# Computer Vision: Lecture 12

#### Carl Olsson

2020-02-26



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Computer Vision: Lecture 12

## **Todays Lecture**

#### Stereo

- Stereo cameras
- Disparity and depth
- Dense matching
- Normalized cross correlation
- The plane sweep approach
- Regularization
- Silhouettes, Visual hull.



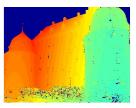
### Dense Stereo

#### Goal

- Estimate the depth in every pixel. Dense depth map.
- Requires every point in the image to be matched!









## Dense Stereo

#### Rectified images

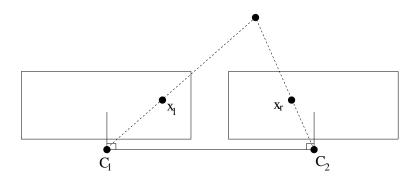
Assumptions:

- The image-planes are parallel, and the second camera center is translated in the x-direction of the first. (Can always be achieved by transforming the images.)
- The cameras have the same inner parameters.

$$P_1 = K[I \ 0] \text{ and } P_2 = K \begin{bmatrix} I & b \\ 0 \\ 0 \end{bmatrix}$$



### **Rectified Cameras**

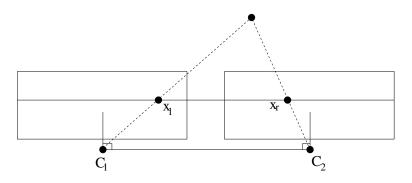




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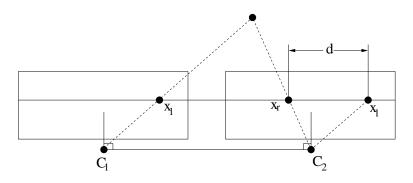
### **Rectified Cameras**



Epipolar lines are parallel to the x-axis.



### **Rectified Cameras**



Difference between the x-coordinates of  $x_l$  and  $x_r$  is called the disparity.

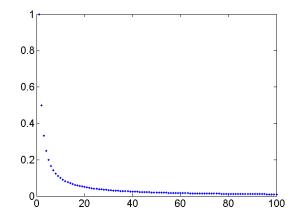


## Disparity and Depth

See lecture notes.



## Disparity vs. Depth



Disparity (in pixels) vs. depth when  $f_x b = 1$ . Higher resolution when the depth is small/the disparity is large.

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#### Why not SIFT?

- Need measurements everywhere.
- Cameras known  $\Rightarrow$  don't need scale, rotation invariance.

#### NCC

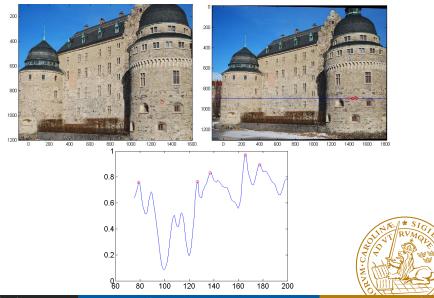
If  $I_1$  and  $I_2$  are gray levels of two patches,

$$NCC(l_1, l_2) = \frac{1}{n-1} \sum_{i=1}^{n} \frac{(l_1(x_i) - \bar{l}_1)(l_2(x_i) - \bar{l}_2)}{\sigma(l_1)\sigma(l_2)},$$

 $\bar{l}_1, \bar{l}_2$  - mean values of each patch.  $\sigma(l_1), \sigma(l_2)$  - standard deviations of each patch.

 Invariant to translation and rescaling of the grayvalues. (Good for handeling different lighting conditions.)

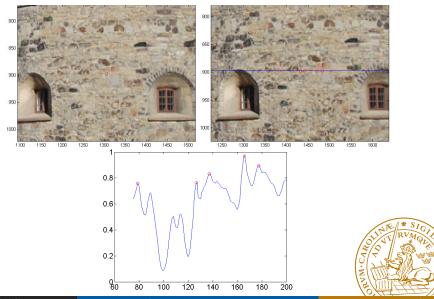
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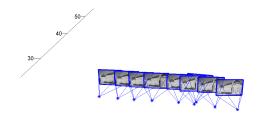
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Demonstration.



## Depth Map Estimation

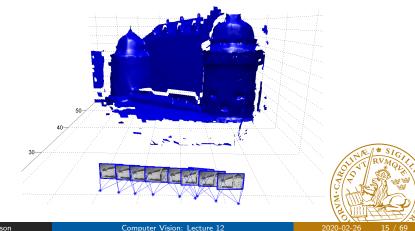
Given images and Cameras, how do we compute a dense surface estimate? (Need to find matches for all the pixels in the image.)





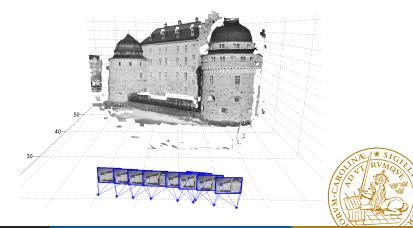
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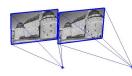


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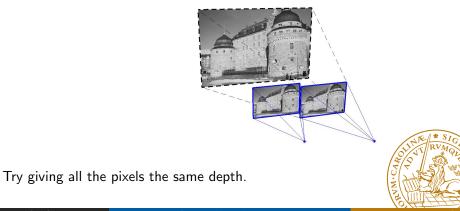
Given 2 cameras. How do we find the depths of all the pixels?



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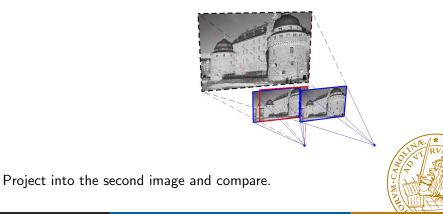
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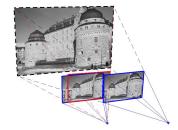
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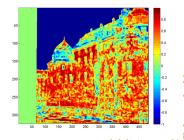
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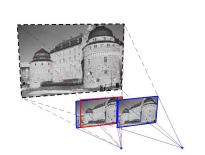


Difference between the original image and the projection.

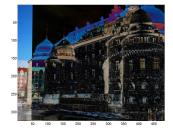


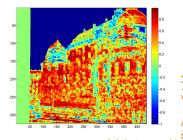


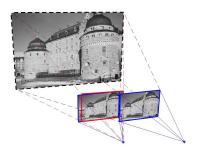
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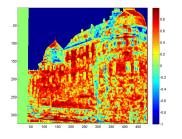
Try several different depths.





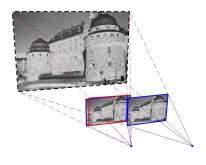


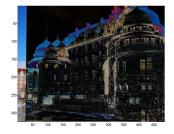


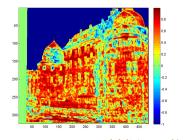


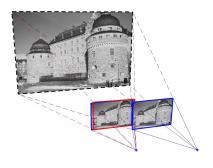
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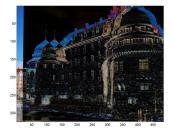
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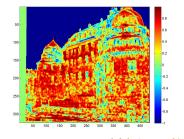








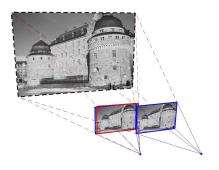


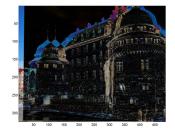


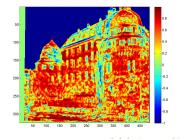
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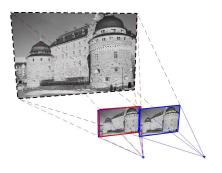
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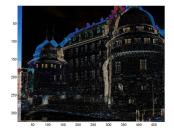
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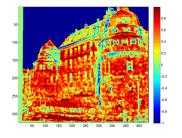








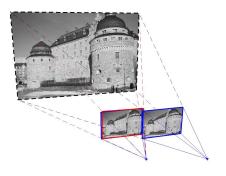


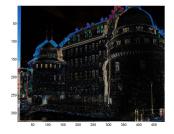


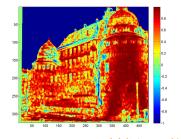
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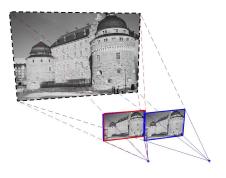
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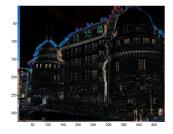


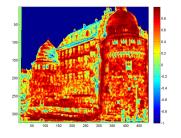




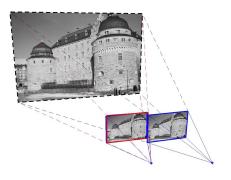
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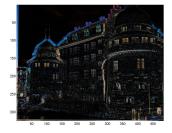


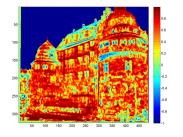


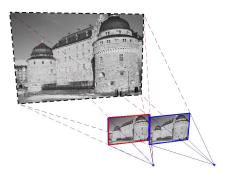


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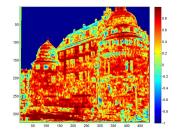








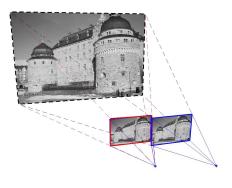


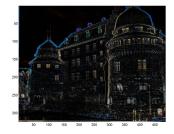


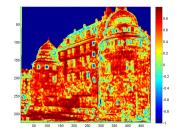
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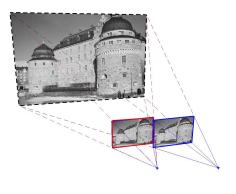
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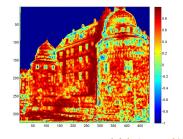


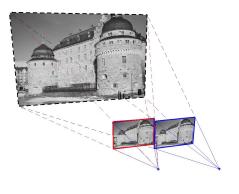




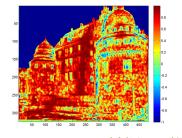


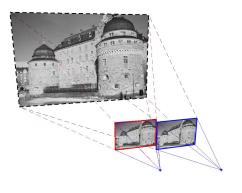


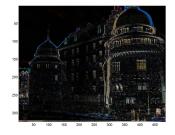


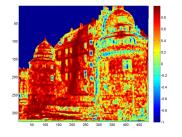


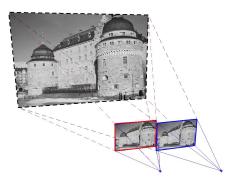


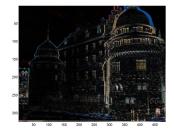


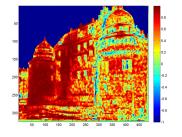


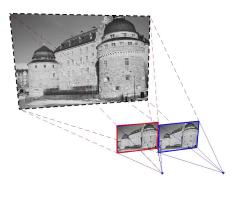




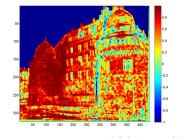


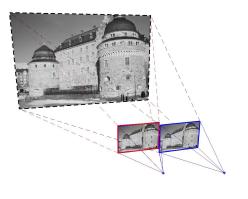


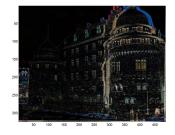


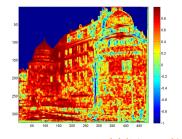




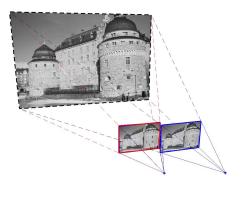


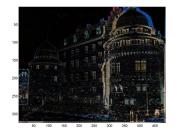


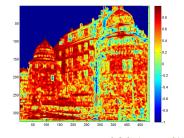


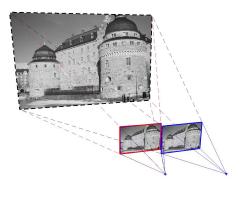


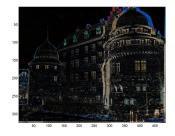
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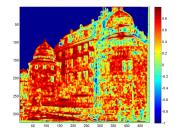










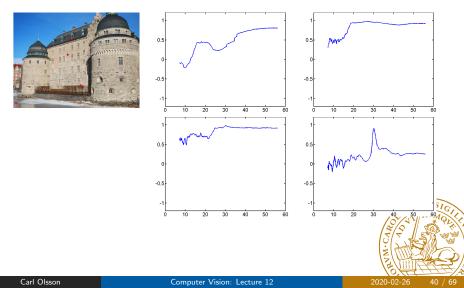


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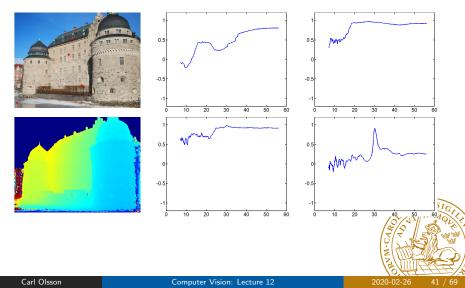
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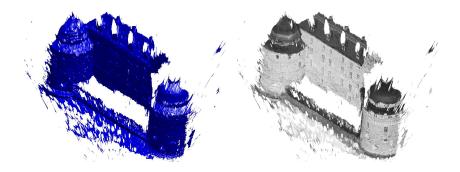
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Gives a function of depth for each pixel:



Gives a function of depth for each pixel:





Select the best value for each pixel

 $\min_{d}\sum_{i}E_{i}(d_{i})$ 

independently of its neighbors.



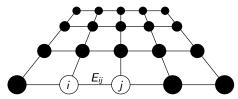
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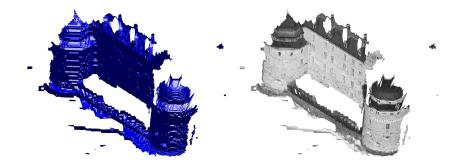
Neighboring pixels tend to have similar depth. Add a regularization term

$$\min_{d} \sum_{i} \sum_{j \in \mathcal{N}(i)} E_{ij}(d_i, d_j) + \sum_{i} E_i(d_i)$$

Each pixel can be seen as a node in a graph.  $E_{ij}$  can be seen as an edge cost for the edge between nodes *i* and *j*.



Can minimize the energy using graph algorithms, e.g. graph cuts message passing.



Penalize neighbors that have different depth

$$\min_{d} \sum_{i} \sum_{j \in \mathcal{N}(i)} \min(|d_i - d_j|, tr) + \sum_{i} E_i(d_i)$$

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Taylor:

$$d_j \approx d_i + \nabla d_i^T (x_j - x_i)$$

 $x_i$ ,  $x_j$  are the coordinates of the pixels *i*, *j*. Therefore

 $|d_i - d_j|$ 

penalizes tilted planes.

Use

$$|d_i + \nabla d_i^T (x_j - x_i) - d_j| \approx |\frac{1}{2} (x_j - x_i)^T \nabla^2 d_i (x_j - x_i)$$

instead. 2nd derivative is zero for affine functions.



Taylor:

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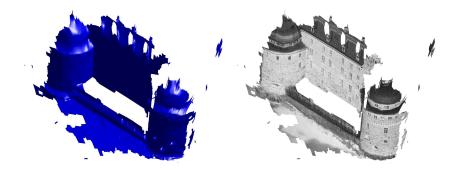
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Use

$$|d_i + 
abla d_i^{\mathsf{T}}(x_j - x_i) - d_j| pprox |rac{1}{2}(x_j - x_i)^{\mathsf{T}} 
abla^2 d_i(x_j - x_i)$$

instead. 2nd derivative is zero for affine functions.



 $\min_{d} \sum_{i} \sum_{j \in \mathcal{N}(i)} \min(|d_i + \nabla d_i^T(x_j - x_i) - d_j|, tr) + \sum_{i} E_i(d_i)$ 

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## Movie





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### Dense Surface Reconstruction

Combine all the depth maps into one surface. (Voxel carving algorithm.)







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### More Movies





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### Silhouettes and Visual Hull

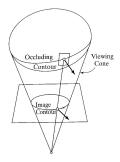


Figure 19.1 The occlusion boundaries of a smooth



Figure 19.3 Shadow boundaries and occluding contours. Reprinted from "Solid Shape," by J.J. Koenderink, MIT Press, (1990). © 1990 by The Massachusetts Institute of Technology.

The viewed object can be constrained to lie within the viewing cone.

(Viewing cone = all rays through the camera center and the interior of the projection.)

Visual hull = intersection of all viewing cones. Largest volume contained in the intersection.

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#### Problem

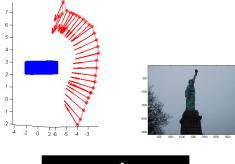
Given cameras P and segmented silhouettes compute a volumetric representation of the viewed object.

#### Algorithm

- For each image, project the (center of the) voxels into the image and determine which ones belong to the exterior of the object.
- Remove the voxels that belongs to the exterior of the object in at least one image.



### Example.





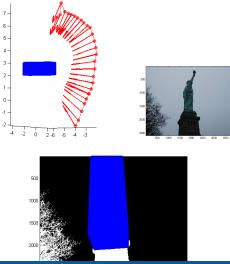


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### Example.



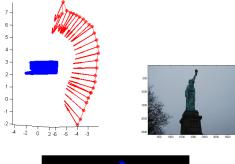


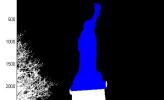
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### Example.



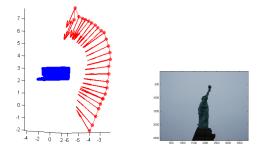




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### Example.



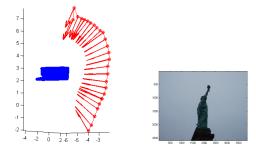




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### Example.





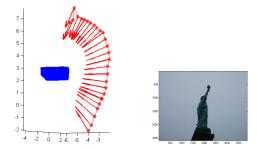


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### Example.





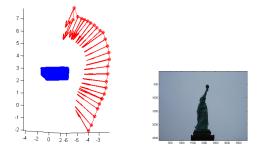


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### Example.





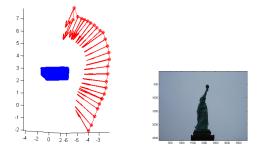


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### Example.



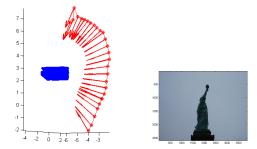




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### Example.





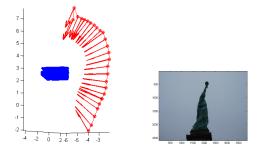


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### Example.





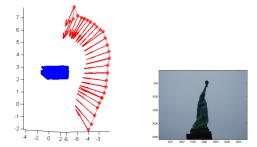


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### Example.



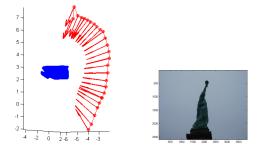




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### Example.

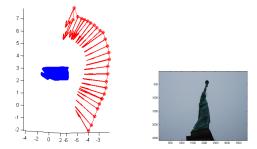






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### Example.





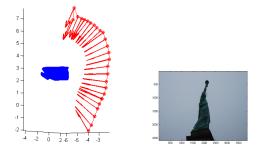


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### Example.





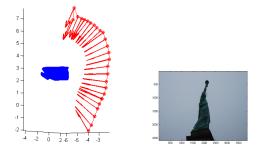


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### Example.





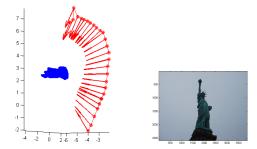


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### Example.





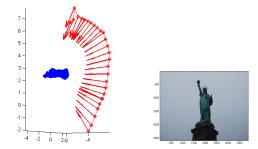


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### Example.







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Project texture on it.



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