Triangulation: Why Optimize?

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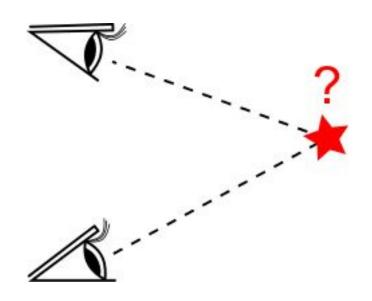




Triangulation:

Locating a 3D point observed from a known baseline.

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





Sorn340, shutterstock.com

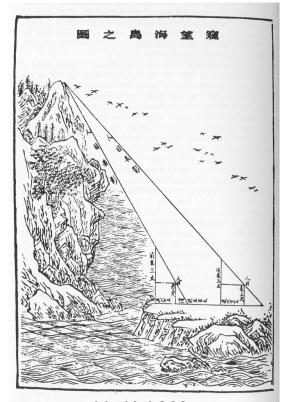


Bill Saxton, NRAO/AUI/NSF

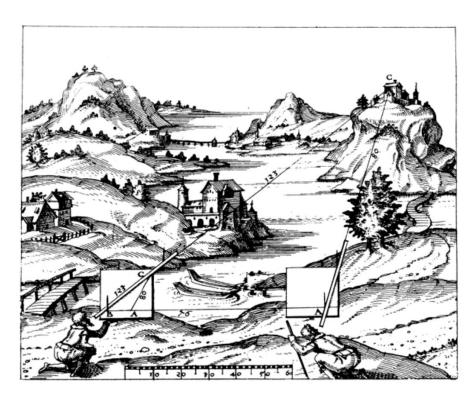


Building Rome in a day. https://grail.cs.washington.edu/rome/

Triangulation is much older than computer vision...!

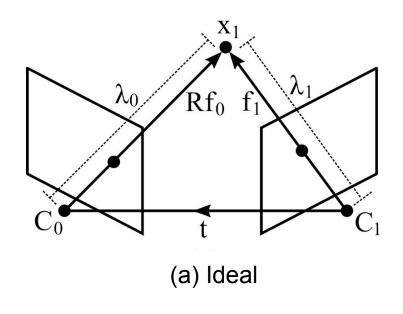


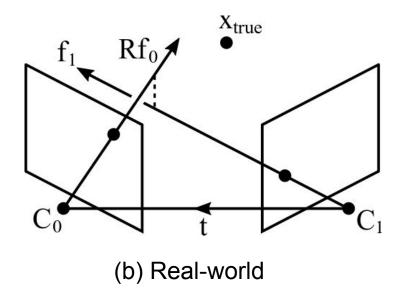
Liu Hui 263. (Illustrated in 1726)



Zubler 1625

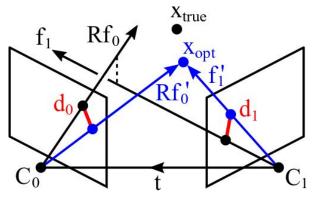
Locating the 3D point given its projections in two views of known calibration and pose.





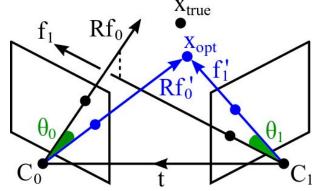
1. Optimal methods:

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_{∞} norm: $max(d_0 + d_1)$

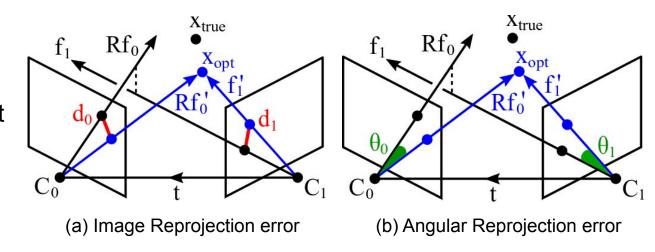
[Hartley 1997, Nister 2001]



- (b) Angular Reprojection error
- L_1 norm: $\theta_0 + \theta_1$
- L_2 norm: $\sin^2(\theta_0) + \sin^2(\theta_1)$
- L_{∞} norm: $max(d_0 + d_1)$ [Oliensis 2002, Lee 2019]

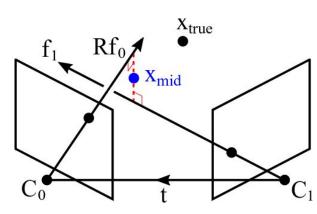
1. Optimal methods:

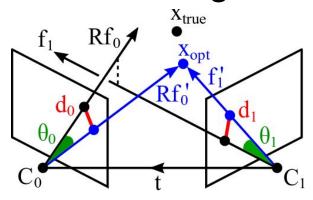
Find intersecting rays that minimize the reprojection cost.

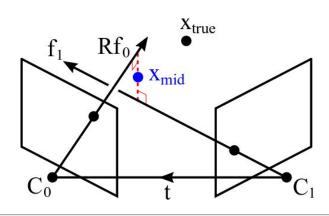


2. Midpoint method:

Find the midpoint of the common perpendicular.



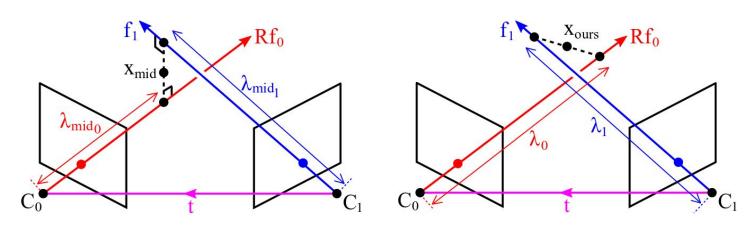




Optimal methods	Midpoint method	
✓ Fast [Lindstrom 10, Lee 19]	✓ Faster	
✓ Minimal 2D (or angular) reproj. error	✗ Large 2D error at low parallax	
✓ Small 3D error at high parallax	✓ Small 3D error at high parallax	
★ Large 3D error at low parallax	✓ Smaller 3D error (than the optimal method) at low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

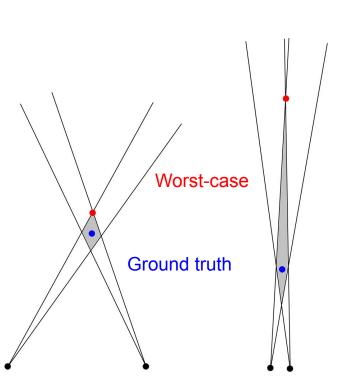
$$\lambda_{\text{mid}0} = \frac{\widehat{\mathbf{p}} \cdot \mathbf{r}}{\|\mathbf{p}\|}, \quad \lambda_{\text{mid}1} = \frac{\widehat{\mathbf{p}} \cdot \mathbf{q}}{\|\mathbf{p}\|}$$

Proposed Depths

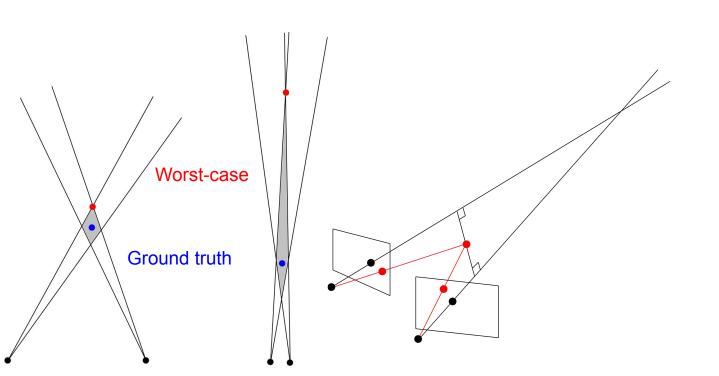
$$\lambda_0 = \frac{\|\mathbf{r}\|}{\|\mathbf{p}\|}, \quad \lambda_1 = \frac{\|\mathbf{q}\|}{\|\mathbf{p}\|}$$

- 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!

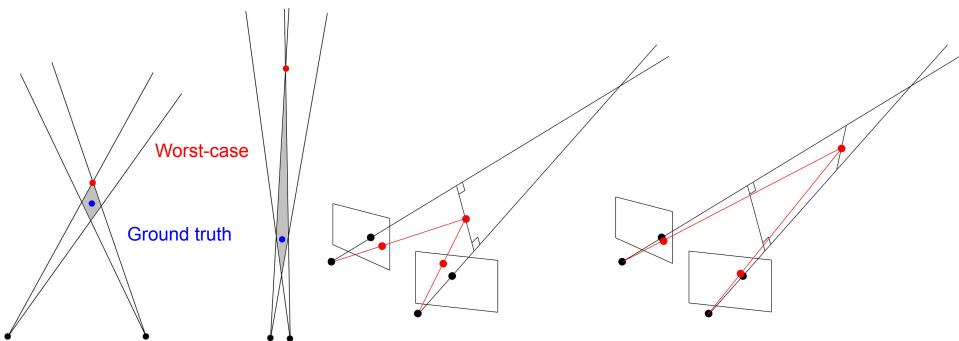


- Optimal methods tend to locate the point too far → Large 3D error!
- Midpoint method tends to locate the point too close → Large 2D error!



- 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.

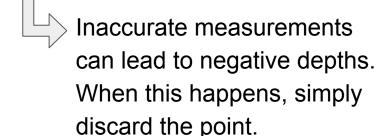
→ Small 2D and 3D error (sweet spot)!



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.,

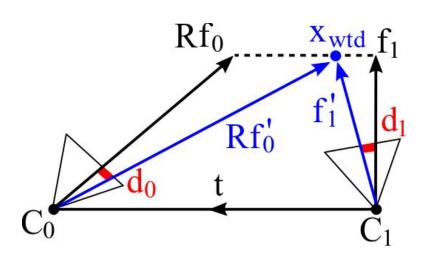
$$\|\textbf{t} + \lambda_0 \textbf{R}\widehat{\textbf{f}}_0 - \lambda_1 \widehat{\textbf{f}}_1\|^2 \geq \min \Big(\|\textbf{t} + \lambda_0 \textbf{R}\widehat{\textbf{f}}_0 + \lambda_1 \widehat{\textbf{f}}_1\|^2, \|\textbf{t} - \lambda_0 \textbf{R}\widehat{\textbf{f}}_0 - \lambda_1 \widehat{\textbf{f}}_1\|^2,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

Contribution #3: Inverse Depth Weighting

Unweighted Midpoint

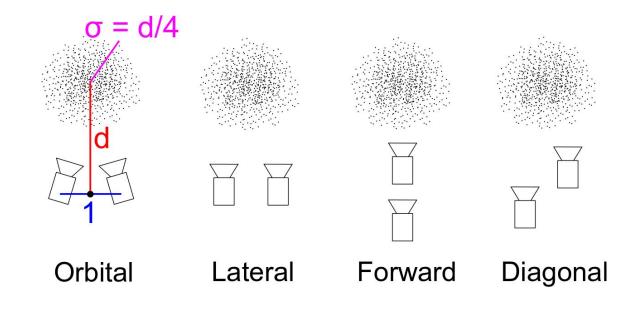
$$x_{\text{unwtd}} = \frac{\mathbf{t} + \lambda_0 \mathbf{R} \widehat{\mathbf{f}_0} + \lambda_1 \widehat{\mathbf{f}_1}}{2}$$

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

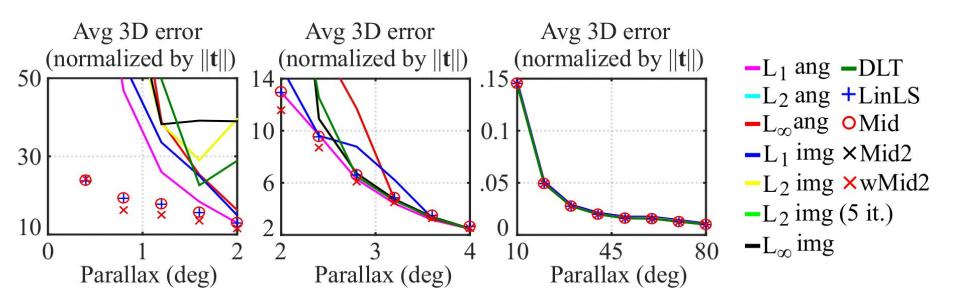


- d = {0.5, 1, 2, ..., 64} x baseline
- Image noise level = 1, 2, 3, ..., 8 pix.

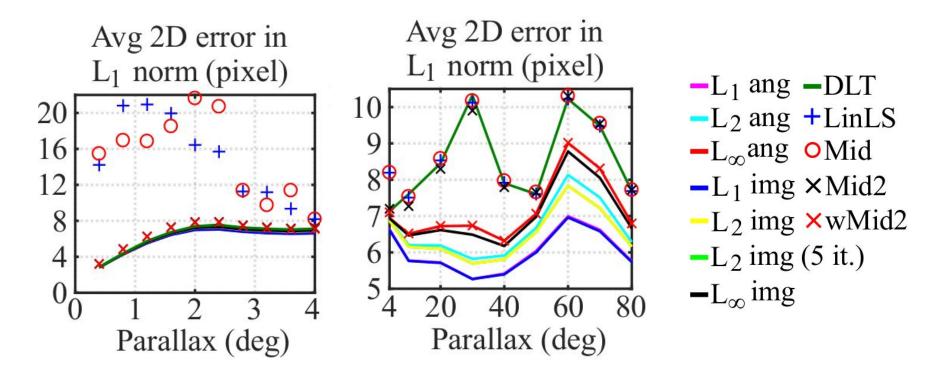


Over a million unique triangulation problems

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.

