# Triangulation: Why Optimize?

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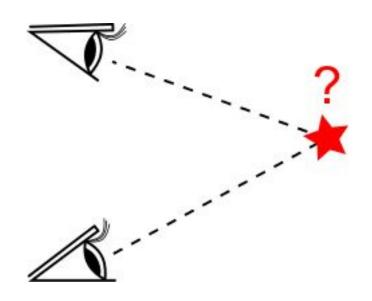




# Triangulation:

Locating a 3D point observed from a known baseline.

Used in surveying, astrometry, navigation, computer vision, etc.





Sorn340, shutterstock.com

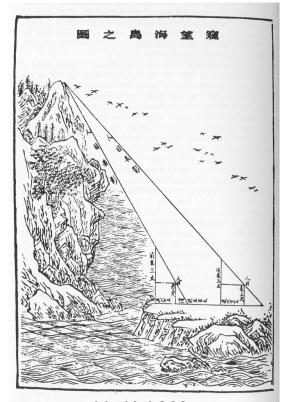


Bill Saxton, NRAO/AUI/NSF

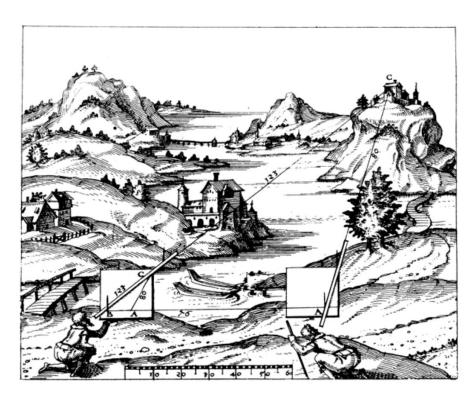


Building Rome in a day. https://grail.cs.washington.edu/rome/

### Triangulation is much older than computer vision...!

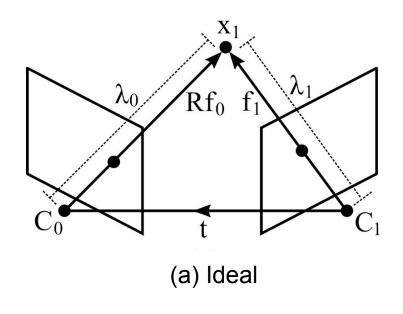


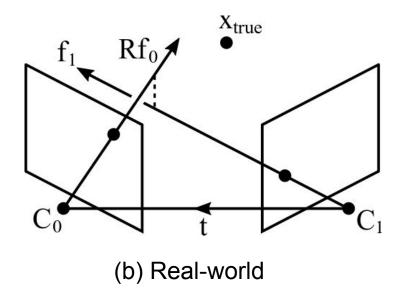
Liu Hui 263. (Illustrated in 1726)



Zubler 1625

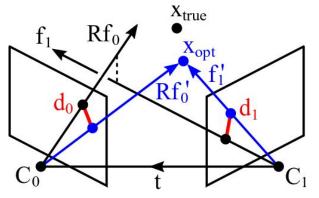
Locating the 3D point given its projections in two views of known calibration and pose.





#### 1. Optimal methods:

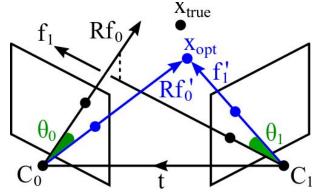
Find intersecting rays that minimize the reprojection cost.



(a) Image Reprojection error

- $L_1$  norm:  $d_0 + d_1$
- $L_2$  norm:  $d_0^2 + d_1^2$

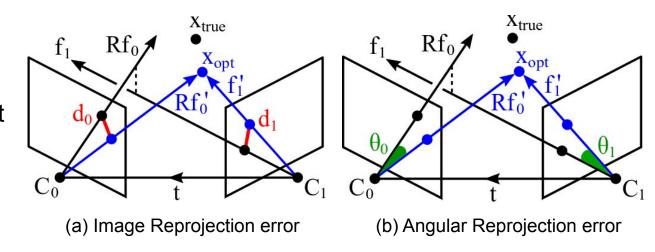
•  $L_{\infty}$  norm:  $max(d_0 + d_1)$ [Hartley 1997, Níster 2001]



- (b) Angular Reprojection error
- L<sub>1</sub> norm:  $\theta_0 + \theta_1$
- $L_2$  norm:  $\sin^2(\theta_0) + \sin^2(\theta_1)$
- $L_{\infty}$  norm:  $\max(d_0 + d_1)$ [Oliensis 2002, Lee 2019]

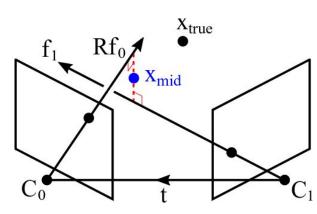
#### 1. Optimal methods:

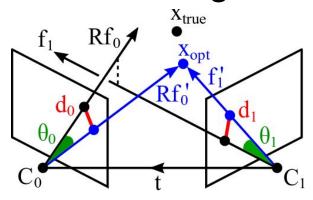
Find intersecting rays that minimize the reprojection cost.

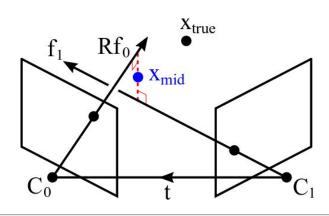


#### 2. Midpoint method:

Find the midpoint of the common perpendicular.



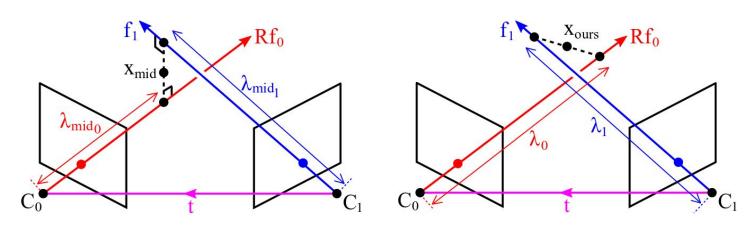




Optimal methods	Midpoint method	
✓ Fast [Lindstrom 10, Lee 19]	✓ Faster	
✓ Minimal 2D (or angular) reproj. error	✗ Large 2D error at low parallax	
✓ Small 3D error at high parallax	✓ Small 3D error at high parallax	
★ Large 3D error at low parallax	✓ Smaller 3D error (than the optimal method) at low parallax	

The discrepancy between 2D and 3D accuracy was reported in [Hartley 97]...!

# Contribution #1: Alternative Midpoint Method



Let 
$$p=R\widehat{f}_0 imes\widehat{f}_1,\,q=R\widehat{f}_0 imes t$$
 and  $r=\widehat{f}_1 imes t$  .

#### Classic Midpoint Depths

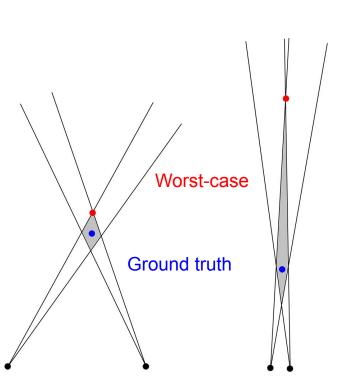
$$\lambda_{\text{mid}0} = \frac{\widehat{\mathbf{p}} \cdot \mathbf{r}}{\|\mathbf{p}\|}, \quad \lambda_{\text{mid}1} = \frac{\widehat{\mathbf{p}} \cdot \mathbf{q}}{\|\mathbf{p}\|}$$

#### **Proposed Depths**

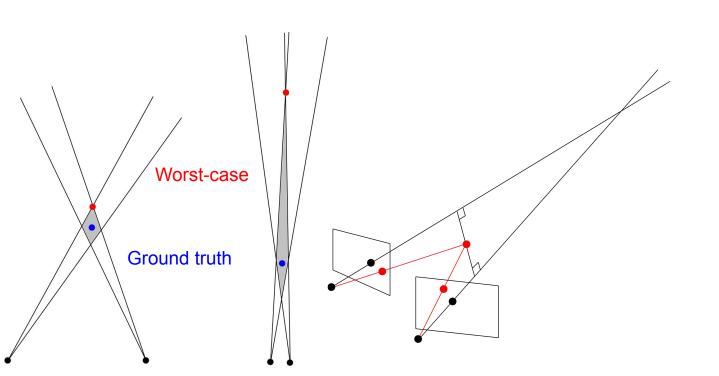
$$\lambda_0 = \frac{\|\mathbf{r}\|}{\|\mathbf{p}\|}, \quad \lambda_1 = \frac{\|\mathbf{q}\|}{\|\mathbf{p}\|}$$

- When the rays intersect, this is just the sine rule.
- $\lambda_{mid0} \leq \lambda_0 \ \ \text{and} \ \lambda_{mid1} \leq \lambda_1$

- Optimal methods tend to locate the point too far → Large 3D error!

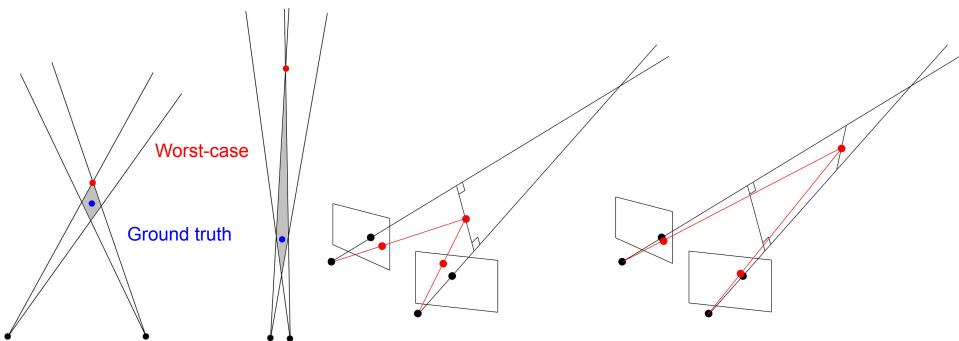


- Optimal methods tend to locate the point too far → Large 3D error!
- Midpoint method tends to locate the point too close → Large 2D error!



- Optimal methods tend to locate the point too far → Large 3D error!
- Midpoint method tends to locate the point too close → Large 2D error!
- Recall  $\lambda_{mid0} \leq \lambda_0$  and  $\lambda_{mid1} \leq \lambda_1 \rightarrow$  Our midpoint is farther, but not too far.

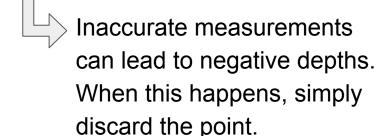
→ Small 2D and 3D error (sweet spot)!



# Contribution #2: Alternative Cheirality Check

#### Classic Midpoint Depths

$$\lambda_{\mathrm{mid}0} = \frac{\widehat{\mathbf{p}} \cdot \mathbf{r}}{\|\mathbf{p}\|}, \quad \lambda_{\mathrm{mid}1} = \frac{\widehat{\mathbf{p}} \cdot \mathbf{q}}{\|\mathbf{p}\|}$$



**Proposed Depths** 

$$\lambda_0 = \frac{\|\mathbf{r}\|}{\|\mathbf{p}\|}, \quad \lambda_1 = \frac{\|\mathbf{q}\|}{\|\mathbf{p}\|}$$



The depths are always positive.

Discard the point if assuming a negative depth brings the two points on each ray closer together, i.e.,

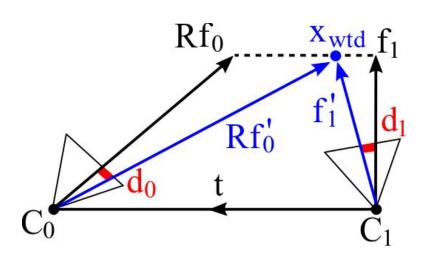
$$\|\textbf{t} + \lambda_0 \textbf{R}\widehat{\textbf{f}}_0 - \lambda_1 \widehat{\textbf{f}}_1\|^2 \geq \min \Big( \|\textbf{t} + \lambda_0 \textbf{R}\widehat{\textbf{f}}_0 + \lambda_1 \widehat{\textbf{f}}_1\|^2, \|\textbf{t} - \lambda_0 \textbf{R}\widehat{\textbf{f}}_0 - \lambda_1 \widehat{\textbf{f}}_1\|^2, \|\textbf{t} - \lambda_0 \textbf{R}\widehat{\textbf{f}}_0 + \lambda_1 \widehat{\textbf{f}}_1\|^2 \Big)$$

# Contribution #3: Inverse Depth Weighting

**Unweighted Midpoint** 

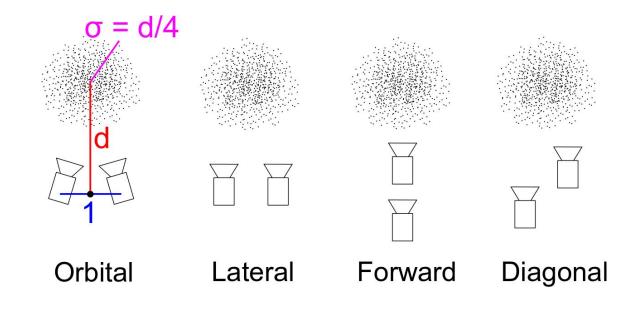
$$x_{\text{unwtd}} = \frac{\mathbf{t} + \lambda_0 \mathbf{R} \widehat{\mathbf{f}_0} + \lambda_1 \widehat{\mathbf{f}_1}}{2}$$

Inverse Depth Weighted Midpoint



$$x_{\text{wtd}} = \frac{\lambda_0^{-1} (\mathbf{t} + \lambda_0 \mathbf{R} \widehat{\mathbf{f}}_0) + \lambda_1^{-1} (\lambda_1 \widehat{\mathbf{f}}_1)}{\lambda_0^{-1} + \lambda_1^{-1}}$$

# Synthetic Dataset

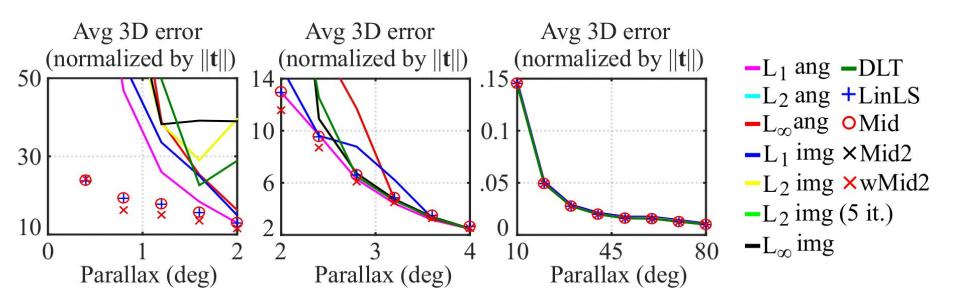


- d = {0.5, 1, 2, ..., 64} x baseline
- Image noise level = 1, 2, 3, ..., 8 pix.

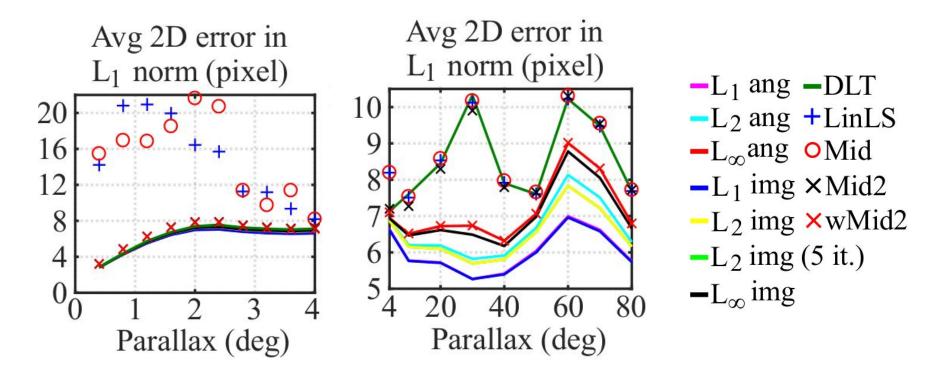


Over a million unique triangulation problems

# 3D error evaluation on synthetic dataset



# 2D error evaluation on synthetic dataset



# Speed

Method	Speed (Points/ sec)
Classic Midpoint	38M
L1 angular optimal [Lee 19]	29M
Ours (unweighted)	21M
L∞ angular angular [Lee 19]	13M
Ours (weighted)	12M
L2 image optimal [Lindstrom 10]	550K

# Summary

Optimal Methods	Classic Midpoint	Our Weighted Midpoint
✓ Fast [Lindstrom 10, Lee 19]	✓ Fastest	✓ Fast
✓ Minimal 2D error	✗ Large 2D error	✓ Small 2D error
✓ Small 3D error at high parallax	✓ Small 3D error at high parallax	✓ Small 3D error at high parallax
Large 3D error at low parallax	✓ Smaller 3D error (than the optimal methods) at low parallax	✓ Smaller 3D error (than the optimal methods) at low parallax

#### Why Optimize?

- For parallax < 4 deg, DO NOT OPTIMIZE and use our unweighted midpoint method instead.
  - Although our method is not optimal in a geometrically meaningful way, it clearly outperforms the existing optimal and non-optimal methods at low parallax.
  - Inverse depth weighting does not help much at low parallax.
- For parallax > 4 deg, DO OPTIMIZE using L1 angular method [Lee 19].
  - Similar 3D accuracy, yet optimal in L1 angular reproj error and as fast as the midpoint.

#### References

[Hartley 97] *Triangulation*, R. Hartley and P. Sturm, Computer Vision and Image Understanding, 1997

[Níster 01] Automatic dense reconstruction from uncalibrated video sequences, D. Níster, PhD thesis, 2001

[Oliensis 02] Exact two-Image structure from motion, J. Oliensis, IEEE Transactions on Pattern Analysis and Machine Intelligence, 2002

[Lindstrom 10] *Triangulation made easy*, P. Lindstrom, IEEE Conference on Computer Vision and Pattern Recognition, 2010

**[Lee 19]** Closed-form optimal two-view triangulation based on angular errors, S. Lee and J. Civera, IEEE International Conference on Computer Vision, 2019