Back to the Homography: The Why



- In Lecture 9 we said that a homography is a transformation that maps a projective plane to another projective plane.
- We shamelessly dumped the following equation for homography without explanation:

$$w \begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} a & b & c \\ d & e & f \\ g & h & i \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

• Let's revisit our transformation in the (new) light of perspective projection.

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Figure: We have our object in two different worlds, in two different poses relative to camera, two different photographers, and two different cameras.

Sanja Fidler

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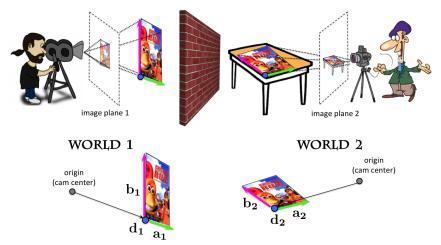


Figure: Our object is a plane. Each plane is characterized by one point d on the plane and two independent vectors a and b on the plane.

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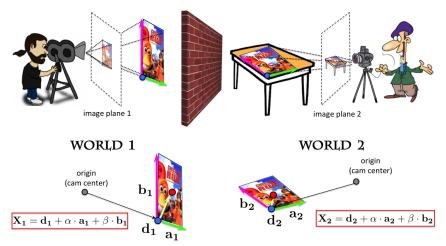


Figure: Then any other point **X** on the plane can be written as: $\mathbf{X} = \mathbf{d} + \alpha \mathbf{a} + \beta \mathbf{b}$.

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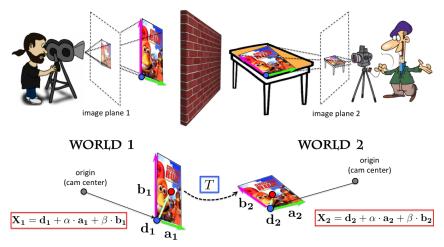


Figure: Any two Chicken Run DVDs on our planet are related by some transformation T. We'll compute it, don't worry.

• Let's revisit our transformation in the (new) light of perspective projection.

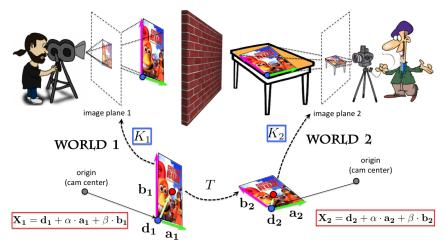


Figure: Each object is seen by a different camera and thus projects to the corresponding image plane with different camera intrinsics.

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CSC420: Intro to Image Understanding

• Let's revisit our transformation in the (new) light of perspective projection.

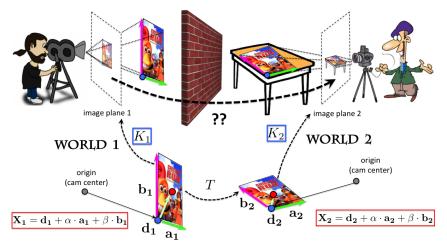


Figure: Given this, the question is what's the transformation that maps the DVD on the first image to the DVD in the second image?

Sanja Fidler

Each point on a plane can be written as: X = d + α · a + β · b, where d is a point, and a and b are two independent directions on the plane.

• Let's have two different planes in 3D:

First plane : $\mathbf{X}_1 = \mathbf{d}_1 + \alpha \cdot \mathbf{a}_1 + \beta \cdot \mathbf{b}_1$ Second plane : $\mathbf{X}_2 = \mathbf{d}_2 + \alpha \cdot \mathbf{a}_2 + \beta \cdot \mathbf{b}_2$

Via α and β , the two points X_1 and X_2 are in the same location relative to each plane.

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Via α and β , the two points X_1 and X_2 are in the same location relative to each plane.

• We can rewrite this using homogeneous coordinates:

First plane :
$$\mathbf{X}_{1} = \begin{bmatrix} \mathbf{a}_{1} & \mathbf{b}_{1} & \mathbf{d}_{1} \end{bmatrix} \begin{bmatrix} \alpha \\ \beta \\ 1 \end{bmatrix} = A_{1} \begin{bmatrix} \alpha \\ \beta \\ 1 \end{bmatrix}$$

Second plane : $\mathbf{X}_{2} = \begin{bmatrix} \mathbf{a}_{2} & \mathbf{b}_{2} & \mathbf{d}_{2} \end{bmatrix} \begin{bmatrix} \alpha \\ \beta \\ 1 \end{bmatrix} = A_{2} \begin{bmatrix} \alpha \\ \beta \\ 1 \end{bmatrix}$

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• Careful: $A_1 = \begin{bmatrix} \mathbf{a_1} & \mathbf{b_1} & \mathbf{d_1} \end{bmatrix}$ and $A_2 = \begin{bmatrix} \mathbf{a_2} & \mathbf{b_2} & \mathbf{d_2} \end{bmatrix}$ are 3 × 3 matrices.

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• In 3D, a transformation between the planes is given by:

$$X_2 = T X_1$$

There is one transformation T between every pair of points X_1 and X_2 .

• Expand it:

$$A_{2}\begin{bmatrix} \alpha\\ \beta\\ 1\end{bmatrix} = T A_{1}\begin{bmatrix} \alpha\\ \beta\\ 1\end{bmatrix} \quad \text{for every } \alpha, \beta$$

- Then it follows: $T = A_2 A_1^{-1}$, with T a 3 × 3 matrix.
- Let's look at what happens in projective (image) plane. Note that we have each plane in a separate image and the two images may not have the same camera intrinsic parameters. Denote them with K_1 and K_2 .

$$w_1 \begin{bmatrix} x_1 \\ y_1 \\ 1 \end{bmatrix} = K_1 \mathbf{X}_1 \quad \text{and} \quad w_2 \begin{bmatrix} x_2 \\ y_2 \\ 1 \end{bmatrix} = K_2 \mathbf{X}_2$$

• From previous slide:

$$w_1 \begin{bmatrix} x_1 \\ y_1 \\ 1 \end{bmatrix} = K_1 \mathbf{X}_1 \quad \text{and} \quad w_2 \begin{bmatrix} x_2 \\ y_2 \\ 1 \end{bmatrix} = K_2 \mathbf{X}_2$$

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$$w_2 \begin{bmatrix} x_2 \\ y_2 \\ 1 \end{bmatrix} = K_2 T \mathbf{X}_1 = K_2 T (K_1^{-1} K_1) \mathbf{X}_1$$

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• Insert $X_2 = T X_1$ into equality on the right:

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• And finally:

$$w_2 \begin{bmatrix} x_2 \\ y_2 \\ 1 \end{bmatrix} = \begin{bmatrix} a & b & c \\ d & e & f \\ g & h & i \end{bmatrix} \begin{bmatrix} x_1 \\ y_1 \\ 1 \end{bmatrix}$$

- The nice thing about homography is that once we have it, we can compute where any point from one projective plane maps to on the second projective plane. We do not need to know the 3D location of that point. We don't even need to know the camera parameters.
- We still owe one more explanation for Lecture 9.

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Remember Panorama Stitching from Lecture 9?



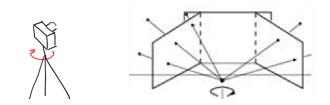


Take a tripod, rotate camera and take pictures

[Source: Fernando Flores-Mangas]

Remember Panorama Stitching from Lecture 9?





• Each pair of images is related by homography. Why?

[Source: Fernando Flores-Mangas]

Rotating the Camera

Rotating my camera with R is the same as rotating the 3D points with R^T (inverse of R):

$$\mathbf{X}_2 = R^T \mathbf{X}_1$$

where X_1 is a 3D point in the coordinate system of the first camera and X_2 the 3D point in the coordinate system of the rotated camera.

• We can use the same trick as before, where we have T = R:

$$w_{1} \begin{bmatrix} x_{1} \\ y_{1} \\ 1 \end{bmatrix} = K \mathbf{X}_{1} \quad \text{and} \quad w_{2} \begin{bmatrix} x_{2} \\ y_{2} \\ 1 \end{bmatrix} = K \mathbf{X}_{2}$$
$$w_{2} \begin{bmatrix} x_{2} \\ y_{2} \\ 1 \end{bmatrix} = w_{1} \underbrace{KRK^{-1}}_{3 \times 3 \text{ matrix}} \begin{bmatrix} x_{1} \\ y_{1} \\ 1 \end{bmatrix}$$

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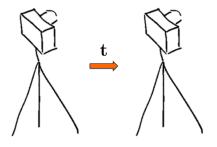
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- So if I take a picture and then rotate the camera and take another picture, the first and second picture are related via homography (assuming the scene didn't change in between)
- What if I move my camera?



• If I move the camera by \mathbf{t} , then: $\mathbf{X}_2 = \mathbf{X}_1 - \mathbf{t}$. Let's try the same trick again:

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• If I move the camera by t, then: $X_2 = X_1 - t$. Let's try the same trick again:

$$w_{2}\begin{bmatrix} x_{2} \\ y_{2} \\ 1 \end{bmatrix} = \mathcal{K} \mathbf{X}_{2} = \underbrace{\mathcal{K} (\mathbf{X}_{1} - \mathbf{t})}_{w_{1} \begin{bmatrix} x_{1} \\ y_{1} \\ 1 \end{bmatrix}}$$

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- Hmm... Different values of w_1 give me different points in the second image.
- So even if I have K and t it seems I can't compute where a point from the first image projects to in the second image.

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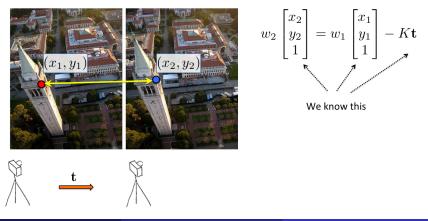
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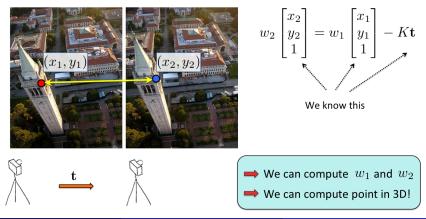
• Where (x_1, y_1) maps to in the 2nd image depends on the 3D location of X_1 !

- Summary: So if I move the camera, I can't easily map one image to the other. The mapping depends on the 3D scene behind the image.
- What about the opposite, what if I know that points (x₁, y₁) in the first image and (x₂, y₂) in the second belong to the same 3D point?

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- What about the opposite, what if I know that points (x_1, y_1) in the first image and (x_2, y_2) in the second belong to the same 3D point?
- This great fact is called stereo
- This brings us to the two-view geometry, which we'll look at next

Summary – Stuff You Need To Know

Perspective Projection:

• If point **Q** is in camera's coordinate system:

•
$$\mathbf{Q} = (X, Y, Z)^T \rightarrow \mathbf{q} = \left(\frac{f \cdot X}{Z} + p_x, \frac{f \cdot Y}{Z} + p_y\right)^T$$

• Same as: $\mathbf{Q} = (X, Y, Z)^T \rightarrow \begin{bmatrix} w \cdot x \\ w \cdot y \\ w \end{bmatrix} = K \begin{bmatrix} X \\ Y \\ Z \end{bmatrix} \rightarrow \mathbf{q} = \begin{bmatrix} x \\ y \end{bmatrix}$
where $K = \begin{bmatrix} f & 0 & p_x \\ 0 & f & p_y \\ 0 & 0 & 1 \end{bmatrix}$ is camera intrinsic matrix

• If **Q** is in world coordinate system, then the full projection is characterized by a 3×4 matrix **P**:

$$\begin{bmatrix} w \cdot x \\ w \cdot y \\ w \end{bmatrix} = \underbrace{\mathbf{K} \begin{bmatrix} \mathbf{R} \mid \mathbf{t} \end{bmatrix}}_{\mathbf{P}} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

Summary – Stuff You Need To Know

Perspective Projection:

- All parallel lines in 3D with the same direction meet in one, so-called vanishing point in the image
- All lines that lie on a plane have vanishing points that lie on a line, so-called vanishing line
- All parallel planes in 3D have the same vanishing line in the image

Orthographic Projection

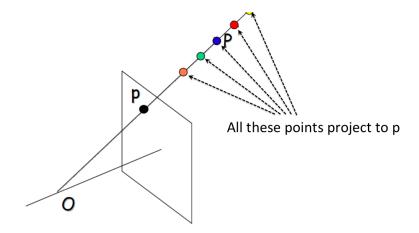
• Projections simply drops the Z coordinate:

$$\mathbf{Q} = \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix} \longrightarrow \begin{bmatrix} X \\ Y \\ 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

• Parallel lines in 3D are parallel in the image

Stereo

• We know that it's impossible to get depth from a single image



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[Pic from: S. Lazebnik]

• But when present, we can use certain cues to get depth (3D) from one image

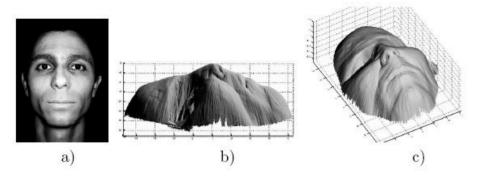


Figure: Shape from Shading

[Slide credit: J. Hays, pic from: Prados & Faugeras 2006]

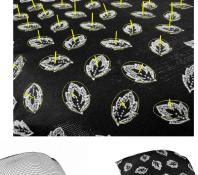
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Figure: Shape from Texture: What do you see in the image?

[From the PhD Thesis: A.M. Loh. The recovery of 3-D structure using visual texture patterns]

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(a) Estimated surface shape (b) Texture projected onto surface

Figure: Shape from Texture [From the PhD Thesis: A.M. Loh. The recovery of 3-D structure using visual texture patterns]

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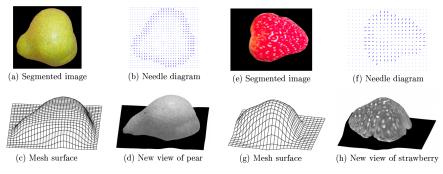


Figure: Shape from Texture

[From the PhD Thesis: A.M. Loh. The recovery of 3-D structure using visual texture patterns]

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Waterlilies:

non-homogeneous



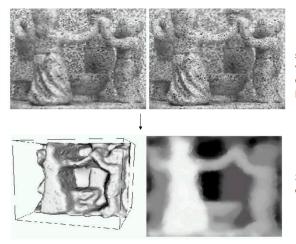




Figure: Shape from Texture: And quite a lot of stuff around us is textured

[From the PhD Thesis: A.M. Loh. The recovery of 3-D structure using visual texture patterns]

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Images from same point of view, different camera parameters

3d shape / depth estimates

Figure: Shape from Focus/De-focus

[Slide credit: J. Hays, pics from: H. Jin and P. Favaro, 2002]

Sanja Fidler

CSC420: Intro to Image Understanding

• But when present, we can use certain cues to get depth (3D) from one image



Figure: Occlusion gives us ordering in depth

[Slide credit: J. Hays, Painting: Rene Magritt'e Le Blanc-Seing]

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Figure: Depth from Google: "Borrow" depth from Google's Street View Z-buffer [Paper: C. Wang, K. Wilson, N. Snavely, Accurate Georegistration of Point Clouds using Geographic Data, 3DV 2013. http://www.cs.cornell.edu/projects/georegister/docs/georegister_3dv.pdf] Sanja Fidler CSC420: Intro to Image Understanding 18 / 29

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Figure: Depth from Google: Once you have depth you can render cool stuff http://inear.se/urbanjungle/

• But when present, we can use certain cues to get depth (3D) from one image



Figure: Depth from Google: Recognize this?

http://inear.se/urbanjungle/

• But when present, we can use certain cues to get depth (3D) from one image

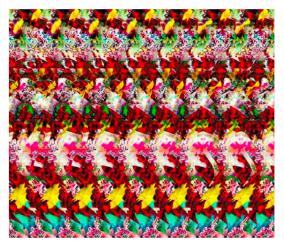


Figure: Depth by tricking the brain: do you see the 3D object?

[Source: J. Hays, Pics from: http://magiceye.com]

• But when present, we can use certain cues to get depth (3D) from one image

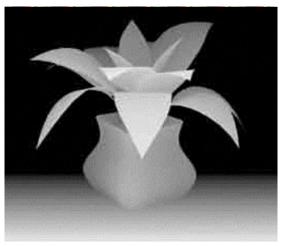


Figure: Depth by tricking the brain

[Source: J. Hays, Pics from: http://magiceye.com]

• All points on projective line to ${\bf P}$ map to ${\bf p}$

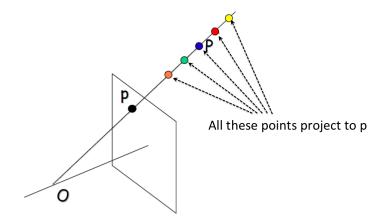


Figure: One camera

• All points on projective line to **P** in left camera map to a **line** in the image plane of the right camera

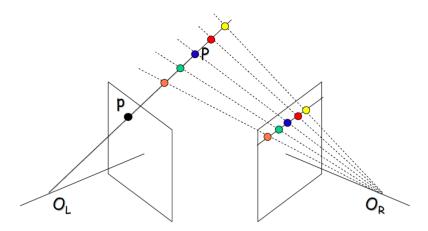


Figure: Add another camera

• If I search this line to find correspondences...

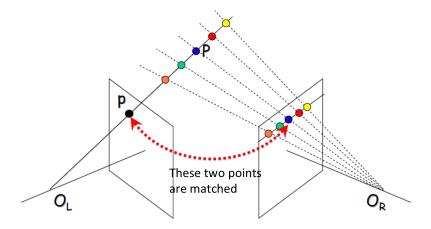


Figure: If I am able to find corresponding points in two images...

• I can get 3D!

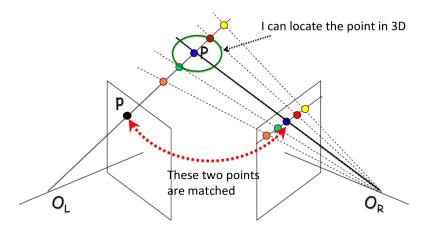


Figure: I can get a point in 3D by triangulation!

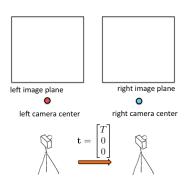
Stereo

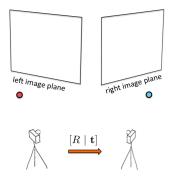
Epipolar geometry

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

Parallel stereo cameras:

General stereo cameras:

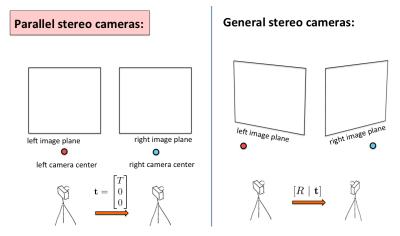




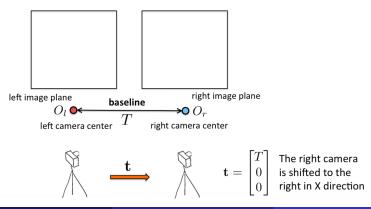
Stereo

Epipolar geometry

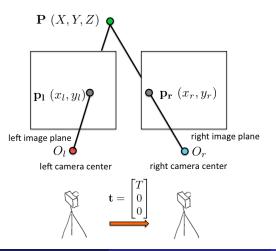
- Case with two cameras with parallel optical axes \leftarrow First this
- General case



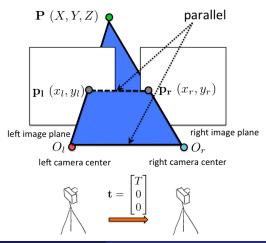
• We assume that the two calibrated cameras (we know intrinsics and extrinsics) are parallel, i.e. the right camera is just some distance to the right of left camera. We assume we know this distance. We call it the **baseline**.



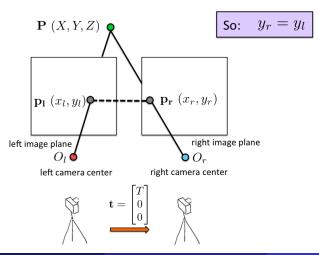
• Pick a point P in the world



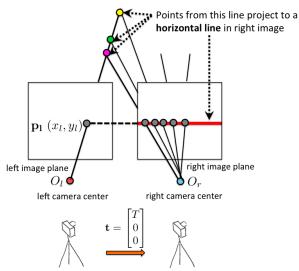
Points O₁, O_r and P (and p₁ and p_r) lie on a plane. Since two image planes lie on the same plane (distance f from each camera), the lines O₁O_r and p₁p_r are parallel.



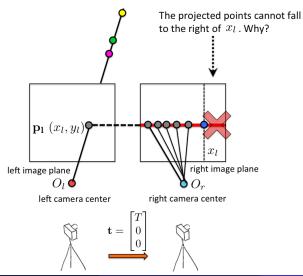
• Since lines O_iO_r and p_ip_r are parallel, and O_i and O_r have the same y, then also p_i and p_r have the same y: $y_r = y_i!$



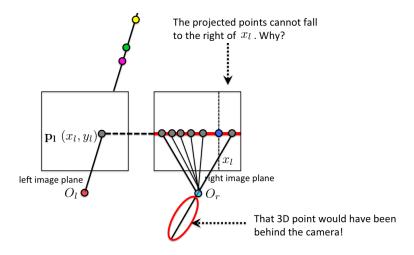
• So all points on the projective line O_1p_1 project to a horizontal line with $y = y_1$ on the right image. This is nice, let's remember this.



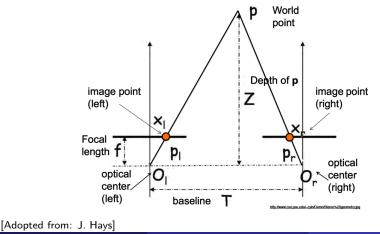
 Another observation: No point from O₁p₁ can project to the right of x₁ in the right image. Why?



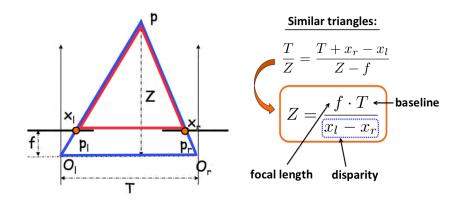
• Because that would mean our image can see behind the camera...



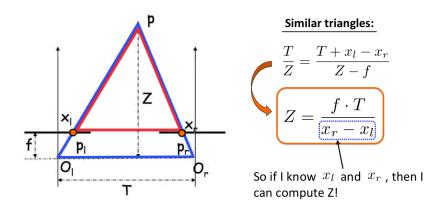
Since our points p_l and p_r lie on a horizontal line, we can forget about y_l for a moment (it doesn't seem important). Let's look at the camera situation from the birdseye perspective instead. Let's see if we can find a connection between x_l, x_r and Z (because Z is what we want).



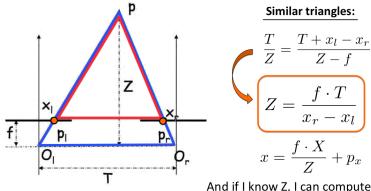
• We can then use similar triangles to compute the depth of the point P



• We can then use similar triangles to compute the depth of the point P



• We can then use similar triangles to compute the depth of the point P



And if I know Z, I can compute X and Y, which gives me the point in 3D

• For each point x_l , how do I get x_r ?



left image

right image

• For each point x_l , how do I get x_r ? By matching.



left image

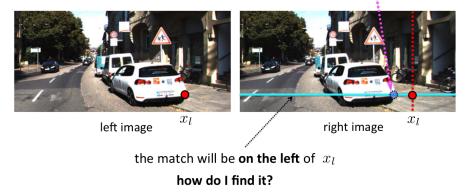
right image

the match will be on this line (same y)

(CAREFUL: this is only true for parallel cameras. Generally, line not horizontal)

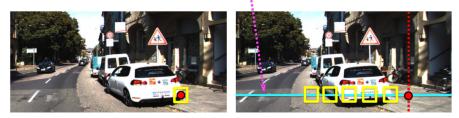
• For each point x_l , how do I get x_r ? By matching.

We are looking for this point



• For each point x_l, how do I get x_r? By matching. Patch around x_r should look similar to the patch around x_l.

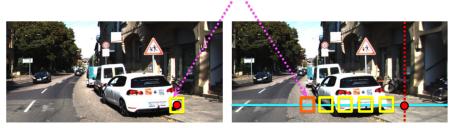
We call this line a scanline



left image

right image

• For each point x_l, how do I get x_r? By matching. Patch around x_r should look similar to the patch around x_l.



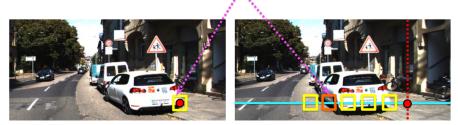
How similar?

left image

right image

 For each point x_l, how do I get x_r? By matching. Patch around x_r should look similar to the patch around x_l.

How similar?

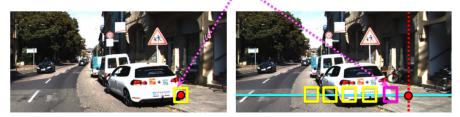


left image

right image

• For each point x_l, how do I get x_r? By matching. Patch around x_r should look similar to the patch around x_l.

Most similar. A match!



left image

right image

 For each point x_l, how do I get x_r? By matching. Patch around x_r should look similar to the patch around x_l.







At each point on the scanline: Compute a matching cost

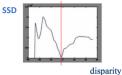
Matching cost: SSD or normalized correlation

 For each point x_l, how do I get x_r? By matching. Patch around x_r should look similar to the patch around x_l.

$$SSD(\text{patch}_l, \text{patch}_r) = \sum_{x} \sum_{y} (I_{\text{patch}_l}(x, y) - I_{\text{patch}_r}(x, y))^2$$



left image



Compute a matching cost Matching cost: SSD (look for minima)

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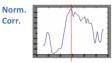
• For each point x₁, how do I get x_r? By matching. Patch around x_r should look similar to the patch around x₁.

$$NC(\text{patch}_l, \text{patch}_r) = \frac{\sum_x \sum_y (I_{\text{patch}_l}(x, y) \cdot I_{\text{patch}_r}(x, y))}{||I_{\text{patch}_l}|| \cdot ||I_{\text{patch}_r}||}$$





left image



Compute a matching cost

Matching cost: Normalized Corr. (look for maxima)

disparity

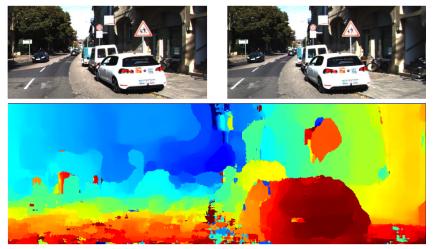
 For each point x_l, how do I get x_r? By matching. Patch around x_r should look similar to the patch around x_l.



left image

Do this for all the points in the left image!

• We get a disparity map as a result

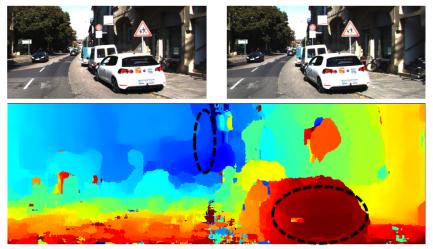


Result: **Disparity map** (red values large disp., blue small disp.)

Sanja Fidler

CSC420: Intro to Image Understanding

• We get a disparity map as a result

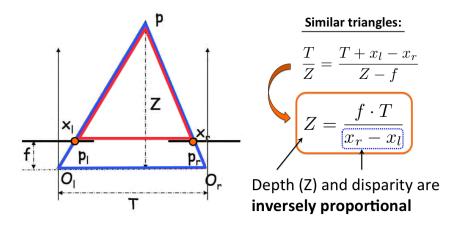


Things that are closer have **larger disparity** than those that are far away from camera. Why?

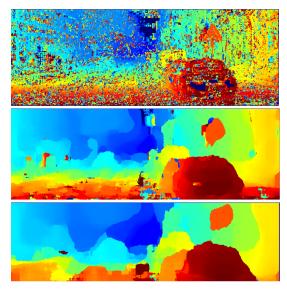
Sanja Fidler

CSC420: Intro to Image Understanding

• Depth and disparity are inversely proportional



• Smaller patches: more detail, but noisy. Bigger: less detail, but smooth



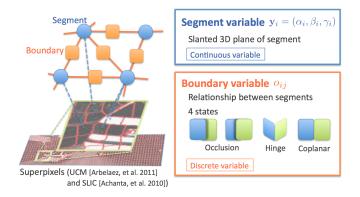
patch size = 5

patch size = 35

patch size = 85

You Can Do It Much Better...

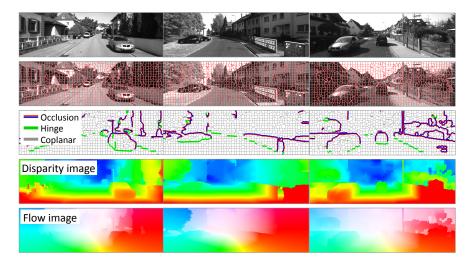
• With Energy Minimization on top, e.g., a Markov Random Field (MRF)



K. Yamaguchi, D. McAllester, R. Urtasun, Efficient Joint Segmentation, Occlusion Labeling, Stereo and Flow Estimation, ECCV 2014 Paper: http://www.cs.toronto.edu/~urtasun/publications/yamaguchi_et_al_eccv14.pdf Code: http://ttic.uchicago.edu/~dmcallester/SPS/index.html

You Can Do It Much Better...

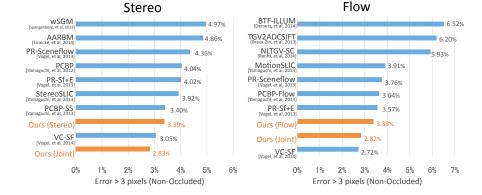
[K. Yamaguchi, D. McAllester and R. Urtasun, ECCV 2014]



Look at State-of-the-art on KITTI

Where "Ours" means: [K. Yamaguchi, D. McAllester and R. Urtasun, ECCV 2014]

• How can we evaluate the performance of a stereo algorithm?



Autonomous driving dataset KITTI: http://www.cvlibs.net/datasets/kitti/

From Disparity We Get...

• Depth: Once you have disparity, you have 3D



Figure: K. Yamaguchi, D. McAllester and R. Urtasun, ECCV 2014

Sanja Fidler

From Disparity We Get...

• Money ;)



Stereo

Epipolar geometry

- Case with two cameras with parallel optical axes
- General case \leftarrow **Next time**

