



Computer Vision: The Quick Tour

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Outline



- Introduction to Computer Vision [20 minutes]
 - What, why, why not?
- Camera Model and Geometry [20 minutes]
- Problems in Computer Vision
 - Recovering world geometry [20 minutes]
 - Reorganizing images [20 minutes]
 - Detection and Recognition [20 minutes]
- Questions and Discussions [10 minutes]

What is Computer Vision?



- Understanding of visual inputs (images/videos) by computers.
- Making sense out of them. Describing them.
- Does computer vision mimic the human vision?
 - Certainly in many of its goals
 - Why? Human vision is among the best!
 - Sophisticated and efficient but not understood well
- Should computers process visual inputs like humans?

Not necessarily!

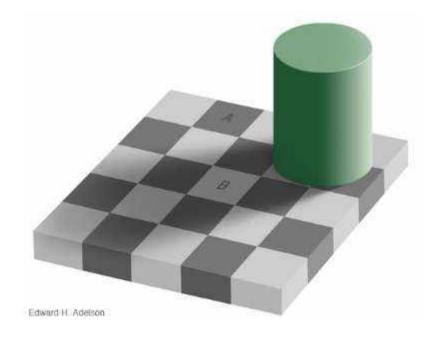
- Human visual system need not limit computer vision
- We draw inspiration from it as often as is convenient

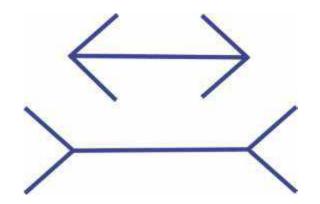
Human perception has its shortcomings...





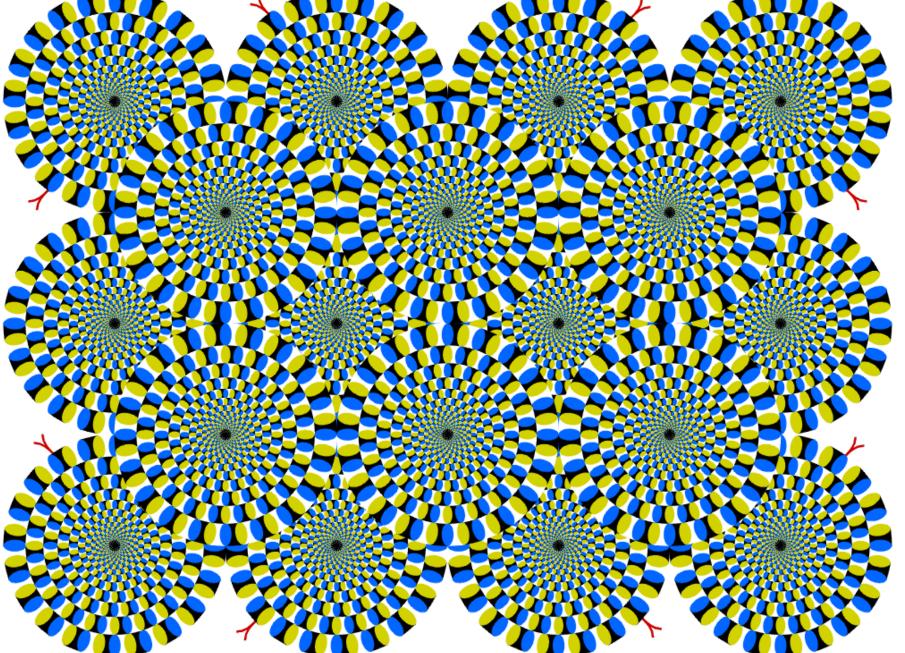
Sinha and Poggio (Image: Ron Rensick)











Three "Urges" on seeing a Picture*



1. To group proximate and similar parts of the image into meaningful "regions".

Called segmentation in computer vision.

2. To connect to memory to recollect previously seen "objects".

Called recognition in computer vision.

3. To measure quantitative aspects such as number and sizes of objects, distances to/between them, etc.

Called reconstruction in computer vision.

The Three Rs of Computer Vision



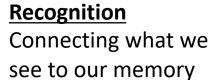
Reorganization (Segm.)





Group semantically similar pixels





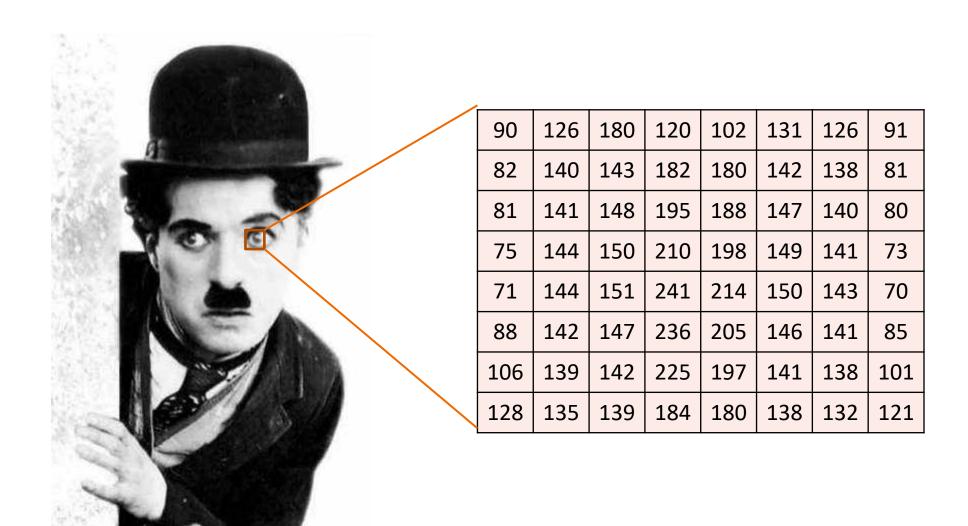


Reconstruction Measure/recreate a

3D model of what we see in the world

Why is it Difficult?





Computer Vision



 Goal: Extract all possible information about a visual scene by computer processing

What? When? Where? Who? How? Why? How many?

- Over 50% of the brain is devoted to vision for humans.
 - Must be important to us!
- Why is it difficult?

Chairs and Chairs

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- Which are chairs?
- Large intra-class variations
- How do we describe a chair?
- Basic property: Sittability!
- We infer a lot from pictures.
 Can we instruct a computer to do the same?
- Do we understand how we infer?



















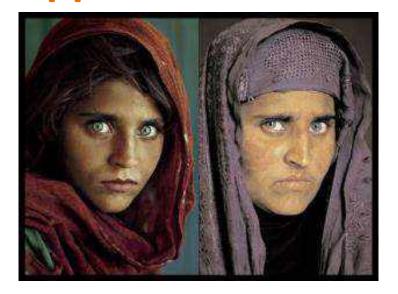
Why Automated Vision?

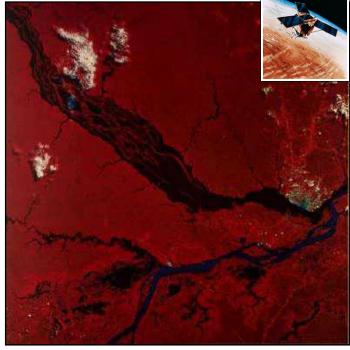


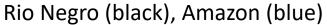
- 1. High reliability
- 2. High repeatability
- 3. More objective evaluation
- 4. Lower cost
- 5. Higher speed
- 6. Ability to operate in hazardous environments

General purpose machine vision system do not exist.

Applications

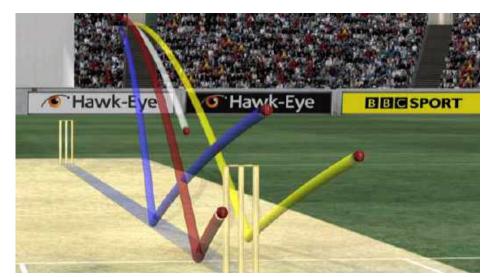






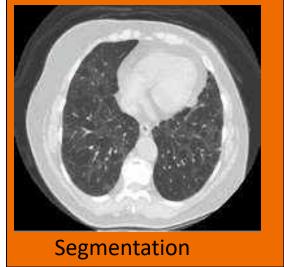






Ball Tracking: Hawk Eye









Manual vs. Automated PCB Inspection

And many many more...



- Surveillance
- Automated Assembly
- Mail Sorting
- Face detection (photography)
- Robot Navigation
- Content-Based Info. Retrieval
- Movies
- Logistics
- Traffic control

- Automotive Safety
- Medical Diagnostics
- Building Automation
- Gaming
- Broadcasting (infographics)
- Crowd Control
- Agriculture
- •

and last bust not the least...

Autonomous Navigating Cars

The Real Problem











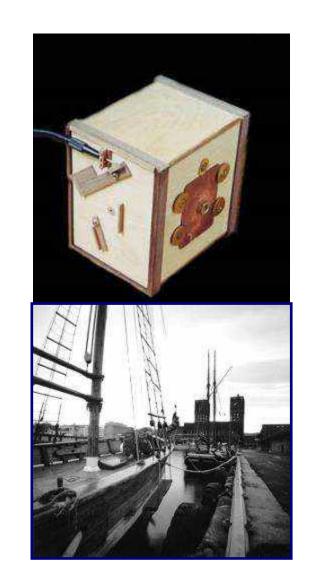




Outline

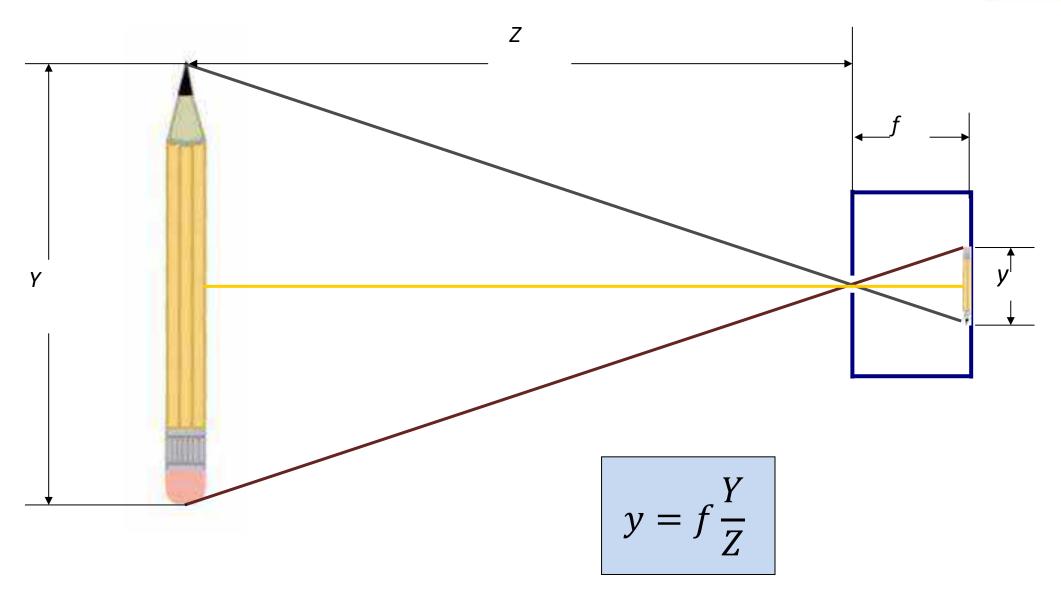


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- Questions and Discussions [10 minutes]



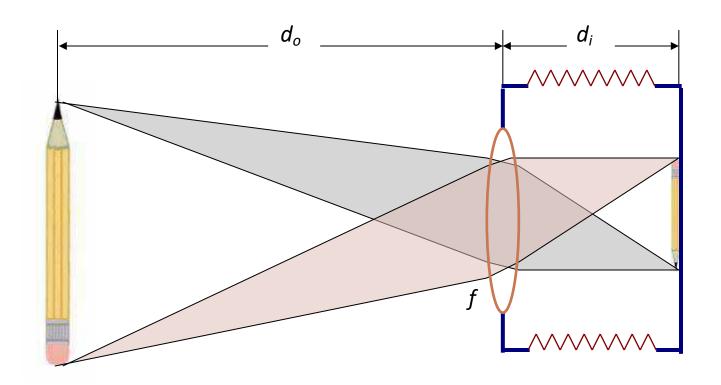
The Pinhole Camera







Camera with Lens



Thin lens equation:
$$\frac{1}{f} = \frac{1}{d_o} + \frac{1}{d_i}$$

$$d_i = f \frac{d_o}{(d_o - f)}$$

Focus and DOF

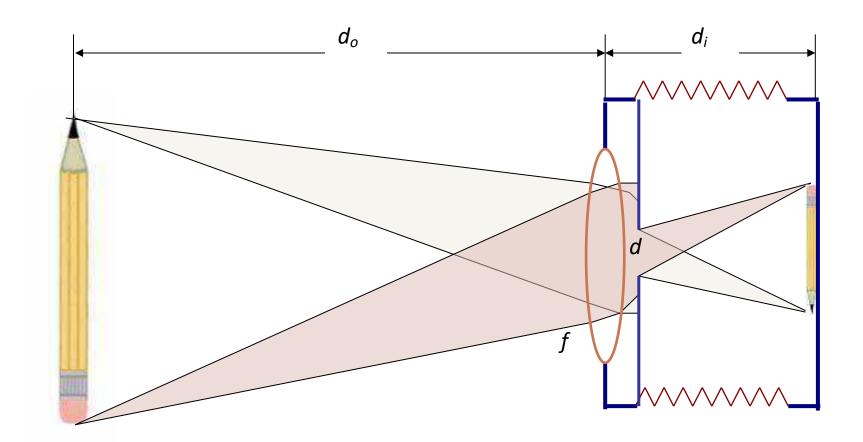








Aperture

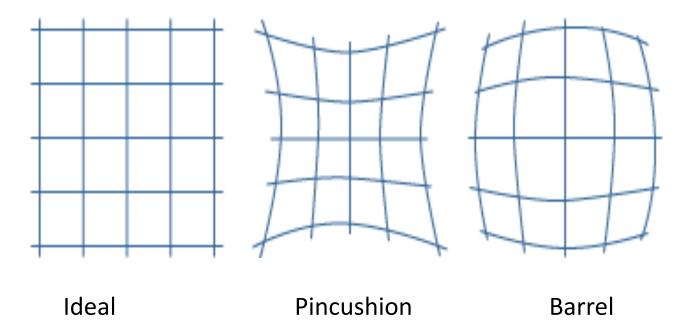


Focal Ratio = f/d





Geometric Distortions

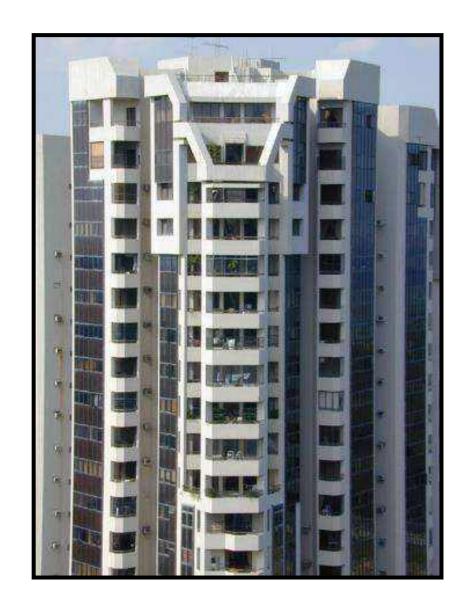








Geometric Distortions

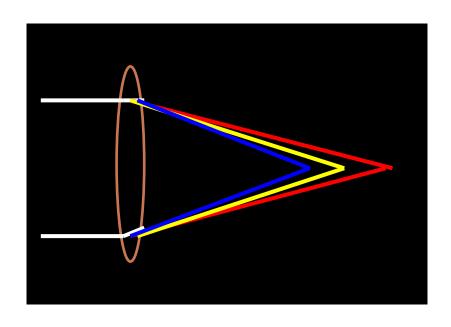






Chromatic Aberration

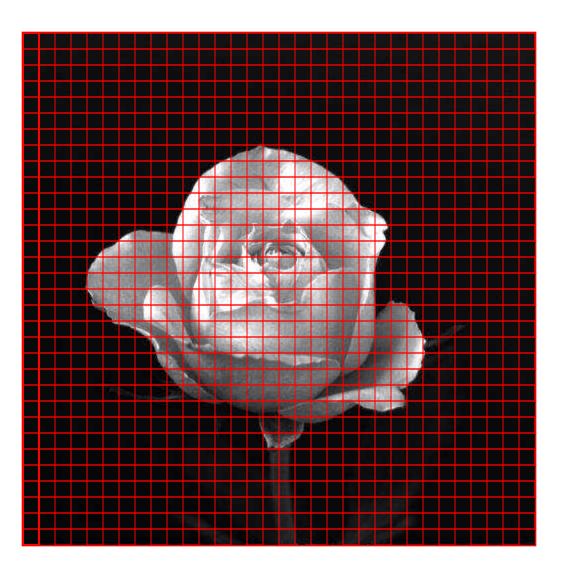
Normal lenses diffract different wavelengths to different degree







Sampling an Image: Resolution

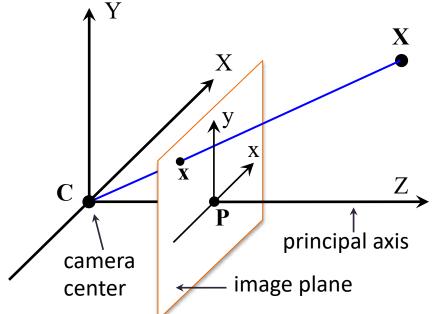




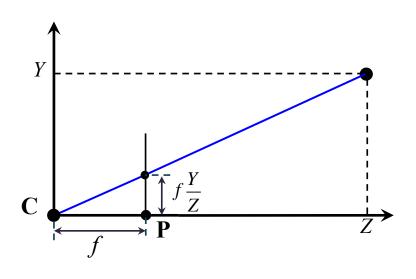
The Camera: A Mathematical Model







Cartesian imagé coordinates:



$$x = f \frac{X}{Z}, \qquad y = f \frac{Y}{Z}$$

• In matrix form (homogeneous):

$$\mathbf{x} = \begin{bmatrix} x \\ y \\ w \end{bmatrix} = \begin{bmatrix} f & 0 & 0 & 0 \\ 0 & f & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix} = \mathbf{PX}$$

Note:

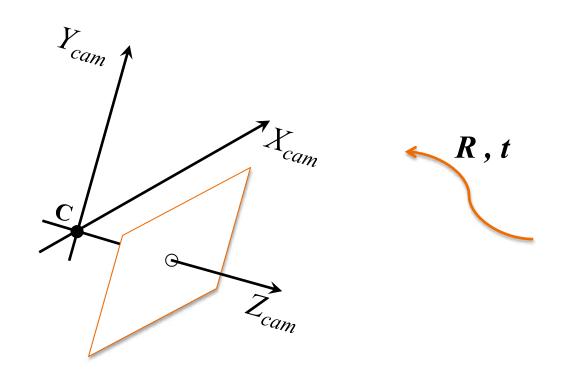
- Camera at origin, Z axis along look vector
- Orthogonal Image axes
- Uniform scale

Moving the Camera from Origin



General Setting: Camera is not at origin and Z is not the optical axis.

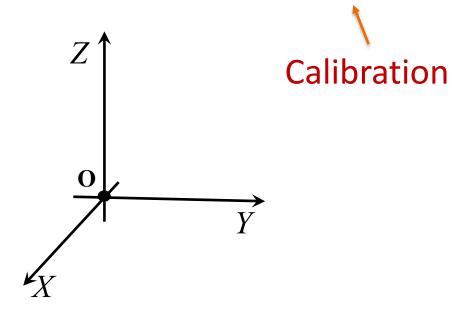
Camera is at a point C in world coordinates. The camera axes are also rotated by a matrix R.



In General,

•
$$\mathbf{x} = \mathbf{P}\mathbf{X}_{\mathbf{w}}$$

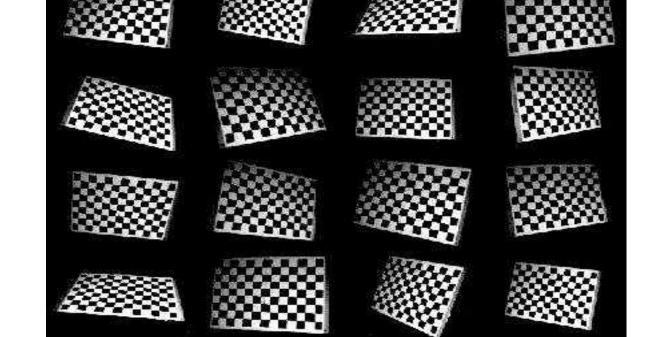
• Camera matrix P = K [R | t]

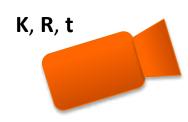


Calibration Methods



- 1. 3D Reference Object based calibration
- 2. Calibration from a precisely moving plane (R.Y. Tsai)
- 3. Calibration using a plane with unknown motion





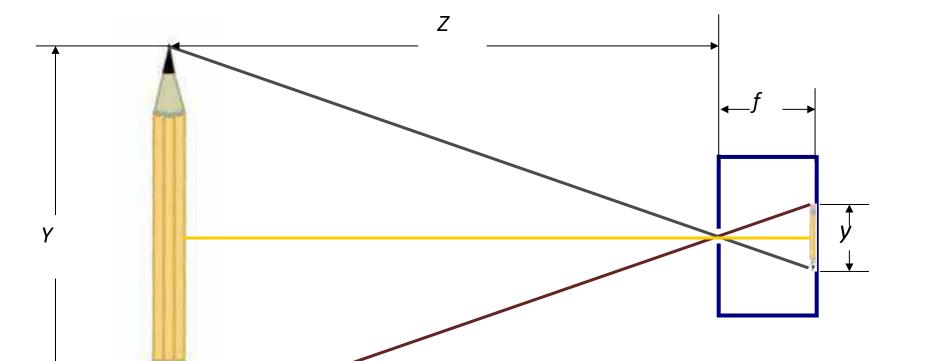
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The Pinhole Camera



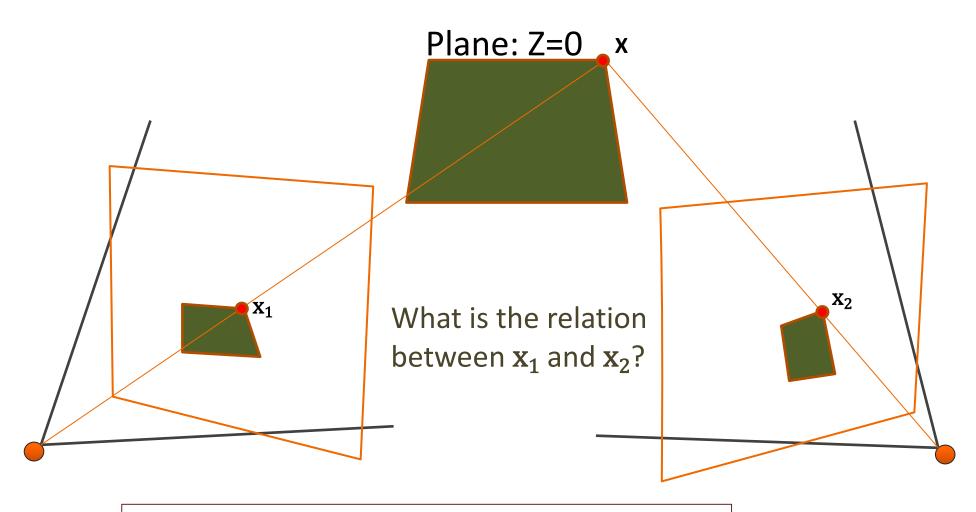


 You have taken a picture of a building from 100 meters away using a camera of focal length 20mm. The height of the image is 10mm.

What is the height of the building?

Two-View Geometry: Planar World





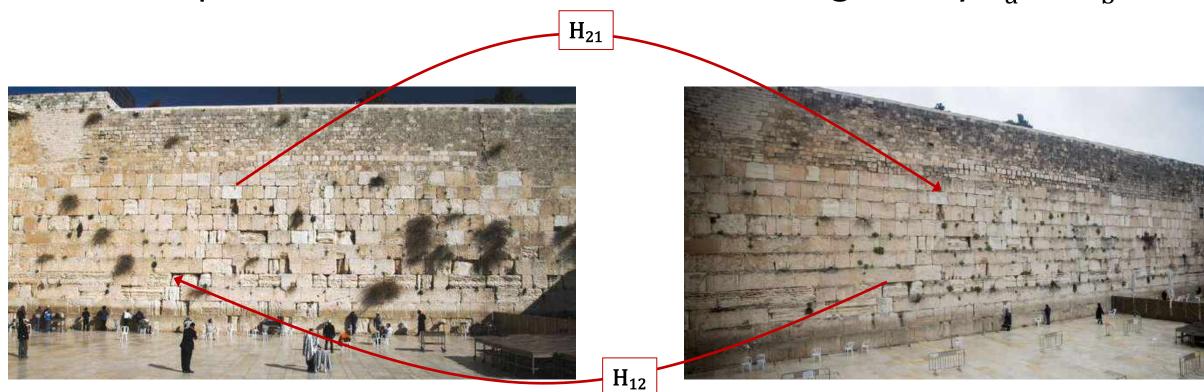
$$\mathbf{x}_1 = \mathbf{H}_{12}\mathbf{x}_2; \quad \mathbf{x}_2 = \mathbf{H}_{21}\mathbf{x}_1$$

where H is a 3×3 non-singular matrix

Planar Homography



• Given two images of a planar world, every pixel in an image can be computer from the other. Its location is given by $x_a = Hx_b$

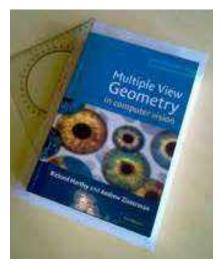


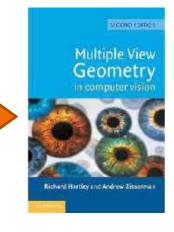
Planar Homography: Applications

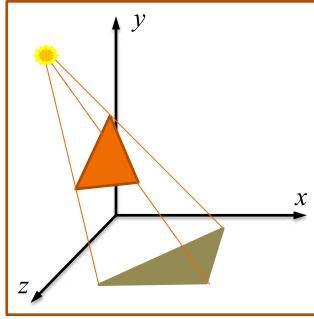
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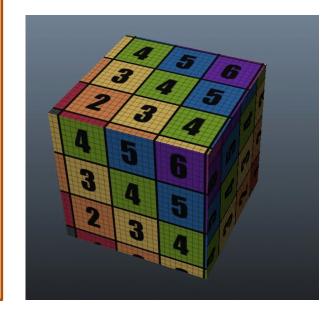
- Removing perspective distortion
- Rendering planar textures
- Rendering planar shadows
- Estimating Camera Pose; AR





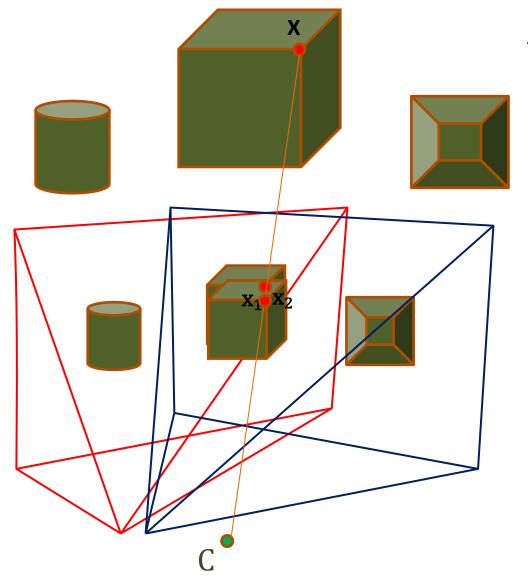






Two-View; Case 2: Same Camera Center





Arbitrary world

What is the relation between x_1 and x_2 ?

$$\mathbf{x}_1 = \mathbf{H}_{12}\mathbf{x}_2; \qquad \mathbf{x}_2 = \mathbf{H}_{21}\mathbf{x}_1$$

where H is a 3×3 non-singular matrix

Homography: Applications



- Image Mosaicing
- Detecting camera translation
- Multi-frame Super-resolution





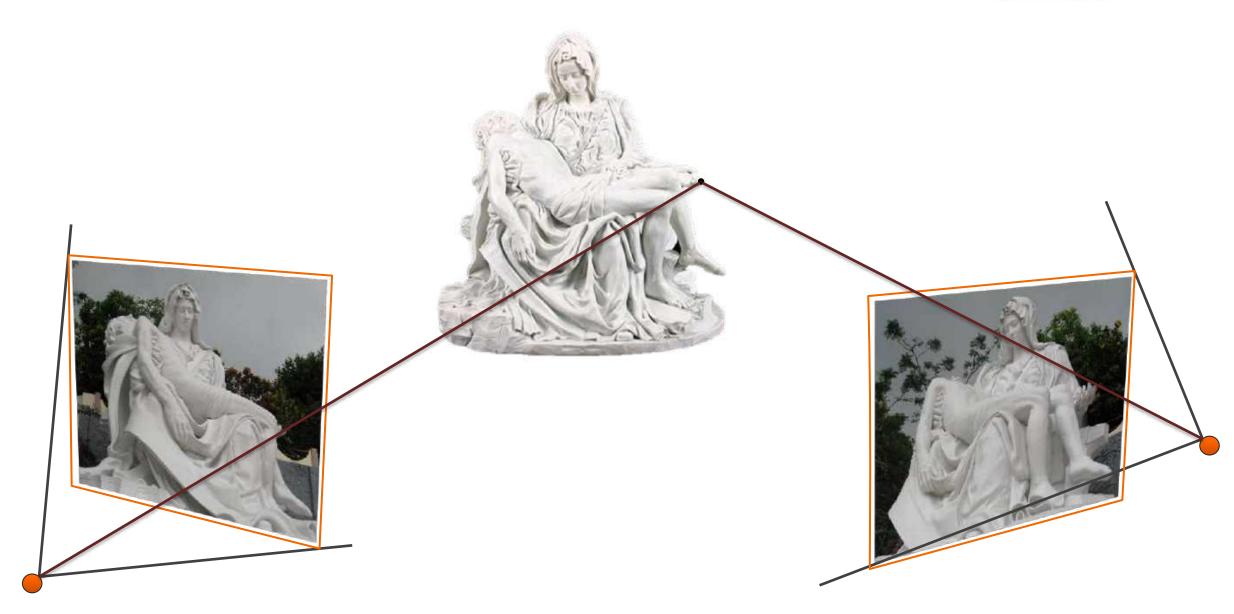






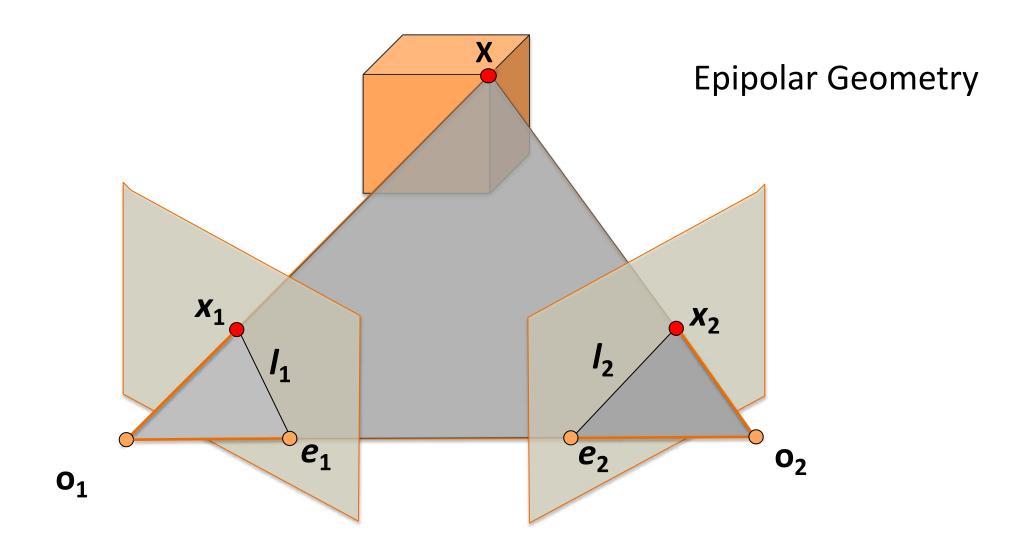
Case 3: Generic 3D World and Cameras





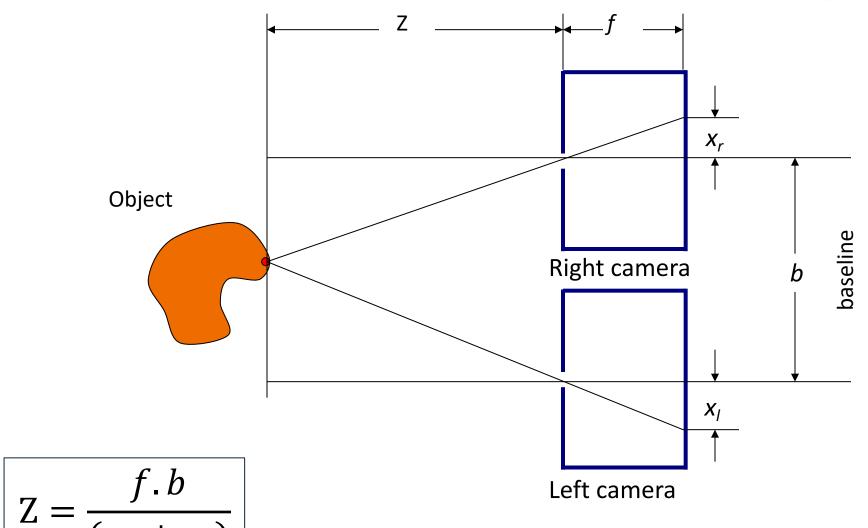
Case 3: Generic 3D World and Cameras





Stereo

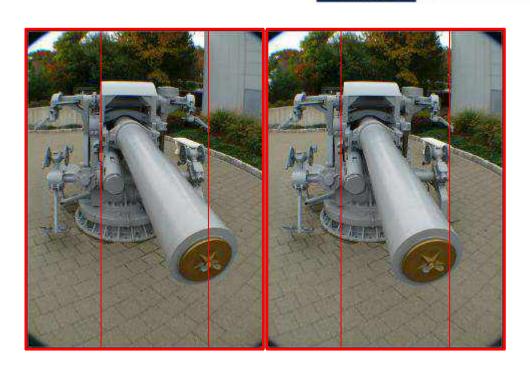




Stereo Geometry

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- Farther the point, smaller the disparity and vice versa
- A large baseline can give more reliable estimates of depth.
 However, matching becomes harder
- Basic step: Identify common points in the two camera views
 - How do we find the images of a single world point in two views?
 - Search for similar appearance
 - Use Epipolar Geometry to reduce search



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Thresholding



Decide each pixel to be part of an object or background depending on its gray value

$$t(m,n) = \begin{cases} 1 & \text{if } u(m,n) > T \\ 0 & \text{if } u(m,n) \le T \end{cases}$$



Original



Thresholded (T=95)

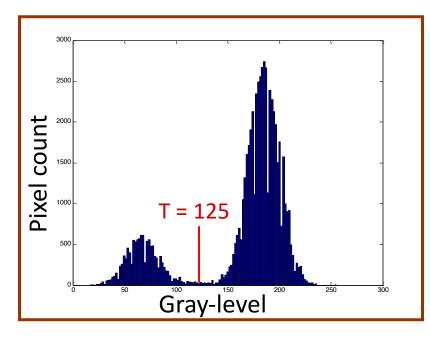
Histogram and Segmentation



A count of pixels of each graylevel (or range of graylevels) in an image



Grayscale Image



Histogram



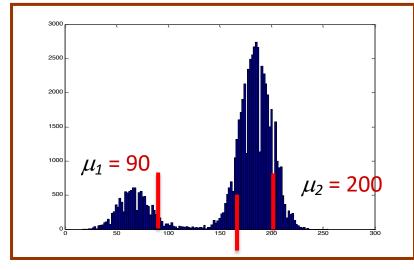
Thresholded (T=125)

Automatic Thresholding

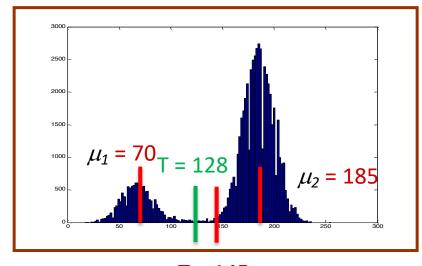
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- 1. Select an initial estimate of T
- 2. Segment the image using T. Compute the mean gray values of the regions, μ_1 and μ_2
- 3. Set the new threshold $T=(\mu_1+\mu_2)/2$
- 4. Repeat 2 and 3 until T stabilizes

Assumptions: normal distribution, low noise



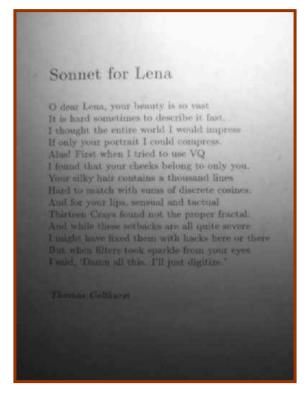




T = 145

Adaptive Thresholding

e.g., Chow & Kaneko Thresholding:



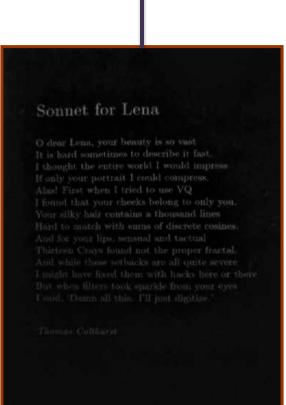




Sonnet for Lena

Thomas Coltharst

O dess. Lens., your benefit in so wast.
It is hard superious to describe it fast.
I shought the entire world. I would impress.
If only your portrait, I could compress.
Alas? Ernet when I tried to use VQ.
I found that your cheeds belong to only you.
Your silk; hair contains a thousand lines.
Hard to mark with sums of discress contains.
And for your lips, remaind said the trial.
Thirtees, Cross, bound not the proper fractal.
And while those websides are all quite severe.
Lingids have fixed them, with has the ever of then
But when librar took spatish from your eyes.
Load. This on this, I 23 jour lingings.



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Original Single Threshold

Low-pass filtered

Difference

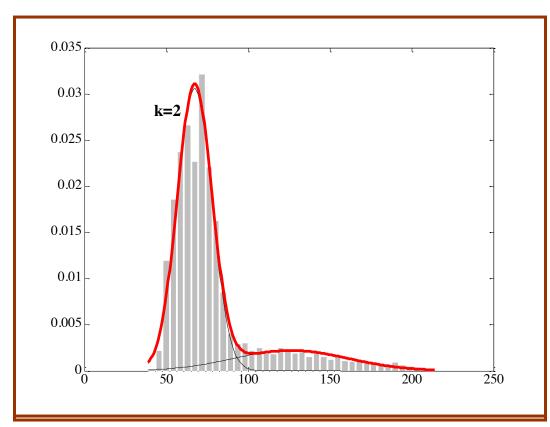
Optimal Thresholding



• The graylevel histogram is approximated using a mixture of two gaussians and threshold chosen to minimize the segmentation error



Grayscale Image



Histogram with bimodal fit

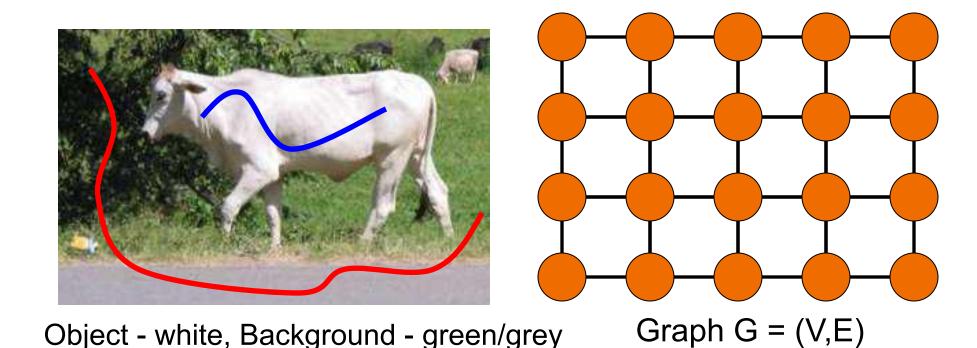


Thresholded (T=94)

Graph Cuts for Binary Image Segmentation





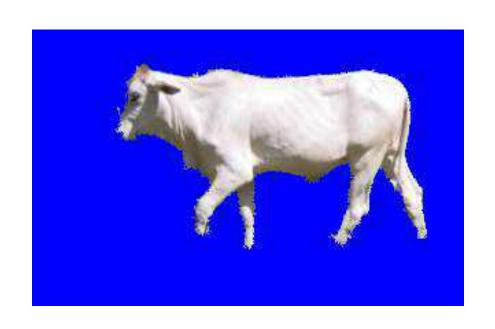


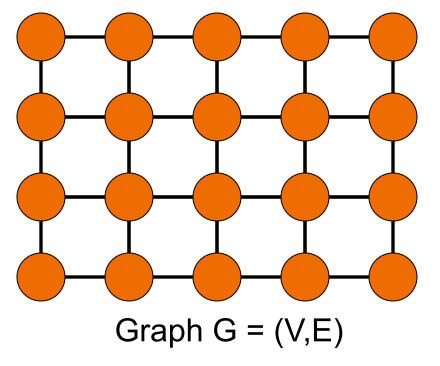
Q(f;
$$\theta$$
) = $\sum_{a} \theta_{a;f(a)} + \sum_{(a,b)} \theta_{ab;f(a)f(b)}$
Pairwise Potential

Problem: Find the labeling with minimum cost f*

Graph Cuts for Binary Image Segmentation







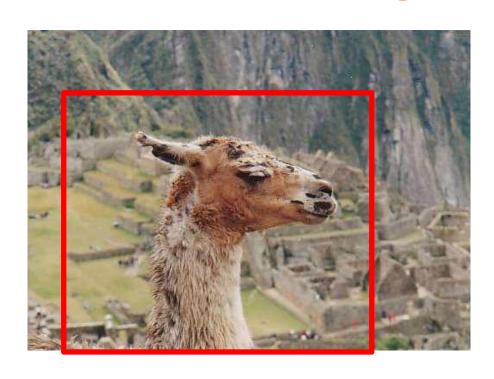
$$L = \{fg, bg\}$$

Vertex corresponds to a pixel Edges define grid graph

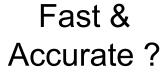
Several other methods to optimize over the graph (MRF)

GrabCuts: An Intelligent Extension











- Less user input: only rectangle
- Handle color
- Extract matte as post-process



"Grabcut: Interactive Foreground Extraction using Iterated Graph Cuts", by Rother, Kolmogorov and Blake, Siggraph 2004.

Approach: Iterated Graph Cuts





User Initialisation



Learn foreground color model



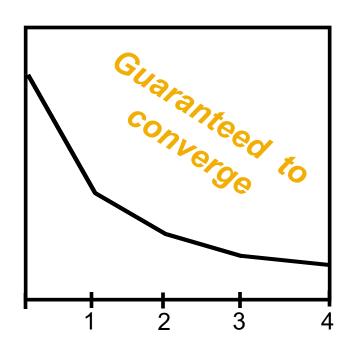
Graph cuts to infer the foreground



Iterated Graph Cuts







Result

Energy after each Iteration

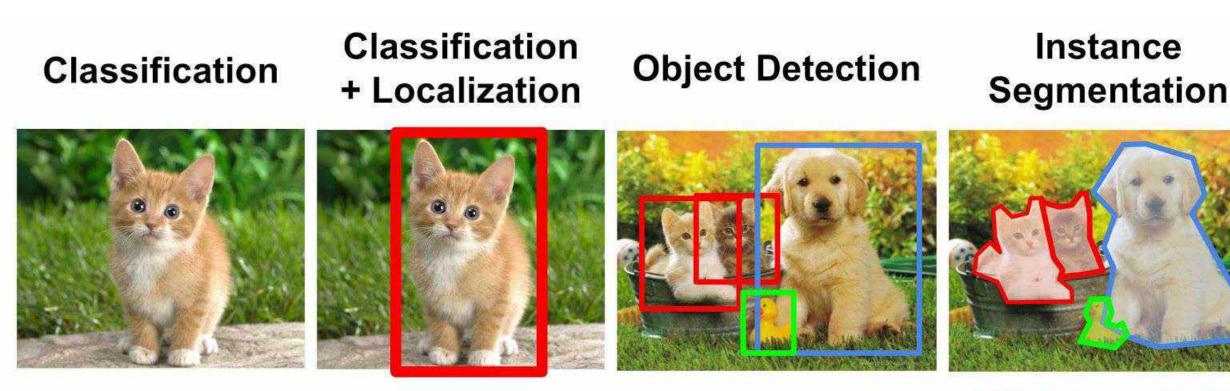


Semantic and Instance Segmentation

CAT



CAT, DOG, DUCK



Single object

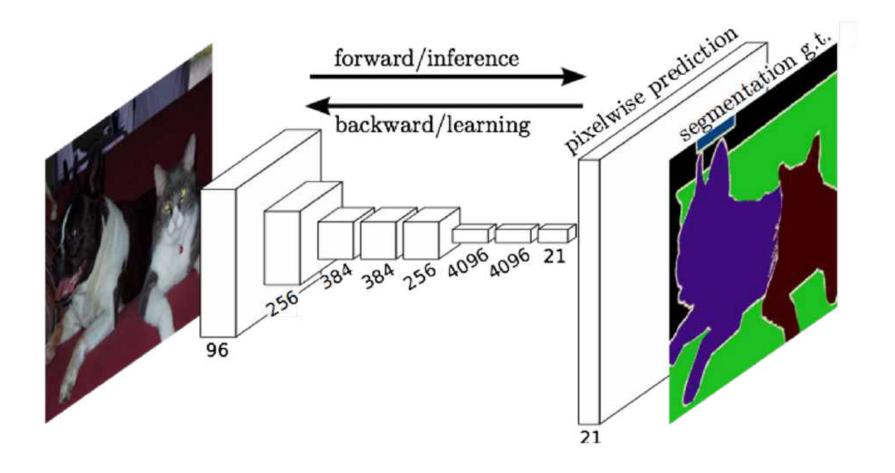
Multiple objects

CAT, DOG, DUCK

CAT

FCN for Semantic Segmentation



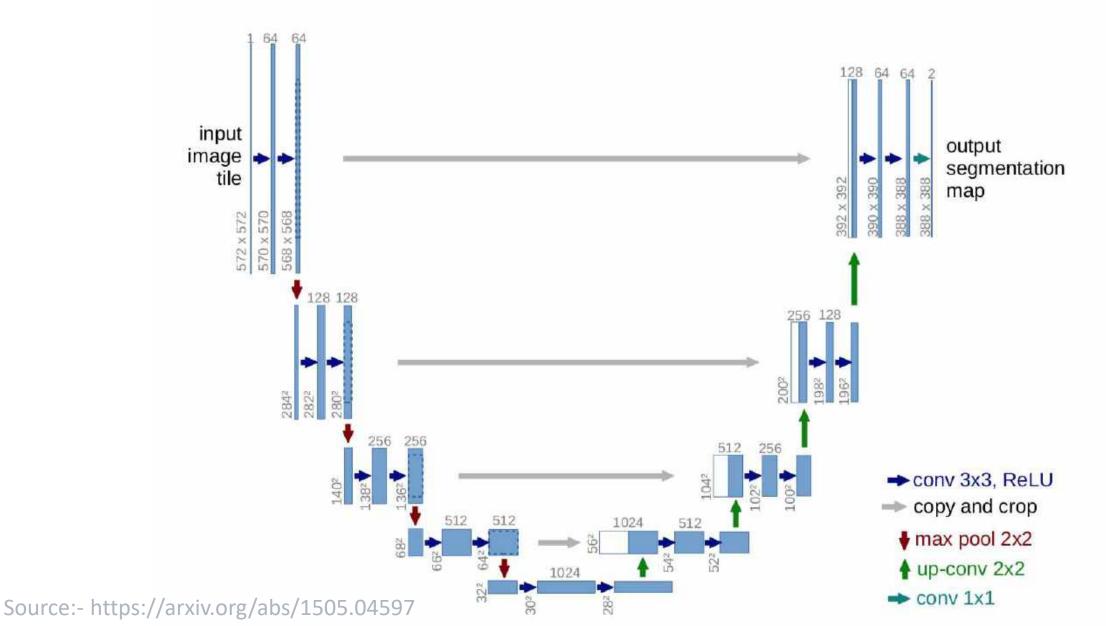


- Challenge: Segmentation = Classification + Localization
- Classification needs larger context and location invariance
- Localization needs sensitivity to location

Unet: Skip Connections







DeepLab V3+: Dilation, Spatial Pyramids, Depthwise Sep.

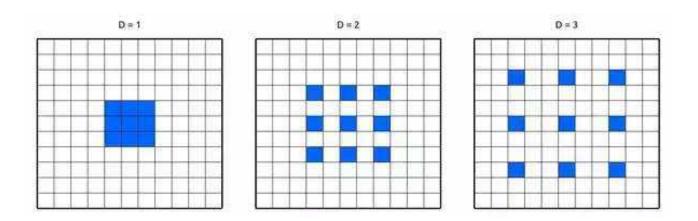


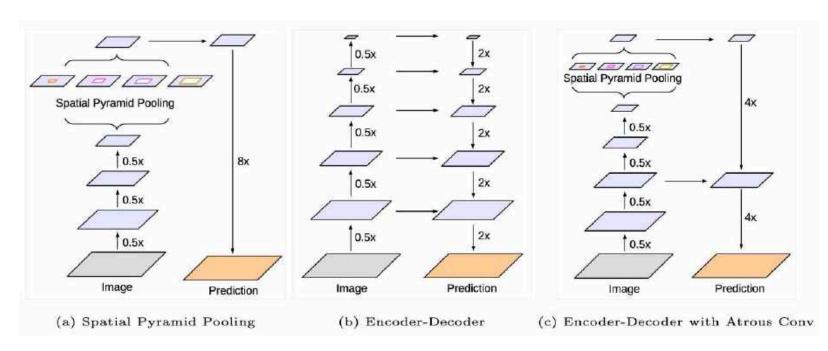


Atrous Convolutions

Spatial Pyramids + Enc-Dec + Atrous Conv.

Depth-wise Separable Conv. (Xception Model)



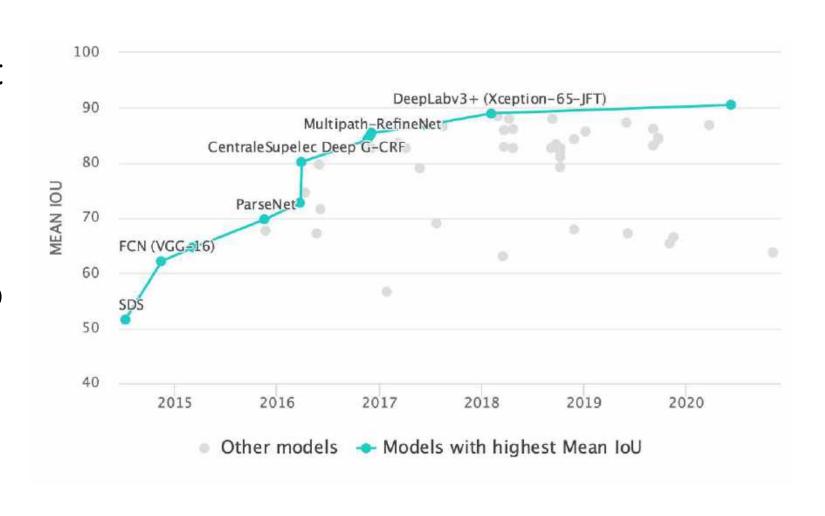


Evolution of Segmentation





- GCN: Larger Kernels,
 Boundary Refinement
- CRF for regularization
- Better Training
 - Self Training
- Use of LSTM for video segmentation



Applications



- Portrait Mode
- Background removal in online meetings
- Virtual Makeup, Virtual Try-on
- Monocular Depth Estimation
 - Autonomous Navigation
 - Map Generation
- Image Editing

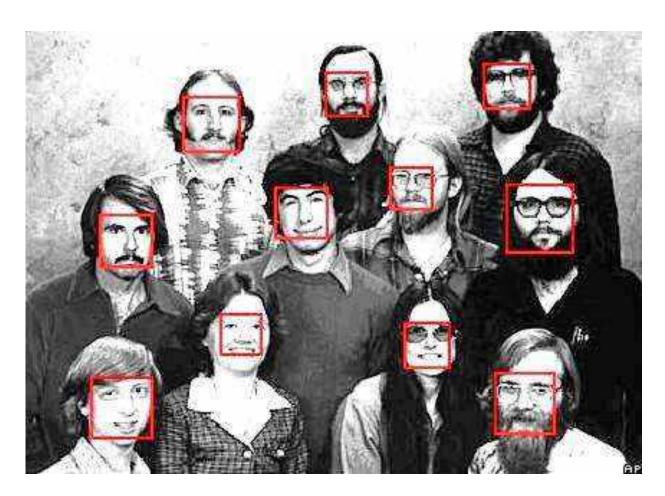
Outline

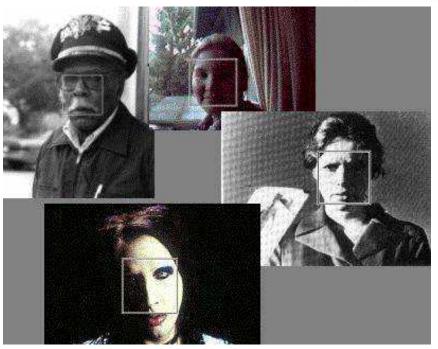


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The Task: Say Face Detection









Approach 1: Classify Each Window



Slide a window across image and evaluate a face model at every location



How Many Windows (Speed)



1280×1024 image;
 24×24 to 1024×1024
 windows



- # of Windows?
 - ~ 1 million locations
 - 18 scales/window sizes at 1.25 multiples
 - 14.5 million potential face candidates
 - Features to be extracted for each candidate window

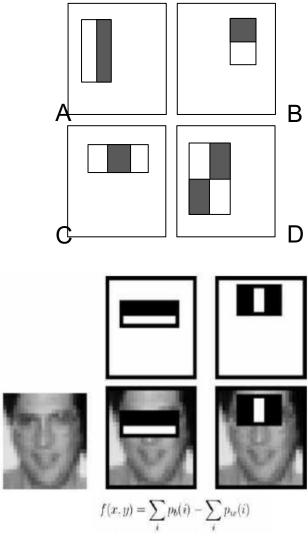




- Classify each as face or non-face
 - What should be the accuracy (False Positive Rate)?
- Faces are rare: 0-10 per image
 - For computational efficiency, we should try to spend as little time as possible on the non-face windows
 - To avoid having a false positive in every image, the false positive rate has to be less than 10⁻⁶

The Viola/Jones Face Detector

- A seminal approach to real-time object detection
- Key ideas
 - Haar Features + Integral images for fast feature evaluation
 - Attentional cascade for fast rejection of non-face windows



- P. Viola and M. Jones. *Rapid Object Detection using a Boosted Cascade of Simple Features*. CVPR 2001.
- P. Viola and M. Jones. *Robust Real-Time Face Detection*. IJCV 57(2), 2004.

Approach 2: Generate a few Region Proposals





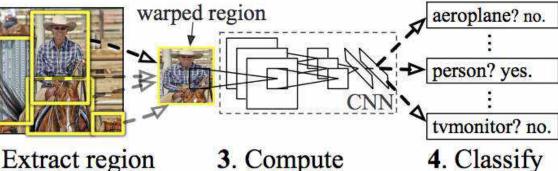
R-CNN: Regions with CNN features



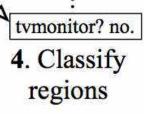
1. Input image

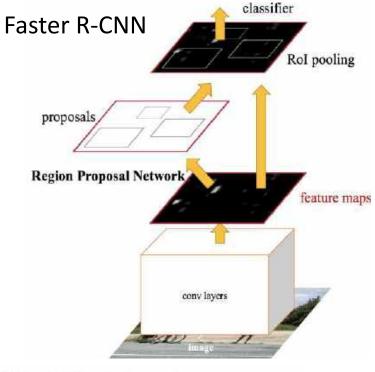


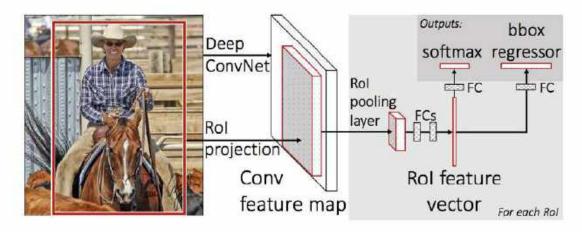
2. Extract region proposals (~2k)



CNN features

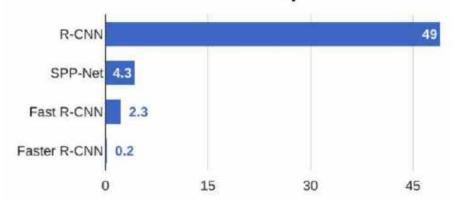






Fast R-CNN

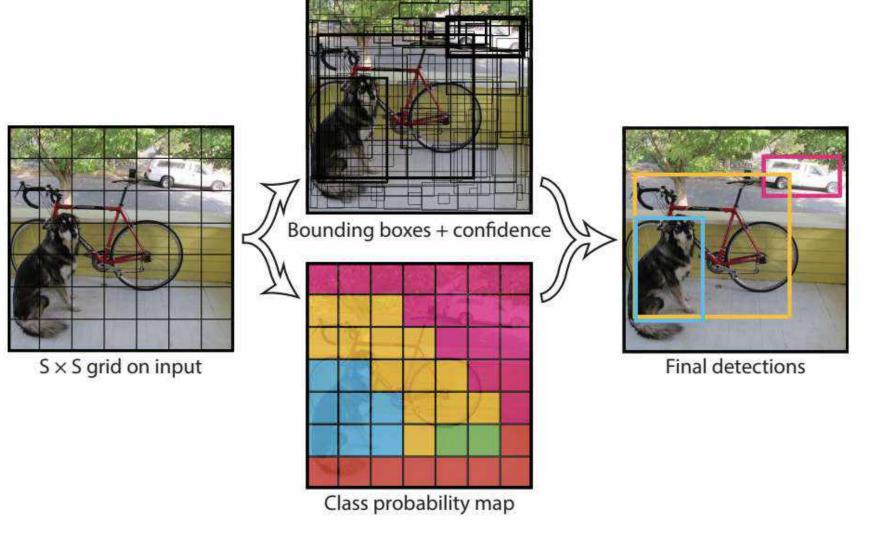
R-CNN Test-Time Speed



Approach 3: Single Stage for Speed



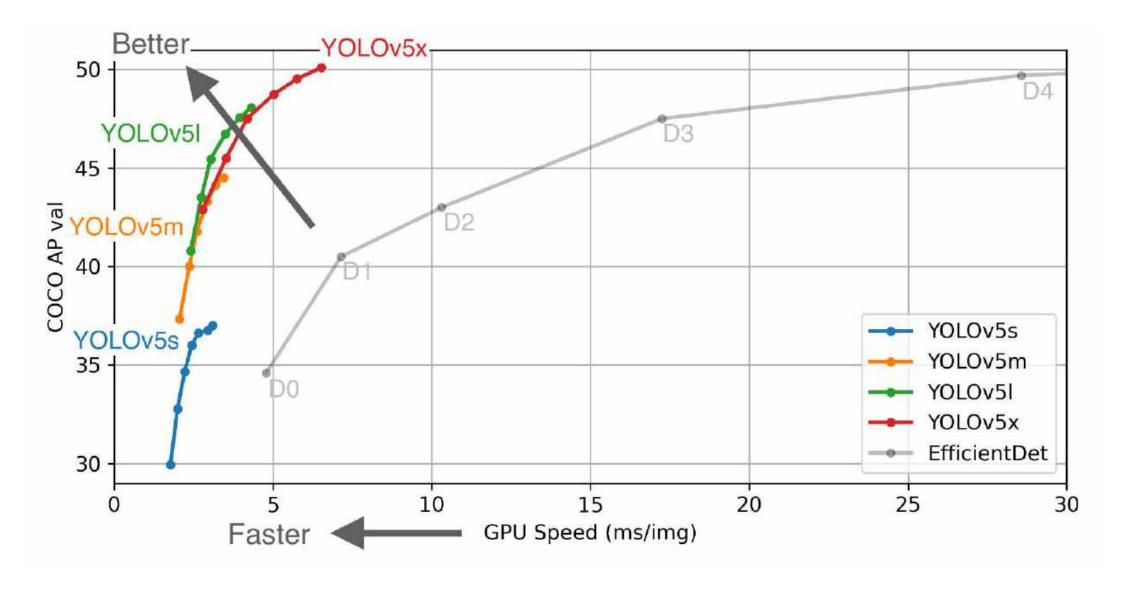
- YOLO v1 .. v5
- SSD
- RetinaNet
- Efficient-Det



Accuracy vs. Speed of Detection







Further Reading



- Most modern approaches is a potpourri of different Network
 Architectures, Additional Connections, Normalizations, Activations, Data
 Augmentation, Regularization, Spatial Attention, Training strategies, etc.
- Most popular Dataset: MS-COCO
- Nice Summary of Approaches:
 - Alexey Bochkovskiy, Chien-Yao Wang, Hong-Yuan Mark Liao, "YOLOv4: Optimal Speed and Accuracy of Object Detection"

A few other topics in Computer Vision



- Photometry & Radiometry
 - Model Surface Properties
 - Measurement, Inspection, ...
- Computational Imaging
 - Computational Illumination
 - Computational Optics
 - Modified/Simplified Sensors
 - Post Processing
- Shape-From-X
 - Multi-View
 - Single Image
 - Other Cues

- Video Processing
 - Video Prediction
 - Behaviour Classification
- Image Generation
 - Graphics + Vision
 - GANs
- Application Areas
 - Biometrics
 - Robotics
 - Medical Image Analysis
 - **—** ...



Thanks!!

Questions?