Bundle Adjustment with Feature Scale Constraint for Enhanced Estimation Accuracy

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TASP | Technion Autonomous System Program

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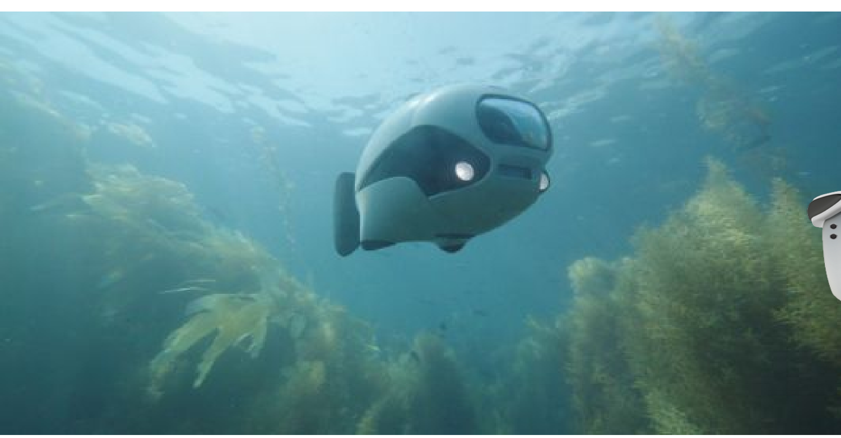
Vision-based navigation

- Aerial unmanned vehicles
- Self-driving cars
- Augmented reality
- Underwater operations
- Space operations



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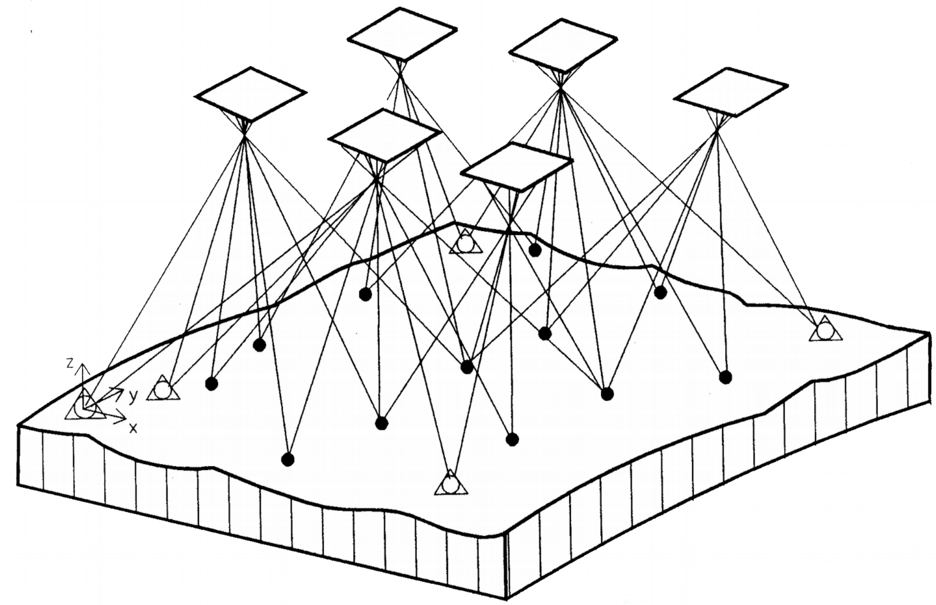
Problem description

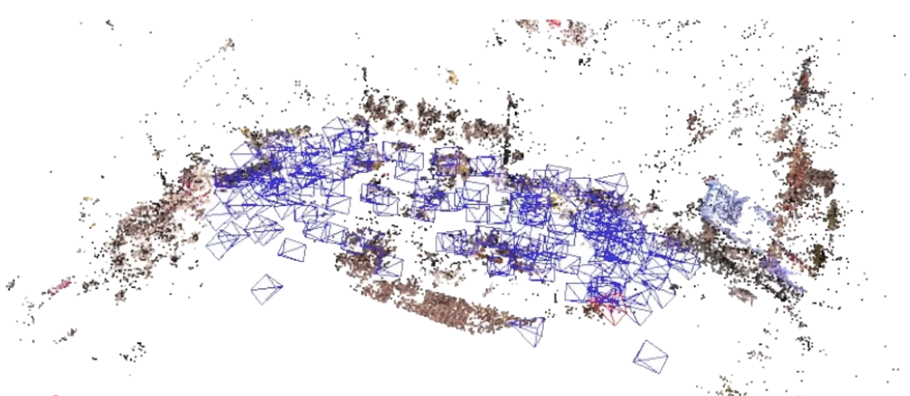
<u>Problems:</u>

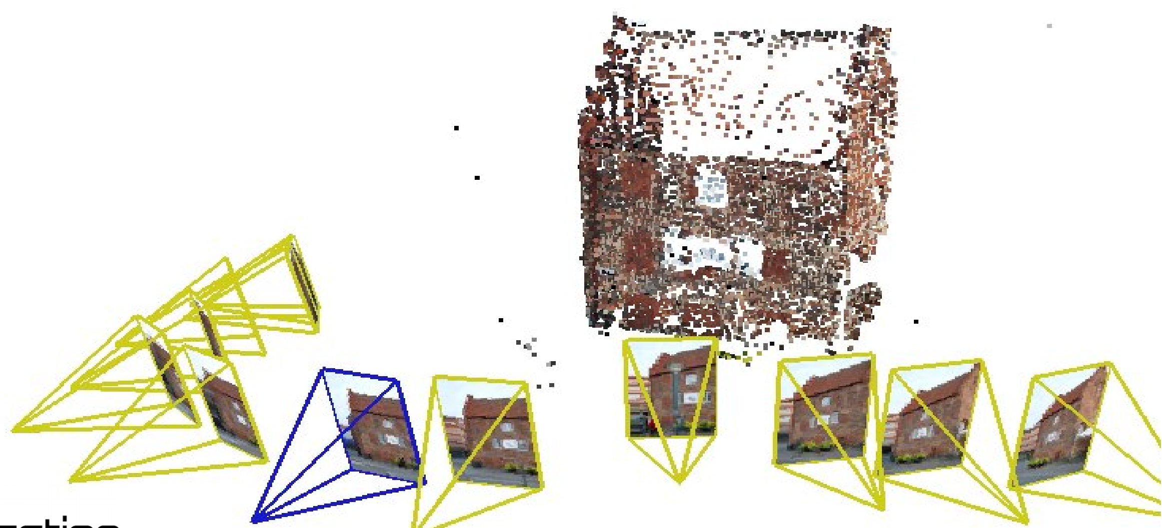
- Mapping
- 3D reconstruction
- Accurate self-pose estimation

<u>Common approach to use:</u>

Bundle Adjustment





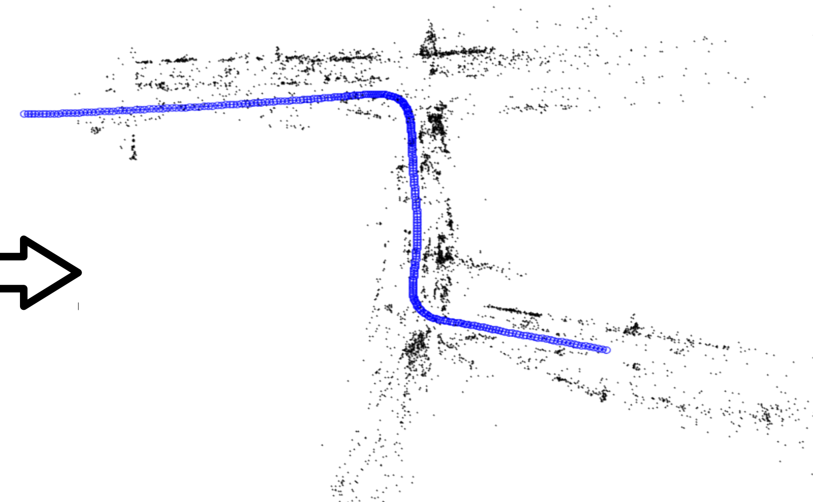


Monocular SLAM

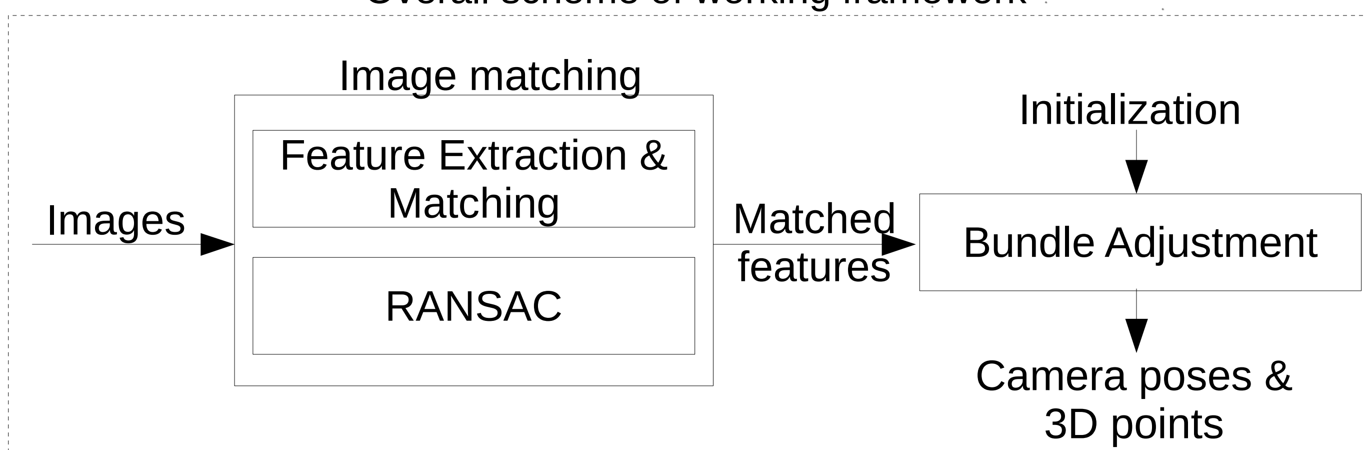
Input: sequence of images

Preprocessing: Feature matching and tracking

Output: 3D-reconstruction



Overall scheme of working framework



Assumptions:
- no initial map
- no GPS
- only a single camera sensor

Related work

- BA: minimize re-projection errors
[B. Triggs Bundle Adjustment — A Modern Synthesis]

- visual feature-based SLAM - online
[M. Kaess – iSAM2]

- using feature scale for identifying far-away landmarks
[D.-N. Ta – Vistas and parallel tracking]

- correcting monocular scale drift by placing a prior on the size of the objects
[D. P. Frost – Object-Aware Bundle Adjustment]

Monocular SLAM scale drift problem

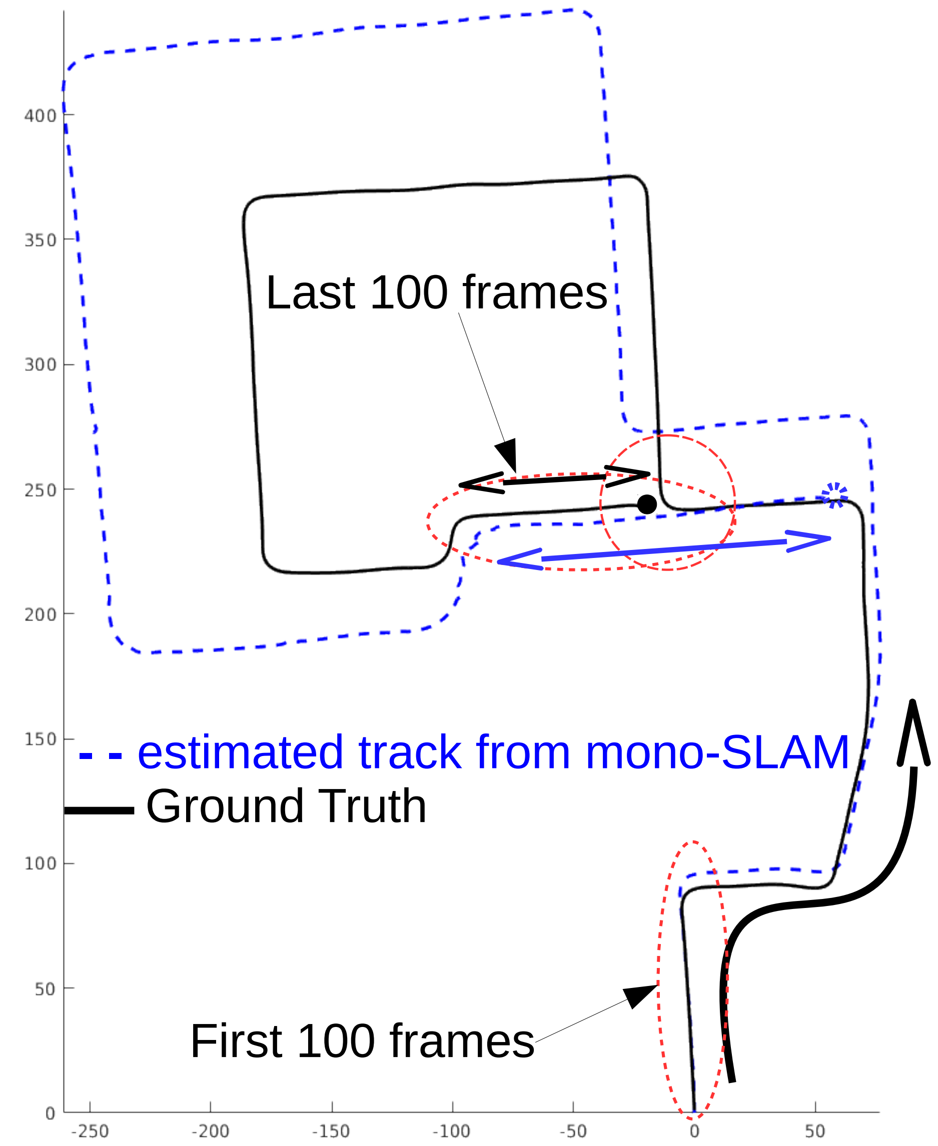
Known problem is **scale drift along optical axis** with time.

Example:

Error along optical axis is growing with time

For the first 100 frames:
Error: 8.6%

For the last 100 frames:
Error: 94.6%



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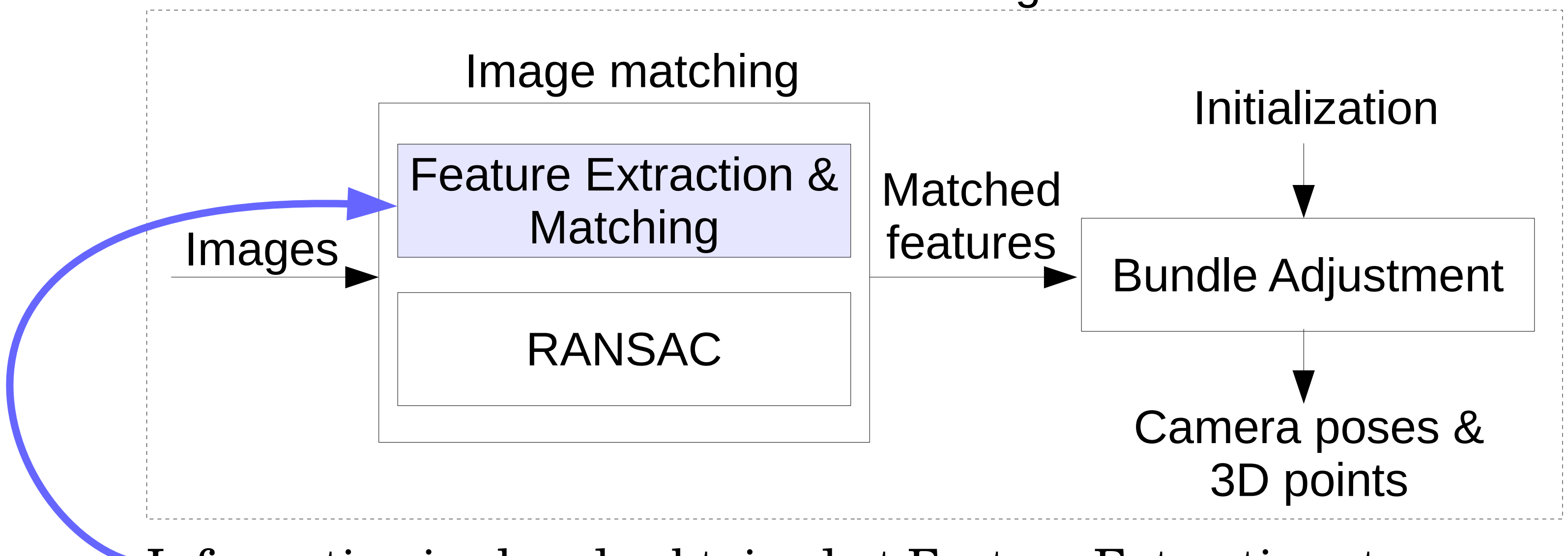
Contribution

We introduce scale constraints into Bundle Adjustment aiming to improve accuracy along optical axis direction.

Overall scheme of working framework

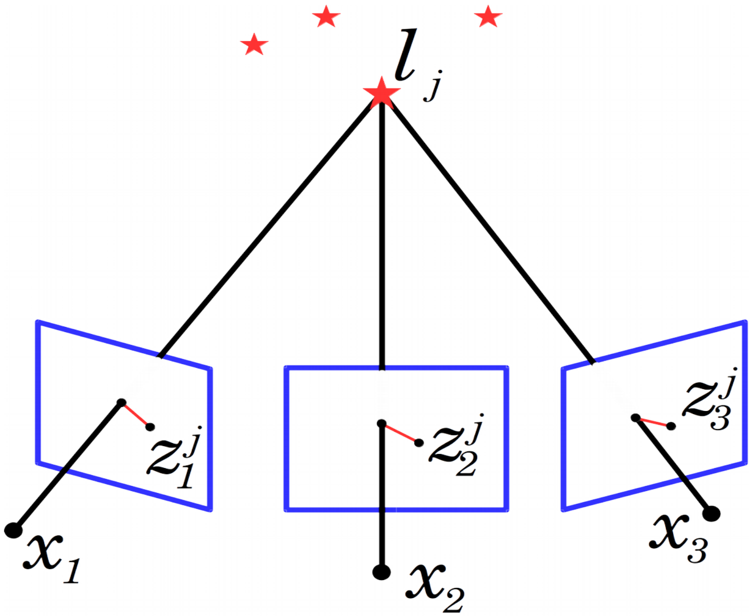


Information is already obtained at Feature Extraction step.

Outline

- Background:
  - Bundle Adjustment (BA)
  - SIFT features
- Our approach:
  - Adding new constraints to BA
  - Improving accuracy of detected feature scale
- Results
- Variations with new constraints
- Conclusions

BA notations



Landmark set

$$L \doteq \{l_1, \ldots, l_j, \ldots, l_M\}$$

Pose set

$$X \doteq \{x_1, \ldots, x_i, \ldots, x_N\}$$

Single observation of landmark ***j*** from pose ***i***: z_i^j

All measurements set

$$\mathcal{Z} \doteq \{z_i^j\}$$

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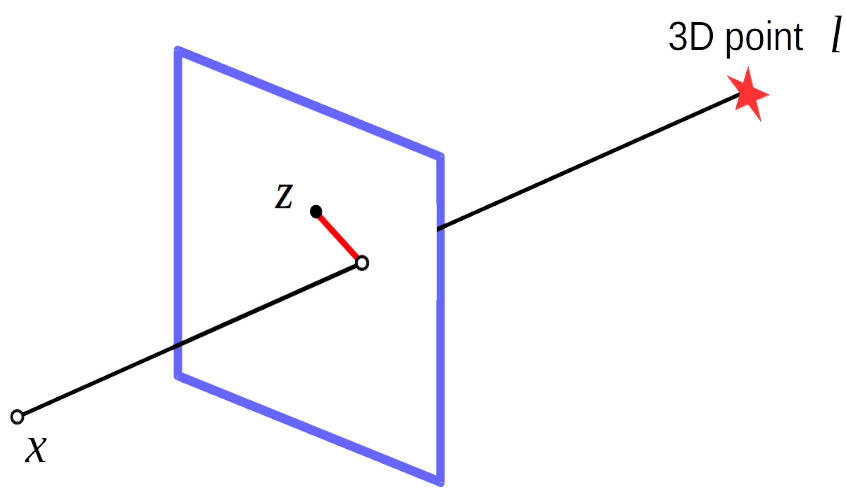
BA Probabilistic Representation

Measurement model: $z = \pi(x, l) + v \qquad v \sim N(0, \Sigma_v)$

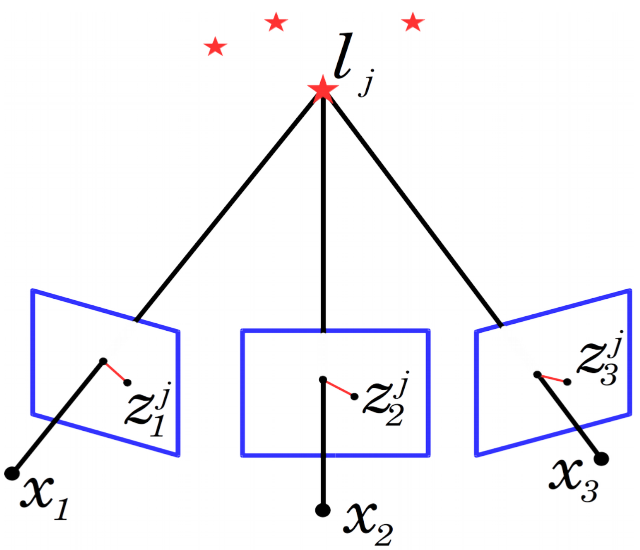
Projection operator: $\pi(x, l)$

Measurement likelihood:

$$p(z|x, l) = \frac{1}{\sqrt{det(2\pi\Sigma_v)}} exp\left(-\frac{1}{2}\underbrace{||z - \pi(x, l)||^2_{\Sigma_v}}_{\text{re-projection error}}\right)$$



BA Probabilistic Representation



Using Bayes rule we have:

$$p(x,l|z) = \frac{p(x,l)p(z|x,l)}{p(z)} \propto \underbrace{p(x,l)}_{\text{Prior}}\underbrace{p(z|x,l)}_{\text{Measurement likelihood}}$$

Objective: calculate the joint posterior distribution

$$p\left(X, L|\mathcal{Z}\right)$$

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BA Probabilistic Representation

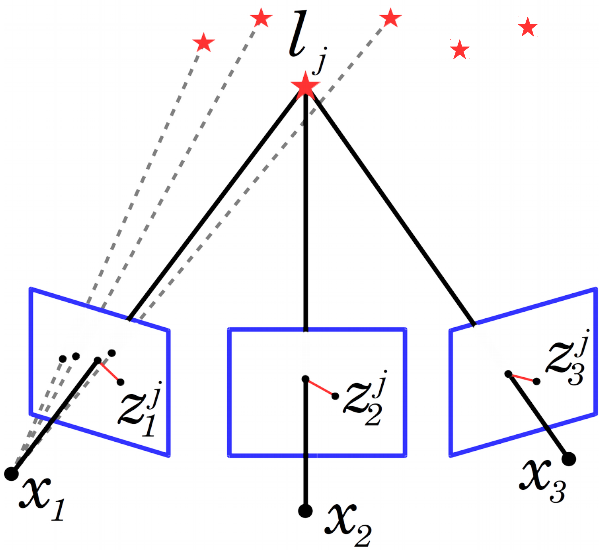
For N images:

$$p(X, L|\mathcal{Z}) = priors \cdot \prod_{i}^{N} \prod_{j \in \mathcal{M}_i} p\left(z_i^j | x_i, l_j\right)$$

Where $\mathcal{M}_i$ is a landmark subset observed from camera i

$$p\left(z_i^j | x_i, l_j\right) \propto \exp\left(-\frac{1}{2}\left\|z_i^j - \pi\left(x_i, l_j\right)\right\|_{\Sigma_v}^2\right)$$

Example:
For 1st camera pose all observed landmarks belong to subset $\mathcal{M}_1$



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BA Probabilistic Representation

Maximum a posteriori solution:

$$X^*, L^* = \arg\max_{X,L} p\left(X, L | \mathcal{Z}\right)$$

After omitting prior terms cost function to minimize is:

$$J_{BA}\left(X, L\right) = \sum_{i}^{N} \sum_{j \in \mathcal{M}_i} \left\| z_i^j - \pi\left(x_i, l_j\right) \right\|_{\Sigma_v}^2$$

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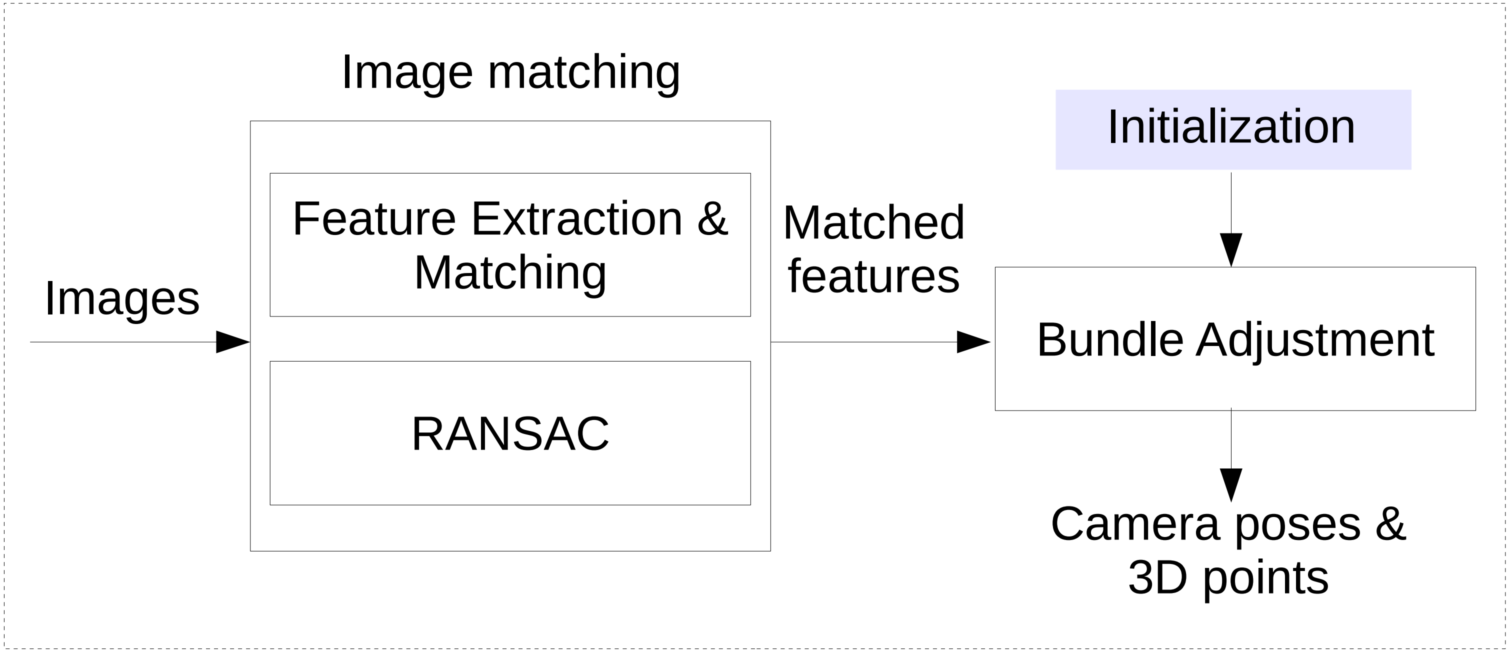
Variable initialization

Overall scheme of working framework

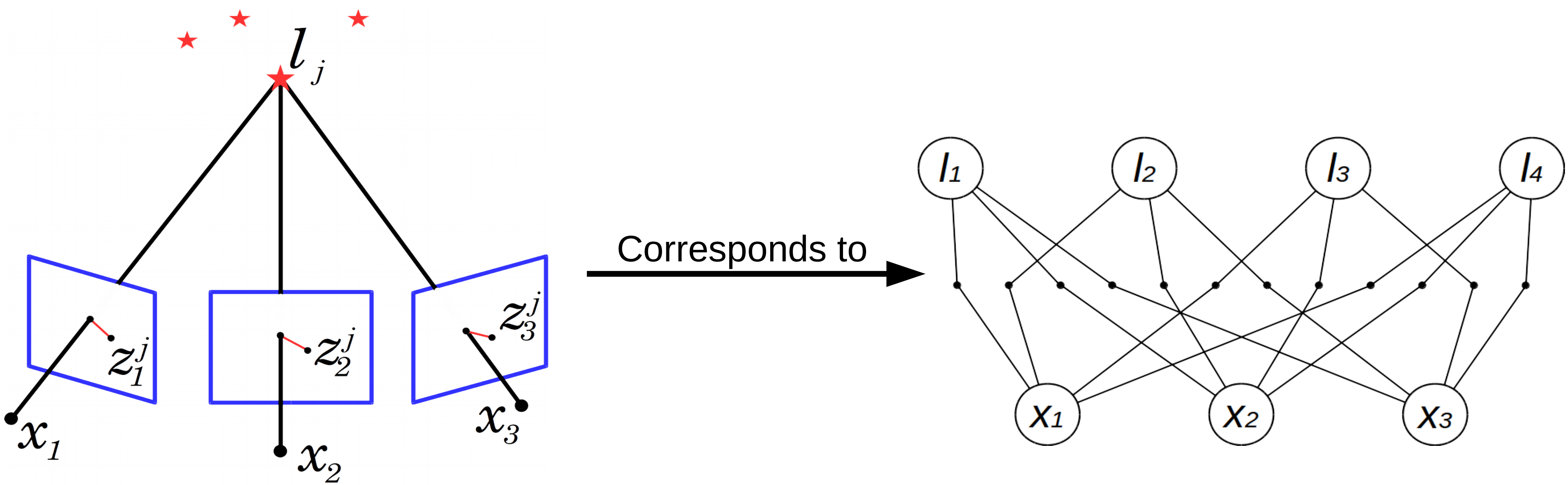


For optimization process we need to initialize the variables.

- Pose variables: via visual odometry
- Landmark variables: via triangulation

Factor Graph BA representation

<u>Example</u>: *all landmarks L are observed from all poses X.*



$$p\left(z_i^j | x_i, l_j\right) \propto \exp\left(-\frac{1}{2}\left\|z_i^j - \pi\left(x_i, l_j\right)\right\|_{\Sigma_v}^2\right) \doteq f_{proj}$$

Currently **only image feature coordinates** are involved.

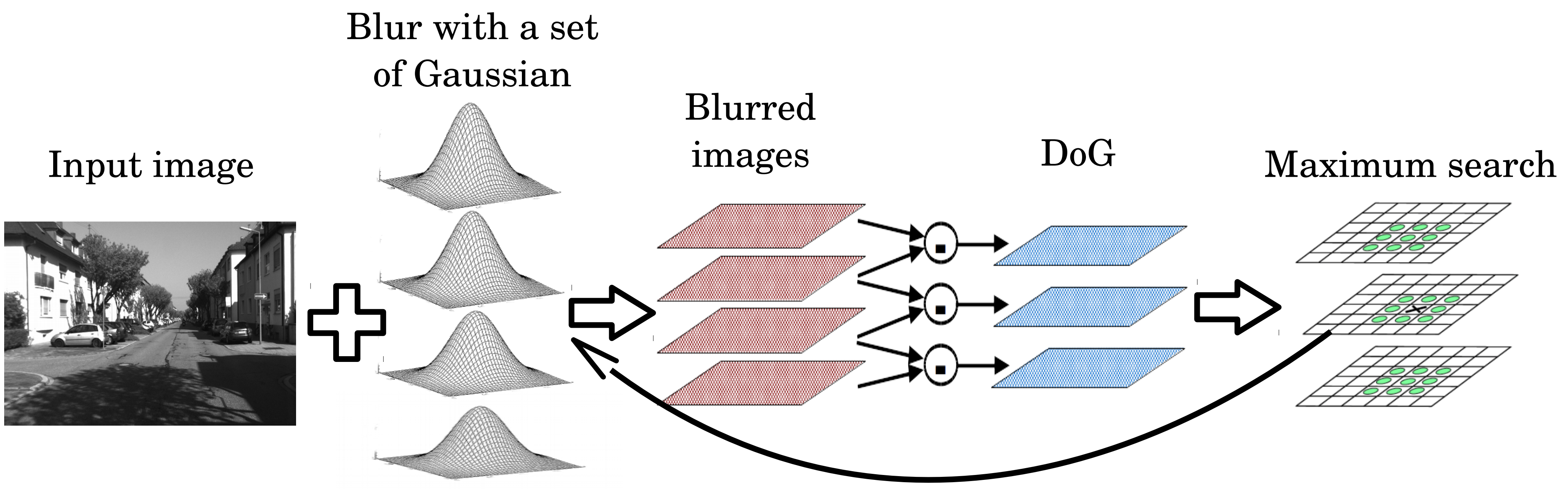
Outline

- Background:
  - Bundle Adjustment (BA)
  - **SIFT features**
- Our approach:
  - Adding new constraints to BA
  - Improving accuracy of detected feature scale
- Results
- Variations with our approach
- Conclusions

SIFT features

- Each feature is represented by image coordinates, scale and orientation.
- Only image feature coordinates are involved in BA optimization.

SIFT feature scale



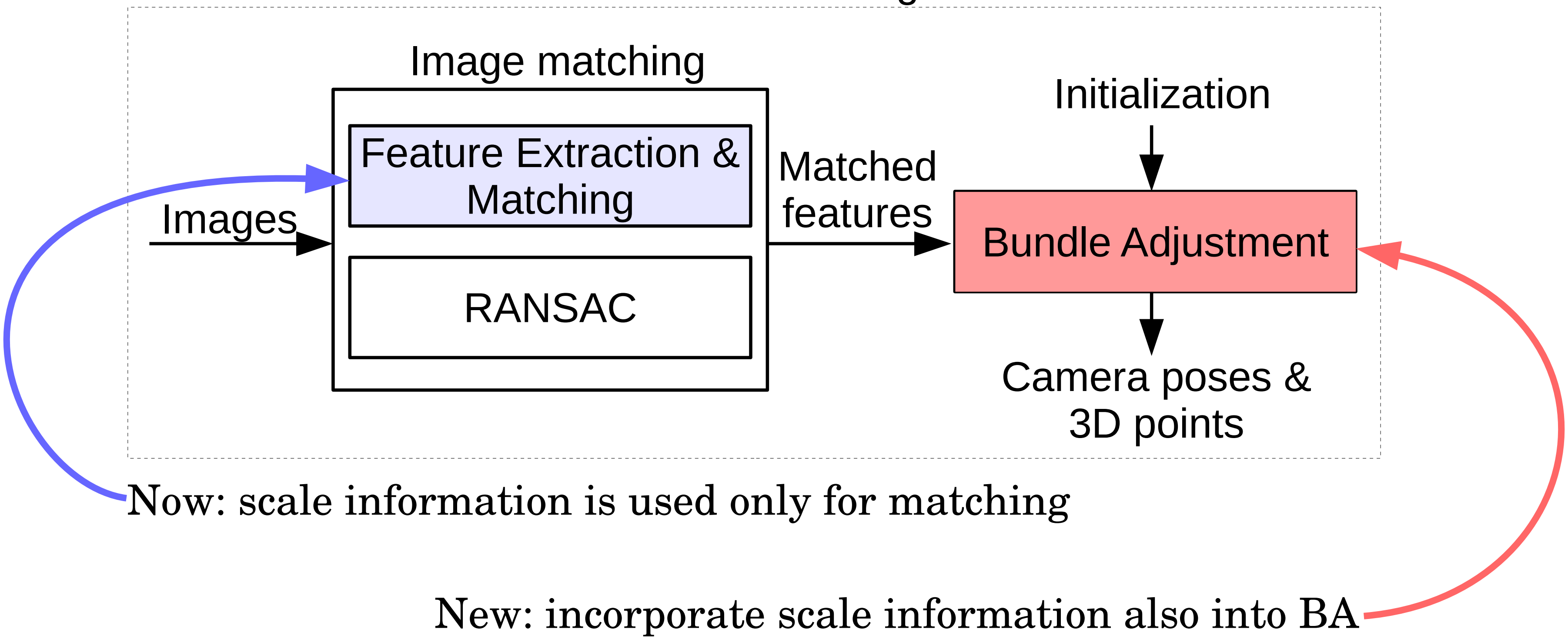
- Blur each input image with a set of Gaussian kernels with given covariance.
- Calculate Difference of Gaussians.
- Search for local maxima (features) among layers and pixels.
- Feature scale is equal to Gaussian kernel covariance corresponding to the layer where the local maxima is found.

Key observation

- Scale changes consistently across frames.
- Each feature scale is a function of environment and camera pose.
- We can use this property to predict landmark scale in the next frame!

“Big” picture

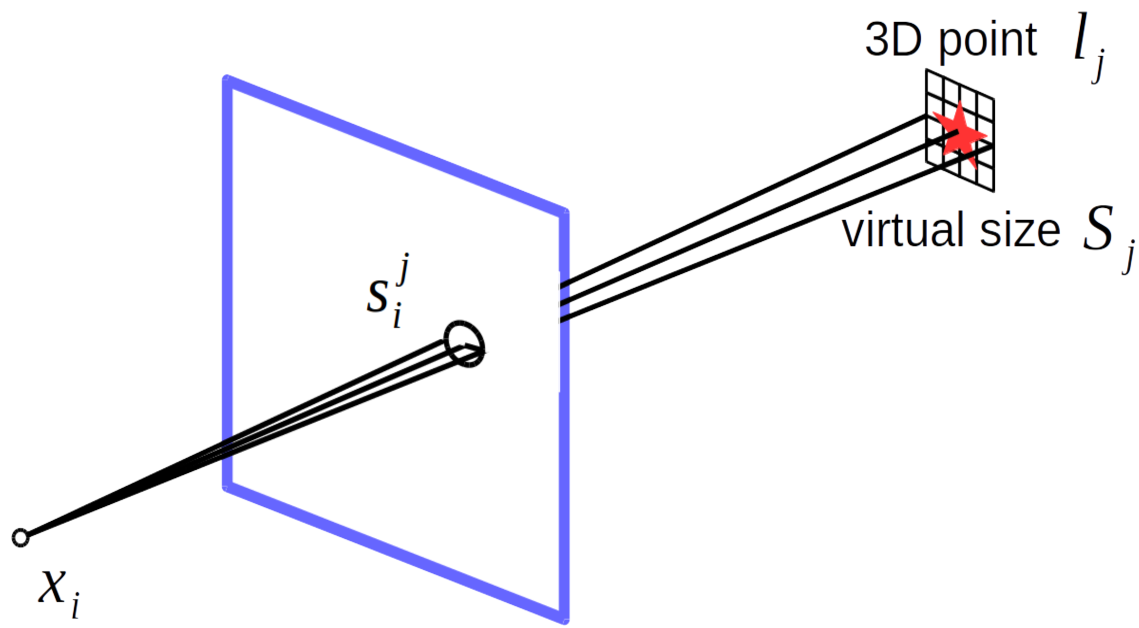
Overall scheme of working framework



Scale constraint

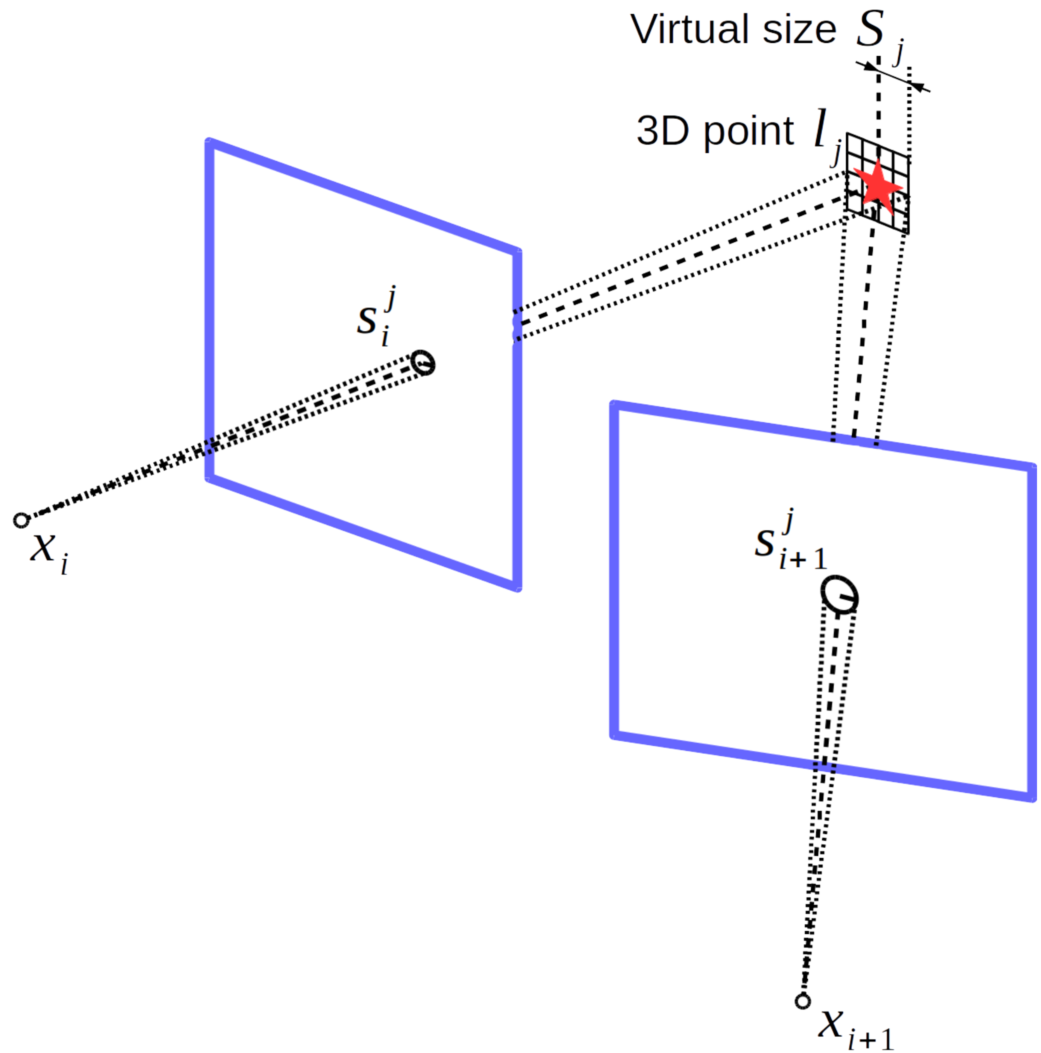
Consider an image feature in the i-th image that corresponds to a landmark with a 3D position l_j

- Denote the detected feature scale by s_i^j
- Denote by S_j the corresponding environment patch, or virtual landmark size, centered around landmark l_j



Scale constraint

SIFT is a <u>scale invariant</u> feature!

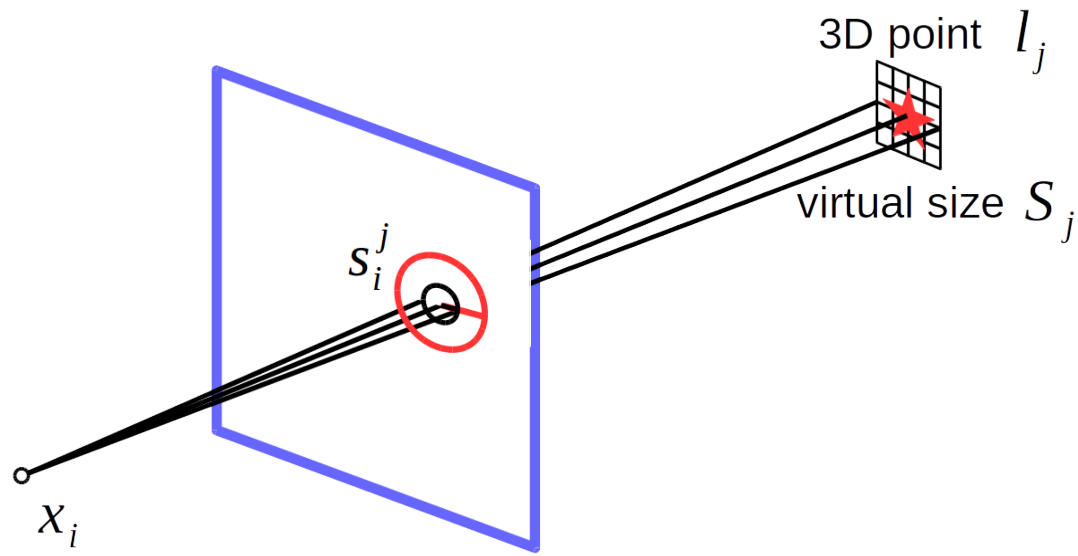


Scale constraint

Scale observation model:

$$s_i^j = f\frac{S_j}{d_i^j} + v_i$$

measured predicted



We model the noise is Gaussian

$$v_i \sim N\left(0, \Sigma_{fs}\right)$$

Scale constraint

<u>Intuition:</u>

Feature scale depends on the distance along optical axis (and not on range between camera and landmark).

Scale observation model:

$$s_i^j = f\frac{S_j}{d_i^j} + v_i \qquad\qquad v_i \sim N\left(0, \Sigma_{fs}\right)$$

Virtual landmark size:

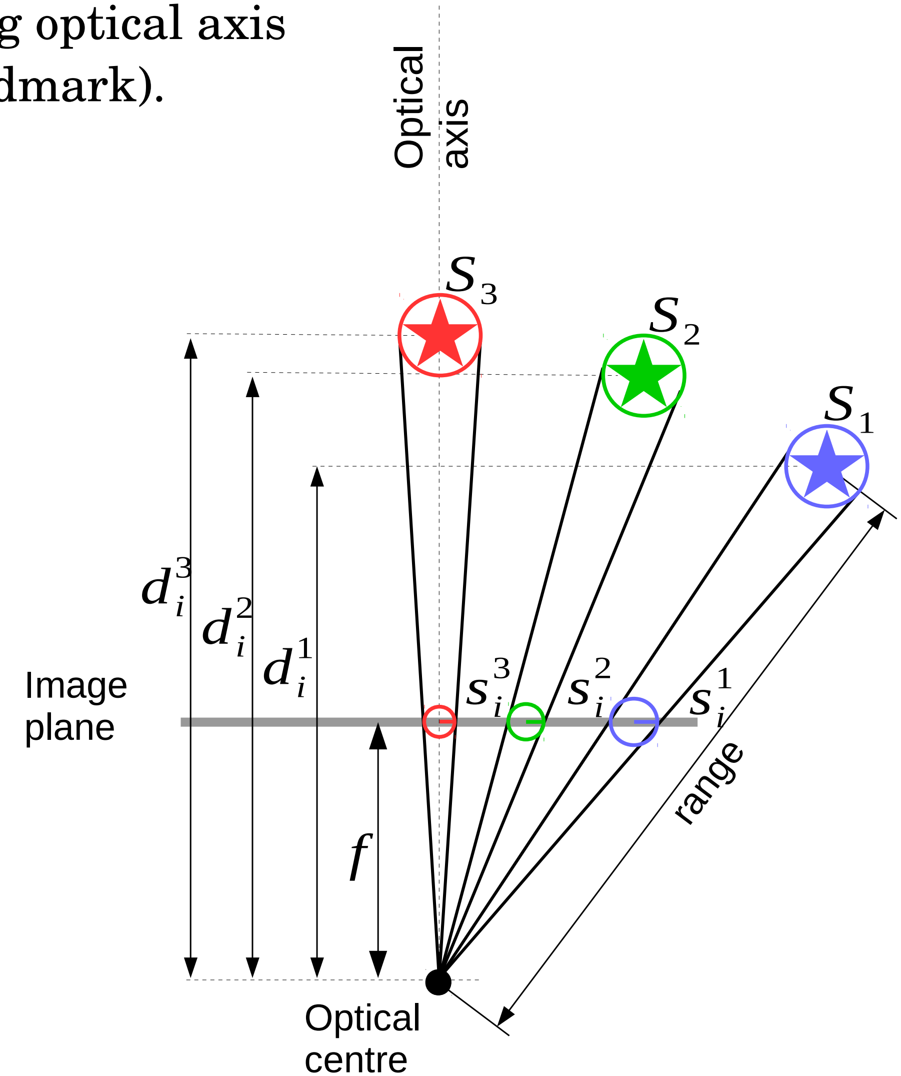
$$S_1 = S_2 = S_3$$

Feature scale:

$$s_i^1 > s_i^2 > s_i^3$$

Distance along optical axis:

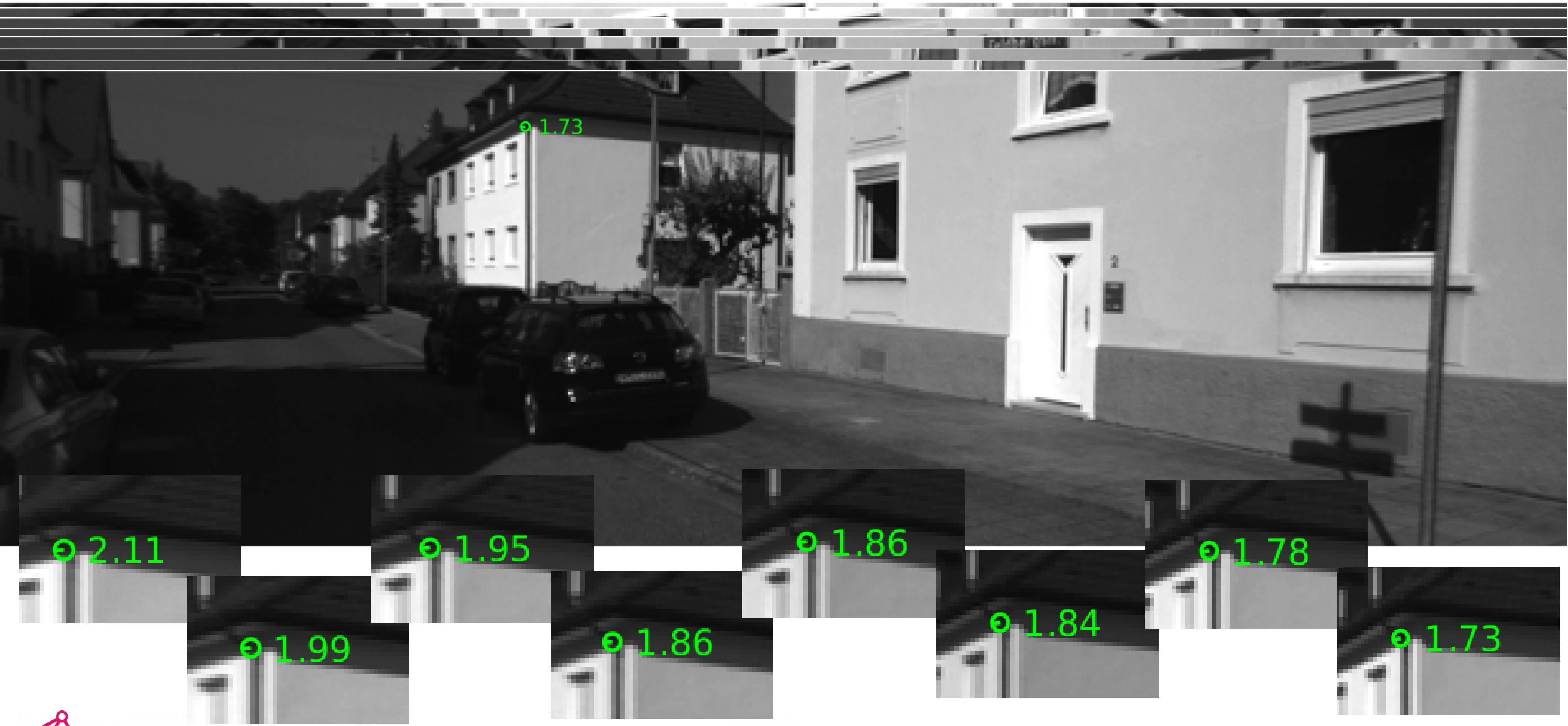
$$d_i^1 < d_i^2 < d_i^3$$



Scale constraint

Intuition:

Feature scale is changing correspondingly to distance along optical axis from camera pose to represented environment patch.



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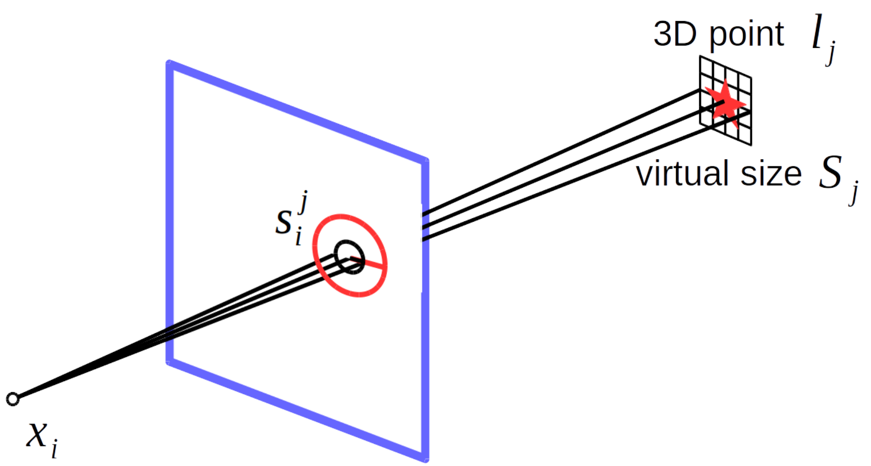
Scale constraints



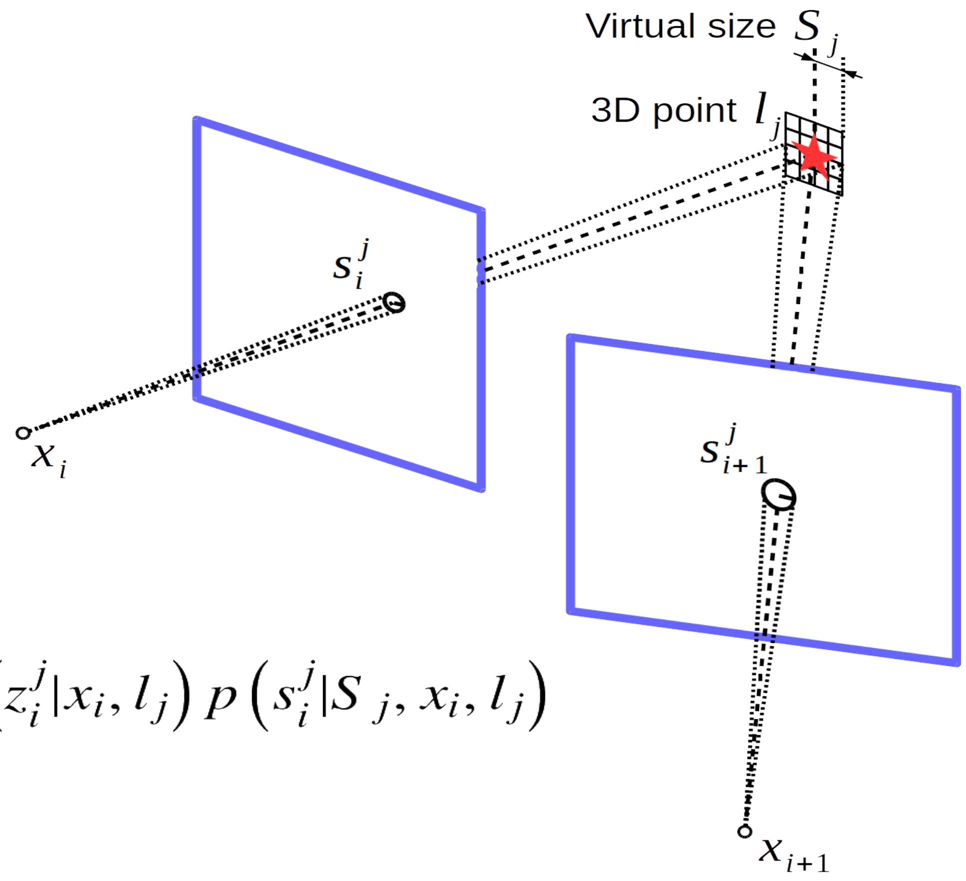
Scale observation model:

$$s_i^j = f\frac{S_j}{d_i^j} + v_i$$

Scale Measurement likelihood:

$$p\left(s_i^j | S_j, x_i, l_j\right) \propto \exp\left[-\frac{1}{2}\left\|s_i^j - f\frac{S_j}{d_i^j}\right\|^2_{\Sigma_{fs}}\right]$$

Scale constraints



New variable: S

New Objective joint posterior distribution:

$$p\left(X, L, S \mid \mathcal{Z}\right)$$

Joint posterior distribution

$$p\left(X, L, S \mid \mathcal{Z}\right) = priors \cdot \prod_{i}^{N} \prod_{j \in \mathcal{M}_i} p\left(z_i^j \mid x_i, l_j\right) p\left(s_i^j \mid S_j, x_i, l_j\right)$$

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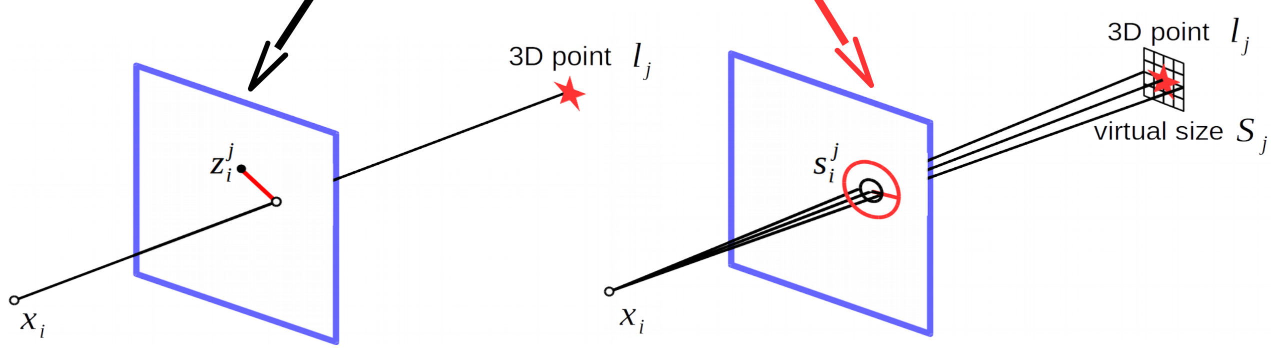
Joint cost function

Standard cost-function used in BA

$$J_{BA}(X,L) = \sum_{i}^{N} \sum_{j \in \mathcal{M}_i} \left\| z_i^j - \pi\left(x_i, l_j\right) \right\|_{\Sigma_v}^2$$

Cost-function used in BA with scale constraints

$$J(X,L,S) = \sum_{i}^{N} \sum_{j \in \mathcal{M}_i} \underbrace{\left\| z_i^j - \pi\left(x_i, l_j\right) \right\|_{\Sigma_v}^2}_{\text{re-projection error}} + \underbrace{\left\| s_i^j - f\frac{S_j}{d_i^j} \right\|_{\Sigma_{fs}}^2}_{\text{scale error}}$$



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Variable initialization

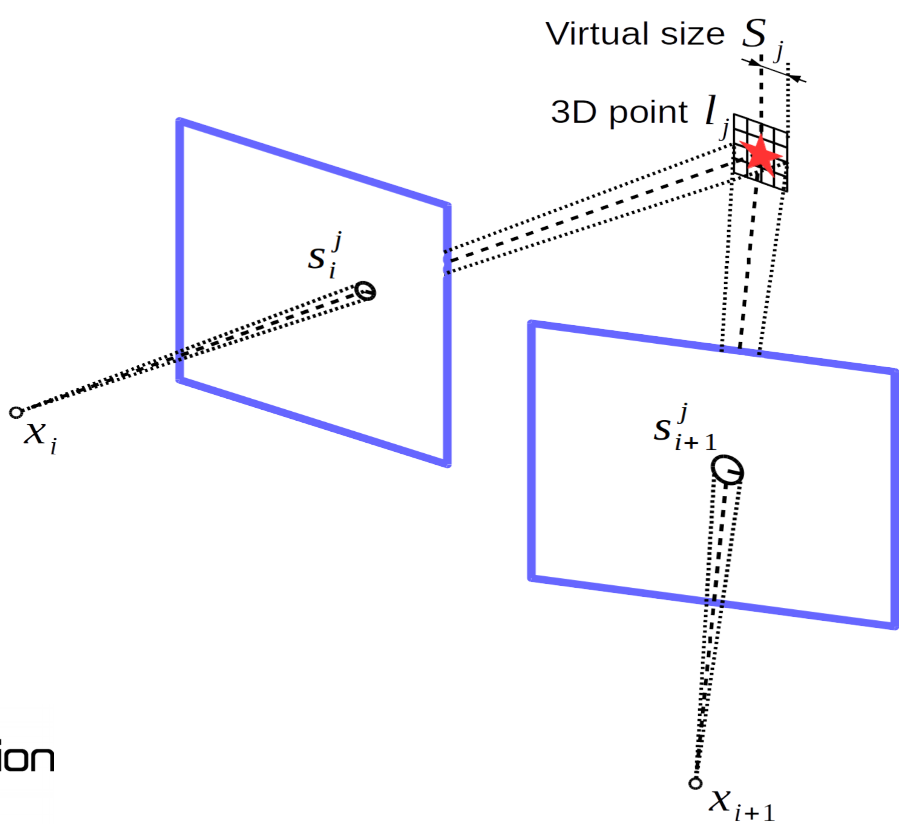
Reminder:

- Consider an image feature in the i-th image that corresponds to a landmark with a 3D position l_j
- Denote the detected feature scale by s_i^j
- Denote by S_j the corresponding environment patch, or virtual landmark size, centered around landmark l_j

Virtual landmark size initialization:

→ Landmark triangulation
→ Distance to landmark is known
→ Initialize landmark size

$$S_j = s_i^j \frac{d_i^j}{f}$$



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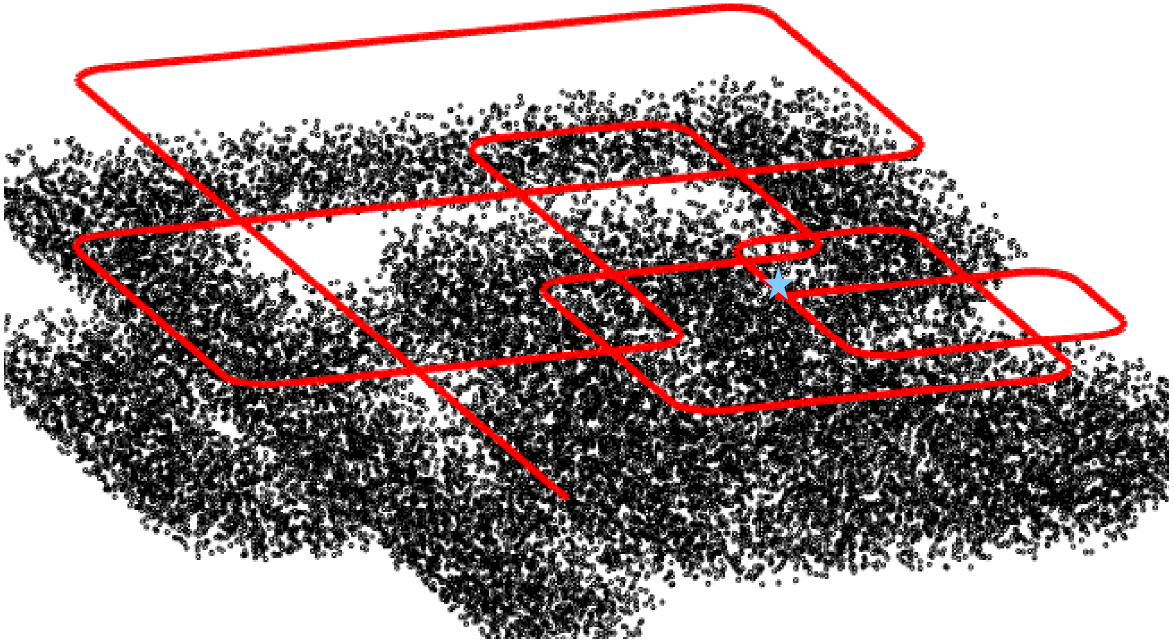
Simulation

Scenario:

- Downward-facing camera
- Constant height
- Landmarks scattered in 3D-space



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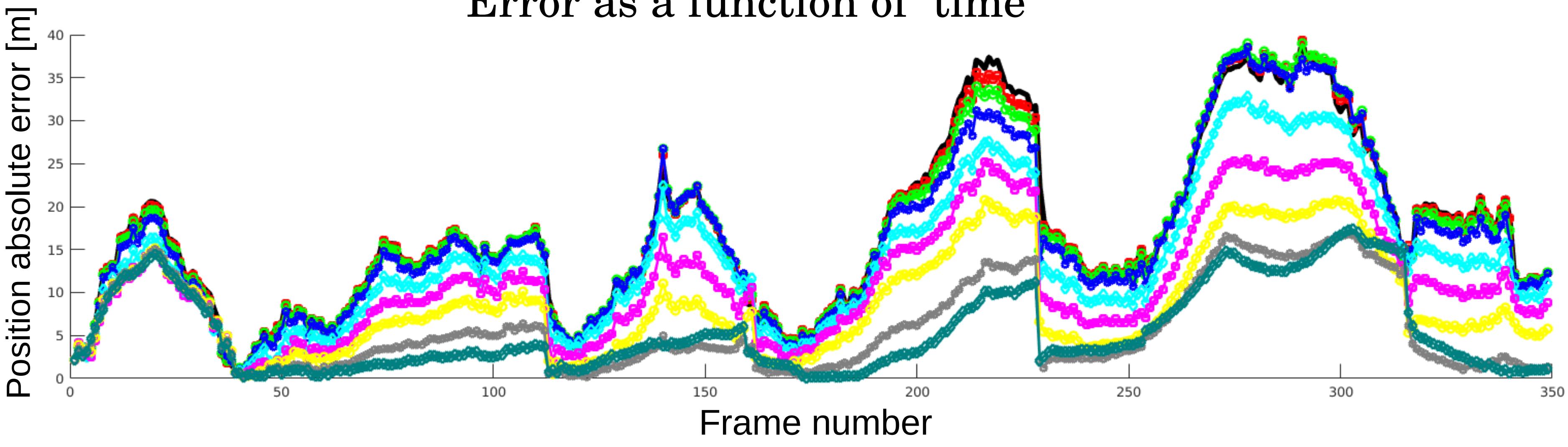
Simulation

Cost-function using projection and scale constraints

$$J\left(X,L,S\right)=\sum_{i}^{N}\sum_{j\in\mathcal{M}_i}\left\|z_i^j-\pi\left(x_i,l_j\right)\right\|_{\Sigma_v}^2+\left\|s_i^j-f\frac{S_j}{d_i^j}\right\|_{\Sigma_{fs}}^2$$

Represents noise in scale measurements

Error as a function of time



Each coloured curve corresponds to simulation with a fixed Σ_{fs}

Outline

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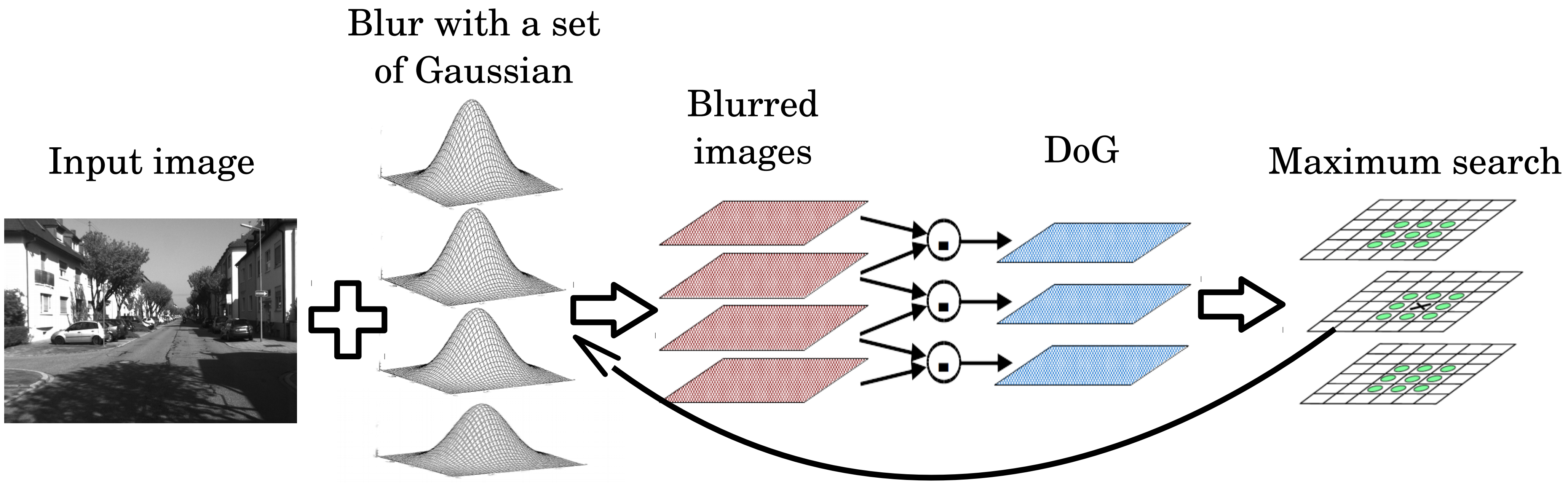
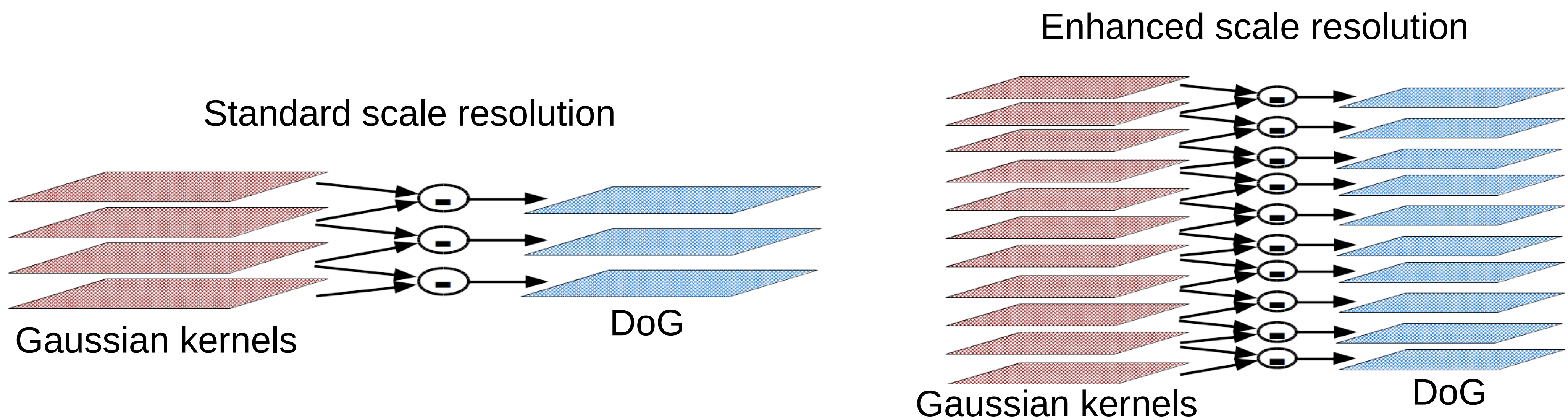
Reminder: SIFT feature scale



- Blur each input image with a set of Gaussian kernels with given covariance.
- Calculate Difference of Gaussians.
- Search for local maxima (features) among layers and pixels.
- Feature scale is equal to Gaussian kernel covariance corresponding the layer where the local maxima is found.

SIFT scale: increasing resolution

- Estimation accuracy is improved only if feature scale measurements are sufficiently accurate.
- Key observation:
  - Can get higher-accuracy scale measurements by increasing number of layers per octave
  - Noise of enhanced-resolution scale measurements can be statistically described with lower Σ_{fs}

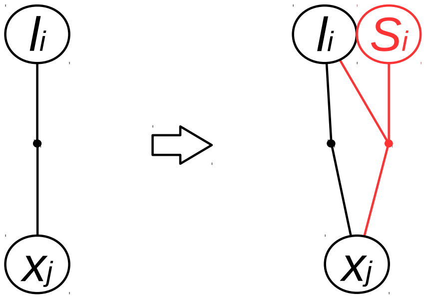


Factor graph modifications

BA + scale constraints cost-function:

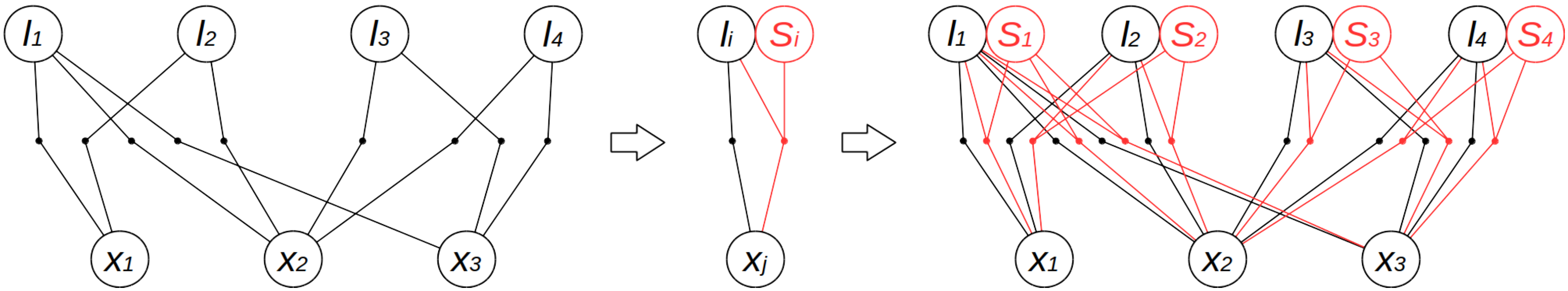
$$J(X, L, S) = \sum_{i}^{N} \sum_{j \in \mathcal{M}_i} \left\| z_i^j - \pi\left(x_i, l_j\right) \right\|_{\Sigma_v}^2 + \left\| s_i^j - f \frac{S_j}{d_i^j} \right\|_{\Sigma_{fs}}^2$$

re-projection error — scale error



Influence on optimization time

Naive implementation taking all scale constraints:



- Number of edges (variables) increased significantly
- Number of links (constraints) increased significantly

→ Optimization time increased.

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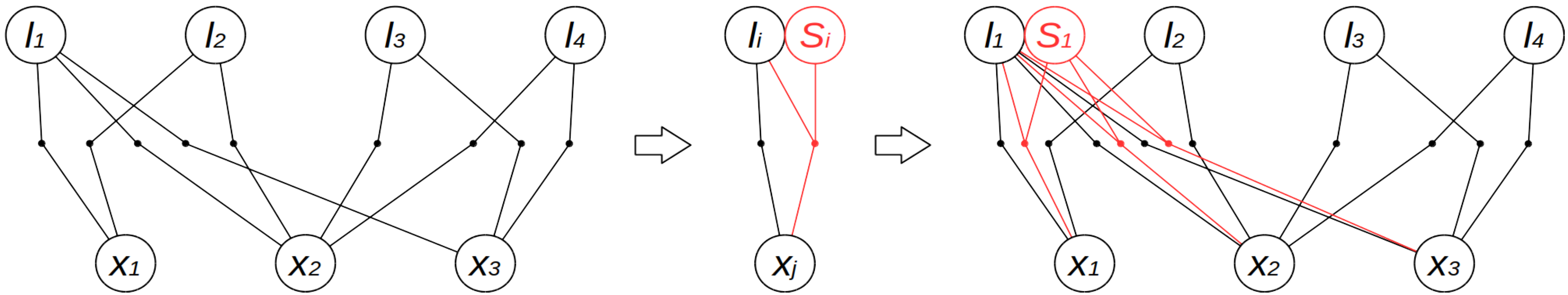
Influence on optimization time

Heuristic: add scale constraints only for long-track features.



- Number of edges (variables) increased slightly (about 10%)

  → we keep number of optimization variables as small as possible

- Number of links (constraints) increased.

  → Optimization time increased, but much less!

Results

We tested our approach with the following datasets:

- Aerial dataset (Kagaru): a single downward-facing, flat ground surface scenario.
  - SIFT based scale approach
- Ground vehicle dataset (KITTI): single forward-looking camera, urban scenario.
  - Full set of feature scales
  - Using only scales corresponding to “long” features

KITTI dataset

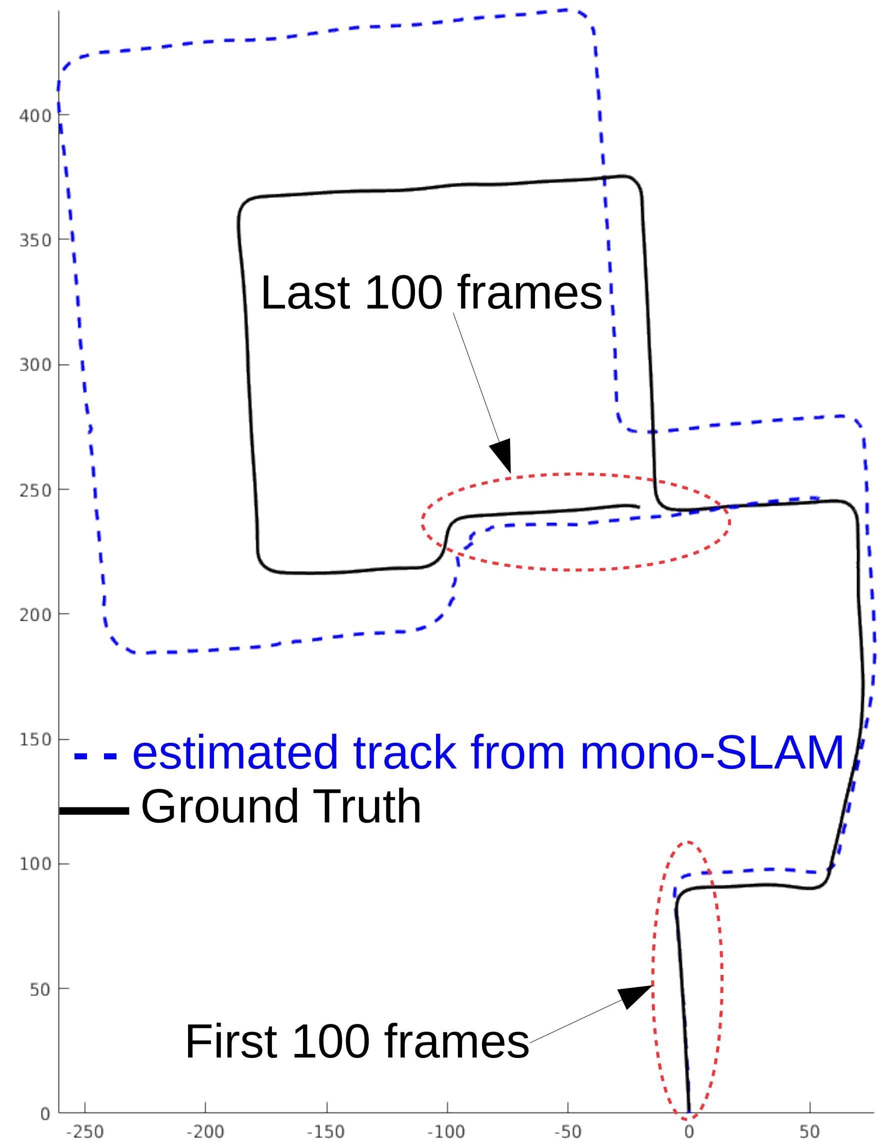
Accurate ground truth is provided by a Velodyne laser scanner and a GPS localization system.
Dataset videos are captured by driving around a city.

+ Ground truth synchronized with camera frame rate
+ Images at 10 fps
+ Camera calibration

Typical images from dataset

Monocular SLAM scale drift problem

Known problem is **scale drift along optical axis** with time.



<u>Example:</u>

Error rate along optical axis is growing with time

For the <u>first</u> 100 frames:
<u>Error rate: 8.6%</u>

For the <u>last</u> 100 frames:
<u>Error rate: 94.6%</u>

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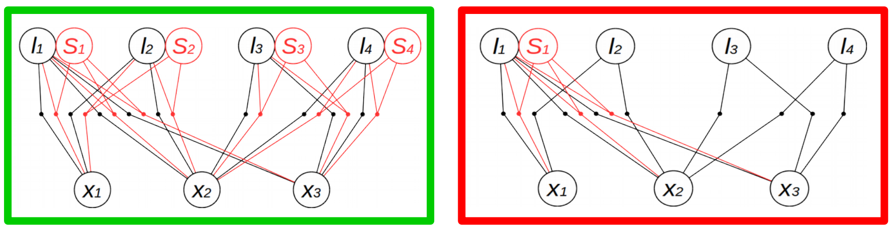
KITTI dataset

Difference between red and green track: amount of scale constraints.



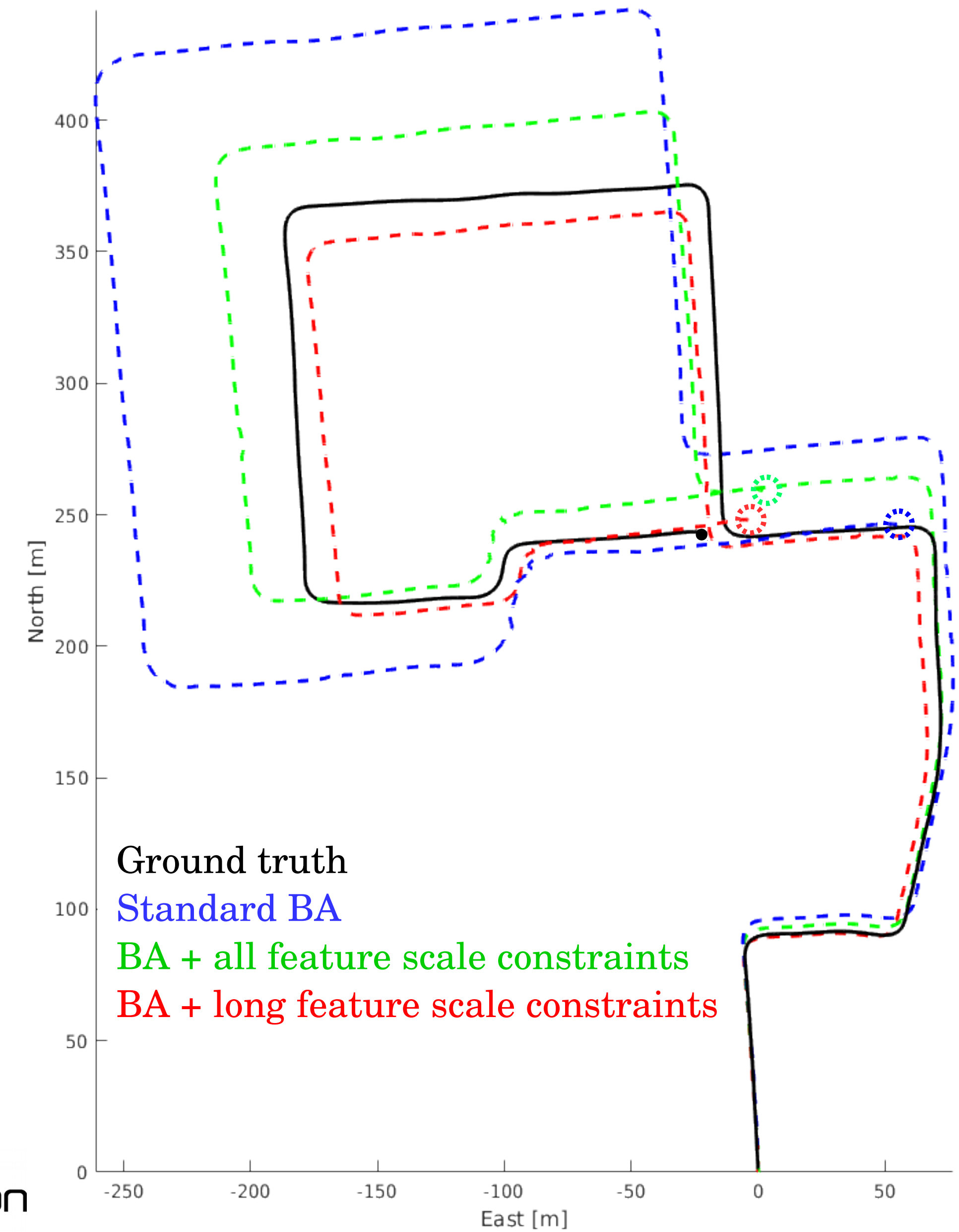
Error rate along optical axis

For the <u>first</u> 100 frames:

Error rate: 8.6% 5% 1%

For the <u>last</u> 100 frames:

Error rate: 94.6% 27.3% 8.8%



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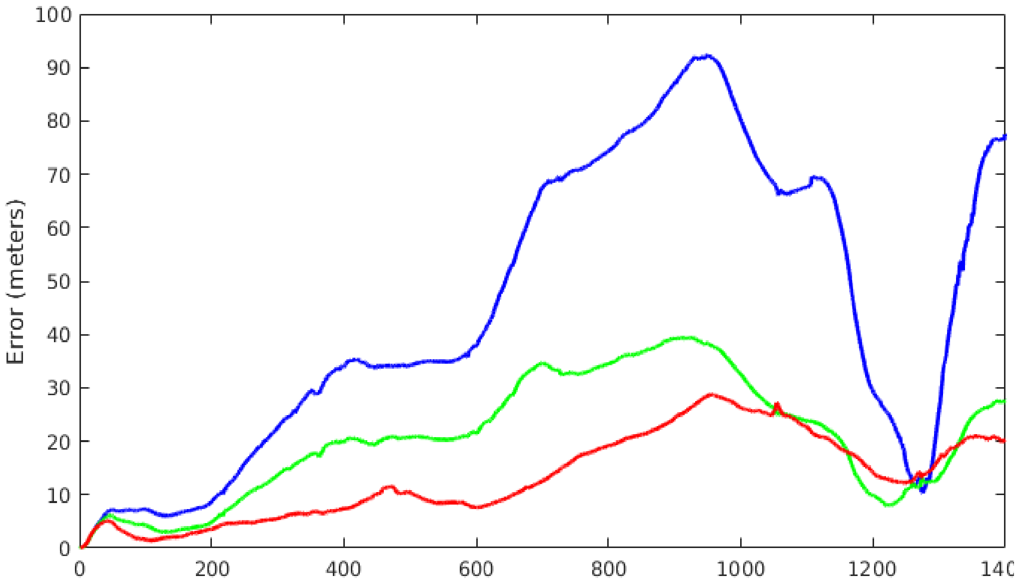
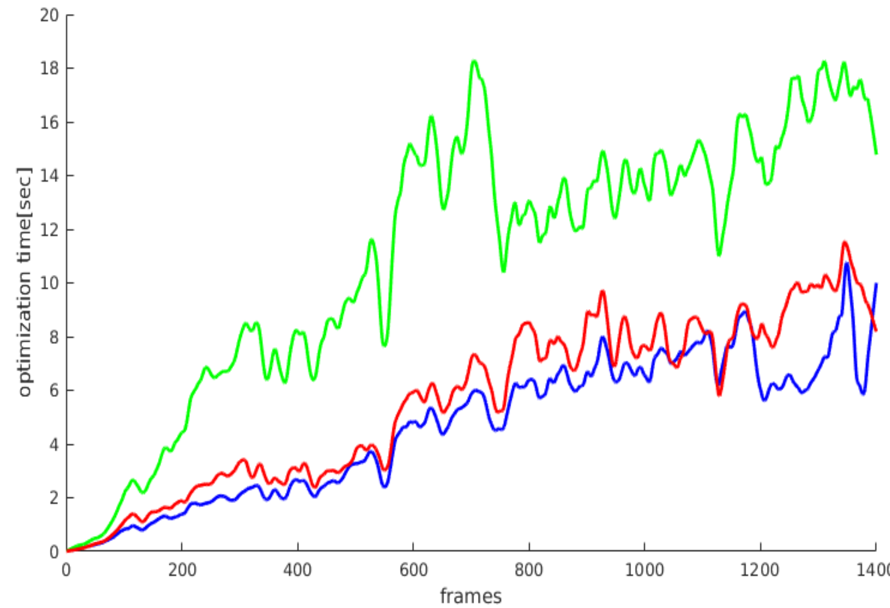
KITTI dataset

Position error



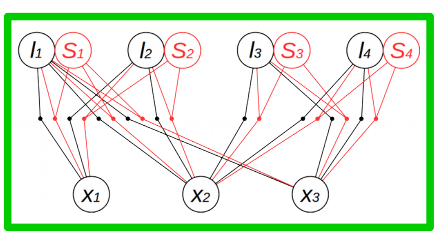
Optimization time

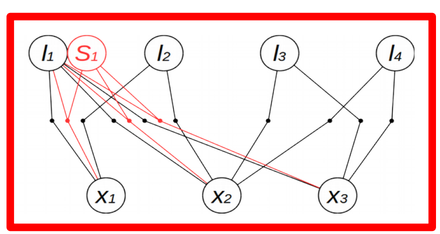


standard BA

standard BA + all feature scale constraints

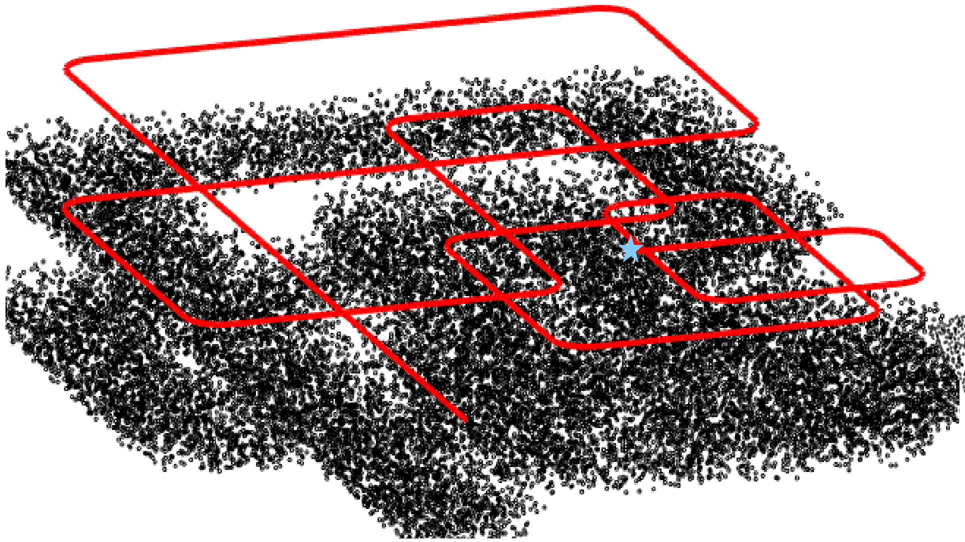
standard BA + long-term feature scale constraints



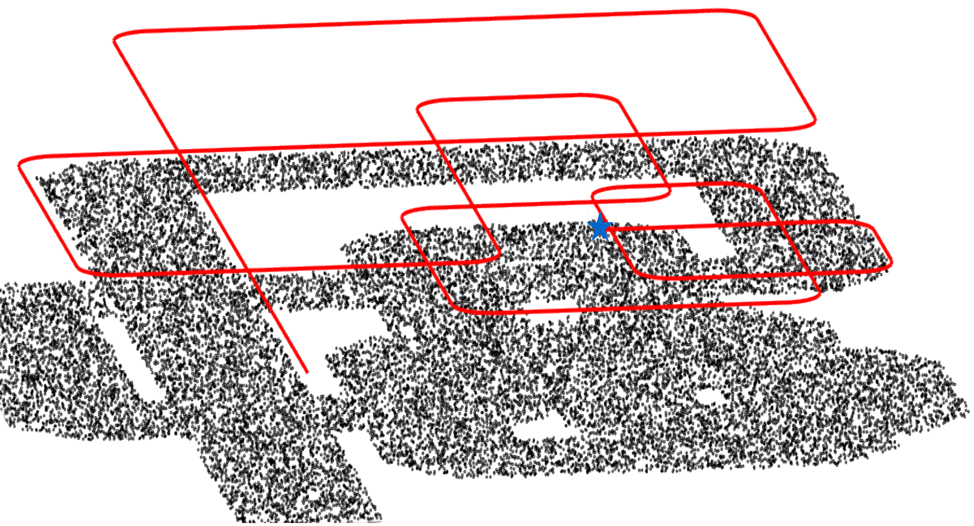


Aerial simulation

Simulation scenario with landmarks spread over height



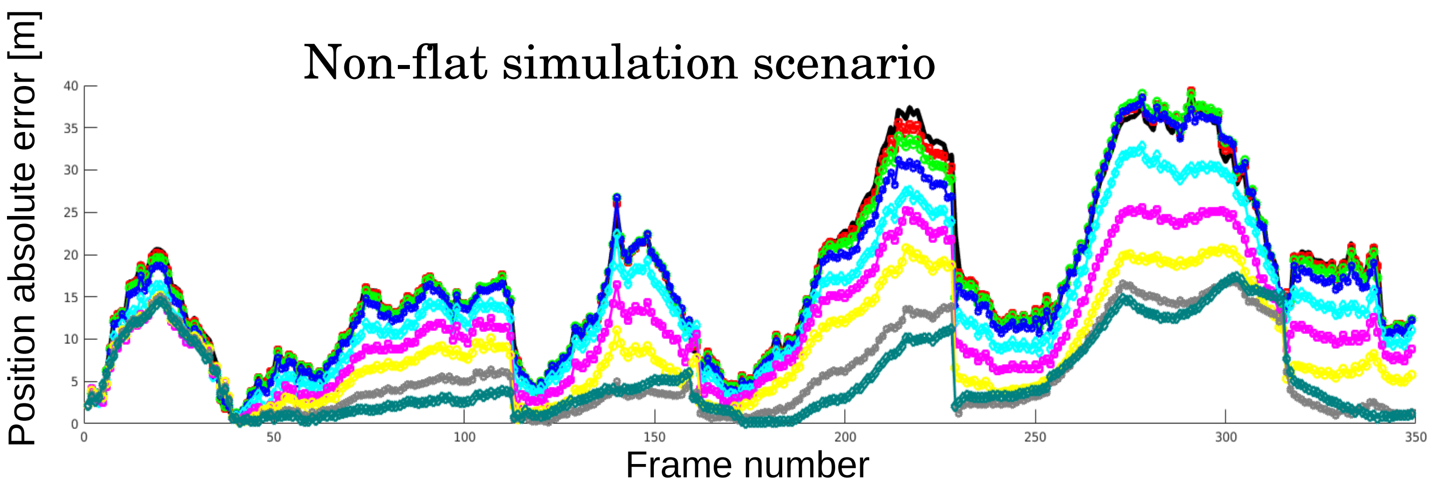
Flat simulation scenario

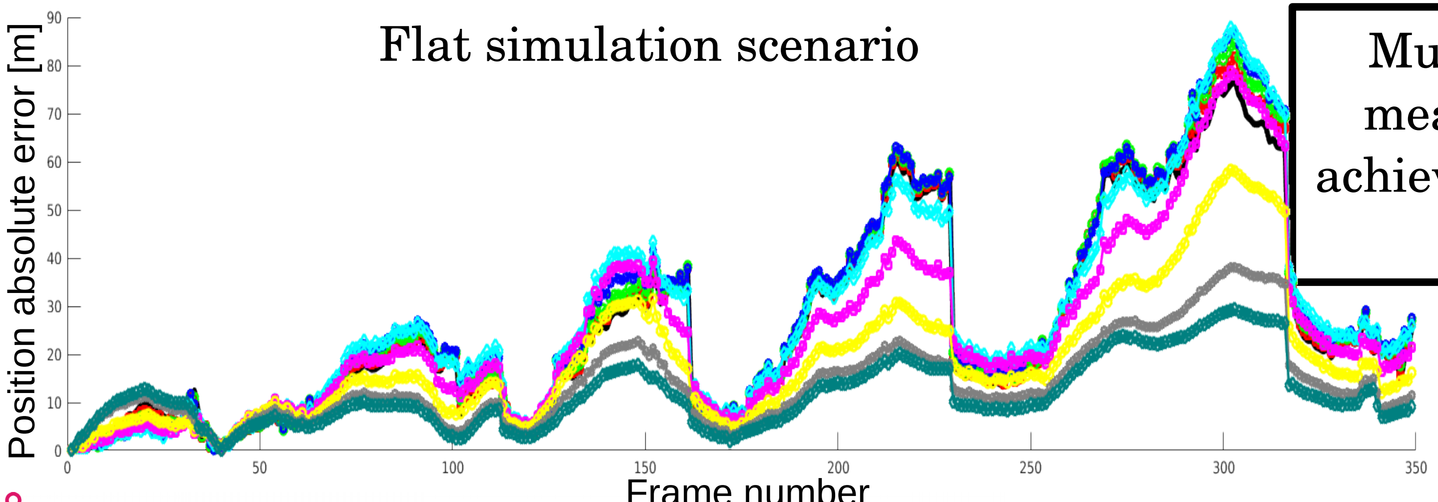


Aerial simulation

Error as a function of Σ_{fs} values.

Each coloured curve corresponds to simulation with a fixed Σ_{fs}





Much more accurate scale measurements required to achieve accuracy improvement for flat scenario.

Kagaru dataset

- Ground truth from an XSens Mti-g INS/GPS
- Downward facing camera
- The dataset traverses over farmland and includes views of grass, an air-strip, roads, trees, ponds, parked aircraft and buildings

+ Ground truth synchronized with camera frame rate
+ Images at 1 fps
+ Camera calibration

Plane used for dataset creation

Typical images from the dataset

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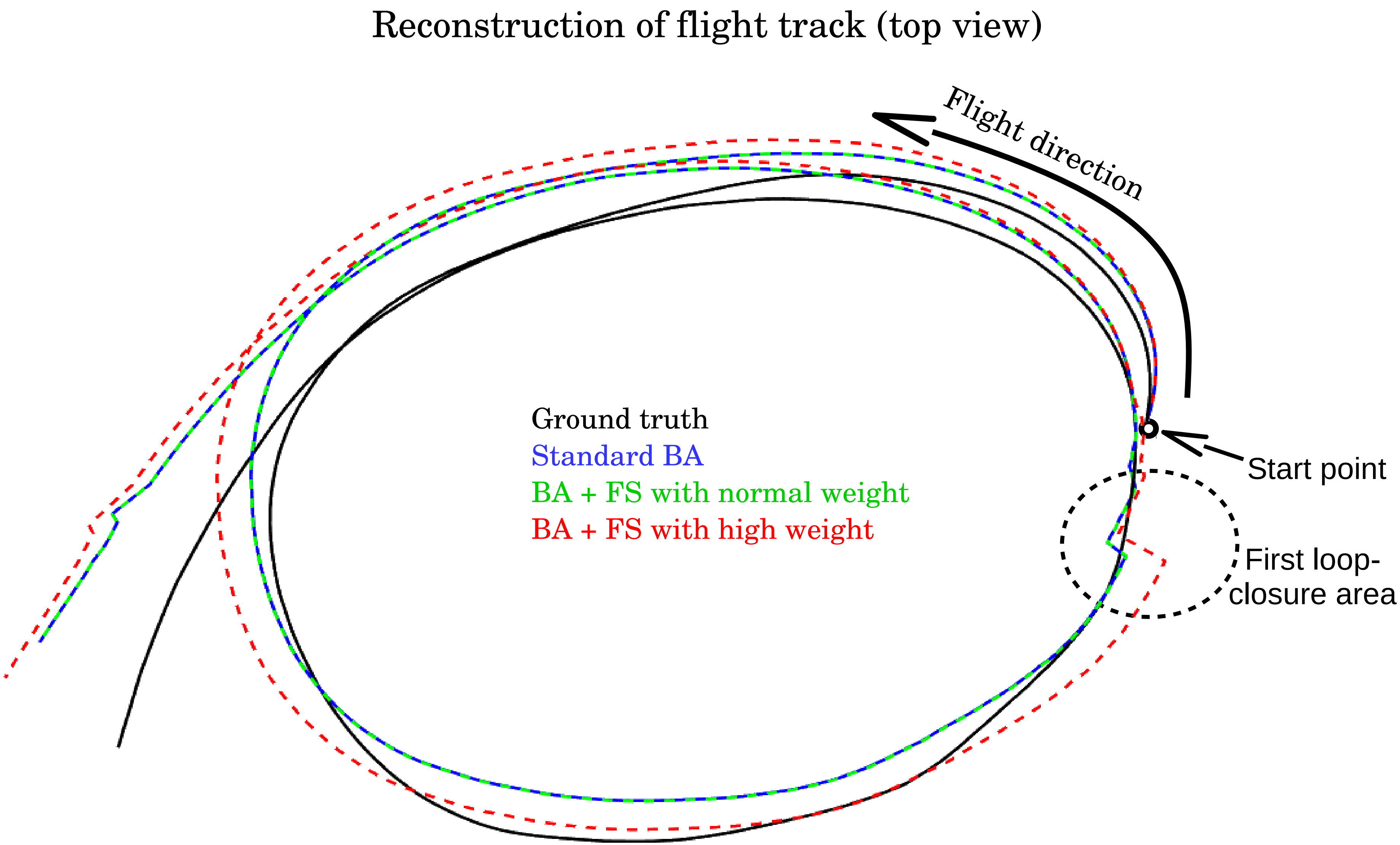
Kagaru dataset



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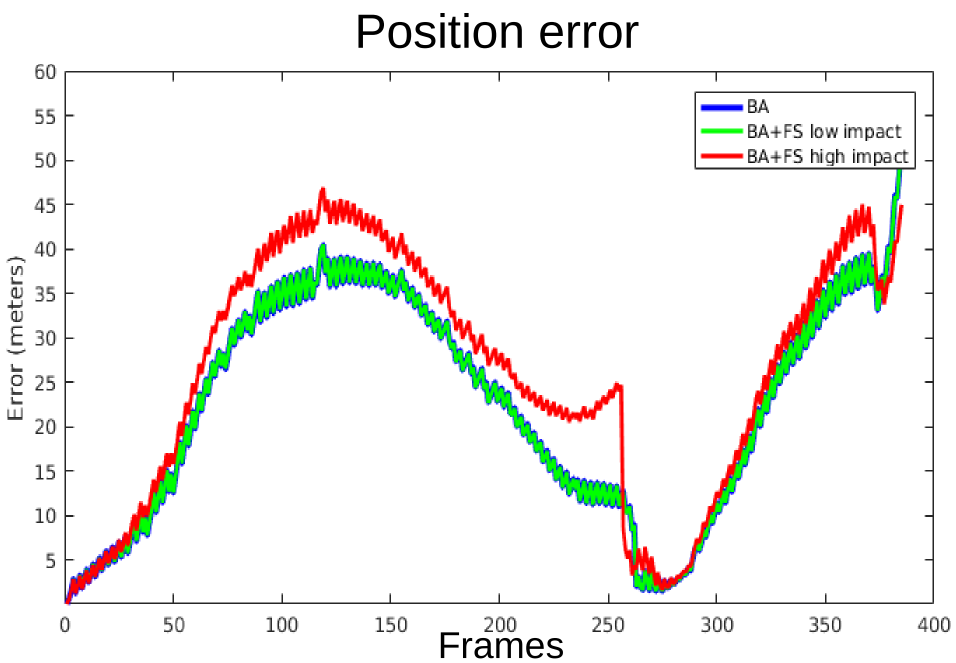
Kagaru dataset

→ No accuracy improvement along optical axis
→ No position accuracy improvement



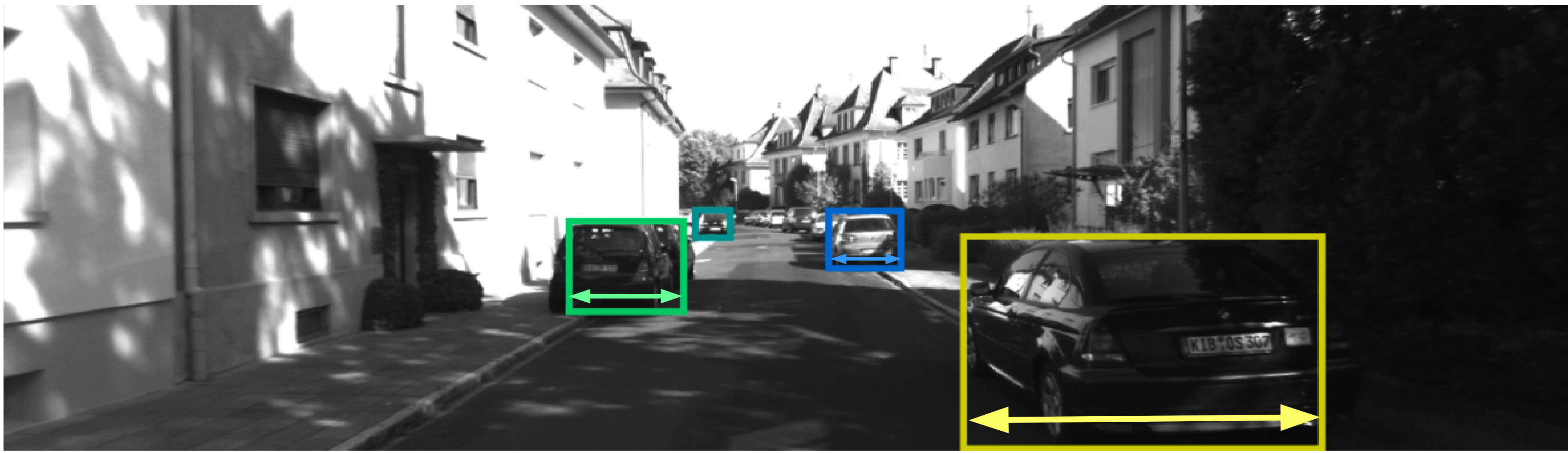
Cost-function: $$J(X,L,S) = \sum_{i}^{N} \sum_{j \in \mathcal{M}_i} \left\| z_i^j - \pi\left(x_i, l_j\right) \right\|_{\Sigma_v}^2 + \left\| s_i^j - f \frac{S_j}{d_i^j} \right\|_{\Sigma_{fs}}^2$$

Outline

- Background:
  - Bundle Adjustment (BA)
  - SIFT features
- Our approach:
  - Adding new constraints to BA
  - Improving accuracy of detected feature scale
- Results
- **Variations with our approach**
- Conclusions

Object scale

- Detect objects
- Track objects across the frames
- Use bounding boxes width as scale to create scale constraints.

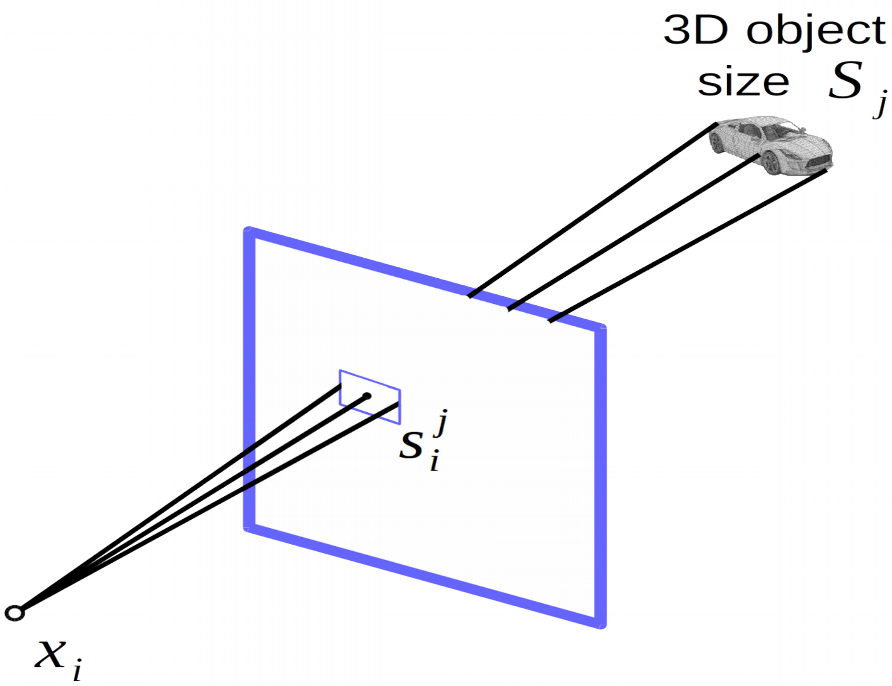


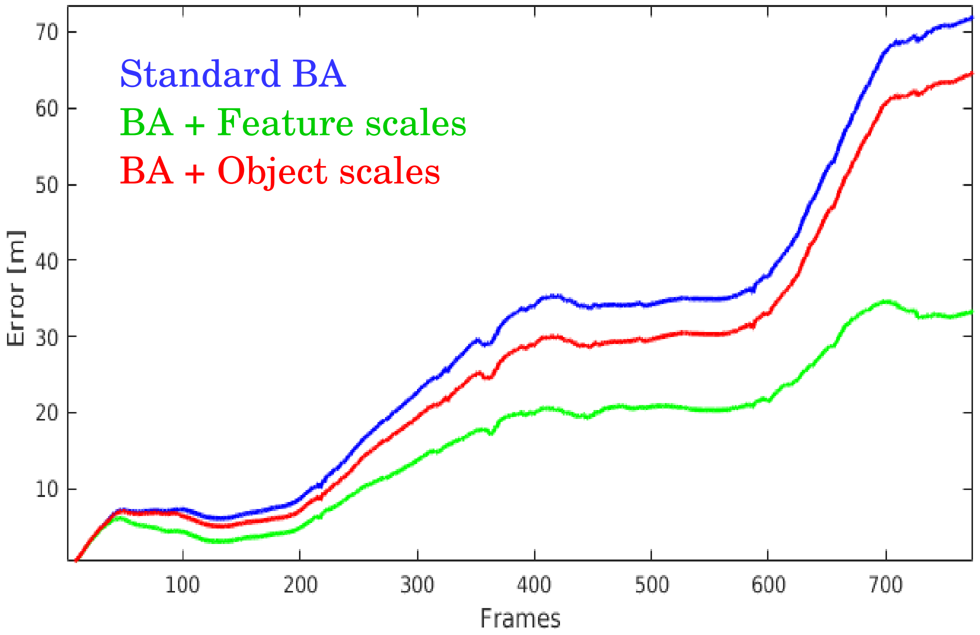
- ➢ Feature scale → object bounding box size (width or height)
- ➢ Virtual landmark size → object size
- ➢ Landmark position → object centre position

Object scale

Main idea:

Objects bounding boxes width/height instead feature scale.





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Conclusions

Improved accuracy of bundle adjustment and monocular SLAM along optical axis direction:

- Developed and introduced scale constraints within BA
- Feature scale information is already available from feature detector
- Enhanced feature scale measurement by increasing scale resolution in SIFT
- Application of feature scale constraints to object-level BA

Thank you for your attention!

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