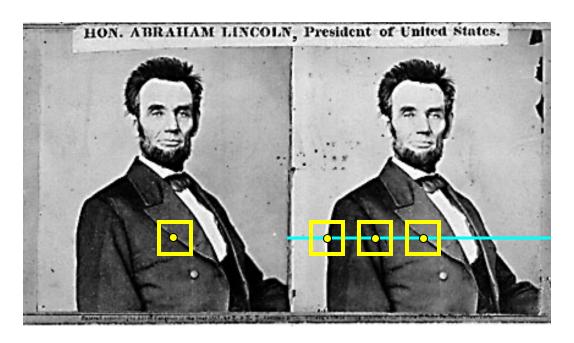
Solving for Stereo Correspondence

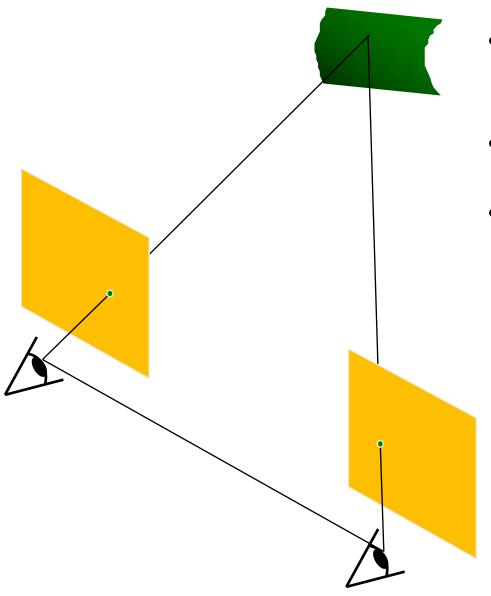
Many slides drawn from Lana Lazebnik, UIUC

Basic stereo matching algorithm



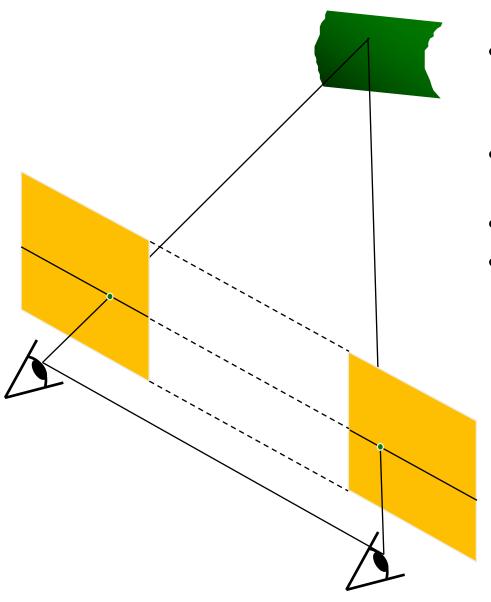
- For each pixel in the first image
 - Find corresponding epipolar line in the right image
 - Examine all pixels on the epipolar line and pick the best match
 - Triangulate the matches to get depth information

Simplest Case: Parallel images



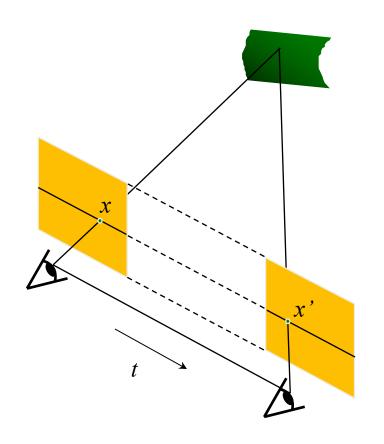
- Image planes of cameras are parallel to each other and to the baseline
- Camera centers are at same height
- Focal lengths are the same

Simplest Case: Parallel images



- Image planes of cameras are parallel to each other and to the baseline
- Camera centers are at same height
- Focal lengths are the same
- Then epipolar lines fall along the horizontal scan lines of the images

Essential matrix for parallel images



Epipolar constraint:

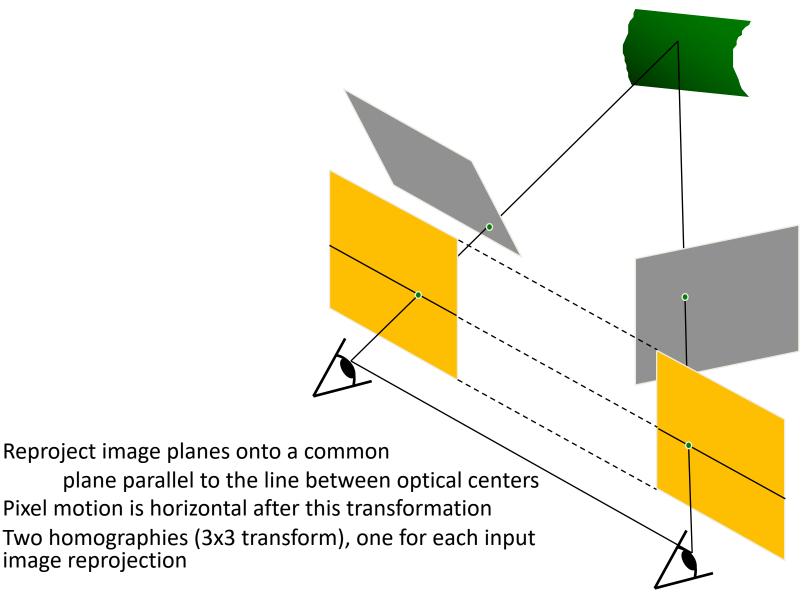
$$\mathbf{x'}^T \mathbf{E} \mathbf{x} = 0, \quad \mathbf{E} = [\mathbf{t}_{\times}] \mathbf{R}$$

$$\mathbf{R} = \mathbf{I} \qquad \mathbf{t} = (T, 0, 0)$$

$$\boldsymbol{E} = [\boldsymbol{t}_{\times}] \boldsymbol{R} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & -T \\ 0 & T & 0 \end{bmatrix}$$

The y-coordinates of corresponding points are the same!

Stereo image rectification



•C. Loop and Z. Zhang. Computing Rectifying Homographies for Stereo Vision. IEEE Conf. Computer Vision and Pattern Recognition, 1999.

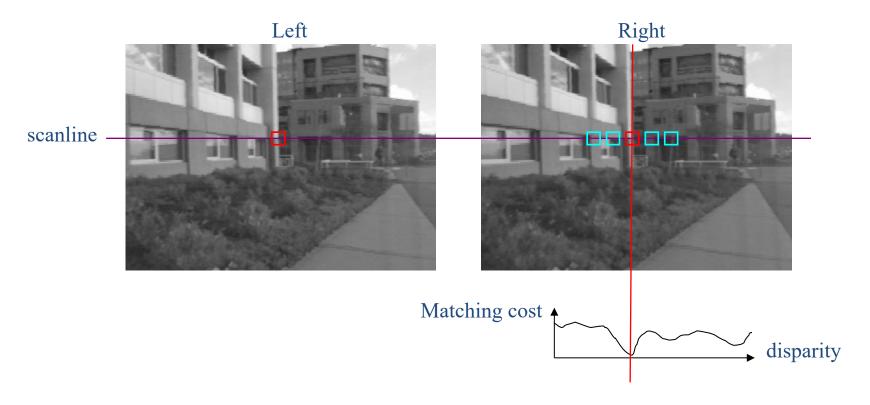
image reprojection

Rectification example



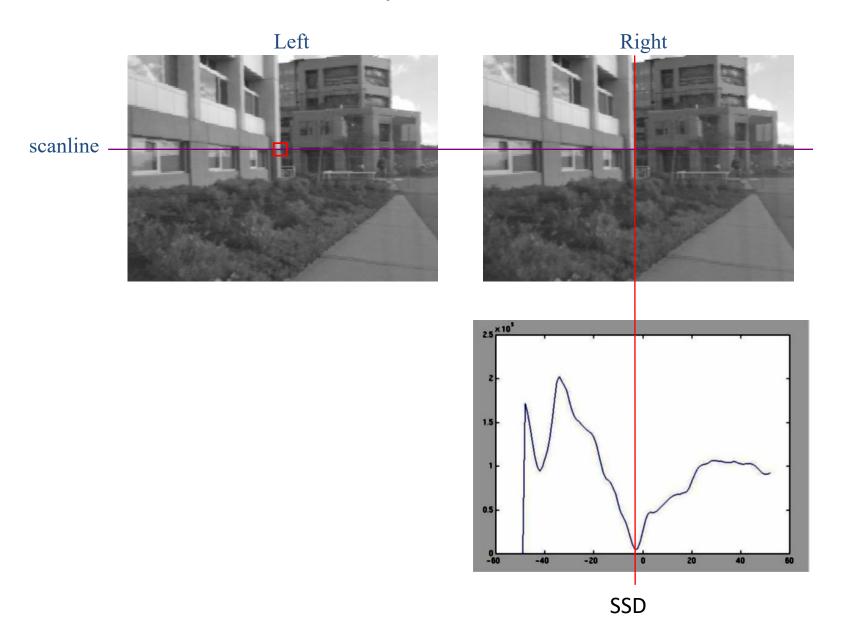


Correspondence search

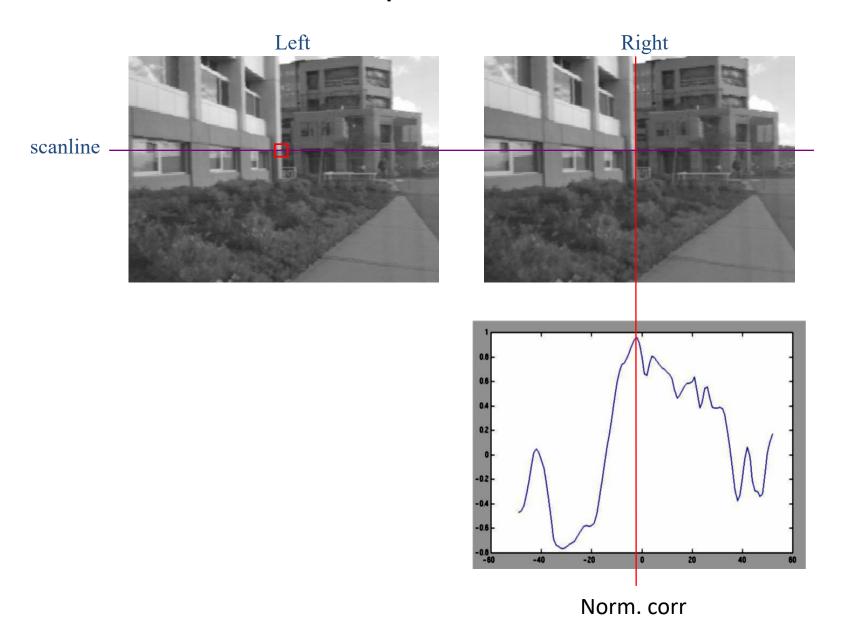


- Slide a window along the right scanline and compare contents of that window with the reference window in the left image
- Matching cost: SSD or normalized correlation

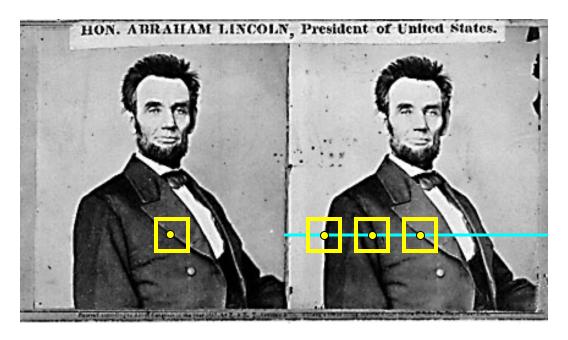
Correspondence search



Correspondence search

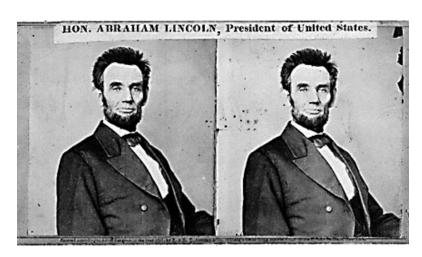


Basic stereo matching algorithm



- If necessary, rectify the two stereo images to transform epipolar lines into scanlines
- For each pixel x in the first image
 - Find corresponding epipolar scanline in the right image
 - Examine all pixels on the scanline and pick the best match x'
 - Compute disparity x-x' and set depth(x) = B*f/(x-x')

Failures of correspondence search



Textureless surfaces



Occlusions, repetition





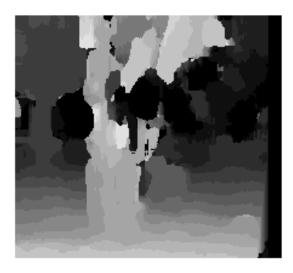
Non-Lambertian surfaces, specularities



Effect of window size







W = 3

W = 20

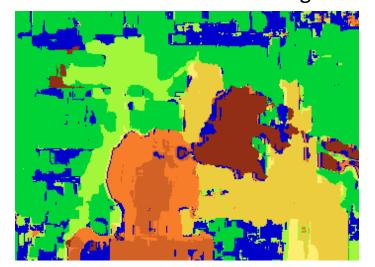
- Smaller window
 - + More detail
 - More noise
- Larger window
 - + Smoother disparity maps
 - Less detail

Results with window search

Data



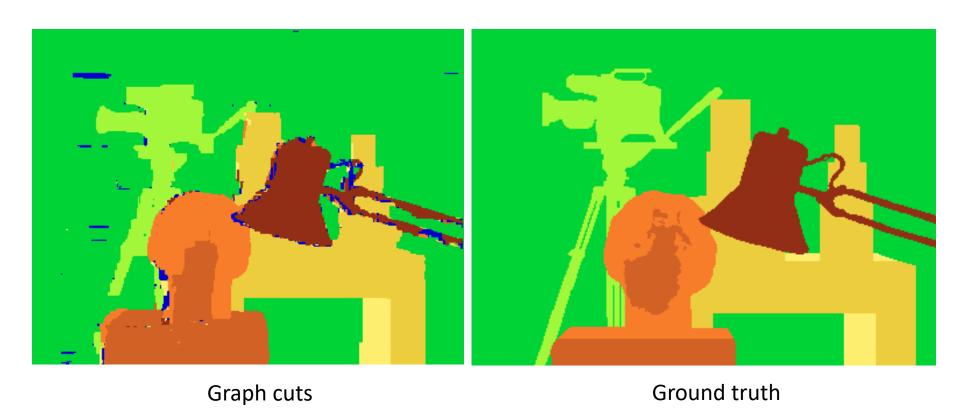
Window-based matching



Ground truth



Better methods exist...



Y. Boykov, O. Veksler, and R. Zabih, <u>Fast Approximate Energy Minimization</u> via Graph Cuts, PAMI 2001

For the latest and greatest: http://www.middlebury.edu/stereo/



This CVPR 2020 paper is the Open Access version, provided by the Computer Vision Foundation.

Except for this watermark, it is identical to the accepted version;
the final published version of the proceedings is available on IEEE Xplore.

SuperGlue: Learning Feature Matching with Graph Neural Networks

Paul-Edouard Sarlin^{1*} Daniel DeTone² Tomasz Malisiewicz² Andrew Rabinovich²

¹ ETH Zurich ² Magic Leap, Inc.

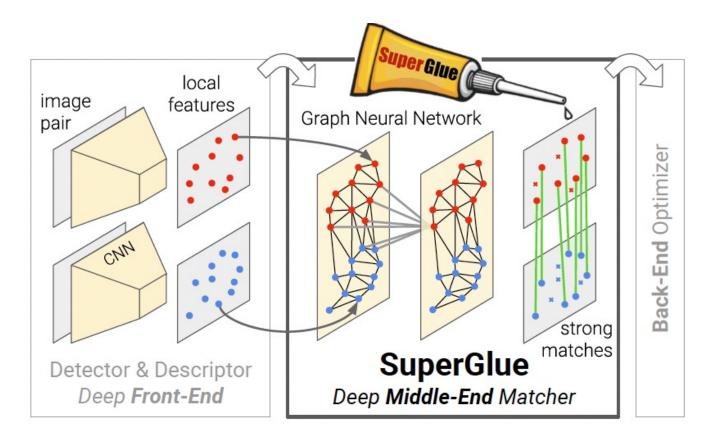


Figure 1: **Feature matching with SuperGlue.** Our approach establishes pointwise correspondences from off-the-shelf local features: it acts as a middle-end between hand-crafted or learned front-end and back-end. SuperGlue uses a graph neural network and attention to solve an assignment optimization problem, and handles partial point visibility and occlusion elegantly, producing a partial assignment.