

Performance evaluation of the five-point relative pose with emphasis on planar scenes

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- 3D rotation + translation up to scale (5 DOF)
- absolute scale can not be recovered by monocular vision

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Applications:

- autonomous navigation and/or mapping
- offline and online 3D modelling
- augmented reality
- compression
- automated inspection

We address **performance evaluation** of the novel **5pt** algorithm

- 5pt algorithm performance on **planar scenes**
- comparison with **homography** (planar, near-planar)
- comparison with **conditioned 8pt** algorithms (near-planar)

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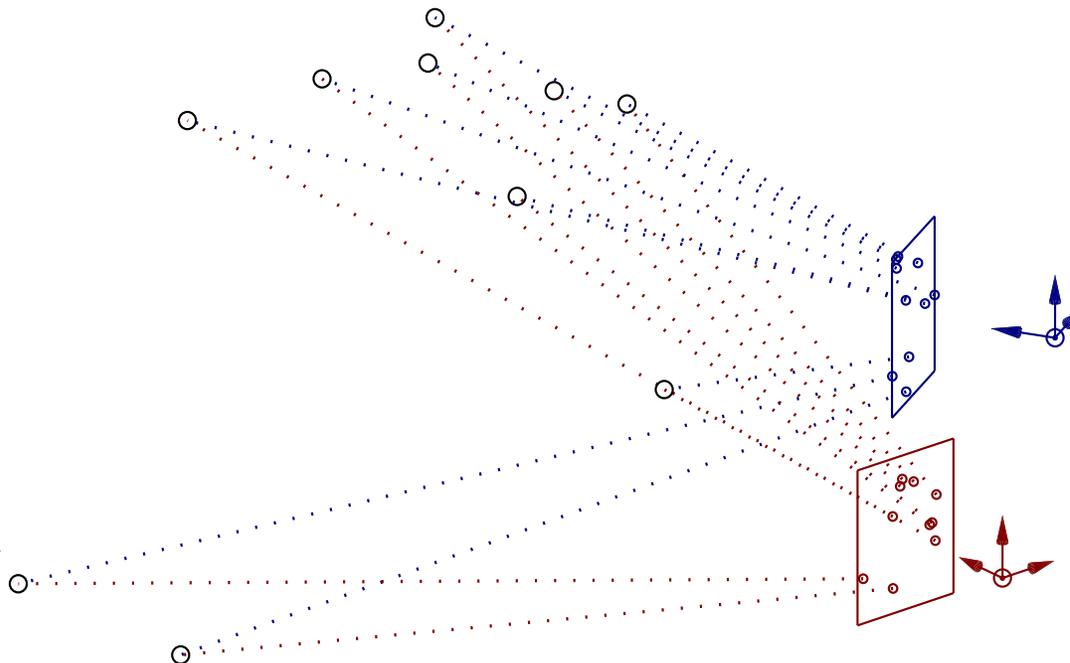
- The problem description
- The three considered algorithms
- Experimental setup
- Results
- Conclusion

The relative pose is recovered from **image correspondences**:

- many correspondence approaches, all seek a compromise between **genuine matches** and **outliers**
- the main approaches: **wide-baseline matching**, **tracking**
- the **subpixel** matching accuracy essential

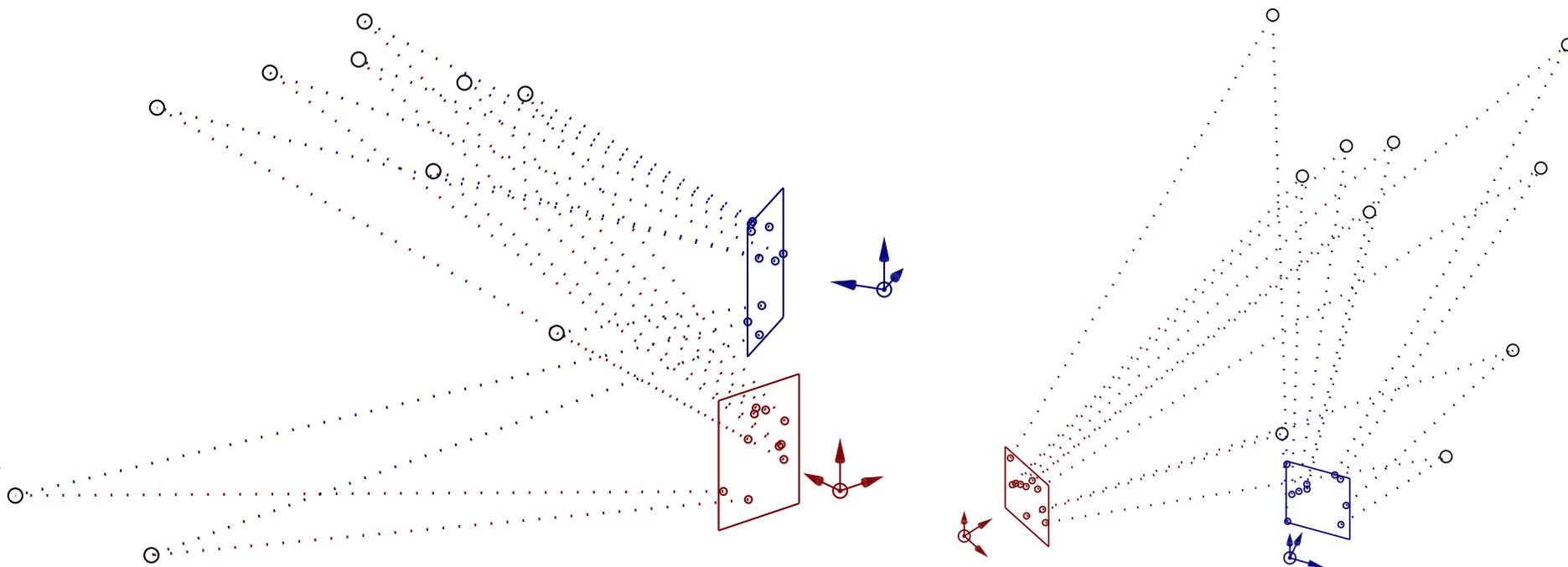
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Three main contexts:

- **minimal** case, with exact solutions (RANSAC loop)
- **overconstrained** case: optimizing an algebraic criterion (closed-form re-estimation on the set of inliers)
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What can be recovered in **closed-form** from two views?

- the **essential** matrix[†] (epipolar geometry)
 $\mathbf{q}_{iB}^\top \cdot \mathbf{E} \cdot \mathbf{q}_{iA} = 0$ ($\mathbf{E} = [\mathbf{t}]_\times \mathbf{R}$, decomposition **unique**)
- the **homography** matrix[‡] (geometry of a planar scene)
 $\mathbf{H} \cdot \mathbf{q}_{iA} \sim \mathbf{q}_{iB}$ ($\mathbf{H} \sim \mathbf{R} + \frac{1}{d} \mathbf{T} \cdot \mathbf{n}^\top$, decomposition **not** unique)
- the affine epipolar geometry, affine homography (not considered here)

The **eight point** (8pt) algorithm:

- recovers the essential matrix as a solution to the homogeneous linear system $A_{n \times 9} \cdot e = 0$
- requires at least **8** correspondences in general position
- badly conditioned by default (**forward bias**), can be improved in the **overconstrained** case
- does not work with **planes**: “wrong” matrices satisfy the epipolar constraint.

The **five point** algorithm:

- epipolar geometry + the “calibrated” constraint:

$$2 \cdot \mathbf{E}\mathbf{E}^T\mathbf{E} - \text{trace}(\mathbf{E}\mathbf{E}^T)\mathbf{E} = 0$$

- operates on matrices E_i obtained as the lowest four null-vectors of $\mathbf{A}_{n \times 9}$
- the linear combination $\mathbf{E} = a \cdot \mathbf{E}_6 + b \cdot \mathbf{E}_7 + c \cdot \mathbf{E}_8 + d \cdot \mathbf{E}_9$ plugged into the calibrated constraint
- the resulting cubic system solved for a, b, c, d
- up to ten solutions (needs disambiguation)

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- up to ten solutions (needs disambiguation)
- can operate with only five correspondences
- very good results in minimal cases (5 + 1 points)
- can operate on planar scenes
(but not with the plane at infinity!)

The **linear recovery** of the homography:

- requires **4** or more correspondences, well conditioned

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The issue of **planar ambiguity**:

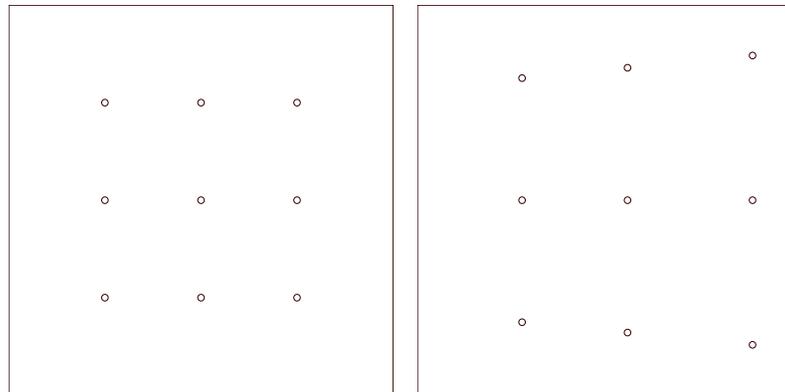
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- the **visibility constraint** eliminates **6** or **7** of the 8
- the ambiguity arises when all imaged points are closer to one of the two cameras!

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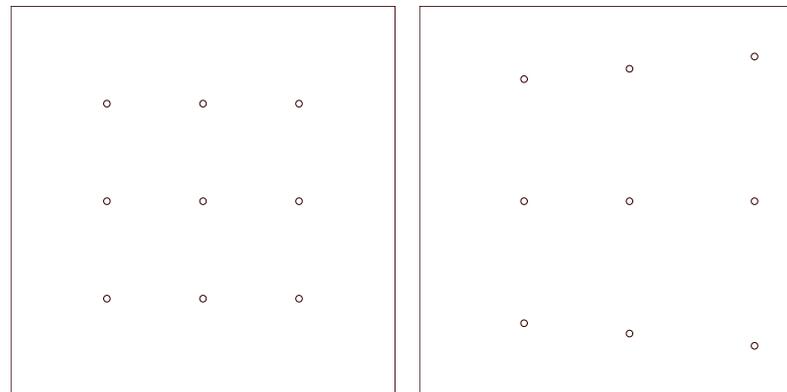
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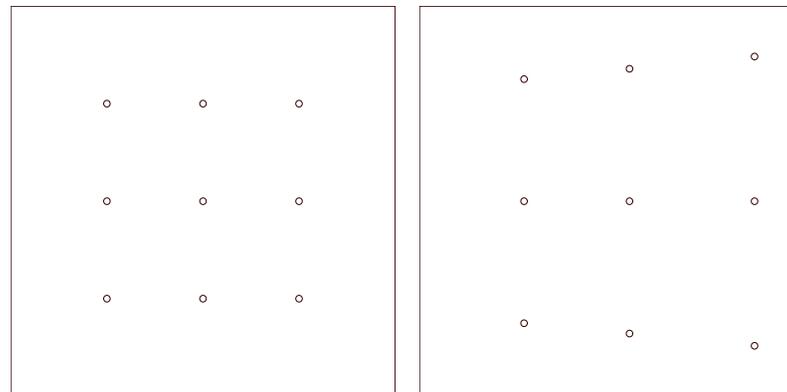


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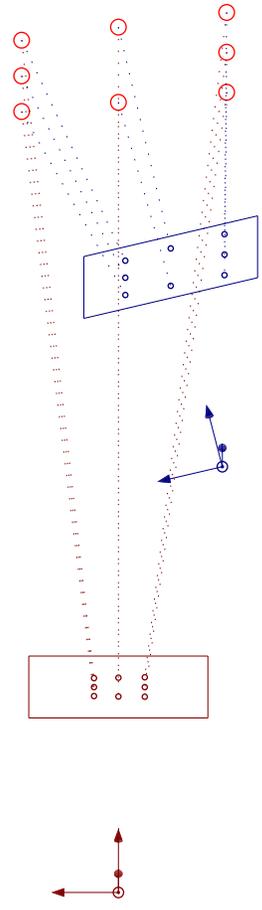
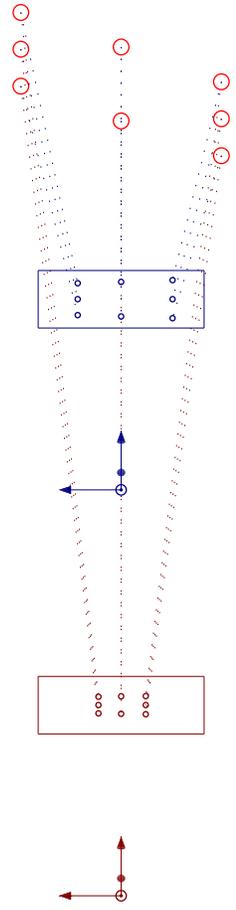
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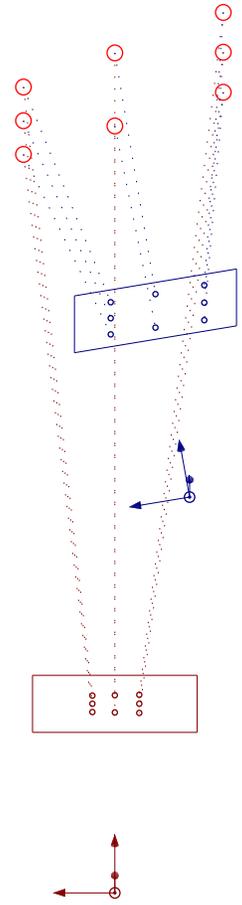
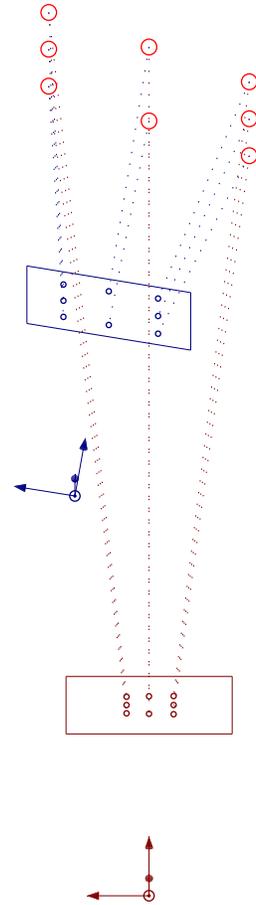
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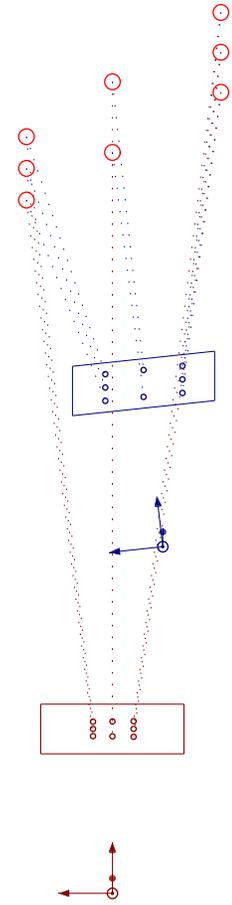
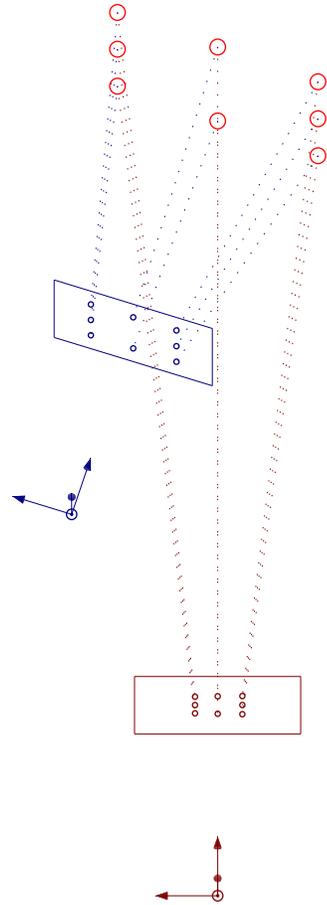
$\theta = 00^\circ$:



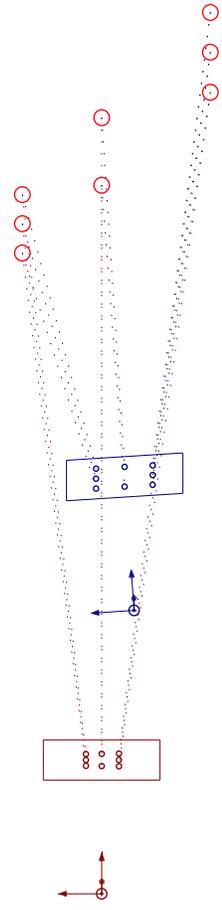
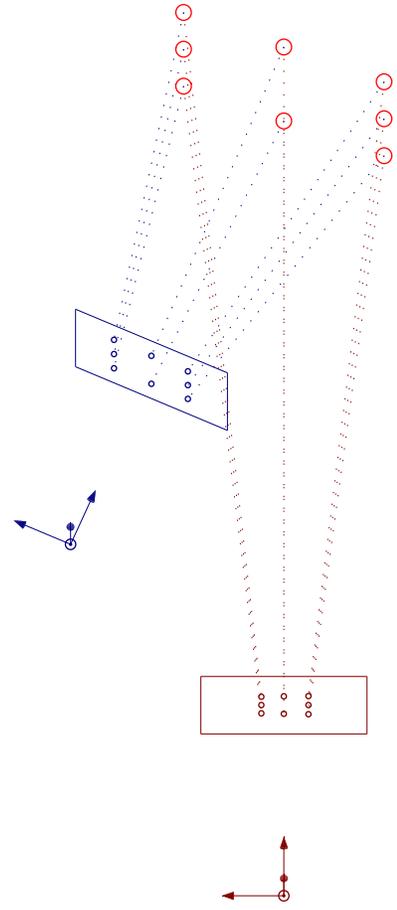
$\theta = 10^\circ$:



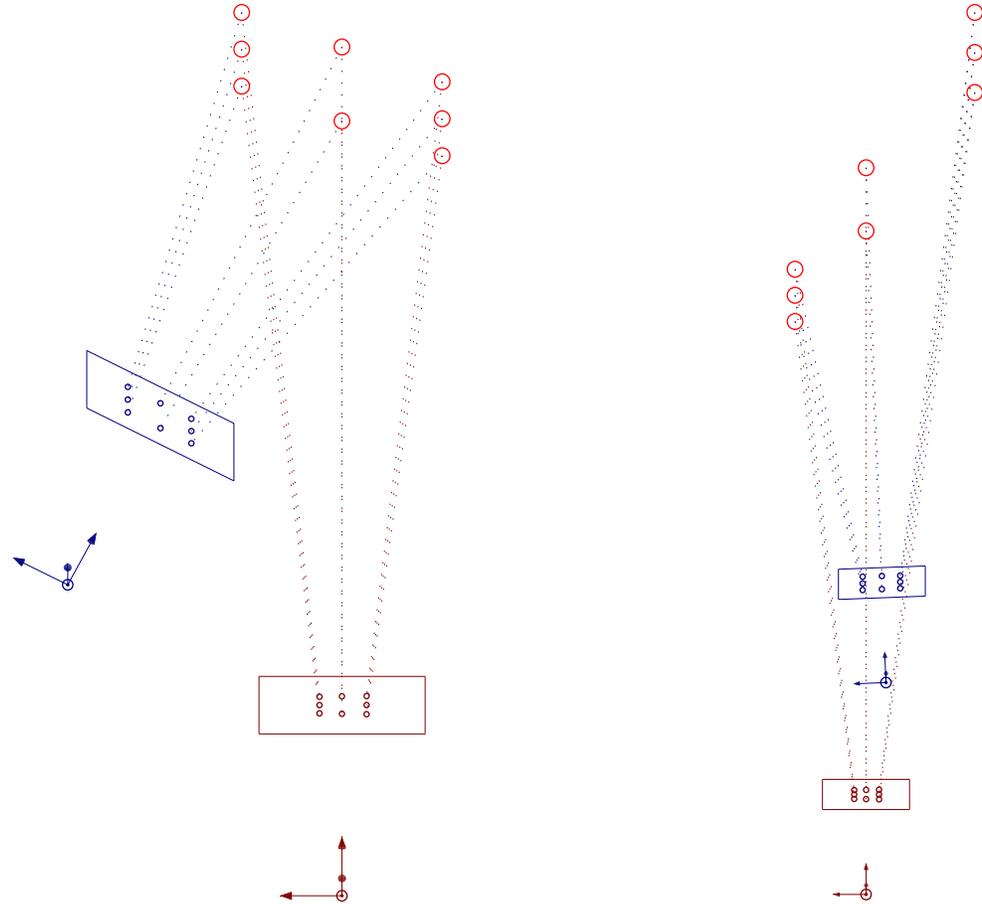
$\theta = 20^\circ$:



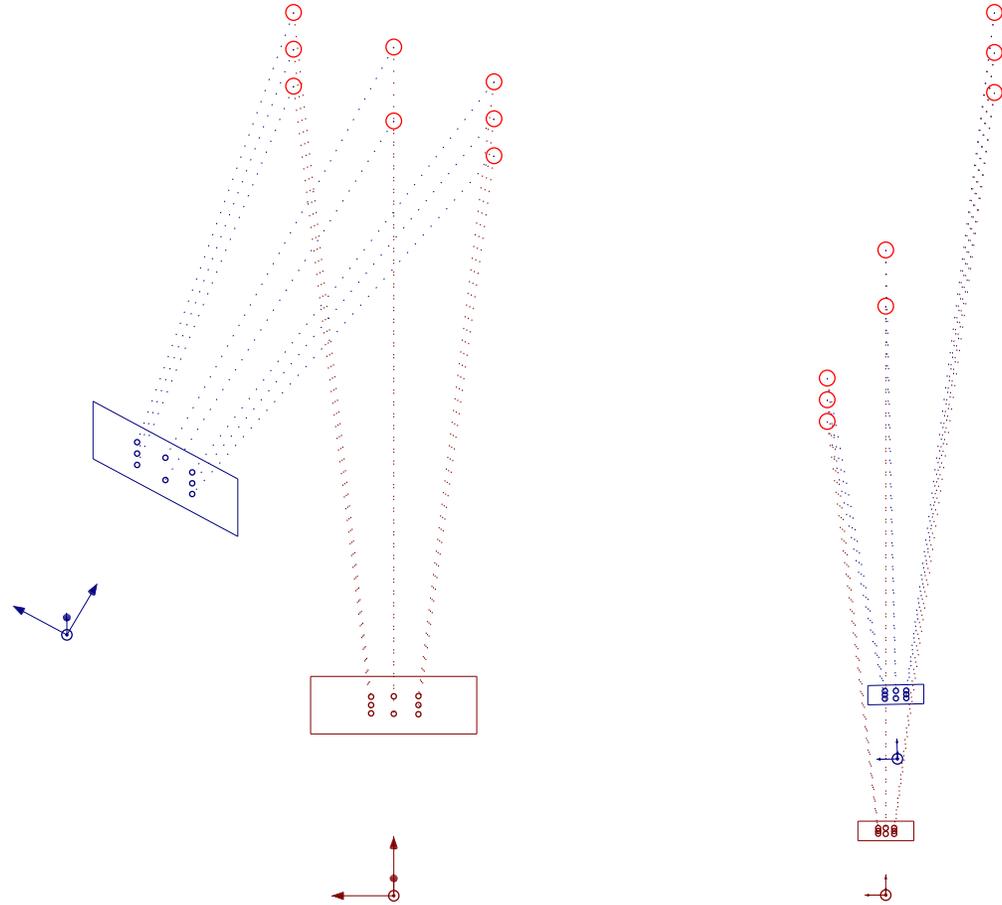
$\theta = 30^\circ$:



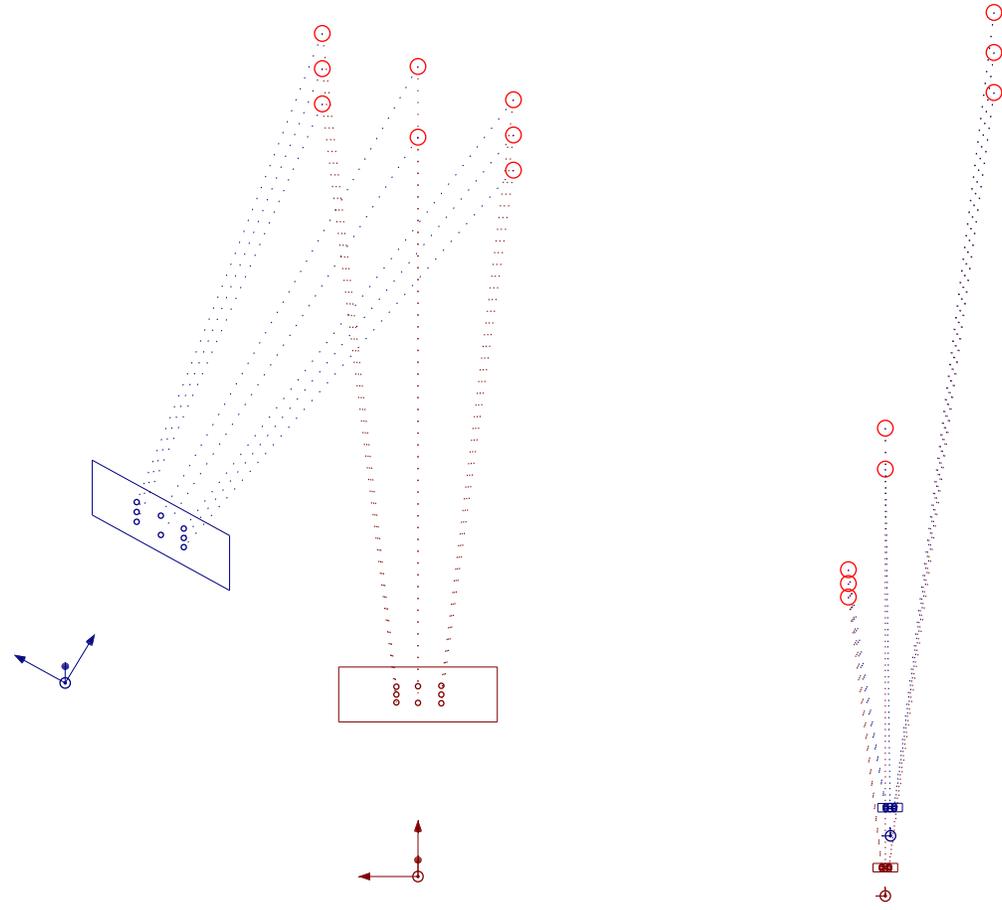
$\theta = 40^\circ$:



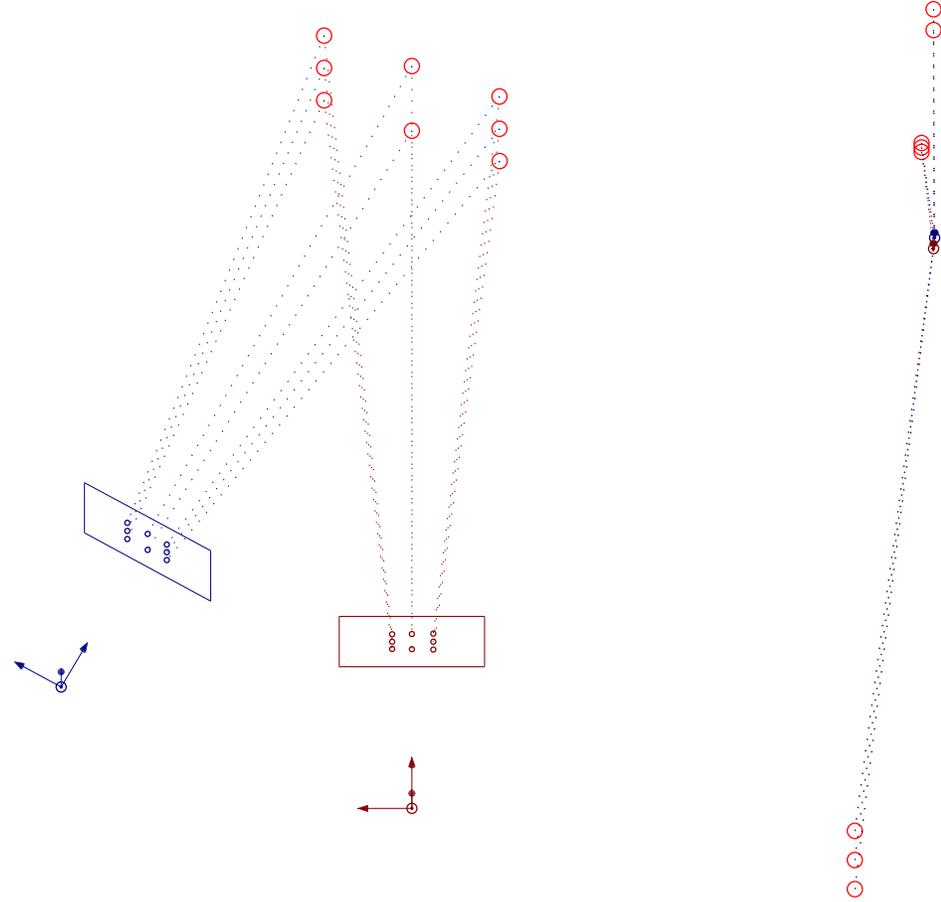
$\theta = 50^\circ$:



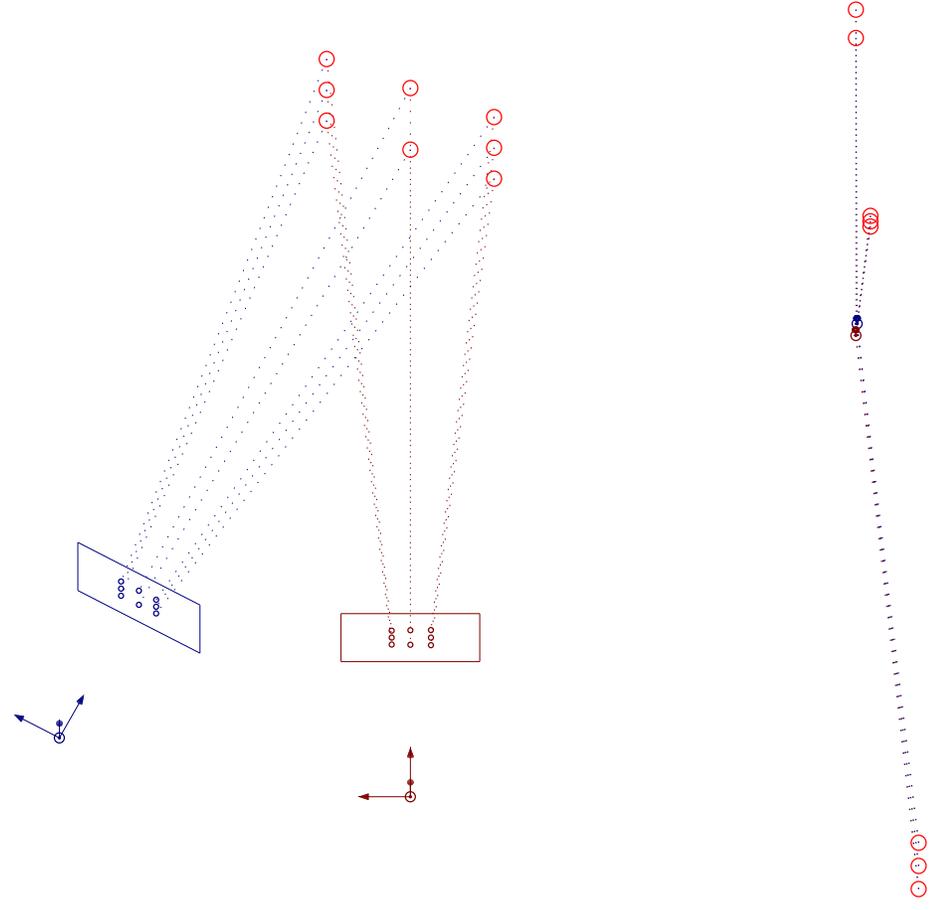
$\theta = 60^\circ$:



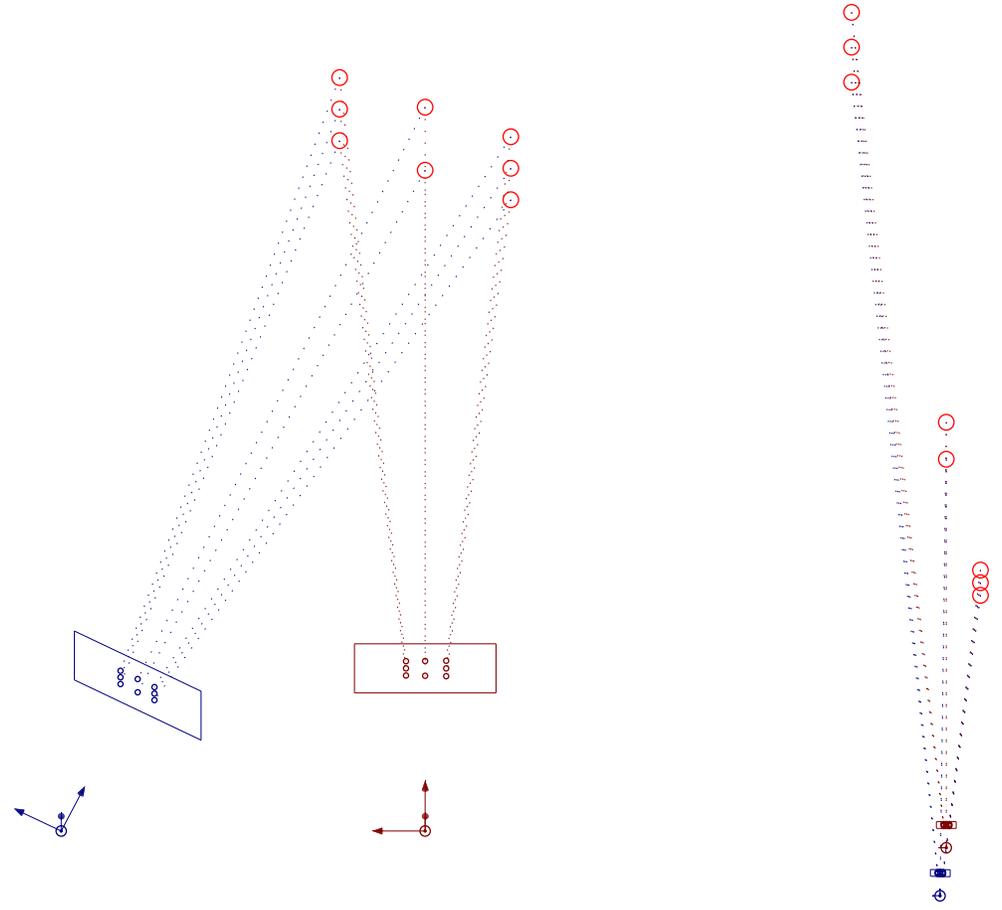
$\theta = 70^\circ$:



$\theta = 80^\circ$:



$\theta = 90^\circ$:



Improving the **numeric conditioning** of the 8pt algorithm:

- the standard 8pt algorithm:

$$\min |\mathbf{A} \cdot \mathbf{e}|, \text{ subject to } |\mathbf{e}| = 1$$

- in the overconstrained case, the choice of \mathbf{W}_L and \mathbf{W}_R below dramatically affects the solution:

$$\mathbf{W}_L \cdot \mathbf{A} \cdot \mathbf{W}_R \cdot \mathbf{e}' = 0, \text{ where } \mathbf{e}' = \mathbf{W}_R^{-1} \cdot \mathbf{e}$$

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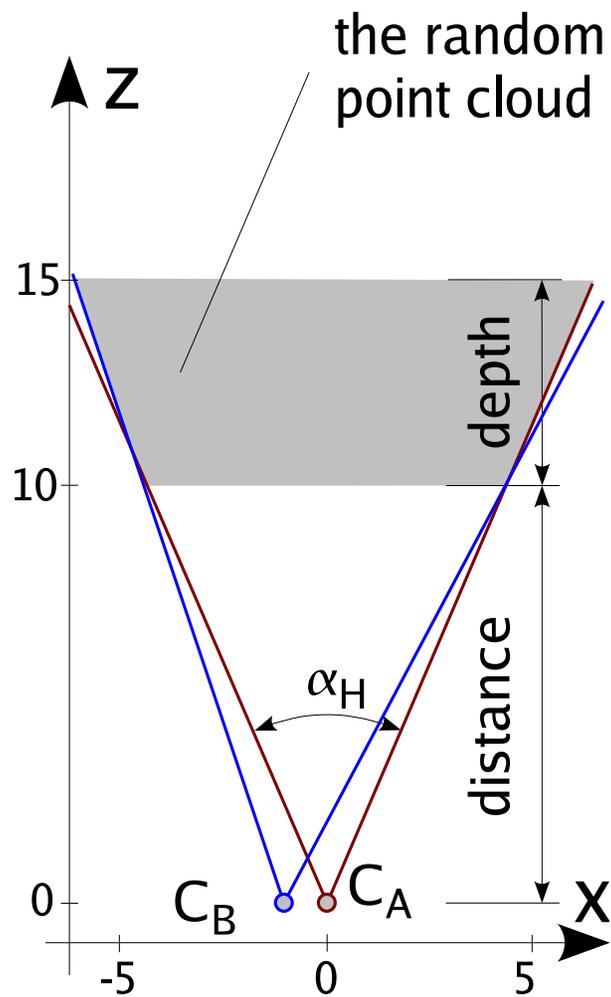
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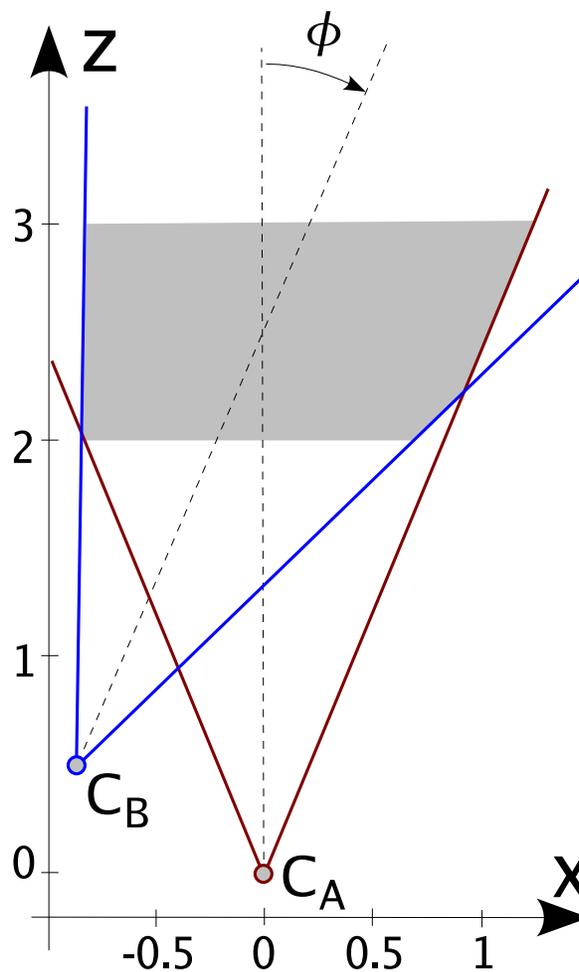
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- how to choose \mathbf{W}_L and \mathbf{W}_R (**equilibrate** the system)?
→ Mühlich provides a convincing recipe for \mathbf{W}_R
- Hartley's normalization recovers $\mathbf{E}' = \mathbf{T}_2^{-\top} \mathbf{E} \mathbf{T}_1^{-1}$ relating the transformed points $\mathbf{q}'_{ik} = \mathbf{T}_k \mathbf{q}_{ik}$, $k = A, B$
- normalization is a proper subset of right equilibration.

The artificial **experimental setup**:

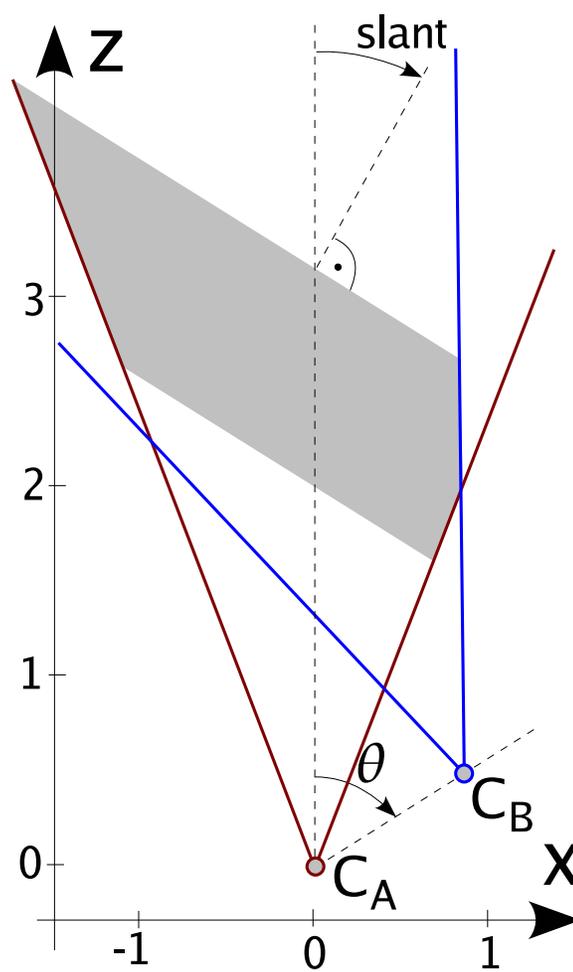
- planar motion along a unit circle:
1 DOF rotation (ϕ) + 1 DOF translation (θ)
around the common y axis
- the target point cloud instantiated between two planes
(distance, depth, slant)
- i.i.d. Gaussian noise σ expressed in pixels of a 384×288
image



$(-5^\circ, 90^\circ, 10, 5, 0^\circ)$



$(-23^\circ, 60^\circ, 2, 1, 0^\circ)$



$(23^\circ, -60^\circ, 2, 1, -30^\circ)$

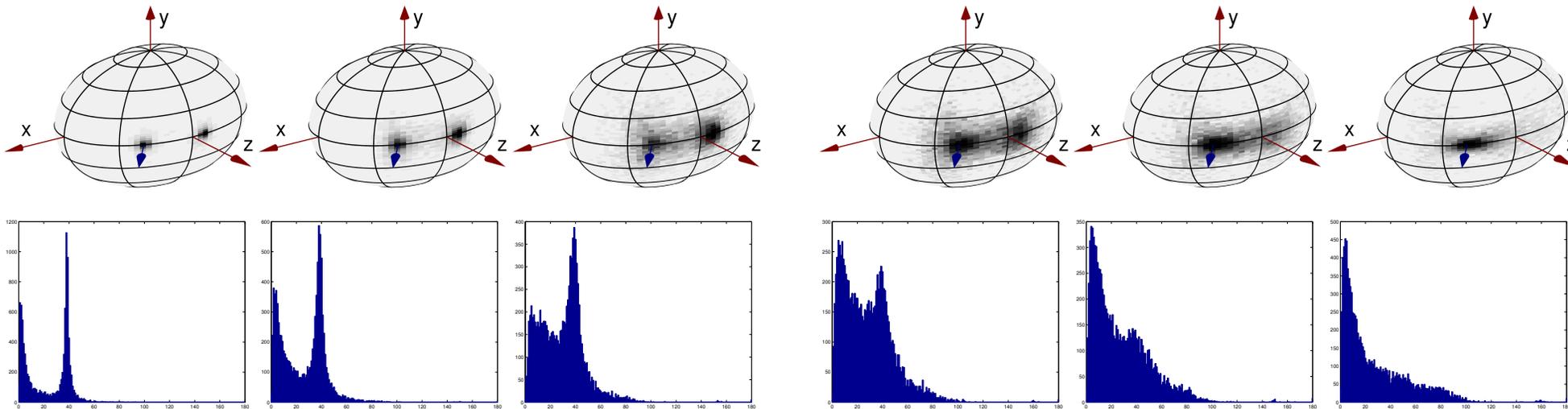
$(\phi, \theta, \text{distance}, \text{depth}, \text{slant})$

Experimental design:

- we look at the distribution of the angular error in the recovered **epipole**, $\Delta t := \angle(t, \hat{t})$, for $n=10000$
- $q_1\{\Delta t\}$ (**minimal**), $med\{\Delta t\}$ (**overconstrained**)
- the experiments were performed in
 - Matlab (prototype, 3D figures)
 - C++ with a little help from Python (production)
- used 5pt implementations by the original authors (Matlab) and from the library VW34 from Oxford (C++)

The 5pt (6) algorithm and the **planar scenes**:

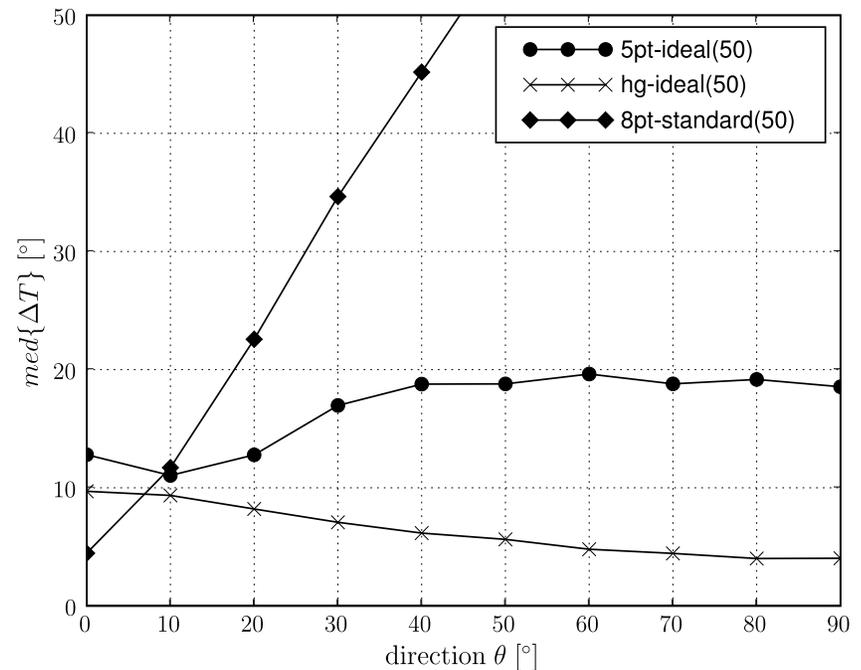
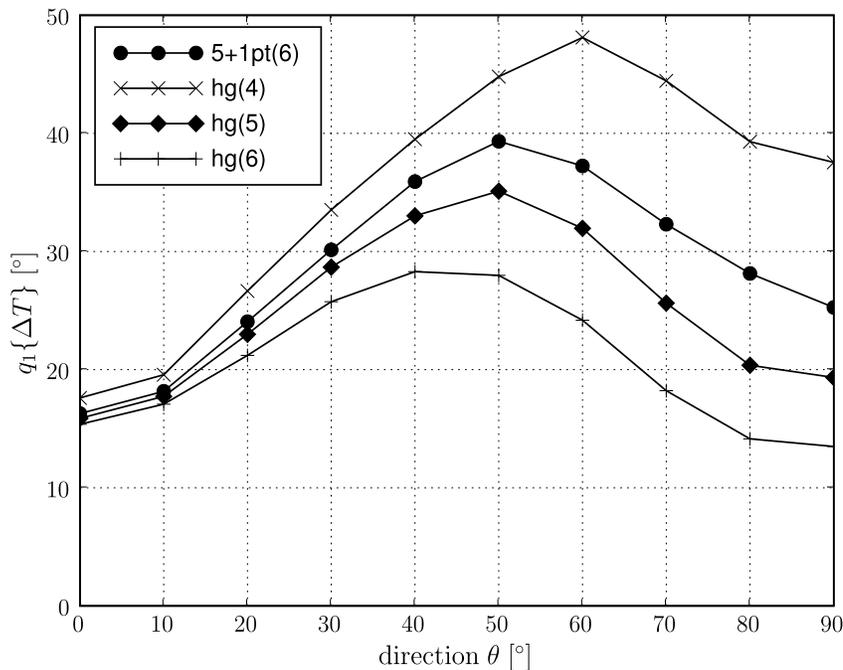
- frequency distributions of t (top), and Δt (bottom)
- the **unlabeled arrow** denotes \hat{t}
- in the presence of ambiguity, both solutions are recovered (preference may be present!)



Left: depth=0, $\sigma=(0.05,0.1,0.2)$; Right: depth=(1,2,5), $\sigma=0.2$
 $\theta=150^\circ$, slant= 10°

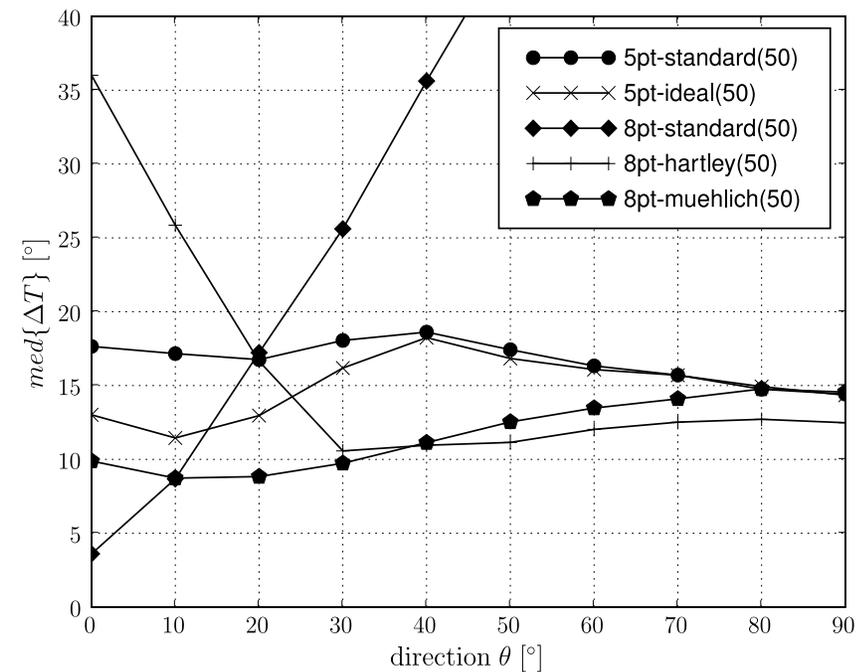
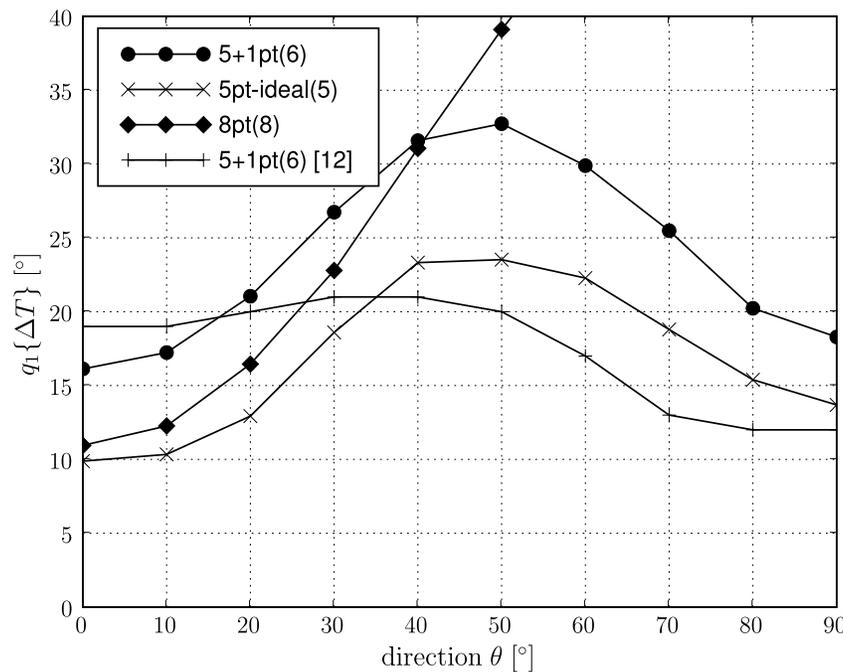
5pt algorithm vs. homography (5pt vs. hg) for planar scenes:

- minimal (left), and overconstrained cases (right)
- makes sense to compare: 5pt(6) vs hg(6)
(and 5pt-ideal(5) vs hg-ideal(5))
- the homography is better in minimal cases, and even more better in the overconstrained cases



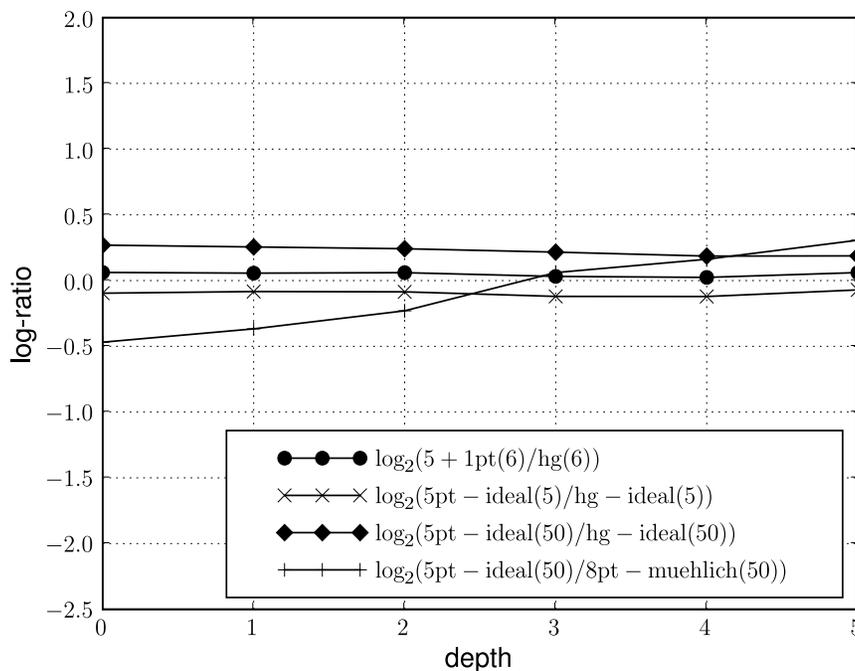
5pt vs. 8pt for 3D scenes (depth=5):

- minimal (left), and overconstrained cases (right)
- 5pt (6) beats 8pt (8) (with less information!)
- in the default overconstrained case 8pt-muehlich is better (this depends on sample size, depth, distance, σ , α_H)

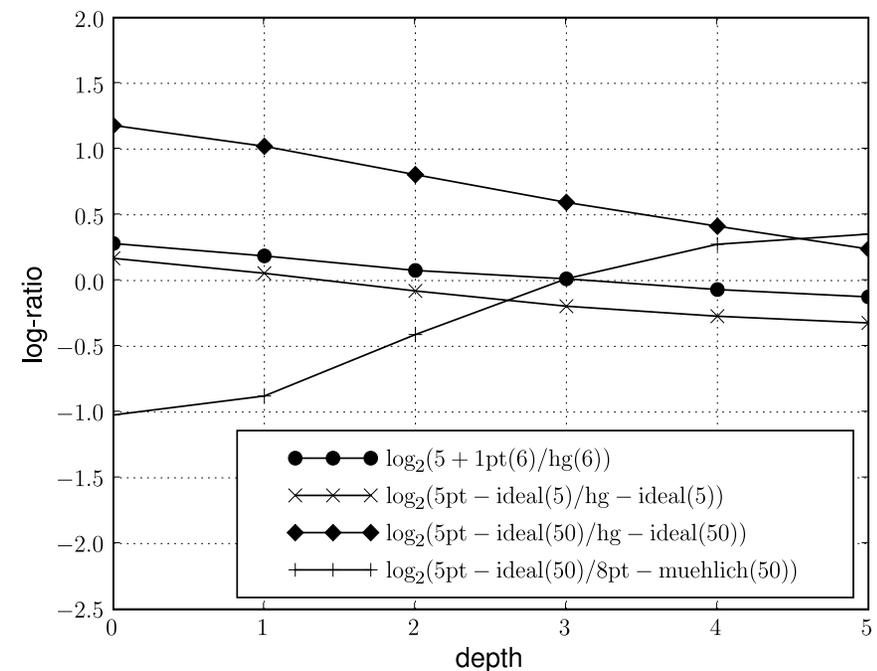


5pt vs. 8pt vs. hg for near-planar scenes:

- log-ratio of $\{q_1, med\}$ against the depth, $\theta=0^\circ, 45^\circ, 90^\circ$
- hg and 5pt level-off between depth=2 and depth=4
- in the overconstrained cases, 5pt is never the best option



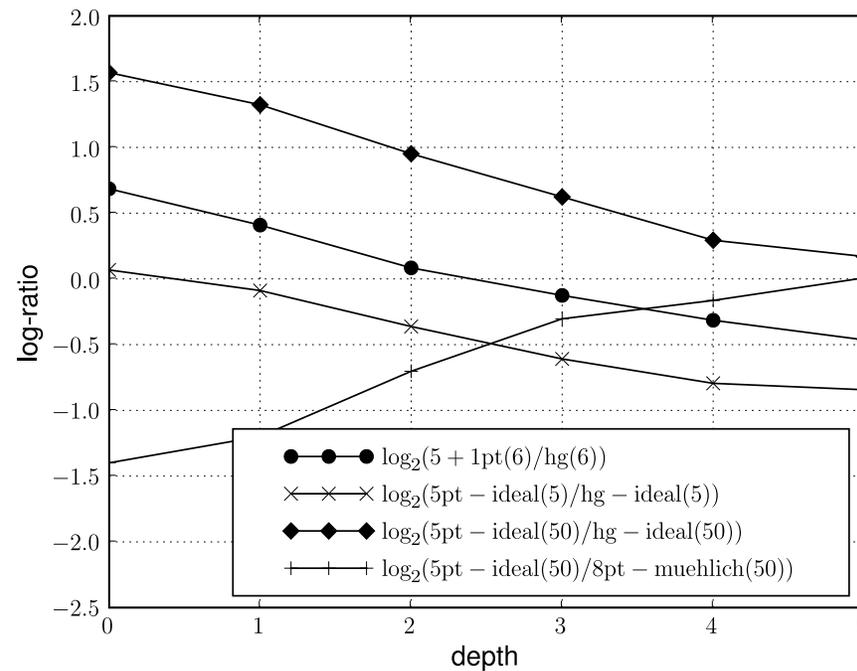
$\theta=0^\circ$



$\theta=45^\circ$

5pt vs. 8pt vs. hg for near-planar scenes (cont.):

□ log-ratio of the accuracy against the depth



$\theta = 90^\circ$

The addressed **issues**:

- “planar degradation” of the 5pt algorithm
- comparison 5_{pt} vs hg (planar, near-planar scenes)
- comparison 5_{pt} vs conditioned 8_{pt} (near-planar, 3D scenes)

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Conclusions:

- 5_{pt} is usually **not** a method of choice in the overconstrained cases (planar and 3D)
- 5_{pt} is **the best** option in minimal 3D cases
- 5_{pt} is a viable option in a minimal planar case, but hg scores better
- **Model selection** required for best results