Dynamic Covariance Scaling for Robust Robot Mapping

Workshop on Robust and Multimodal Inference in Factor Graphs

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Maps are Essential for Effective Navigation
Graph-based SLAM

Robot pose

Constraint
Graph-based SLAM

Robot pose
Constraint
Graph-based SLAM
Graph-based SLAM
Graph-based SLAM

a single outlier ...
Graph-based SLAM

a single outlier ...
Graph-based SLAM

Vegas!!

Paris!!

a single outlier ...
Graph-based SLAM

a single outlier ... ruins the map
Graph-SLAM Pipeline

Front end  Validation  Back end

Assumption:
No Outliers

Impossible to have perfect validation
SLAM Back End Fails in the Presence of Outliers

1 Outlier

10 Outliers

100 Outliers
SLAM Back End Depends on the Initial Guess
SLAM Back End Depends on the Initial Guess

Good Initial Guess

Bad Initial Guess
Typical Assumptions

- Gaussian assumption is violated
  - Perceptual aliasing
  - Measurement error
  - Multipath GPS measurements
Typical Assumptions

- Gaussian assumption is violated
  - Perceptual aliasing
  - Measurement error
  - Multipath GPS measurements

- Linear approximation is invalid
  - Linearization is only valid if close to optimum
Typical Assumptions in Graph-SLAM

- No outliers
- Good initial guess
- Current methods both independently
- Our method approaches both problems
Typical Assumptions in Graph-SLAM

- No outliers
- Good initial guess
- Current methods solve both independently
- Our method approaches both problems

Our Approach

- Dynamic Covariance Scaling
Our Approach: Dynamic Covariance Scaling

- Successfully **rejects** outliers
- More robust to **bad initial guess**
- Does not increase state space
- Is a robust M-estimator
Standard Gaussian Least Squares

\[ X^* = \arg\min_X \sum_{i,j} e_{ij}(X)^T \Omega_{ij} e_{ij}(X) \]
Dynamic Covariance Scaling

\[ X^* = \arg\min_X \sum_{i,j} \left( e_{ij}(X)^T \Omega_{ij} e_{ij}(X) \right) \chi^2_{ij} \]

\[ X^* = \arg\min_X \sum_{i,j} e_{ij}(X)^T \left( s_{ij}^2 \Omega_{ij} \right) e_{ij}(X) \]
How to Determine $s$?

$$X^* = \arg\min_X \sum_{ij} e_{ij}(X)^T \left( s_{ij}^2 \Omega_{ij} \right) e_{ij}(X)$$
How to Determine $s$?

$$X^* = \arg\min_X \sum_{ij} \mathbf{e}_{ij}(X)^T (s_{ij}^2 \Omega_{ij}) \mathbf{e}_{ij}(X)$$

$$\vdots$$

$$s_{ij} = \min \left(1, \frac{2\Phi}{\Phi + \chi^2_{ij}}\right)$$

**Closed form** approximation of Switchable Constraints with a M-estimator
Dynamic Covariance Scaling

![Graph showing different lines representing squared error, scaling function, and scaled error for different s values.](image)
Dynamic Covariance Scaling

Both have squared error
Dynamic Covariance Scaling

Original error

Scaled error
Dynamic Covariance Scaling

![Graph showing dynamic covariance scaling with linearization](image-url)
Dynamic Covariance Scaling
Robust SLAM with Our Method

Ground Truth

Initialization

Gauss Newton

Our Method

Sphere2500 (1000 Outliers)

Manhattan3500 (1000 Outliers)
Dynamic Covariance Scaling with Front-end Outliers

Bicocca multisession dataset
Dynamic Covariance Scaling with Front-end Outliers

Lincoln-labs multisession dataset
Robust SLAM with Our Method

Dynamic Covariance Scaling

Standard Gauss-Newton

Victoria Park Initialization (Odometry)
Robust SLAM with Our Method

Dynamic Covariance Scaling

Standard Gauss-Newton
Robust SLAM with Our Method

Dynamic Covariance Scaling

Standard 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**
Convergence – 1000 Outliers

- **Switchable Constraints**
- **Dynamic Covariance Scaling**

**Manhattan3500**

**Sphere2500**

![Graphs showing convergence with different constraints](image-url)
Convergence – 1000 Outliers

**Switchable Constraints**

**Dynamic Covariance Scaling**

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**Manhattan3500**

**Sphere2500**
Convergence with Outliers

Switchable Constraints

Dynamic Covariance Scaling

Switchable Constraints (SC) Manhattan Olson Dynamic Covariance Scaling (DCS)

Iteration 0
Conclusion

- **Rejects outliers** for 2D & 3D SLAM
- **No increase in computational complexity**
- More robust to **bad initial guess**
- Now **integrated in g2o**
Thank you for your attention!