

Experimental Analysis of Dynamic Covariance Scaling for Robust Map Optimization Under Bad Initial Estimates

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Gian Diego Tipaldi¹, Luciano
Spinello¹, Wolfram Burgard¹ and
Cyrill Stachniss^{1,2}**



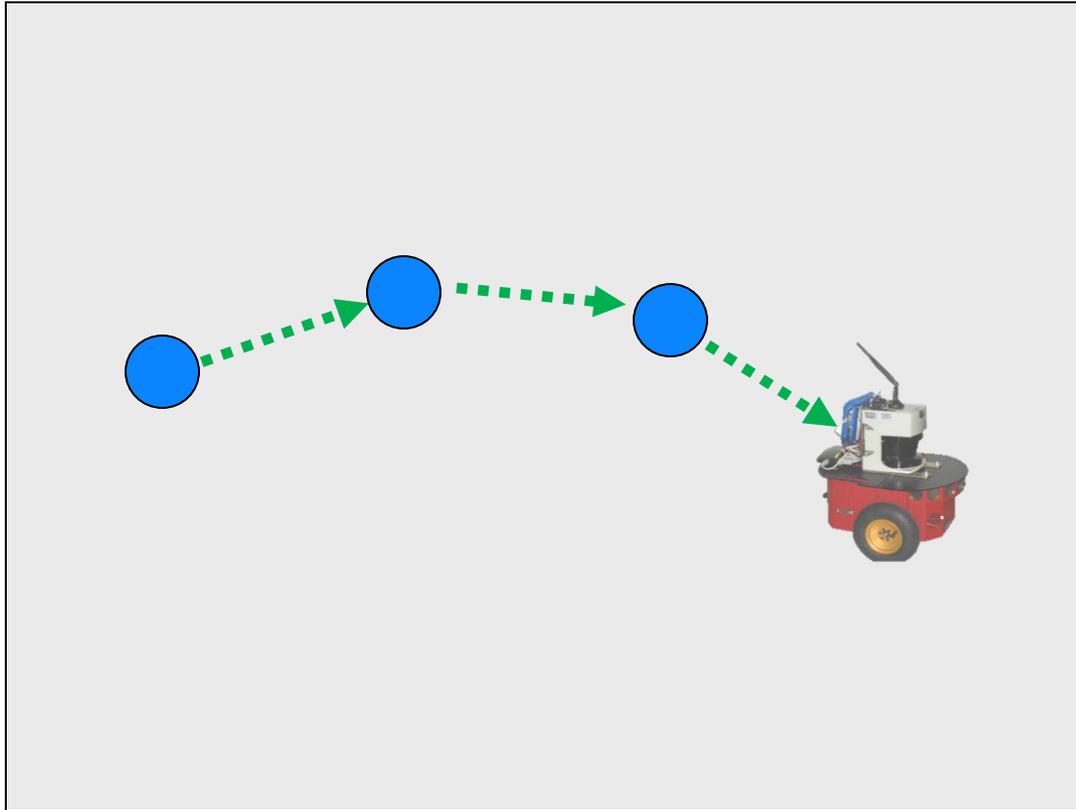
¹University of Freiburg, Germany

² University of Bonn, Germany

³ La Sapienza University of Rome, Italy



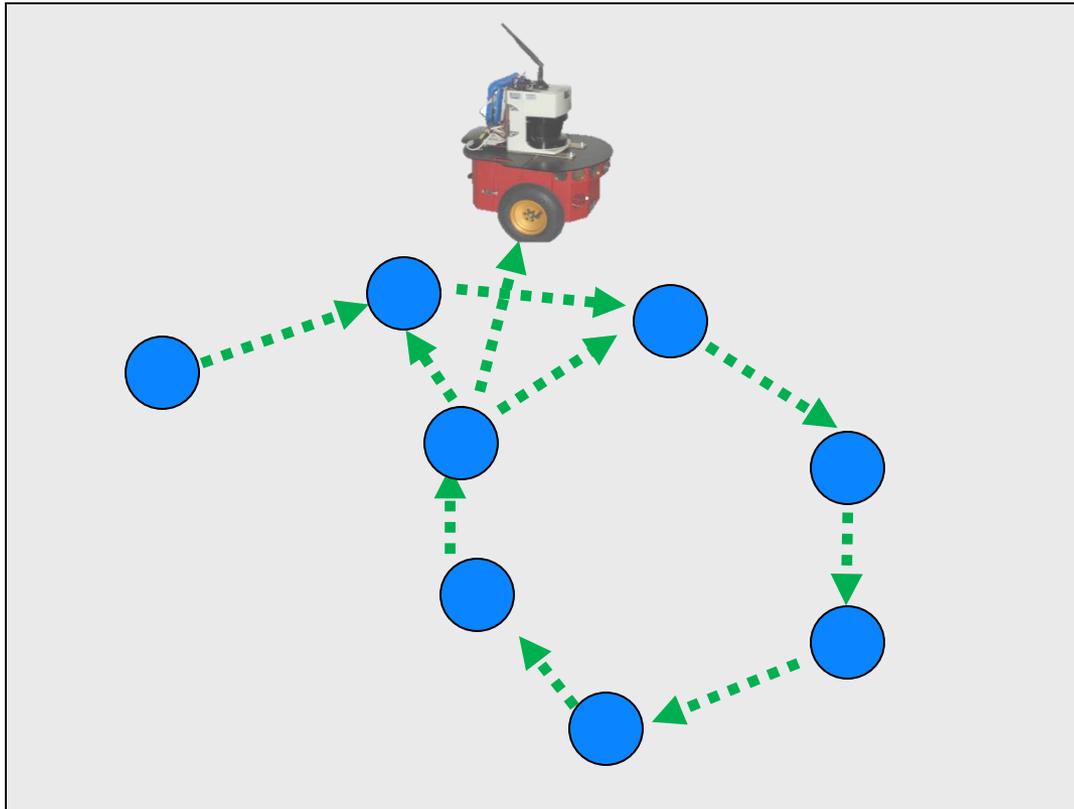
Graph-Based SLAM



● Robot pose

→ Constraint

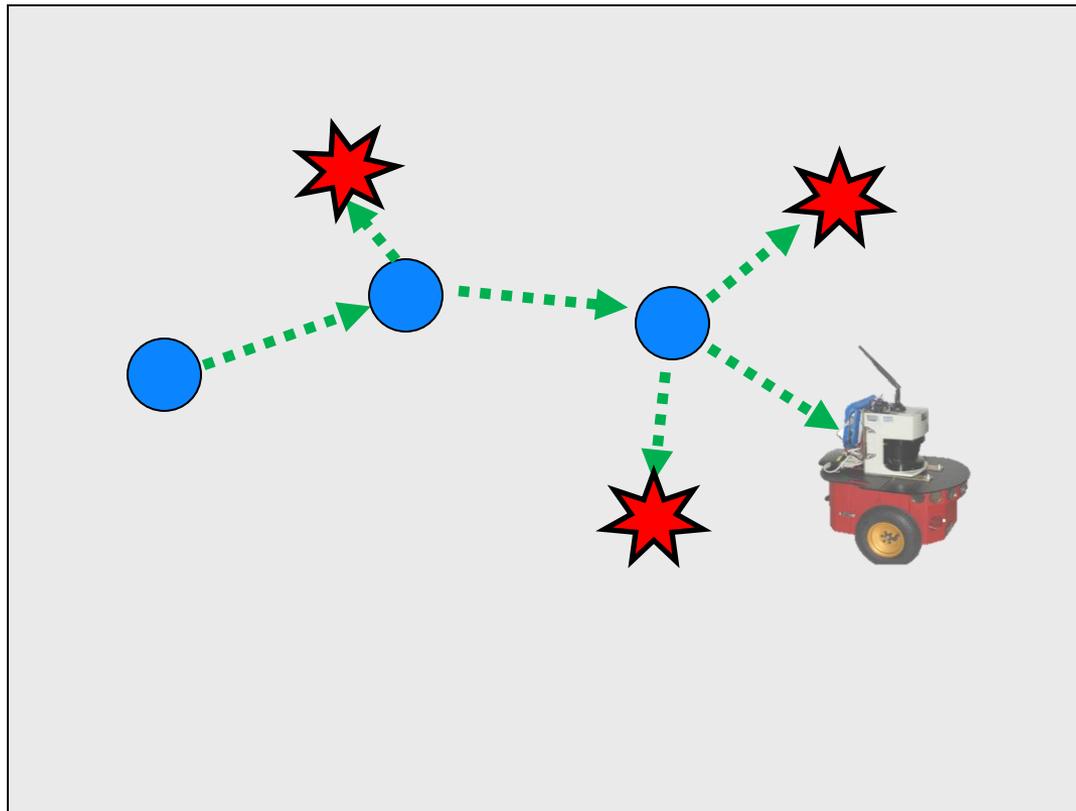
Graph-Based SLAM



● Robot pose

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Graph-Based SLAM

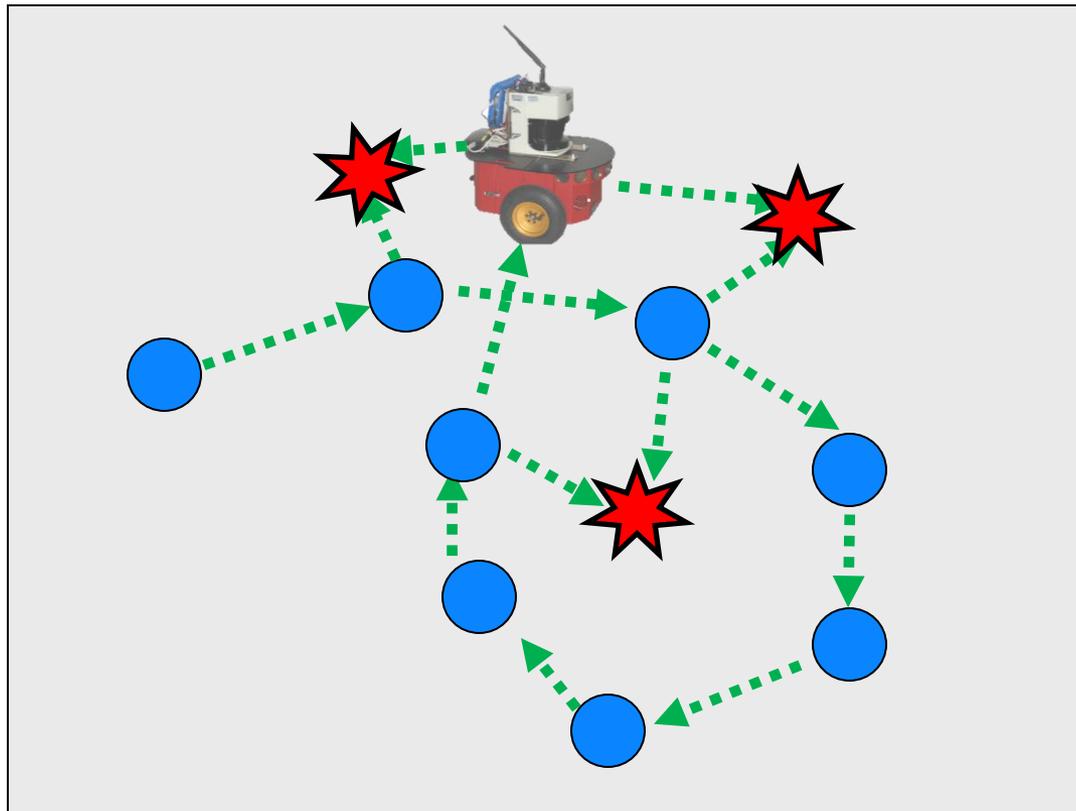


● Robot pose

→ Constraint

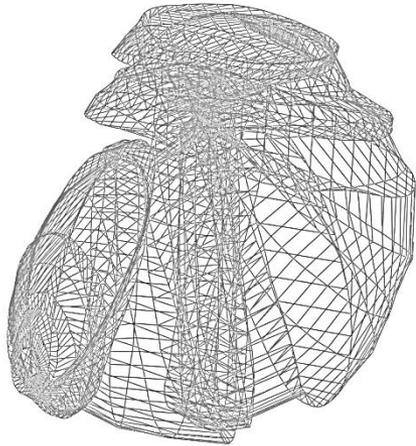
★ Landmark

Graph-Based SLAM

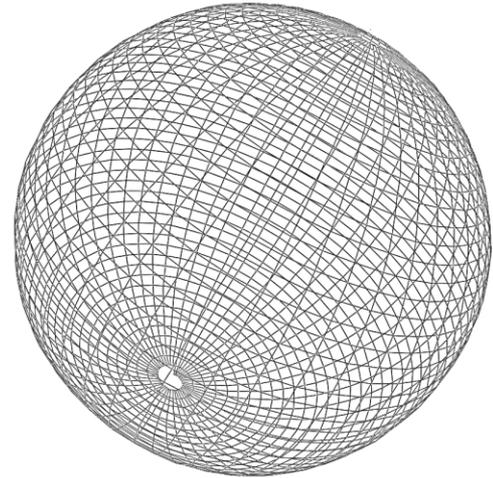


- Robot pose
- Constraint
- ★ Landmark

Graph-SLAM Pipeline

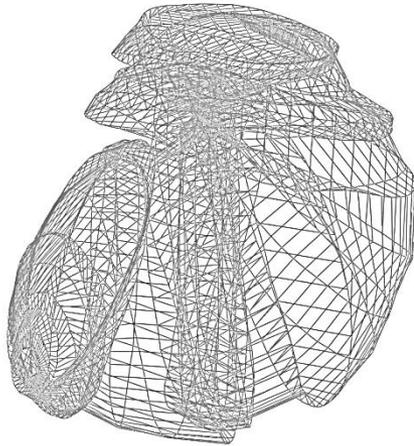


**Front
end**

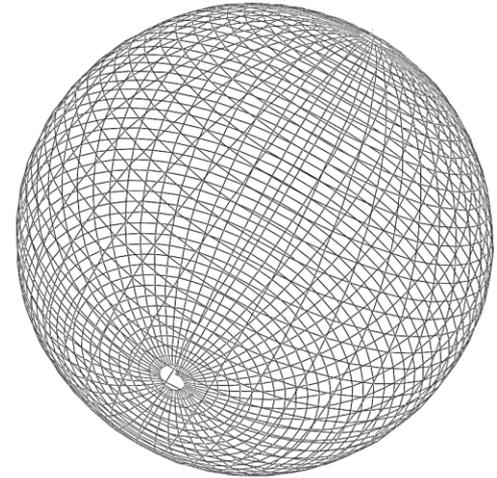


**Back
end**

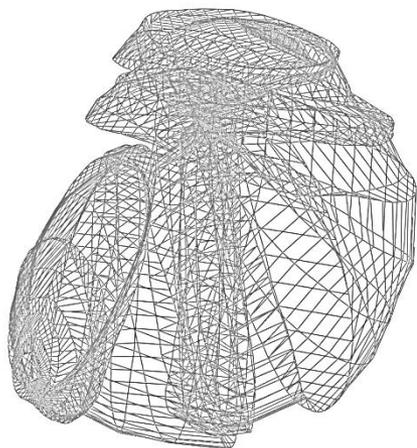
SLAM Back End Depends on the Initial Guess



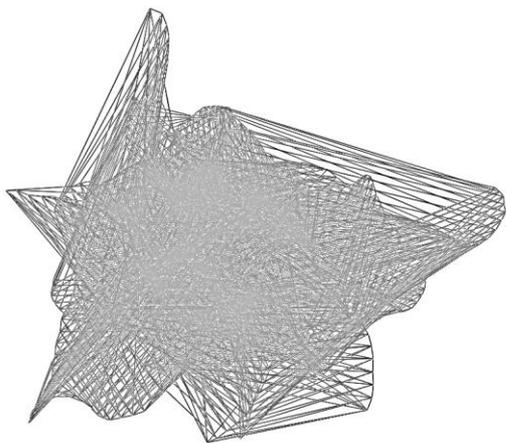
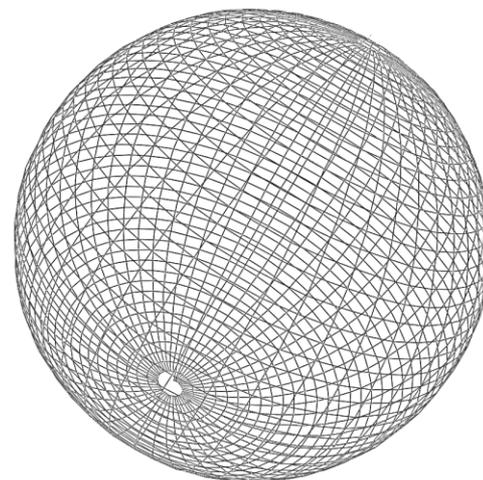
**Good
Initialization**



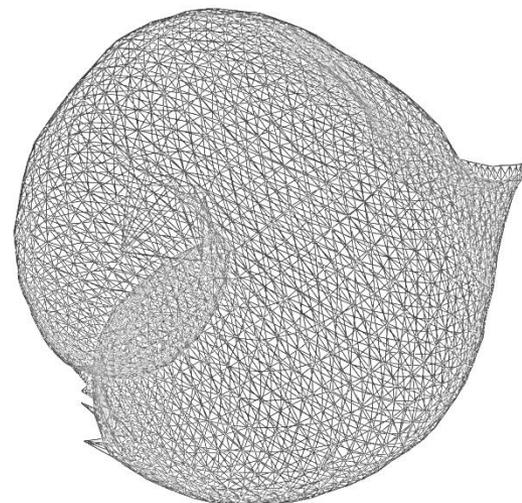
SLAM Back End Depends on the Initial Guess



**Good
Initialization**



**Bad
Initialization**



Typical Assumptions in Graph-SLAM

- **No outliers**
- **Initial guess** close to correct solution

Typical Assumptions in Graph-SLAM

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Outliers violate Gaussian assumption

- **Initial guess** close to correct solution

Bad initialization violates linear approximation

Typical Assumptions in Graph-SLAM

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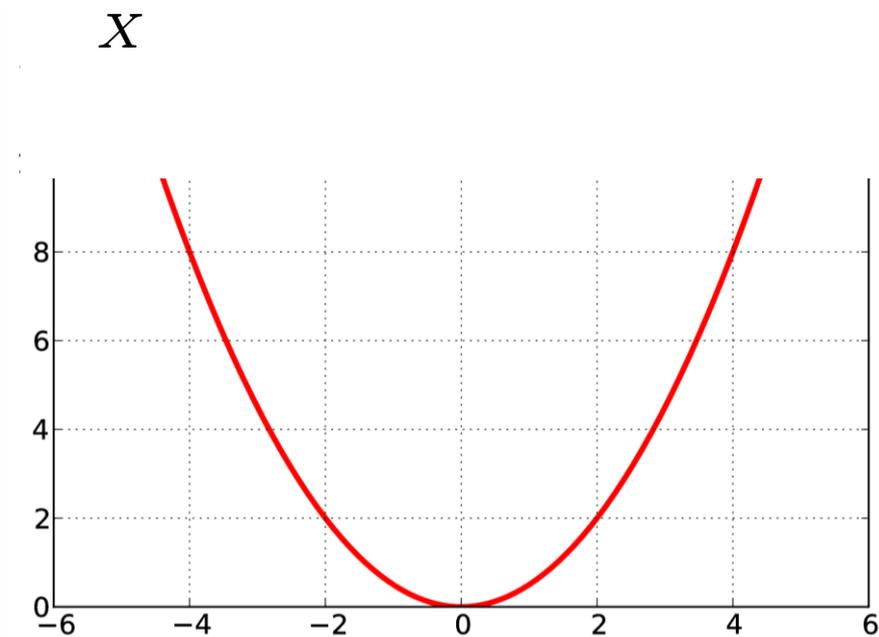
Bad initialization violates linear approximation

DCS addresses **both problems**

Standard least squares

$$X^* = \arg \min_X \sum_{ij} \mathbf{e}_{ij}(X)^T \mathbf{e}_{ij}(X)$$

$$X^* = \arg \min_X \sum r^2$$

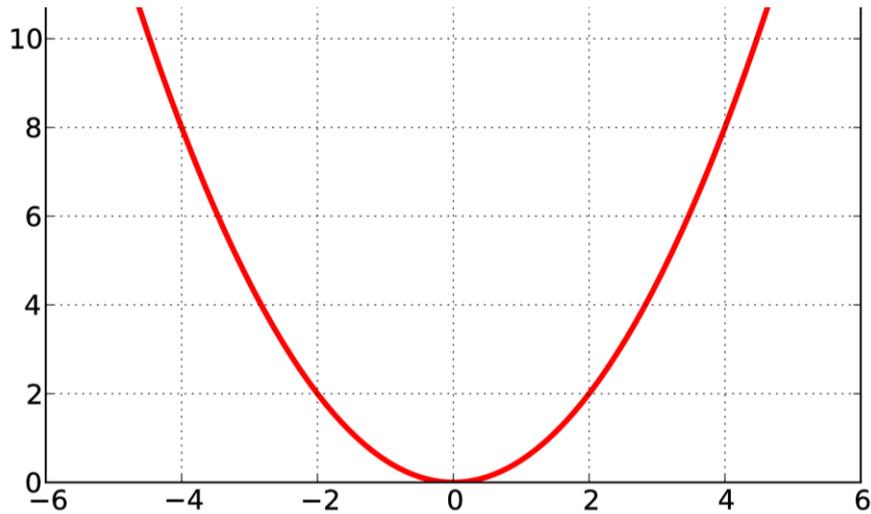


Robust M-Estimation

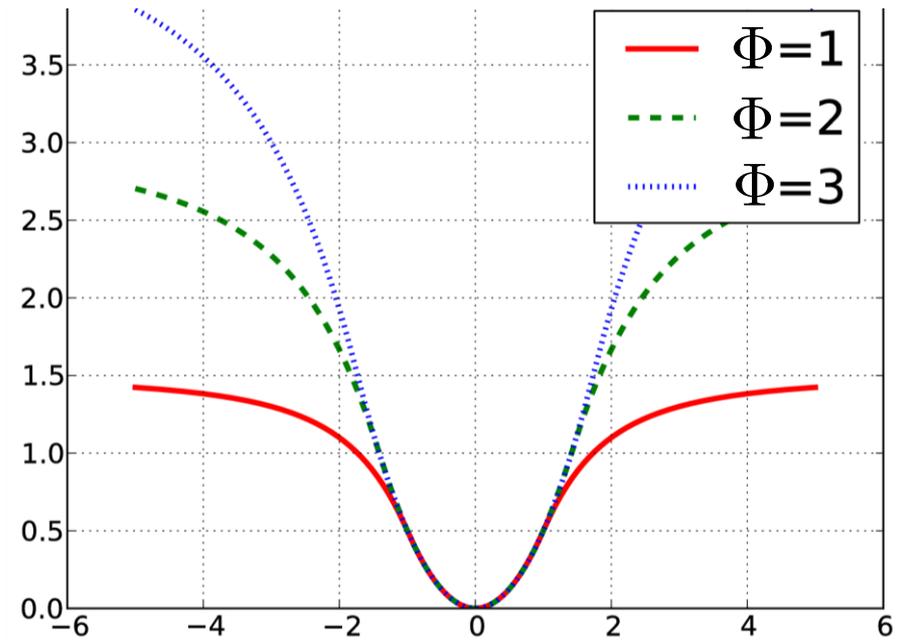
$$X^* = \arg \min_X \sum r^2$$

$$X^* = \arg \min_X \sum \rho(r^2)$$

DCS vs Standard Squared Error



Squared



DCS

Robust SLAM with Our Method

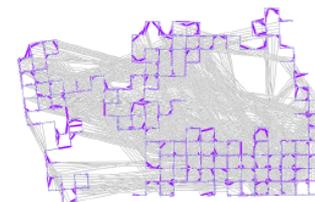
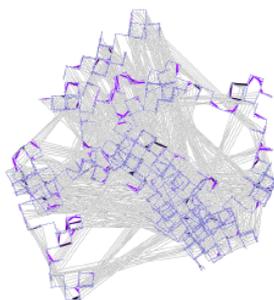
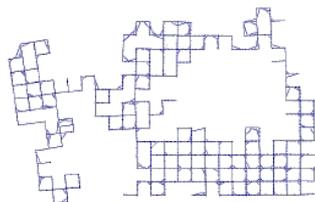
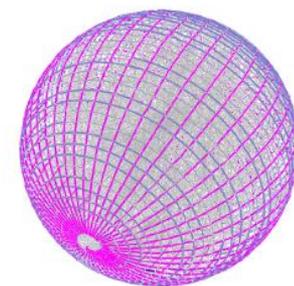
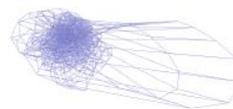
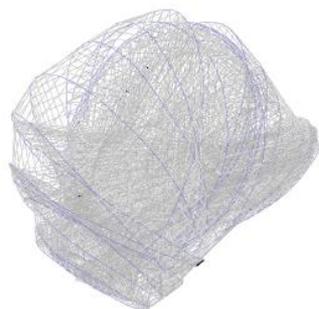
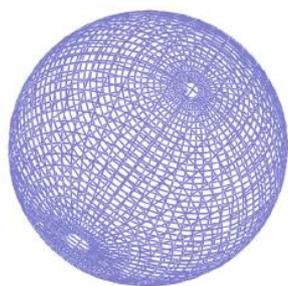
Ground Truth

Initialization

Gauss Newton

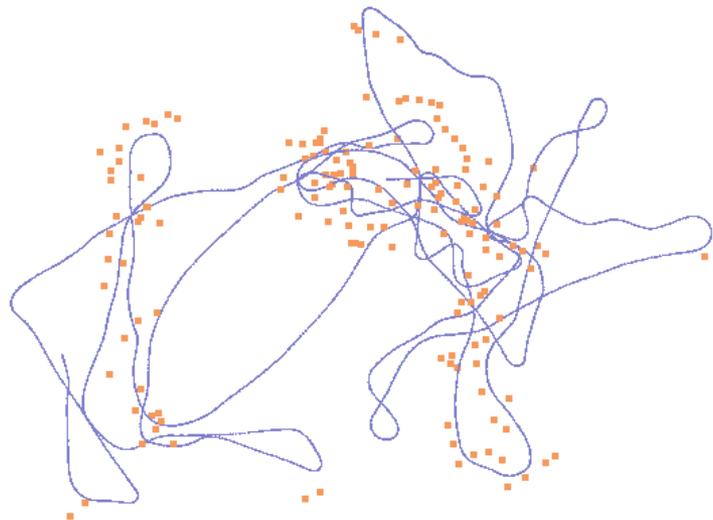
Our Method

Manhattan3500 (1000 Outliers)
Sphere2500 (1000 Outliers)



ICRA' 13

Robust SLAM with Our Method

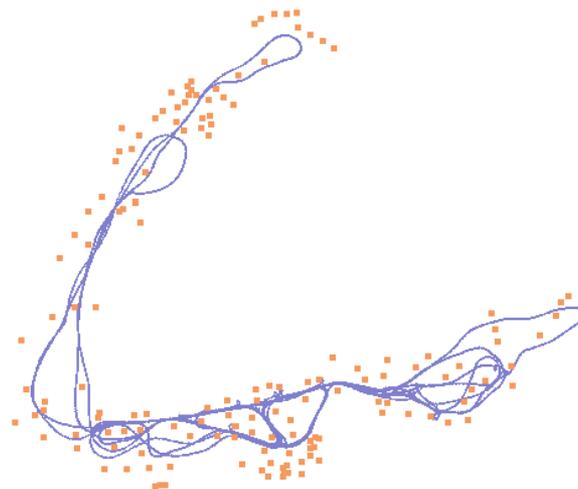


Victoria Park
Odometry Initialization

**Dynamic
Covariance
Scaling**



Gauss
Newton



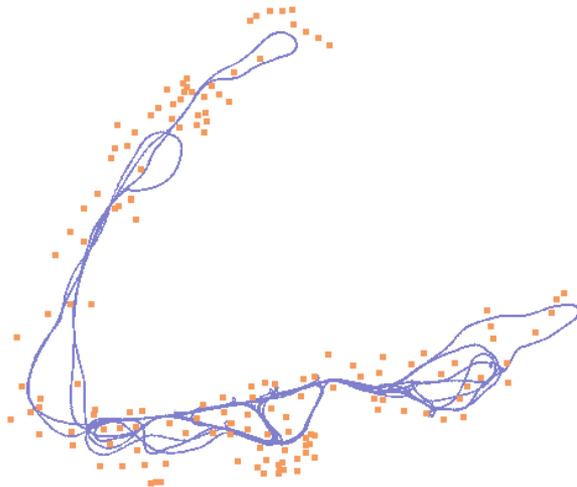
Courtesy E. Nebot

Robust SLAM with Our Method

**Dynamic
Covariance
Scaling**



Gauss
Newton

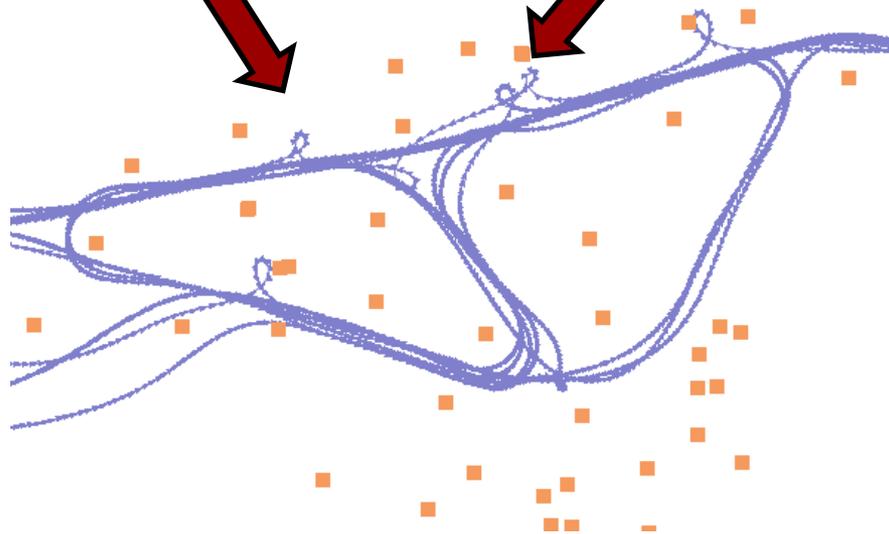
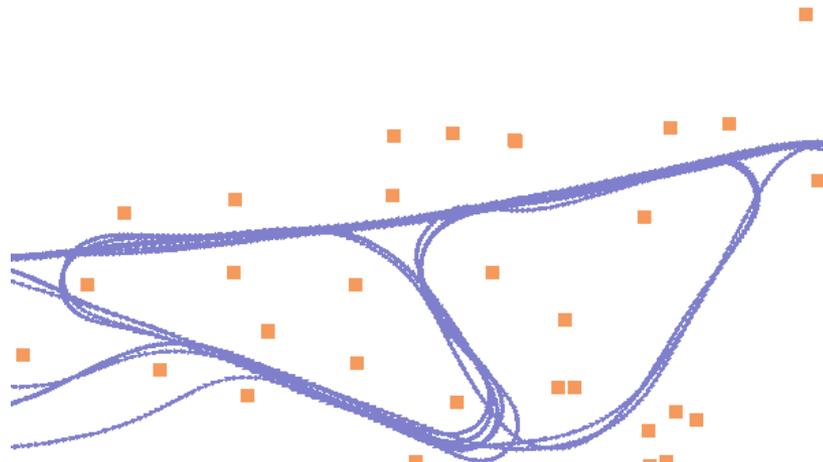
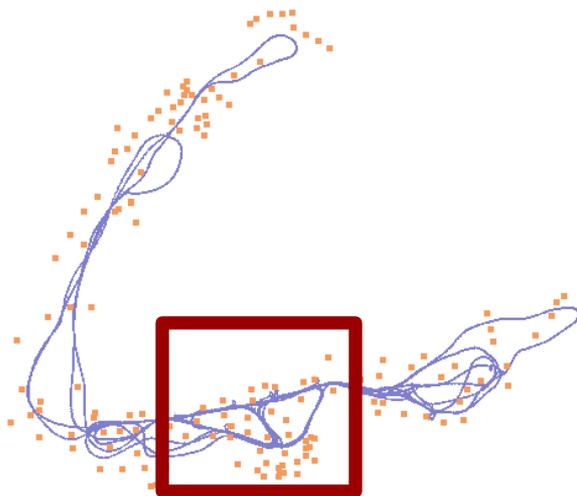


Robust SLAM with Our Method

**Dynamic
Covariance
Scaling**

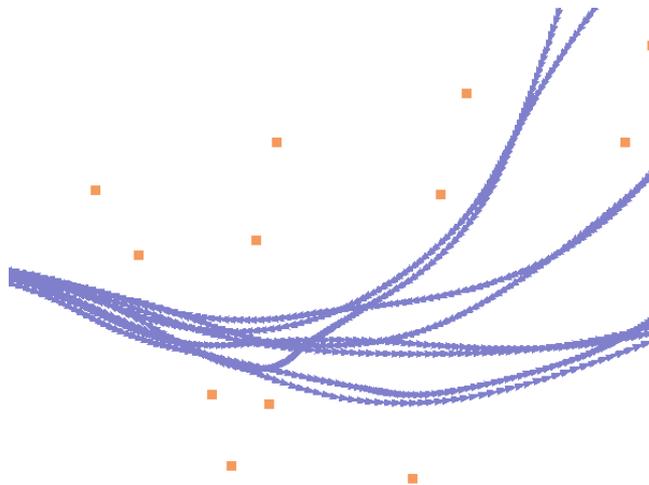
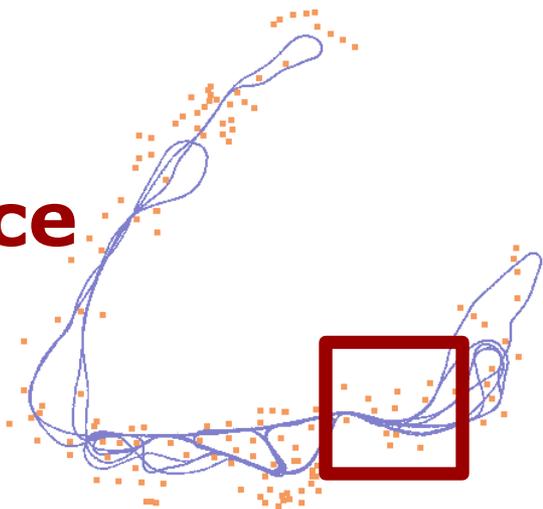


Gauss
Newton

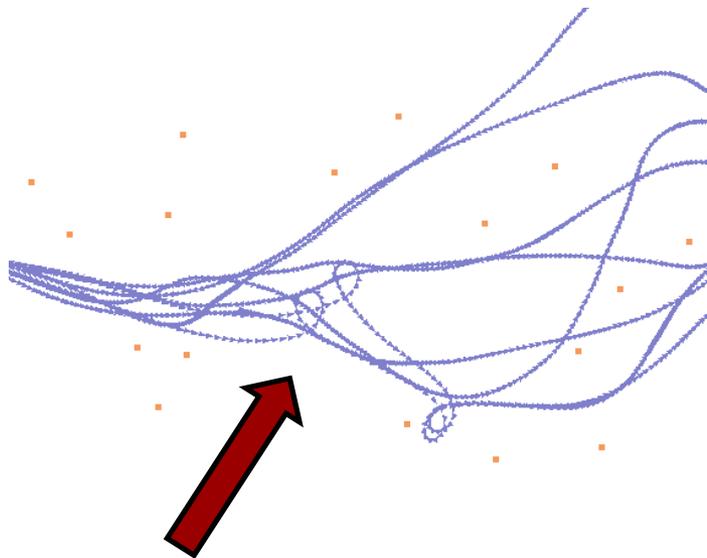
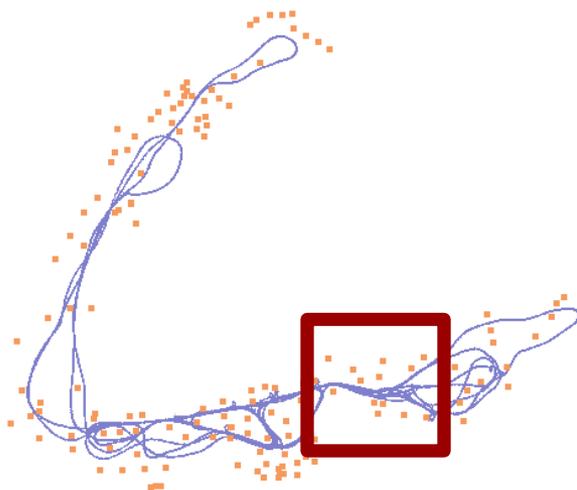


Robust SLAM with Our Method

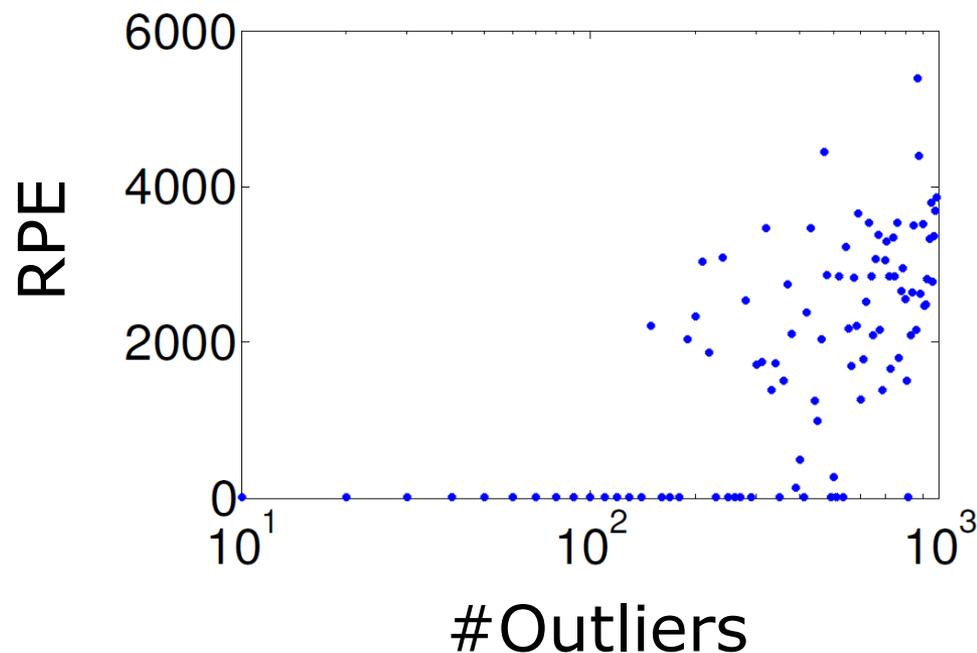
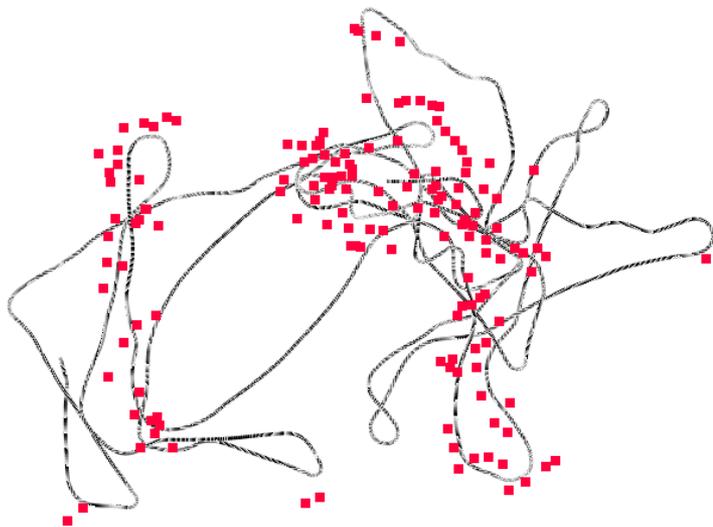
**Dynamic
Covariance
Scaling**



Gauss
Newton



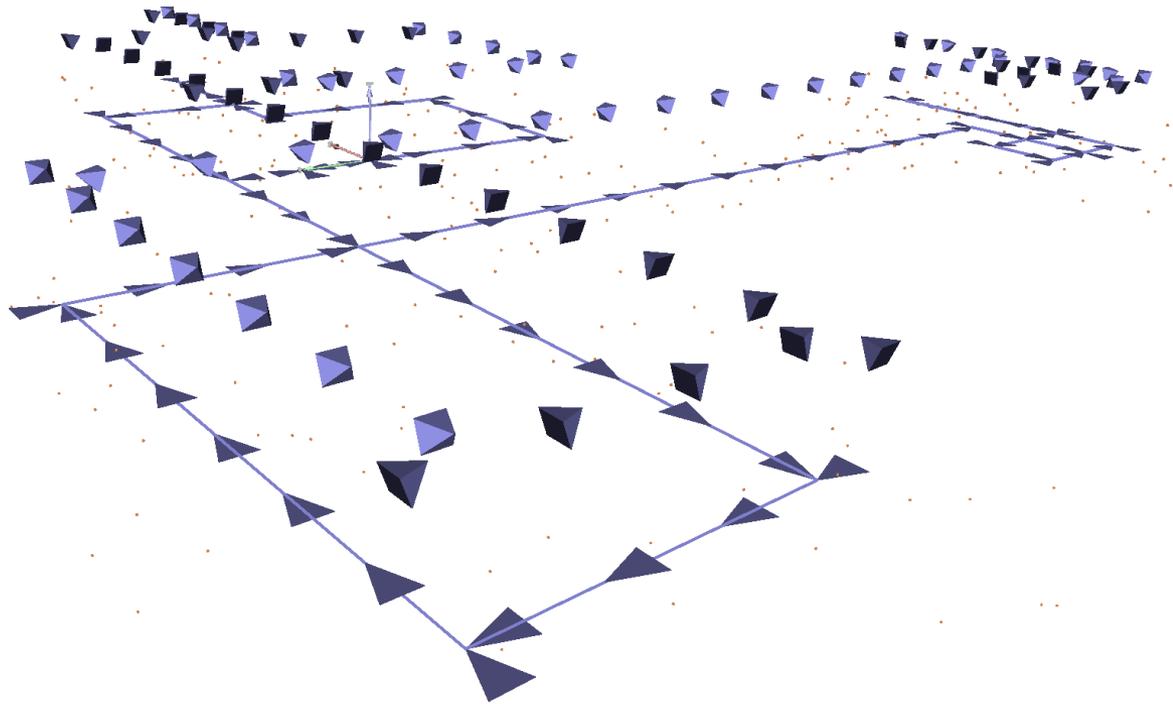
Dynamic Covariance Scaling with Outliers in Victoria Park



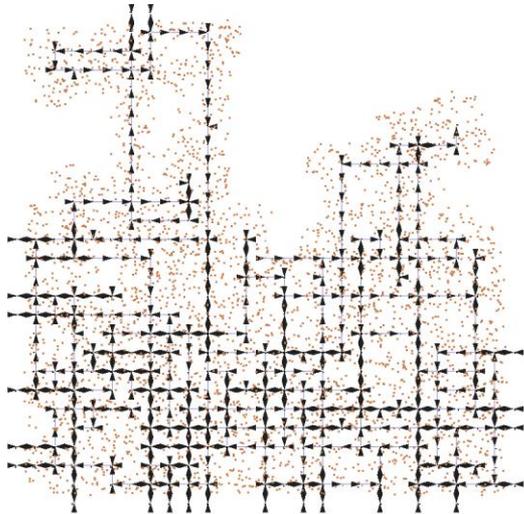
- DCS recovers correct solution
- GN fails to converge to the correct solution even for **outlier-free case**

Robust Visual SLAM with Our Method

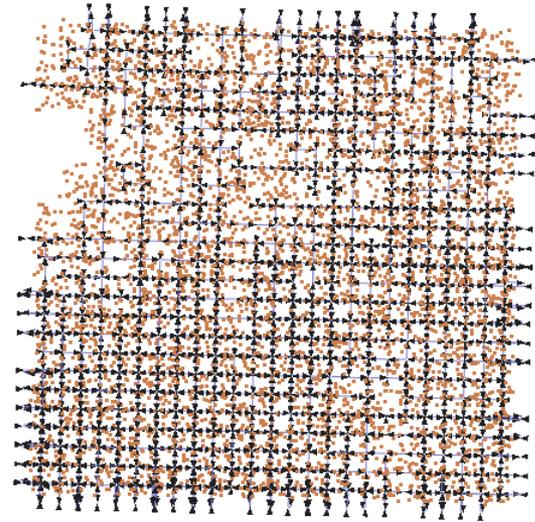
- 3D grid worlds of different sizes
- Robot perceives point landmarks



Robust Visual SLAM with Our Method



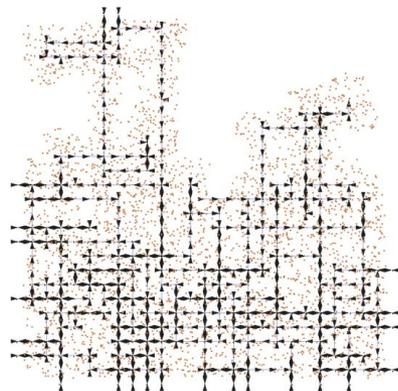
~1000 camera poses
~4000 features
~20K constraints



~5000 camera poses
~5000 features
~100K constraints

Robust Visual SLAM with DCS

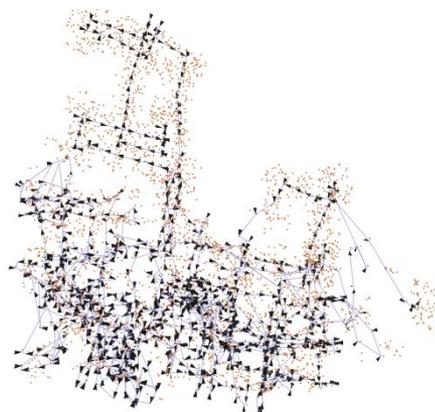
Ground
Truth



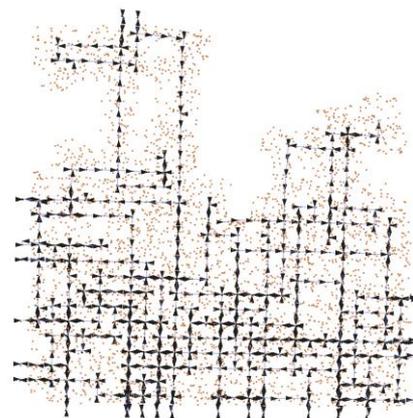
Initialization
(Odometry)



Simulated Stereo
(Bad initial guess)



Levenberg-Marquardt
(100 iterations)

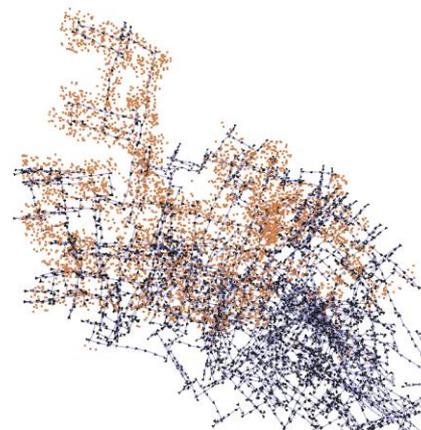
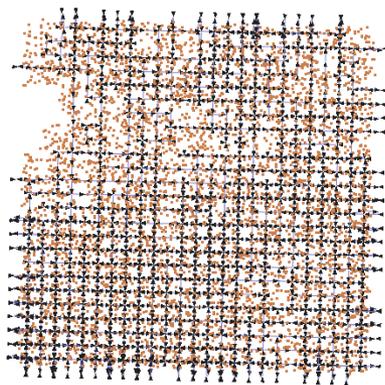


Our Method
(15 iterations)

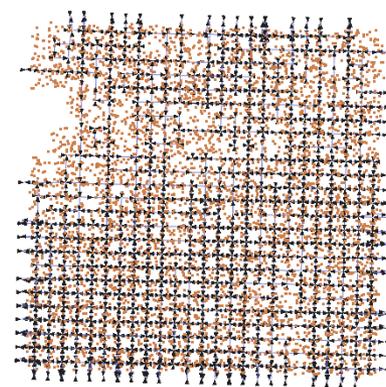
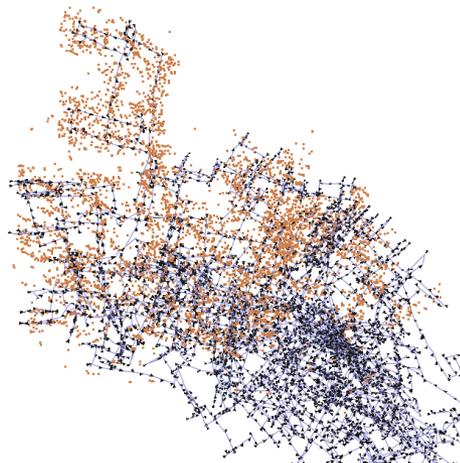
Robust Visual SLAM with DCS

Ground
Truth

Initialization
(Odometry)



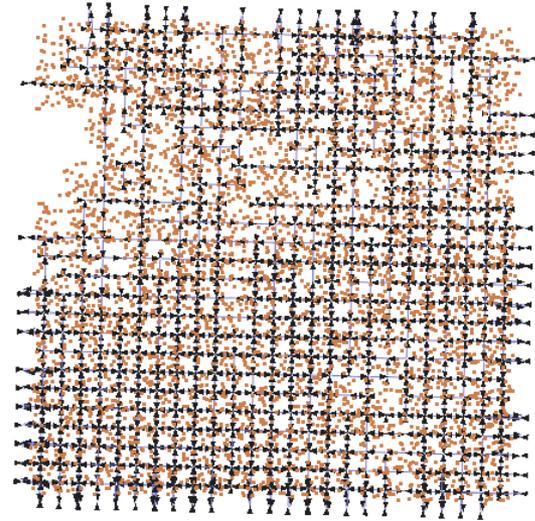
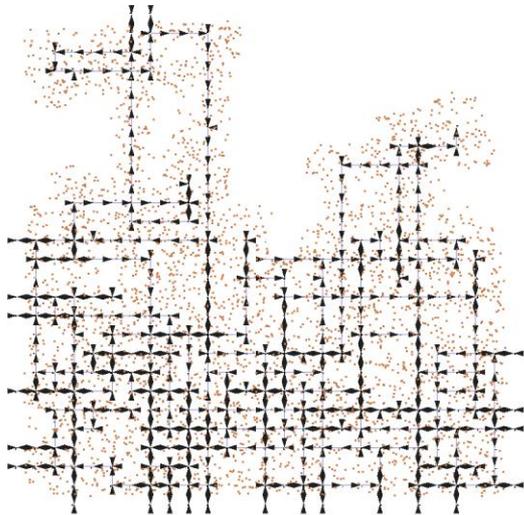
Simulated Stereo
(Bad initial guess)



Levenberg-Marquardt
(150 iterations)

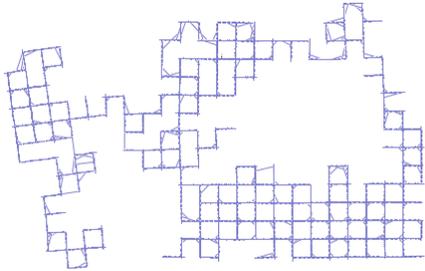
Our Method
(15 iterations)

Robust Visual SLAM with DCS

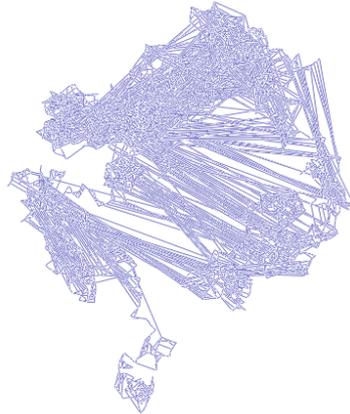


- DCS recovers correct solution in the presence of up to **25% outliers**
- LM fails to converge to the correct solution even for **outlier-free cases**

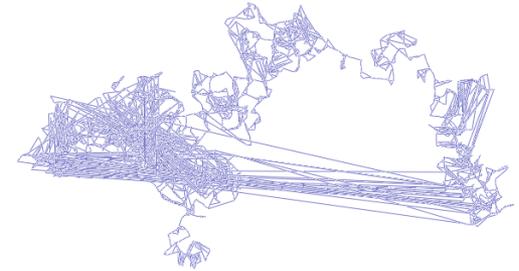
Increased Noise Manhattan3500



Ground Truth



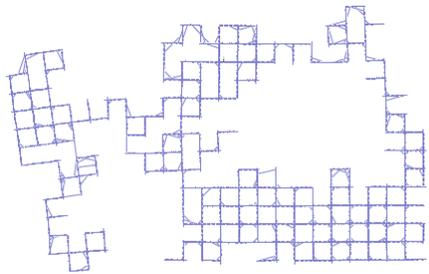
Odometry
Initialization



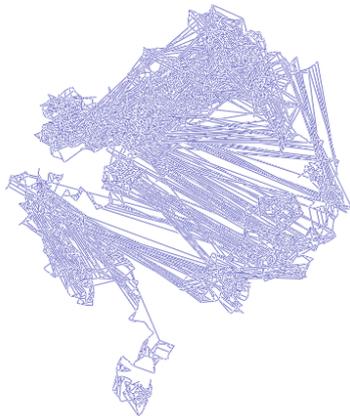
Spanning Tree
Initialization

Courtesy Edwin Olson
Reprocessed by Carlone & Censi, TRO'14

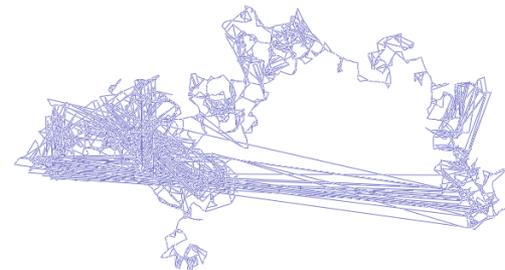
Increased Noise Manhattan3500



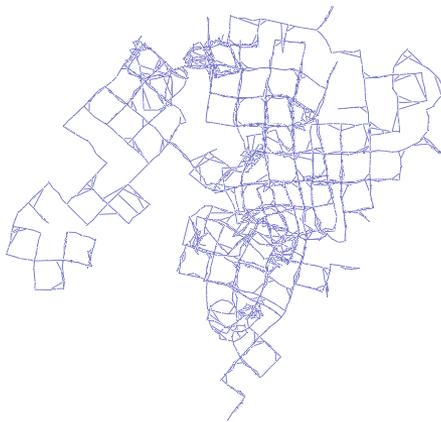
Ground Truth



Odometry
Initialization

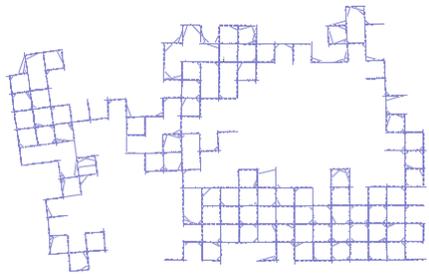


Spanning Tree
Initialization

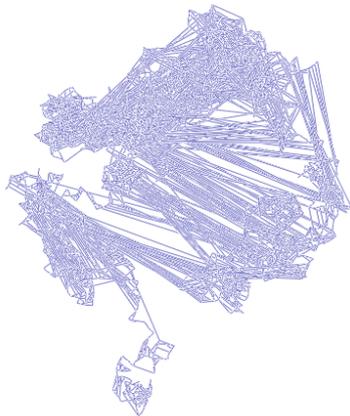


Gauss-Newton

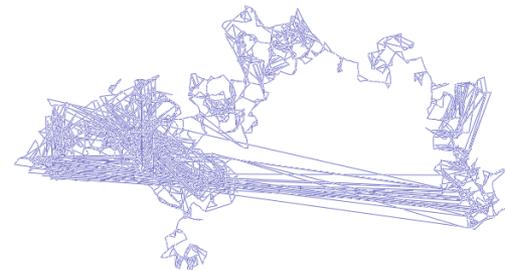
Increased Noise Manhattan3500



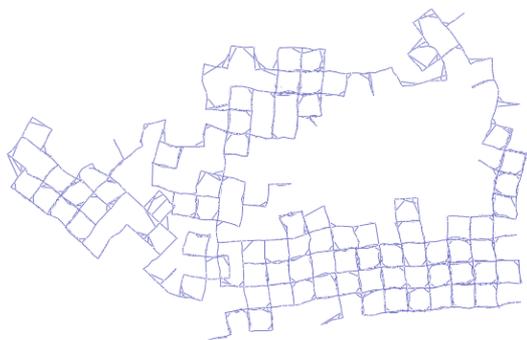
Ground Truth



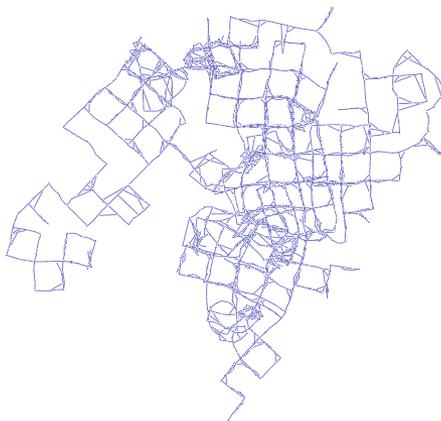
Odometry
Initialization



Spanning Tree
Initialization

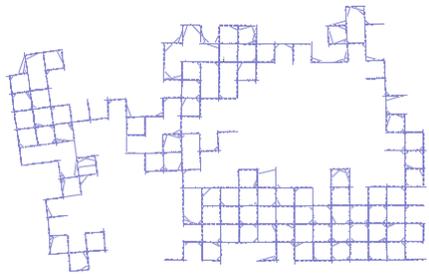


Carlone & Censi
TRO'14

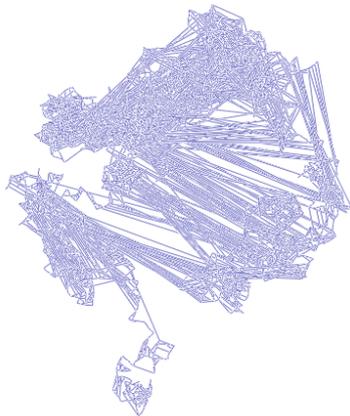


Gauss-Newton

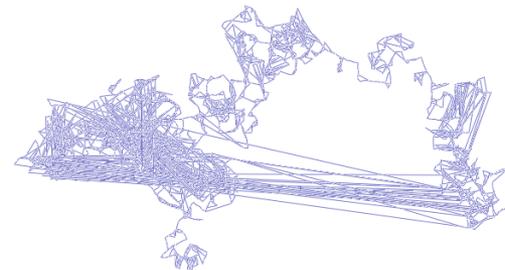
Increased Noise Manhattan3500



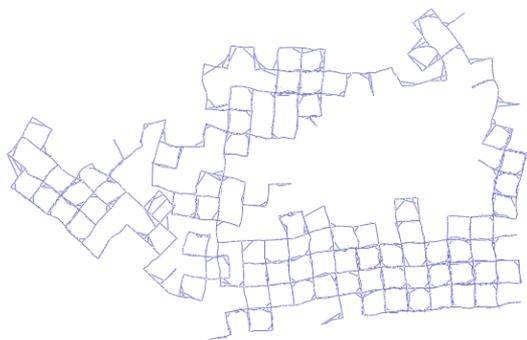
Ground Truth



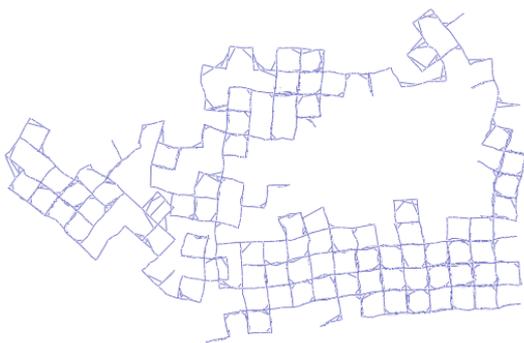
Odometry
Initialization



Spanning Tree
Initialization



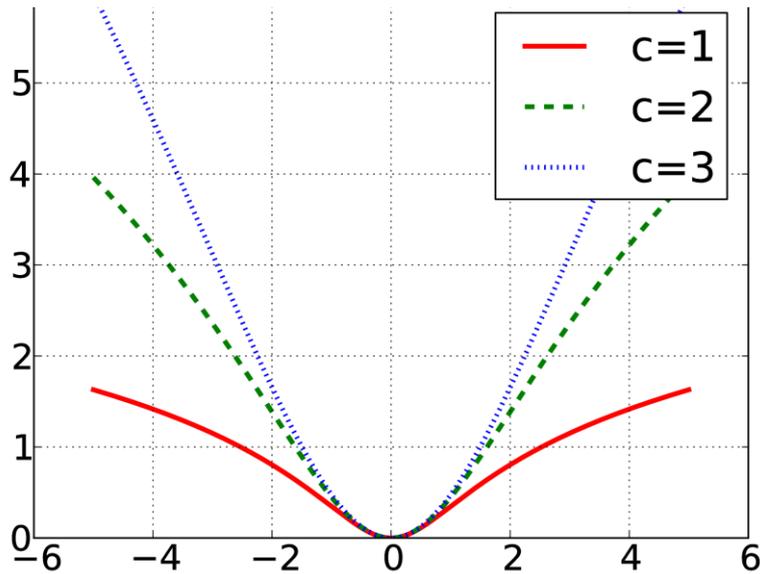
Carlone & Censi
TRO'14



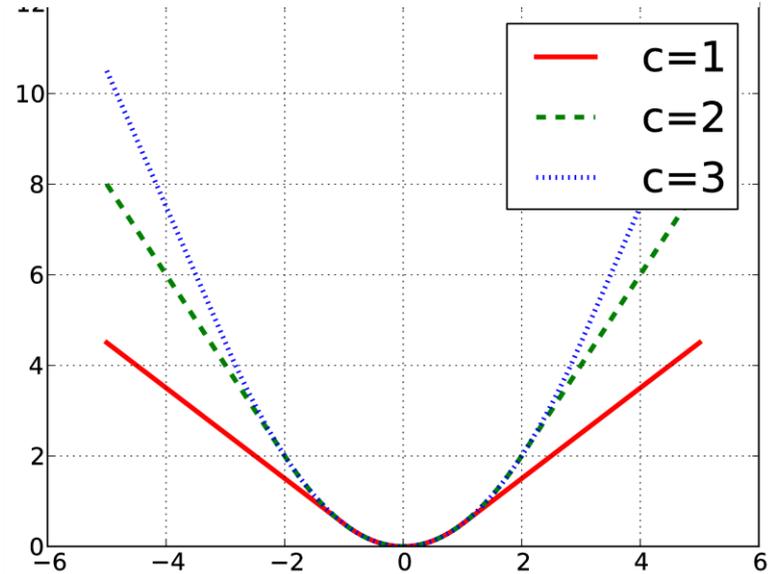
Our Method
DCS

Comparison to M-estimators

How do other M-estimators perform?



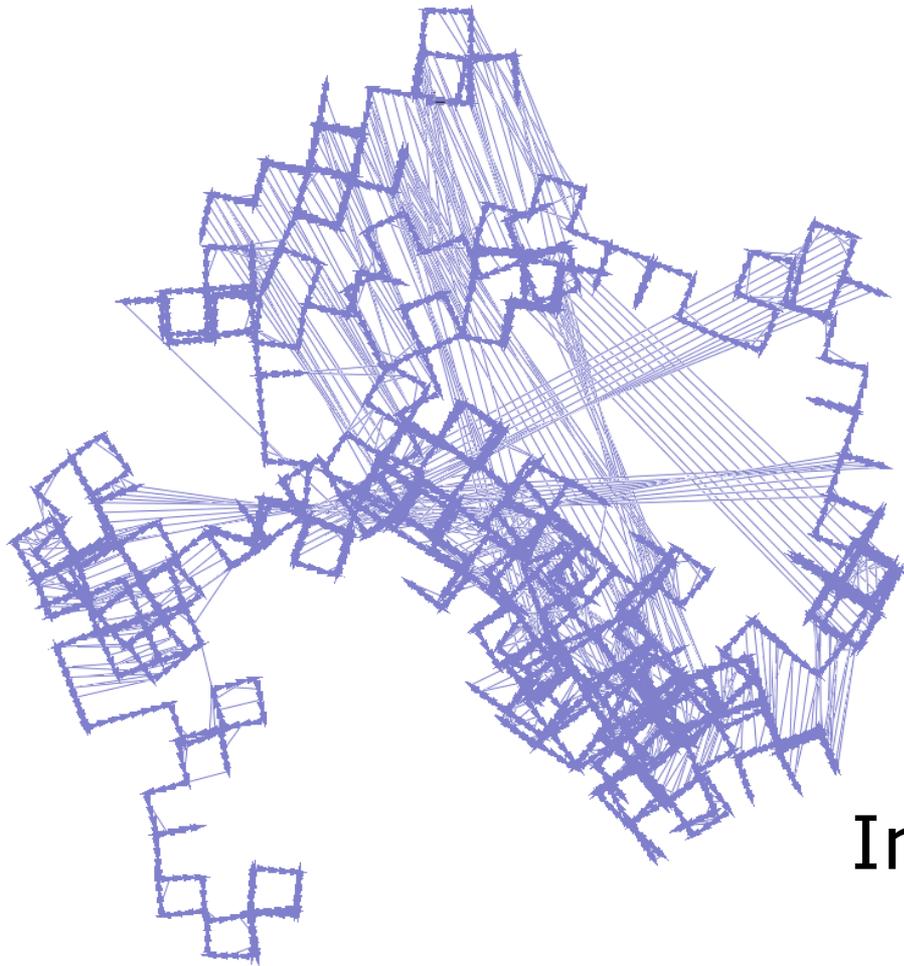
Cauchy



Huber

Comparison to M-estimators

Compare against **Cauchy** and **Huber**



Manhattan3500

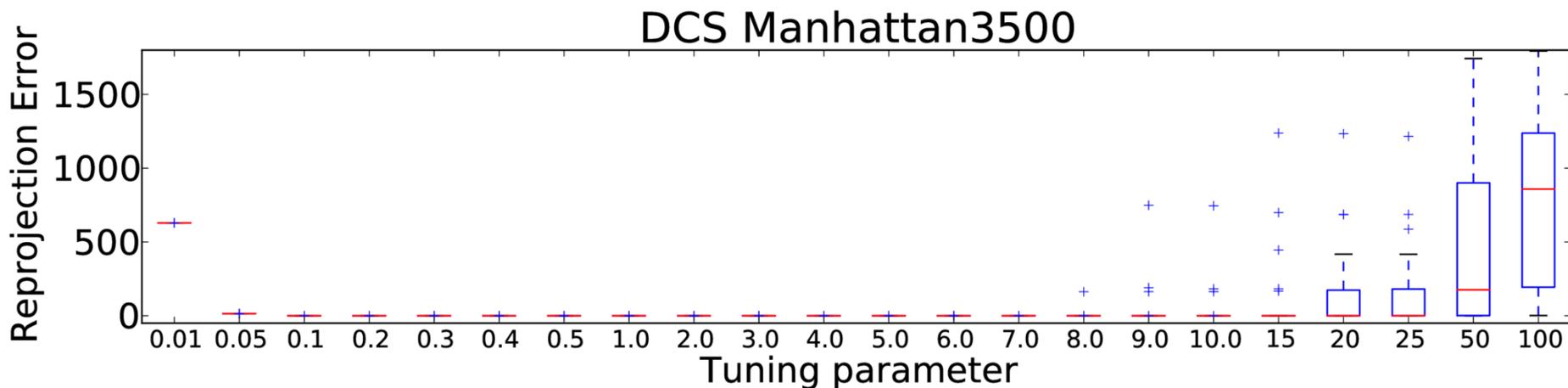
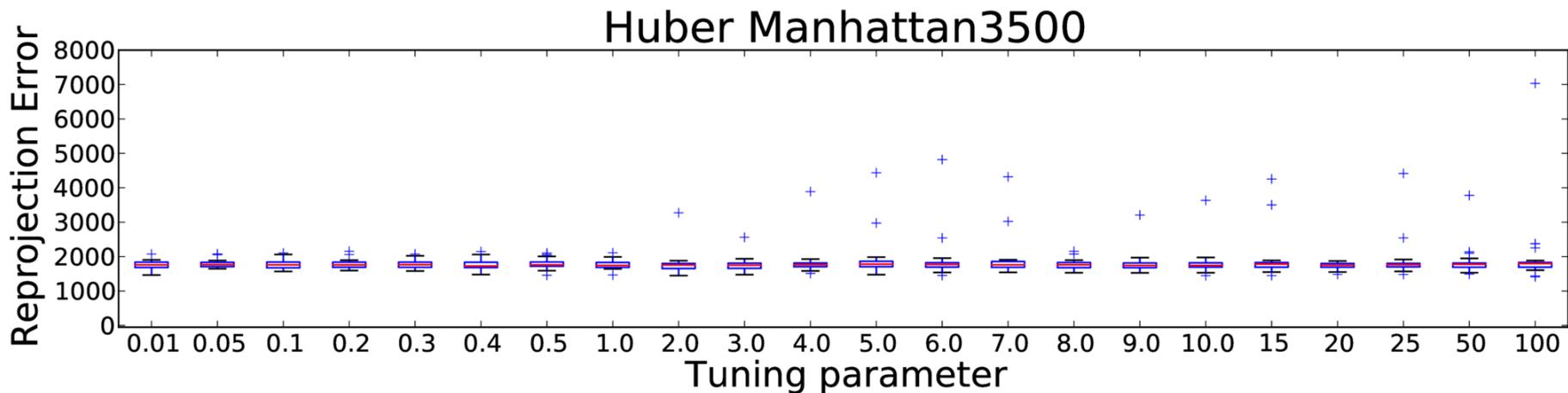
100 outliers

groups of 10

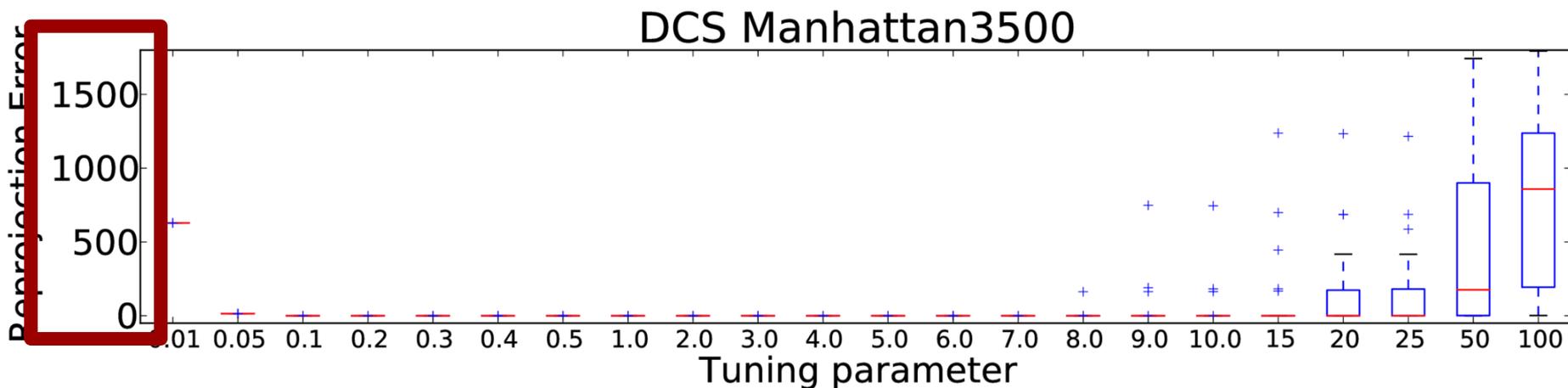
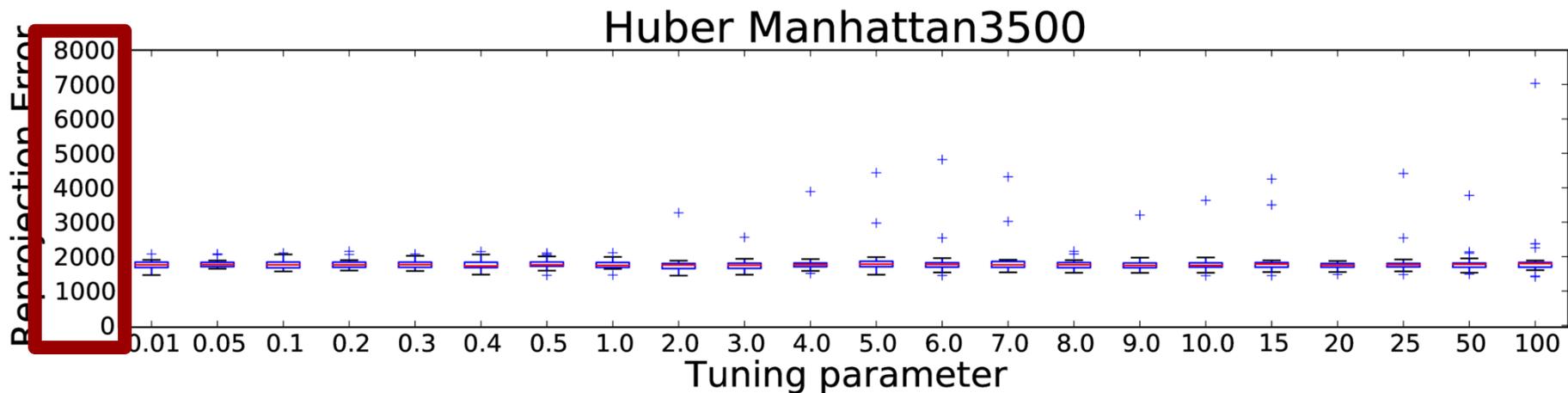
25 instances

Initialization with odometry

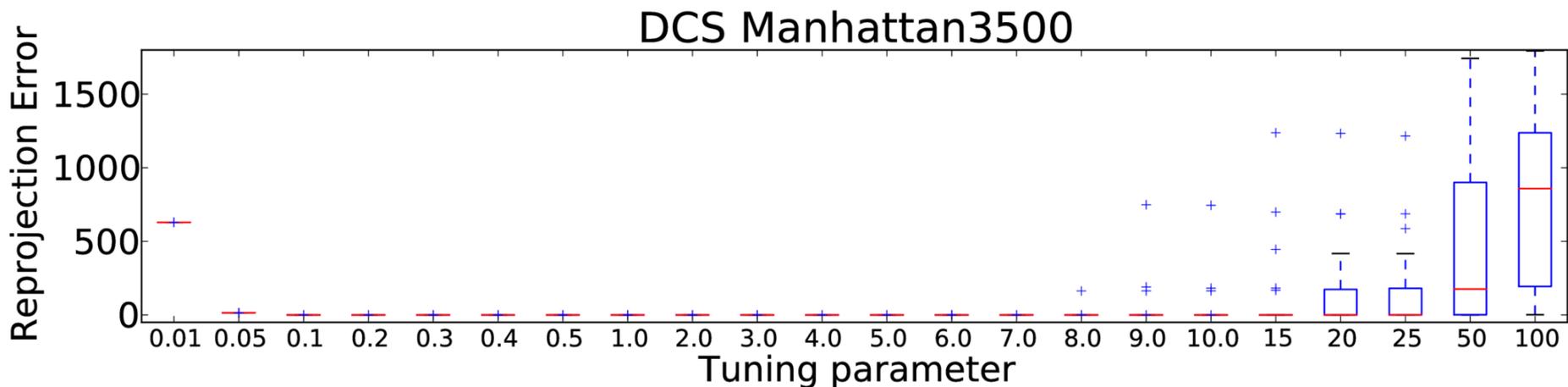
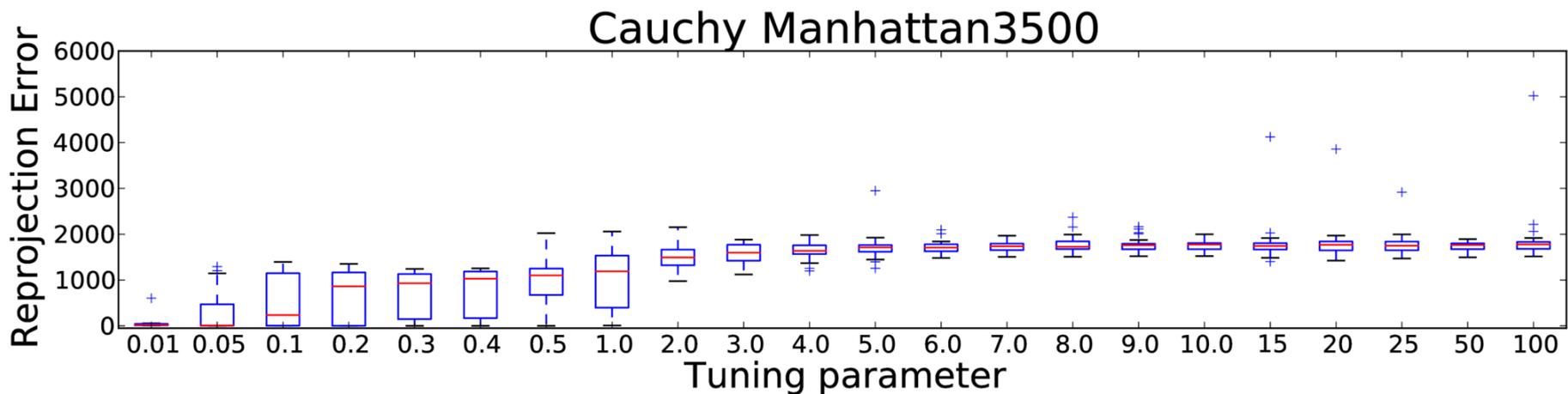
Comparison to Huber



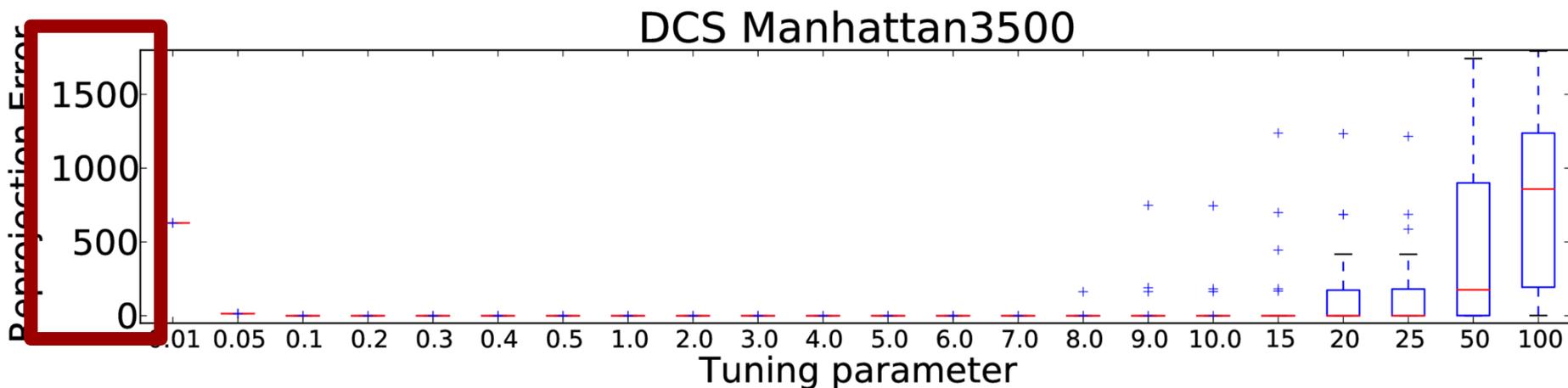
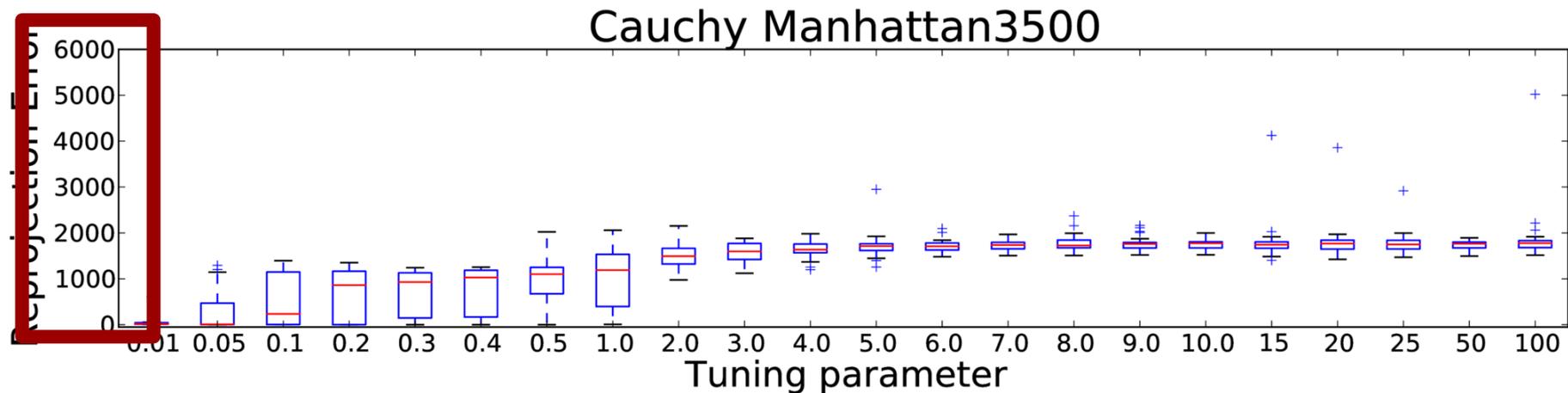
Comparison to Huber



Comparison to Cauchy



Comparison to Cauchy



Conclusion

- Good kernel for 2D & 3D SLAM
- Robust to **initialization & outliers**
- Outperforms **Huber and Cauchy** on evaluated scenarios
- Integrated in current **g2o** release

Thank you for your attention!