Institute for Computer Graphics and Vision

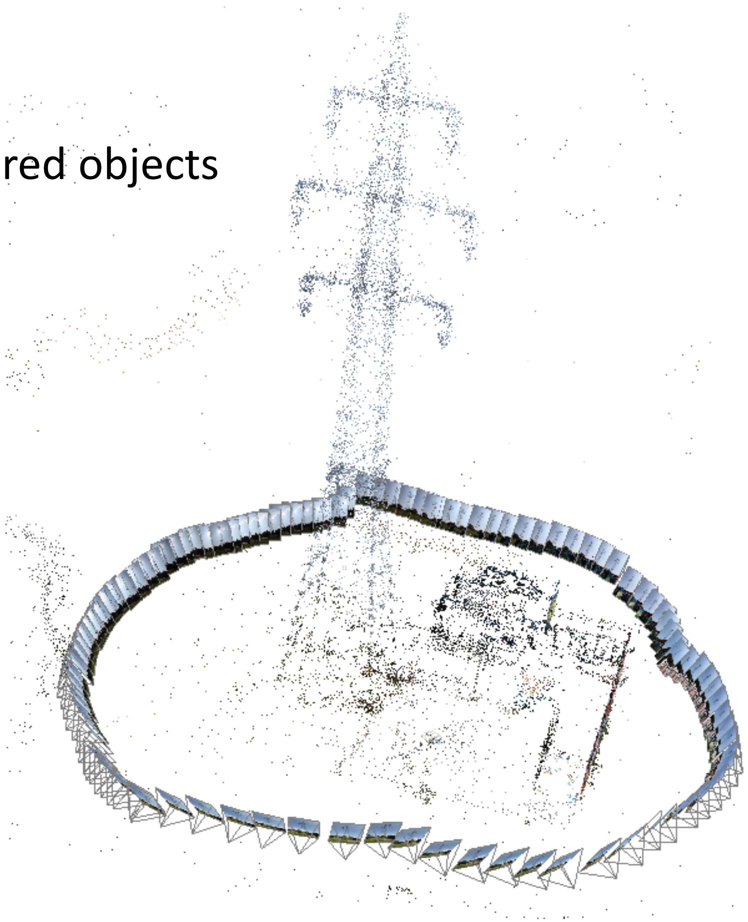
BMVC 2013

Incremental Line-based 3D Reconstruction using Geometric Constraints

Manuel Hofer, Andreas Wendel, Horst Bischof

Motivation

- Traditional Structure-from-Motion (SfM)
  - Using multiple images
  - Usually point based
  - Delivers accurate results for highly textured objects
    → many feature points
  - **Untextured scenes? (wiry objects, …)**



Motivation

- Alternative: Line-based 3D Reconstruction
  - Suitable for urban- and indoor scenes containing texture-less objects
  - Procedure similar to point-based methods:

	Points	Line-segments
Feature detection	e.g. SIFT [Lowe, 2004]	e.g. LSD [Gioi et al., 2010]
Feature description + matching		e.g. MSLD [Zhiheng et al., 2009]
Pose estimation + reconstruction	e.g. [Irschara et al., 2010]	e.g. [Elqursh and Elgammal, 2011]

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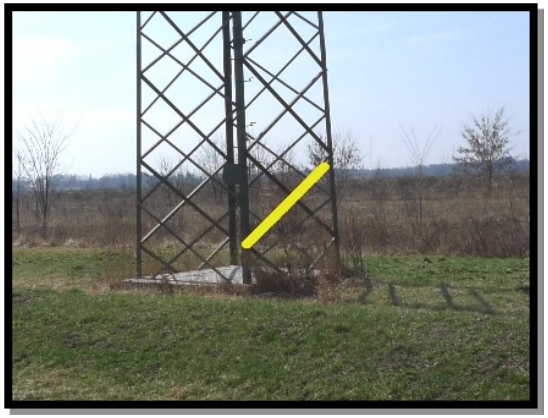
Line-segment Matching

- Usually appearance-based
  - Local descriptor based on gradient and color information from rectangular patch around the segment
    MSLD [Zhiheng et al., 2009], SILT [Khaleghi et al., 2009]
  - Color histograms along the line
    [Bay et al., 2005]
  - **Does not work for wiry structures!**



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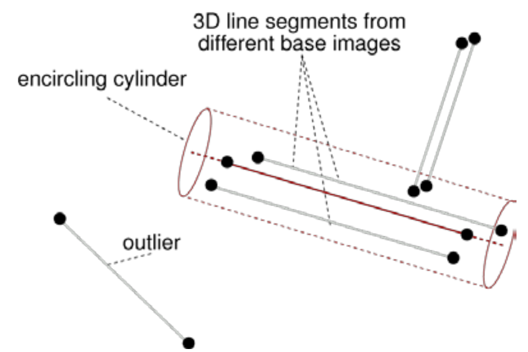
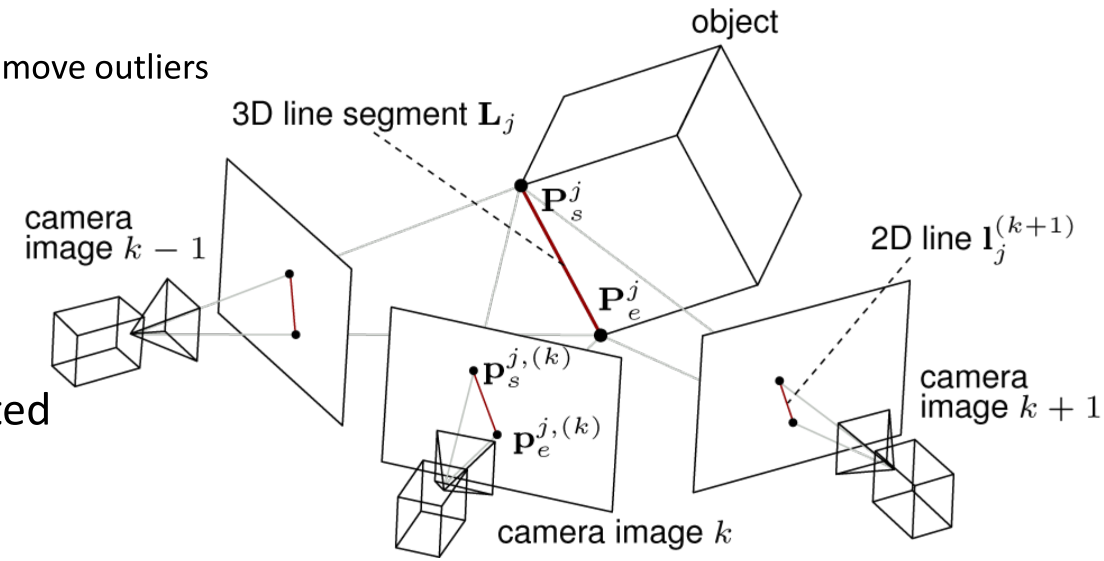
Appearance-less Approaches

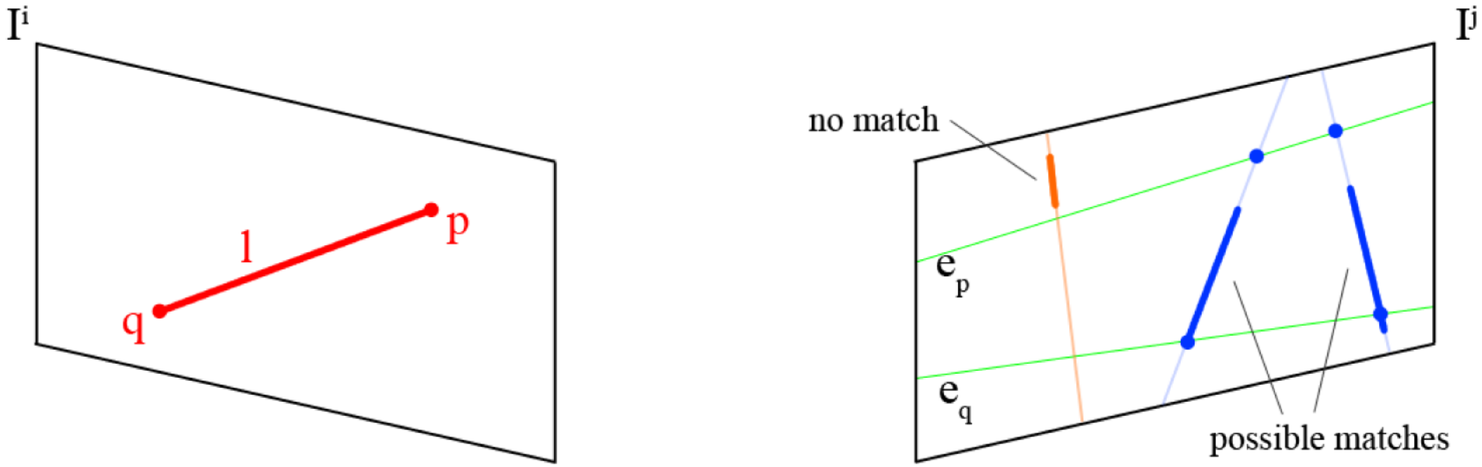
- Jain et al., 2010
  - Assumes known cameras
  - Line-segments are not directly matched
  - Estimation of 3D line position:
    - Compute all possible locations in a certain sweeping range
    - Evaluate using multi-view backprojection and gradient scoring
    - Obtain final result and remove outliers by spatial clustering
  - **Accurate results, but very time-consuming!** (several hours for one image sequence, reported in the paper)





Appearance-less Approaches

- Hofer et al., 2013
  - Lines cannot be located at any 3D position
  - Use epipolar guided multi-view matching to compute discrete hypotheses set for each segment
  - Adapt gradient scoring and clustering from [Jain et al., 2010]
  - **Faster, but still slow…**



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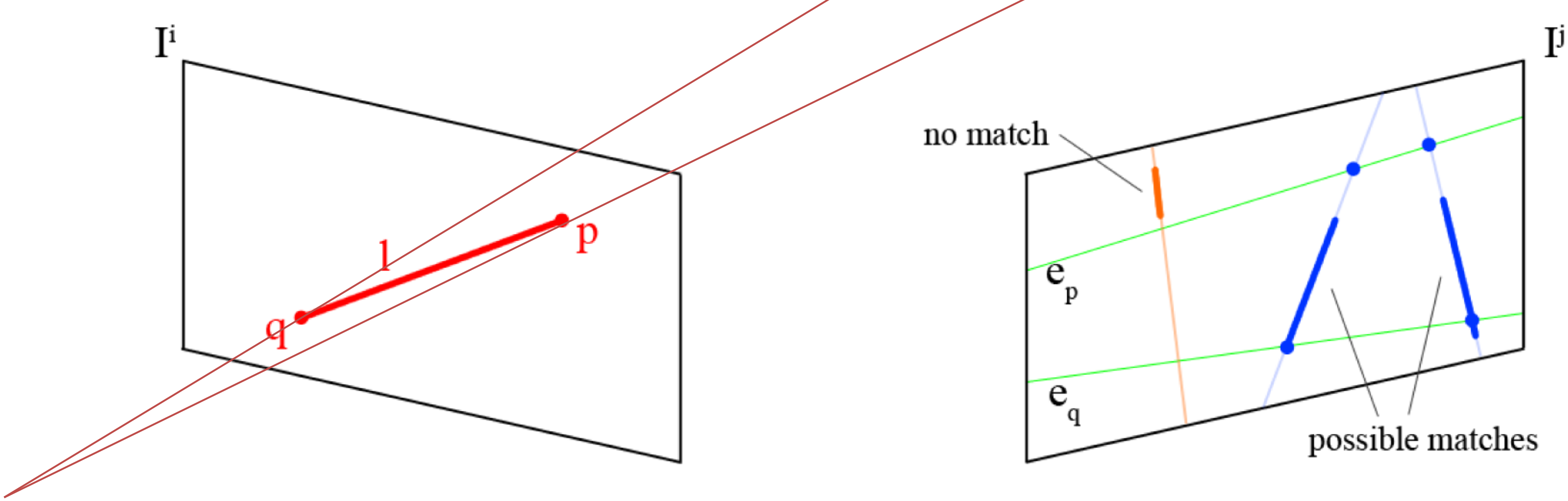

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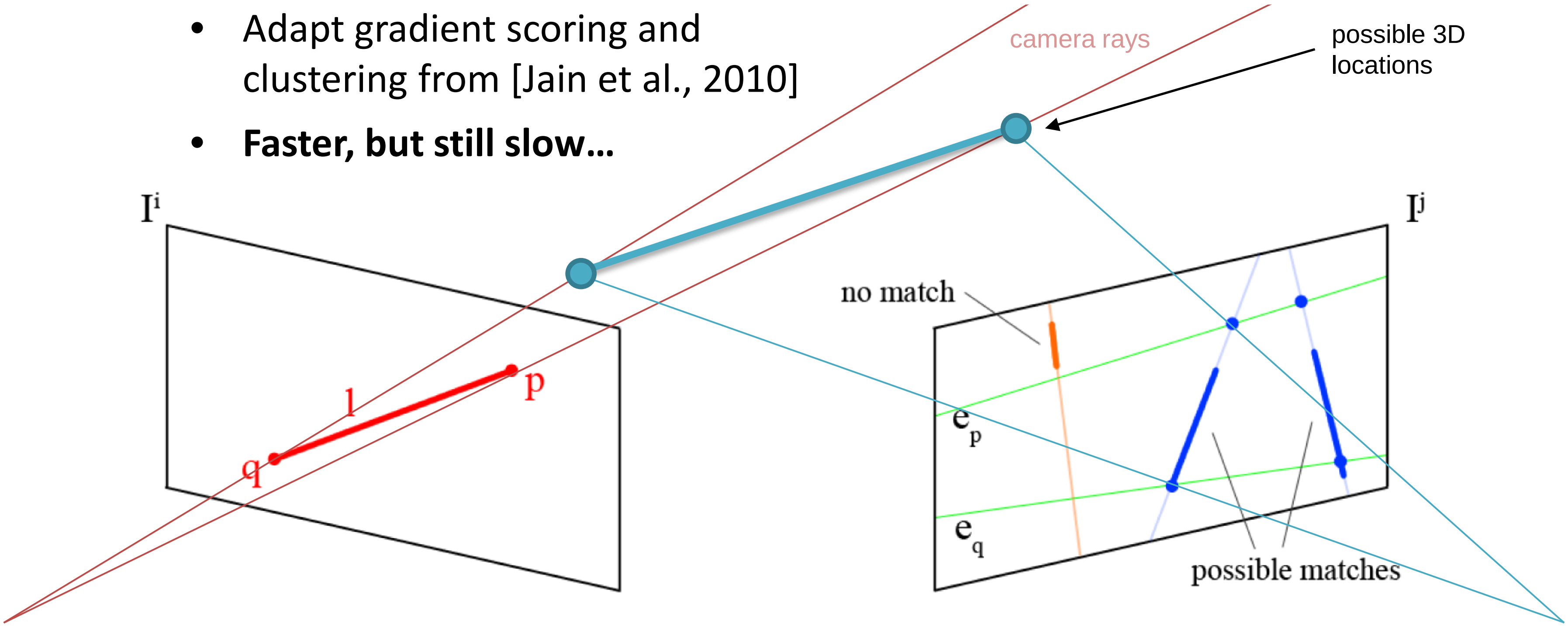

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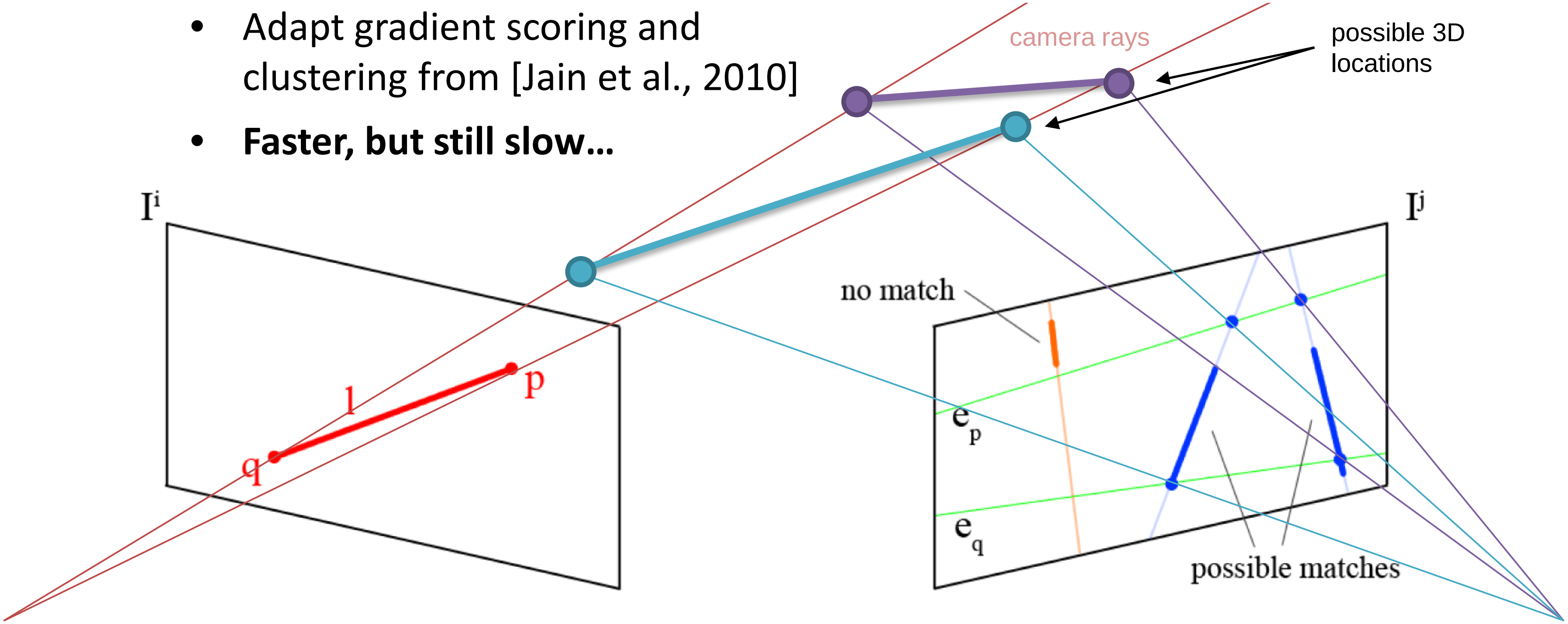
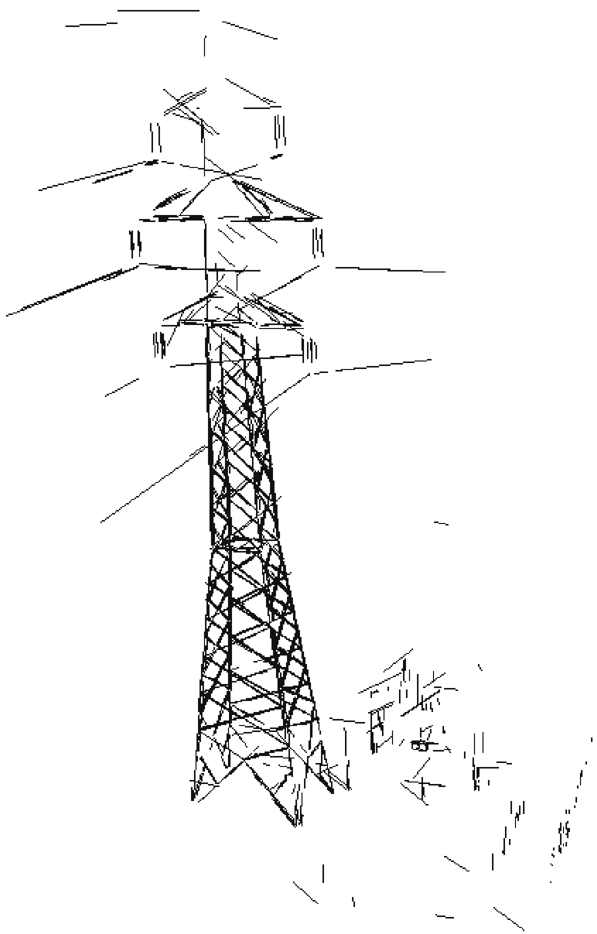


Example Result

- Power Pylon (106 images)
  - Using [Hofer et al., 2013]



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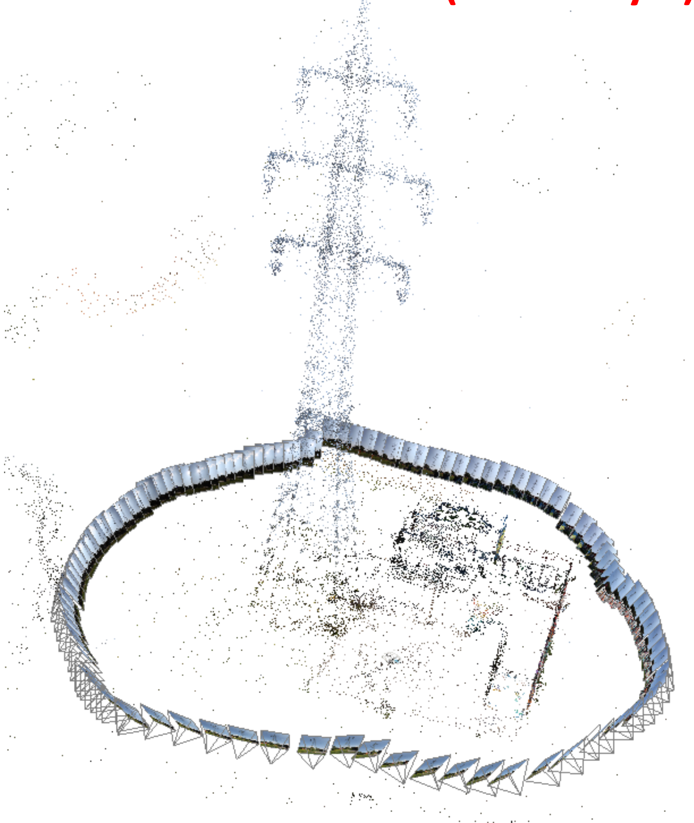
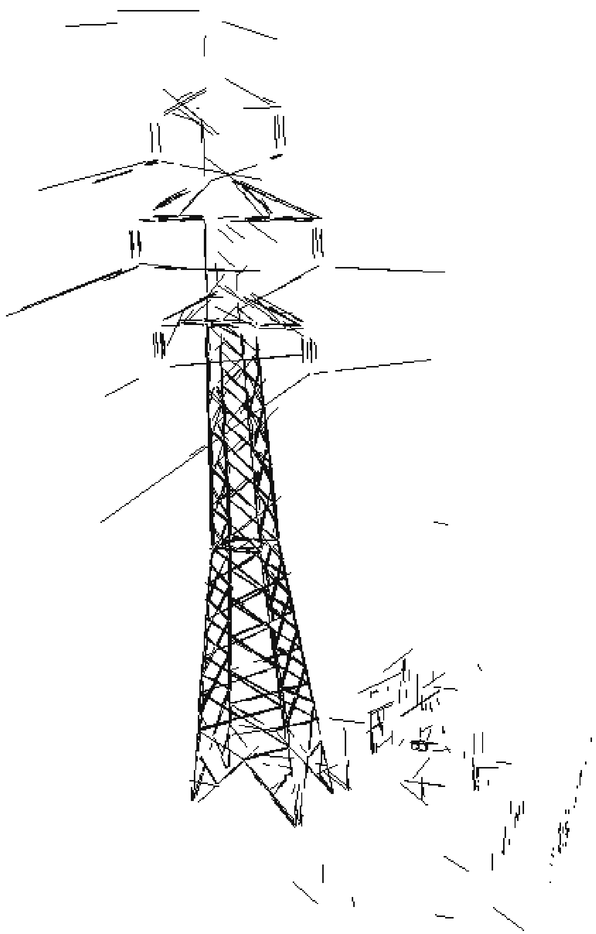
•Time: 67min (lines only…)





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    - Bottlenecks are the gradient scoring and the clustering procedure at the end
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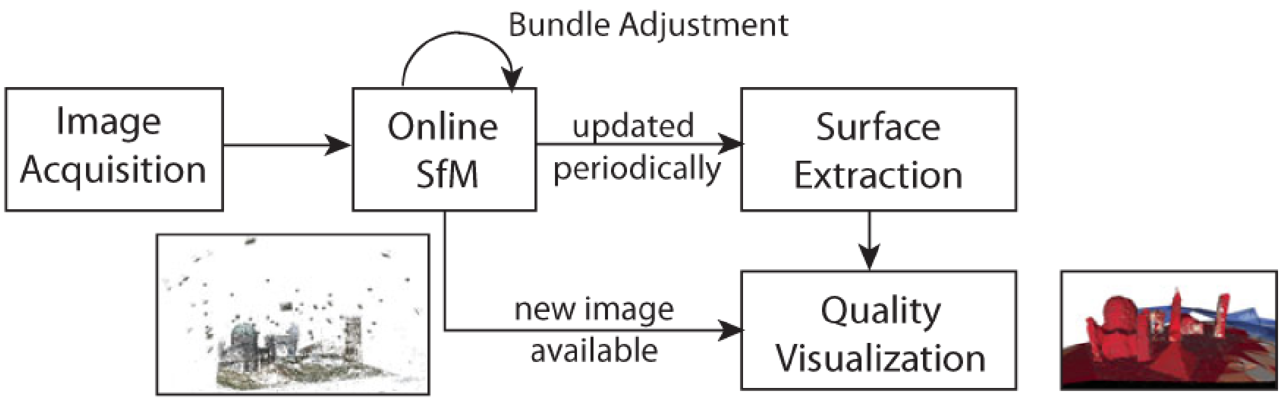
3. Reconstruction scale has to be known
    - Spatial clustering otherwise not possible
    - **Is it possible to derive the clustering radius from the image space without knowing the exact reconstruction scale?**

Incremental 3D Reconstruction

- We integrate the line reconstruction process into an online SfM system [Hoppe et al., 2012], to obtain live camera poses
- Uses SIFT feature matching [Lowe, 2004]



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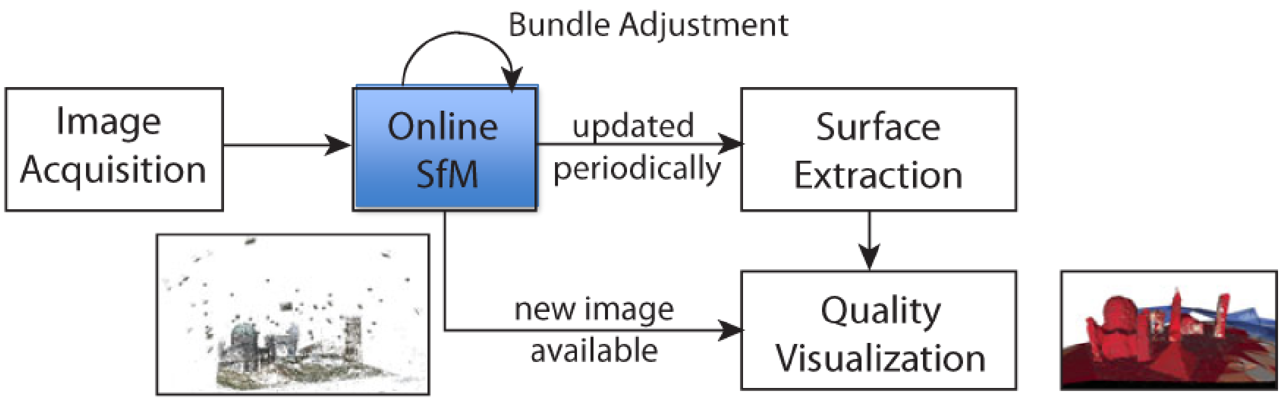

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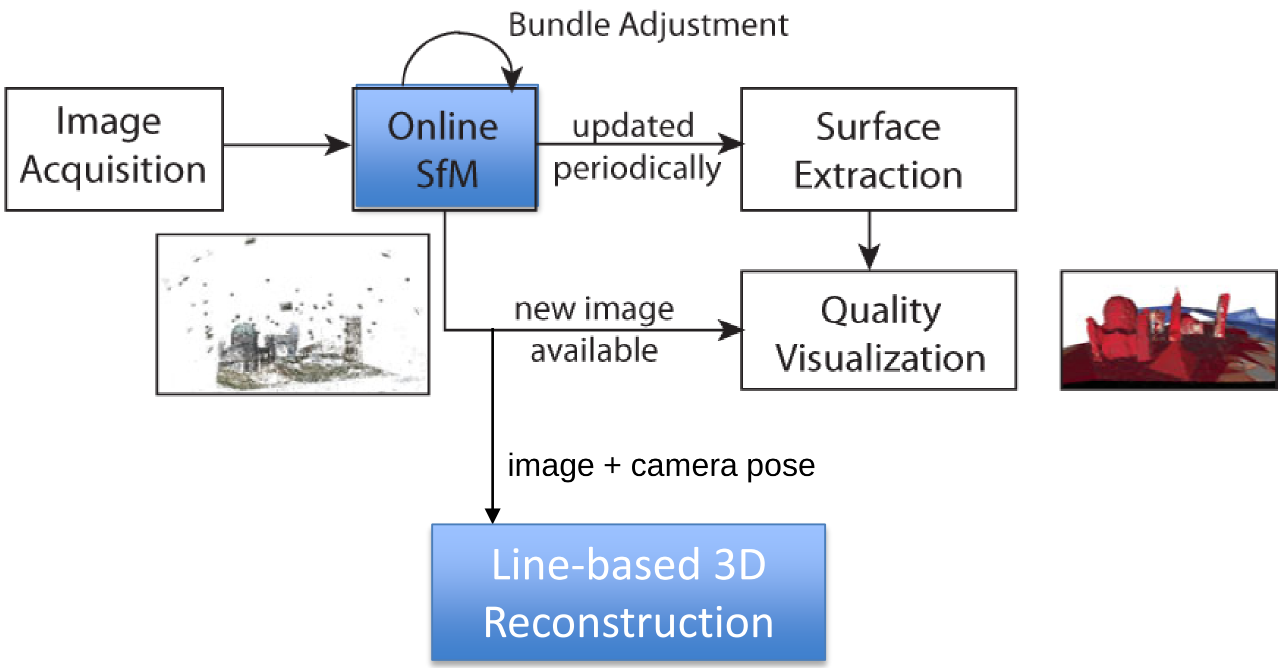

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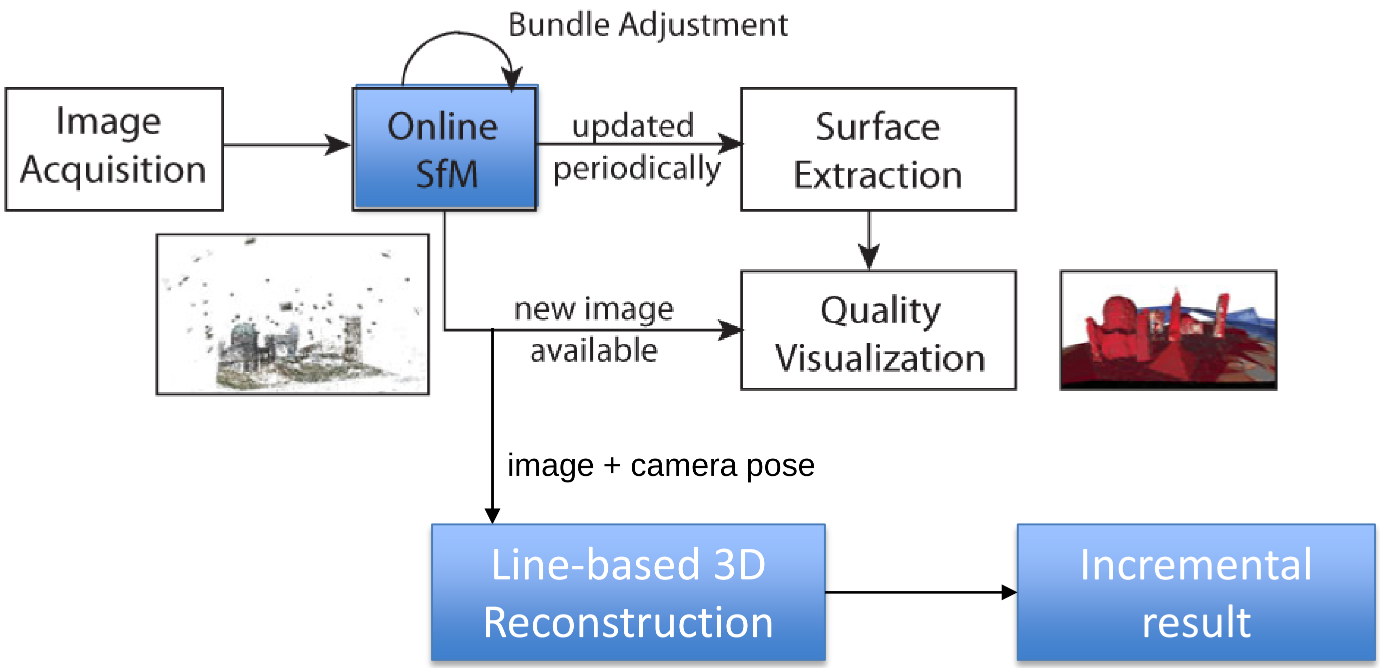

Incremental 3D Reconstruction

- Line matching procedure similar to [Hofer et al., 2013]
  - Epipolar guided matching
  - One 2D segment → several possible matches
- Instead of keeping <u>one</u> hypothesis per 2D segment, we keep <u>all</u> possible hypotheses until a decision can be made
  - Scene coverage may be still too small to decide which hypothesis is correct
- We perform on the fly grouping to cluster corresponding segments together
  - New line segments are added to existing hypotheses rather than creating new ones for each segment
    → **new incremental result after each new image**

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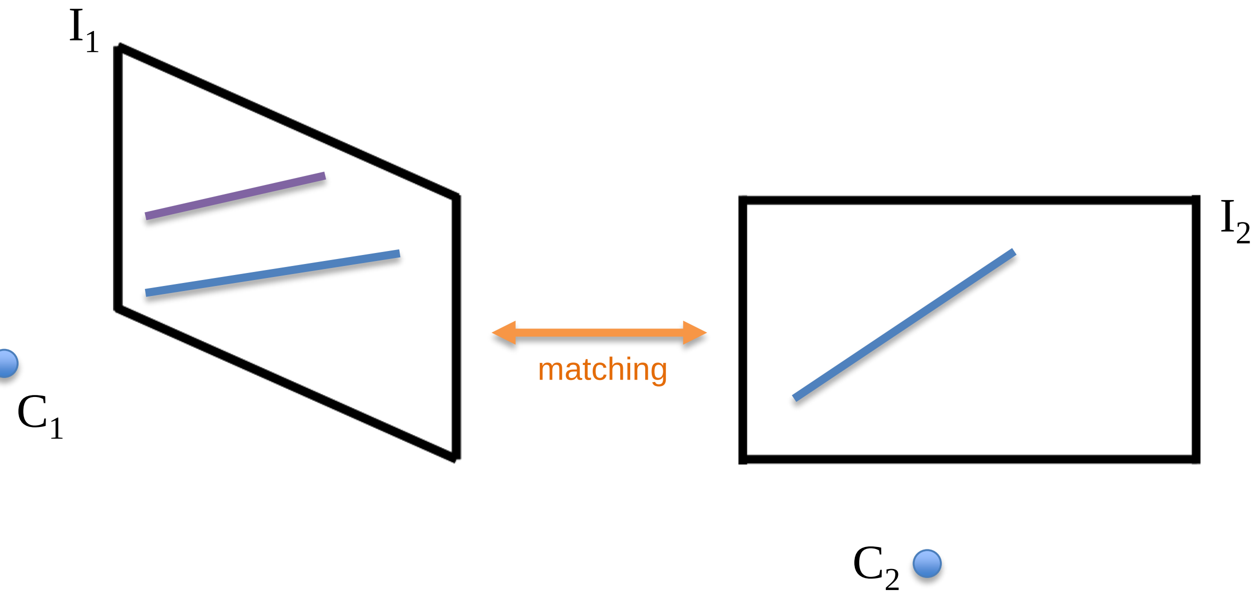

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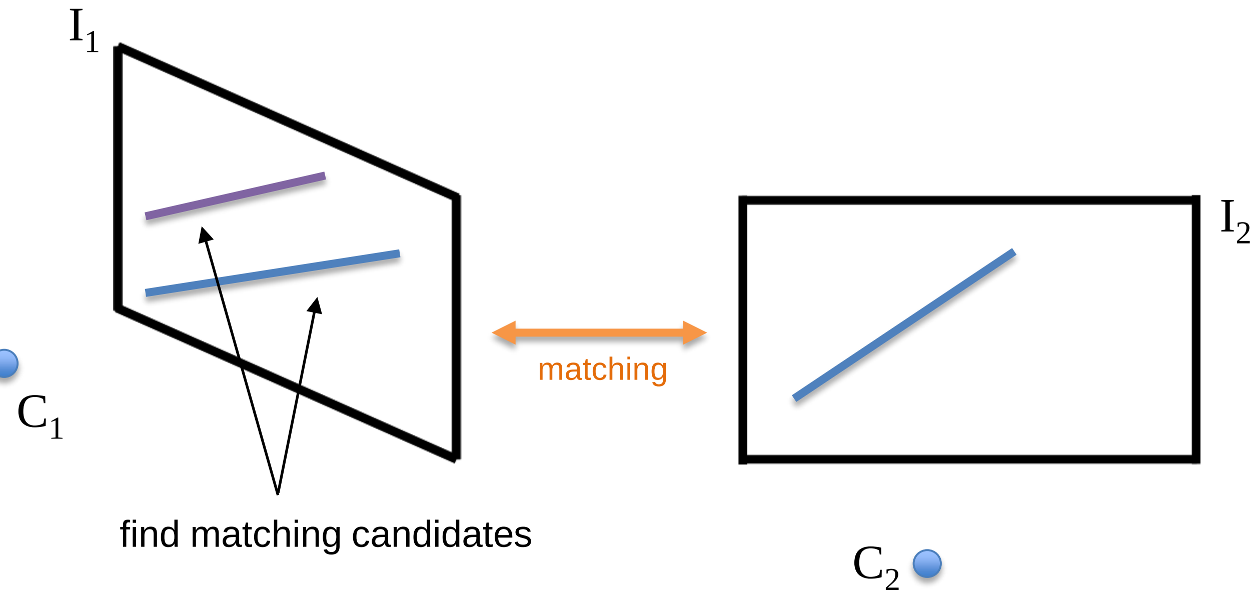

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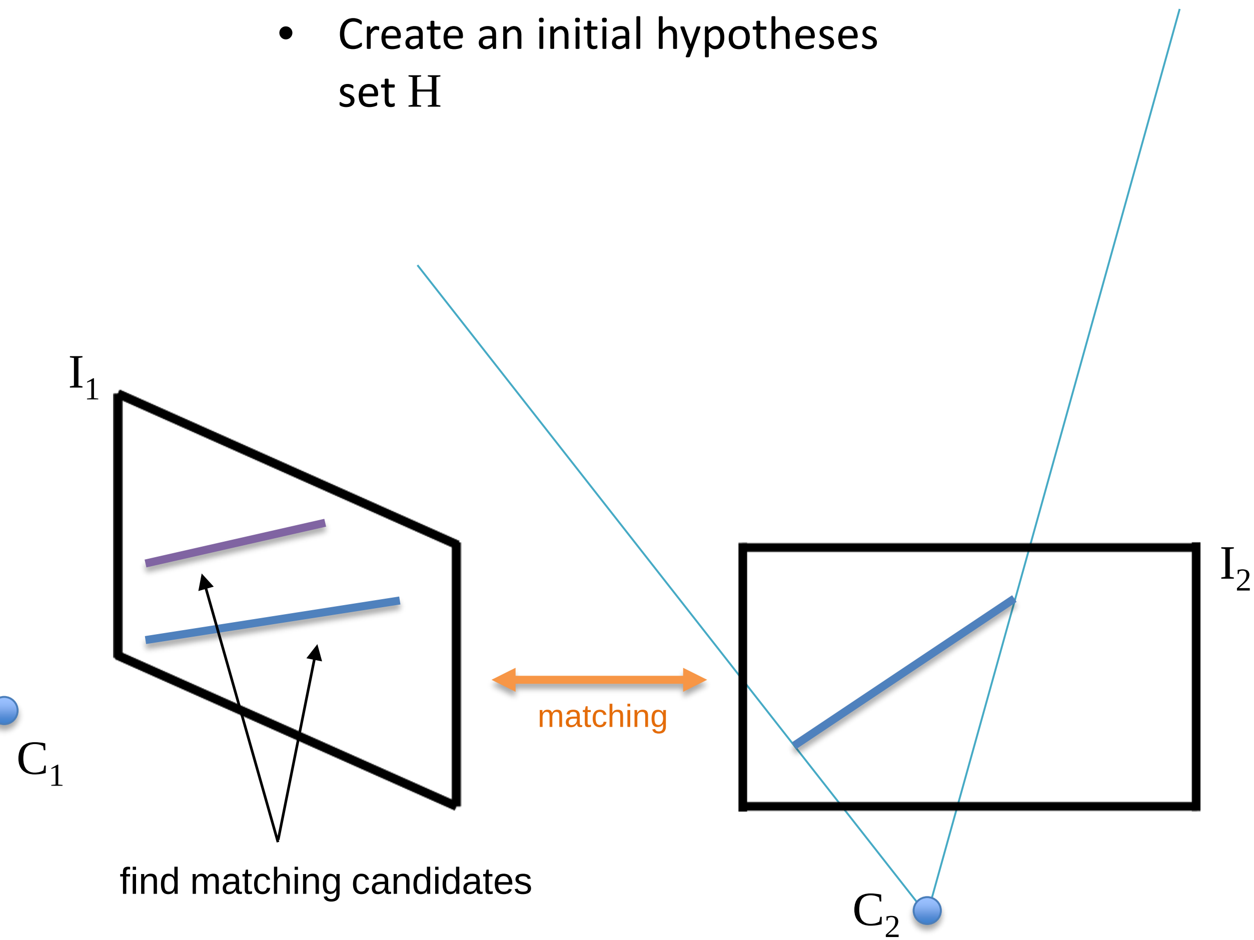

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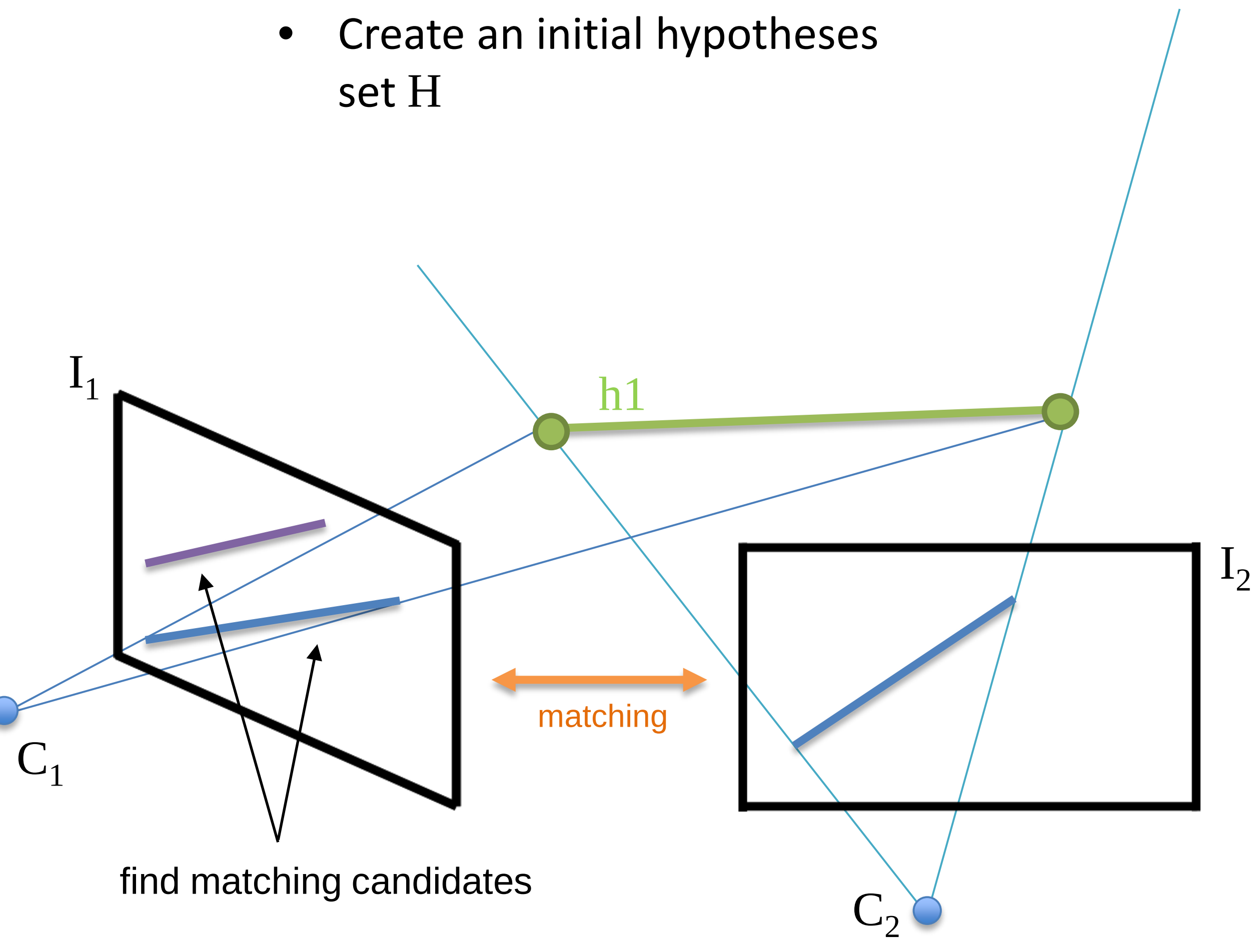

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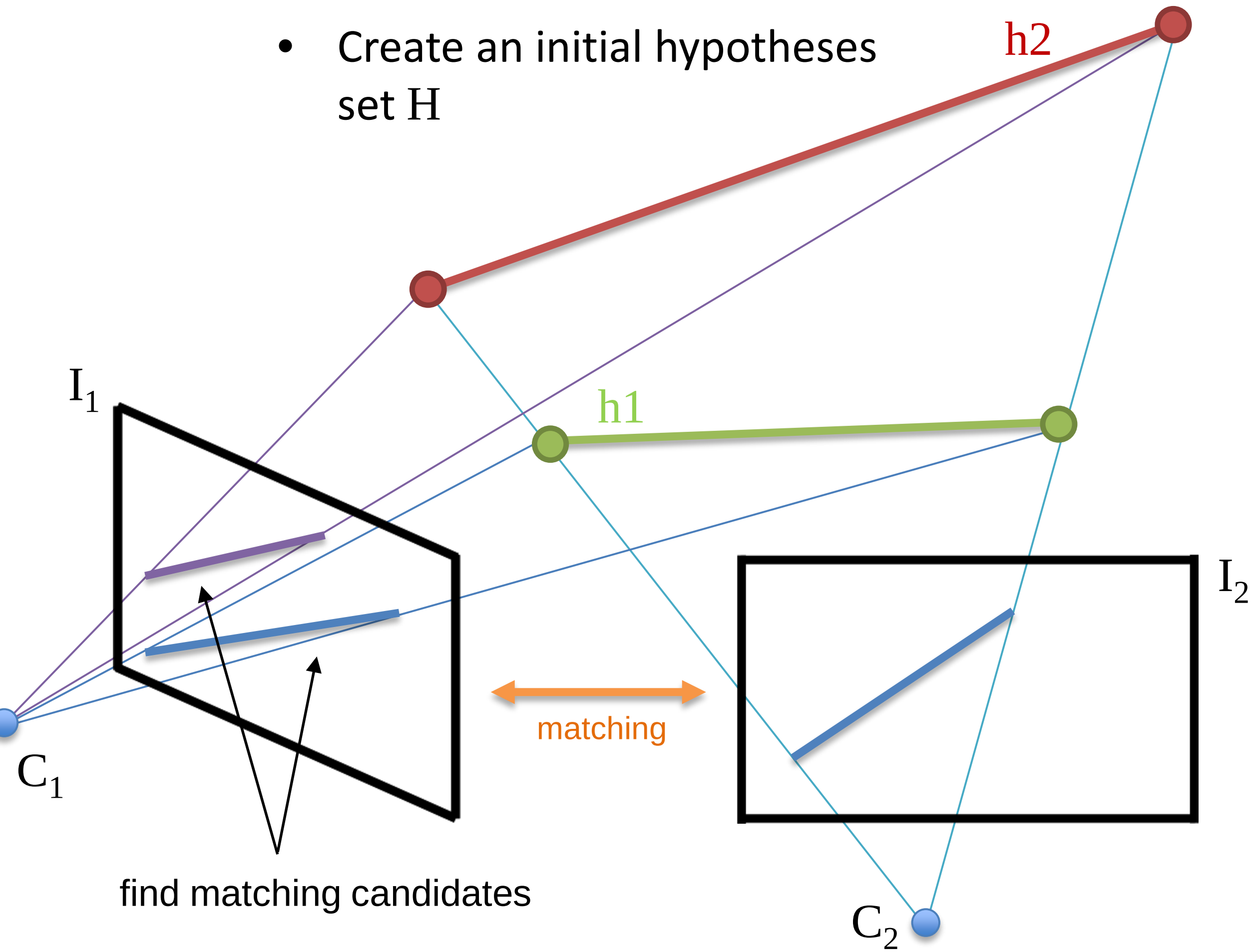

3D Line Segment Hypothesis

- Each hypothesis h consists of:
  - Triangulated line segment Kh
  - Set of corresponding 2D line segments L, and cameras C
  - Score s(h) and corresponding camera C*(h) defined as follows:

$$s(h) = 1 - min\left\{\left|\left\langle \frac{\overrightarrow{K_h}}{\|\overrightarrow{K_h}\|}, \frac{\overrightarrow{C_i}}{\|\overrightarrow{C_i}\|} \right\rangle\right|\right\}, \quad C^*(h) = \underset{C_i}{\operatorname{argmax}}(s(h)), \quad C_i \in C(h)$$

→ score high for hypotheses with a large angle between the 3D line segment and one of the referenced cameras

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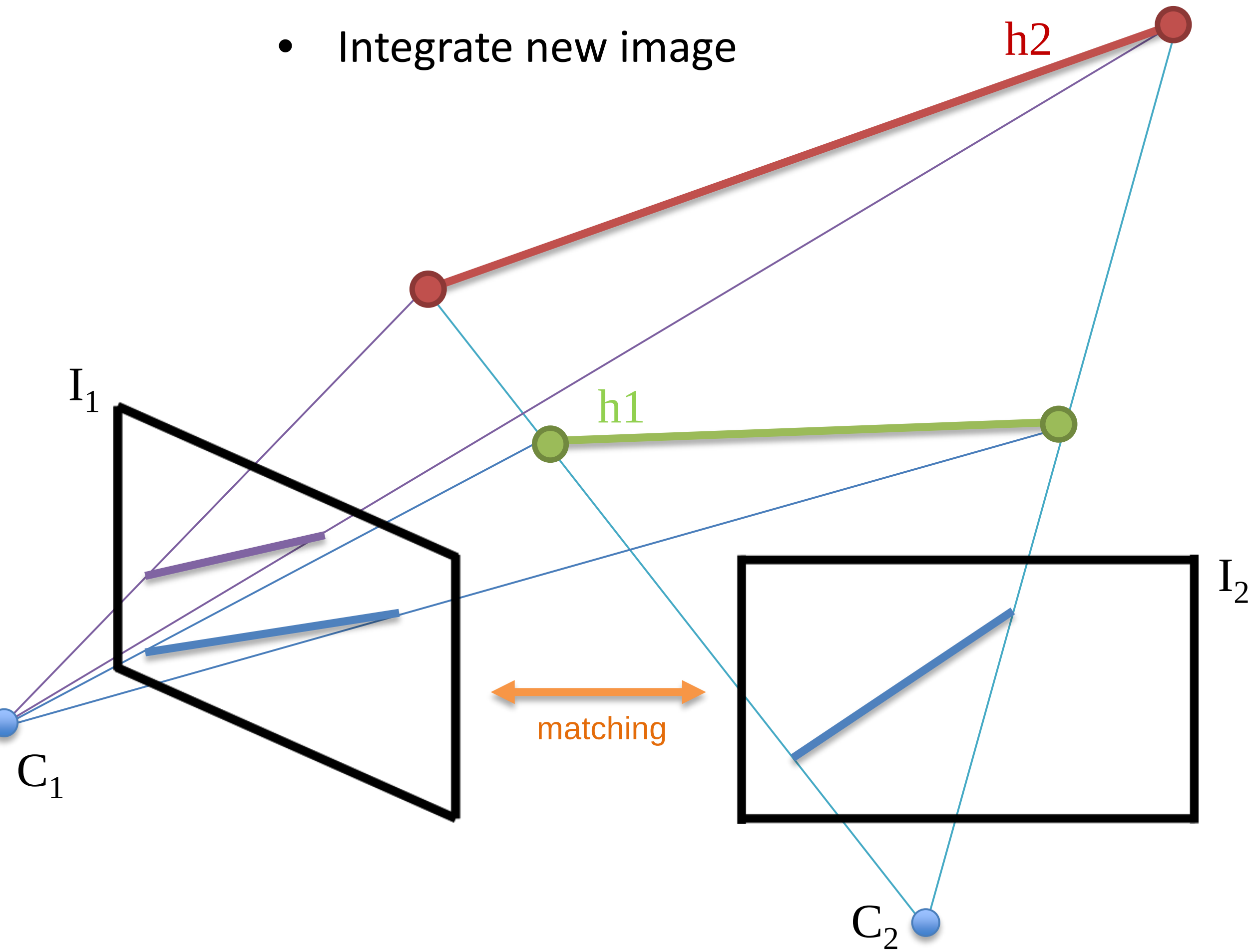
  - Integrate new image



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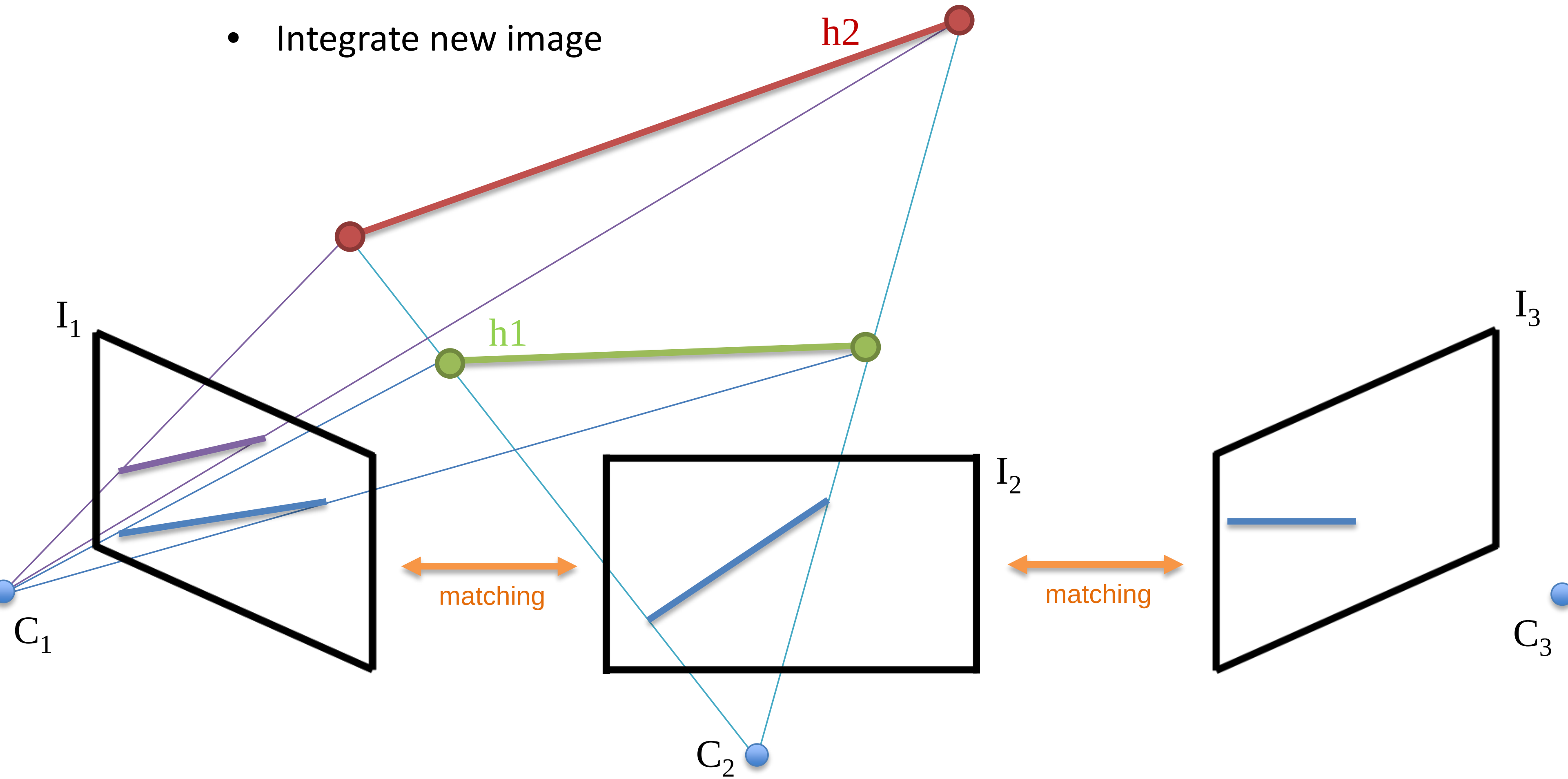

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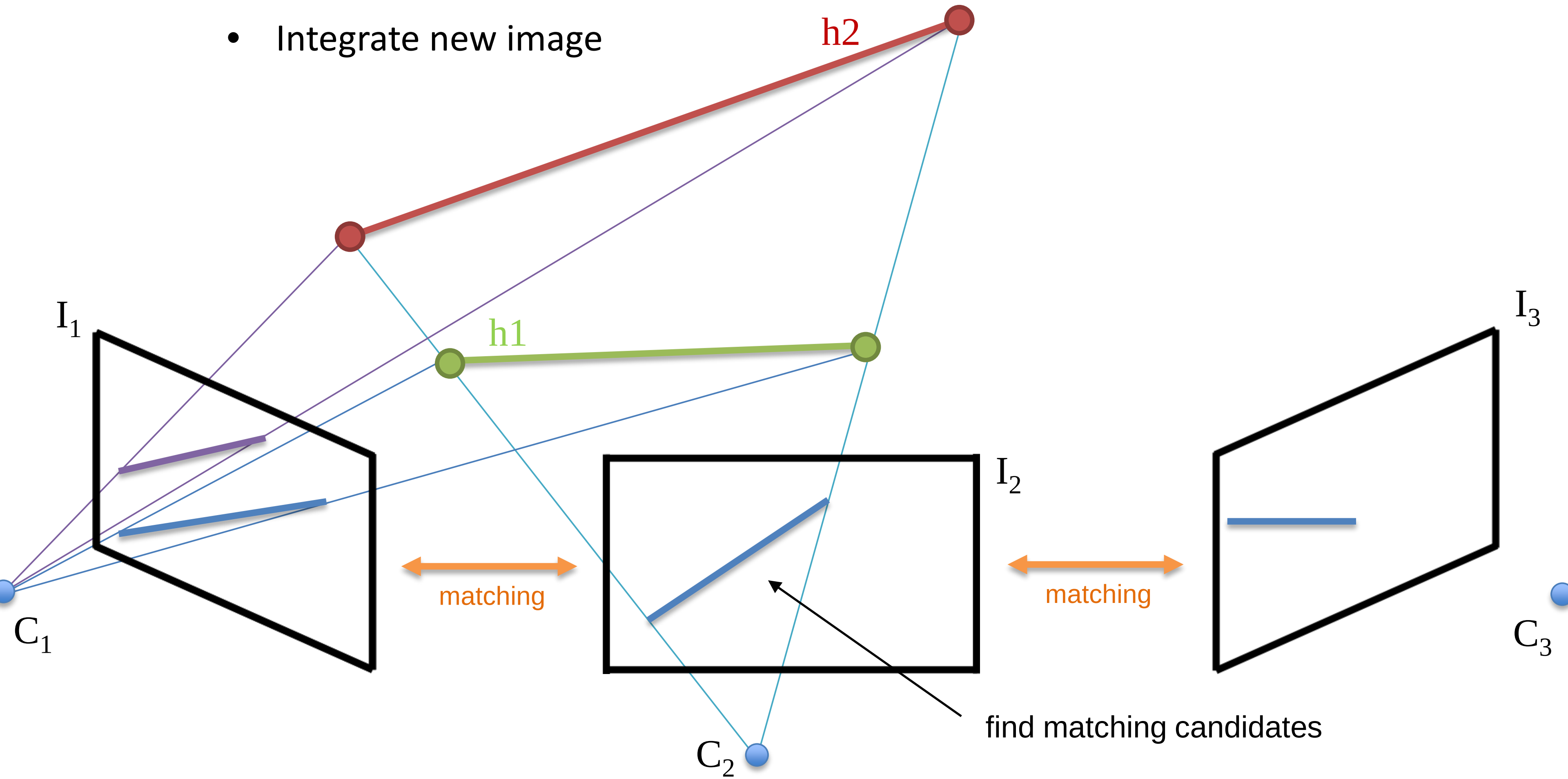

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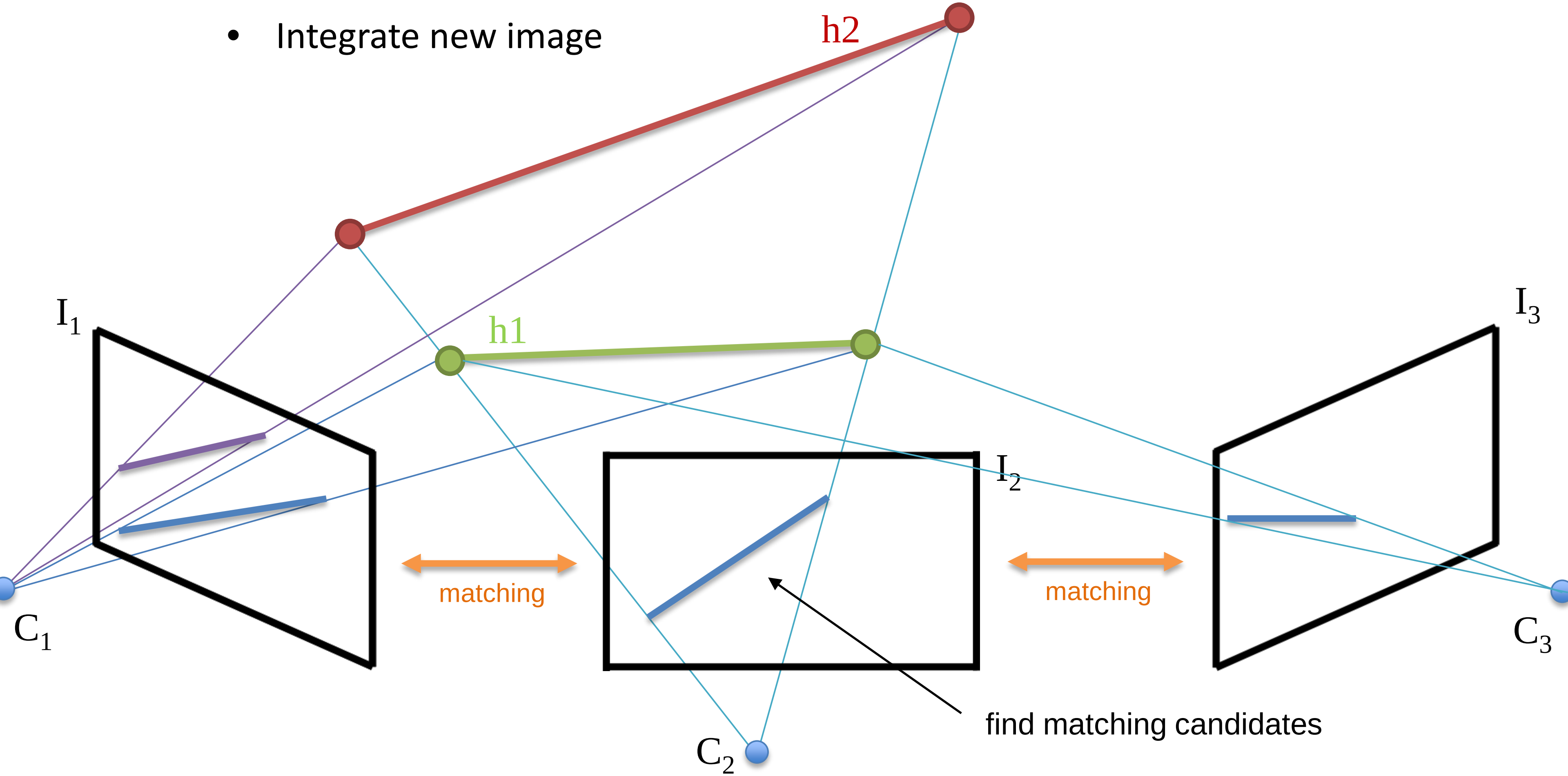

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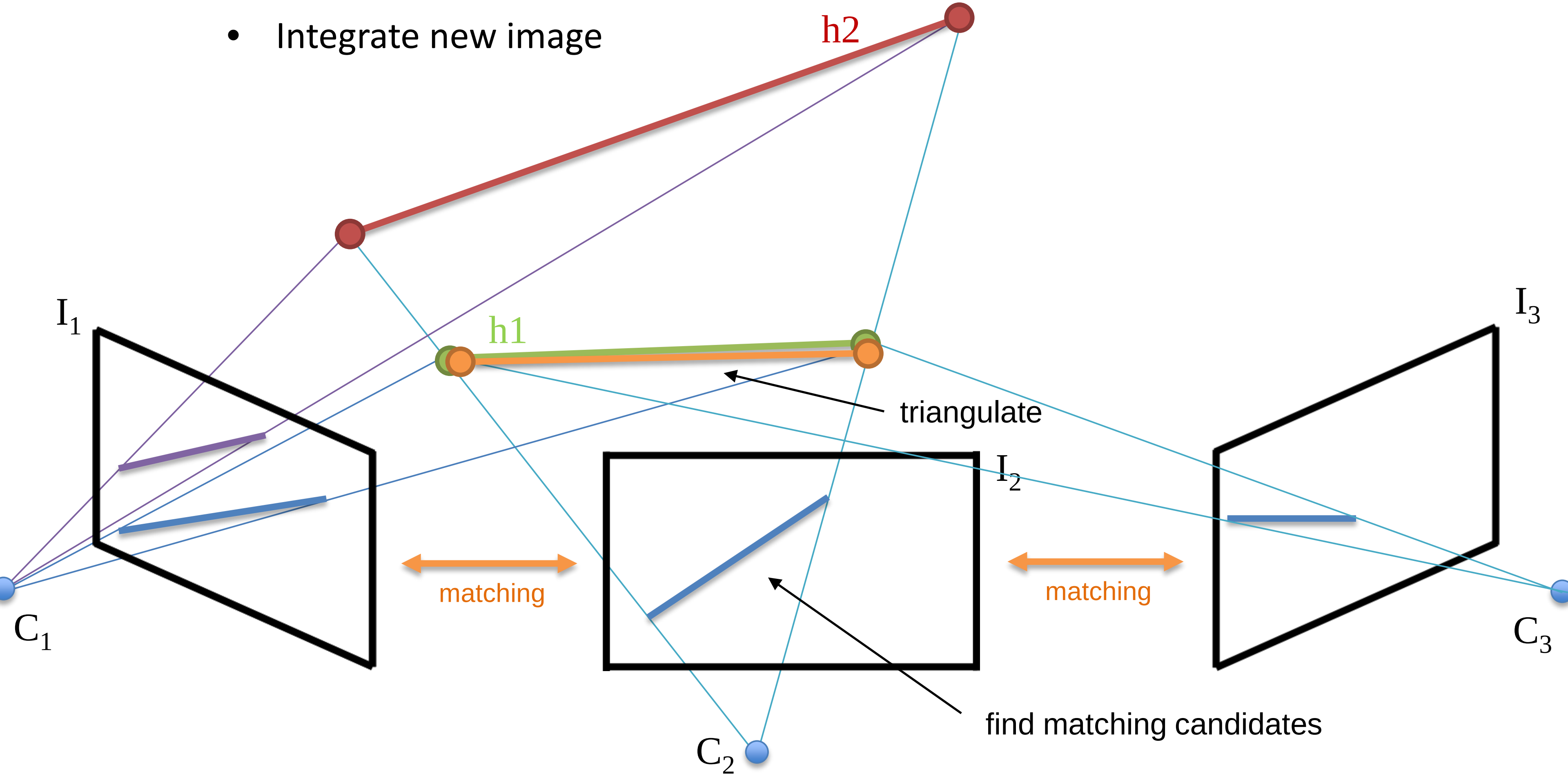

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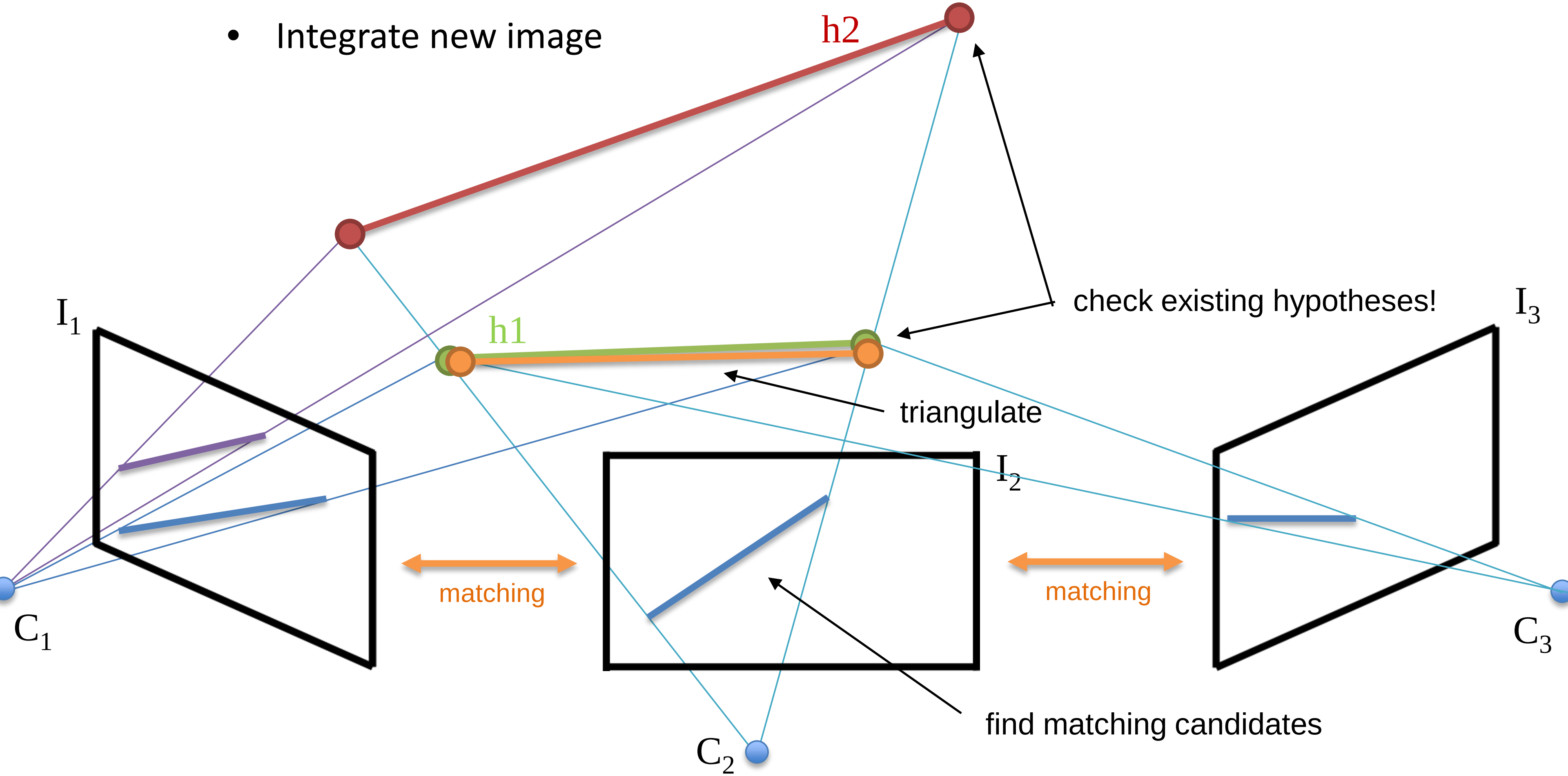

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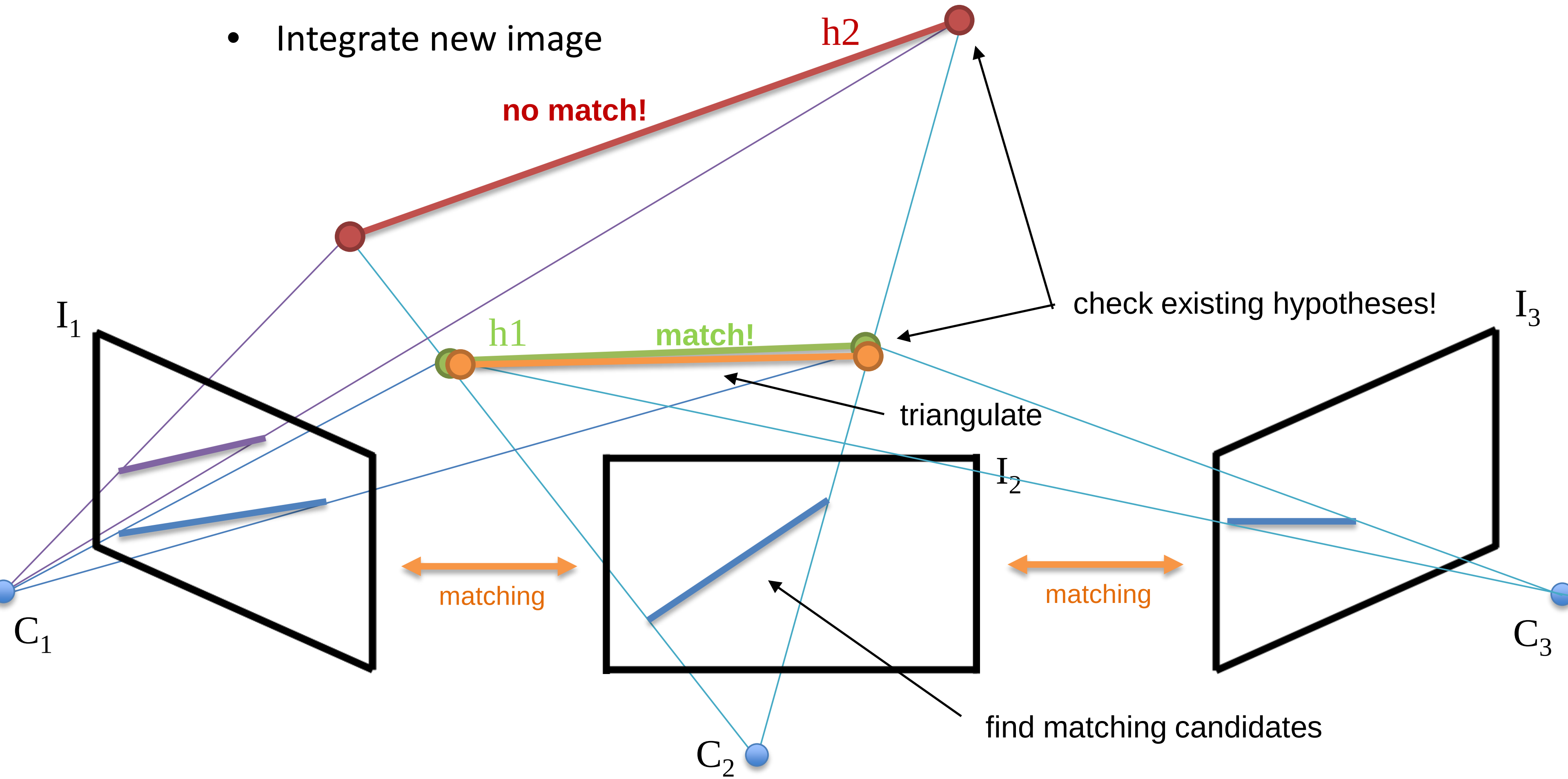

Matching Constraints

- When do we add a new line segment to an existing hypothesis?
  - If distance in 3D is lower than r and distance in image space is lower than σ (→ backprojection)
- How to define these thresholds?
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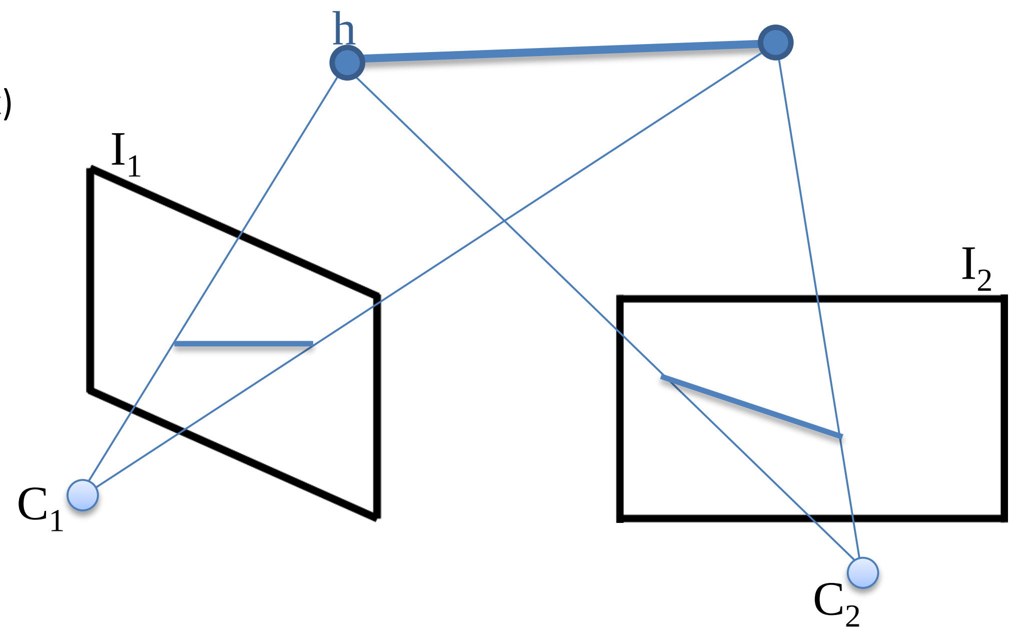

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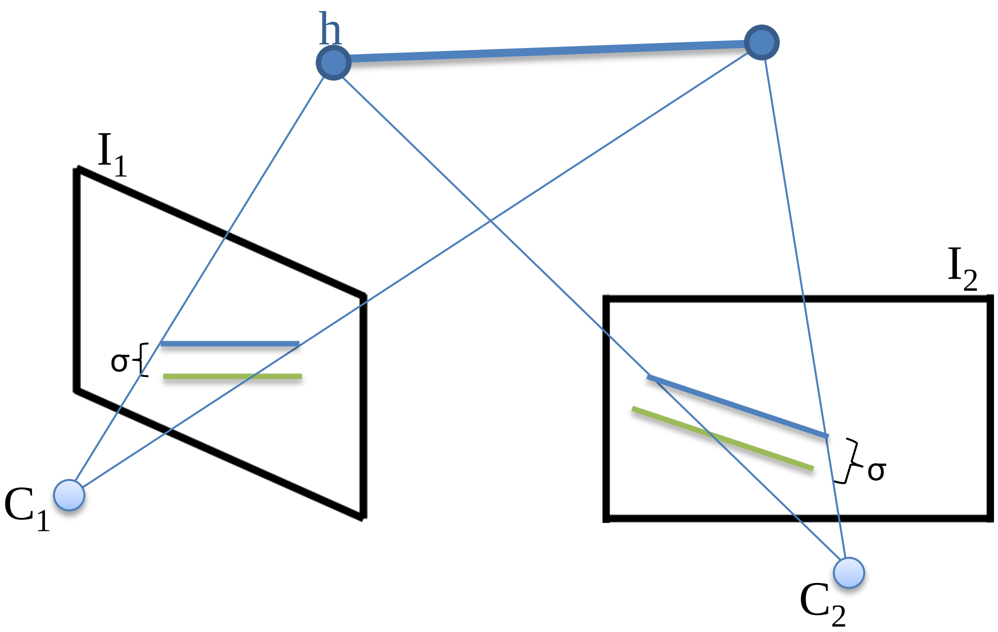

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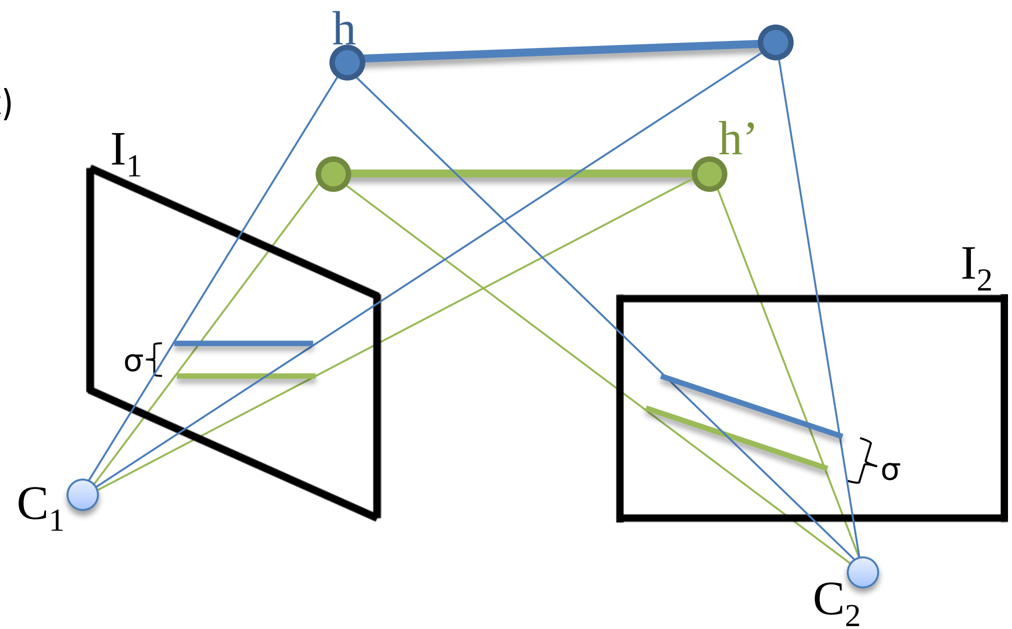

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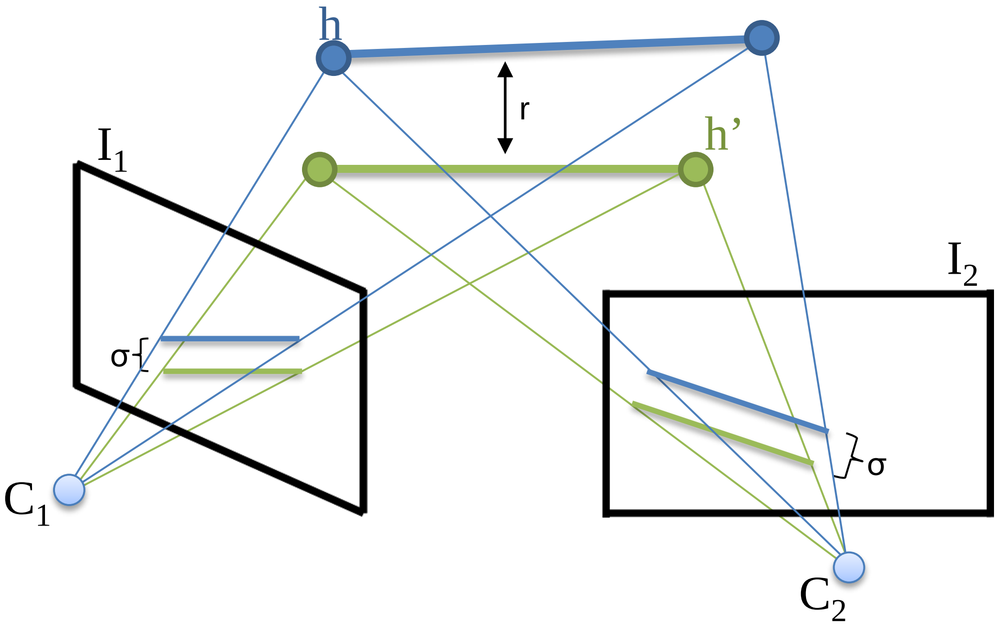

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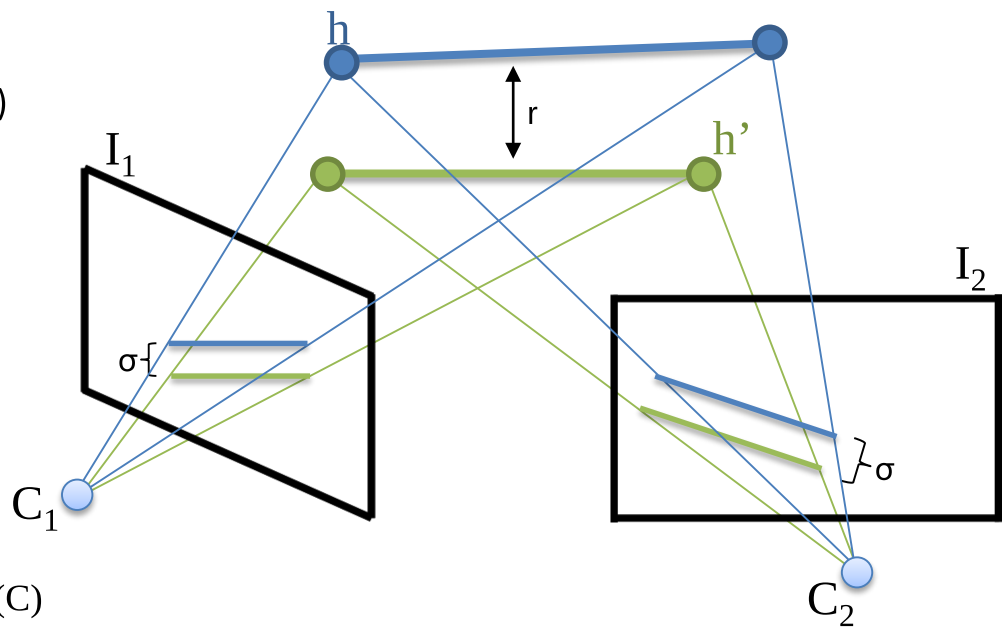

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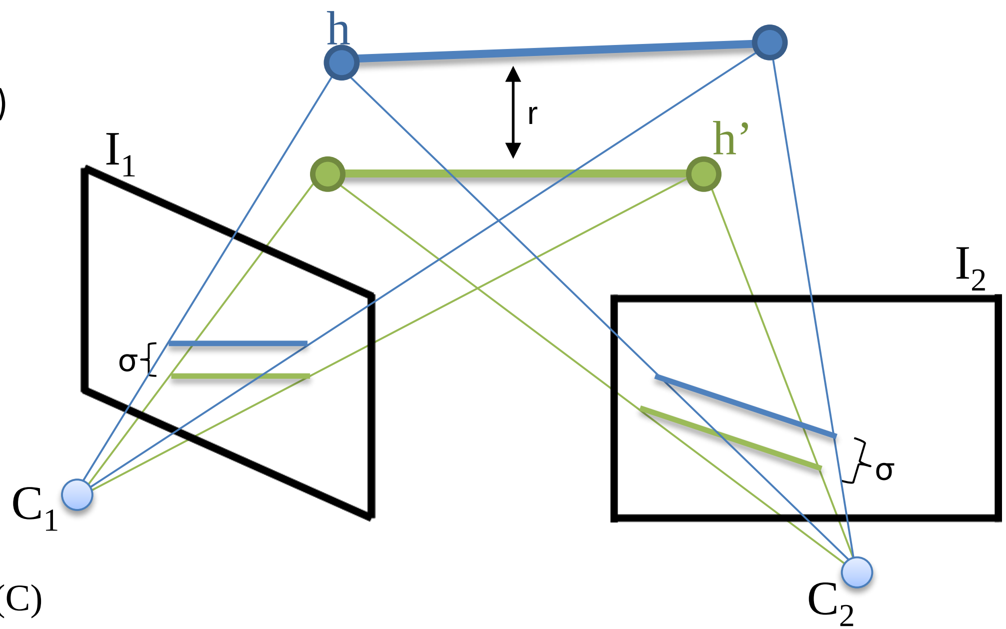

→ No dependence on reconstruction scale!

Incremental Results

- Simple greedy algorithm:
  - Sort current hypotheses set H by number of participating line segments (*hypothesis size*)
  - If equal, sort by reprojection error
  - Iterate over sorted set:
    - If hypothesis size >= λ and $\mathrm{s(h)} > 0.5$ → **inlier** [all other hypotheses referenced by any segment in h are considered to be outliers and skipped (<u>not erased!</u>)]
    - Else → **outlier**
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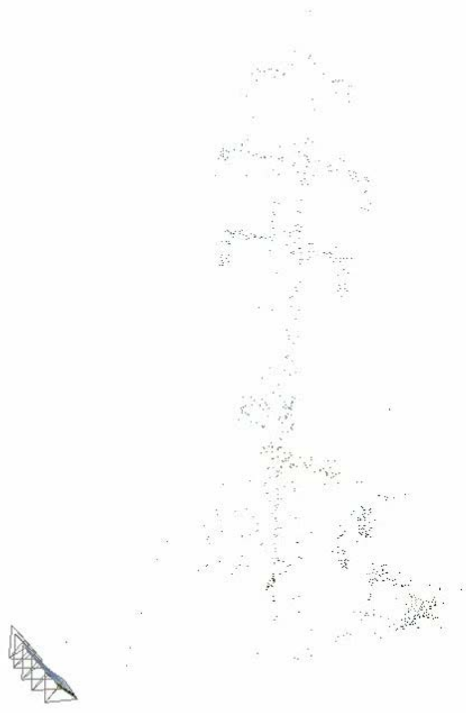

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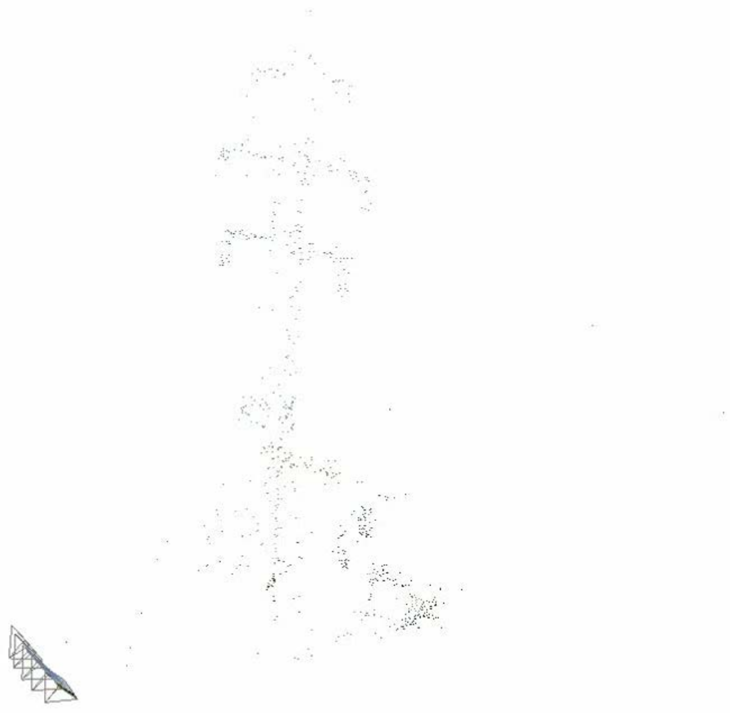
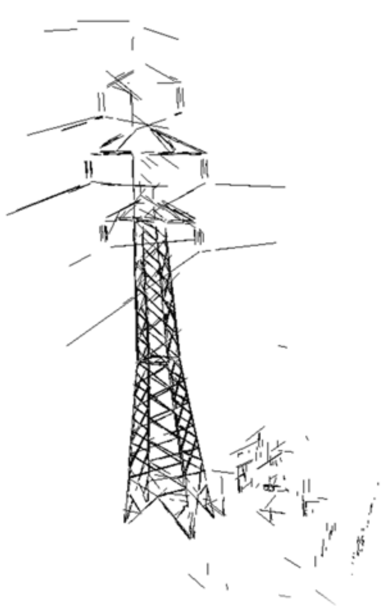


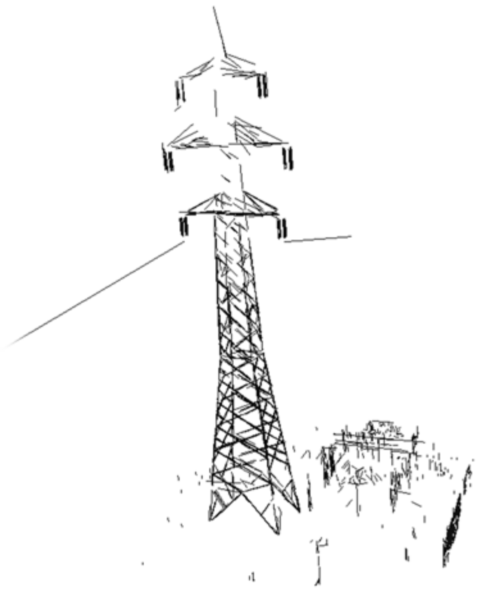
→ **Purely geometric hypothesis verification!**
No gradient scoring necessary!

Comparison: Offline vs. Online

- Pylon Sequence:
  - 106 ground-level images



Offline



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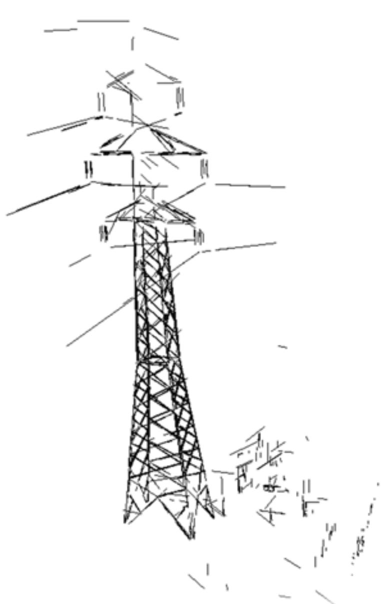
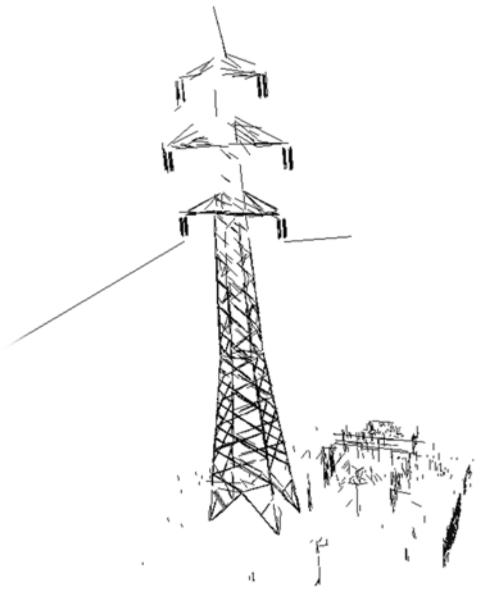


Offline
Runtime: 67 minutes (lines only)



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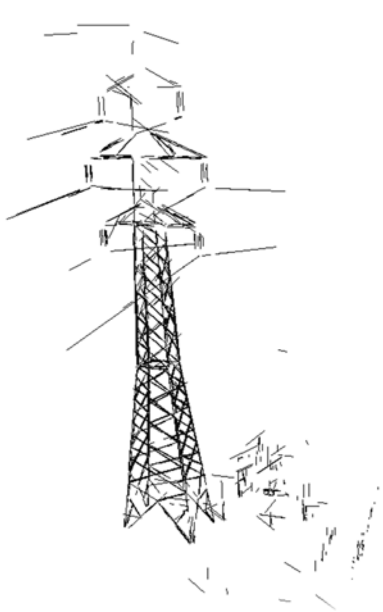
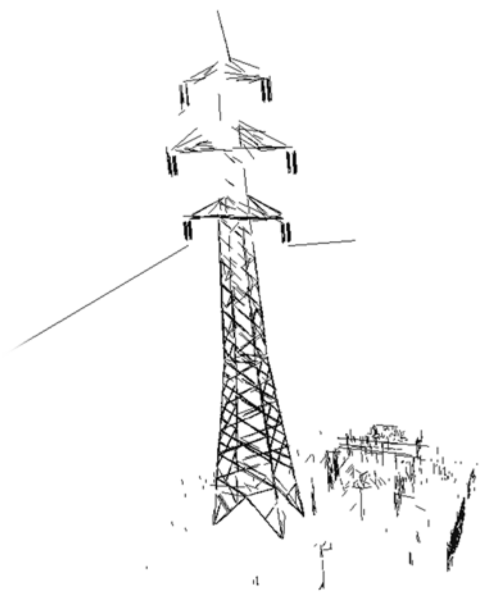


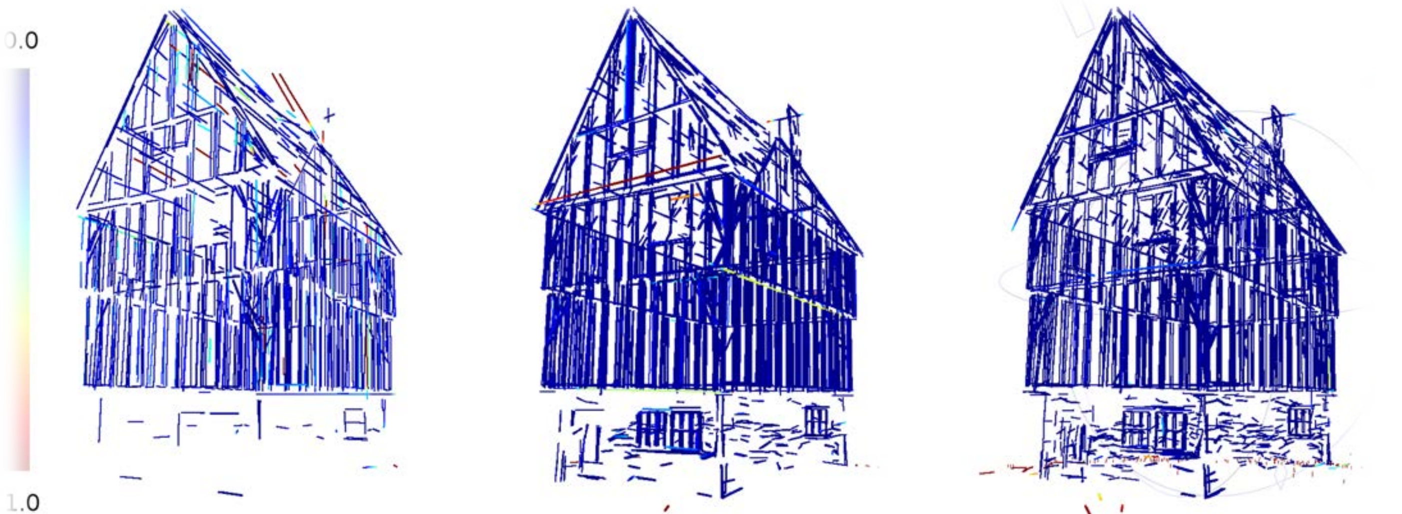


Offline
Runtime: 67 minutes (lines only)

Online
Runtime: 9 minutes (incl. SfM)

Evaluation

- Timber-frame Sequence
  - Synthetic sequence (240 images)
  - Evaluation in terms of root mean square (RMS) error compared to ground truth CAD model



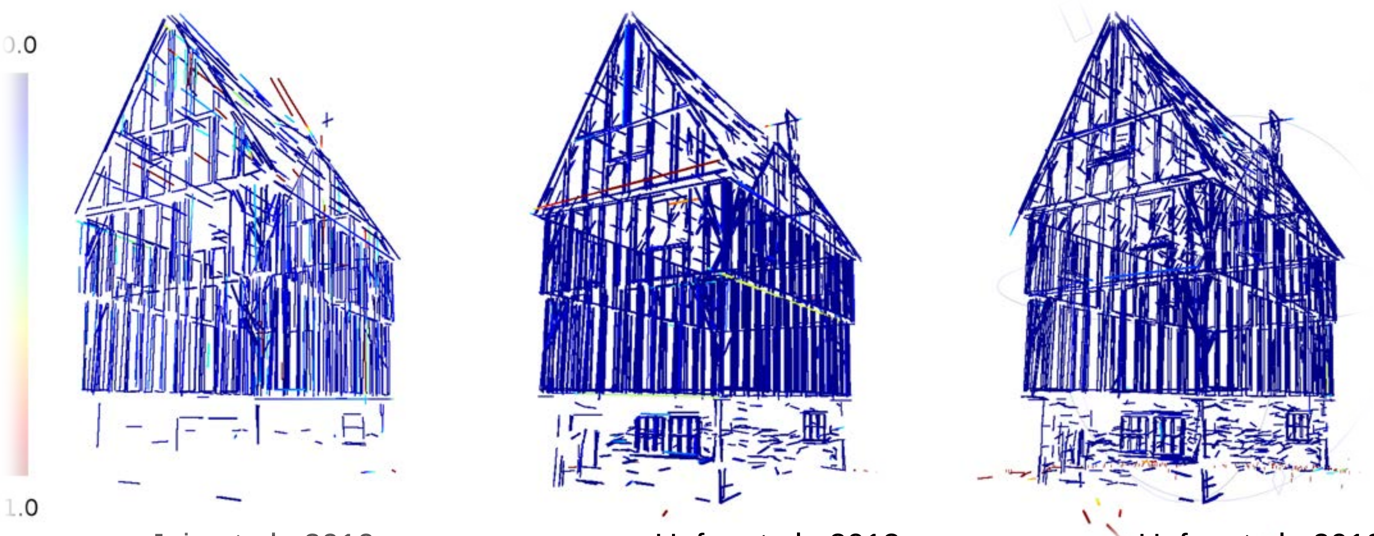
Jain et al., 2010
RMSE: 0.291

Hofer et al., 2013
RMSE: 0.094

Hofer et al., 2013a
RMSE: 0.196

Evaluation

- Timber-frame Sequence
  - Synthetic sequence (240 images)
  - Evaluation in terms of root mean square (RMS) error compared to ground truth CAD model



Jain et al., 2010
RMSE: 0.291
Runtime: **several hours...**

Hofer et al., 2013
RMSE: 0.094

Hofer et al., 2013a
RMSE: 0.196

Evaluation

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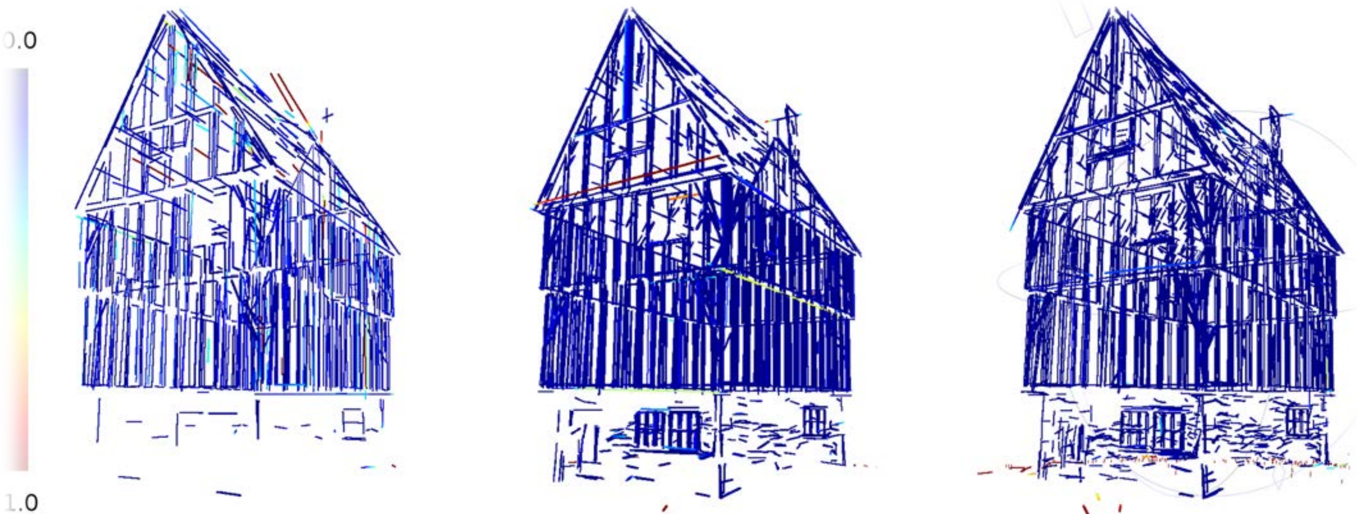

Jain et al., 2010
RMSE: 0.291
Runtime: **several hours...**

Hofer et al., 2013
RMSE: 0.094
Runtime: **45 minutes**

Hofer et al., 2013a
RMSE: 0.196

Evaluation

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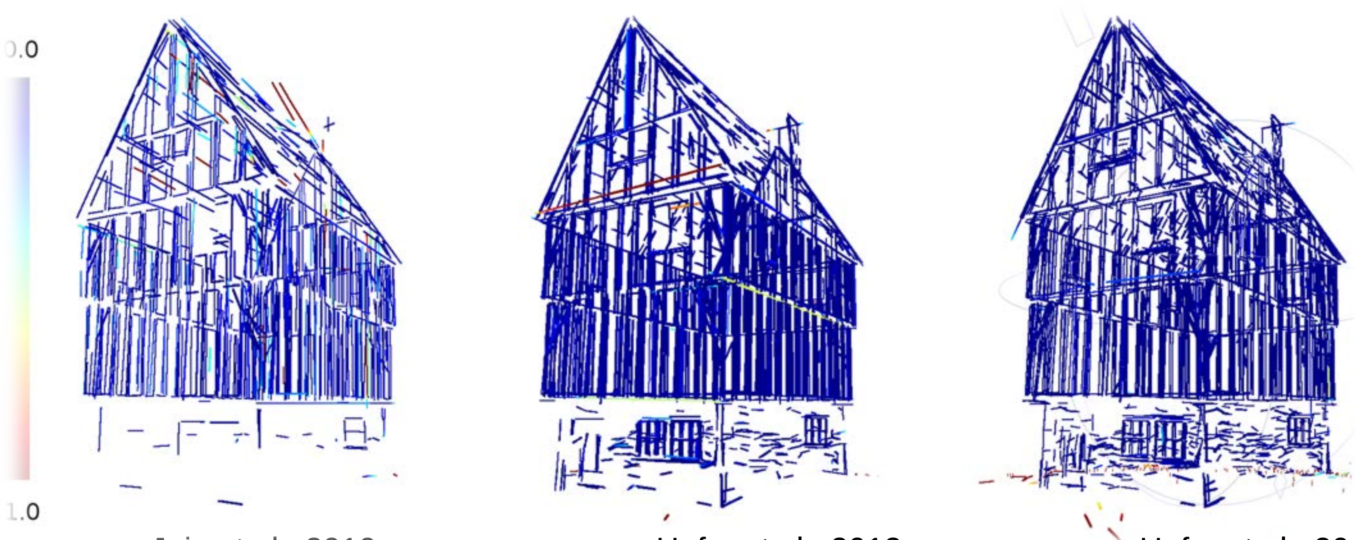

Jain et al., 2010
RMSE: 0.291
Runtime: **several hours...**

Hofer et al., 2013
RMSE: 0.094
Runtime: **45 minutes**

Hofer et al., 2013a
RMSE: 0.196
Runtime: **12 minutes**

Conclusion

Conclusion

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Conclusion

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   - Yes, it is possible to extend the principles introduced by [Jain et al., 2010] and [Hofer et al., 2013] for online processing!

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   - Yes, we can group corresponding line segments together on-the-fly and verify them through their cluster size, without the need for backprojection and gradient scoring.

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3. **Is it possible to derive the clustering radius from the image space without knowing the exact reconstruction scale?**

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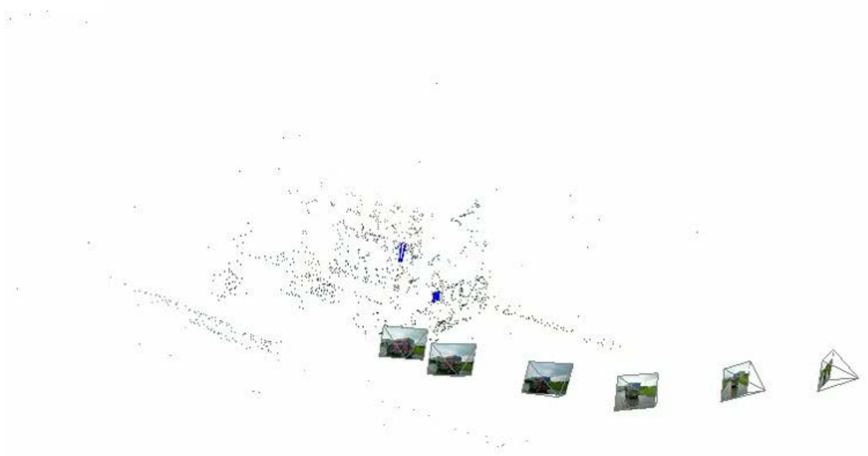
   - Yes, we can group corresponding line segments together on-the-fly and verify them through their cluster size, without the need for backprojection and gradient scoring.
3. **Is it possible to derive the clustering radius from the image space without knowing the exact reconstruction scale?**
   - Yes, it is possible to derive the clustering radius directly from the image space using a pre-defined maximum uncertainty σ.

Thank you for your attention!



More information available at
http://aerial.icg.tugraz.at

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