

Computer Vision Systems Programming VO Specific Object Recognition

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Topics

Introduction to object recognition

Specific object recognition (rigid, nonrigid)

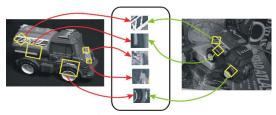


Image from Grauman and Leibe 2013



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)



Taxonomy – Instance vs. Category

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



Taxonomy – Instance vs. Category



Taxonomy - Classification vs. Detection

Object classification

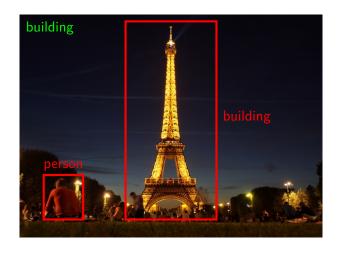
- Recognize main object in image
- Location and other objects not relevant

Object detection

Recognize multiple objects, possibly of different category



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



We want to detect specific planar objects (e.g. markers, books)

Comparatively easy problem

Challenges

- Unknown object pose and scale
- Partial occlusions
- Illumination





Image from youtube.com



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

Our problem formulation is

- Given a pixel location in a query image
- Predict location in reference image of sought object

So we know how to select x and w

- $\mathbf{x} = (x, y)$: location in query image
- $ightharpoonup \mathbf{w} = (u,v)$: corresponding location in reference image

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



Specific Planar Object Detection Model Selection

Images of planar objects are always related by a homography Φ

lacksquare 3 imes 3 matrix mapping between corresponding points

In homogeneous coordinates this means that

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

Specific Planar Object Detection Model Selection

The model of choice is thus (disregarding noise)

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

Learning Model Parameters

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

lacktriangledown definition of eta contains 9 parameters comprising $oldsymbol{\Phi}$

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

► Formulate as a least squares problem instead

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



Specific Planar Object Detection Learning Model Parameters

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



But how can we compute $\{\mathbf x_i, \mathbf w_i\}_{i=1}^n$ automatically?

Next lecture



Bibliography

Grauman, Kristen and Bastian Leibe (2011). *Visual object recognition*. Morgan & Claypool.

Prince, S.J.D. (2012). *Computer Vision: Models Learning and Inference*. Cambridge University Press.

