Object Recognition using Invariant Local Features

Goal: Identify known objects in new images

Training images

Test image

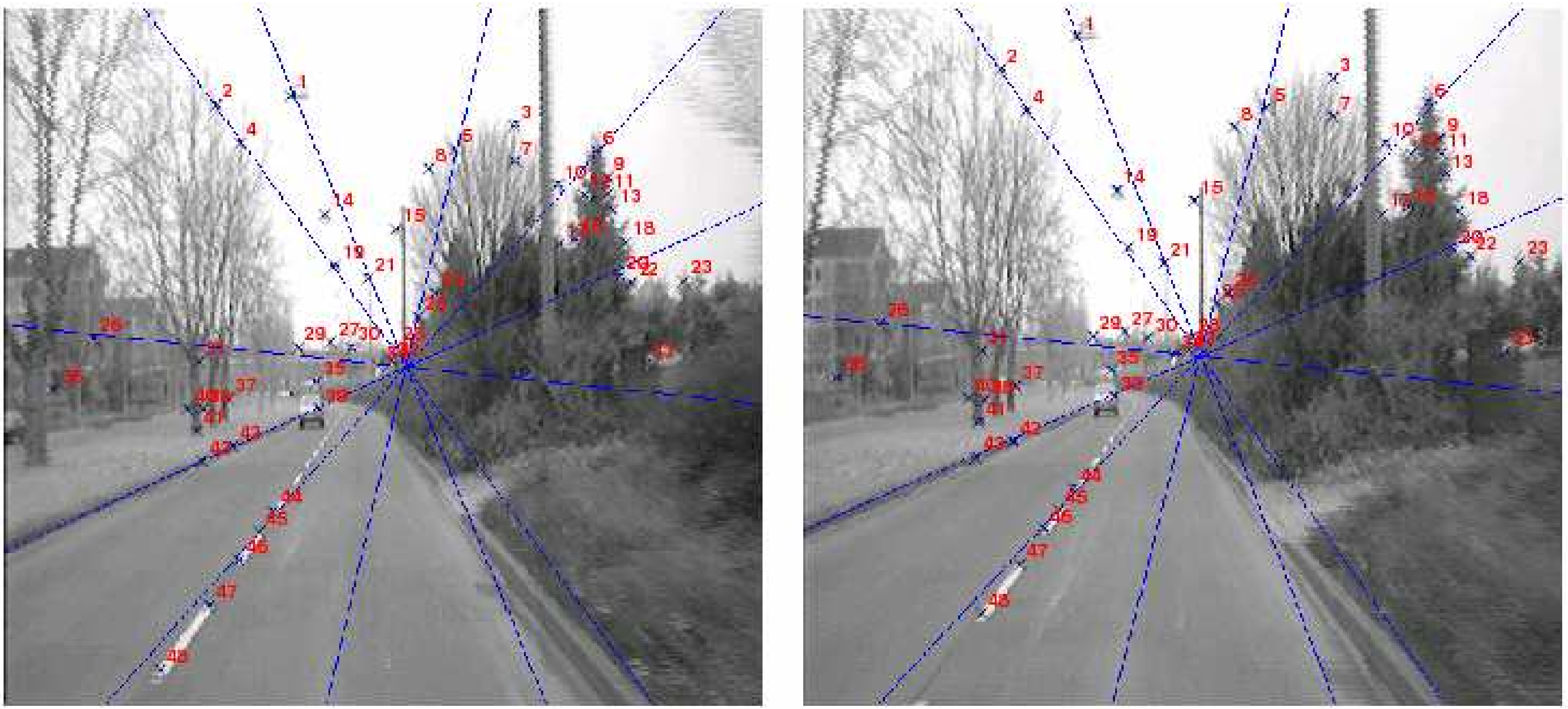
Applications

- Mobile robots, driver assistance
- Cell phone location or object recognition
- Panoramas, 3D scene modeling, augmented reality
- Image web search, toys, retail, …

Local feature matching

Torr & Murray (93); Zhang, Deriche, Faugeras, Luong (95)

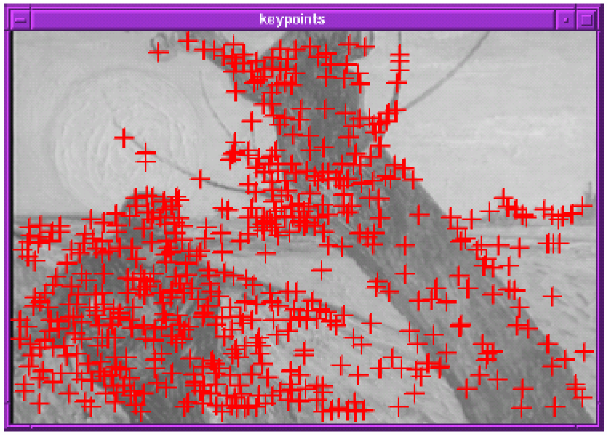
- Apply Harris corner detector
- Match points by correlating only at corner points
- Derive epipolar alignment using robust least-squares

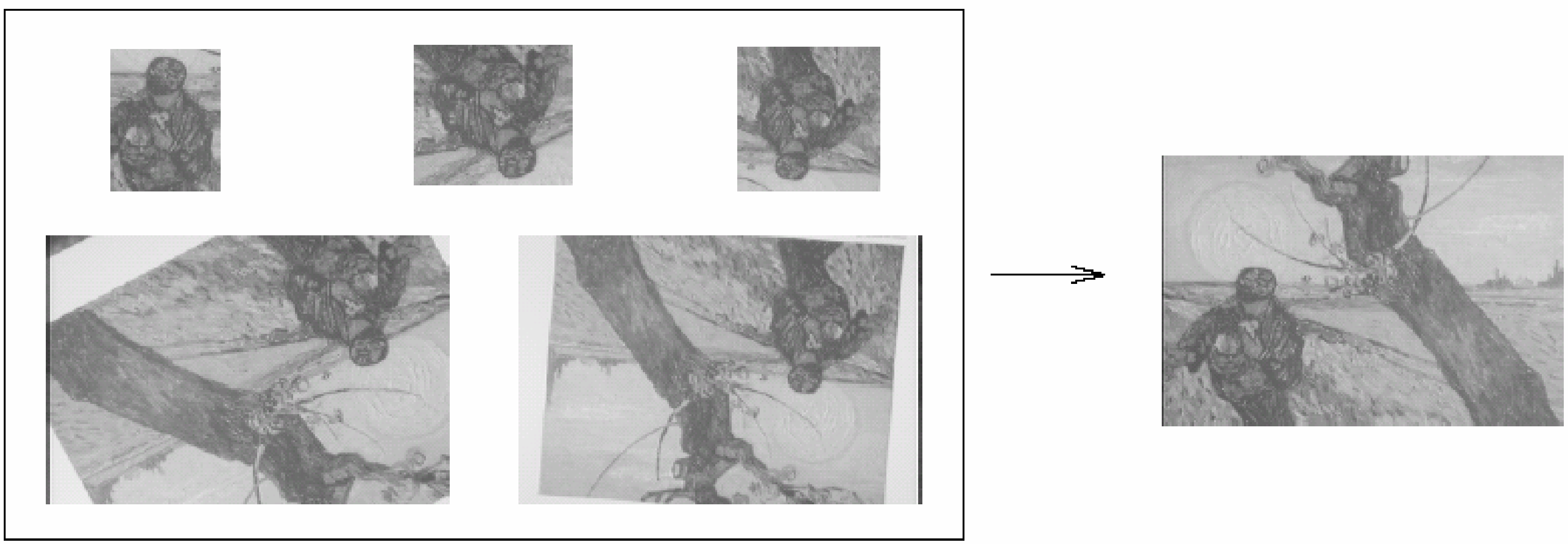


Rotation Invariance

Cordelia Schmid & Roger Mohr (97)

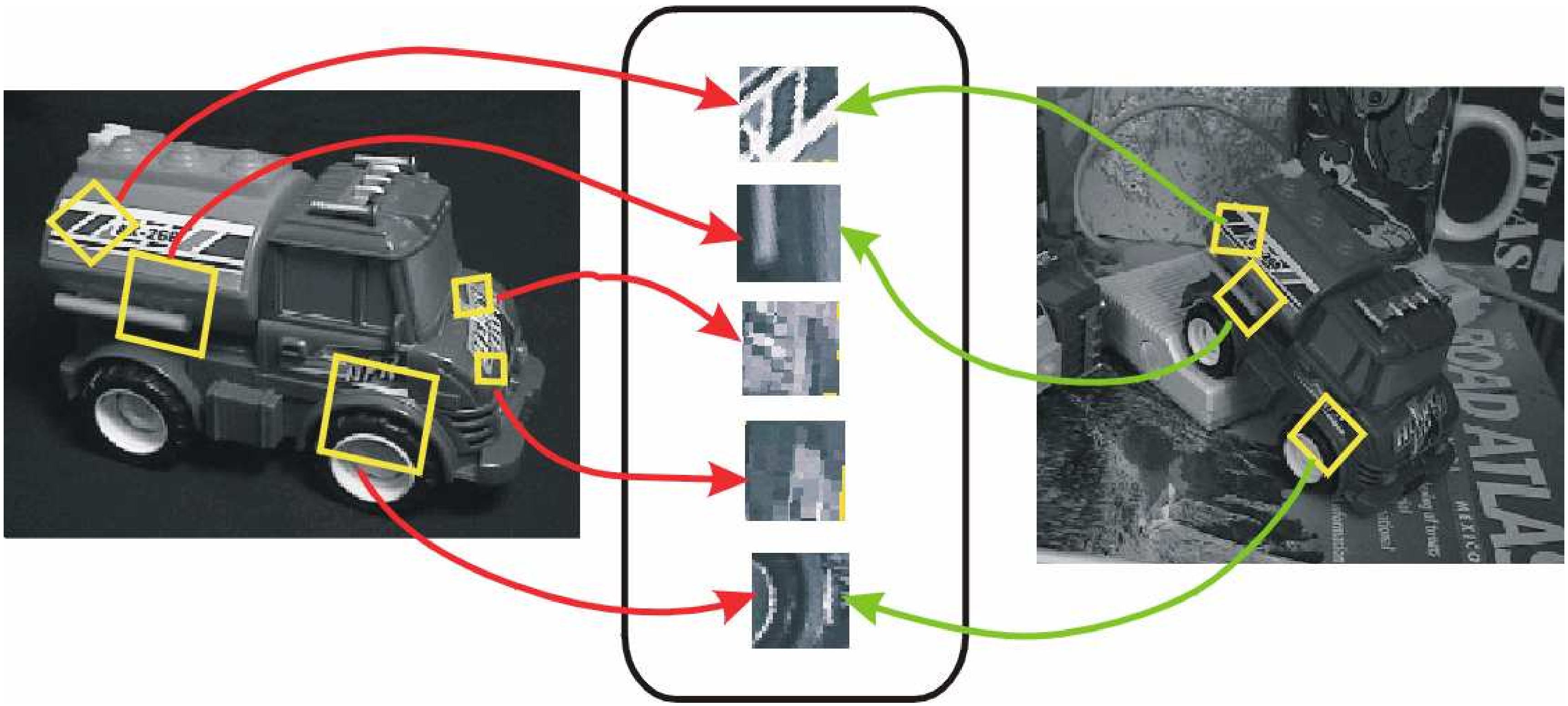
- Apply Harris corner detector
- Use rotational invariants at corner points
  - However, not scale invariant. Sensitive to viewpoint and illumination change.





Scale-Invariant Local Features

- Image content is transformed into local feature coordinates that are invariant to translation, rotation, scale, and other imaging parameters



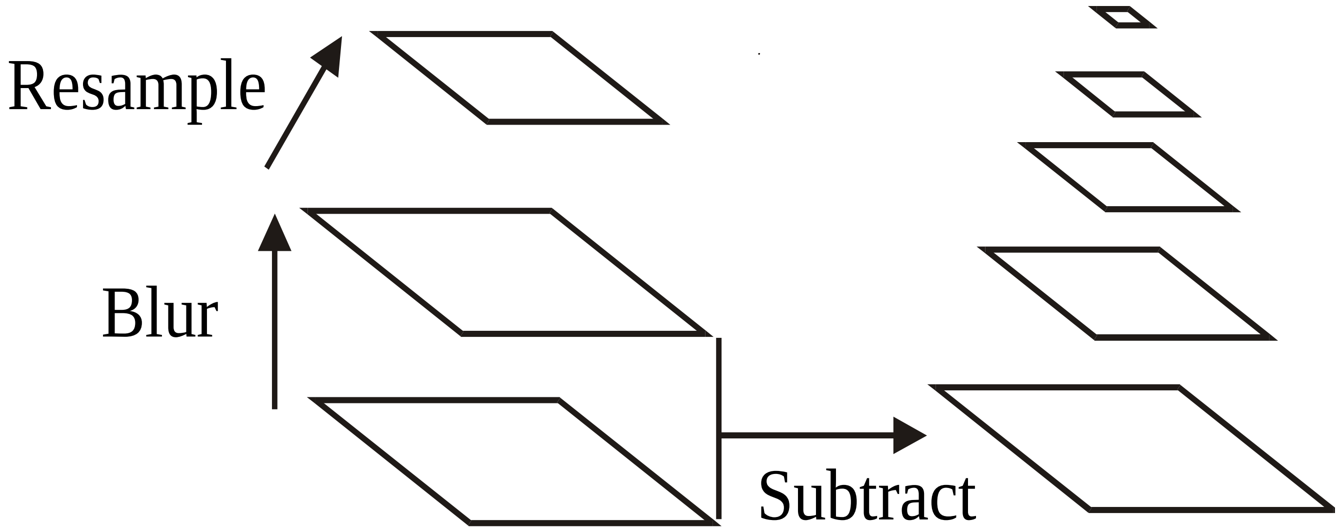
SIFT Features

Advantages of invariant local features

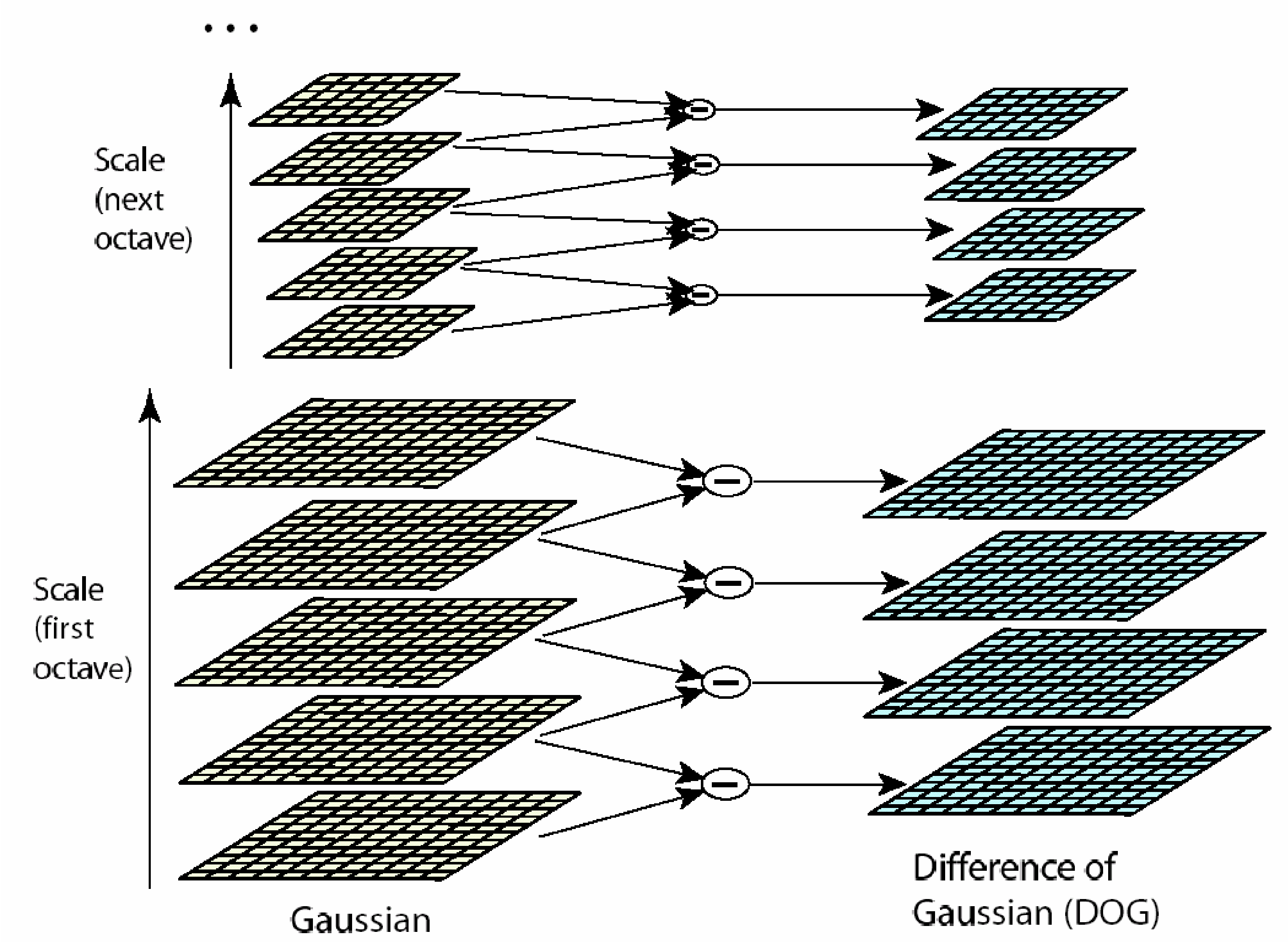
- **Locality:** features are local, so robust to occlusion and clutter (no prior segmentation)
- **Distinctiveness:** individual features can be matched to a large database of objects
- **Quantity:** many features can be generated for even small objects
- **Efficiency:** close to real-time performance
- **Extensibility:** can easily be extended to wide range of differing feature types, with each adding robustness

Build Scale-Space Pyramid

- All scales must be examined to identify scale-invariant features
- An efficient function is to compute the Difference of Gaussian (DOG) pyramid (Burt & Adelson, 1983)

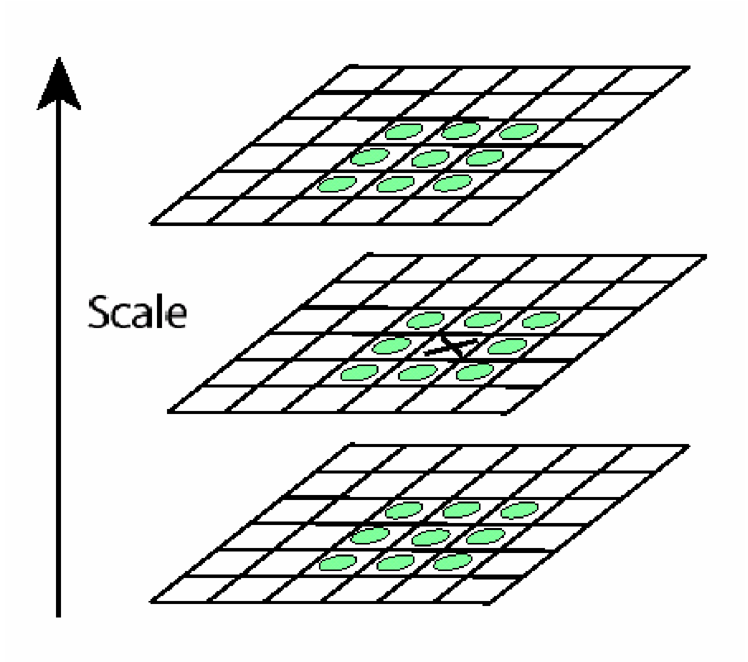


Scale space processed one octave at a time



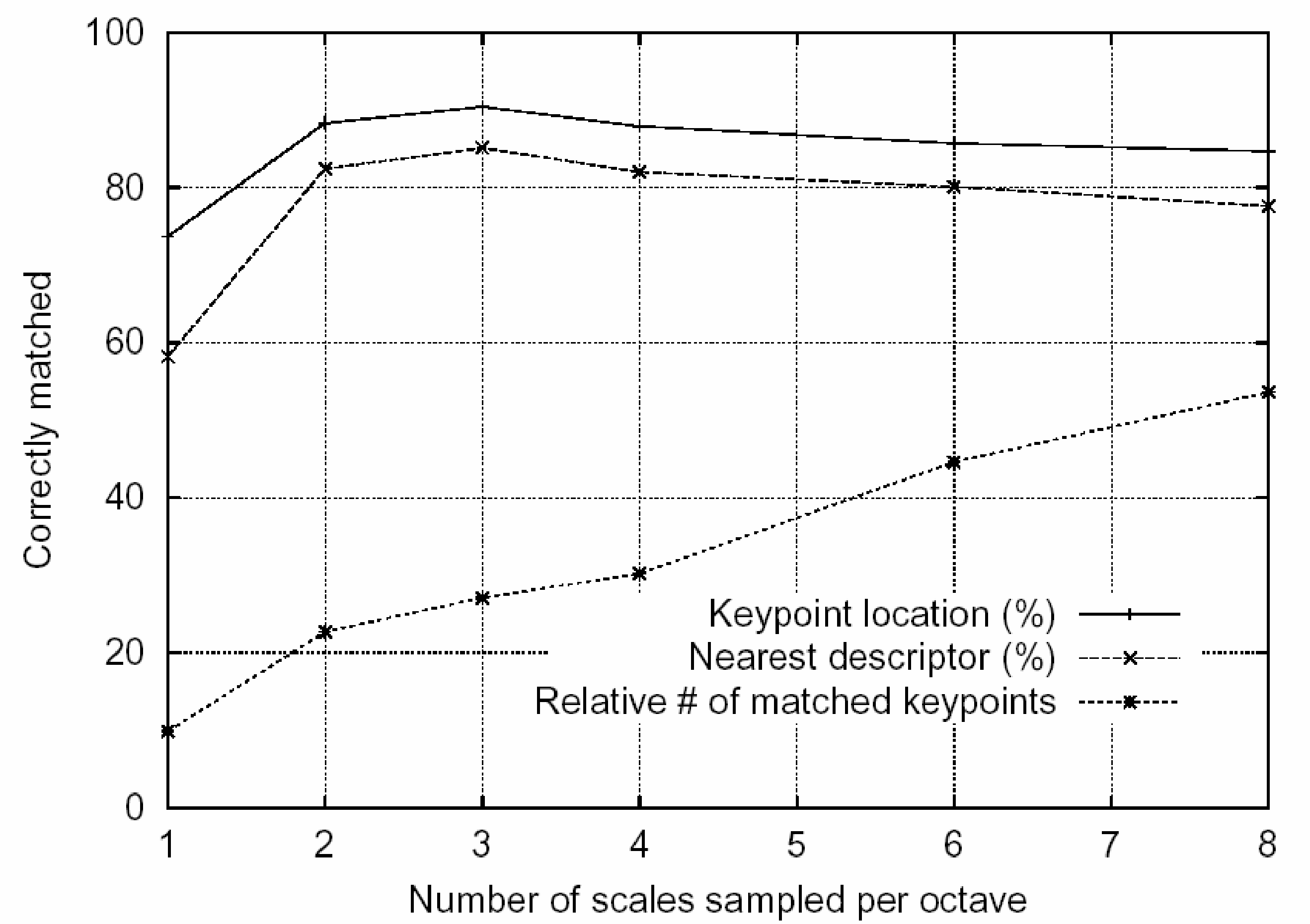
Key point localization

- Detect maxima and minima of difference-of-Gaussian in scale space



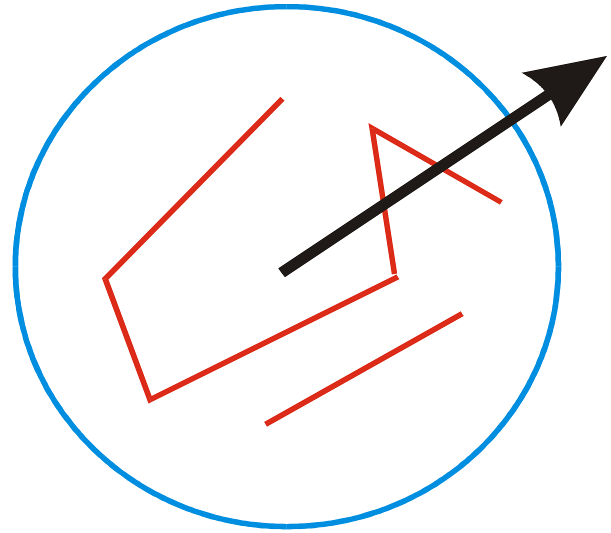
Sampling frequency for scale

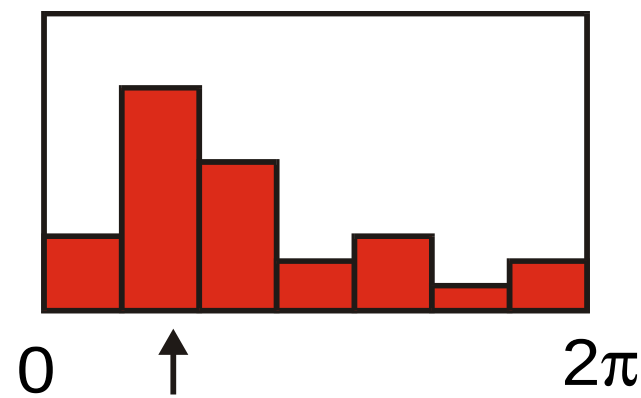
More points are found as sampling frequency increases, but accuracy of matching decreases after 3 scales/octave



Select canonical orientation

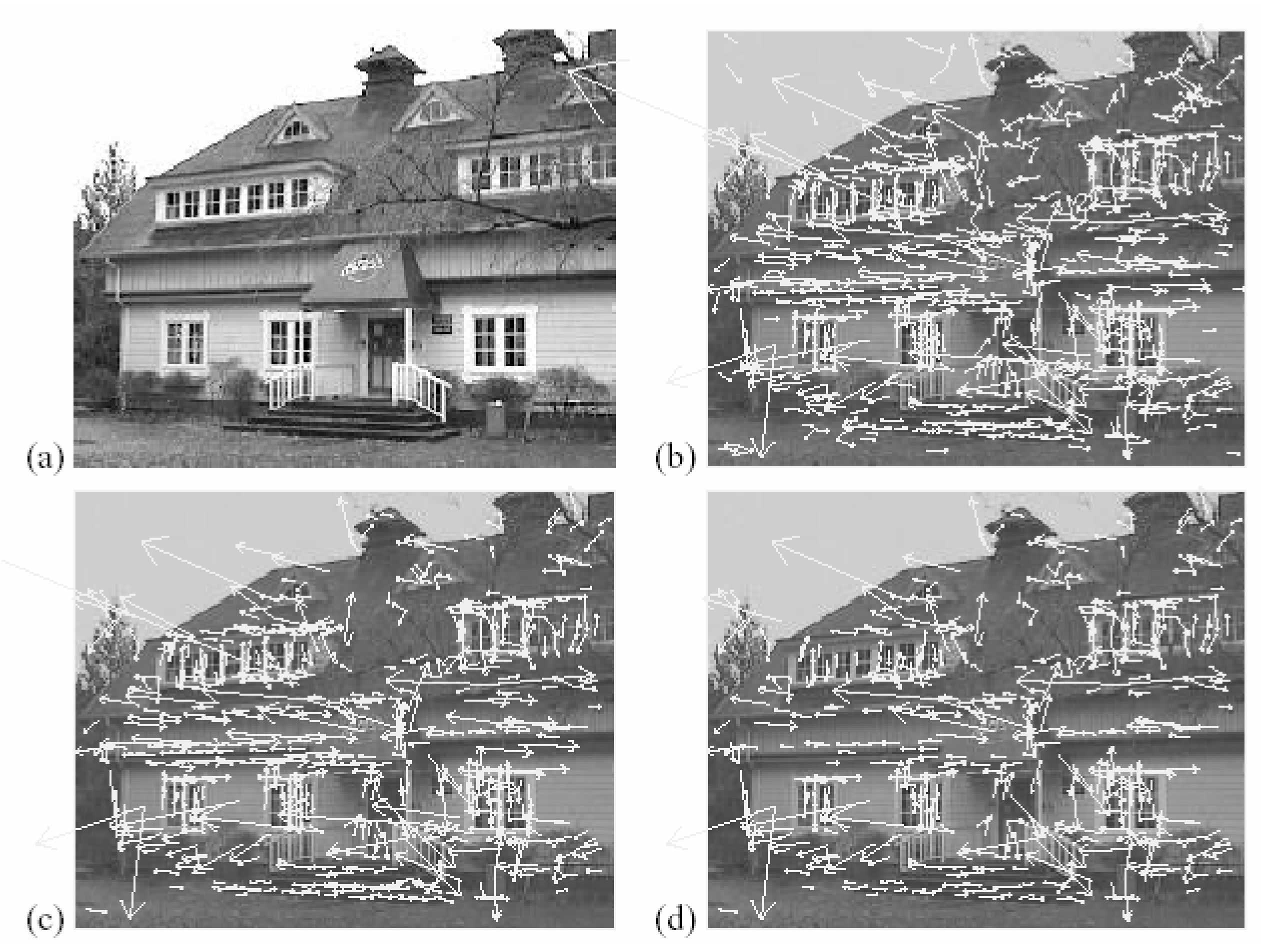
- Create histogram of local gradient directions computed at selected scale
- Assign canonical orientation at peak of smoothed histogram
- Each key specifies stable 2D coordinates (x, y, scale, orientation)





Example of keypoint detection

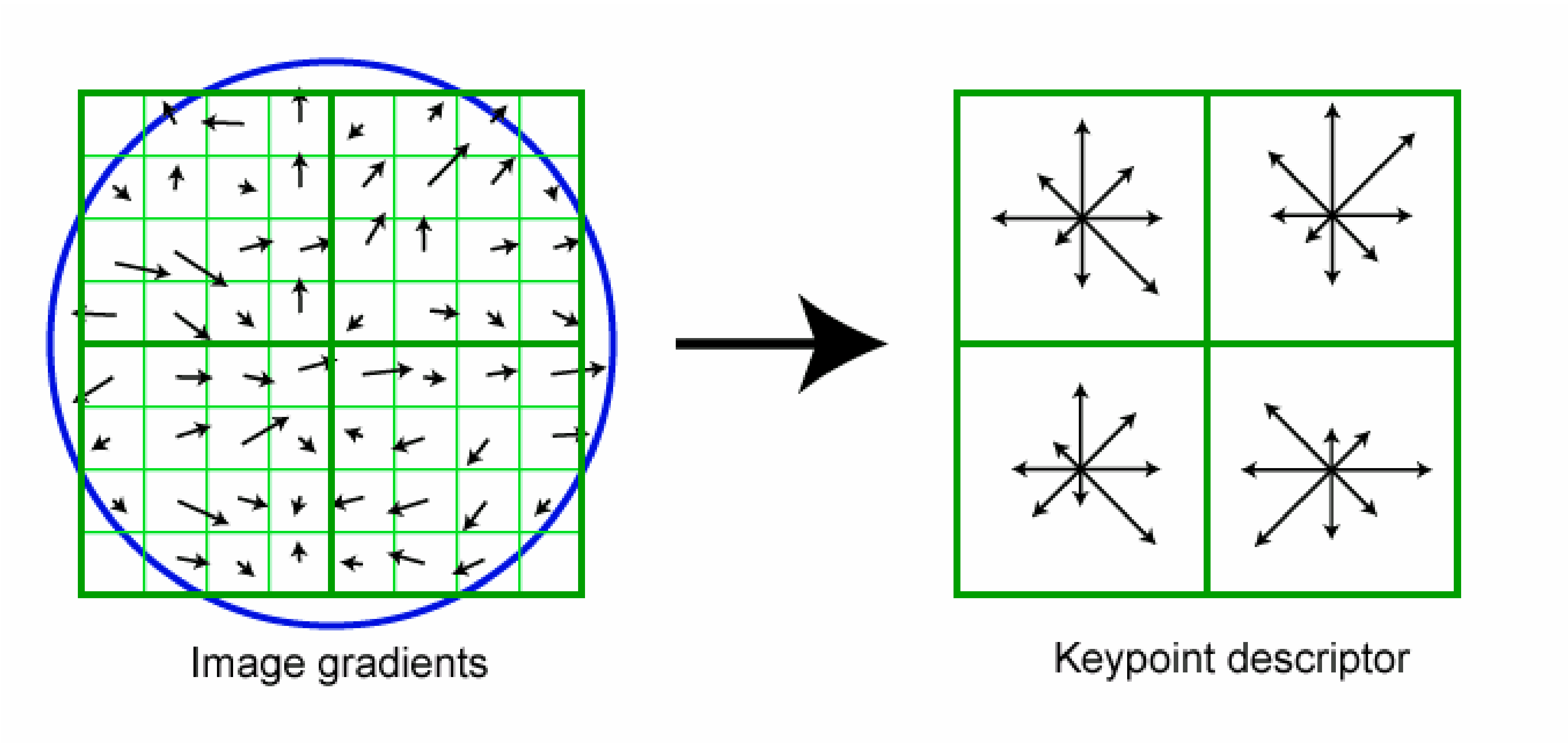
Threshold on value at DOG peak and on ratio of principle curvatures (Harris approach)



(a) 233x189 image
(b) 832 DOG extrema
(c) 729 left after peak value threshold
(d) 536 left after testing ratio of principle curvatures

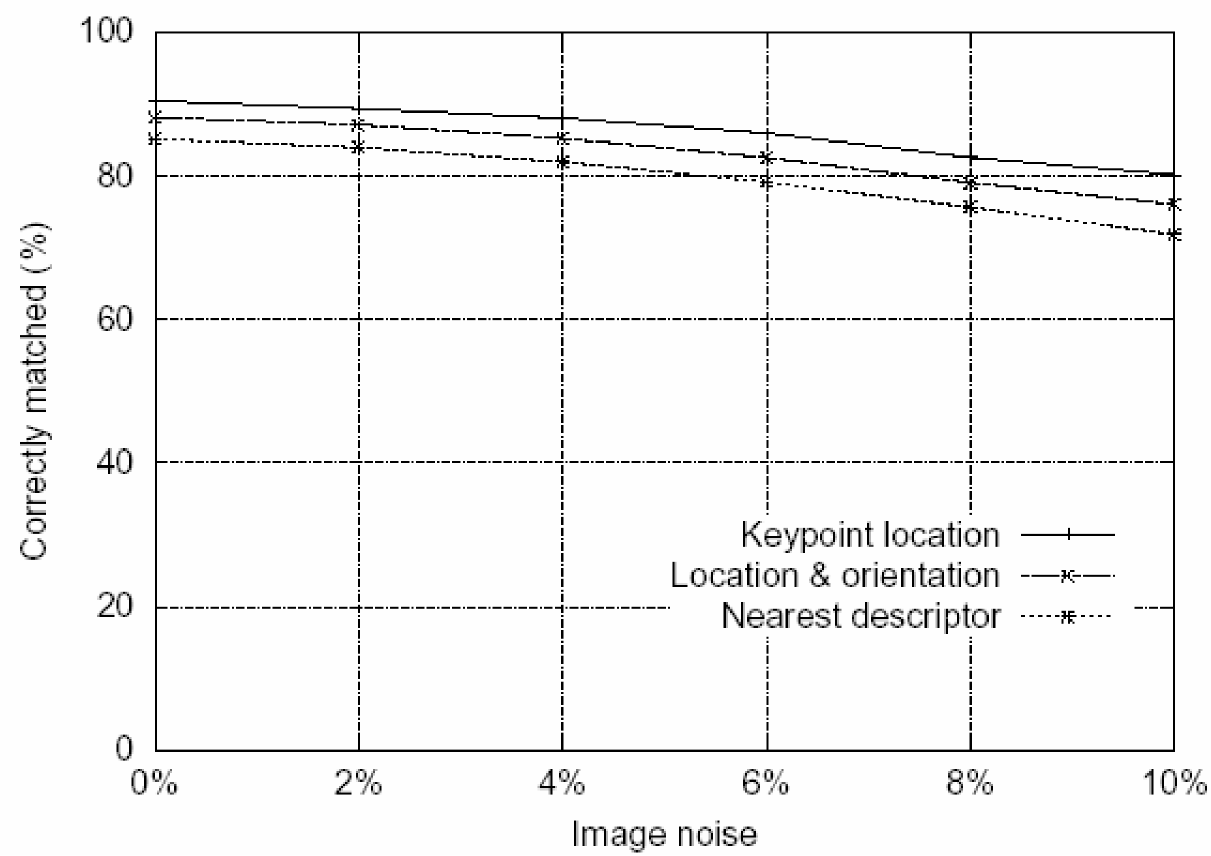
SIFT vector formation

- Thresholded image gradients are sampled over 16x16 array of locations in scale space
- Create array of orientation histograms
- 8 orientations x 4x4 histogram array = 128 dimensions



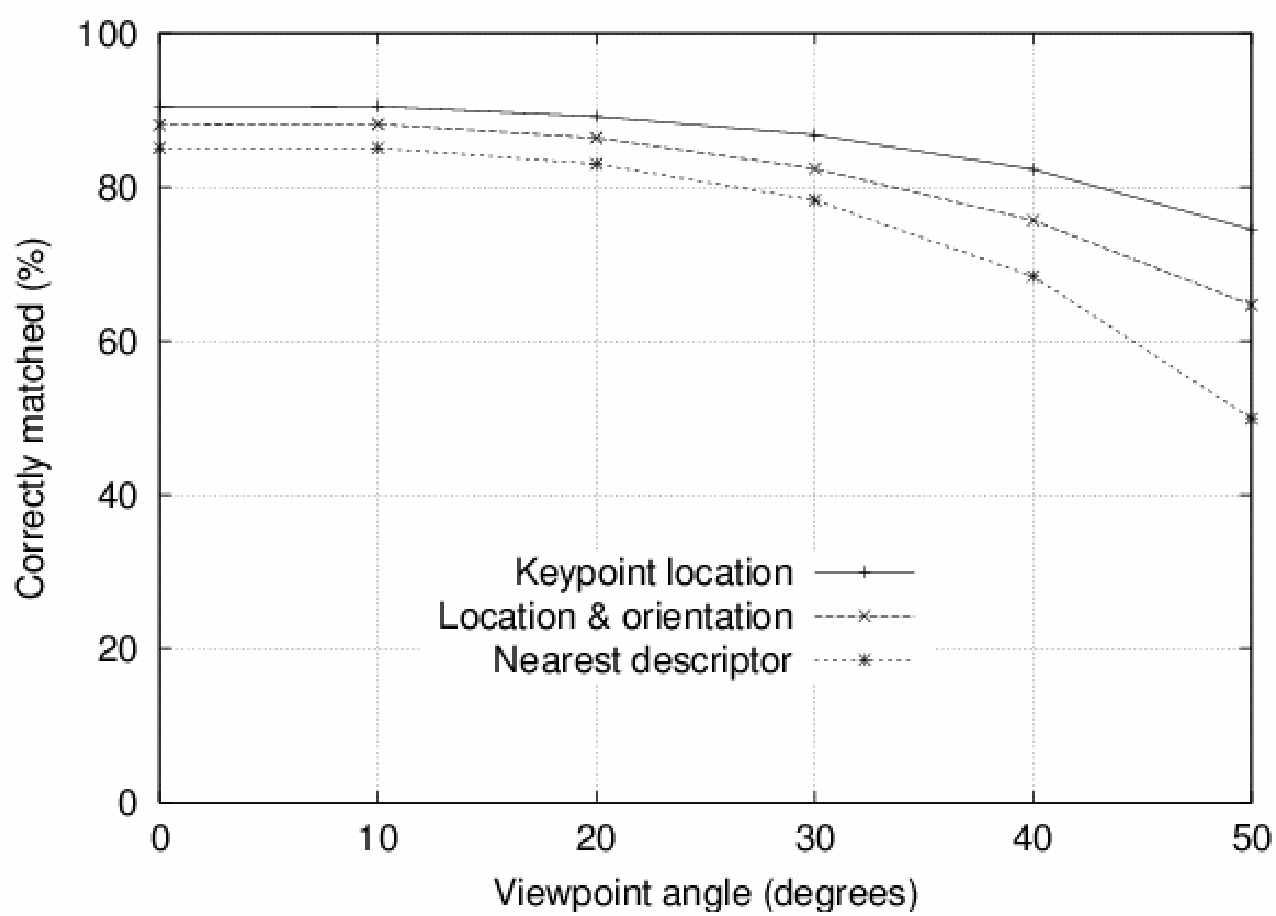
Feature stability to noise

- Match features after random change in image scale & orientation, with differing levels of image noise
- Find nearest neighbor in database of 30,000 features



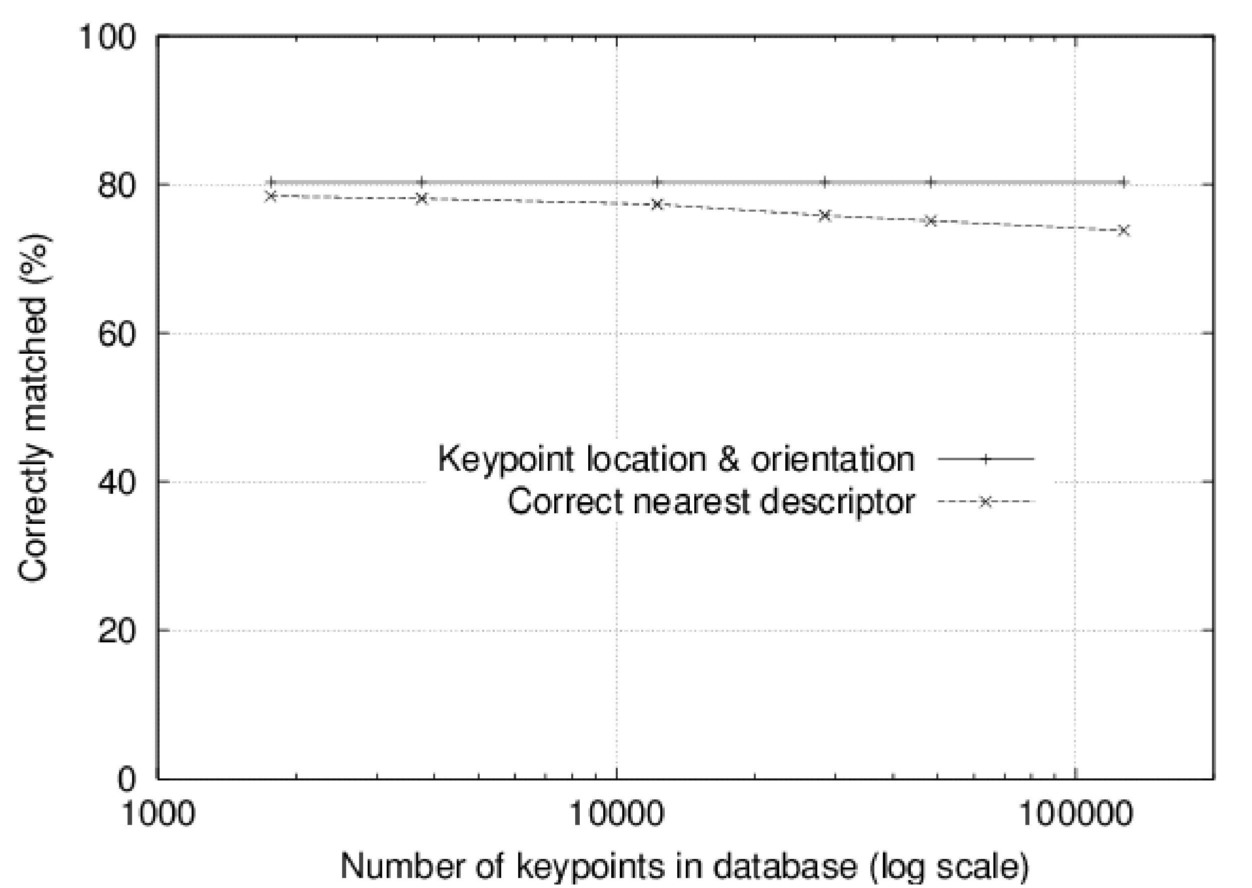
Feature stability to affine change

- Match features after random change in image scale & orientation, with 2% image noise, and affine distortion
- Find nearest neighbor in database of 30,000 features



Distinctiveness of features

- Vary size of database of features, with 30 degree affine change, 2% image noise
- Measure % correct for single nearest neighbor match



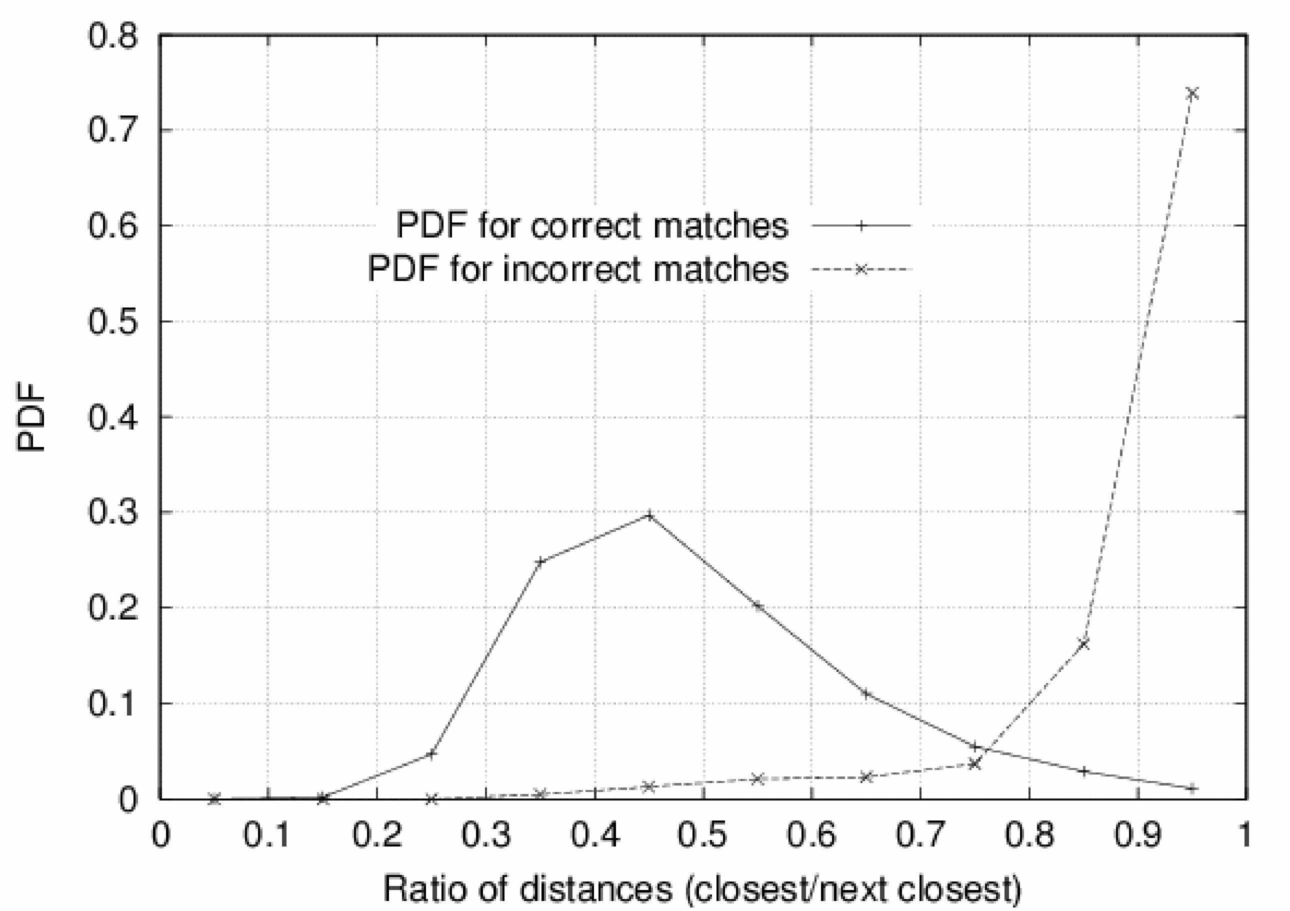
Detecting 0.1% inliers among 99.9% outliers

- We need to recognize clusters of just 3 consistent features among 3000 feature match hypotheses
- RANSAC would be hopeless!

- **Generalized Hough transform**
  - Vote for each potential match according to model ID and pose
  - Insert into multiple bins to allow for error in similarity approximation
  - Check collisions

Probability of correct match

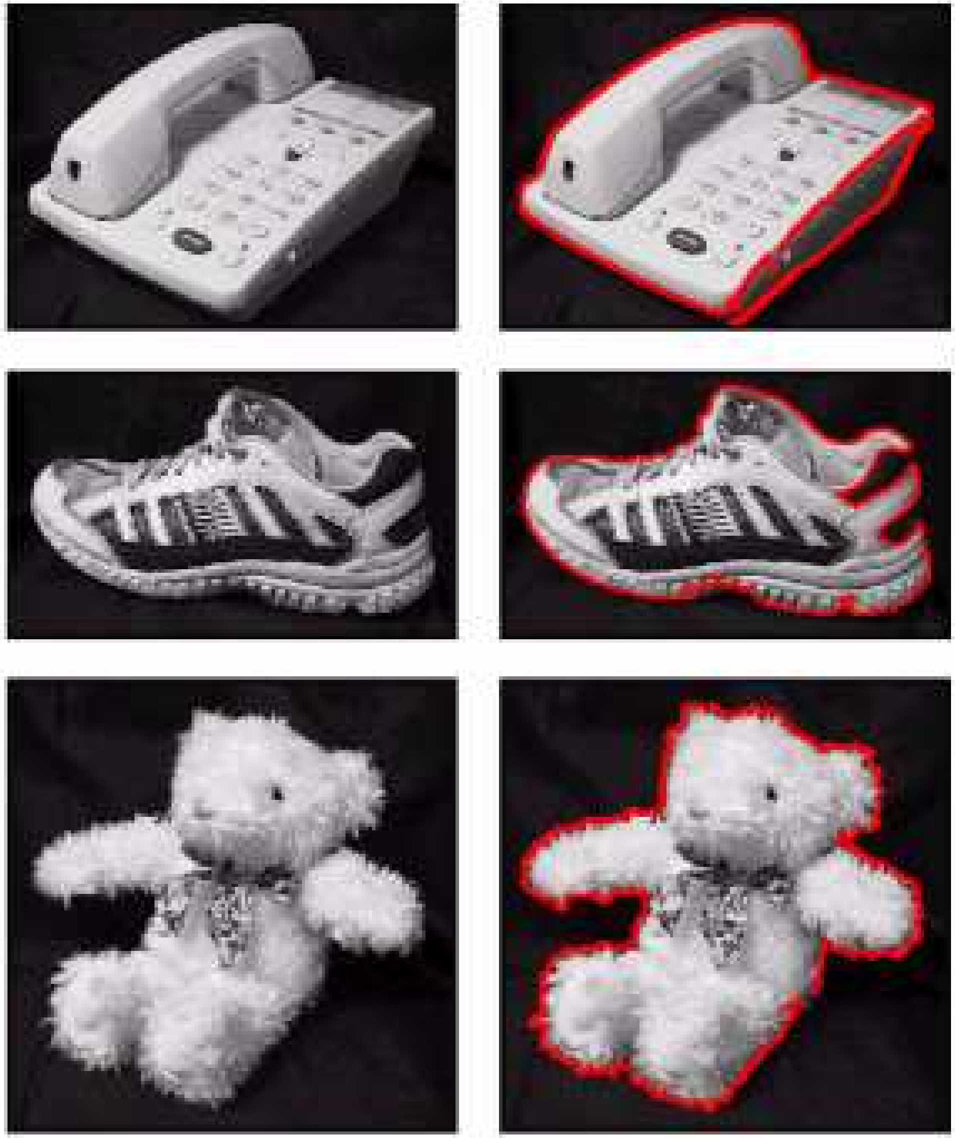
- Compare distance of **nearest** neighbor to **second** nearest neighbor (from different object)
- Threshold of 0.8 provides excellent separation



Model verification

1. Examine all clusters with at least 3 features
2. Perform least-squares affine fit to model.
3. Discard outliers and perform top-down check for additional features.
4. Evaluate probability that match is correct

3D Object Recognition

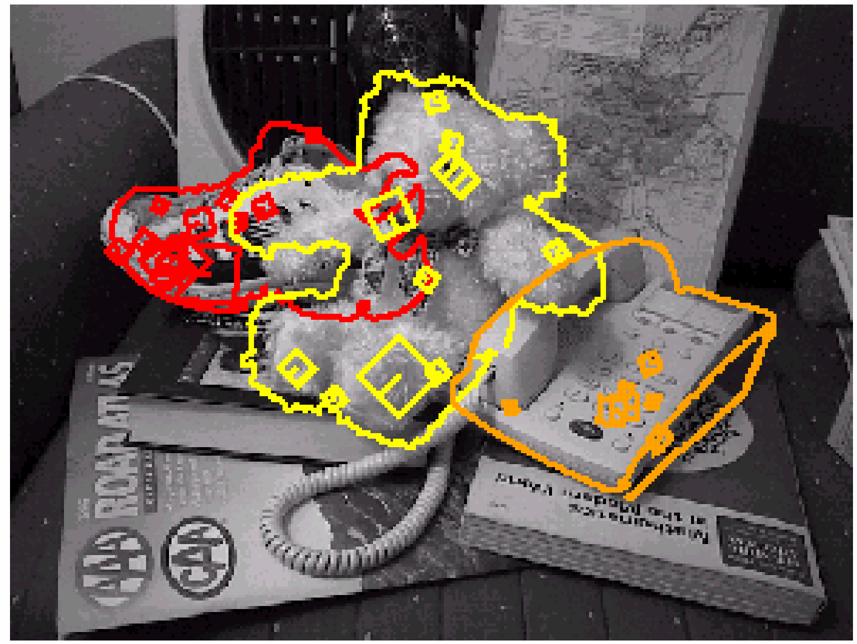


- Extract outlines with background subtraction

3D Object Recognition

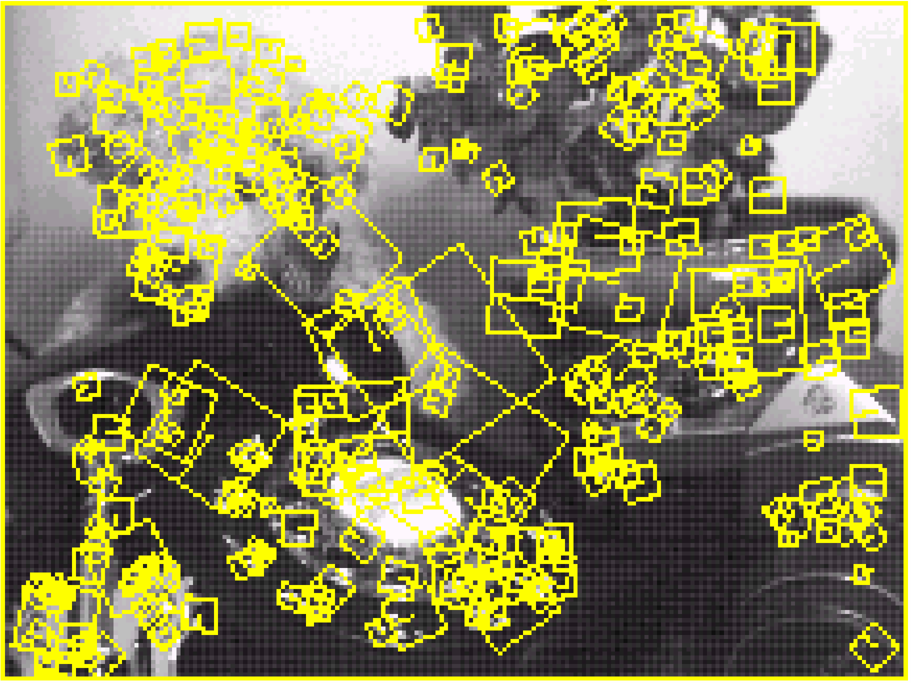
- Only 3 keys are needed for recognition, so extra keys provide robustness
- Affine model is no longer as accurate

Recognition under occlusion



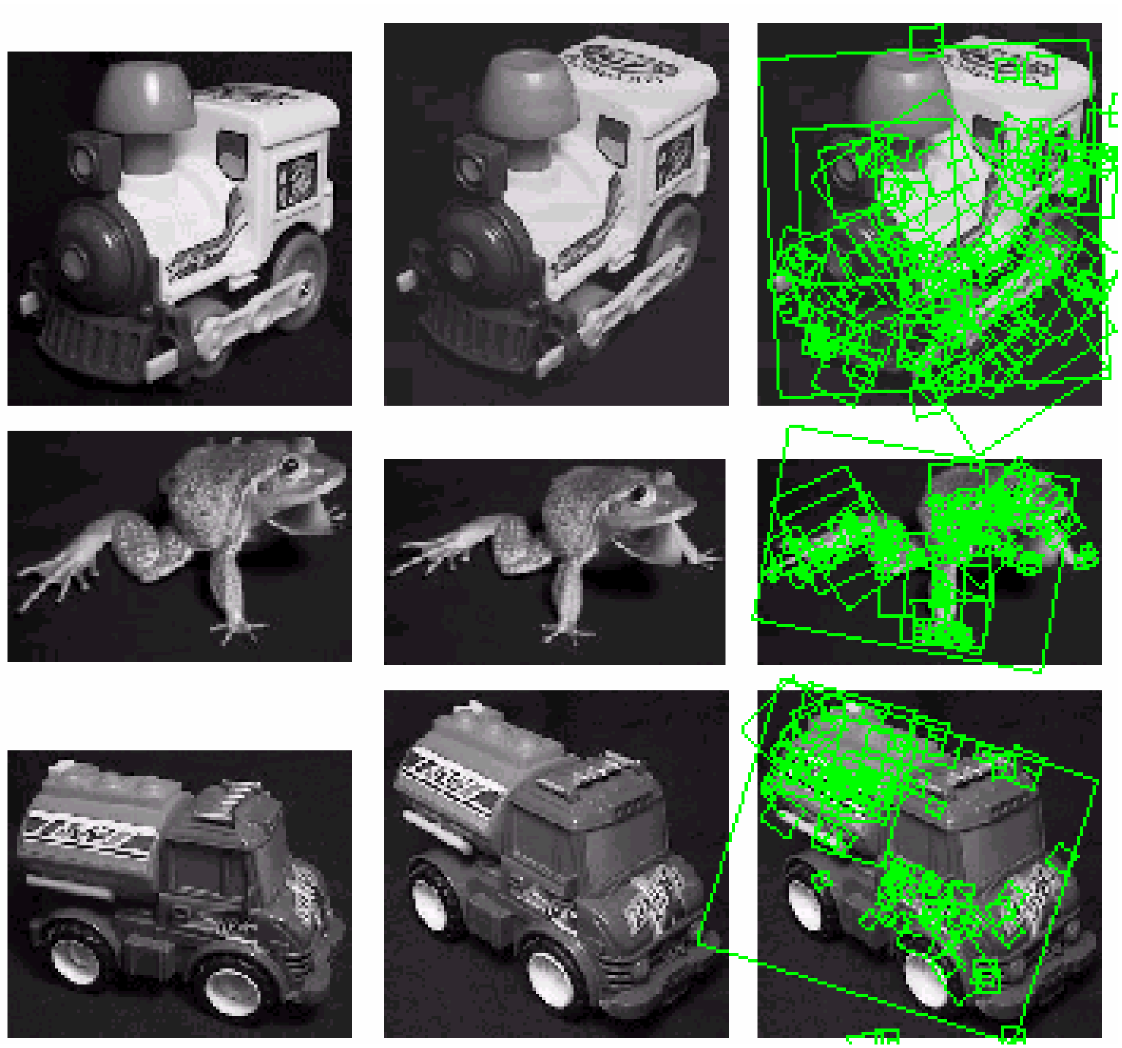
Test of illumination invariance

- Same image under differing illumination

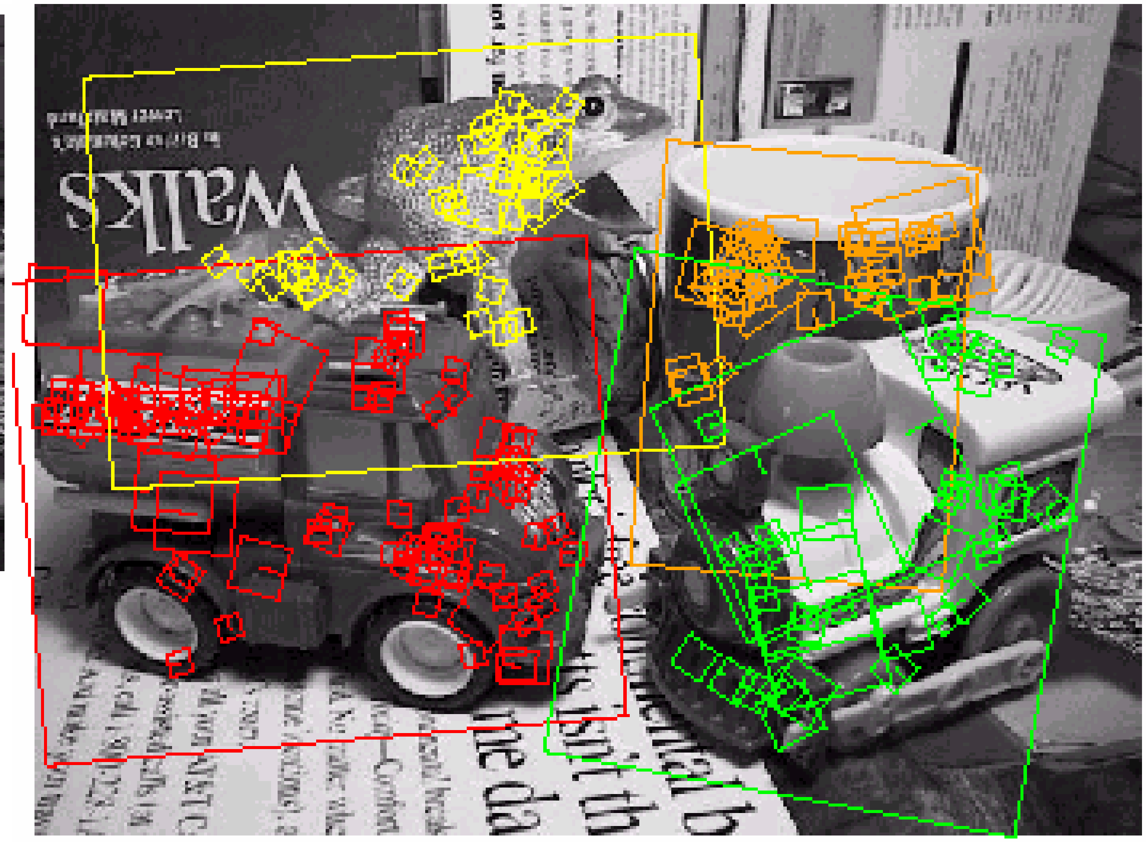


273 keys verified in final match

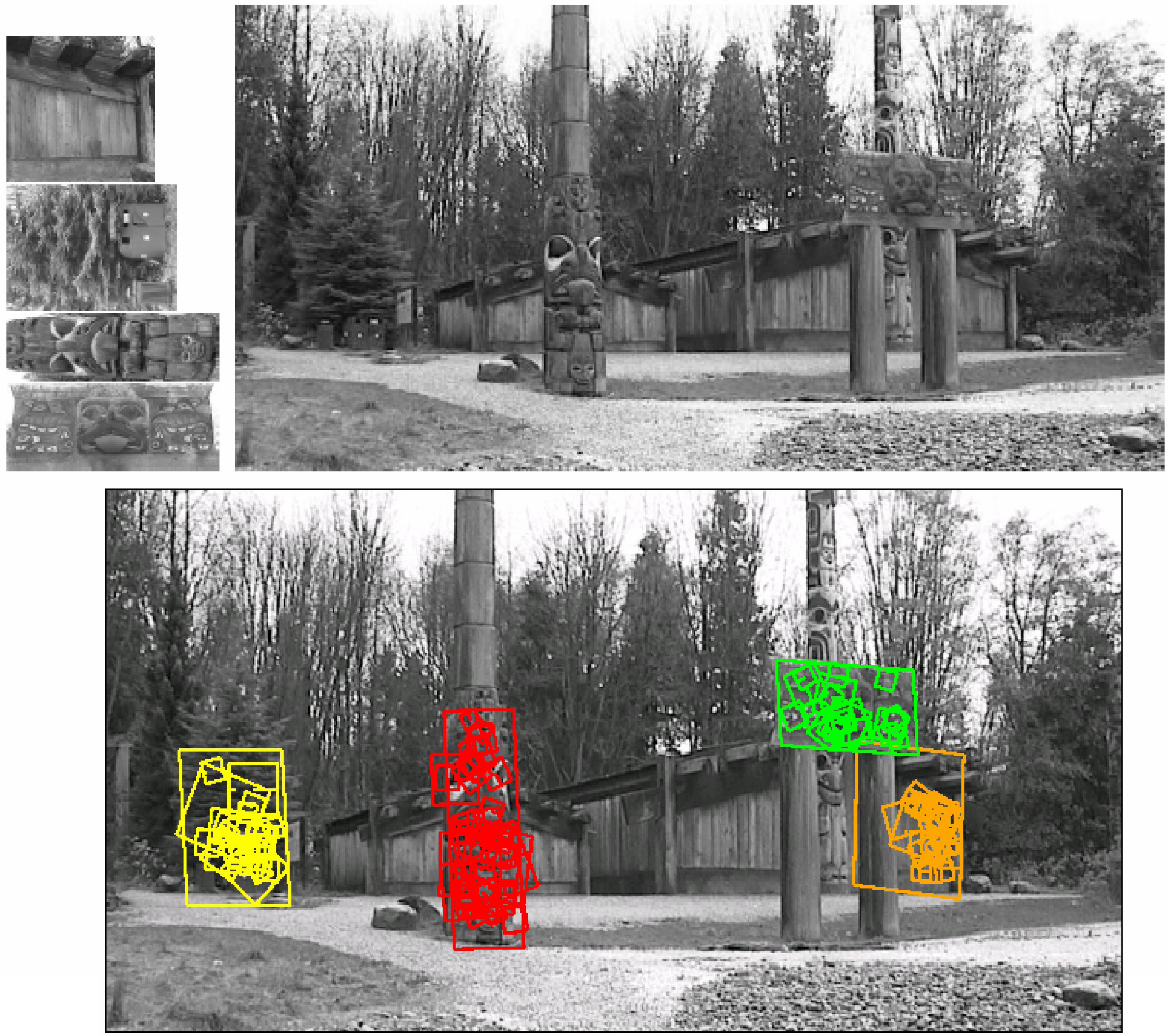
Examples of view interpolation



Recognition using View Interpolation



Location recognition

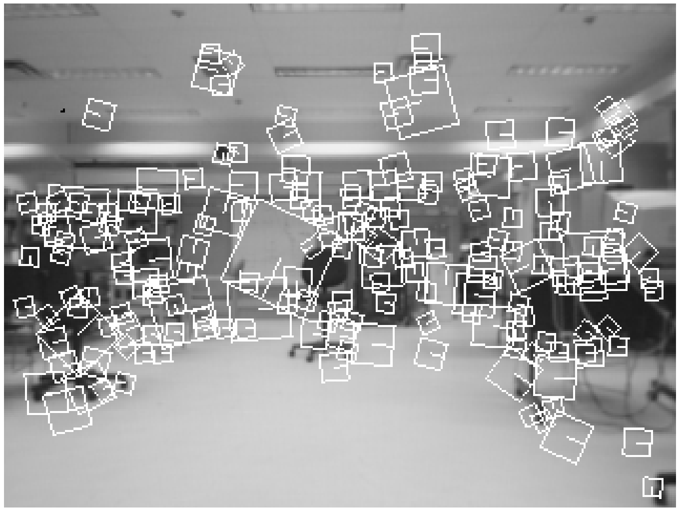


Robot localization results

- Joint work with Stephen Se, Jim Little

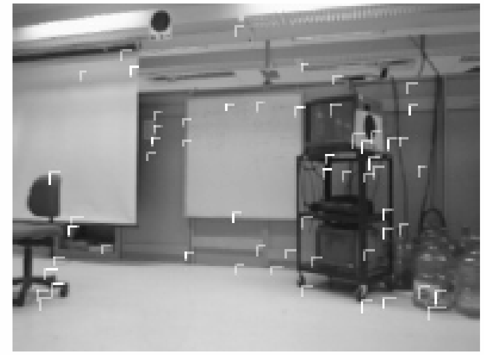
- **Map registration:** The robot can process 4 frames/sec and localize itself within 5 cm
- **Global localization:** Robot can be turned on and recognize its position anywhere within the map
- **Closing-the-loop:** Drift over long map building sequences can be recognized. Adjustment is performed by aligning submaps.

Robot Localization



(a)

(b)



(c)

(d)

(e)

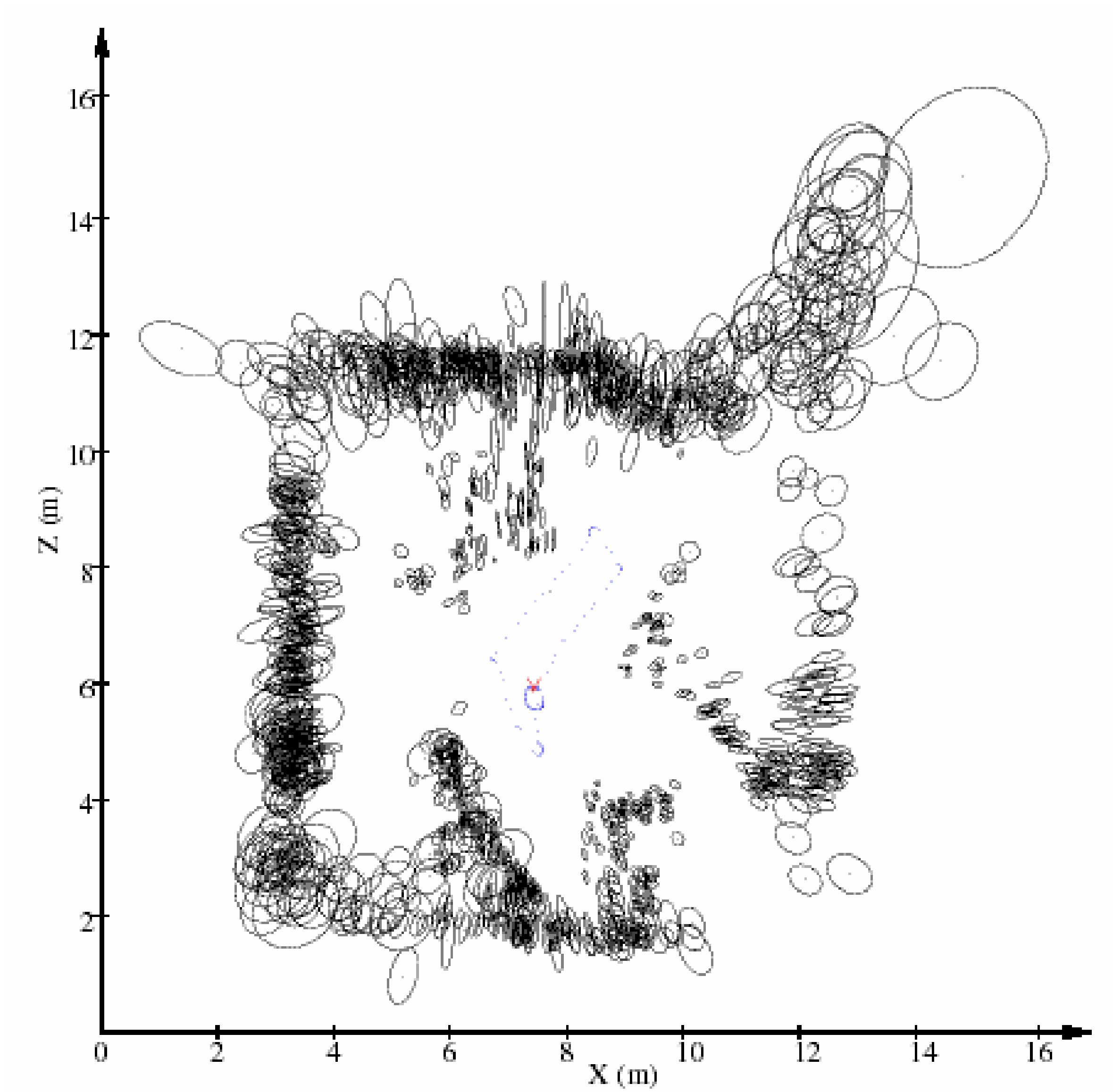
(f)

(g)

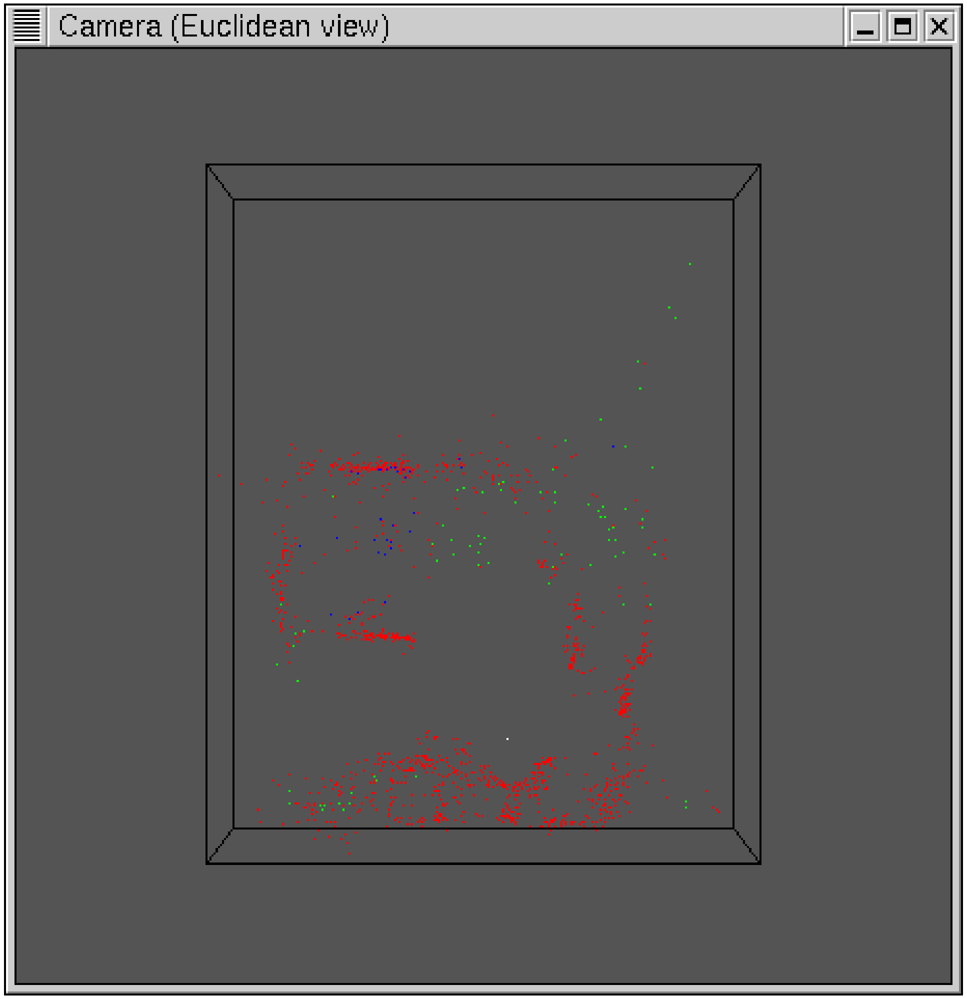
(h)

(i)

Map continuously built over time



Locations of map features in 3D



Sony Aibo (Evolution Robotics)

SIFT usage:

- **Recognize charging station**
- **Communicate with visual cards**