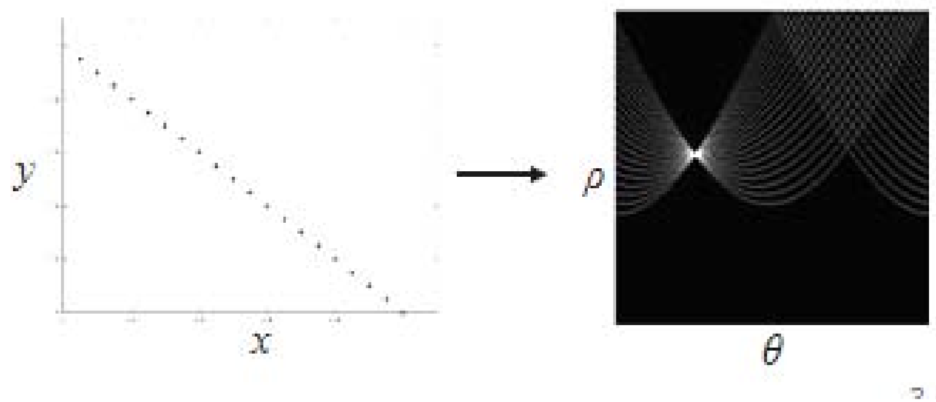
# Hough Transform





Jiří Matas

Center for Machine Perception

Department of Cybernetics, Faculty of Electrical Engineering

Czech Technical University, Prague


Many slides thanks to Kristen Grauman and Bastian Leibe

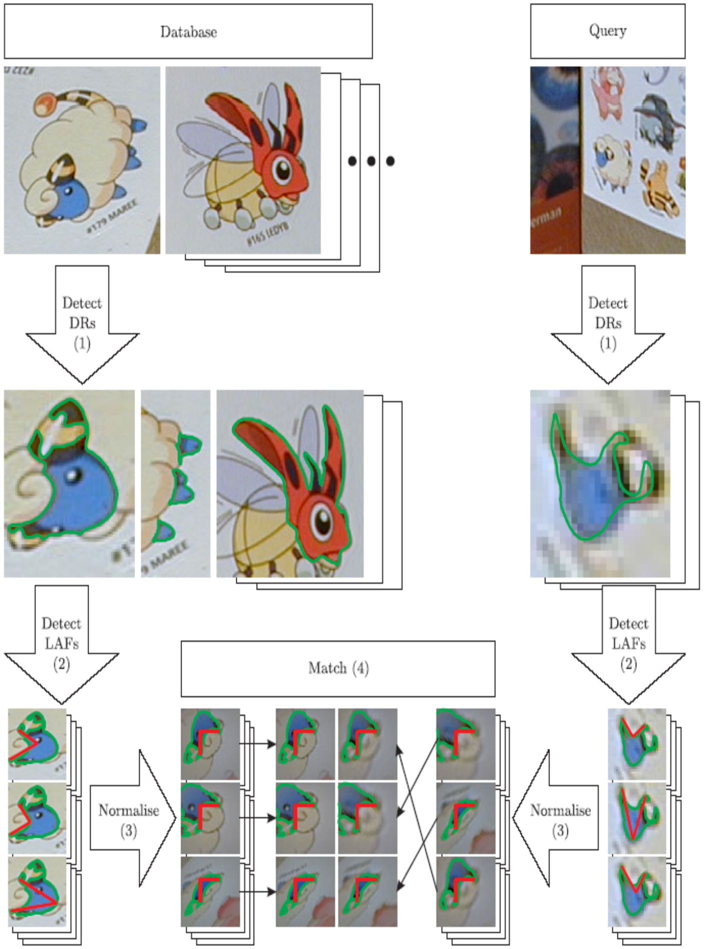
# Recognition with Local Features

**Strengths:**

- applicable to many objects (e.g. in image stitching)
- is real-time
- scales well to very large problems (retrieval of millions of images)
- handles occlusion well
- insensitive to a broad class of image transformations

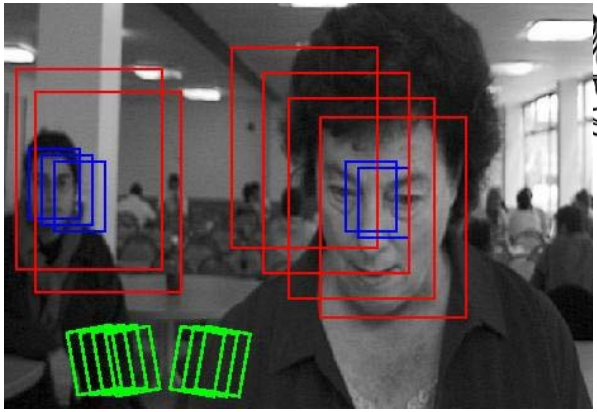
**Weaknesses:**

- applicable to recognition of specific objects (no categorization)
- applicable only to objects with distinguished local features



# Recognition with the Scanning Window (Viola-Jones)

**Strengths:**



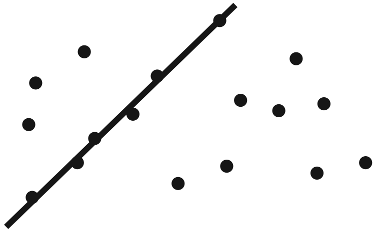
- applicable to many <u>classes</u> of objects
- not restricted to specific objects
- often real-time

**Weaknesses:**

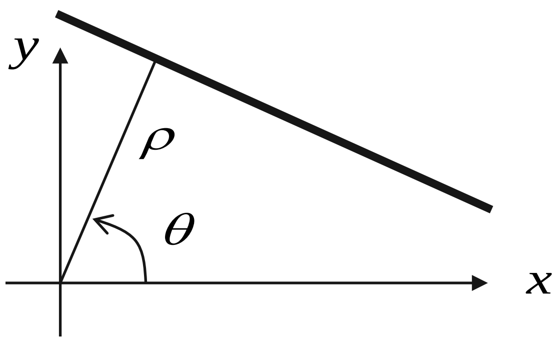
- extension to a large number of classes not straightforward (standard implementation: linear complexity in the number of classes)
- occlusion handling not easy
- full 3D recognition requires too many windows to be checked
- training time is potentially very long

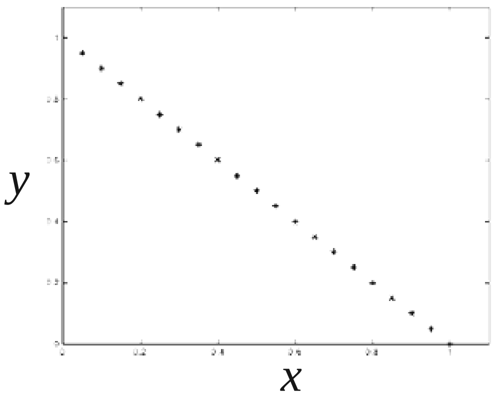
# Hough Transform

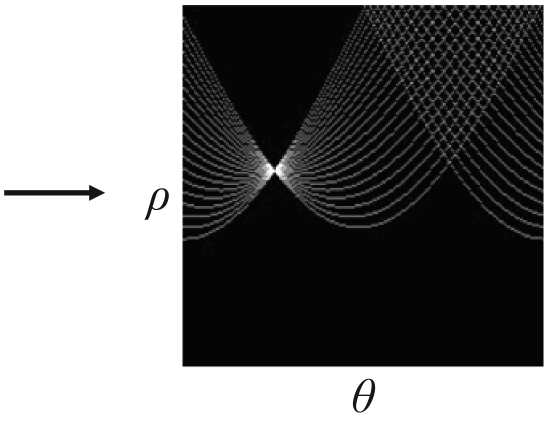
- Origin: Detection of straight lines in clutter
  - Basic idea: each candidate point votes for all lines that it is consistent with.
  - Votes are accumulated in quantized array
  - Local maxima correspond to candidate lines



- Representation of a line
  - Usual form $y = a\,x + b$ has a singularity around 90°.
  - Better parameterization: $x\cos(\theta) + y\sin(\theta) = \rho$



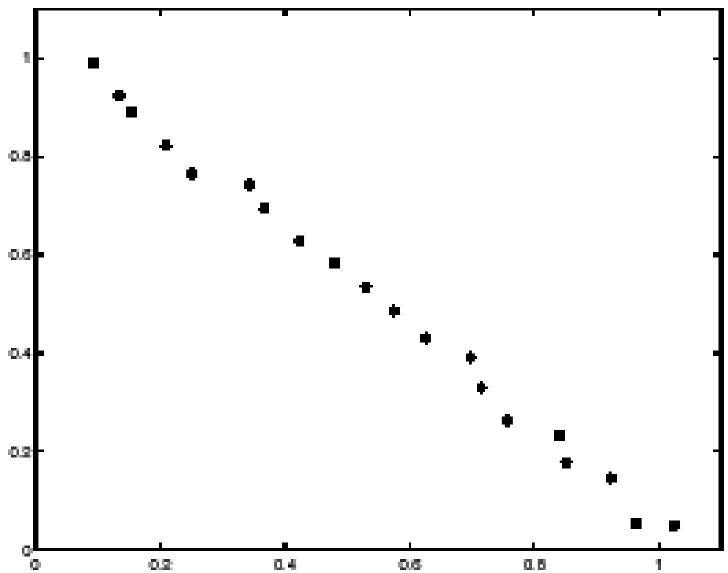



# Hough Transform for Straight Lines

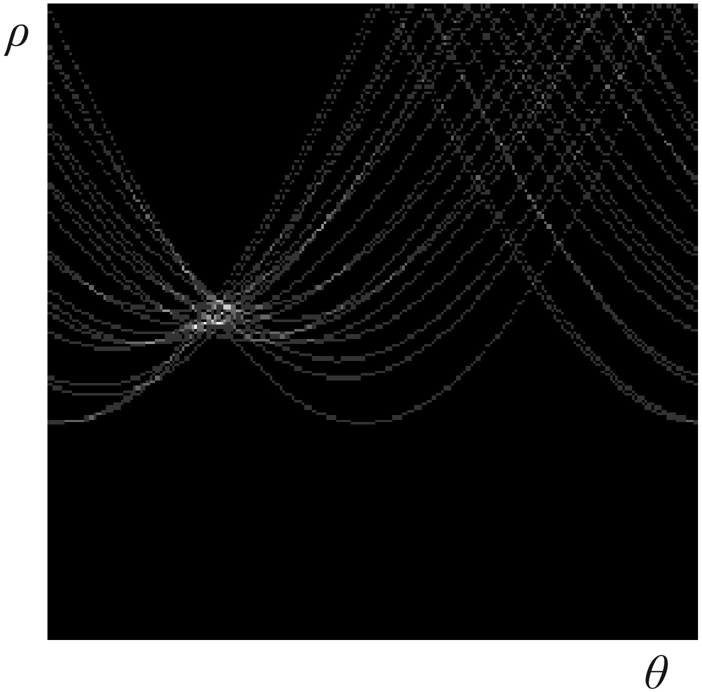
CENTER FOR MACHINE PERCEPTION

- Define the parametrisation of the space of lines.
  Most common: $\rho$, $\theta$.
  Other options: slope + intercept, nearest point to center, …
- Quantize the Hough space: identify the maximum and minimum values of $\rho$ and $\theta$, and the number of cells,
- Create an accumulator array $A(\rho, \theta)$; set all values to zero
- (if grandient available)
  For all edge points $(x_i, y_i)$ in the image
  - if available, use gradient direction for $\theta$
  - Compute $\rho$ from the equation
  - Increment $A(\rho, \theta)$ by one
- (if grandient not available)
  For all edge points $(x_i, y_i)$ in the image
  - Increment $A(\rho, \theta)$ by one for all lines incident on x,y
- For all cells in $A(\rho, \theta)$
  - Search for the maximum value of $A(\rho, \theta)$
  - Calculate the equation of the line
- To reduce the effect of noise more than one element (elements in a neighborhood) in the accumulator array are increased

# Hough Transform: Noisy Line




**Tokens**

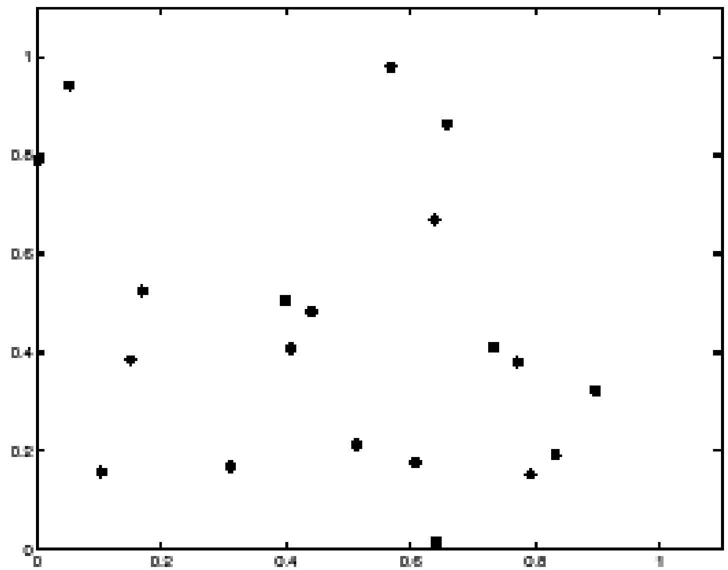



**Votes**

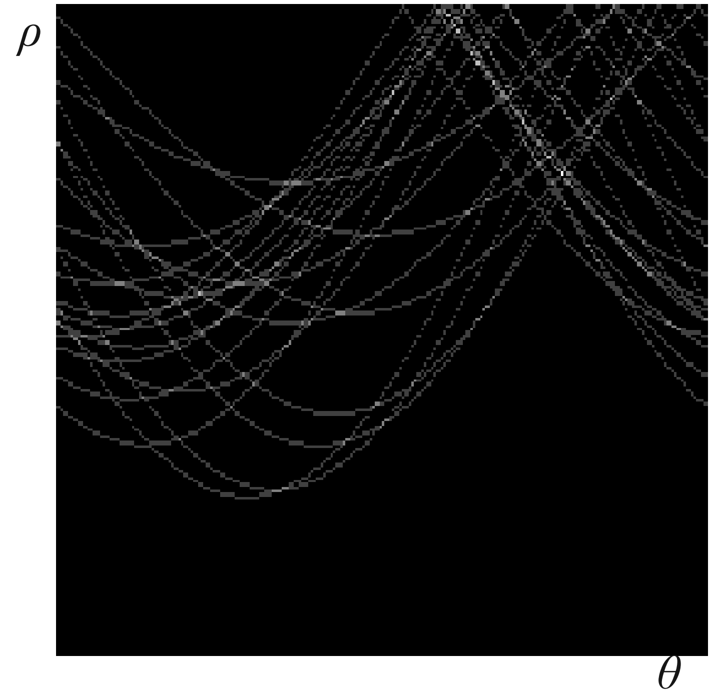
- Problem: Finding the true maximum

# Hough Transform: Noisy Input






**Tokens**

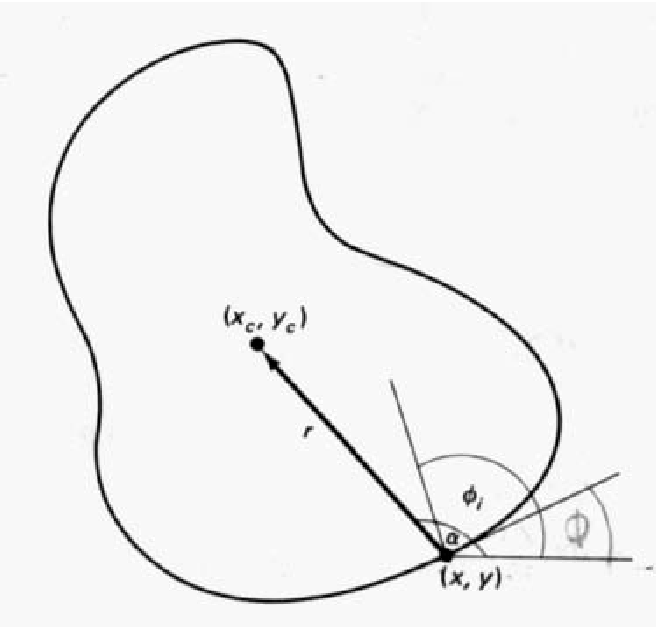



**Votes**

- Problem: Lots of spurious maxima

# Generalized Hough Transform [Ballard81]

- Generalization for an arbitrary contour or shape
  - Choose reference point for the contour (e.g. center)
  - For each point on the contour remember where it is located w.r.t. to the reference point
  - Remember radius $r$ and angle $\phi$ relative to the contour tangent
  - Recognition: whenever you find a contour point, calculate the tangent angle and 'vote' for all possible reference points

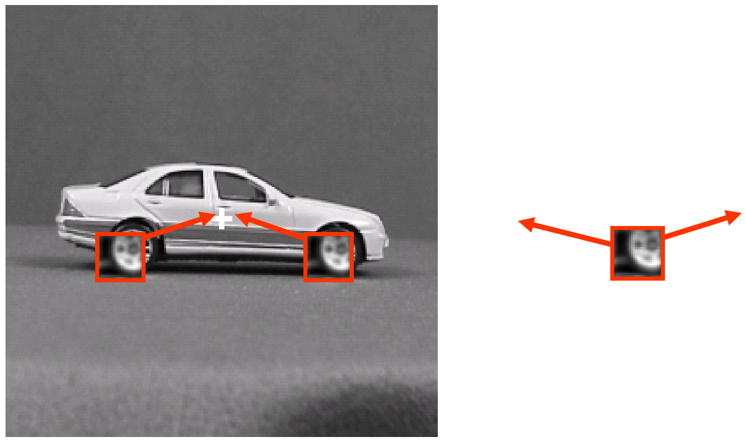



  - Instead of reference point, can also vote for transformation

$\Rightarrow$ The same idea can be used with local features!

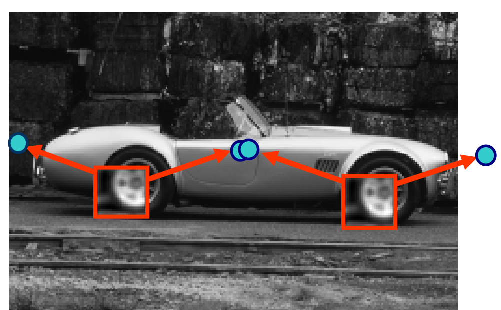
# Gen. Hough Transform with Local Features

- For every feature, store possible "occurrences"



- Object identity
- Pose
- Relative position

**For new image, let the matched features vote for possible object positions**



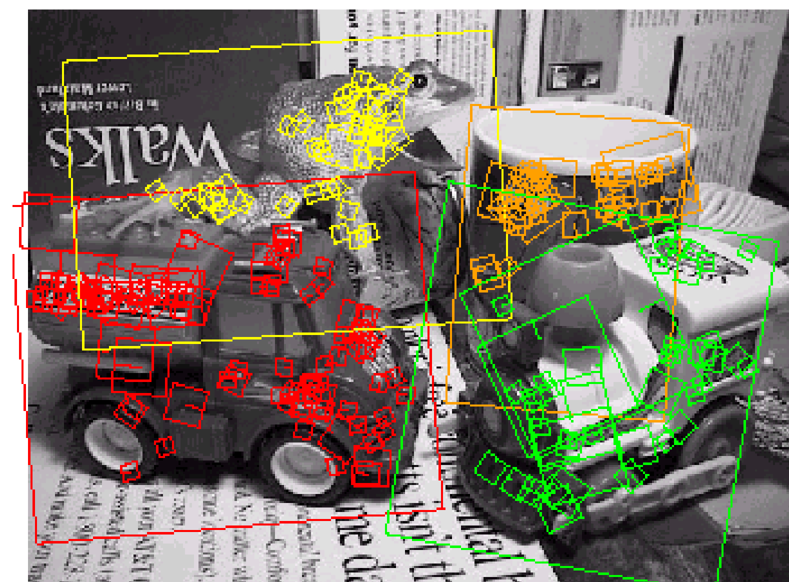
K. Grauman, B. Leibe

# Finding Consistent Configurations



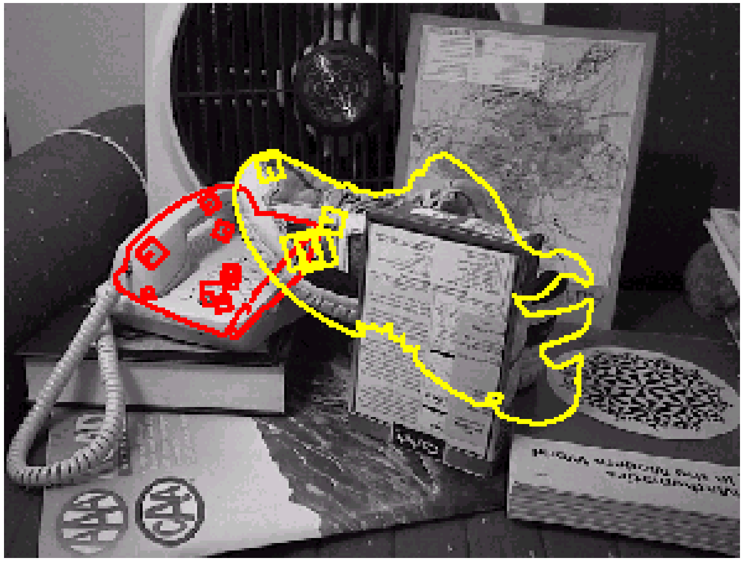
- Global spatial models
  - Generalized Hough Transform [Lowe99]
  - RANSAC [Obdrzalek02, Chum05, Nister06]
  - Basic assumption: object is planar

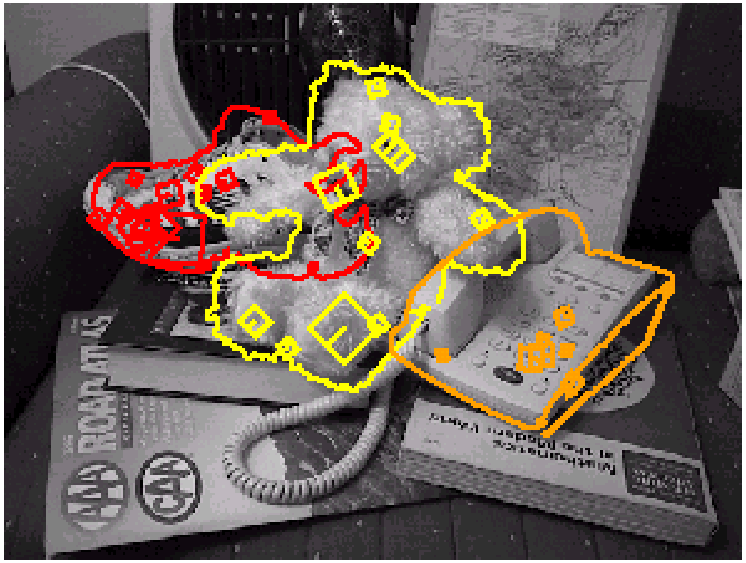
- Assumption is often justified in practice
  - Valid for many structures on buildings
  - Sufficient for small viewpoint variations on 3D objects



# 3D Object Recognition

- Gen. HT for Recognition
  - Typically only 3 feature matches needed for recognition
  - Extra matches provide robustness
  - Affine model can be used for planar objects





K. Grauman, B. Leibe

# Comparison

CENTER FOR MACHINE PERCEPTION

## Gen. Hough Transform

- Advantages
  - Very effective for recognizing arbitrary shapes or objects
  - Can handle high percentage of outliers (¿95%)
  - Extracts groupings from clutter in linear time
- Disadvantages
  - Quantization issues
  - Only practical for small number of dimensions (up to 4)
- Improvements available
  - Probabilistic Extensions
  - Continuous Voting Space

  } **[Leibe08]**

## RANSAC

- Advantages
  - General method suited to large range of problems
  - Easy to implement
  - Independent of number of dimensions
- Disadvantages
  - Only handles moderate number of outliers (¡50%)
- Many variants available, e.g.
  - PROSAC: Progressive RANSAC [Chum05
  - Preemptive RANSAC [Nister05]

Thank you for your attention.