Computer Vision Systems Programming VO

Object Recognition

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Topics

Taxonomy of recognition problems

Selection of popular applications involving object recognition

Taxonomy of Object Recognition

Instance vs. category recognition

Instance : my face, the Eiffel tower

Category : faces, buildings, people

Taxonomy of Object Recognition

Levels of Recognition – Classification

Predict class of main object in image

Top 5:
pencil sharpener
pool table
hand blower
oil filter
packet

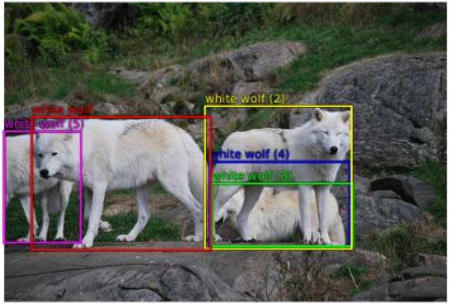
Groundtruth:
pencil sharpener

ILSVRC2012_val_00010000.JPEG

Image from Pierre Sermanet's slides

Taxonomy of Object Recognition
Levels of Recognition – Localization

Predict class and location(s) of main object in image



Groundtruth:
white wolf
white wolf (2)
white wolf (3)
white wolf (4)
white wolf (5)

Image from Pierre Sermanet's slides

Taxonomy of Object Recognition
Levels of Recognition – Detection

Any number of different objects

Groundtruth:
tv or monitor
tv or monitor (2)
tv or monitor (3)
person
remote control
remote control (2)

Image from Pierre Sermanet's slides

Challenges

Instances of same category can look very differently

- Illumination, pose, viewpoint, occlusions, background

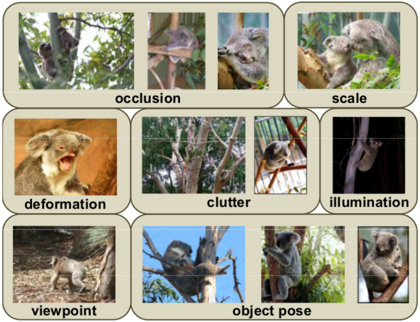


Image from Grauman and Leibe 2011

Instance Recognition

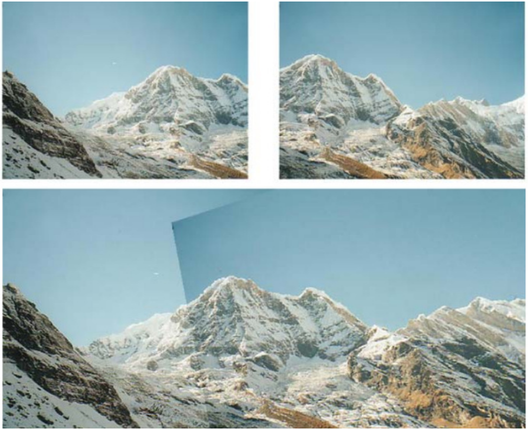


Image adapted from Brown and Lowe 2007

Instance Recognition

Assume that objects are rigid (nonrigid later)

Often accomplished via **local feature matching**

Given an image of the instance and a search image

- Compute local features in both images
- Match features between images to find correspondences
- Perform geometric verification

Local features form a sparse object representation

- Features capture characteristic structure
- Allow for efficient matching between images
- Representation robust to occlusion and clutter

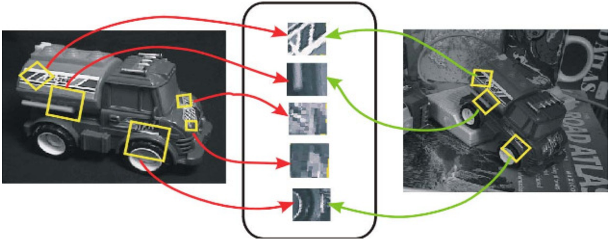


Image from Grauman and Leibe 2011

Many different feature extractors available

- SIFT, SURF, BRISK, FREAK, ...

Notes on feature extractor selection

- Features should be invariant to expected transformations
- But not to other transformations
- Extraction and matching speeds differ

Features are n-dimensional vectors

- Perform nearest neighbor matching in this feature space

Popular matching strategy

- Given feature $\mathbf{x}$ in first image
- Find two nearest neighbors $\mathbf{y}_1, \mathbf{y}_2$ from second image
- $\{\mathbf{x}, \mathbf{y}_1\}$ correspond if $\|\mathbf{x} - \mathbf{y}_1\| / \|\mathbf{x} - \mathbf{y}_2\| < 0.8$

Assume that the object in question is planar

- Images of planar objects are related by a homography
- Also applies to local feature locations

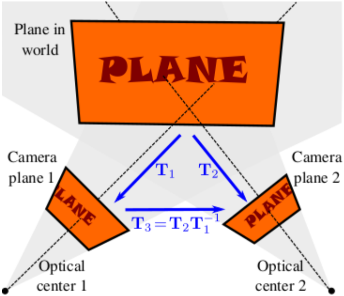


Image from Prince 2012

Relation allows for detecting erroneous correspondences

- Estimate homography T from correspondences
- Discard correspondences for which $\|\mathbf{x} - T(\mathbf{y}_1)\| > t$

Verification also possible for nonplanar scenes

- Epipolar geometry constraints (previous lecture)

Detection and pose estimation of rigid objects

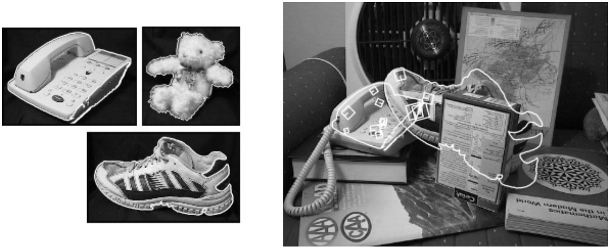
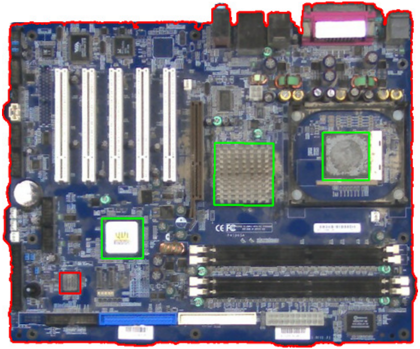


Image adapted from Lowe 2004

Instance Recognition
Applications – Object Detection

Industrial applications like PCB recycling



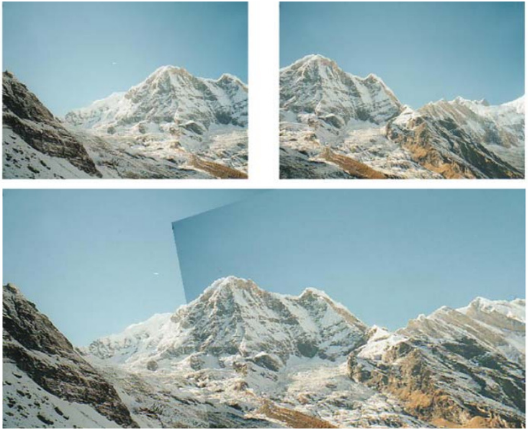


Image adapted from Brown and Lowe 2007

Face Localization

Image from `olympus-europa.com`

Face Localization

Many applications, such as

- Smart cameras (autofocus on faces)
- Security (preprocessing step to face recognition)
- Augmented reality & gaming

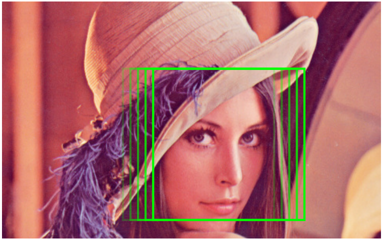
We focus on the popular method from [Viola and Jones 2001]

- Fast enough to run on e.g. cameras

Face Localization
Viola and Jones 2001 – Approach

Sliding window approach

- Slide window over image
- Infer label $w \in \{0, 1\}$ based on measurements $\mathbf{x}$
- Perform non-maximum suppression of confidence scores



Face Localization
Viola and Jones 2001 – Features

Simple features – difference d in rectangular subwindow of $\mathbf{x}$

- Can be computed in constant time using integral images
- Limited number of such features $\{f_t\}_{t=1}^{T}$

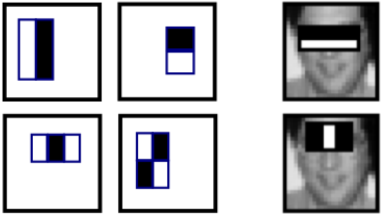


Image adapted from Prince 2012

Classification using a cascading classifier

- Cascade of $K \leq T$ weak but fast classifiers $c_k = f_k > t_k$
- Early rejection of non-face windows for speed
- Final classification is $C(\mathbf{x}) = \text{sign}(w_0 + \sum_k w_k c_k)$

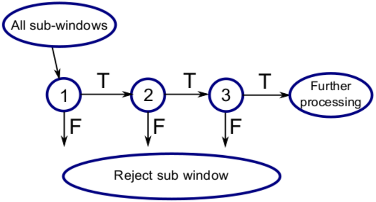


Image from Prince 2012

Face Localization
Viola and Jones 2001 – Classifier

Subset of K classifiers, order, and weights w are learned

Accomplished via **boosting** – for each $k = 1 \cdots K$

- Find best classifier according to training set, set as c_k
- Raise weights of samples misclassified by c_k

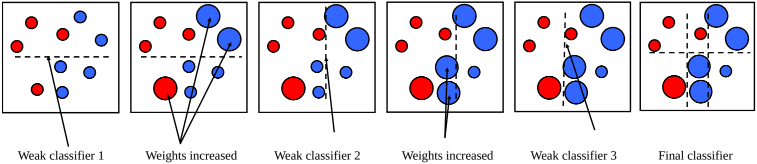


Image from Szeliski 2010

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Bibliography II

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