# Computer Vision Systems Programming VO

## Specific Object Recognition

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# Topics

Introduction to object recognition

Specific object recognition

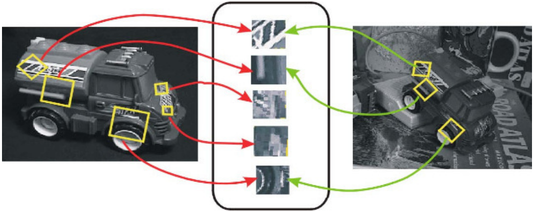


Image from Grauman and Leibe 2011

# Object Recognition

Fundamental problem in Computer Vision

Many applications

- Panorama stitching, 3D reconstruction
- HCI and surveillance (face recognition)
- Image understanding (recall Fei-Fei Li's TED talk)

Instance recognition (specific object recognition)

- Recognize a specific, uniquely looking object
- Face of a certain person, the Eiffel tower

Object category recognition

- Recognize objects of a certain category
- Human faces, buildings

# Object Recognition
## Taxonomy – Instance vs. Category

Object classification

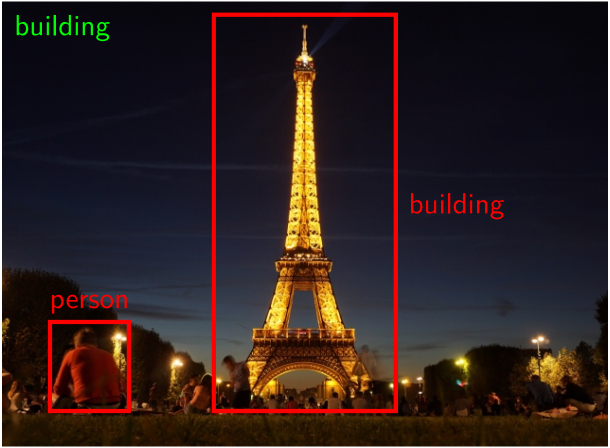
- Recognize main object in image
- Location and other objects not relevant

Object detection

- Recognize multiple objects, possibly of different category

# Object Recognition

## Taxonomy – Classification vs. Detection



# Object Recognition
## Challenges

Instances of same category can look very differently

- Illumination, pose, viewpoint, occlusions, background

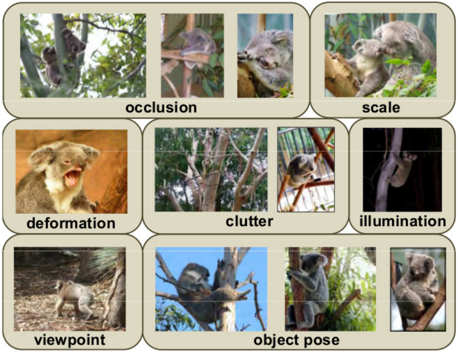



Image from Grauman and Leibe 2011

# Planar Rigid Object Detection

We want to detect specific rigid planar objects

- Like markers, books
- Comparatively easy problem

Challenges

- Unknown object pose and scale
- Varying illumination
- Partial occlusions

# Planar Rigid Object Detection

## Application: Marker-Based AR

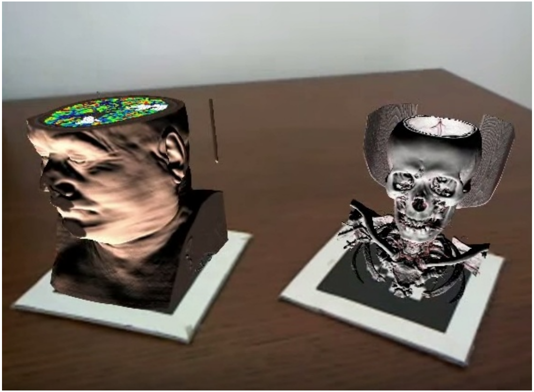


Image from `youtube.com`

# Planar Rigid Object Detection
## Application: Panorama Stitching

Assuming that object is far away (on *plane at infinity*)

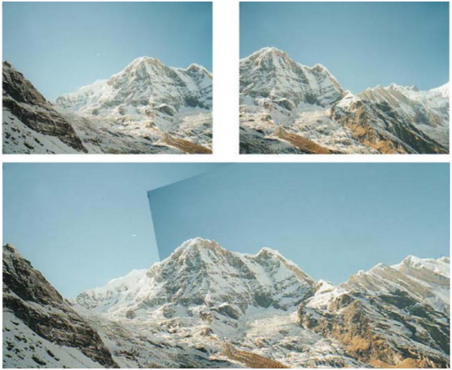


Image adapted from Brown and Lowe 2007

Our problem formulation is

- Given a pixel location in a query image
- Predict location on object surface (image or world)

So we know how to select $\mathbf{x}$ and $\mathbf{w}$

- $\mathbf{x} = (x, y)$ : pixel location in query image
- $\mathbf{w} = (u, v)$ : corresponding location on object surface

As $\mathbf{w} \in \mathbb{R}^2$ this is a regression problem

# Planar Rigid Object Detection
## Selecting $\mathbf{x}$ and $\mathbf{w}$

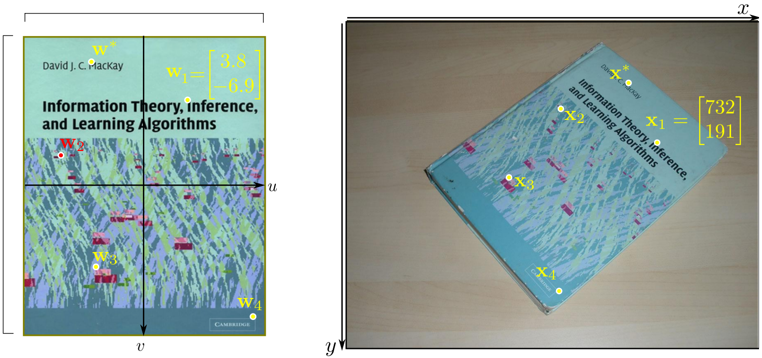



Image adapted from Prince 2012

Images of planar objects are always related by a homography $\mathbf{\Phi}$

- $3 \times 3$ matrix mapping between corresponding points

In homogeneous coordinates this means that

$$\lambda \begin{pmatrix} u \\ v \\ 1 \end{pmatrix} = \mathbf{\Phi} \begin{pmatrix} x \\ y \\ 1 \end{pmatrix}$$

The model of choice is thus (disregarding noise)

$$\mathbf{w} = \Gamma(\mathbf{x}) = \begin{pmatrix} u \\ v \end{pmatrix} \quad , \quad \lambda \begin{pmatrix} u \\ v \\ 1 \end{pmatrix} = \mathbf{\Phi} \begin{pmatrix} x \\ y \\ 1 \end{pmatrix}$$

We again learn parameters $\boldsymbol{\theta}$ from samples $\{(\mathbf{x}_i, \mathbf{w}_i)\}_{i=1}^n$

- $\boldsymbol{\theta}$ contains 9 parameters comprising $\boldsymbol{\Phi}$

Usually no exact solution because of noisy $\mathbf{x}_i$

- Formulate as a least squares problem instead

$$\hat{\boldsymbol{\theta}} = \underset{\boldsymbol{\theta}}{\arg\min} \left[ \sum_{i=1}^{n} (\mathbf{w}_i - \Gamma(\mathbf{x}_i))^\top (\mathbf{w}_i - \Gamma(\mathbf{x}_i)) \right]$$

This least squares approach is optimal

- If noise is distributed normally with spherical covariance

This is a nonlinear optimization problem

- Solvable using any general nonlinear least squares solver
- OpenCV has an own function `findHomography`

$\mathbf{\Phi}$ is a 2D transformation

Where is the object in the world?

- This is called pose estimation
- Required e.g. for marker-based AR like above

This information can be extracted from $\mathbf{\Phi}$

- If we know the intrinsic camera parameters

How can we compute $\{(\mathbf{x}_i, \mathbf{w}_i)\}_{i=1}^{n}$ automatically?

- We first select $\mathbf{w}_i$, then search corresponding $\mathbf{x}_i$

$\mathbf{w}_i$ can be selected

- Manually (e.g. specific corners on markers)
- Automatically (e.g. SIFT)

We opt for the second approach and use SIFT (or similar)

- Features invariant to rotation, scale, illumination
- Robust to affine transformations

Approach

- Compute keypoints and descriptors in both images
- Match descriptors (e.g. nearest neighbor association)
- Use keypoint locations of matches as $\{(\mathbf{x}_i, \mathbf{w}_i)\}_{i=1}^{n}$

There will likely be incorrect matches

- Would greatly impact the least squares solution
- Hence we use a robust alternative like RANSAC

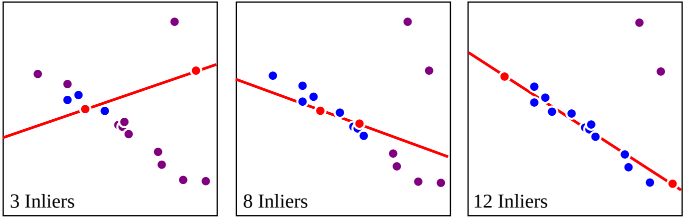



Image adapted from Prince 2012

# Planar Rigid Object Detection

## Obtaining Point Correspondences Using OpenCV

```
// read images (SIFT expects grayscale images)
cv::Mat object = cv::imread("object.jpg", cv::IMREAD_GRAYSCALE);
cv::Mat search = cv::imread("search.jpg", cv::IMREAD_GRAYSCALE);

cv::SIFT sift; // using default arguments here

// compute keypoints
std::vector<cv::KeyPoint> kobject, ksearch;
sift.detect(object, kobject); sift.detect(search, ksearch);

// compute descriptors
cv::Mat dobject, dsearch;
sift.compute(object, kobject, dobject); sift.compute(search, ksearch, dsearch);
```

# Planar Rigid Object Detection
## Obtaining Point Correspondences Using OpenCV

```
// find two nearest neighbors x,x' for each w
cv::FlannBasedMatcher matcher; // fast nearest neighbor search
std::vector<std::vector<cv::DMatch> > kMatches;
matcher.knnMatch(dobject, dsearch, kMatches, 2);

// keep match (x,w) if x is clearly more similar than x'
// this is a popular matching strategy
std::vector<cv::DMatch> matches;
for(const std::vector<cv::DMatch>& match : kMatches)
    if(match[0].distance < match[1].distance * 0.8) // x, x'
        matches.push_back(match[0]); // (x,w)
```

# Planar Rigid Object Detection

## Learning Homography Parameters Using OpenCV

```
// collect feature locations of correspondences from before
std::vector<cv::Point2f> pobject, psearch;
for(const cv::DMatch& match : matches) {
    pobject.push_back(kobject.at(match.queryIdx).pt);
    psearch.push_back(ksearch.at(match.trainIdx).pt);
}

// estimate homography using RANSAC for robustness
cv::Mat inliers; // contains indices of valid correspondences
cv::Mat homography = cv::findHomography(pobject, psearch, CV_RANSAC, 2, inliers);
```

# Nonplanar Rigid Object Detection

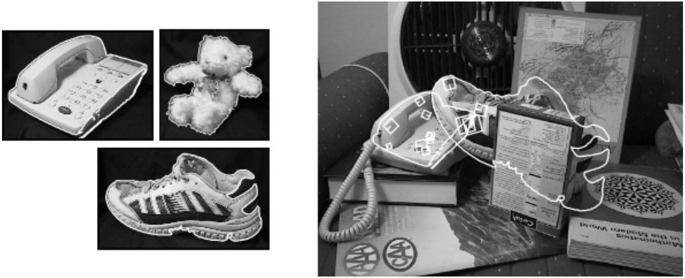
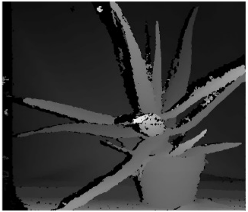


Image adapted from Lowe 2004

# Nonplanar Rigid Object Detection

## Stereo



# Nonplanar Rigid Object Detection

## Structure from Motion

Image from https://www.youtube.com/watch?v=sQegEro5Bfo

# Nonplanar Rigid Object Detection

## Selecting $\mathbf{x}$ and $\mathbf{w}$

We use the same problem formulation as before

- Given a pixel location in an image $\mathbf{x}$
- Predict location on (nonplanar) object surface $\mathbf{w}$

As object is no longer planar, we have $\mathbf{w} = (u, v, w)$

- Location in another image can be computed easily

In this case $\mathbf{x}$ and $\mathbf{w}$ are related by the pinhole camera model

- Generalization of the homography model

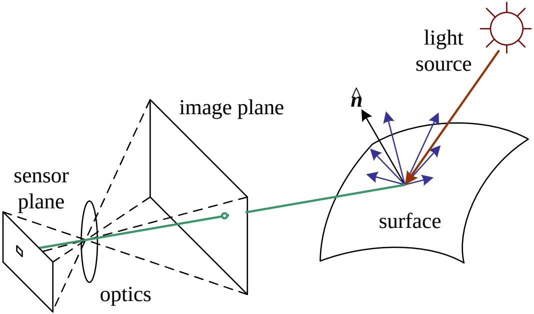



Image from Szeliski 2010

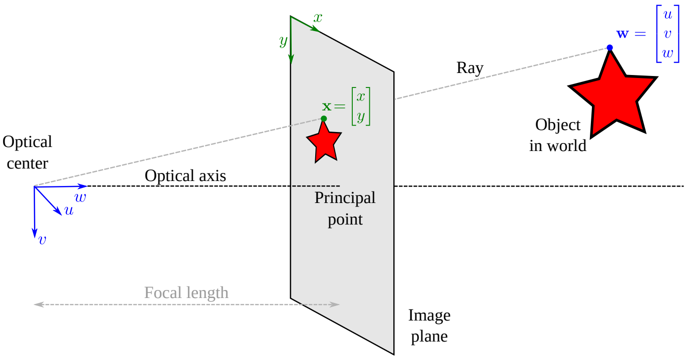



Image adapted from Prince 2012

We see that in homogeneous coordinates

$$\lambda \begin{pmatrix} x \\ y \\ 1 \end{pmatrix} = \begin{pmatrix} f & 0 & p_x & 0 \\ 0 & f & p_y & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix} \begin{pmatrix} u \\ v \\ w \\ 1 \end{pmatrix}$$

With the intrinsic parameters

- $f$ : focal length in pixels
- $p_x, p_y$ : principal point coordinates

World and camera coordinate systems generally differ

- Transform $\mathbf{w}$ to camera coordinates before projection

$$\mathbf{w}' = \begin{pmatrix} u' \\ v' \\ w' \end{pmatrix} = \begin{pmatrix} \omega_{11} & \omega_{12} & \omega_{13} \\ \omega_{21} & \omega_{22} & \omega_{23} \\ \omega_{31} & \omega_{32} & \omega_{33} \end{pmatrix} \begin{pmatrix} u \\ v \\ w \end{pmatrix} + \begin{pmatrix} \tau_u \\ \tau_v \\ \tau_w \end{pmatrix}$$

The extrinsic parameters $\tau$ and $\omega$ encode translation and rotation

We combine this for the full pinhole camera model

- Standard camera model in Computer Vision

$$\lambda \begin{pmatrix} x \\ y \\ 1 \end{pmatrix} = \begin{pmatrix} f & 0 & p_x & 0 \\ 0 & f & p_y & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix} \begin{pmatrix} \omega_{11} & \omega_{12} & \omega_{13} & \tau_u \\ \omega_{21} & \omega_{22} & \omega_{23} & \tau_v \\ \omega_{31} & \omega_{32} & \omega_{33} & \tau_w \\ 0 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} u \\ v \\ w \\ 1 \end{pmatrix}$$

We again learn the parameters from samples $\{(\mathbf{x}_i, \mathbf{w}_i)\}_{i=1}^{n}$

- Using RANSAC and least squares like before
- OpenCV has own functions `solvePnP`, `solvePnPRansac`

Assume we have two images of the object

Let $\mathbf{x}_1, \mathbf{x}_2$ be the projections of $\mathbf{w}$ in these images

Assume we know the camera parameters (Slide 35) but not $\mathbf{w}$

In this case $\mathbf{x}_2$ must lie on the epipolar line of $\mathbf{x}_1$ (and vice versa)

Points on this line fulfill $\tilde{\mathbf{x}}_2^\top \mathbf{E}\,\tilde{\mathbf{x}}_1 = 0$

- Here $\tilde{\mathbf{x}}_i$ is $\mathbf{x}_i$ in homogeneous coordinates
- $\mathbf{E}$ is called essential matrix (encode extrinsic relationship)

# Nonplanar Rigid Object Detection
## Obtaining Point Correspondences

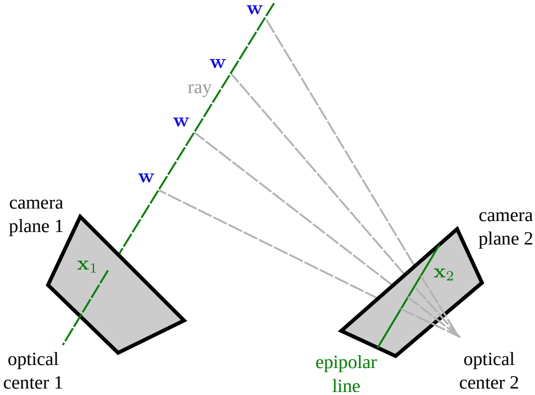



Image adapted from Prince 2012

We can now proceed as follows

- Select points $\{\mathbf{x}_1^i\}_{i=1}^n$ (every pixel, keypoint locations)
- For each $\mathbf{x}_1^i$, search for $\mathbf{x}_2^i$ on the epipolar line of $\mathbf{x}_1^i$
- If we have $\mathbf{x}_2^i$, we can compute $\mathbf{w}_i$ via triangulation

# Nonplanar Rigid Object Detection
## Obtaining Point Correspondences

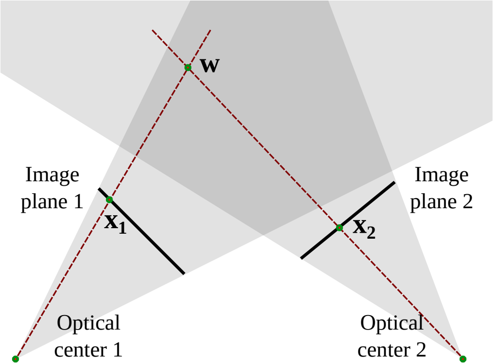



Image adapted from Prince 2012

This is the typical stereo pipeline for 3D reconstruction

```
# dense stereo in OpenCV (Python), left and right are rectified
imgL = cv2.pyrDown(cv2.imread('left.jpg'))
imgR = cv2.pyrDown(cv2.imread('right.jpg'))
stereo = cv2.StereoSGBM(...) # args depend on images
disparity = stereo.compute(imgL, imgR)
```

But what if we do not know the camera parameters?

- Why we wanted to compute $\{(\mathbf{x}_i, \mathbf{w}_i)\}_{i=1}^{n}$ in the first place

If we know only the intrinsics, we can estimate the extrinsics

If not, we can estimate the fundamental matrix $\mathbf{F}$

- Corresponding points must fulfill $\tilde{\mathbf{x}}_2^\top \mathbf{F}\, \tilde{\mathbf{x}}_1 = 0$
- Metric reconstruction of $\mathbf{w}$ no longer possible

# Nonplanar Rigid Object Detection
## Remarks

With 3 or more images we can estimate all parameters and $\mathbf{w}$

Camera parameters and $\mathbf{w}$ influence each other

- We want to jointly optimize all parameters and all $\mathbf{w}$
- This technique is called bundle adjustment

Lecture 183.129 has more 3D vision

# Nonplanar Rigid Object Detection
## Remarks

We have treated 3D reconstruction as an object detection problem

- Somewhat unorthodox but fits in nicely

This approach to object detection is powerful but has limitations

- Slow, less robust if images are very dissimilar (Slide 27)
- Alternatives more popular if “coarse” detection suffices

# Nonplanar Nonrigid Object Detection

What about *general* specific object recognition?

- Living things are neither planar nor rigid

Image from attackofthecute.com

Constellation models can be used for this

- Describe object as set of parts and their spatial relations

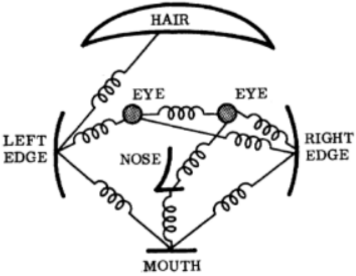



Image from Fischler and Elschlager 1973

We first select $\mathbf{x}$ and $\mathbf{w}$

- $\mathbf{x}$ : features encoding the appearance of part $i$
- $\mathbf{w} = (u, v)$ : location of part $i$ in the image

We define a generative probabilistic model

- $\Pr(\mathbf{x}_i|\mathbf{w}_i)$ encodes appearance information
- $\Pr(\mathbf{w}_i|\mathbf{w}_j)$ encodes spatial information

And the overall probability as (assuming $n$ parts)

$$\Pr(\mathbf{x}_1, \ldots, \mathbf{x}_n | \mathbf{w}_1, \ldots, \mathbf{w}_n) = \prod_{i=1}^{n} \Pr(\mathbf{x}_i | \mathbf{w}_i) \prod_{j,k} \Pr(\mathbf{w}_j | \mathbf{w}_k)$$

Finally we again

- Specify the distributions $\Pr(\mathbf{x}_i|\mathbf{w}_i)$ and $\Pr(\mathbf{w}_i|\mathbf{w}_j)$
- Learn the parameters $\boldsymbol{\theta}$ from training data

This overall distribution is hard to compute

So we draw samples instead

- For each part $i$ find locations $\mathbf{w}$ for which $\mathrm{Pr}(\mathbf{x}_i|\mathbf{w}_i) > t_i$
- Evaluate the overall distribution for all combinations $\mathbf{w}_j, \mathbf{w}_k$
- Pick the $\mathbf{w}_1 \cdots \mathbf{w}_n$ with the maximum likelihood

This blows up quickly

- With $m$ candidate locations per part we have $O(m^n)$
- But if the relation graph is acyclic this reduces to $O(m^2 n)$

Work well if shape change is limited

- Not for cats, but for faces, upright human bodies

If we have lots of data, CNNs often perform best

- We will cover CNNs in next lecture

Outperform humans (!) in face verification

- Given two images, do they depict same person?
- Important for HCI, security applications

# Bibliography I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Lowe, David G (2004). *Distinctive image features from scale-invariant keypoints*.

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# Bibliography II

Szeliski, Richard (2010). *Computer vision: algorithms and applications*. Springer.