

Computer Vision - Lecture 17

Epipolar Geometry & Stereo Basics

19.01.2016

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Announcements

Exam Dates

> 1st try: 29.02. 13:30 - 17:30h in AH I/II + AH VI, UMIC 025

> 2nd try: 31.03. 09:40 - 12:40h in UMIC 025 + AH IV

We will send around an email announcing the precise start/end times and your assigned exam rooms.



Announcements (2)

- Seminar in the summer semester
 - "Current Topics in Computer Vision and Machine Learning"
 - Block seminar, presentations at beginning of semester break
 - Registration period: 14.01.2016 27.01.2016
 - https://www.graphics.rwth-aachen.de/apse/check.php

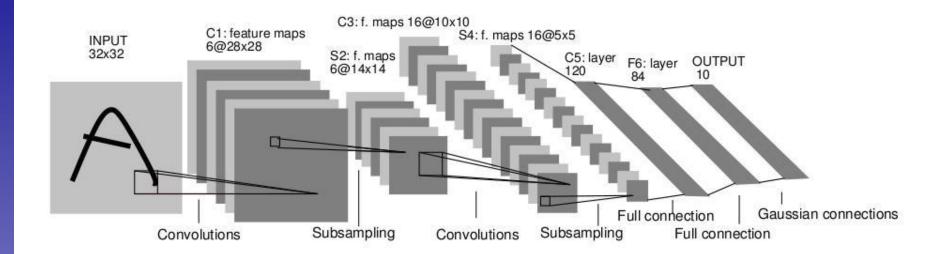


Course Outline

- Image Processing Basics
- Segmentation & Grouping
- Object Recognition
- Local Features & Matching
- Object Categorization
- 3D Reconstruction
 - Epipolar Geometry and Stereo Basics
 - Camera calibration & Uncalibrated Reconstruction
 - Multi-view Stereo
- Optical Flow

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Recap: Convolutional Neural Networks

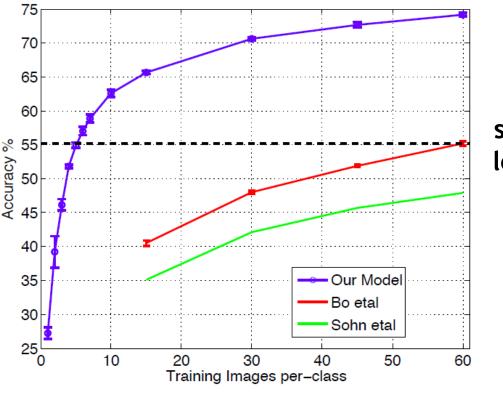


- Neural network with specialized connectivity structure
 - Stack multiple stages of feature extractors
 - Higher stages compute more global, more invariant features
 - Classification layer at the end

Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, <u>Gradient-based learning applied to document recognition</u>, Proceedings of the IEEE 86(11): 2278-2324, 1998.



The Learned Features are Generic



state of the art level (pre-CNN)

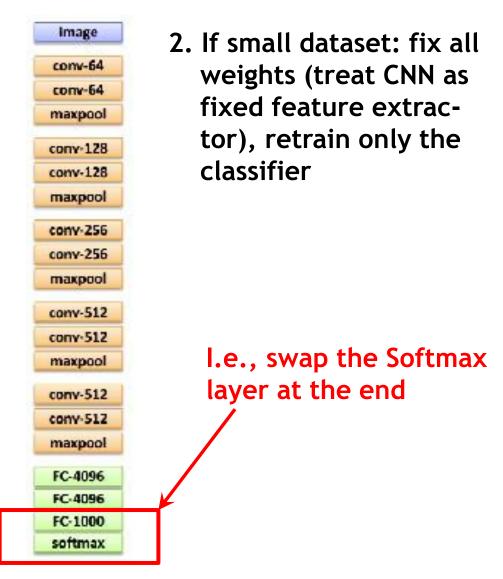
- Experiment: feature transfer
 - Train AlexNet-like network on ImageNet
 - Chop off last layer and train classification layer on CalTech256
 - ⇒ State of the art accuracy already with only 6 training images!



Transfer Learning with CNNs



1. Train on ImageNet





Transfer Learning with CNNs



1. Train on ImageNet



3. If you have medium sized dataset, "finetune" instead: use the old weights as initialization, train the full network or only some of the higher layers.

Retrain bigger portion of the network

conv-512
maxpool

FC-4096

FC-4096

FC-1000

softmax



Other Tasks: Detection

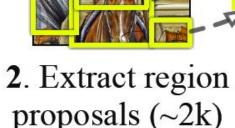
R-CNN: Regions with CNN features

warped region



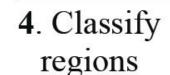
1. Input image











tvmonitor? no.

aeroplane? no.

person? yes.

Results on PASCAL VOC Detection benchmark

Pre-CNN state of the art: 35.1% mAP [Uijlings et al., 2013]

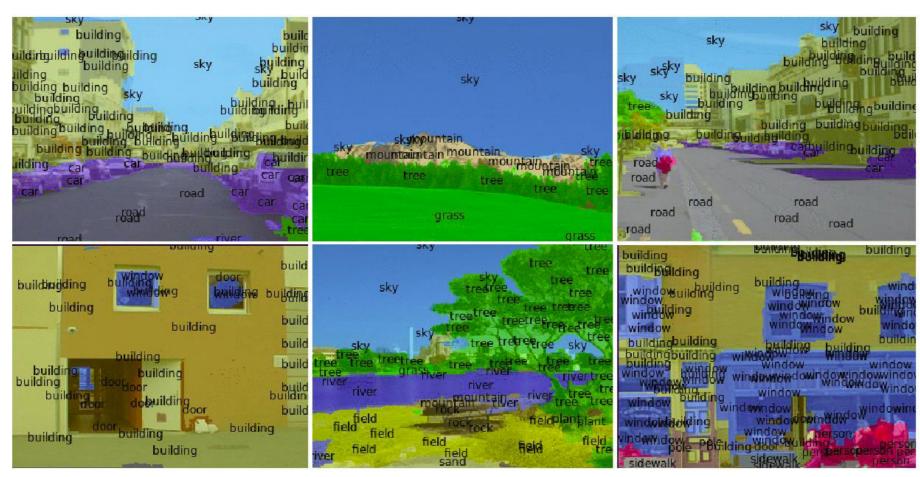
> 33.4% mAP **DPM**

R-CNN: 53.7% mAP

R. Girshick, J. Donahue, T. Darrell, and J. Malik, Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation, CVPR 2014

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Other Tasks: Semantic Segmentation

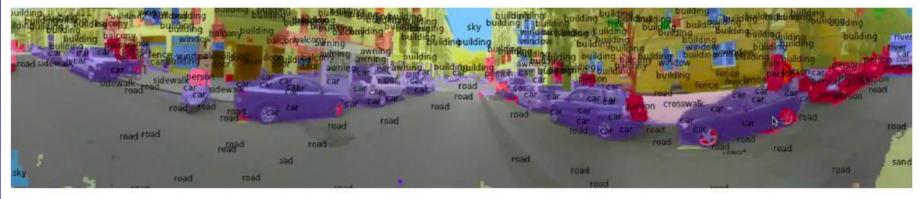


[Farabet et al. ICML 2012, PAMI 2013]



Other Tasks: Semantic Segmentation

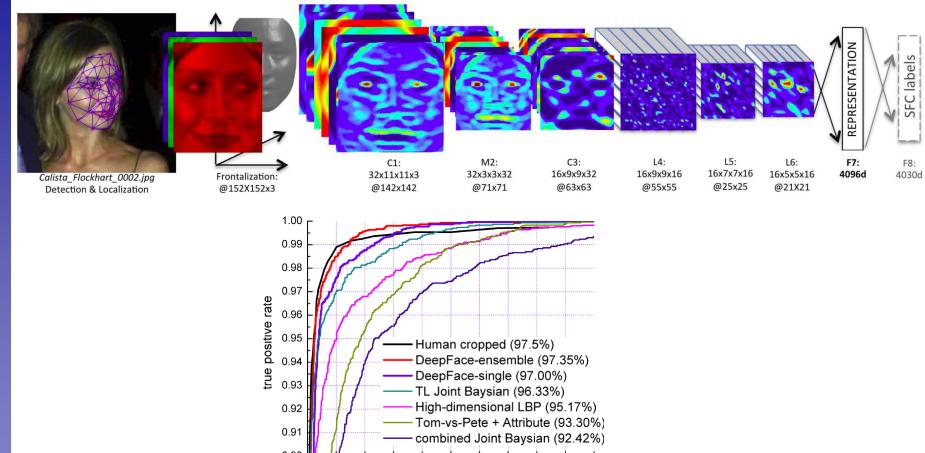




[Farabet et al. ICML 2012, PAMI 2013]



Other Tasks: Face Verification



Y. Taigman, M. Yang, M. Ranzato, L. Wolf, <u>DeepFace: Closing the Gap to Human-Level Performance in Face Verification</u>, CVPR 2014

0.00 0.05 0.10 0.15 0.20 0.25 0.30 0.35 0.40 0.45 0.50 false positive rate

Slide credit: Svetlana Lazebnik



Commercial Recognition Services

• E.g., clarifai

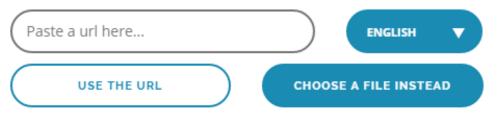






Try it out with your own media

Upload an image or video file under 100mb or give us a direct link to a file on the web.

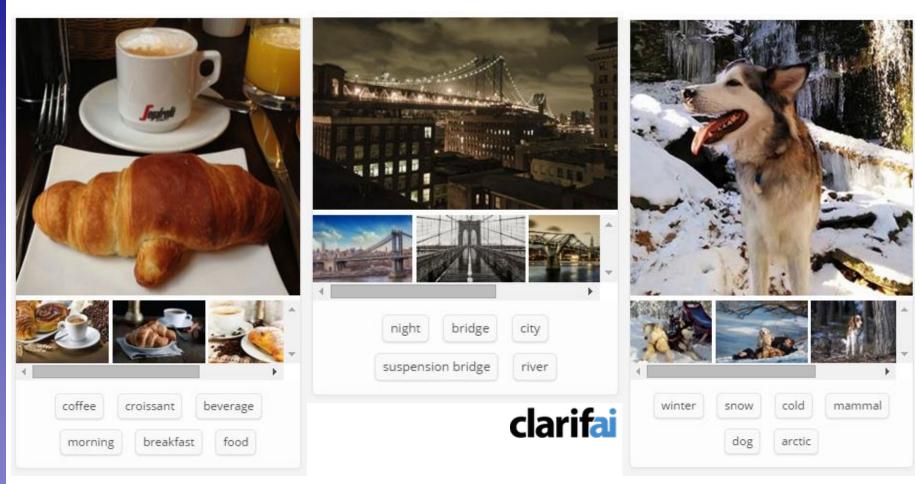


*By using the demo you agree to our terms of service

Image source: clarifai.com



Commercial Recognition Services



- Be careful when testing with images from Google Search
 - Chances are they may have been seen in the training set...



Topics of This Lecture

- Geometric vision
 - Visual cues
 - Stereo vision
- Epipolar geometry
 - Depth with stereo
 - Geometry for a simple stereo system
 - Case example with parallel optical axes
 - General case with calibrated cameras
- Stereopsis & 3D Reconstruction
 - Correspondence search
 - Additional correspondence constraints
 - Possible sources of error
 - Applications



Geometric vision

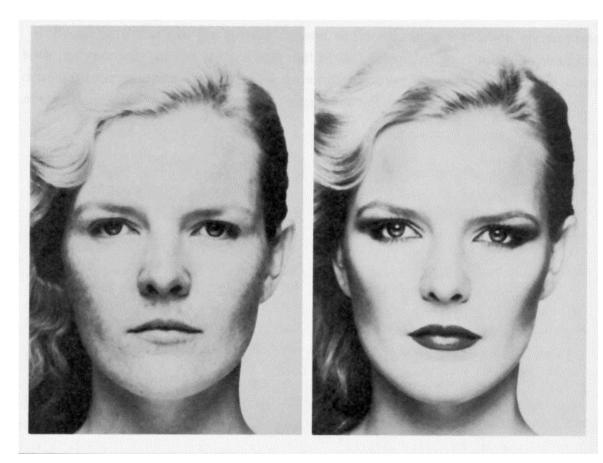
- Goal: Recovery of 3D structure
 - What cues in the image allow us to do this?



Slide credit: Svetlana Lazebnik



Shading



Merle Norman Cosmetics, Los Angeles



Shading

Texture



The Visual Cliff, by William Vandivert, 1960



Shading

Texture

Focus





From The Art of Photography, Canon



Shading

Texture

Focus

Perspective



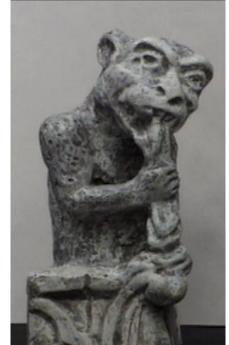
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Visual Cues

Shading

Texture

Focus







Figures from L. Zhang

Perspective

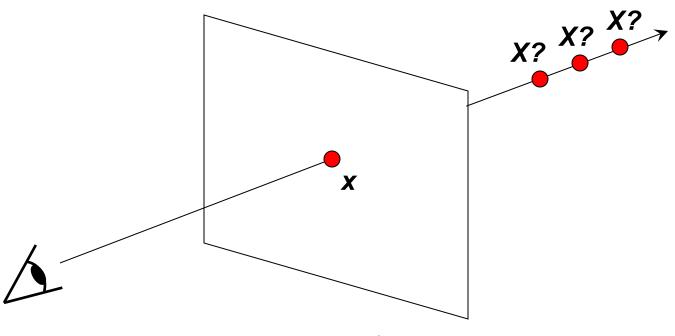
Motion





Our Goal: Recovery of 3D Structure

- We will focus on perspective and motion
- We need multi-view geometry because recovery of structure from one image is inherently ambiguous



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To Illustrate This Point...

• Structure and depth are inherently ambiguous from single views.





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Stereo Vision





http://www.well.com/~jimg/stereo/stereo_list.html

Slide credit: Kristen Grauman



 Generic problem formulation: given several images of the same object or scene, compute a representation of its 3D shape

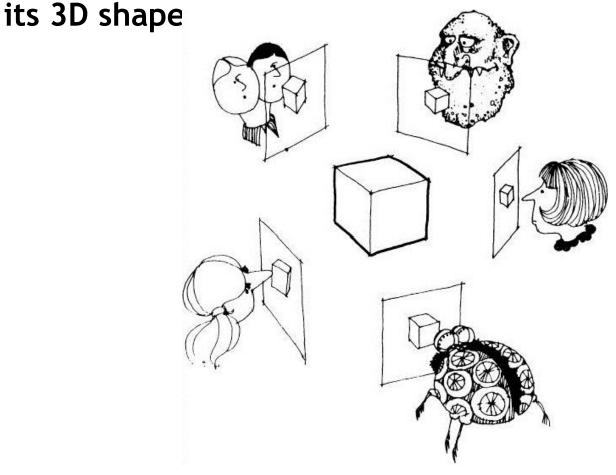








 Generic problem formulation: given several images of the same object or scene, compute a representation of





 Narrower formulation: given a calibrated binocular stereo pair, fuse it to produce a depth image

Image 1



Image 2



Dense depth map

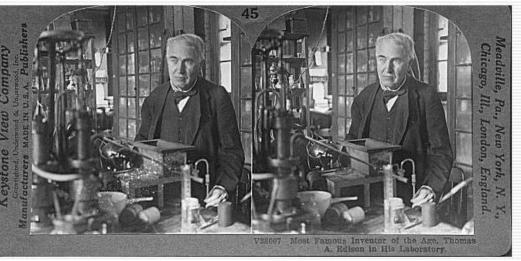


Slide credit: Svetlana Lazebnik, Steve 5citz



- Narrower formulation: given a calibrated binocular stereo pair, fuse it to produce a depth image.
 - Humans can do it





Stereograms: Invented by Sir Charles Wheatstone, 1838



- Narrower formulation: given a calibrated binocular stereo pair, fuse it to produce a depth image.
 - Humans can do it



Autostereograms: http://www.magiceye.com



- Narrower formulation: given a calibrated binocular stereo pair, fuse it to produce a depth image.
 - Humans can do it



Autostereograms: http://www.magiceye.com

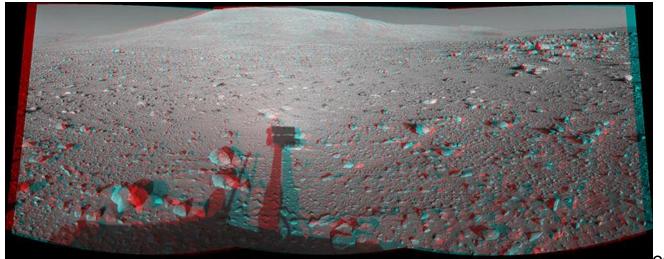
Application of Stereo: Robotic Exploration



Nomad robot searches for meteorites in Antartica



Real-time stereo on Mars



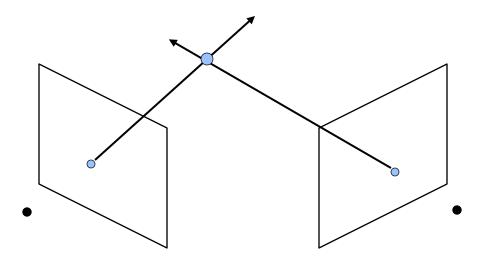


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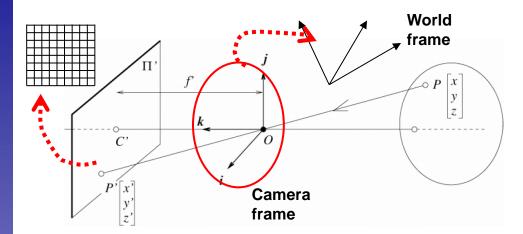
Depth with Stereo: Basic Idea



- Basic Principle: Triangulation
 - Gives reconstruction as intersection of two rays
 - Requires
 - Camera pose (calibration)
 - Point correspondence



Camera Calibration



Extrinsic parameters:
Camera frame ↔ Reference frame

Intrinsic parameters: Image coordinates relative to camera ↔ Pixel coordinates

Parameters

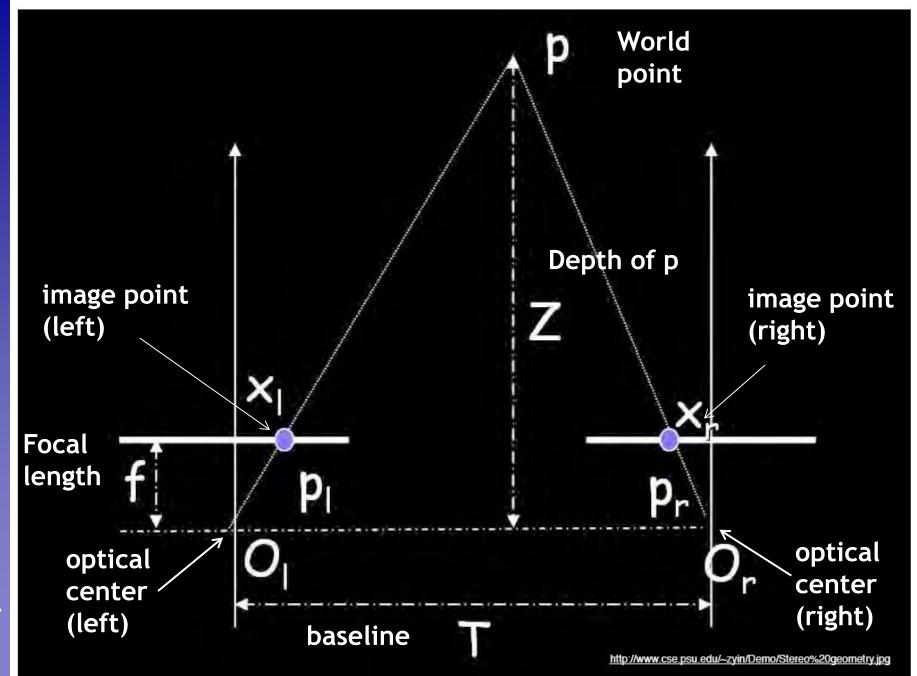
- > Extrinsic: rotation matrix and translation vector
- Intrinsic: focal length, pixel sizes (mm), image center point, radial distortion parameters

We'll assume for now that these parameters are given and fixed.

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Geometry for a Simple Stereo System

 First, assuming parallel optical axes, known camera parameters (i.e., calibrated cameras):

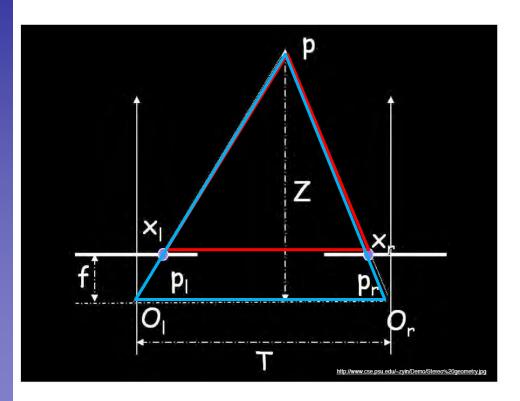


Slide credit: Kristen Grauman



Geometry for a Simple Stereo System

 Assume parallel optical axes, known camera parameters (i.e., calibrated cameras). We can triangulate via:



Similar triangles (p_l, P, p_r) and (O_1, P, O_r) :

$$\frac{T - (x_r - x_l)}{Z - f} = \frac{T}{Z}$$

$$Z = f \frac{T}{x_r - x_l}$$

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Depth From Disparity

Image I(x,y)

Disparity map D(x,y)

Image I'(x',y')





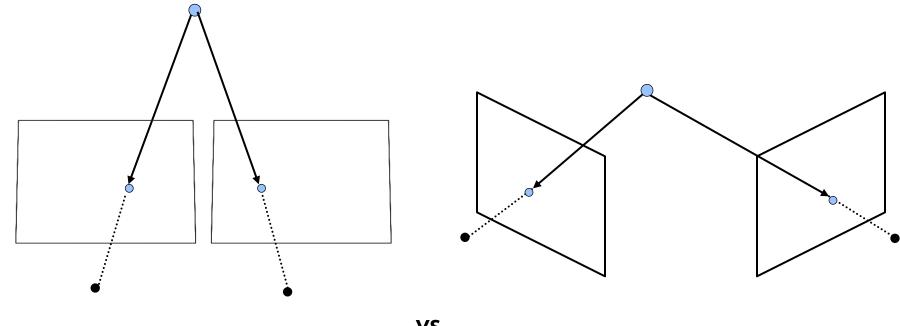


$$(x',y') = (x+D(x,y),y)$$

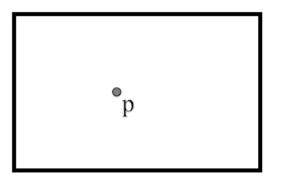


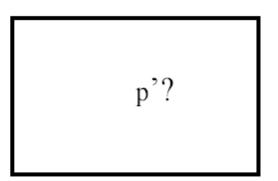
General Case With Calibrated Cameras

• The two cameras need not have parallel optical axes.



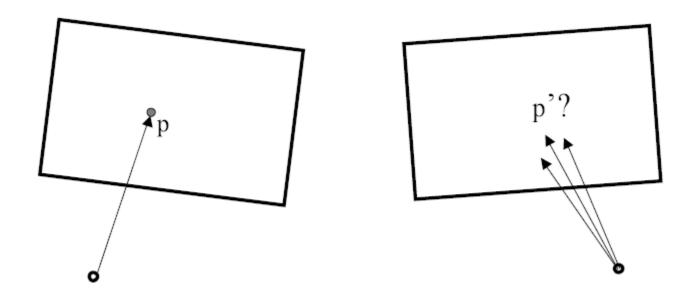






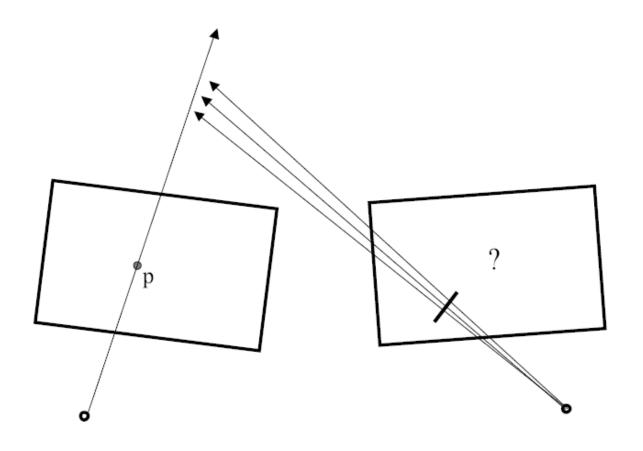
• Given p in the left image, where can the corresponding point p' in the right image be?





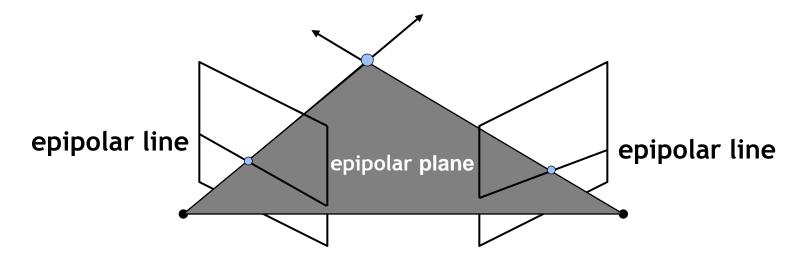
• Given p in the left image, where can the corresponding point p' in the right image be?







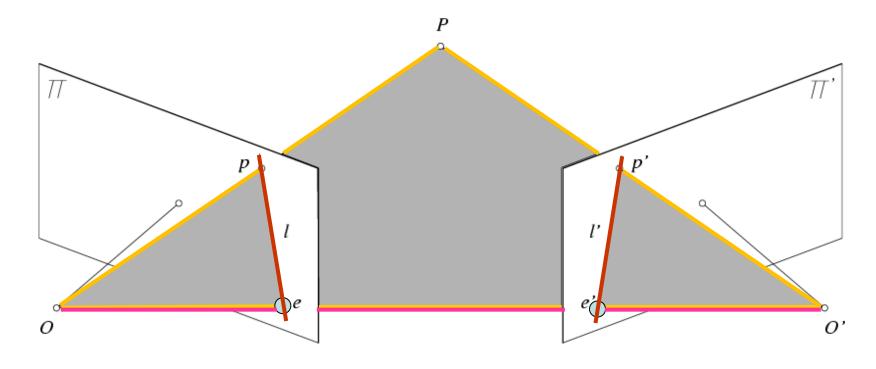
 Geometry of two views allows us to constrain where the corresponding pixel for some image point in the first view must occur in the second view.



- Epipolar constraint: Why is this useful?
 - Reduces correspondence problem to 1D search along conjugate epipolar lines.



Epipolar Geometry



- Epipolar Plane
- Epipoles

- Baseline
- Epipolar Lines

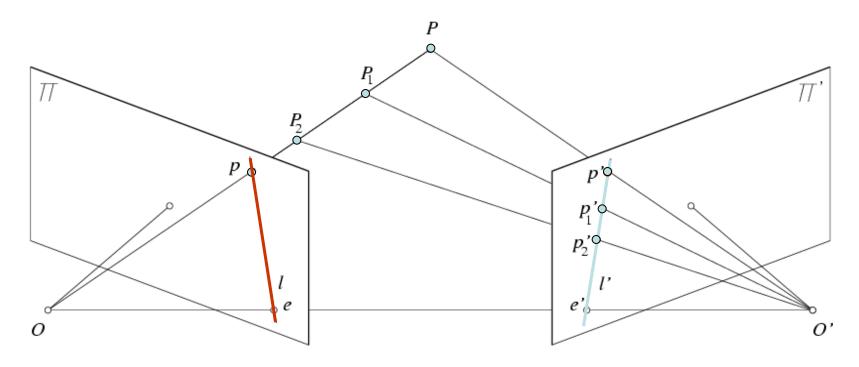


Epipolar Geometry: Terms

- Baseline
 - Line joining the camera centers
- Epipole
 - Point of intersection of baseline with the image plane
- Epipolar plane
 - Plane containing baseline and world point
- Epipolar line
 - Intersection of epipolar plane with the image plane
- Properties
 - All epipolar lines intersect at the epipole.
 - An epipolar plane intersects the left and right image planes in epipolar lines.



Epipolar Constraint



- Potential matches for p have to lie on the corresponding epipolar line l.
- Potential matches for p' have to lie on the corresponding epipolar line l.

http://www.ai.sri.com/~luong/research/Meta3DViewer/EpipolarGeo.html

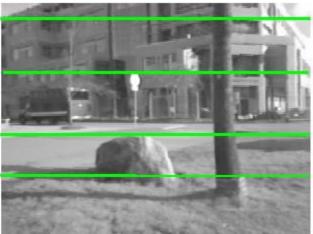


Example



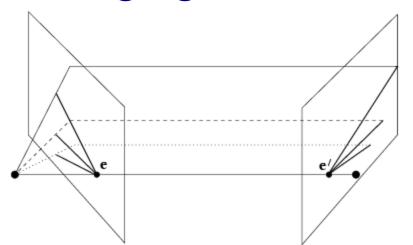








Example: Converging Cameras

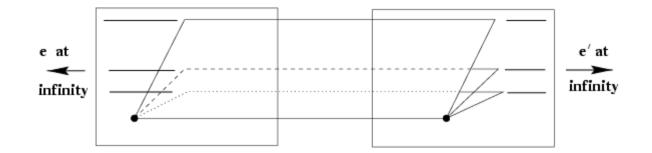


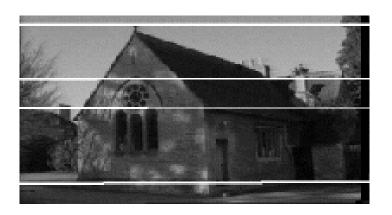
As position of 3D point varies, epipolar lines "rotate" about the baseline

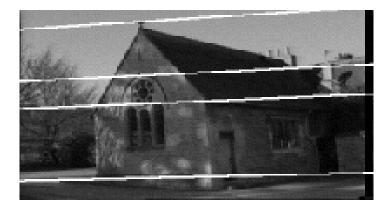




Example: Motion Parallel With Image Plane



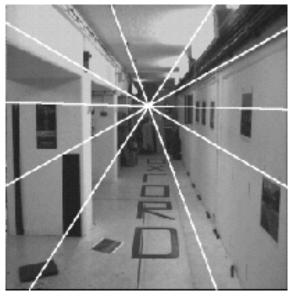


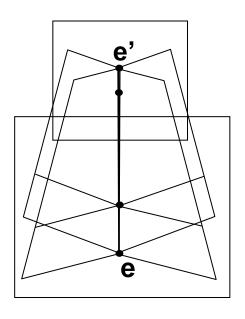




Example: Forward Motion







- Epipole has same coordinates in both images.
- Points move along lines radiating from e: "Focus of expansion"



Let's Formalize This!

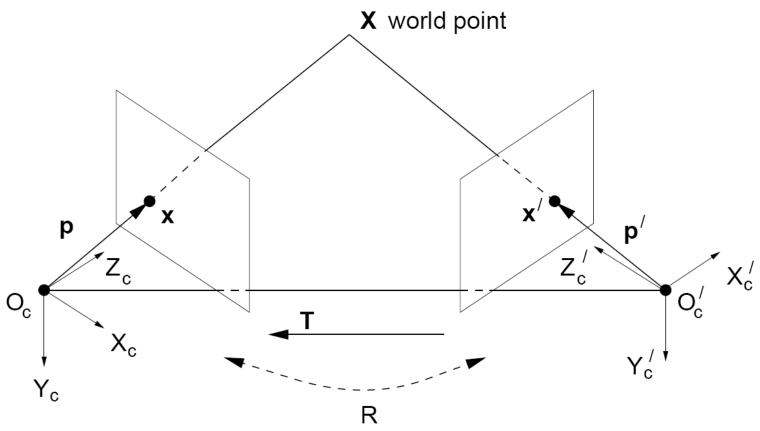
 For a given stereo rig, how do we express the epipolar constraints algebraically?

• For this, we will need some linear algebra.

But don't worry! We'll go through it step by step...

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Stereo Geometry With Calibrated Cameras



- If the rig is calibrated, we know:
 - How to rotate and translate camera reference frame 1 to get to camera reference frame 2.
 - Rotation: 3 x 3 matrix; translation: 3 vector.

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Rotation Matrix

$$\mathbf{R}_x(lpha) = egin{bmatrix} 1 & 0 & 0 \ 0 & \coslpha & -\sinlpha \ 0 & \sinlpha & \coslpha \end{bmatrix}$$
 Express 3D rotations series of rotations around coordinate

$$\mathbf{R}_y(eta) = egin{bmatrix} \coseta & 0 & \sineta \ 0 & 1 & 0 \ -\sineta & 0 & \coseta \end{bmatrix}$$

$$\mathbf{R}_z(\gamma) = egin{bmatrix} \cos \gamma & -\sin \gamma & 0 \ \sin \gamma & \cos \gamma & 0 \ 0 & 0 & 1 \end{bmatrix}$$

Express 3D rotation as around coordinate axes by angles α , β , γ

Overall rotation is product of these elementary rotations:

$$\mathbf{R} = \mathbf{R}_x \mathbf{R}_y \mathbf{R}_z$$





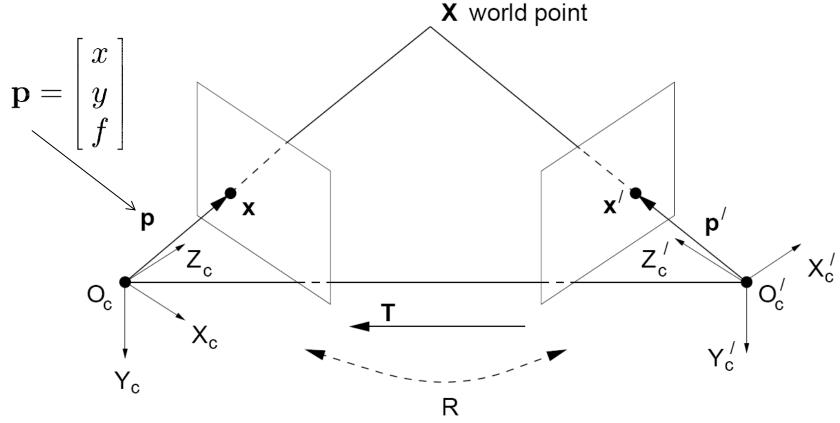
3D Rigid Transformation

$$egin{bmatrix} X' \ Y' \ Z' \end{bmatrix} = egin{bmatrix} r_{11} & r_{12} & r_{13} \ r_{21} & r_{22} & r_{23} \ r_{31} & r_{32} & r_{33} \end{bmatrix} egin{bmatrix} X \ Y \ Z \end{bmatrix} + egin{bmatrix} T_x \ T_y \ T_z \end{bmatrix}$$

$$X' = RX + T$$



Stereo Geometry With Calibrated Cameras



 Camera-centered coordinate systems are related by known rotation R and translation T:

$$X' = RX + T$$



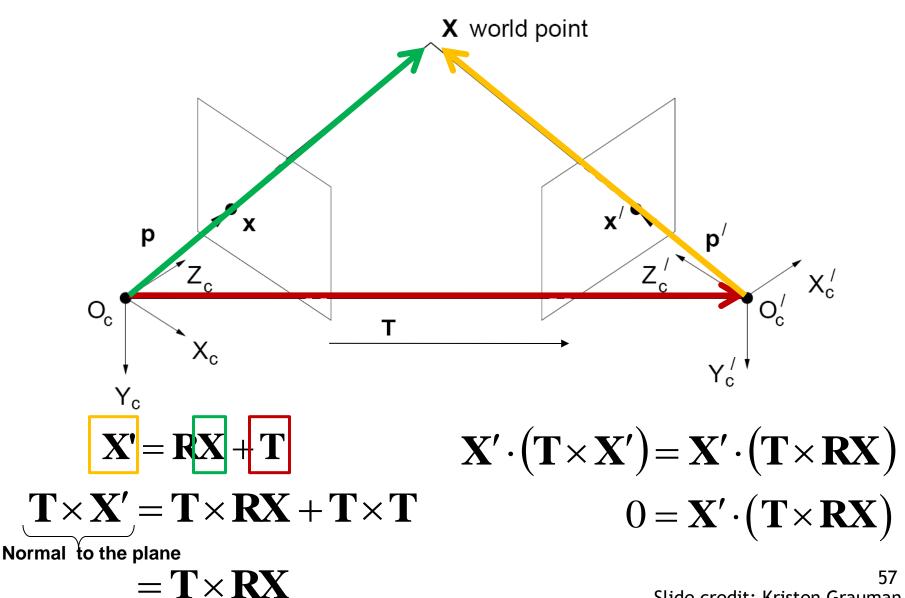
Excursion: Cross Product

$$ec{a} imes ec{b} = ec{c}$$
 $ec{a} \cdot ec{c} = 0$ $ec{b} \cdot ec{c} = 0$

- Vector cross product takes two vectors and returns a third vector that's perpendicular to both inputs.
- So here, c is perpendicular to both a and b, which means the dot product is 0.



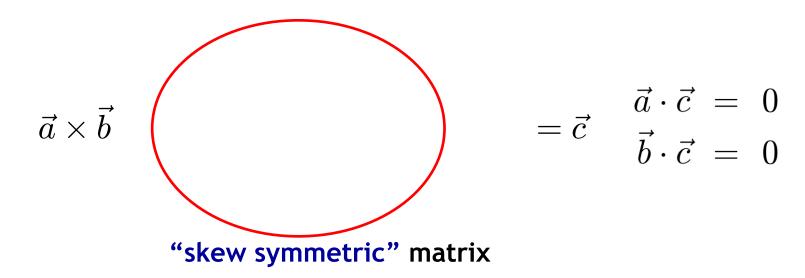
From Geometry to Algebra

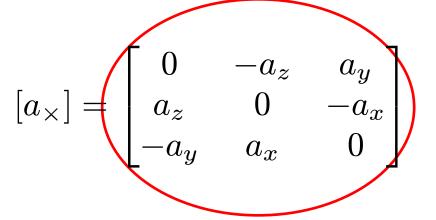






Matrix Form of Cross Product



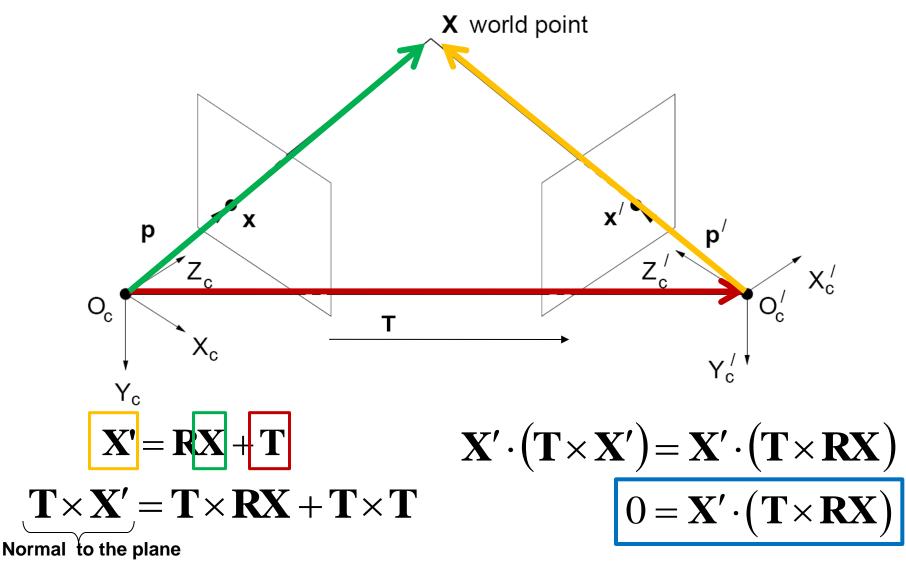


$$\vec{a} \times \vec{b} = [a_{\times}] \, \vec{b}$$



From Geometry to Algebra

 $= \mathbf{T} \times \mathbf{R} \mathbf{X}$



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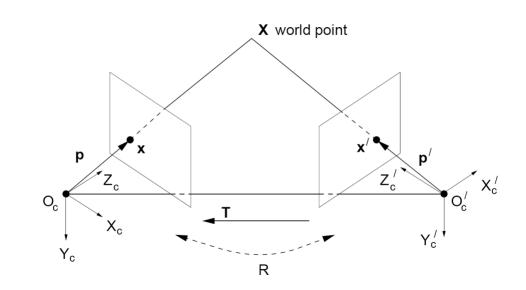
Essential Matrix

$$\mathbf{X}' \cdot \left(\mathbf{T} \times \mathbf{R} \mathbf{X}\right) = 0$$

$$\mathbf{X}' \cdot \left(\mathbf{T}_x \ \mathbf{R}\mathbf{X}\right) = 0$$

Let
$$\mathbf{E} = \mathbf{T}_{x}\mathbf{R}$$

$$\mathbf{X}'^T \mathbf{E} \mathbf{X} = 0$$



• This holds for the rays p and p' that are parallel to the camera-centered position vectors X and X', so we have:

$$\mathbf{p}^{T} \mathbf{E} \mathbf{p} = 0$$

 E is called the essential matrix, which relates corresponding image points [Longuet-Higgins 1981]

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Essential Matrix and Epipolar Lines

$$\mathbf{p'}^{\mathrm{T}}\mathbf{E}\mathbf{p} = 0$$

Epipolar constraint: if we observe point p in one image, then its position p in second image must satisfy this equation.

 $m{l'} = m{Ep}$ is the coordinate vector representing the epipolar line for point p

(i.e., the line is given by: $l'^{\top}\mathbf{x} = 0$)

 $oldsymbol{l} oldsymbol{l} = oldsymbol{E}^T oldsymbol{p}'$ is the coordinate vector representing the epipolar line for point p'



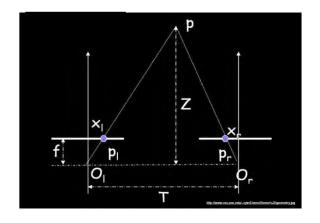
Essential Matrix: Properties

- Relates image of corresponding points in both cameras, given rotation and translation.
- Assuming intrinsic parameters are known

$$\mathbf{E} = \mathbf{T}_{x}\mathbf{R}$$



Essential Matrix Example: Parallel Cameras



$$\mathbf{R} =$$

$$T =$$

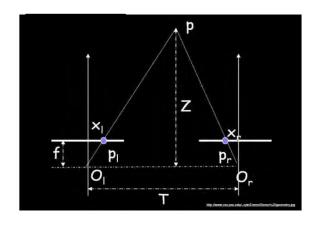
$$\mathbf{E} = [\mathbf{T}_{\mathbf{x}}]\mathbf{R} =$$

$$\mathbf{p'}^{\mathrm{T}}\mathbf{E}\mathbf{p} = 0$$

For the parallel cameras, image of any point must lie on same horizontal line in each image plane.

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Essential Matrix Example: Parallel Cameras



$$\mathbf{R} = \mathbf{I}$$

$$\mathbf{T} = [-d, 0, 0]^{\mathrm{T}}$$

$$\mathbf{E} = [\mathbf{T}_{\mathbf{x}}]\mathbf{R} = \begin{bmatrix} \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{d} \\ \mathbf{0} & \mathbf{d} & \mathbf{0} \end{bmatrix}$$

$$\mathbf{p'}^{\mathsf{T}}\mathbf{E}\mathbf{p} = \mathbf{0} \qquad \begin{bmatrix} x' & y' & f \end{bmatrix} \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & d \\ 0 & -d & 0 \end{bmatrix} \begin{bmatrix} x \\ y \\ f \end{bmatrix} = 0$$

For the parallel cameras, image of any point must lie on same horizontal line in each image plane.

$$\Leftrightarrow \begin{bmatrix} x' \ y' \ f \end{bmatrix} \begin{bmatrix} 0 \\ df \\ -dy \end{bmatrix} = 0$$
$$\Leftrightarrow y = y'$$



More General Case

Image I(x,y)

Disparity map D(x,y)

Image I'(x',y')







$$(x',y') = (x+D(x,y),y)$$

What about when cameras' optical axes are not parallel?

Stereo Image Rectification

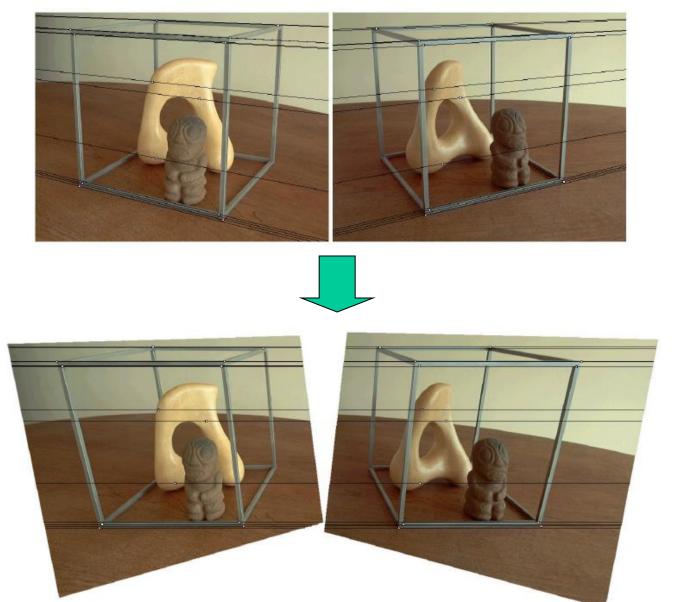
 In practice, it is convenient if image scanlines are the epipolar lines.



- Reproject image planes onto a common plane parallel to the line between optical centers
- Pixel motion is horizontal after this transformation
- > Two homographies (3×3) transforms, one for each input image reprojection

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Stereo Image Rectification: Example



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Source: Alyosha Efros



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Stereo Reconstruction

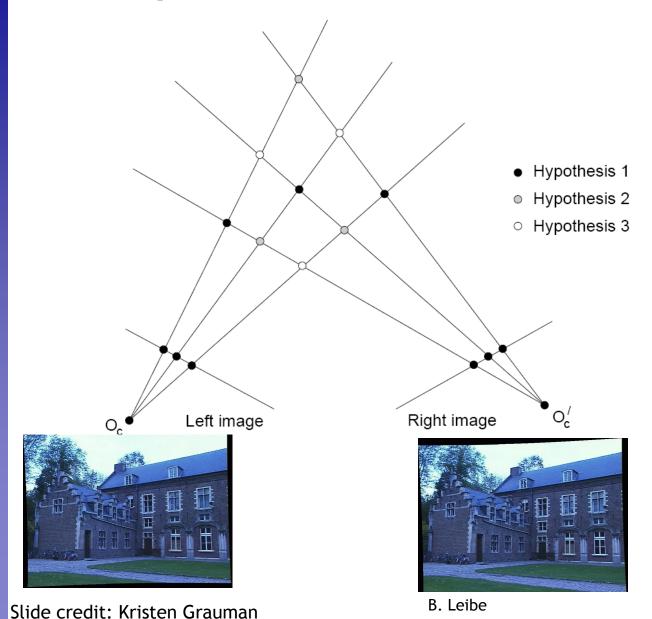
- Main Steps
 - Calibrate cameras
 - Rectify images
 - Compute disparity
 - Estimate depth







Correspondence Problem

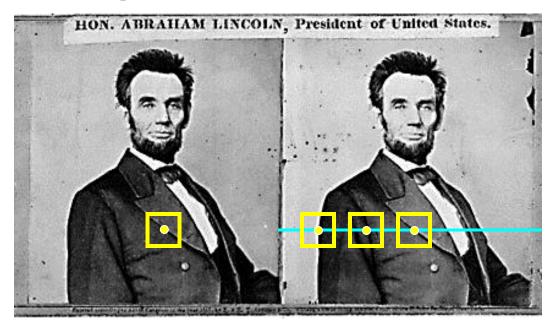


Multiple match hypotheses satisfy epipolar constraint, but which is correct?

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Dense Correspondence Search



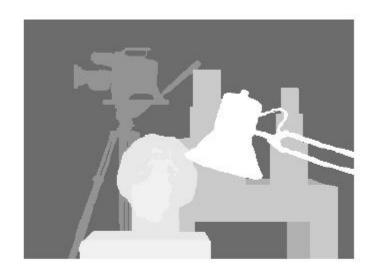
- For each pixel in the first image
 - Find corresponding epipolar line in the right image
 - Examine all pixels on the epipolar line and pick the best match (e.g. SSD, correlation)
 - Triangulate the matches to get depth information
- This is easiest when epipolar lines are scanlines
 - ⇒ Rectify images first



Example: Window Search

Data from University of Tsukuba





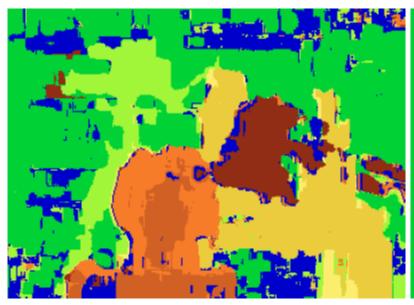
Scene

Ground truth



Example: Window Search

Data from University of Tsukuba





Window-based matching (best window size)

Ground truth



Effect of Window Size





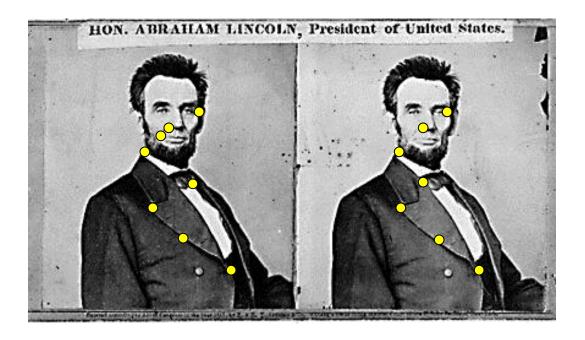


$$W=3$$

W = 20

Want window large enough to have sufficient intensity variation, yet small enough to contain only pixels with about the same disparity.

Alternative: Sparse Correspondence Search



- Idea: Restrict search to sparse set of detected features
- Rather than pixel values (or lists of pixel values) use feature descriptor and an associated feature distance
- Still narrow search further by epipolar geometry

What would make good features?



Dense vs. Sparse

Sparse

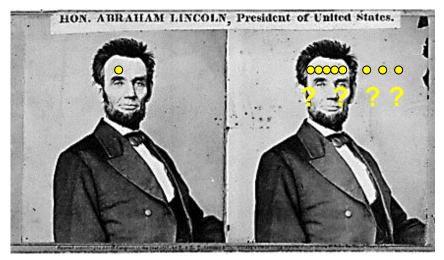
- Efficiency
- Can have more reliable feature matches, less sensitive to illumination than raw pixels
- But...
 - Have to know enough to pick good features
 - Sparse information

Dense

- Simple process
- More depth estimates, can be useful for surface reconstruction
- > **But...**
 - Breaks down in textureless regions anyway
 - Raw pixel distances can be brittle
 - Not good with very different viewpoints



Difficulties in Similarity Constraint



Untextured surfaces



Occlusions

B. Leibe



Possible Sources of Error?

- Low-contrast / textureless image regions
- Occlusions
- Camera calibration errors
- Violations of brightness constancy (e.g., specular reflections)
- Large motions





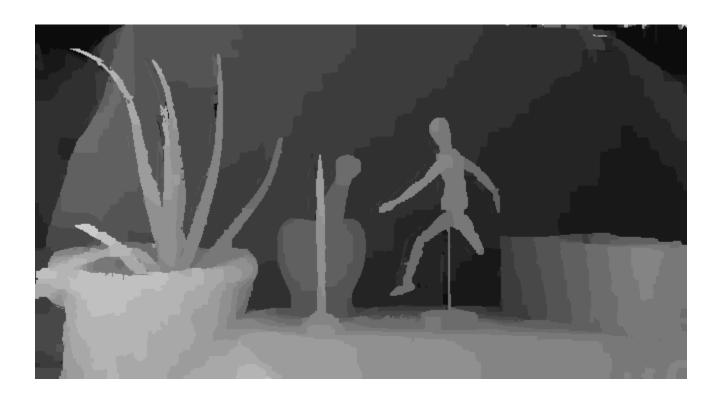
Right Image





Left Image





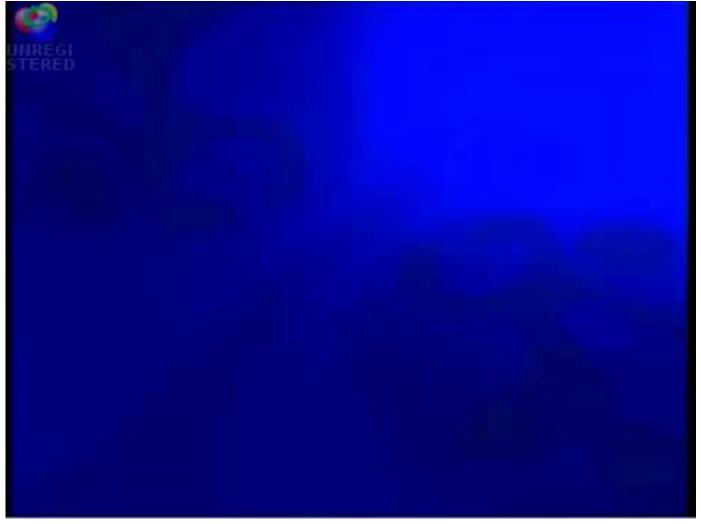
Disparity







Application: Free-Viewpoint Video



http://www.liberovision.com



Summary: Stereo Reconstruction

Main Steps

- Calibrate cameras
- Rectify images
- Compute disparity
- Estimate depth











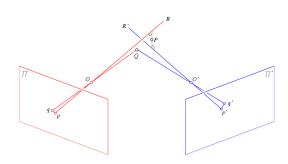
Left





Next lecture

- **Uncalibrated cameras**
- Camera parameters
- Revisiting epipolar geometry
- Robust fitting





Computer

References and Further Reading

 Background information on epipolar geometry and stereopsis can be found in Chapters 10.1-10.2 and 11.1-11.3 of

> D. Forsyth, J. Ponce, Computer Vision - A Modern Approach. Prentice Hall, 2003

 More detailed information (if you really want to implement 3D reconstruction algorithms) can be found in Chapters 9 and 10 of

> R. Hartley, A. Zisserman Multiple View Geometry in Computer Vision 2nd Ed., Cambridge Univ. Press, 2004

