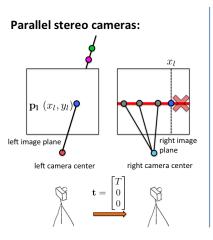
Stereo

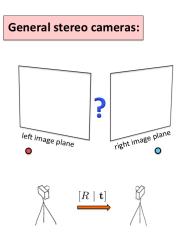
Epipolar Geometry for General Cameras

Stereo

Epipolar geometry

- Case with two cameras with parallel optical axes
- General case ← Now this





 If I can always mount two cameras parallel to each other, why do I need to learn math for the general case?

• Let's say that you want to reconstruct a CN tower in 3D

- Let's say that you want to reconstruct a CN tower in 3D
- One out of endless possibilities of why you would do that:
 - You can print it with a 3D printer to get a nice pocket or not-so-pocket edition (better than those that are sold in Chinatown)
 - Give it to your mum for Christmas (say it's a present from CSC420)





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- Let's say that you want to reconstruct a CN tower in 3D
- You obviously can't get a good 360 shot of the CN tower with just parallel cameras. Particularly not the top of the CN tower which is very high up.

- Let's say that you want to reconstruct a CN tower in 3D
- You obviously can't get a good 360 shot of the CN tower with just parallel cameras. Particularly not the top of the tower.
- But you can download great images of the tower from the web without even needing to leave the house.

• But these images are not taken from parallel cameras...



Photosynth

You could even do part of Venice...

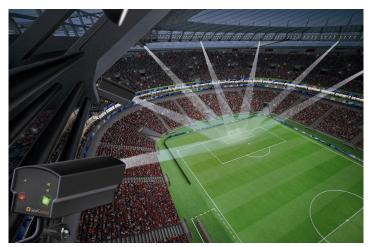


Figure: https://www.youtube.com/watch?v=HrgHFDPJHXo

Noah Snavely, Steven M. Seitz, Richard Szeliski, "Photo tourism: Exploring photo collections in 3D", SIGGRAPH 2006, https://photosynth.net/

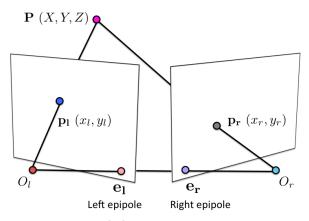
World Cup 2014 - High Tech 3D

- Last World Cup was monitored with 14 high-speed cameras, capturing 500 frames per second, and could accurately detect ball motion to within 5mm.
- 2,000 tests performed, all successful. By German company Goal Control.



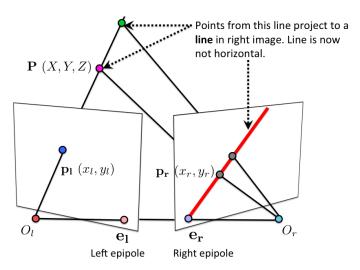
Stereo – General Case Ready for the math?

• Some notation: the left and right epipole

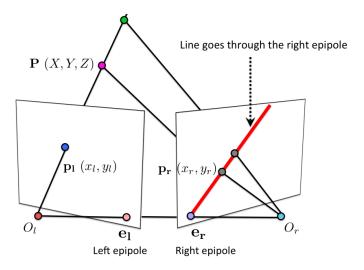


Where line O_lO_r intersects the image planes

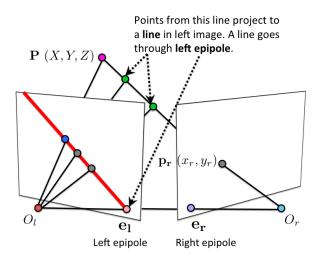
• All points from the projective line O_lp_l project to a line on the right image plane. This time the line is not (necessarily) horizontal.



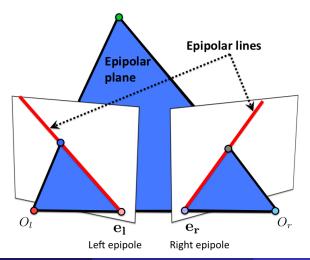
• The line goes through the right epipole.



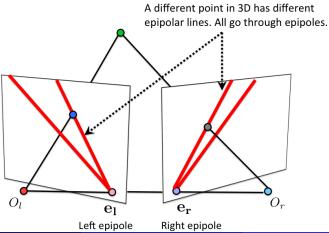
• Similarly, All points from the projective line $O_r p_r$ project to a line on the left image plane. This line goes through the left epipole.



• The reason for all this is simple: points O_I , O_r , and a point P in 3D lie on a plane. We call this the **epipolar plane**. This plane intersects each image plane in a line. We call these lines **epipolar lines**.

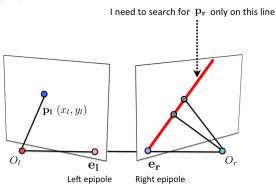


 Obviously a different point in 3D will form a different epipolar plane and therefore different epipolar lines. But these epipolar lines go through epipoles as well.



• Why are we even dumping all this notation? Are epipolar lines, epipoles, etc somehow useful?

- Remember what we did for parallel cameras? We were matching points in the left and right image, giving us a point in 3D. We want the same now.
- Epipolar geometry is useful because it constrains our search for the matches:
 - For each point $\mathbf{p_l}$ we need to search for $\mathbf{p_r}$ only on a epipolar line (much simpler than if I need to search in the full image)
 - All matches lie on lines that intersect in epipoles. This gives another constraint.



Epipolar geometry: Examples

• Example of epipolar lines for converging cameras





[Source: J. Hays, pic from Hartley & Zisserman]

Epipolar geometry: Examples

• How would epipolar lines look like if the camera moves directly forward?

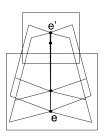
[Source: J. Hays]

Epipolar geometry: Examples

• Example of epipolar lines for forward motion







Epipole has same coordinates in both images.

Points move along lines radiating from e:

"Focus of expansion"

[Source: J. Hays, pic from Hartley & Zisserman]

- ullet We first need to figure out on which line we need to search for the matches for each $egin{matched} \mathbf{p_l} \end{aligned}$
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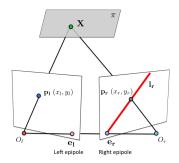
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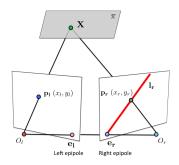
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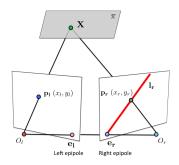
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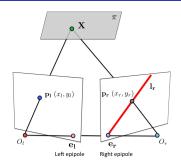
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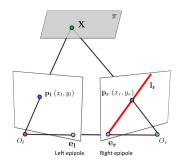
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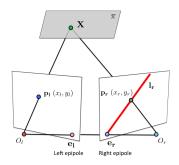
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$$\begin{bmatrix} x_{r,1} x_{l,1} & x_{r,1} y_{l,1} & x_{r,1} & y_{r,1} x_{l,1} & y_{r,1} y_{l,1} & y_{r,1} & x_{l,1} & y_{l,1} & 1 \\ & \vdots & & & & & \\ x_{r,n} x_{l,n} & x_{r,n} y_{l,n} & x_{r,n} & y_{r,n} x_{l,n} & y_{r,n} y_{l,n} & y_{r,n} & x_{l,n} & y_{l,n} & 1 \end{bmatrix} \mathbf{f} = \mathbf{0}$$

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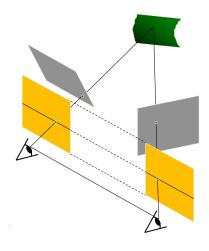
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Rectification

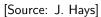
- Once we have F we can compute homographies that transform each image plane such that they are parallel (see Zisserman & Hartley's book)
- Once they are parallel, we know how to proceed (matching, etc)



[Source: J. Hays]

Rectification Example





The Fundamental Matrix: One Last Thing

• Once you have F you can even compute camera projection matrices P_l and P_r (under some ambiguity). You may choose the camera projection matrices like this:

$$P_{left} = [I_{3\times3} | \mathbf{0}]$$
 $P_{right} = [[\mathbf{e_r}]_x F | \mathbf{e_r}]$

where notation
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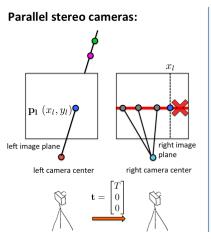
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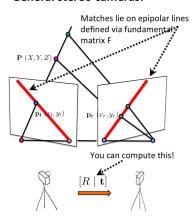
Stereo: Summary

Epipolar geometry

- Case with two cameras with parallel optical axes
- General case



General stereo cameras:



Summary – Stuff You Need To Know

Cameras with parallel optics and known intrinsics and extrinsics:

- You can search for correspondences along horizontal lines
- The difference in *x* direction between two correspondences is called disparity:

disparity =
$$x_I - x_r$$

• Assuming you know the camera intrinsics and the baseline (distance between the left and right camera canter in the world) you can compute the depth:

$$Z = \frac{f \cdot T}{\text{disparity}}$$

- Once you have Z (depth), you can also compute X and Y, giving you full 3D
- Disparity and depth are inversely proportional

Matlab function:

- DISPARITYMAP = DISPARITY(I_{left} , I_{right});
- Function SURF is useful for plotting the point cloud

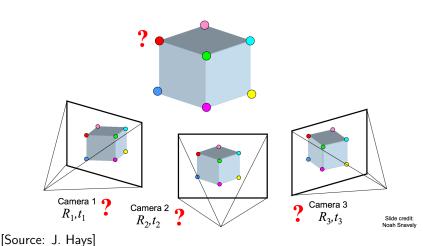
Summary – Stuff You Need To Know

General cameras:

- You first find matches in both images without any restriction. You need at least 7 matches, but the more (reliable) matches the better
- Solve a homogeneous linear system to get the fundamental matrix F
- Given F, you can compute homographies that can rectify both images to be parallel.
- Given F, you can also compute the relative pose between cameras.

Structure From Motion

- What if you have more than two views of the same scene?
- This problem is called structure-from-motion



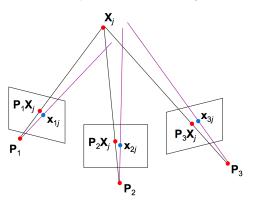
Sanja Fidler

Structure From Motion

Solve a non-linear optimization problem minimizing re-projection error:

$$E(\mathbf{P}, \mathbf{X}) = \sum_{i=1}^{\#cameras} \sum_{j=1}^{\#points} \operatorname{dist}(\mathbf{x}_{ij}, P_i X_j)$$

• This can be done via technique called bundle adjustment



[Source: J. Hays]











Take out your phone, start recording the road and

Drive!

M. Brubaker, A. Geiger and R. Urtasun
Lost! Leveraging the Crowd for Probabilistic Visual Self-Localization
CVPR 2013

Paper & Code: http://www.cs.toronto.edu/~mbrubake/projects/map/

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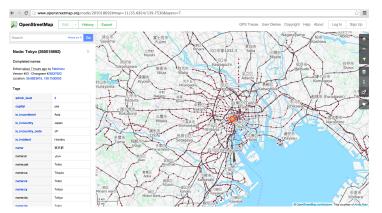


Figure: OpenStreetMap are free downloadable maps (with GPS) of the world

- From consecutive frames you can compute relative camera poses
- The recorded video stream therefore gives you a trajectory you are driving
- Probabilistic model reasons where you can be on a map given your trajectory

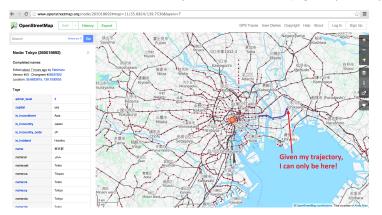
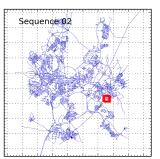


Figure: The shape of my trajectory reveals where I am

- From consecutive frames you can compute relative camera poses
- The recorded video stream therefore gives you a trajectory you are driving
- Probabilistic model reasons where you can be on a map given your trajectory
- This gives you the GPS location!
- With 1 camera up to 18m accuracy, 2 cameras up to 3m accuracy



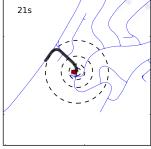


Figure: https://www.youtube.com/watch?v=4Z3shNPOdQA&feature=youtu.be

Vision for Visually Impaired

• You can imagine a more complex version of the system for visually impaired



Pic from: http://www.blogcdn.com/www.engadget.com/media/2012/05/wxzfdgrs.jpg

Vision for Visually Impaired

- You can imagine a more complex version of the system for visually impaired
- How else could depth / 3D help me?



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Vision for Visually Impaired

- You can imagine a more complex version of the system for visually impaired
- How else could depth / 3D help me?
- What else do we need to solve to make a vision system for visually impaired functional?



Pic from: http://www.blogcdn.com/www.engadget.com/media/2012/05/wxzfdgrs.jpg

Another Way to get Stereo: Stereo with Structured Light

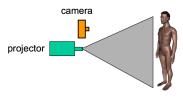






Project "structured" light patterns onto the object

- Simplifies the correspondence problem
- Allows us to use only one camera



L. Zhang, B. Curless, and S. M. Seitz. Rapid Shape Acquisition Using Color Structured Light and Multi-pass Dynamic Programming. 3DPVT 2002 [Source: J. Havs]

Kinect: Structured infrared light



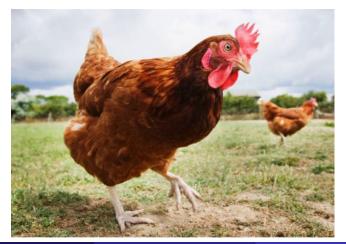
Figure: https://www.youtube.com/watch?v=uq9SEJxZiUg

[Source: J. Hays]

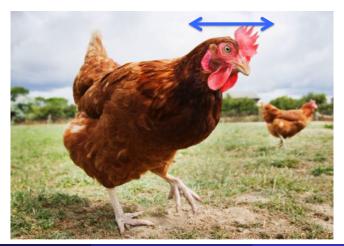
• Humans and a lot of animals (particularly cute ones) have stereoscopic vision



- Most birds don't see in stereo (each eye gets its own picture, no overlap)
- How do these animals get depth? E.g., how can a chicken beak the corn without smashing the head against the floor?



- Most birds don't see in stereo (each eye gets its own picture, no overlap)
- How do these animals get depth? E.g., how can a chicken beak the corn without smashing the head against the floor? Structure-from-motion



• Owls are one of the exceptions (they see stereo)



Birdseye View on What We Learned So Far

Problem	Detection	Description	Matching
Find Planar	Scale Invariant	Local feature:	All features to all features
Distinctive Objects	Interest Points	SIFT	+ Affine / Homography
Panorama Stitching	Scale Invariant	Local feature:	All features to all features
	Interest Points	SIFT	+ Homography
Stereo	Compute in	Intensity or	For each point search
	every point	Gradient patch	on epipolar line

Towards Semantics

- 3D and Projective Geometry can explain a lot of things in the image.
- However, some of the most valuable images cannot be explained by 3D at all.

Towards Semantics

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- However, some of the most valuable images cannot be explained by 3D at all.



100 million \$

"Dora Maar au Chat" Pablo Picasso, 1941



1 cent

"La Picture" Sanja Fidler, yesterday

Towards Semantics

- We shouldn't only look at the 3D behind the image but also at the story behind it.
- We need to also understand the image **semantics**.





It's Fine Without Depth Too



https://www.youtube.com/watch?v=_dPlkFPowCc

It's Fine Without Depth Too

Chickens don't want depth, they want story;)



https://www.youtube.com/watch?v=_dPlkFPowCc

Next Time: Recognition