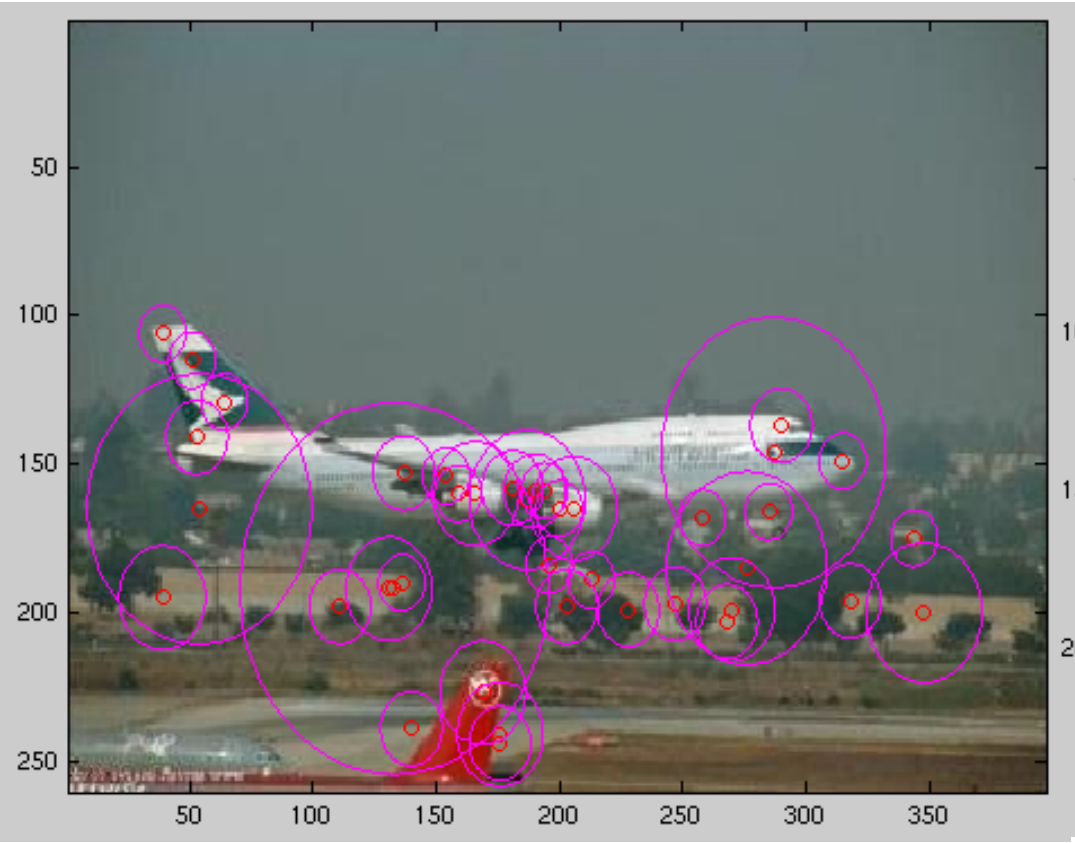
Canny edge detection

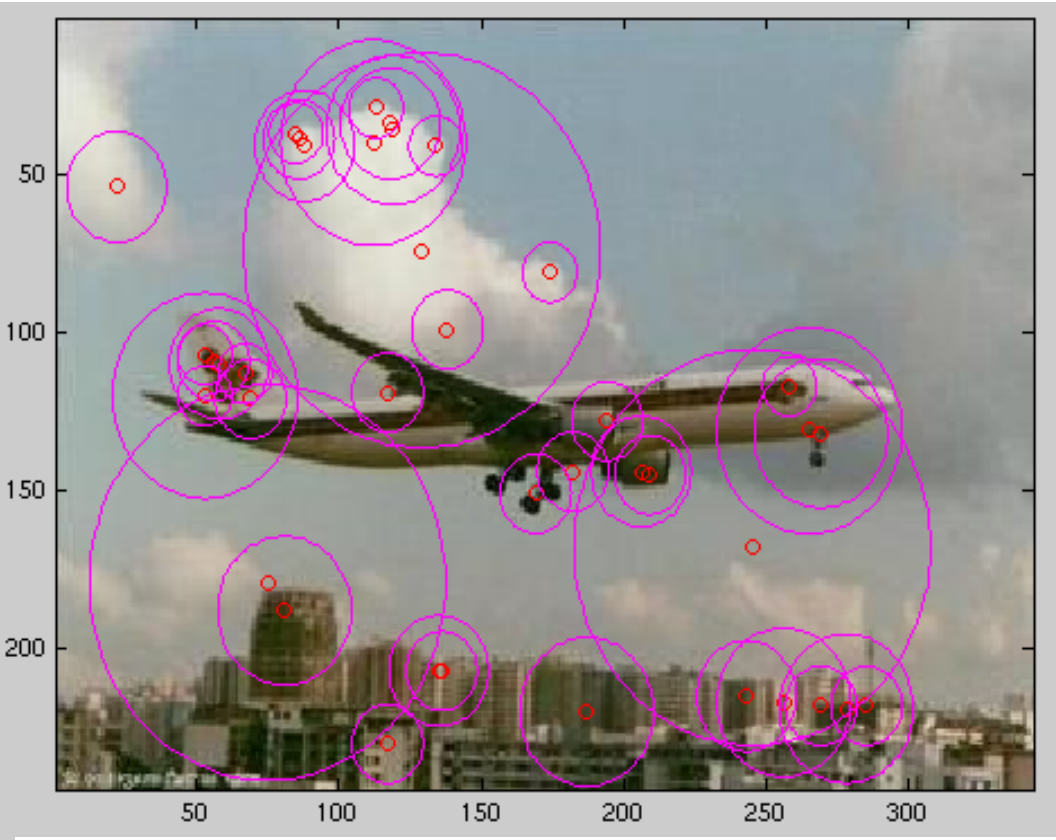
Airplanes – Kadir & Brady operator



Airplanes – Curves

Airplanes – multi-scale Harris operator





Fitting the heterogeneous model

- Learn models with different combinations of Kadir & Brady, Multi-scale Harris, and curve parts

- Choose between models using a validation set

- For the experiments the image datasets are divided into the ratio:

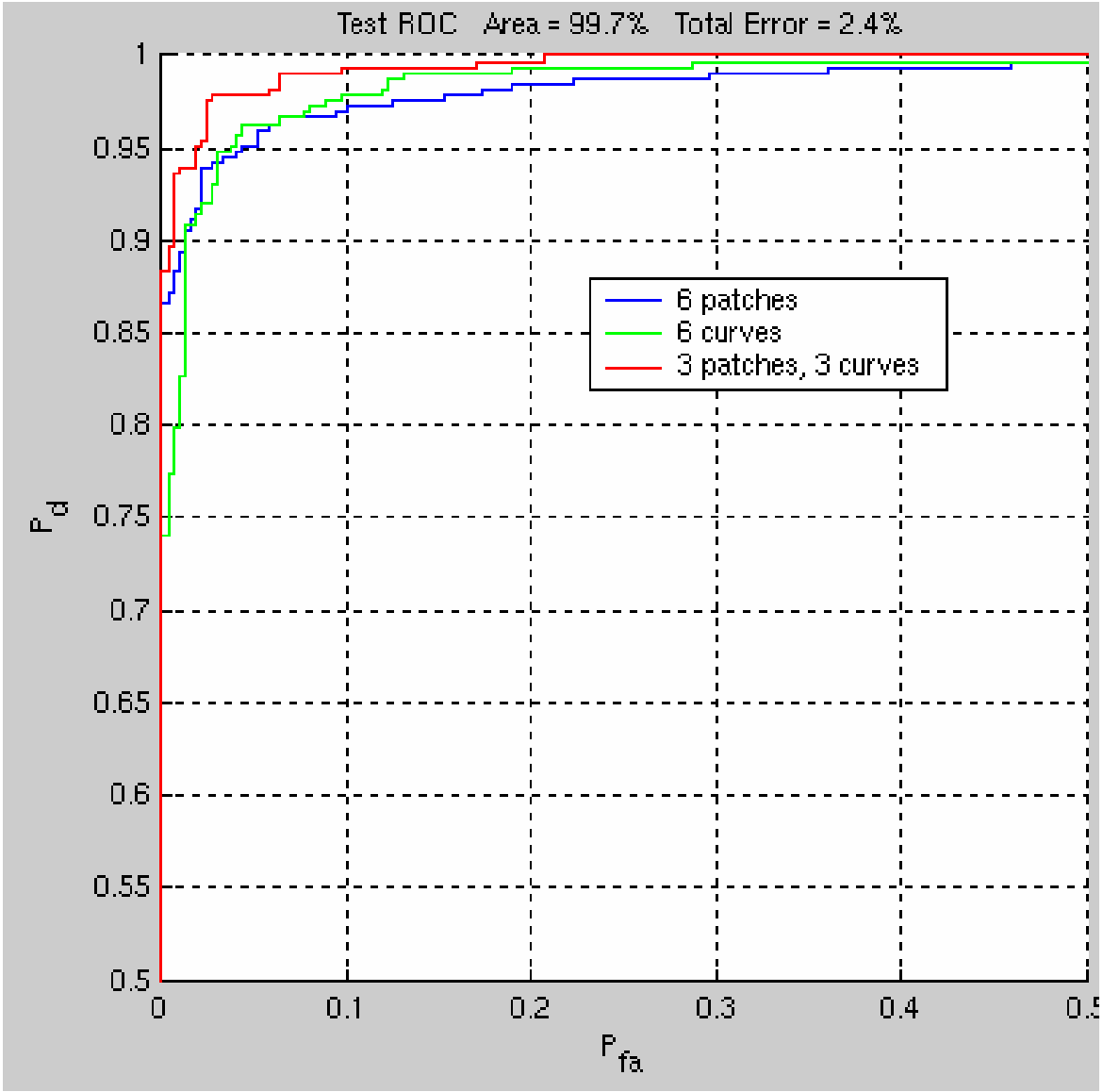
    - 5/12 training

    - 1/6 validation

    - 5/12 testing

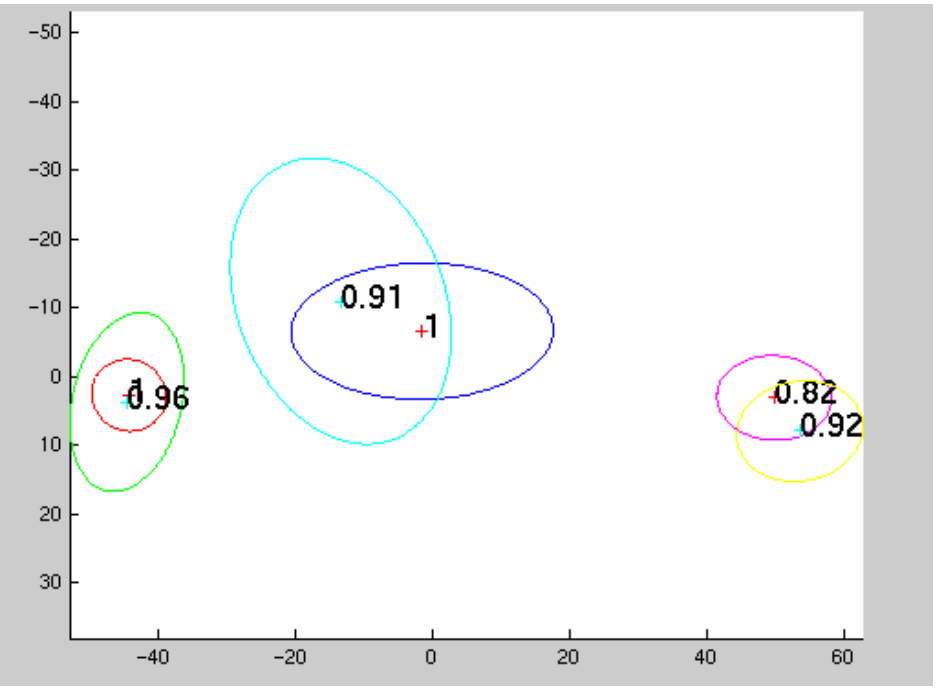
- 6 part independent models learnt

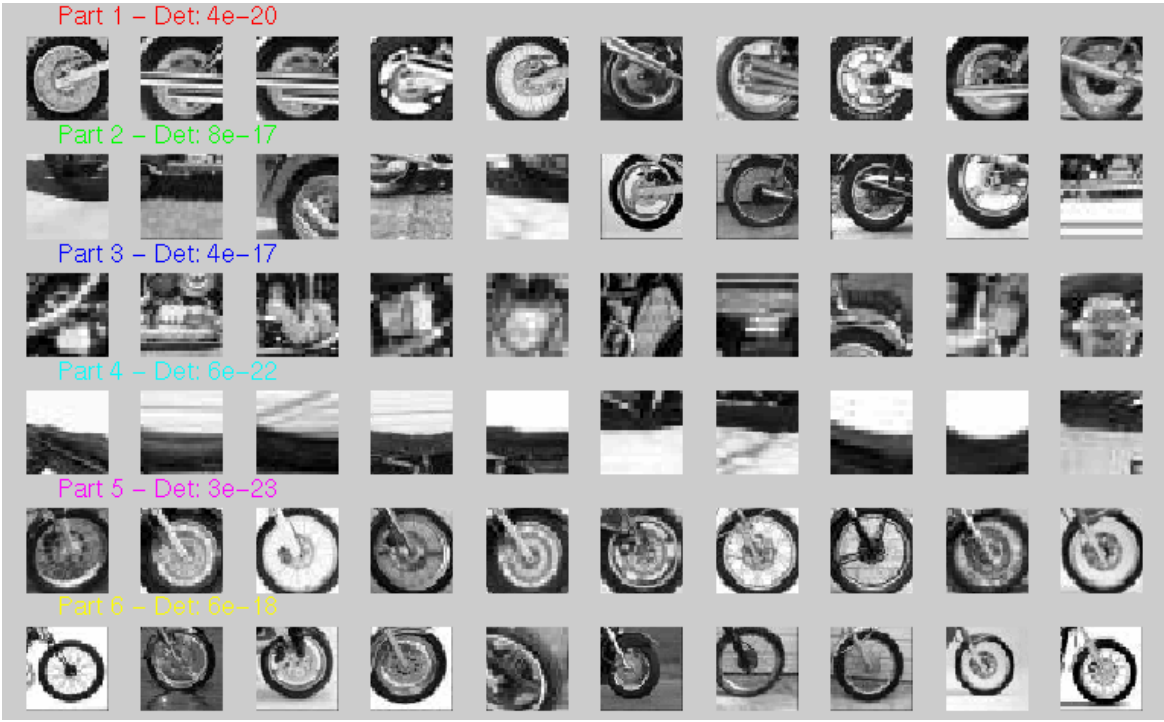
Motorbikes



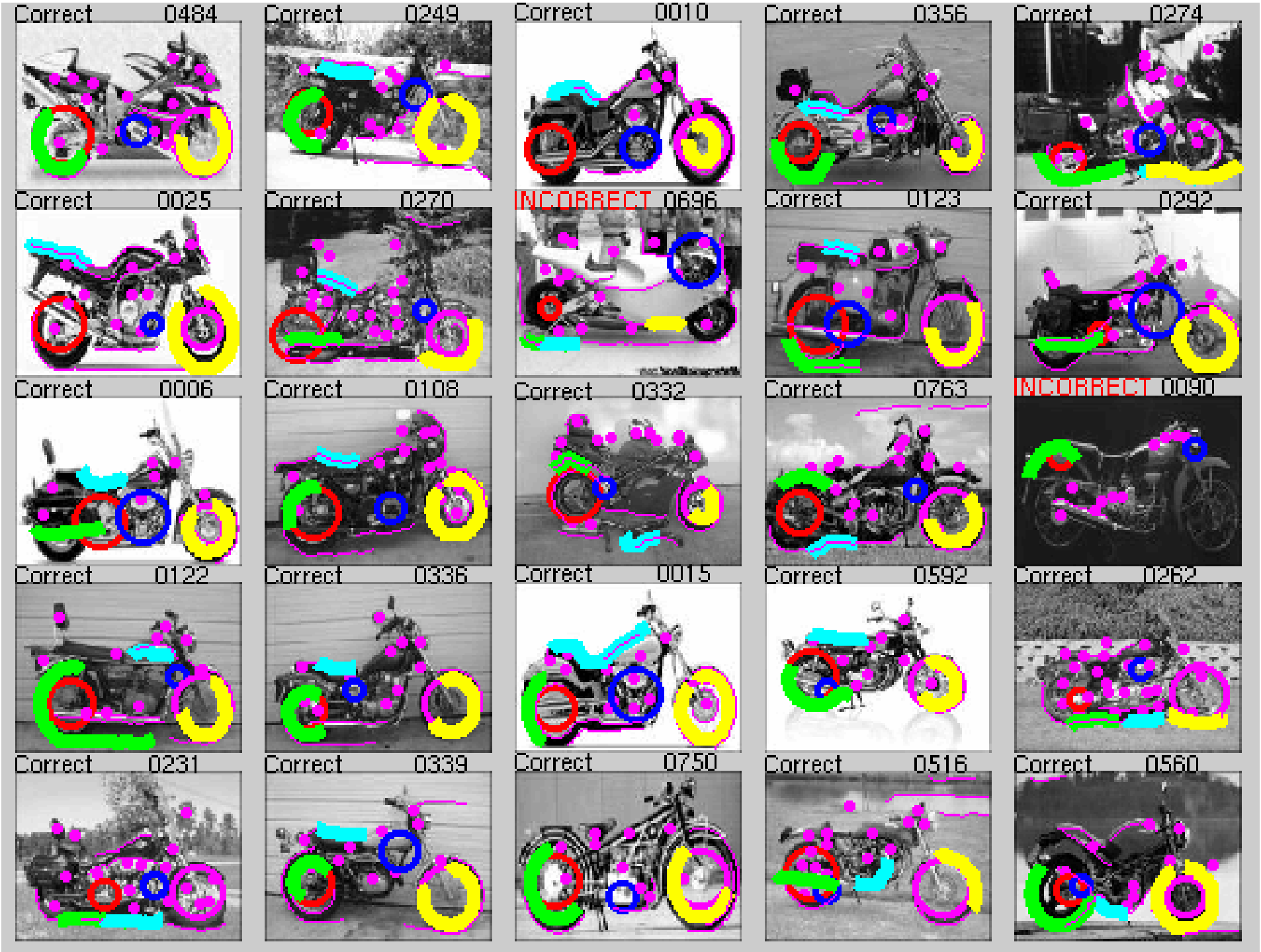
Combination of patches and curves chosen

Motorbike Patch and Curve model

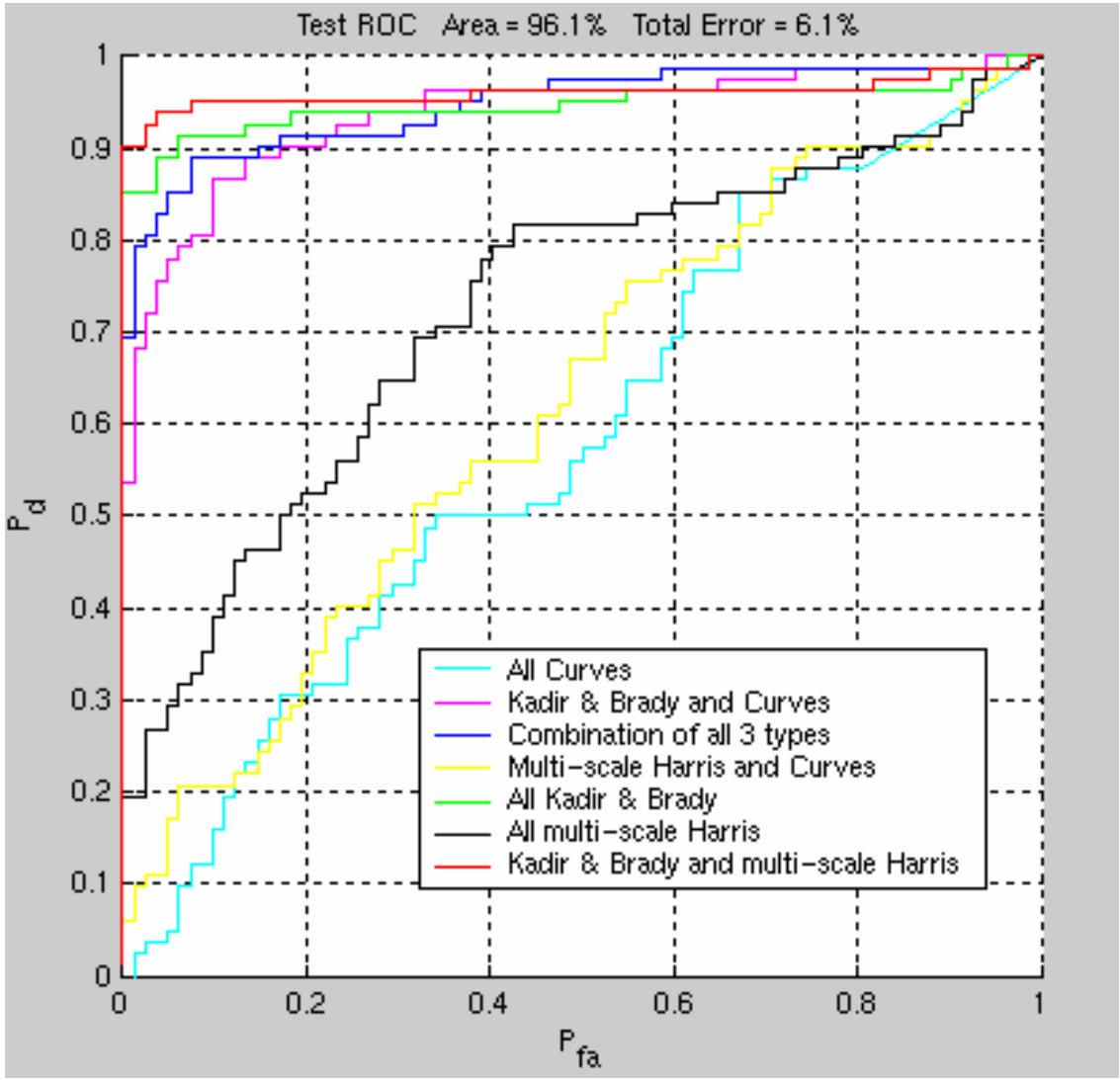




Motorbike results using curve and patch model

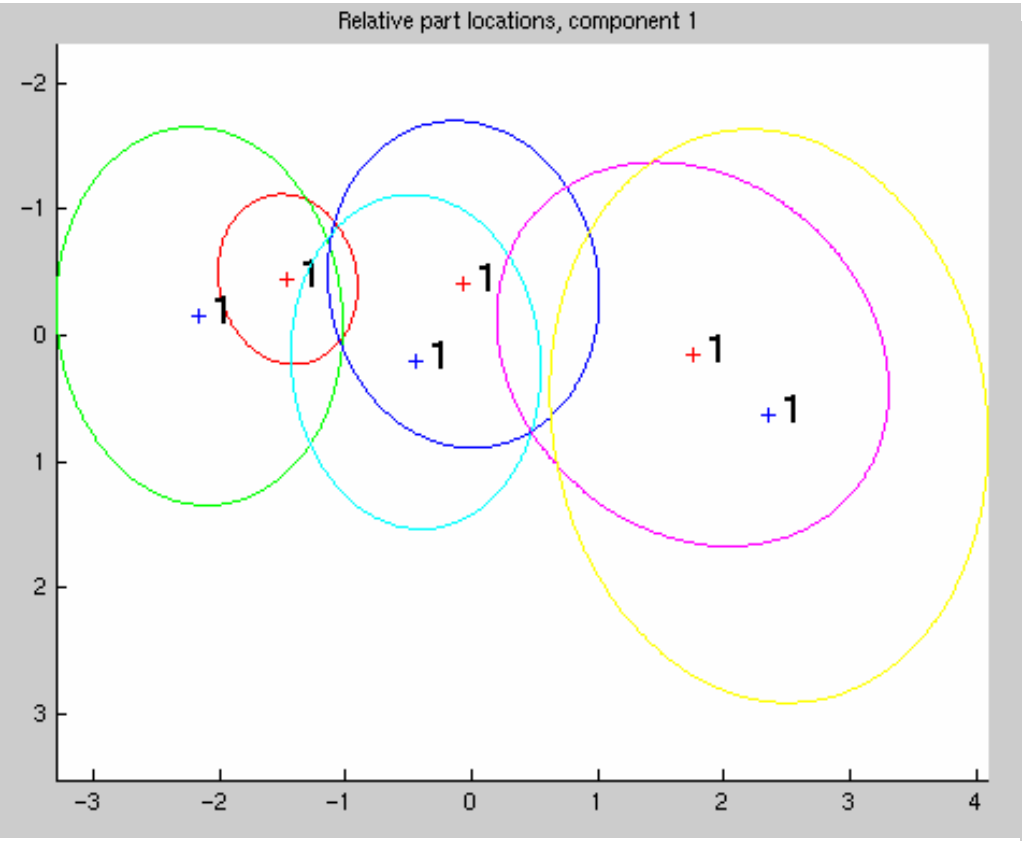


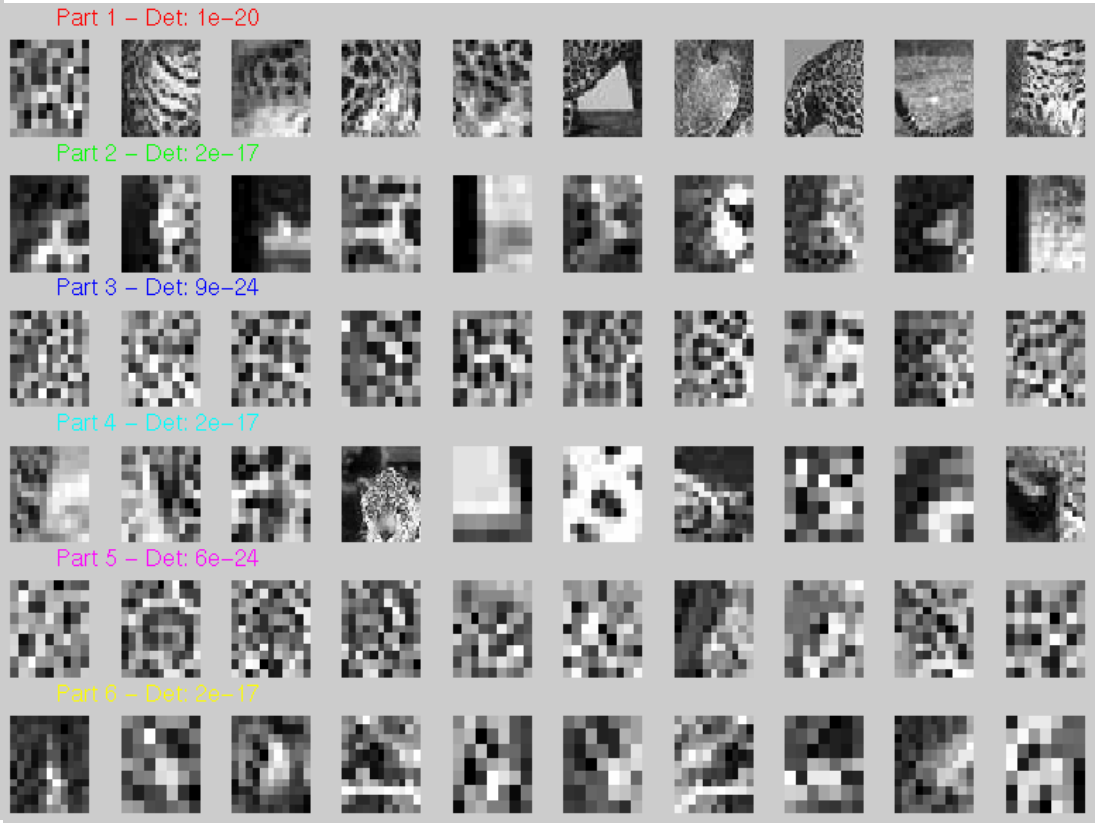
Spotted cats



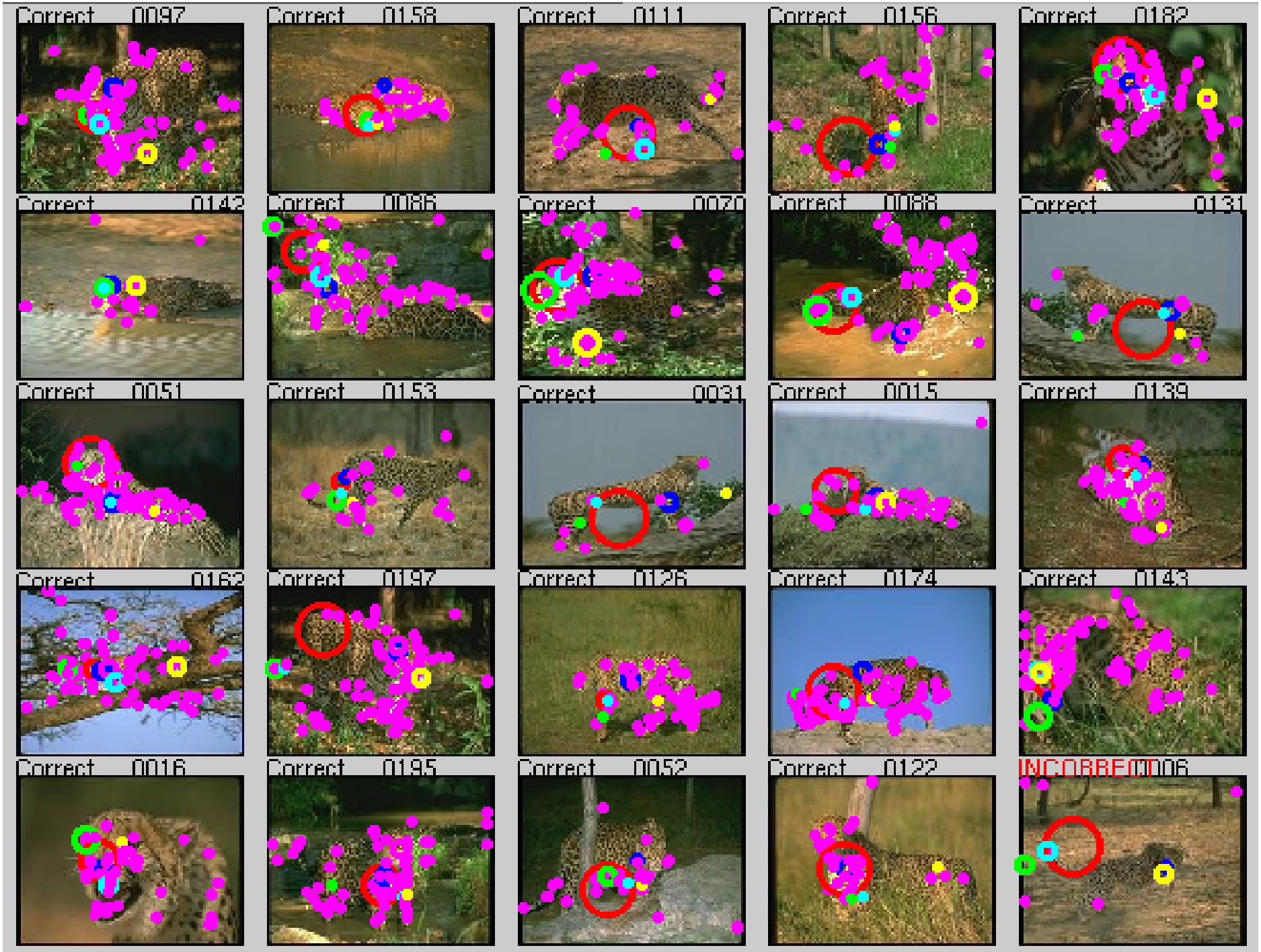
Combination of Kadir & Brady and multi-scale Harris chosen

Spotted cats combination model





Spotted cats results using combination model



4. Summary and open challenges

- ☺ Single visual aspects (e.g. car rear/front)
  - Can learn from unsegmented images
  - Translation and scale invariance
  - Partial occlusion tolerated
  - Background clutter tolerated
  - Futures: greater viewpoint invariance:
  - scale invariant → similarity invariant → affine invariant

- ☹ Multiple visual aspects (e.g. car from any viewpoint)
  - Multiple 2D models ?
  - 3D models ?

Open Research Areas

- Part representation
  - e.g. Intensity (as here), or
  - orientation (Lowe, Carlsson)
- Structure model
  - tight parametric model (e.g. complete Gaussian)
  - loose model (e.g. pairwise relations)

- Comparison of models/methods on same data sets

Pascal Challenge: 101 Object Classes

- Organized by: Chris Williams, Andrew Zisserman and Luc Van Gool

- Levels of training difficulty:
  - Segmented training images
  - Images known to contain object class
  - Some of the images contain the object class

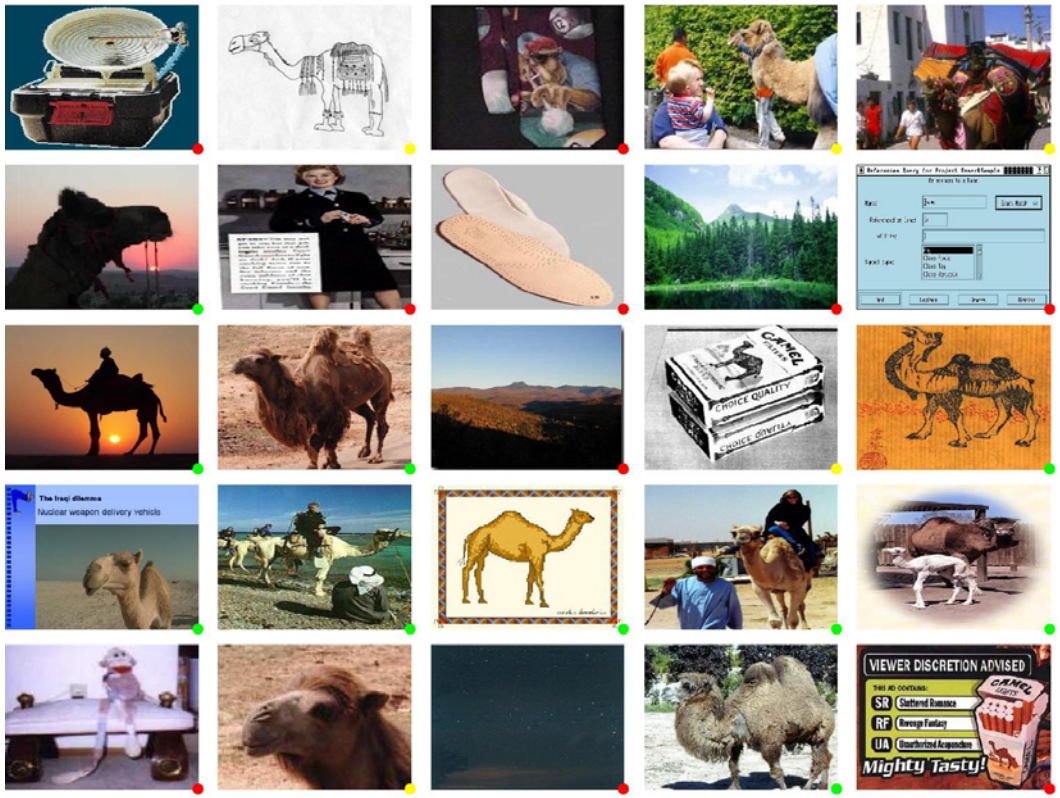
- Levels of visual difficulty
  - Intra-class variability (e.g. cars rear vs dogs)
  - Varying size and pose
  - Partial occlusion

- Standard test measures

Learning from contaminated data

Learning from contaminated data

- Image search engines give easy access to a vast amount of data.
- Just enter keyword (e.g. Camel)
- Large portion of images are junk (i.e. not instances of the class)
- Use raw output from Google Image search to train model

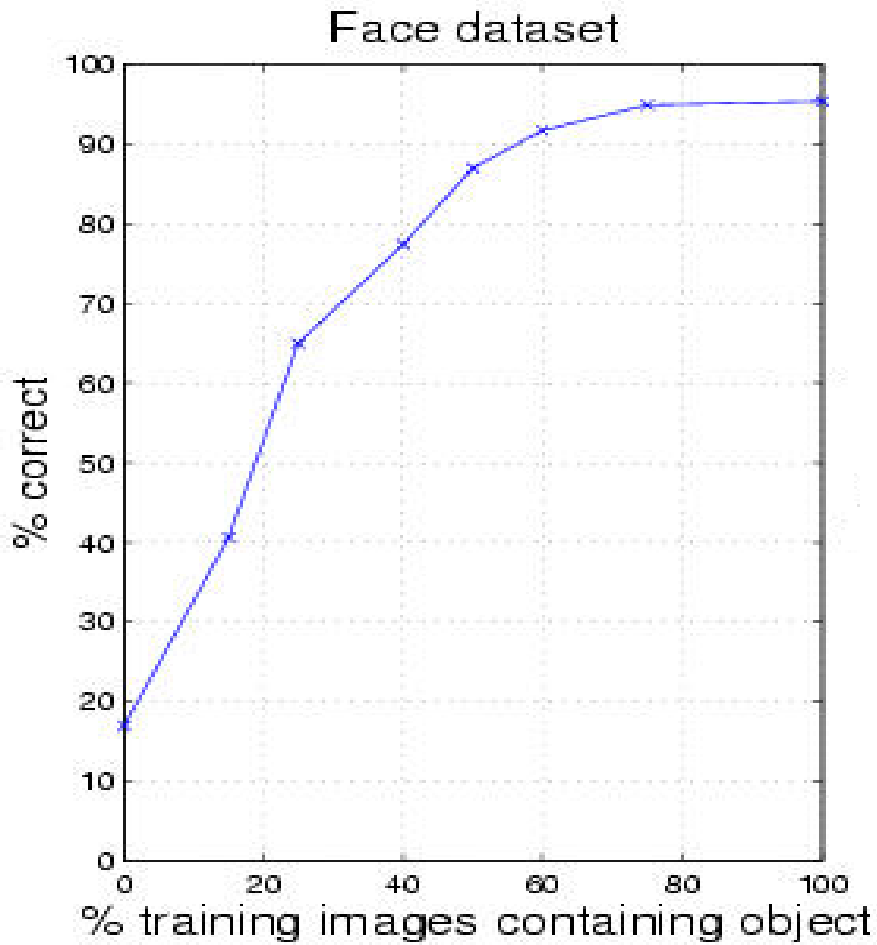


Fergus, Perona & Zisserman, ECCV 2004

Learning from contaminated data

Benign data sets (e.g. frontal faces):

- model can use occlusion term to handle a certain level of junk



Google image sets:

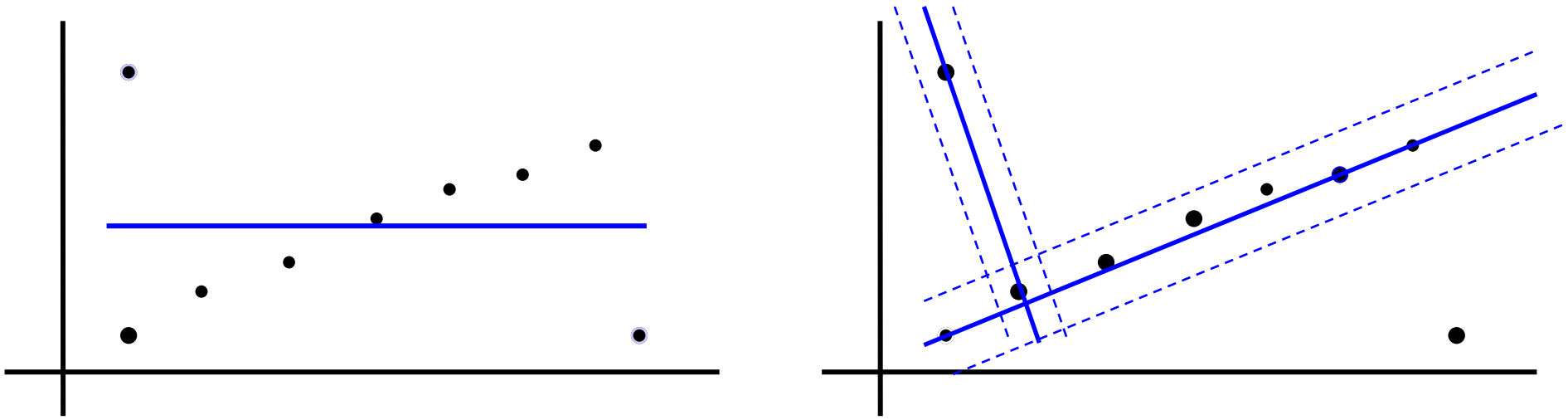
- foreground more varied and weak background model less valid

Approach: frame problem as one of robust estimation

Learning method: Hybrid RANSAC/EM

Robust line estimation - RANSAC

Fit a line to 2D data containing outliers



(RANdom Sample Consensus) [Fishler & Bolles, 1981]

There are two problems

1. a line fit which minimizes perpendicular distance
2. a classification into inliers (valid points) and outliers

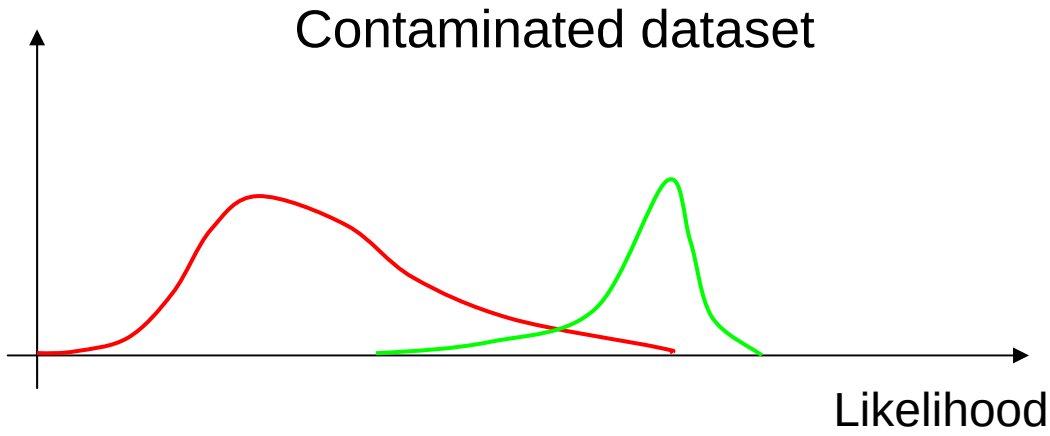
RANSAC robust line estimation

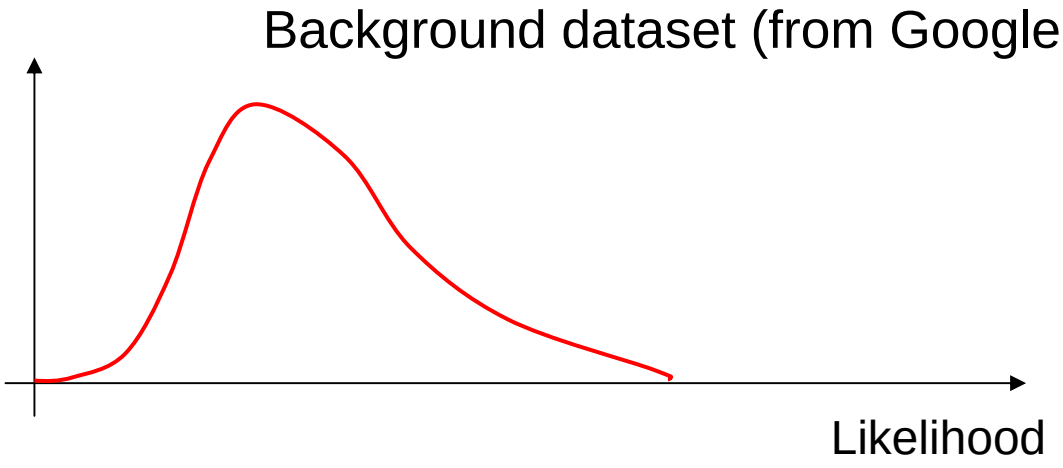
- Repeat
  1. Select random sample of 2 points
  2. Compute the line through these points
  3. Measure support (number of points within threshold distance of the line)
- Choose the line with the largest number of inliers
  - Compute least squares fit of line to inliers (regression)

Fitting to contaminated data

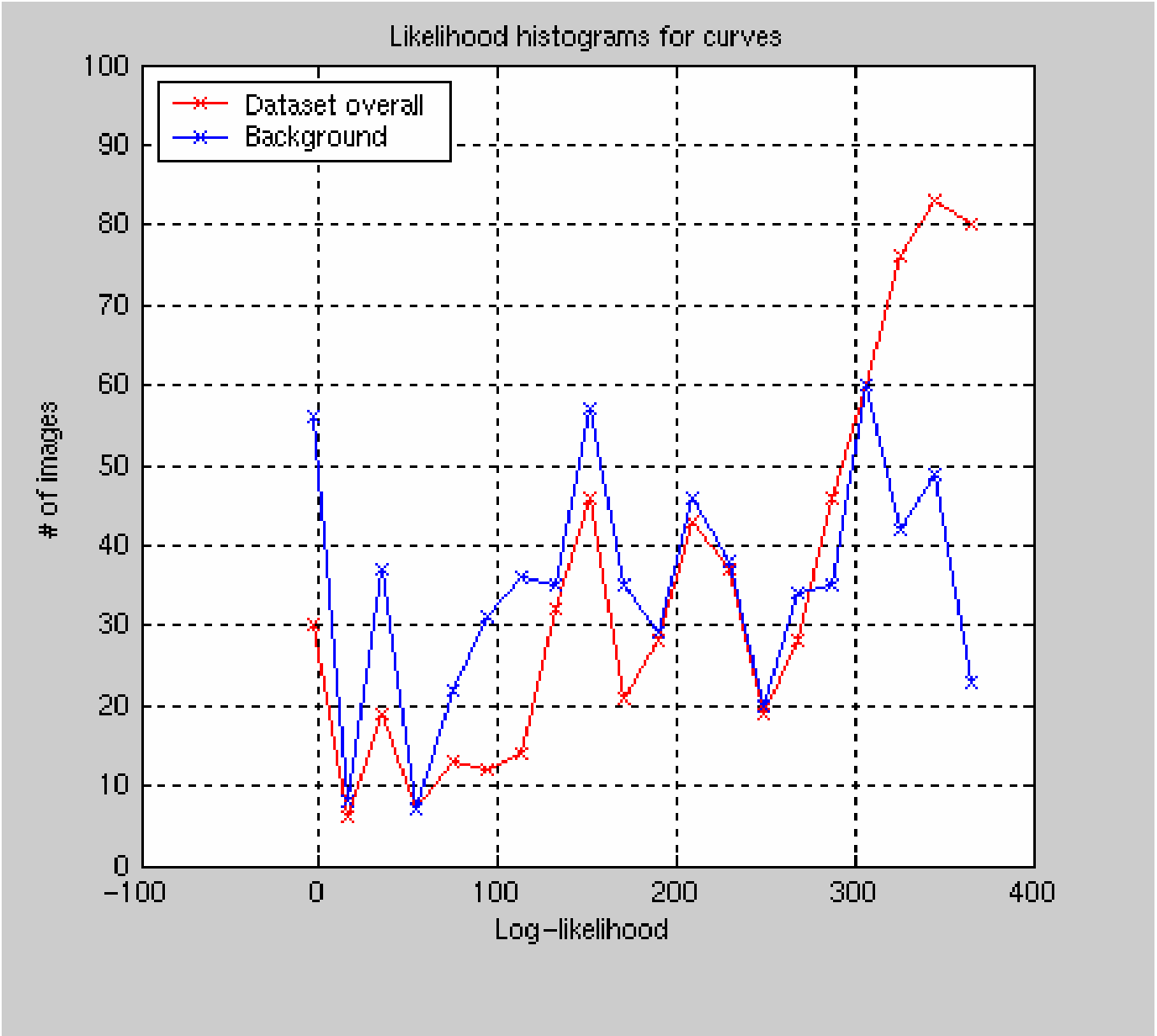
- Repeat
  1. Select random sample of images (say 10)
  2. Learn a model from these images
  3. Measure support of the model
- Choose the model with the largest number of inliers

RANSAC Scoring Function

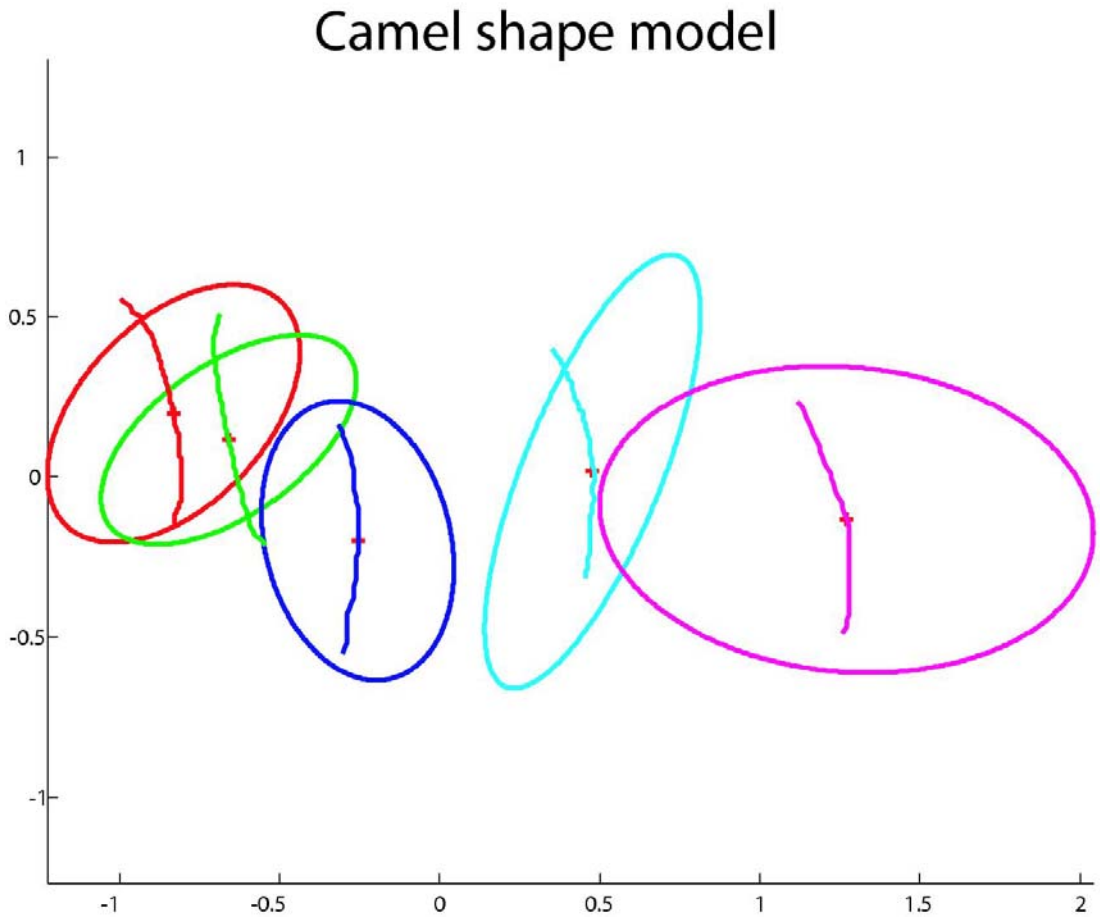


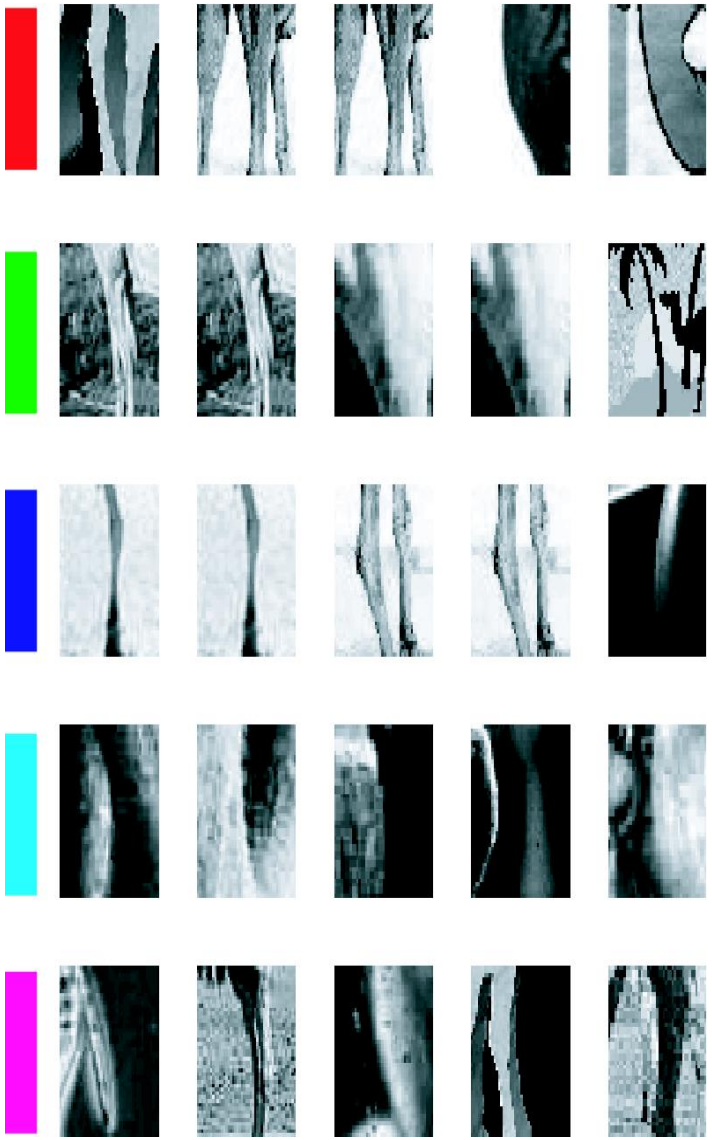


Camel curve model

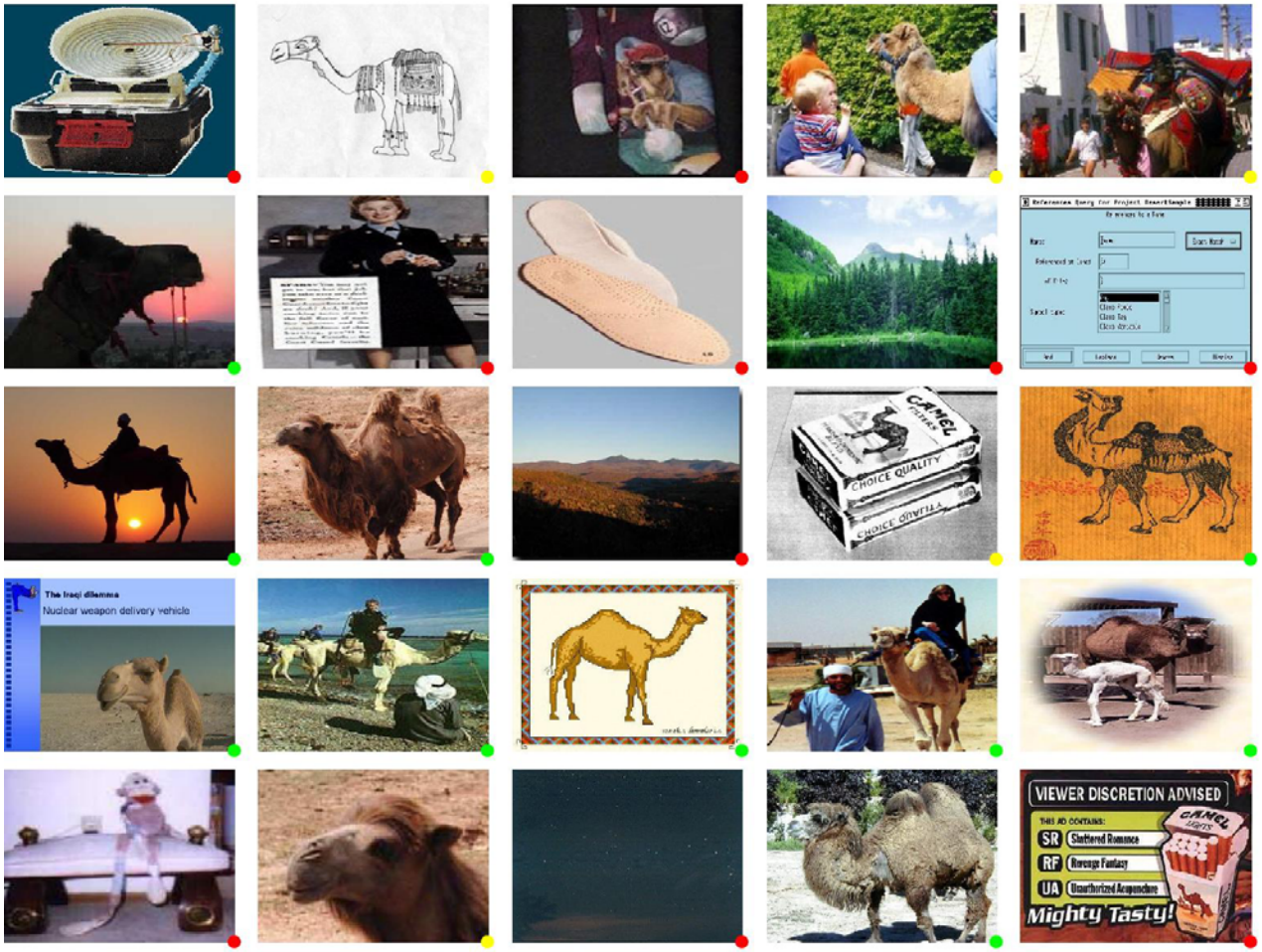


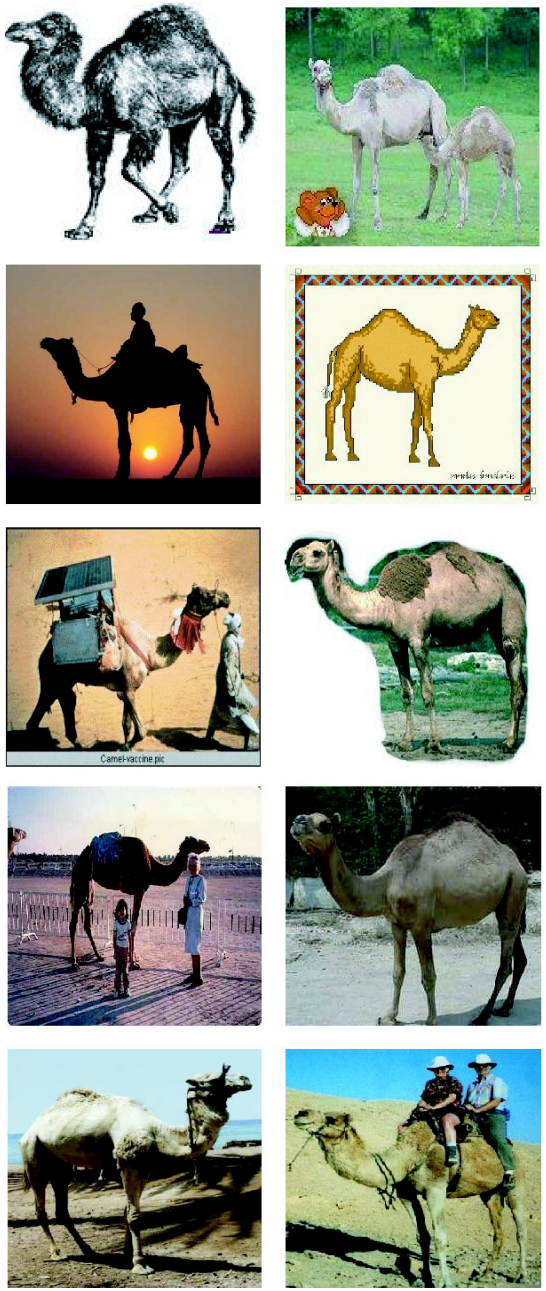
Camel curve model



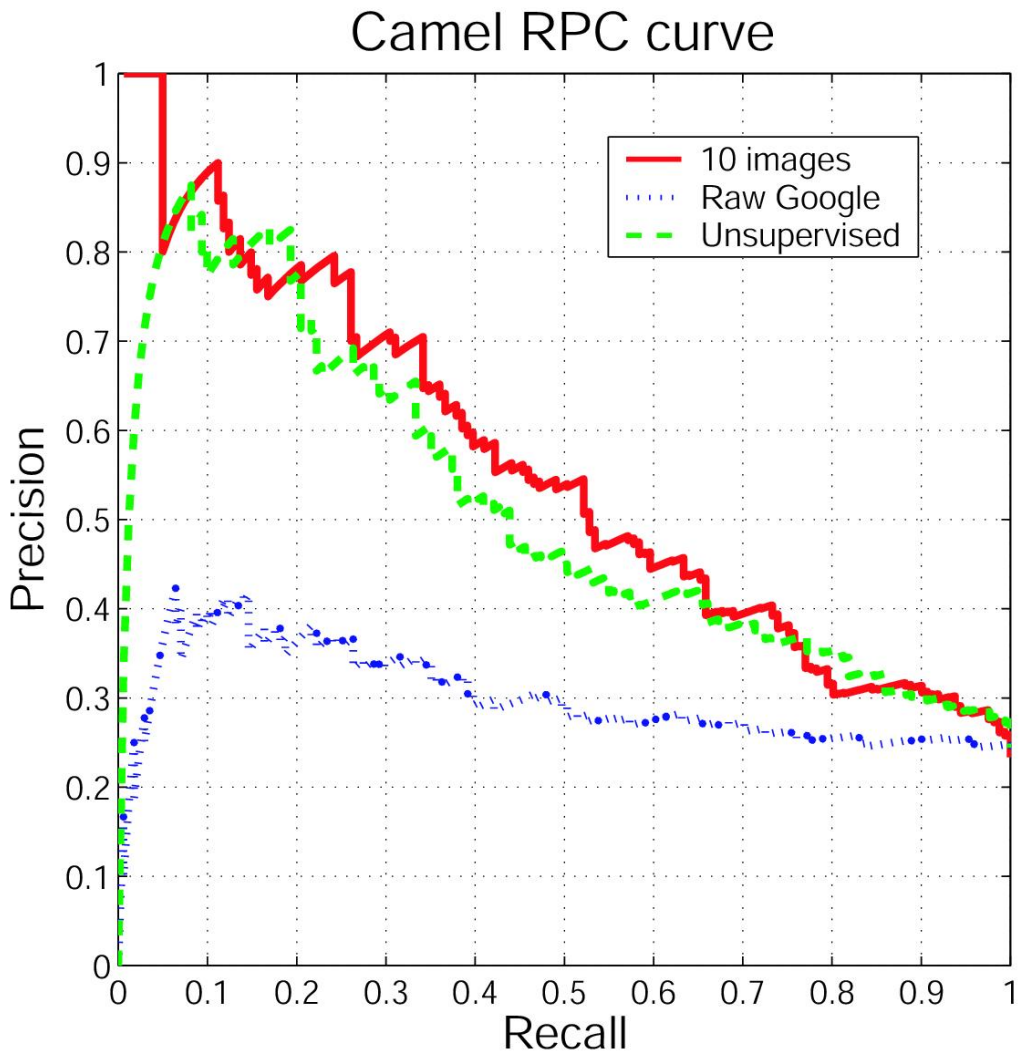


Raw Camel images & 10 picked



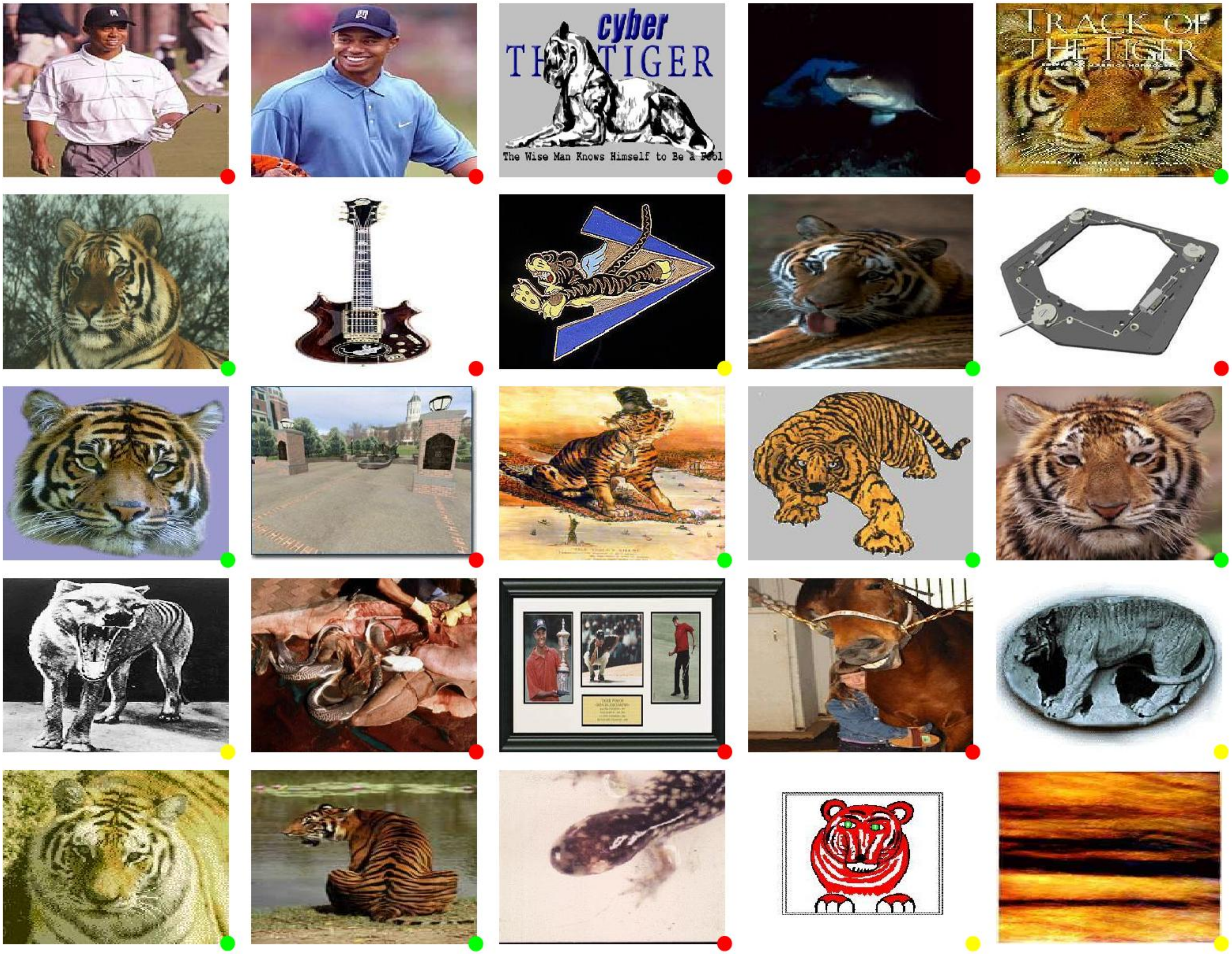


Camel RPC curves



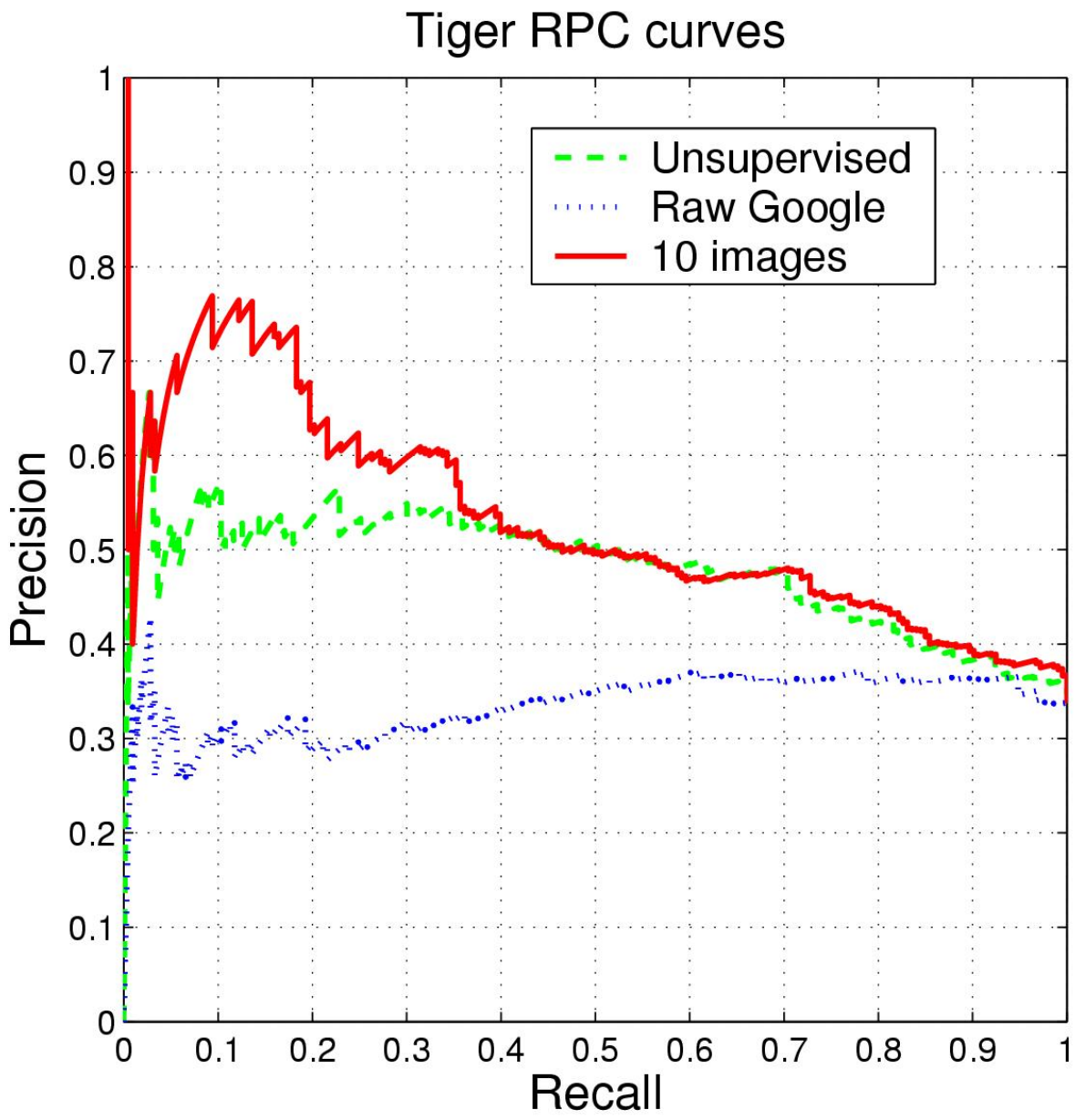
Camel filtered results

Raw Tiger images



Tiger filtered results

Tiger RPC curve



Raw Bottles images



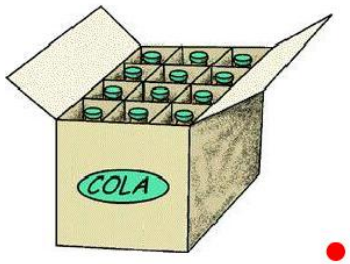


















Bottles filtered results