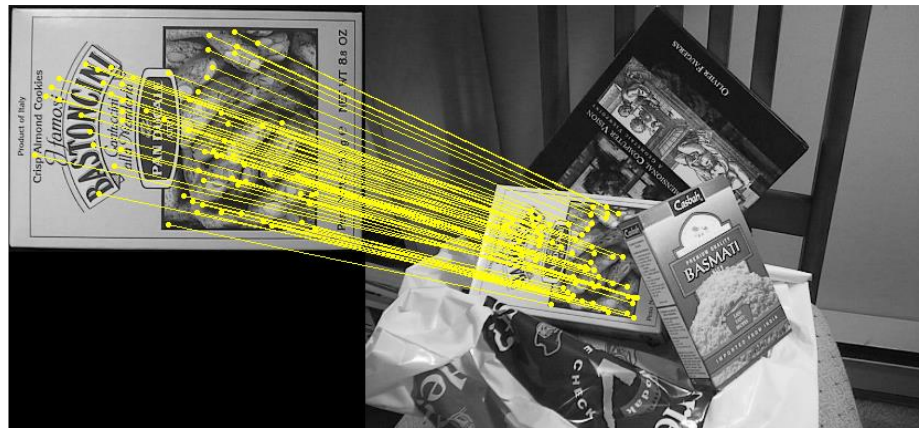


Keypoint Recognition Using Randomized Trees

Lecturer: Sang Hwa Lee

Introduction

- In many vision applications, the runtime performance of the object detection and pose estimation is very important
- We already have several techniques having good object detection performance: SIFT, MSER, Hessian Affine, etc..



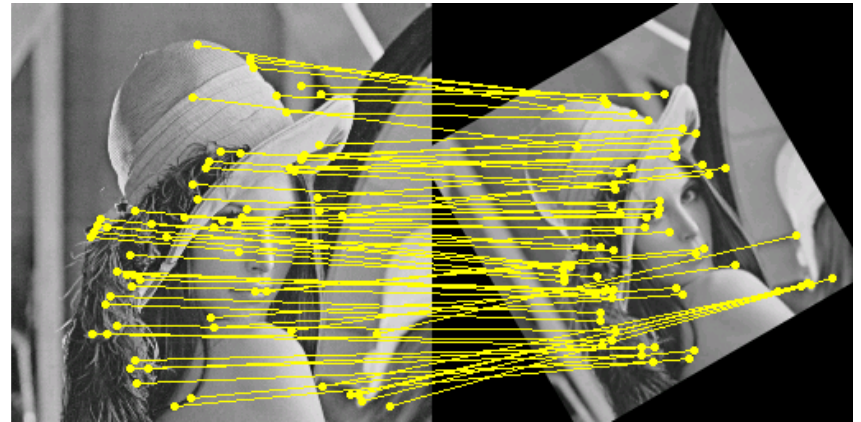
- However, none of them has real-time object detection performance

Introduction

- Generally, we have plenty of time for training detector of known object
- Basic idea:
 - Shift much of the computational burden to the training phase
 - Formulate the matching problem as a **classification problem** using classification trees
 - If we design classification tree well, the detection performance can be increased for the scene having large perspective and scale variations

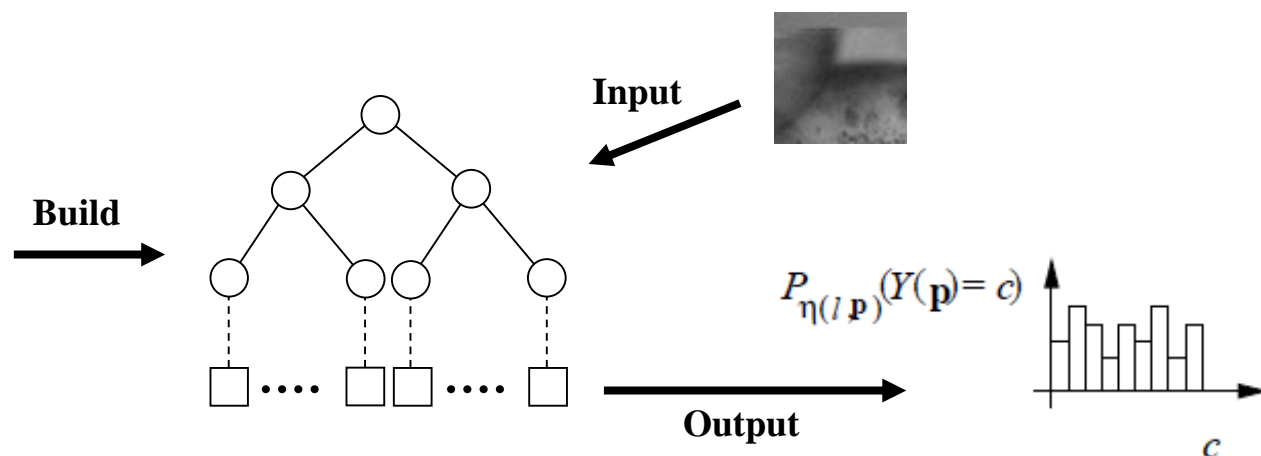
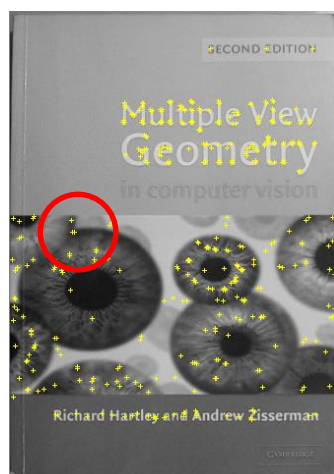
Introduction

- General approach of the object detection (SIFT):
 - Detect keypoint locations
 - Generate keypoint descriptors
 - 128 dimensional feature vector
 - Match keypoint descriptors of input and model scene
 - Nearest neighbor search
 - Model verification



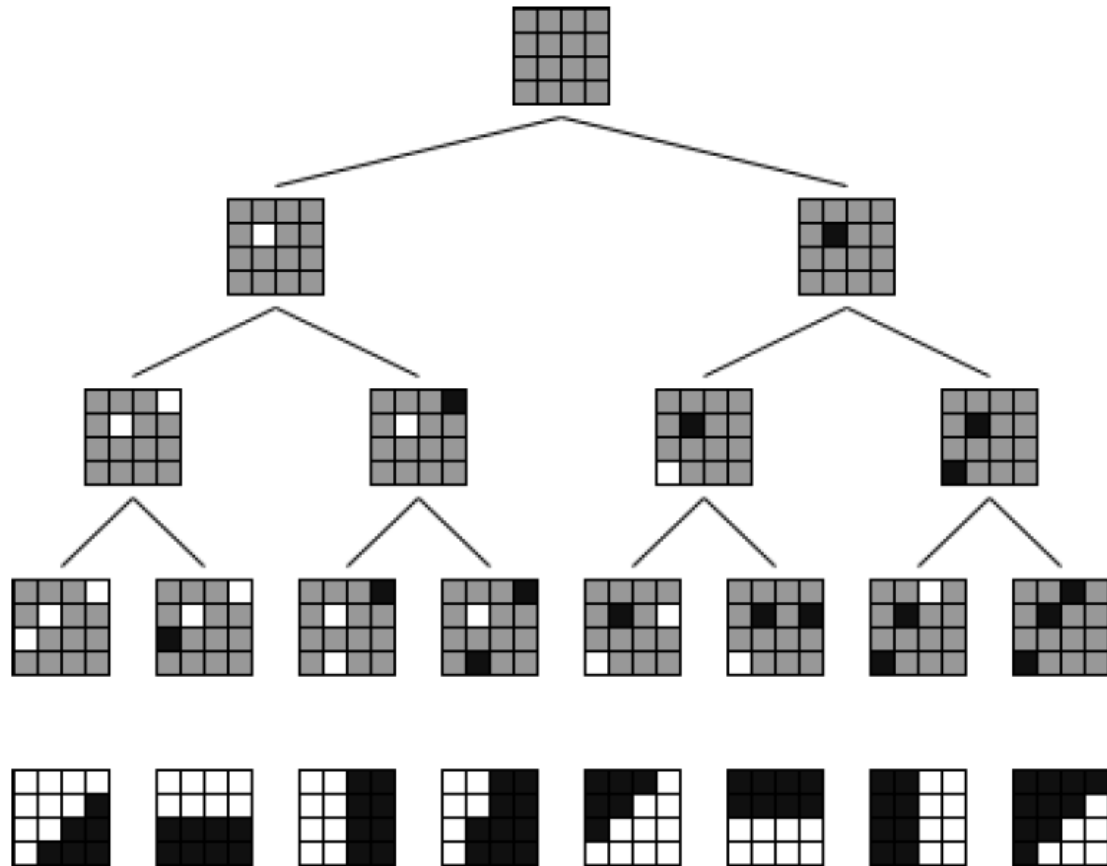
Point Matching as a Classification Problem

- Instead of using the feature vector and NN search, we turn the point matching to the classification problem
- For classification problem, we build the classification tree using a training image
- And for the input image patches from keypoint locations, we get class probabilities using the classification tree
 - Class: the keypoint index of the training image



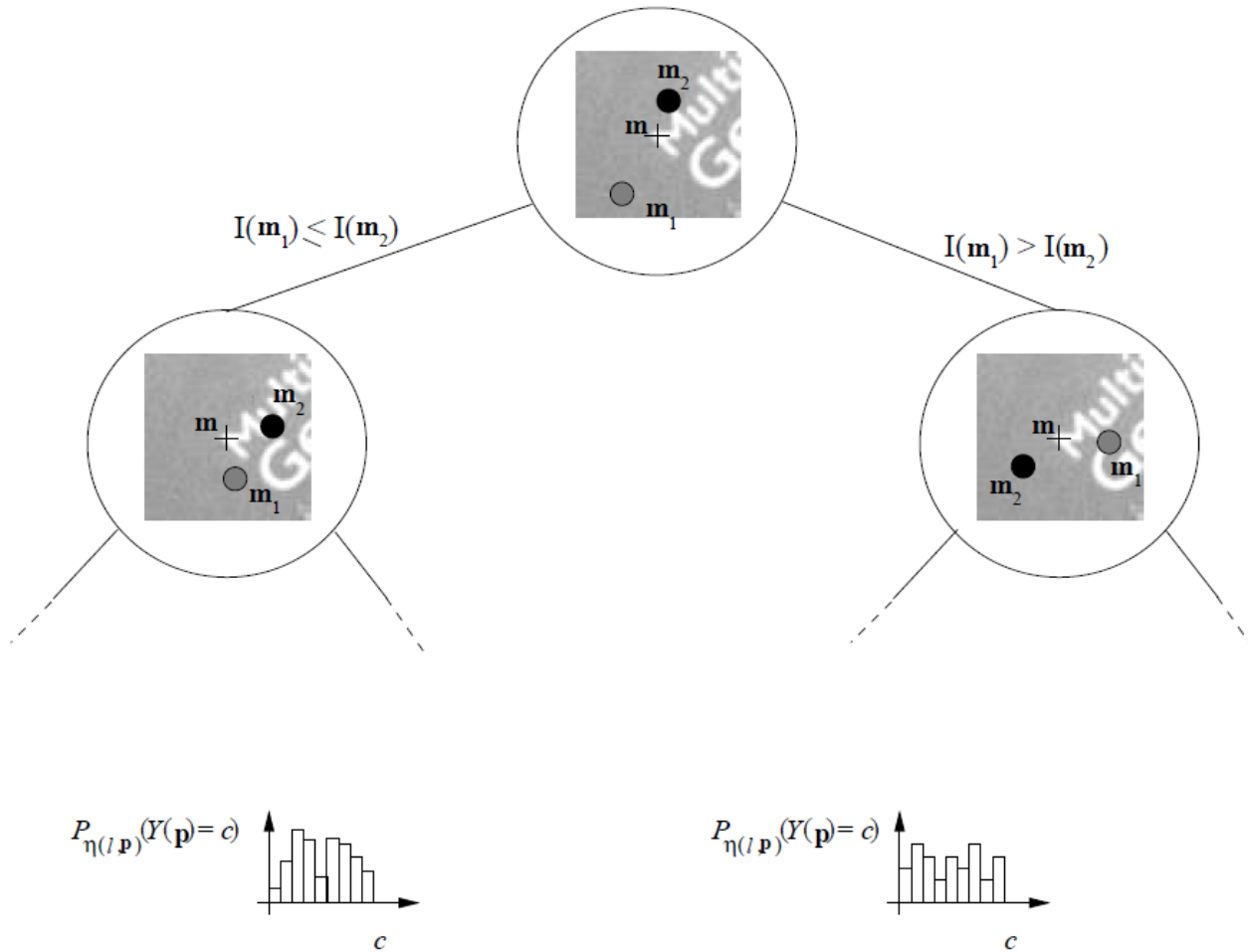
Classification Tree?

- An example (1996, Y. Amit and D. Geman)



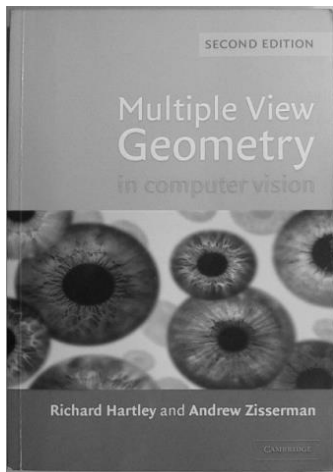
Classification Tree?

- Keypoint Classification Tree



Building the View Sets

- Keypoint selection



→
**Random Affine
Transformation**

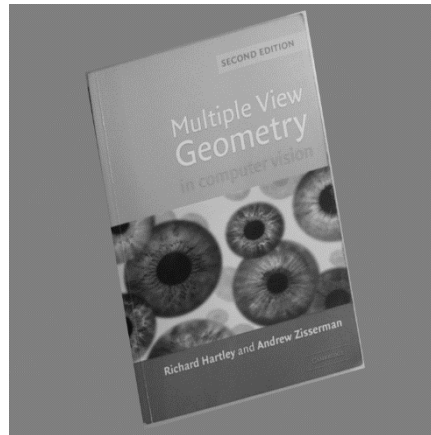


Model Image

Affine parameters:

Scale = [0.6, 1.5]

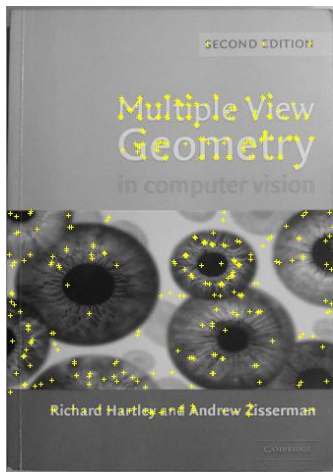
Theta, Phi = [-PI, PI]



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Building the View Sets

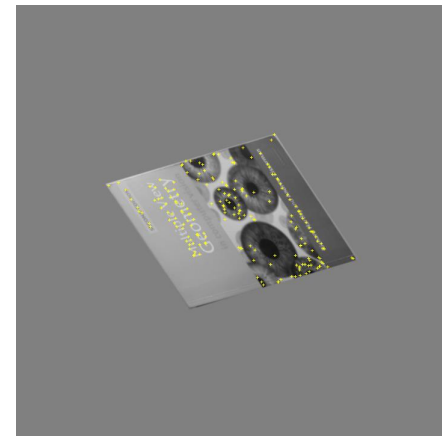
- Keypoint selection



Keypoint Selection



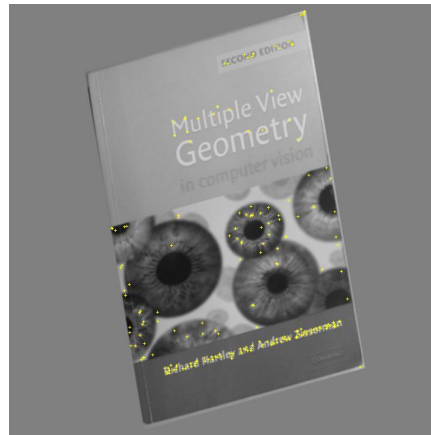
**Agglomerate
clustered keypoints**



Model Image

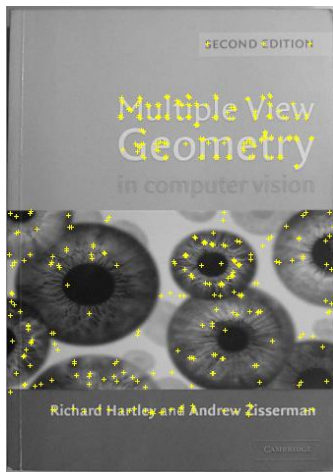
Use 3 Octaves:

**1, 1/2, 1/4 scale of
model image**



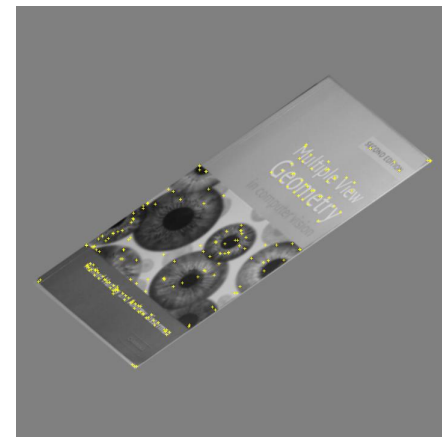
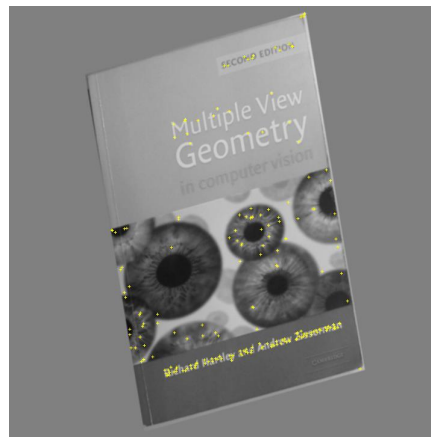
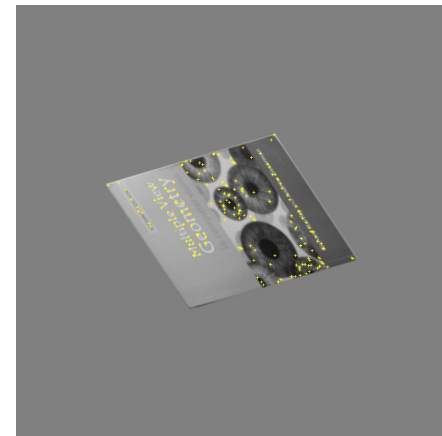
Building the View Sets

- Building the view sets



Model Image

→
**Random Affine
Transformation**

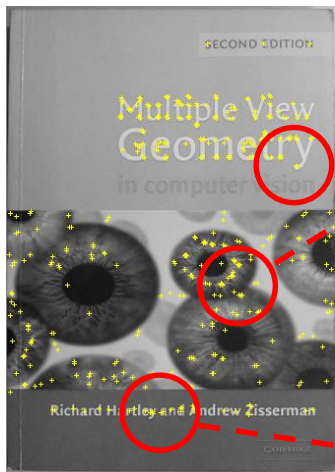


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Building the View Sets

- Building the view sets

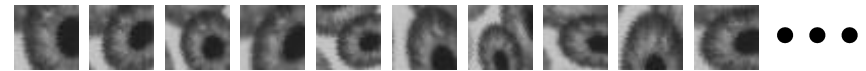
The "View Sets"



Model Image

Random Affine Transformation

Keypoint 1:



Keypoint 2:



⋮

Keypoint N:



Orientation normalization

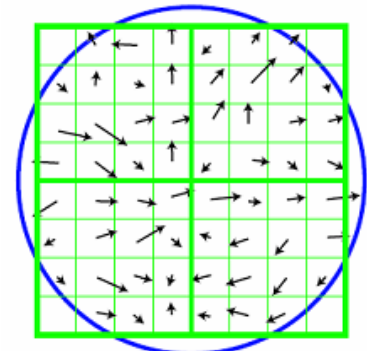
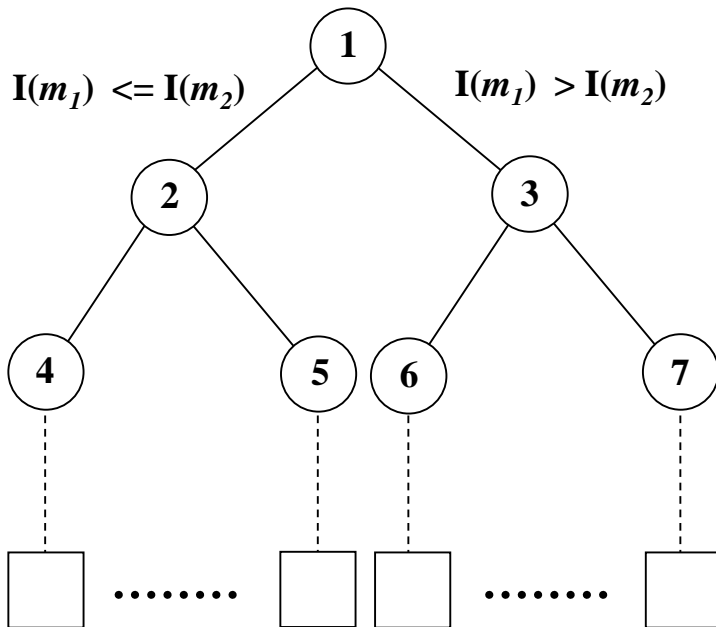


Image gradients

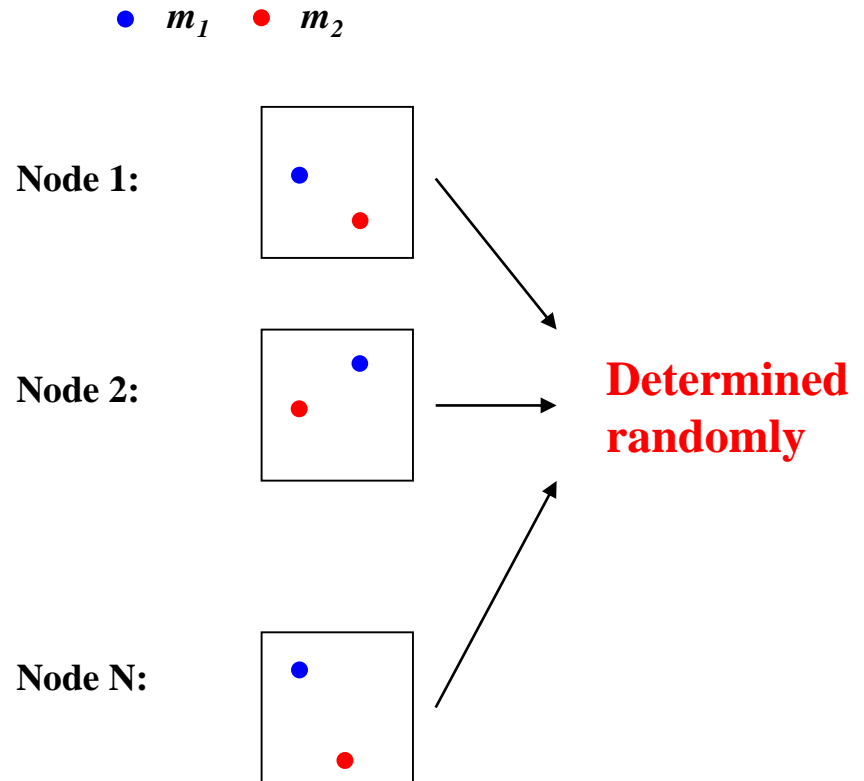
Training the Classification Tree

- Build a tree using random tests
 - The most simple approach



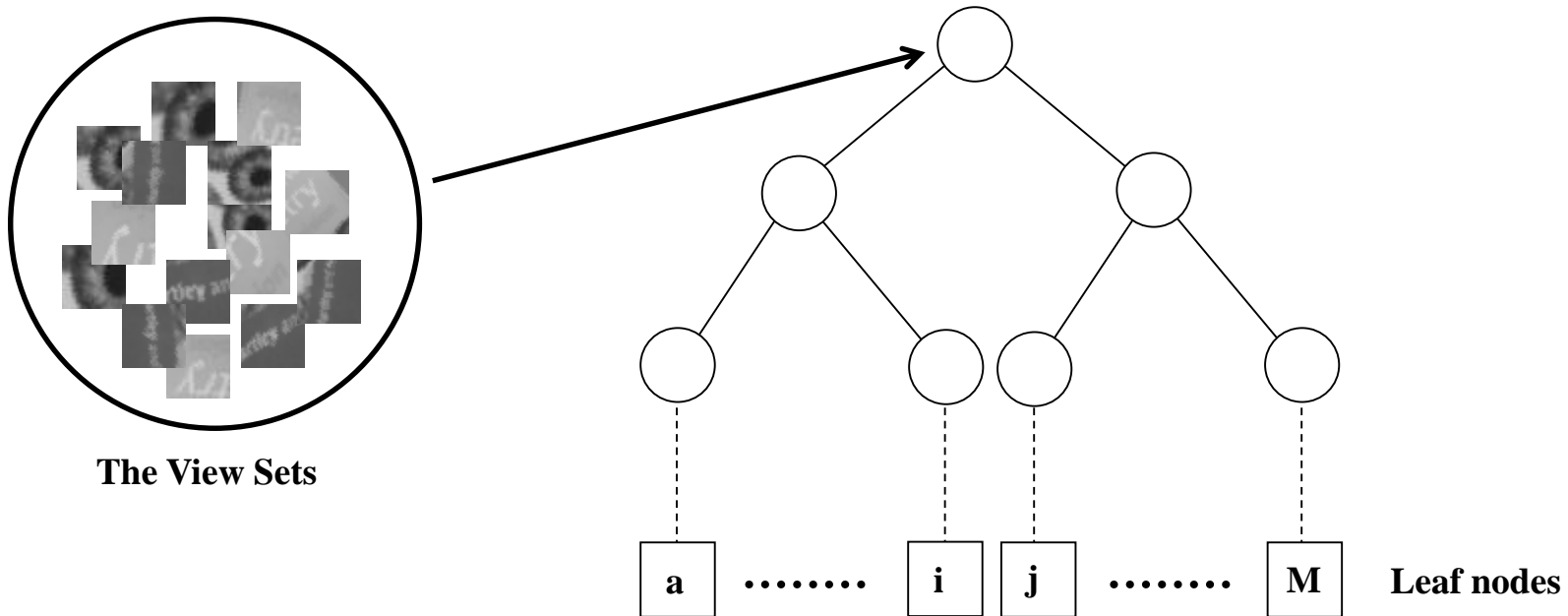
$I(m_1) \leq I(m_2)$: goto the left child node

$I(m_1) > I(m_2)$: goto the right child node

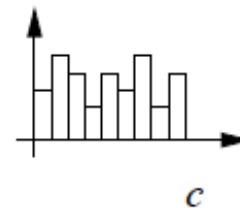
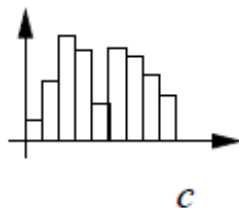


Training the Classification Tree

- Estimate posterior probability at the leaf nodes

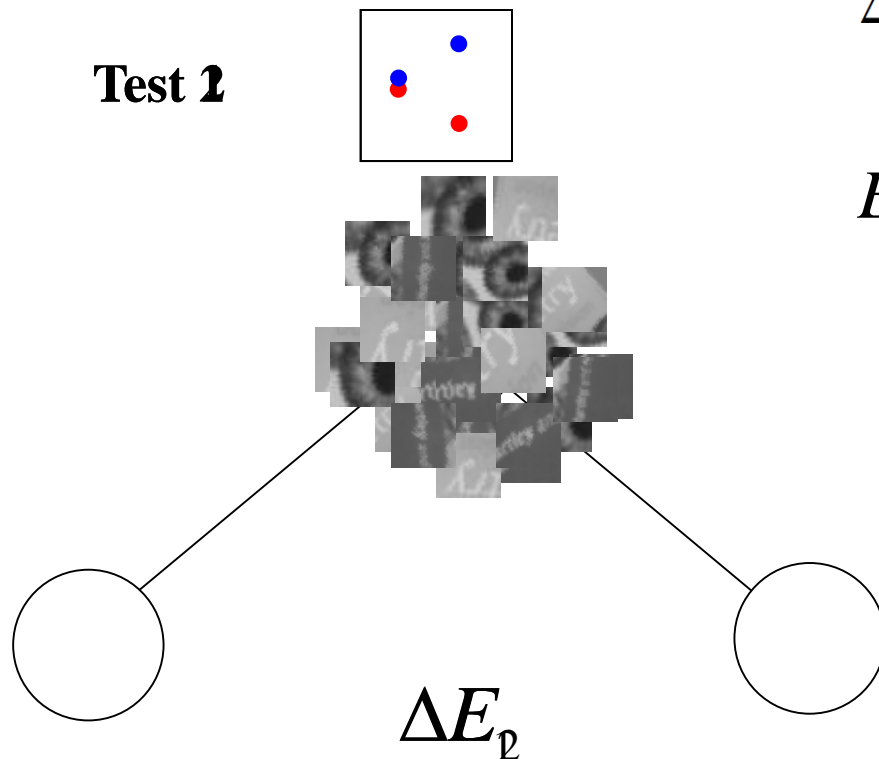


**Estimated
Posterior Probabilities:**



Tree Building Using Entropy Optimization

- The trees are constructed in the top-down manner
- The tests are chosen by a greedy algorithm to best separate the given examples



$$\Delta E = - \sum_i \frac{|S_i|}{|S|} E(S_i)$$

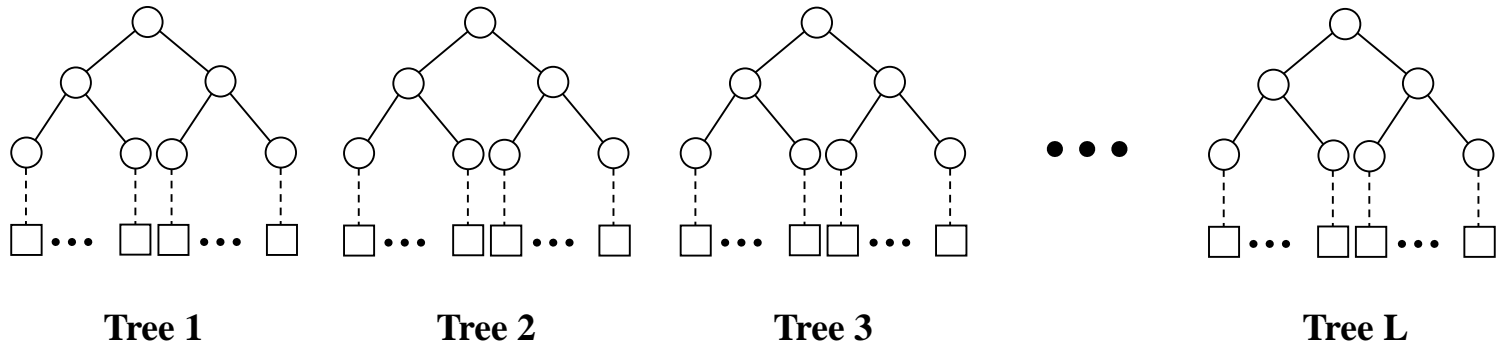
$$E(s) = - \sum_{j=1}^N p_j \log_2(p_j)$$

$$\Delta E_2 > \Delta E_1$$

: We select Test 2

Keypoint Recognition

- Build L classification trees using same methods
 - Each tree divide the patch space in different manner



- Use MAP estimation of the average of the posterior probabilities

$$\tilde{Y}(\mathbf{p}) = \arg \max_c p_c(\mathbf{p}) = \arg \max_c \frac{1}{L} \sum_{l=1 \dots L} P_{\eta(l, \mathbf{p})}(Y(\mathbf{p}) = c)$$

- Input: a image patch \mathbf{p}
- Output: the class index c

Keypoint Recognition

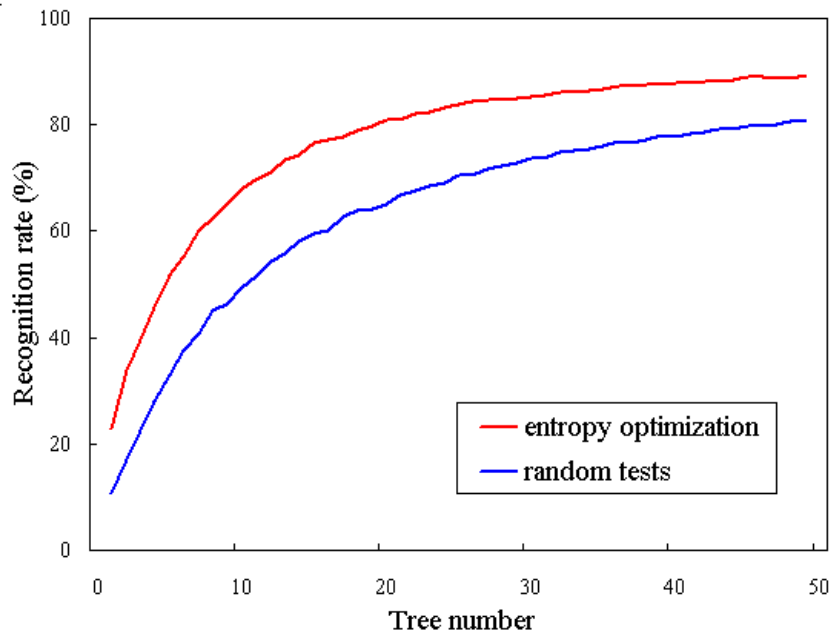
- Estimate a threshold during training to determine background or misclassified keypoints

$$P(Y(\mathbf{p}) = c | \tilde{Y}(\mathbf{p}) = c, p_c(\mathbf{p}) > T_c) > s$$

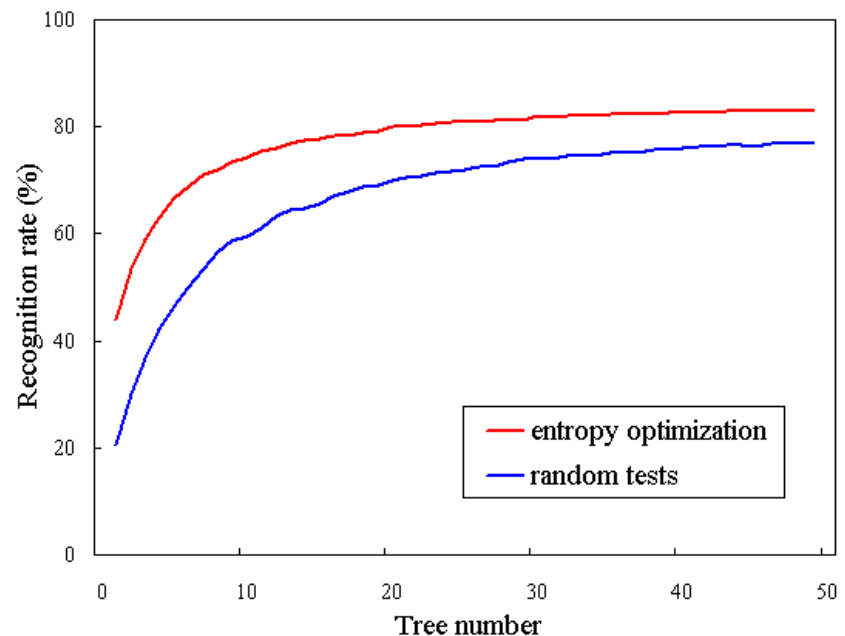
- Usage
 - $c' = \operatorname{argmax}_c p_c(\mathbf{p})$
 - If $p_{c'}(\mathbf{p}) > T_{c'}$, \mathbf{p} is inlier
 - Otherwise, \mathbf{p} is outlier

Experimental Results

- Comparing two tree building methods with or without orientation normalization
- Parameters: 200 keypoints, tree depth = 12, patch size = 32, 1000 view sets (200 x 1000 patches) for training and test trees
- Recognition rate $R = \# \text{ of correctly recognized patches} / \# \text{ of total test patches}$
- Tree building time: few seconds for random tests, tens of minutes for entropy opt.



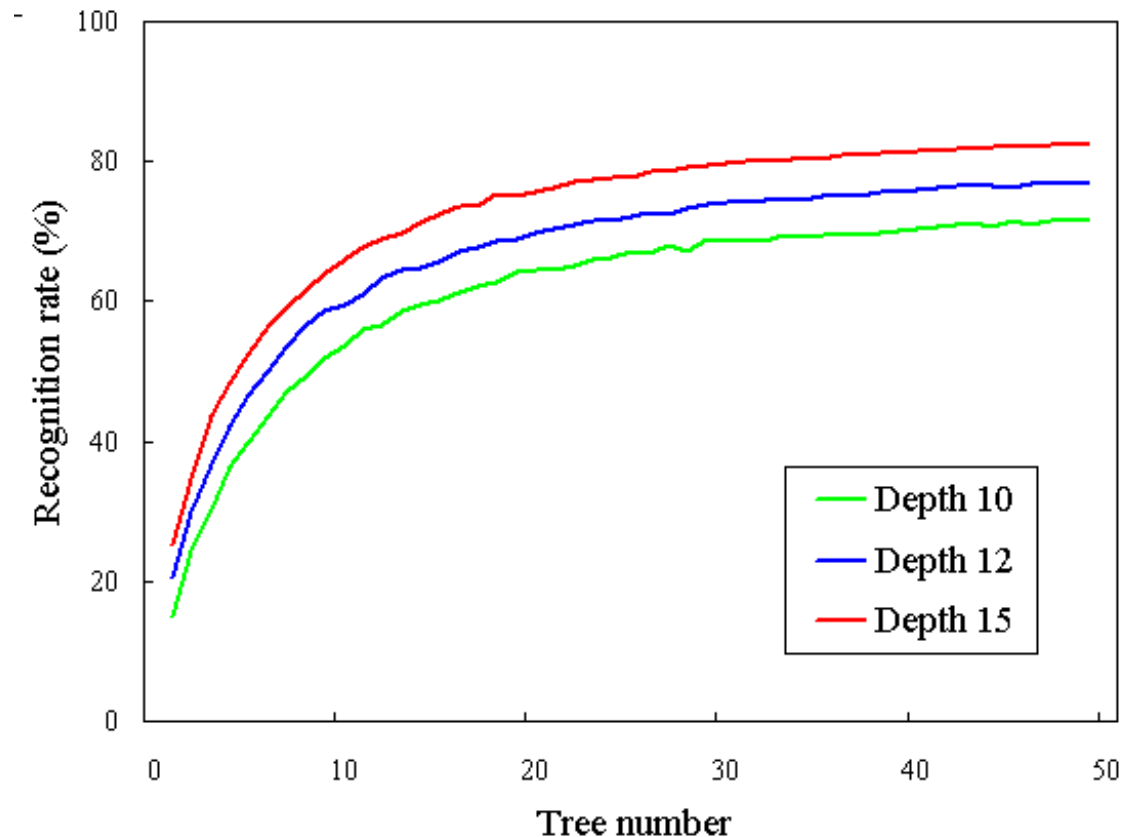
Without orientation normalization



With orientation normalization

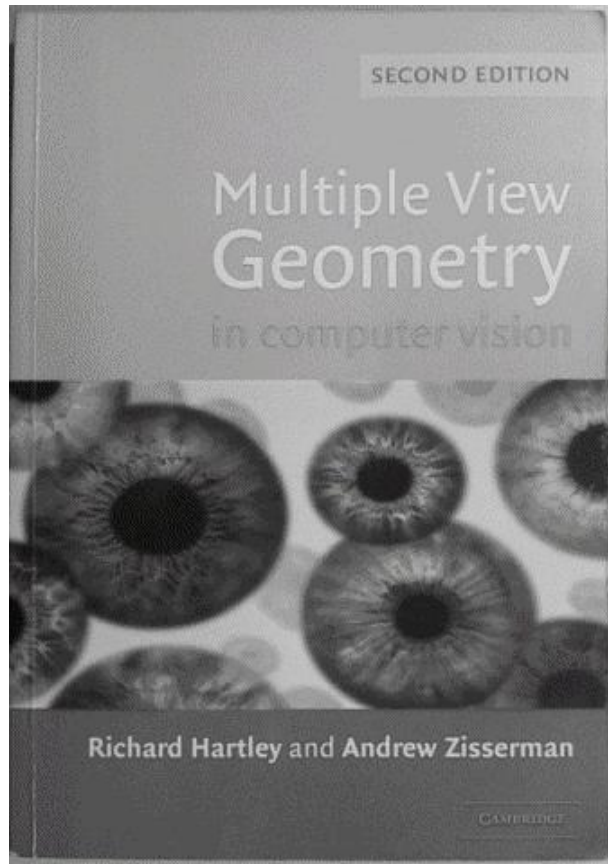
Experimental Results

- Testing the effect of the tree depth
- Parameters: 200 keypoints, 1000 view sets (200 x 1000 patches) for training and test trees



Experimental Results

- Real time object detection and pose estimation test
- Parameters: 400 keypoint, tree depth = 12, tree number = 15, patch size = 32
- Get nearest neighbor by classification tree
- Affine fitting using RANSAC, followed by homography estimation



**About 3 min for learning, under
100 ms for detection for 3.4 Ghz
Pentium machine**

References

- [1] V. Lepetit and P. Fua. Keypoint Recognition using Randomized Trees. *IEEE Trans. Pattern Anal. Machine Intell.*, 28(9):1465–1479, 2006.
- [2] V. Lepetit and P. Fua. Towards Recognizing Feature Points using Classification Trees. EPFL Technical Report, 2004.
- [3] V. Lepetit, J. Pilet, and P. Fua. Point Matching as a Classification Problem. CVPR, 2004.