

# Pose-parameter graph optimisation

Art van Liere

Delft Center for Systems and Control (DCSC)  
Delft University of Technology

This work is supported by Demcon Advanced Mechatronics



1st supervisor: prof.dr.ir. Tamás Keviczky (DCSC)

2nd supervisor: ir. Martijn Krijnen (Demcon)

November 19, 2021

# Outline

- ① Introduction
- ② Pose graph optimisation
- ③ Pose-parameter graph optimisation
  - Motivation
  - Research
  - Parameters
  - Connectivity
- ④ Conclusion
- ⑤ Recommendations

# Outline

- ① Introduction
- ② Pose graph optimisation
- ③ Pose-parameter graph optimisation
  - Motivation
  - Research
  - Parameters
  - Connectivity
- ④ Conclusion
- ⑤ Recommendations

# Introduction

# Introduction

## SLAM

# Introduction

## Simultaneous Localisation And Mapping

# Introduction

## Simultaneous Localisation And Mapping

- Localisation



Figure: Localisation from known map

# Introduction

## Simultaneous Localisation And Mapping

- Localisation
- Mapping



Figure: Localisation from known map

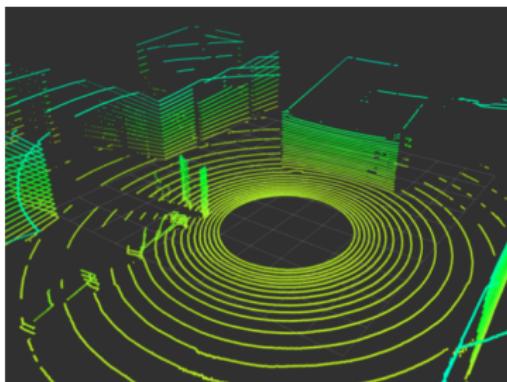


Figure: Mapping from known location

# Introduction

## Graph-based SLAM methods

# Introduction

## Graph-based SLAM methods

Discretise trajectory as set of robot poses  $x_k = (t_x, t_y, \theta) \in \mathbb{R}^3$

# Introduction

## Graph-based SLAM methods

Discretise trajectory as set of robot poses  $x_k = (t_x, t_y, \theta) \in \mathbb{R}^3$

## Pose graph optimisation

- Input:  $\mathcal{Z}$  (set of measurements)
- Output:  $\mathcal{X}^*$  (set of estimated poses)

# Introduction

## Graph-based SLAM methods

Discretise trajectory as set of robot poses  $x_k = (t_x, t_y, \theta) \in \mathbb{R}^3$

### Pose graph optimisation

- Input:  $\mathcal{Z}$  (set of measurements)
- Output:  $\mathcal{X}^*$  (set of estimated poses)

### Pose-parameter graph optimisation

- Input:  $\mathcal{Z}$  (set of measurements)
- Output:  $\mathcal{X}^*$  (set of estimated poses),  $\mathcal{P}^*$  (set of estimated parameters)

# Introduction

## Graph-based SLAM methods

Discretise trajectory as set of robot poses  $x_k = (t_x, t_y, \theta) \in \mathbb{R}^3$

## Pose graph optimisation

- Input:  $\mathcal{Z}$  (set of measurements)
- Output:  $\mathcal{X}^*$  (set of estimated poses)

## Pose-parameter graph optimisation

- Input:  $\mathcal{Z}$  (set of measurements)
- Output:  $\mathcal{X}^*$  (set of estimated poses),  $\mathcal{P}^*$  (set of estimated parameters)

Solves the so-called SCLAM (**S**imultaneous **C**alibration **L**ocalisation **A**nd **M**apping) problem!

# Introduction

## Parameters

Mapping algorithms might depend on robot-specific *parameters*

# Introduction

## Parameters

Mapping algorithms might depend on robot-specific *parameters*; e.g.,

- Wheel radii



# Introduction

## Parameters

Mapping algorithms might depend on robot-specific *parameters*; e.g.,

- Wheel radii
- Sensor placement



Boston D



# Introduction

## Parameters

Mapping algorithms might depend on robot-specific *parameters*; e.g.,

- Wheel radii
- Sensor placement

## Difficulties

# Introduction

## Parameters

Mapping algorithms might depend on robot-specific *parameters*; e.g.,

- Wheel radii
- Sensor placement

## Difficulties

- Parameters may require lengthy sensor-specific calibration procedures

# Introduction

## Parameters

Mapping algorithms might depend on robot-specific *parameters*; e.g.,

- Wheel radii
- Sensor placement

## Difficulties

- Parameters may require lengthy sensor-specific calibration procedures
- Parameters may be subject to change

# Introduction

## Parameters

Mapping algorithms might depend on robot-specific *parameters*; e.g.,

- Wheel radii
- Sensor placement

## Difficulties

- Parameters may require lengthy sensor-specific calibration procedures
- Parameters may be subject to change
- Parameter influence might be unknown

# Outline

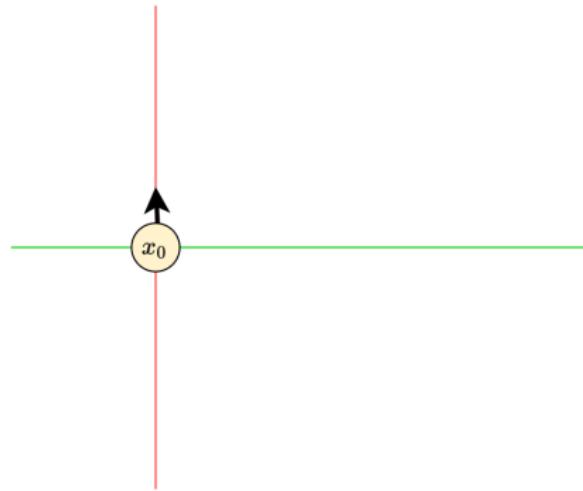
- ① Introduction
- ② Pose graph optimisation
- ③ Pose-parameter graph optimisation
  - Motivation
  - Research
  - Parameters
  - Connectivity
- ④ Conclusion
- ⑤ Recommendations

# Pose graph optimisation

# Pose graph optimisation

## Current status

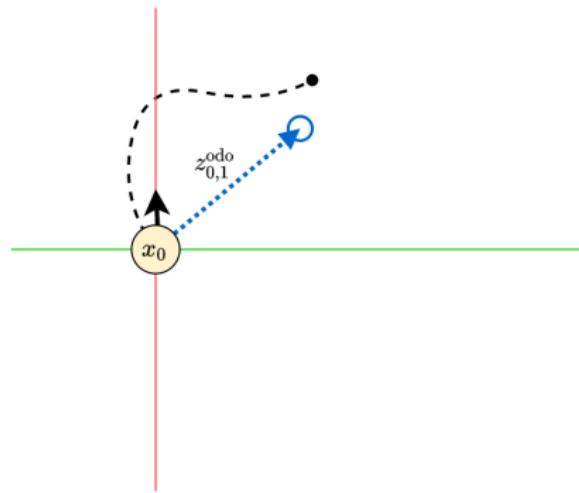
Fix first pose at origin:  $x_0 = (0, 0, 0)$



# Pose graph optimisation

## Current status

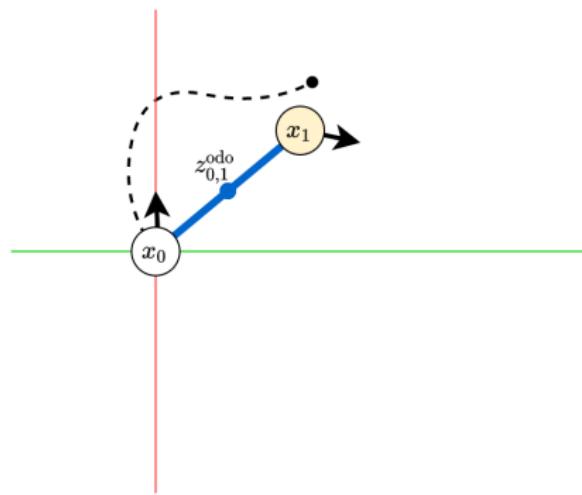
Measure relative pose transformation:  $x_1 - x_0$



# Pose graph optimisation

## Current status

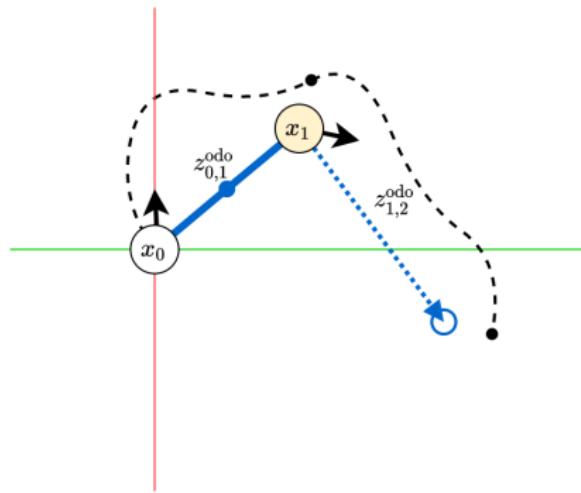
Add odometry constraint:  $z_{0,1}^{\text{odo}}$



# Pose graph optimisation

## Current status

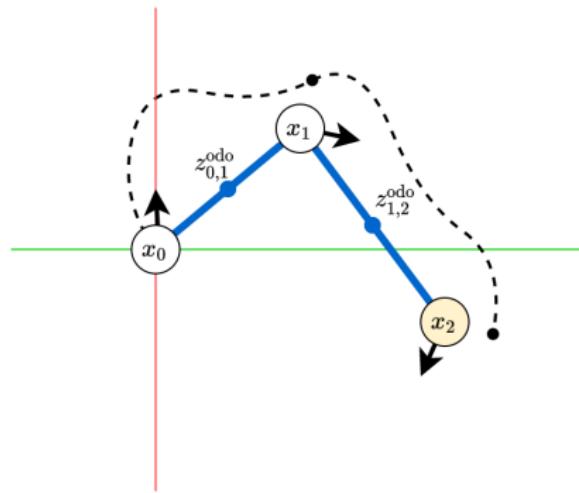
Measure relative pose transformation:  $x_2 - x_1$



# Pose graph optimisation

## Current status

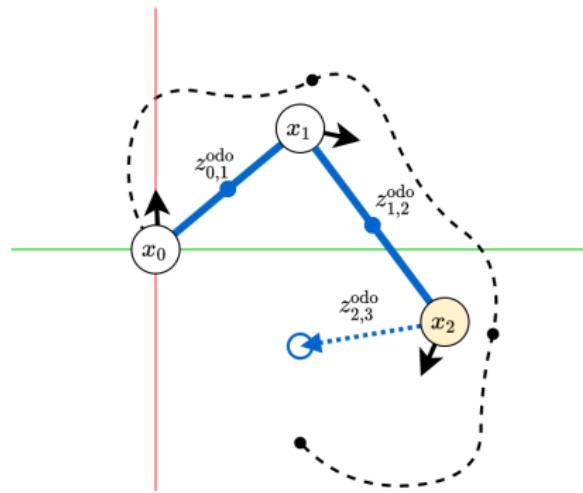
Add odometry constraint:  $z_{1,2}^{\text{odo}}$



# Pose graph optimisation

## Current status

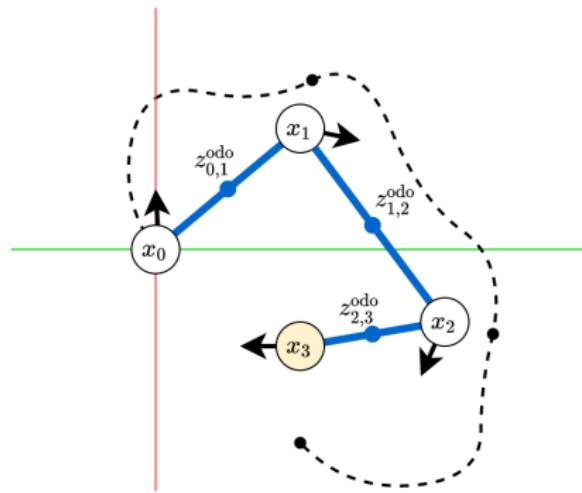
Measure relative pose transformation:  $x_3 - x_2$



# Pose graph optimisation

## Current status

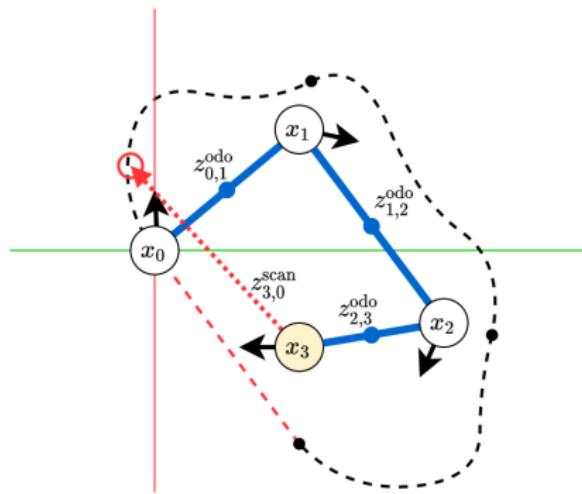
Add odometry constraint:  $z_{2,3}^{\text{odo}}$



# Pose graph optimisation

## Current status

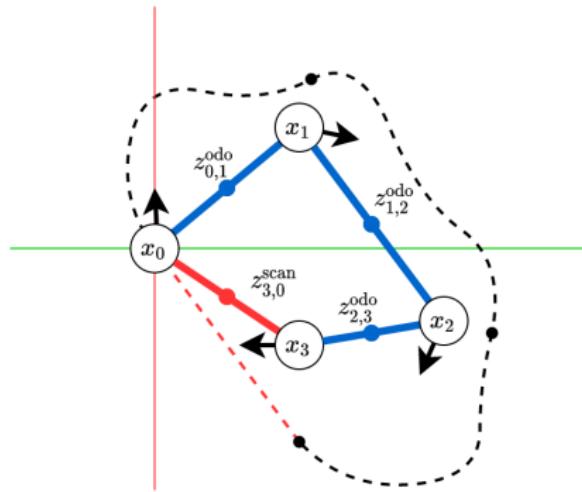
Measure relative pose transformation:  $x_0 - x_3$



# Pose graph optimisation

## Current status

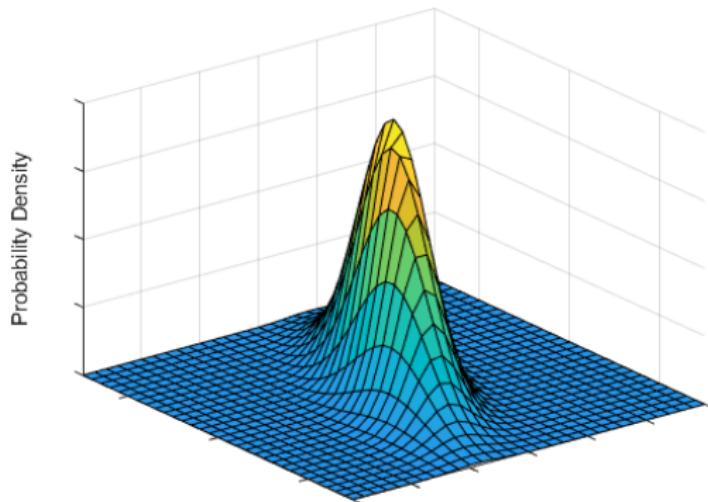
Add scan-matching constraint:  $z_{3,0}^{\text{scan}}$



# Pose graph optimisation

Current status

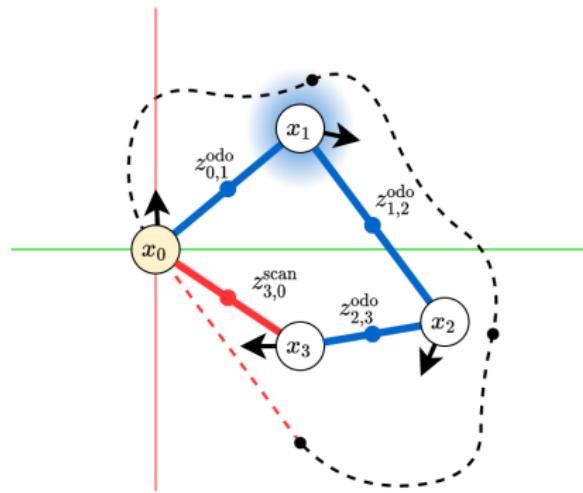
Gaussian probability distribution



# Pose graph optimisation

## Current status

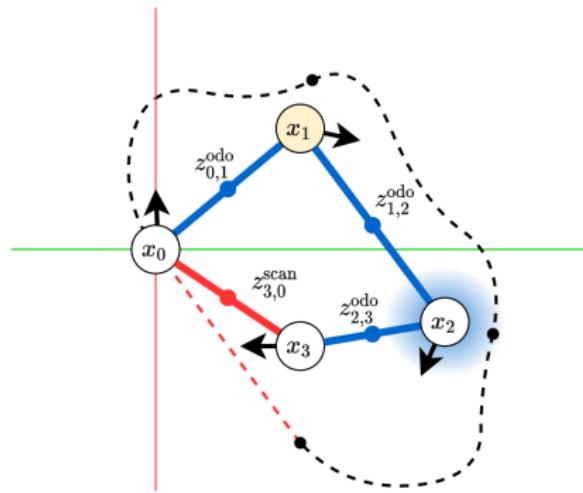
Probability of  $x_1$  due to  $z_{0,1}^{\text{odo}}$



# Pose graph optimisation

## Current status

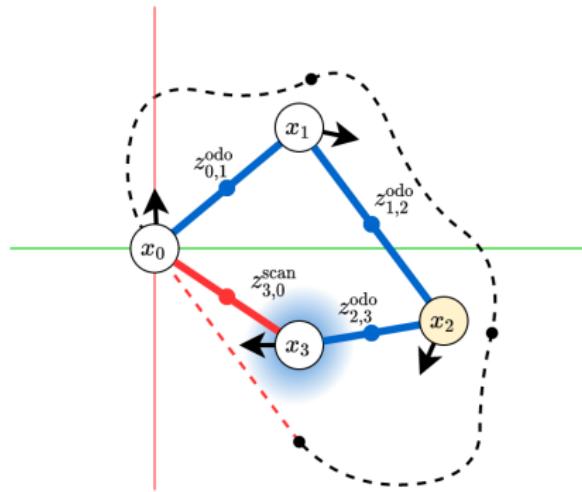
Probability of  $x_2$  due to  $z_{1,0}^{\text{odo}}$



# Pose graph optimisation

## Current status

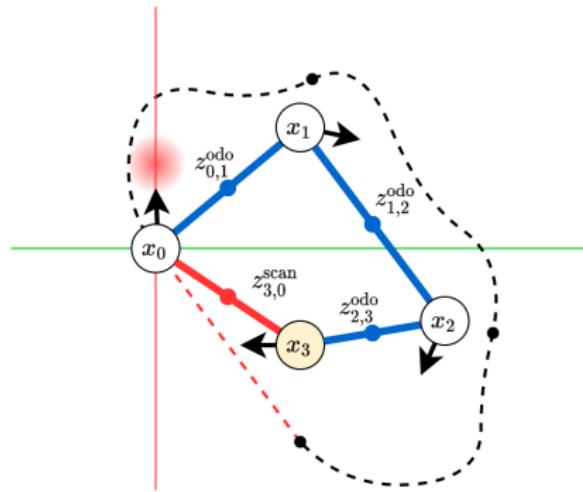
Probability of  $x_3$  due to  $z_{2,1}^{\text{odo}}$



# Pose graph optimisation

## Current status

Probability of  $x_0$  due to  $z_{3,0}^{\text{scan}}$



# Pose graph optimisation

## Cost function

Penalise unlikely pose configurations:

$$\mathbf{e}_{0,1}^{\text{odo}}(x_0, x_1) = \underbrace{f_{0,1}^{\text{odo}}(x_0, x_1)}_{\text{measurement model}} - z_{1,2}^{\text{odo}}$$

# Pose graph optimisation

## Cost function

Penalise unlikely pose configurations:

$$\mathbf{e}_{0,1}^{\text{odo}}(x_0, x_1) = \underbrace{f_{0,1}^{\text{odo}}(x_0, x_1)}_{\text{measurement model}} - z_{1,2}^{\text{odo}}$$

Scale with inverse covariance:

$$F_{0,1}^{\text{odo}}(x_0, x_1) = \|\mathbf{e}_{0,1}^{\text{odo}}(x_0, x_1)\|_{\Sigma_{1,2}^{\text{odo}}}^2$$

# Pose graph optimisation

## Cost function

Penalise unlikely pose configurations:

$$\mathbf{e}_{0,1}^{\text{odo}}(x_0, x_1) = \underbrace{f_{0,1}^{\text{odo}}(x_0, x_1)}_{\text{measurement model}} - z_{1,2}^{\text{odo}}$$

Scale with inverse covariance:

$$F_{0,1}^{\text{odo}}(x_0, x_1) = \|\mathbf{e}_{0,1}^{\text{odo}}(x_0, x_1)\|_{\Sigma_{1,2}^{\text{odo}}}^2$$

Summate error terms over all measurements (with indices  $\mathcal{I}$ ):

$$F_{\text{pgo}}(\mathcal{X}) = F_{0,1}^{\text{odo}}(x_0, x_1) + F_{1,2}^{\text{odo}}(x_1, x_2) + F_{2,3}^{\text{odo}}(x_2, x_3) + F_{3,0}^{\text{scan}}(x_3, x_0)$$

# Pose graph optimisation

## Cost function

Penalise unlikely pose configurations:

$$\mathbf{e}_{0,1}^{\text{odo}}(x_0, x_1) = \underbrace{f_{0,1}^{\text{odo}}(x_0, x_1)}_{\text{measurement model}} - z_{1,2}^{\text{odo}}$$

Scale with inverse covariance:

$$F_{0,1}^{\text{odo}}(x_0, x_1) = \|\mathbf{e}_{0,1}^{\text{odo}}(x_0, x_1)\|_{\Sigma_{1,2}^{\text{odo}}}^2$$

Summate error terms over all measurements (with indices  $\mathcal{I}$ ):

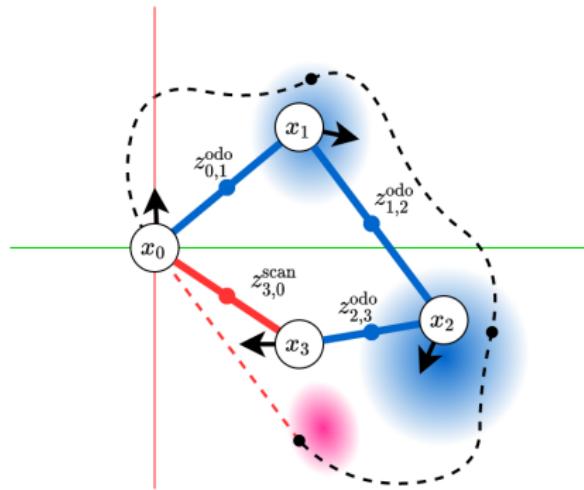
$$F_{\text{pgo}}(\mathcal{X}) = F_{0,1}^{\text{odo}}(x_0, x_1) + F_{1,2}^{\text{odo}}(x_1, x_2) + F_{2,3}^{\text{odo}}(x_2, x_3) + F_{3,0}^{\text{scan}}(x_3, x_0)$$

$$\mathcal{X}^* = \arg \min_{\mathcal{X}} F_{\text{pgo}}(\mathcal{X})$$

# Pose graph optimisation

Current status

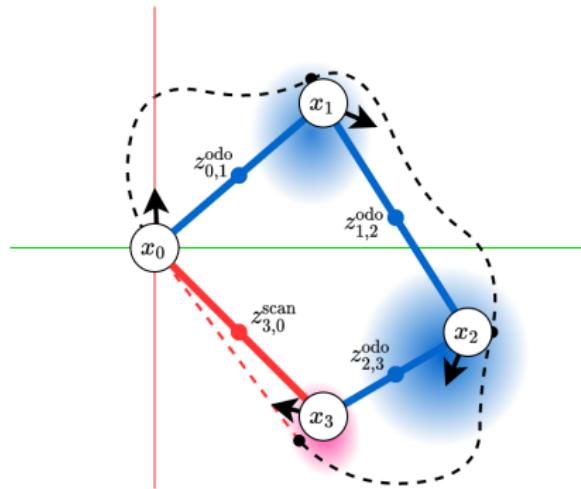
Probability of  $\mathcal{X}$



# Pose graph optimisation

Current status

Optimise pose graph to find  $\mathcal{X}^* = \arg \min_{\mathcal{X}} F_{\text{pgo}}(\mathcal{X})$



# Outline

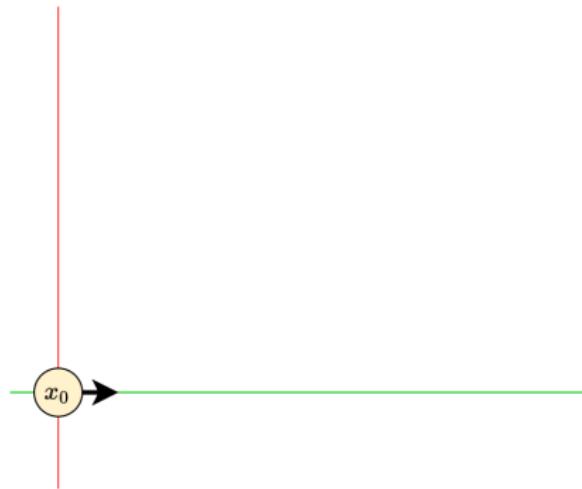
- ① Introduction
- ② Pose graph optimisation
- ③ Pose-parameter graph optimisation
  - Motivation
  - Research
  - Parameters
  - Connectivity
- ④ Conclusion
- ⑤ Recommendations

# Pose-parameter graph optimisation — Motivation

# Pose-parameter graph optimisation — Motivation

## Current status

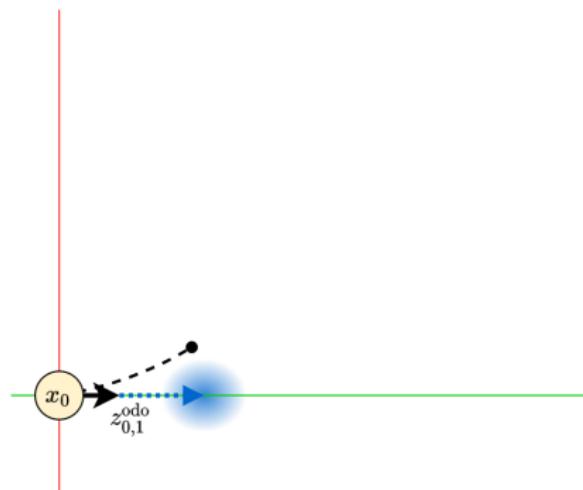
Fix first pose at origin:  $x_0 = (0, 0, 0)$



# Pose-parameter graph optimisation — Motivation

Current status

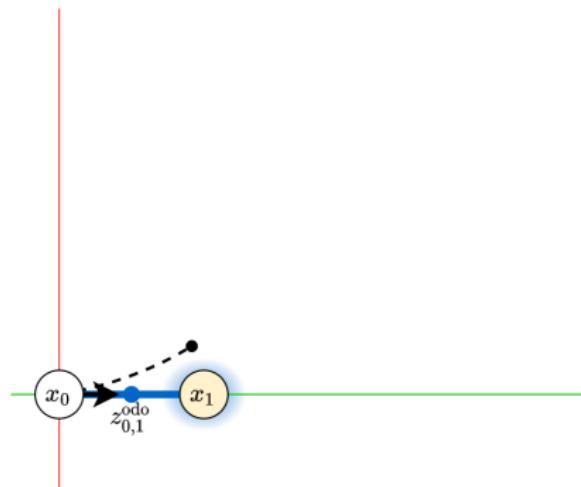
Measure relative pose transformation:  $x_1 - x_0$



# Pose-parameter graph optimisation — Motivation

## Current status

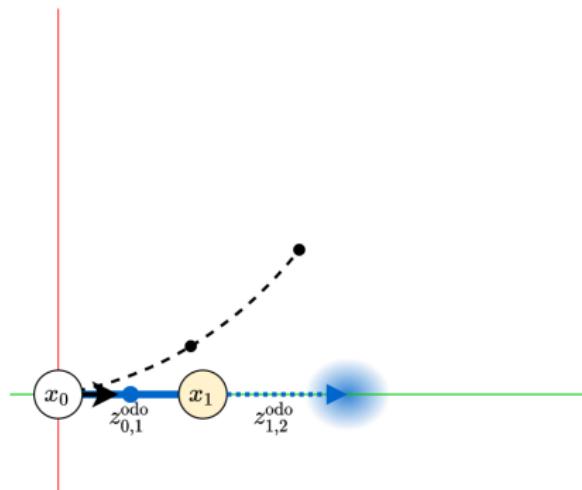
Add odometry constraint:  $z_{0,1}^{\text{odo}}$



# Pose-parameter graph optimisation — Motivation

Current status

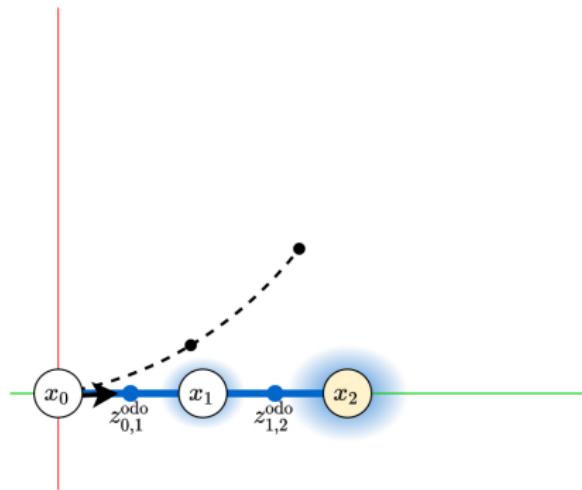
Measure relative pose transformation:  $x_2 - x_1$



# Pose-parameter graph optimisation — Motivation

## Current status

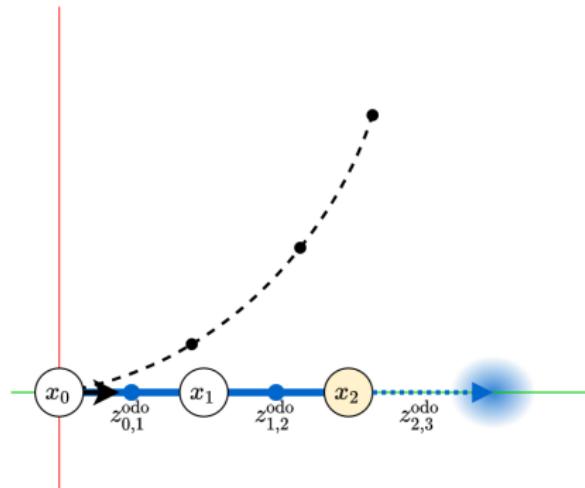
Add odometry constraint:  $z_{1,2}^{\text{odo}}$



# Pose-parameter graph optimisation — Motivation

## Current status

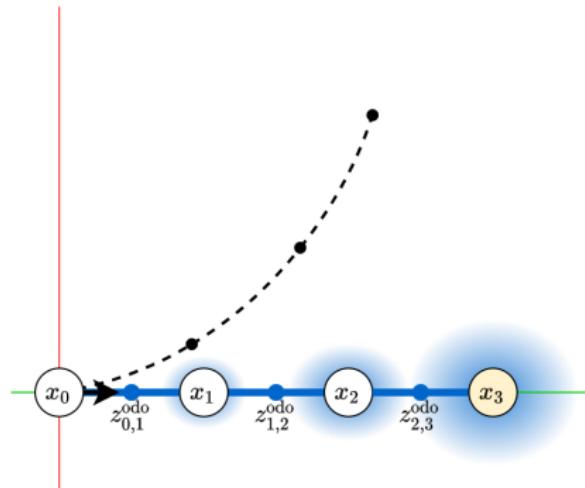
Measure relative pose transformation:  $x_3 - x_2$



# Pose-parameter graph optimisation — Motivation

Current status

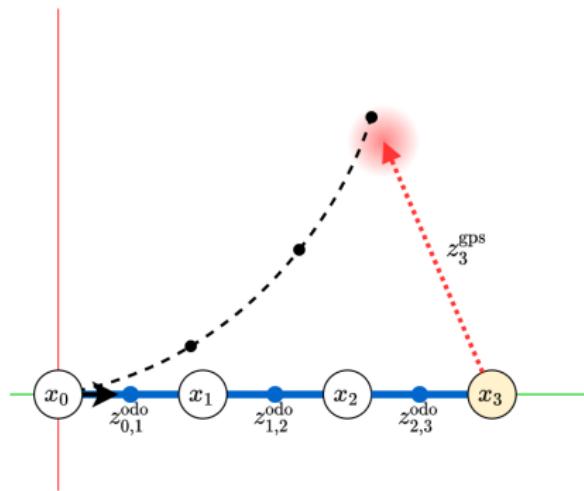
Add odometry constraint:  $z_{2,3}^{\text{odo}}$



# Pose-parameter graph optimisation — Motivation

Current status

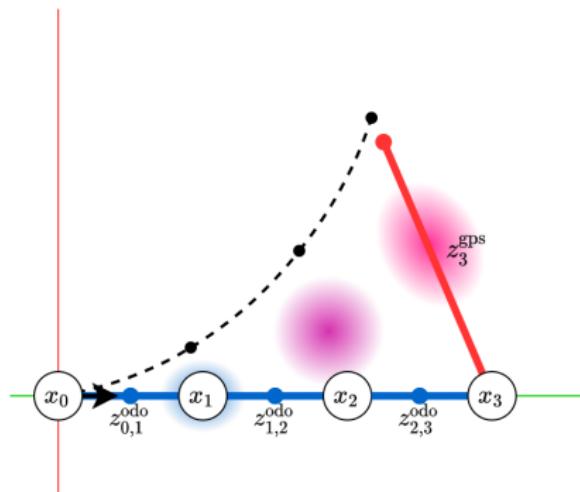
Measure absolute pose transformation:  $x_3$



# Pose-parameter graph optimisation — Motivation

Current status

Add GPS constraint:  $z_3^{\text{gps}}$



# Pose-parameter graph optimisation — Motivation

## Example

Example of error due to rotation bias

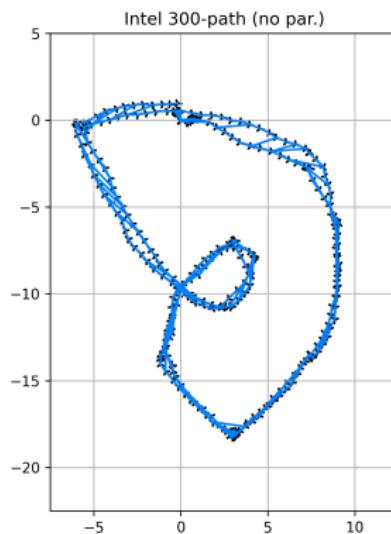
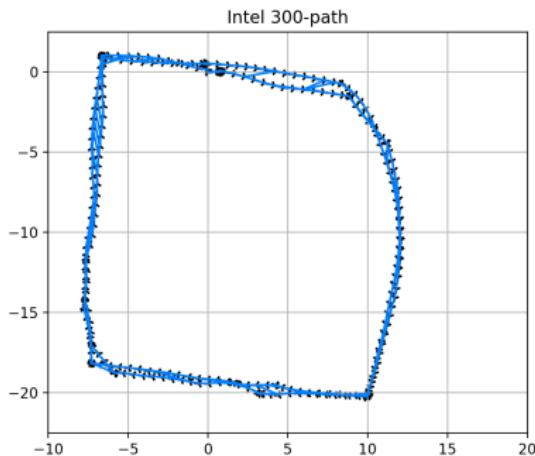


Figure: Intel dataset without and with rotation bias

# Pose-parameter graph optimisation — Motivation

## Possible solution

- ① Add bias component to measurement model

# Pose-parameter graph optimisation — Motivation

## Possible solution

- ① Add bias component to measurement model
- ② Include bias parameter as a graph node

# Pose-parameter graph optimisation — Motivation

## Possible solution

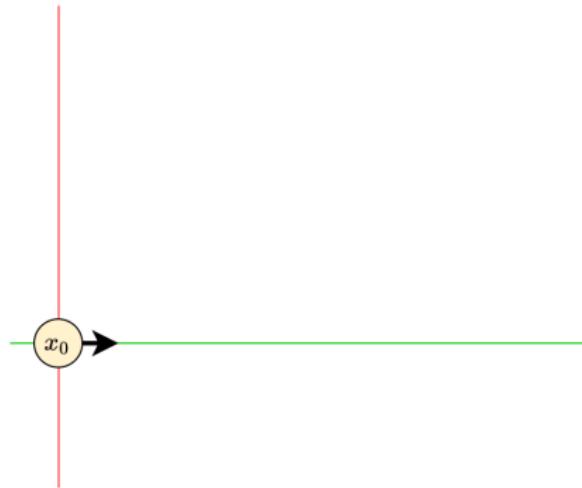
- ① Add bias component to measurement model
- ② Include bias parameter as a graph node

Proposed method: *Pose-parameter graph optimisation* (PPGO)

# Pose-parameter graph optimisation — Motivation

## Current status

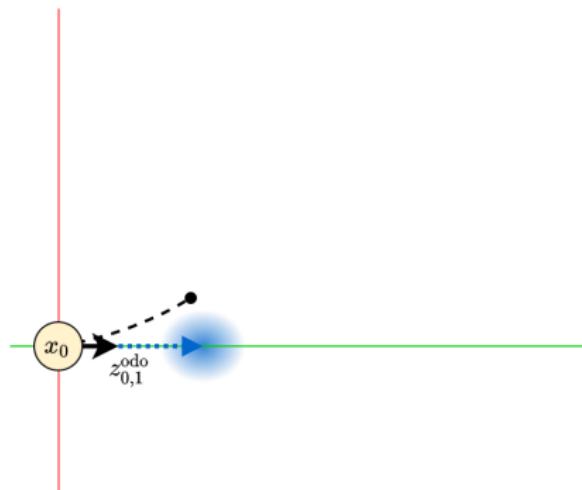
Fix first pose at origin:  $x_0 = (0, 0, 0)$



# Pose-parameter graph optimisation — Motivation

## Current status

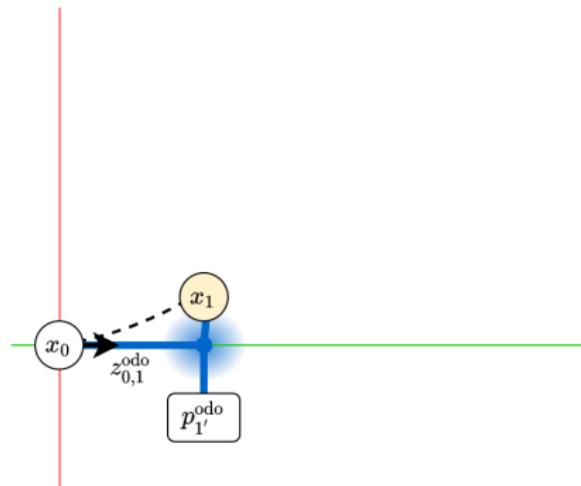
Measure relative pose transformation:  $x_1 - x_0$



# Pose-parameter graph optimisation — Motivation

## Current status

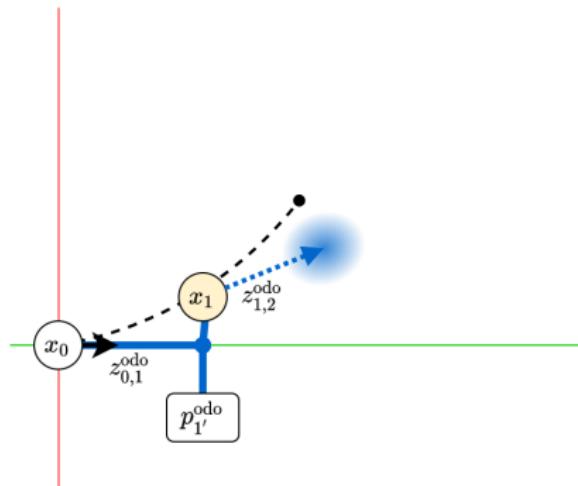
Add odometry constraint:  $z_{0,1}^{\text{odo}}$



# Pose-parameter graph optimisation — Motivation

## Current status

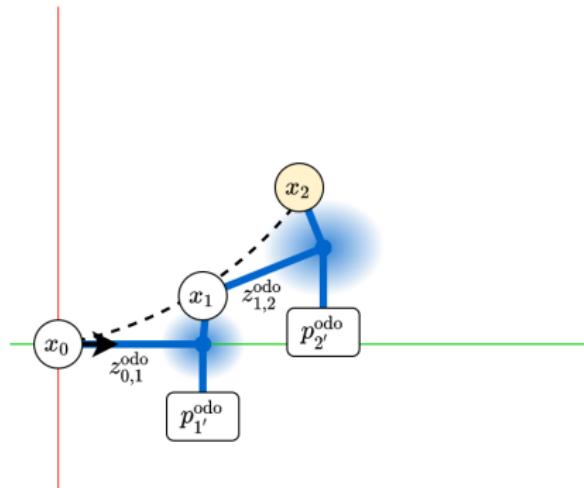
Measure relative pose transformation:  $x_2 - x_1$



# Pose-parameter graph optimisation — Motivation

## Current status

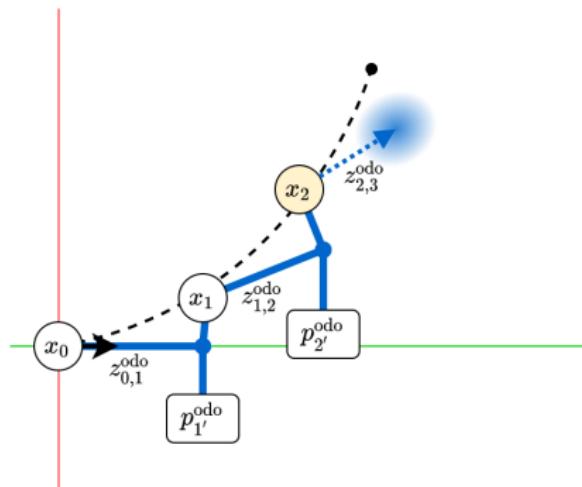
Add odometry constraint:  $z_{1,2}^{\text{odo}}$



# Pose-parameter graph optimisation — Motivation

## Current status

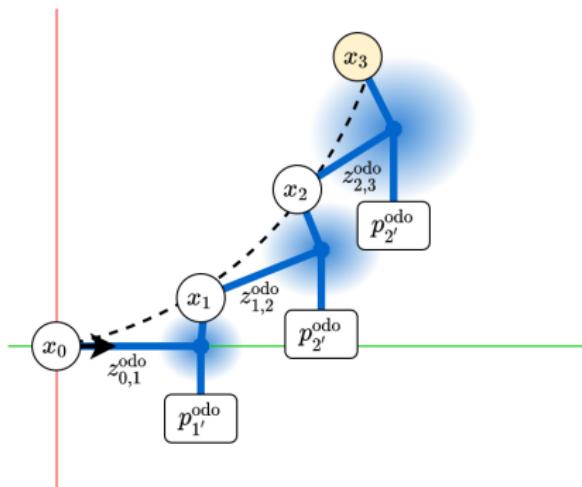
Measure relative pose transformation:  $x_3 - x_2$



# Pose-parameter graph optimisation — Motivation

## Current status

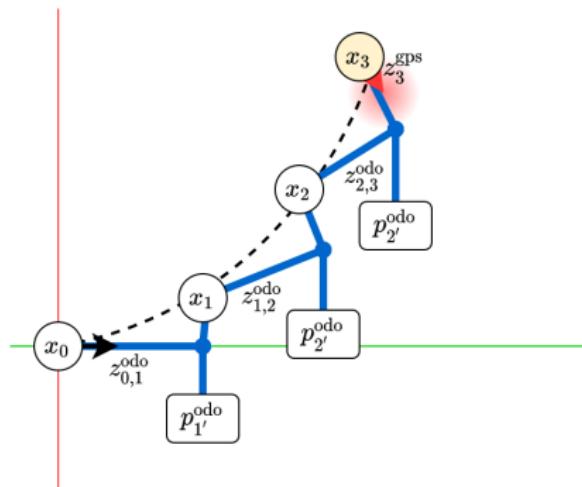
Add odometry constraint:  $z_{2,3}^{\text{odo}}$



# Pose-parameter graph optimisation — Motivation

## Current status

Measure absolute pose transformation:  $x_3$



# Pose-parameter graph optimisation — Motivation

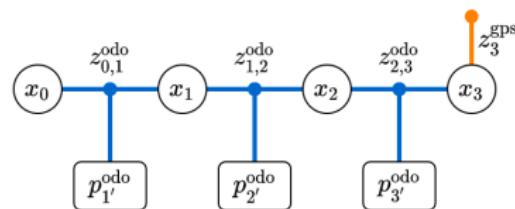


Figure: Schematic pose-parameter graph

# Pose-parameter graph optimisation — Motivation

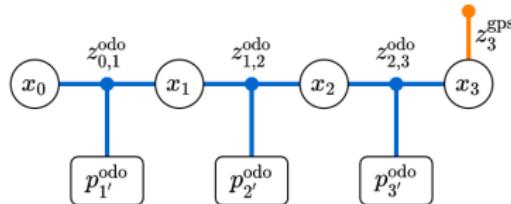


Figure: Schematic pose-parameter graph

## Under-constrained problem

- 4 equations (constraints/measurements)
- 6 unknowns (non-fixed nodes)

# Pose-parameter graph optimisation — Motivation

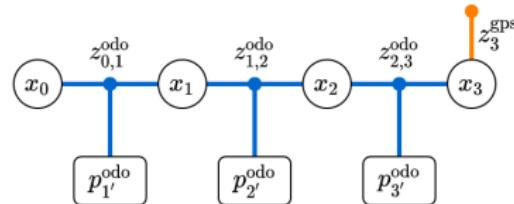


Figure: Schematic pose-parameter graph

## Under-constrained problem

- 4 equations (constraints/measurements)
- 6 unknowns (non-fixed nodes)

We need alternative *connectivity strategies*!

# Pose-parameter graph optimisation — Motivation

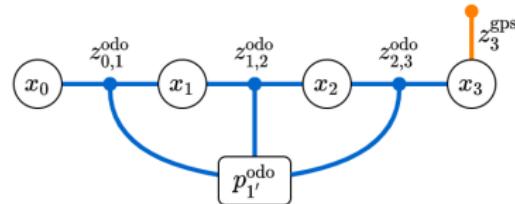


Figure: Schematic pose-parameter graph

## Feasible problem

- 4 equations (constraints/measurements)
- 4 unknowns (non-fixed nodes)

# Pose-parameter graph optimisation — Motivation

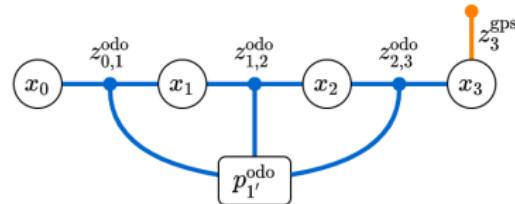


Figure: Schematic pose-parameter graph

## Feasible problem

- 4 equations (constraints/measurements)
- 4 unknowns (non-fixed nodes)

*Static connectivity strategy for constant parameters*

## Aim of this thesis

- Develop simulation framework and pose-parameter graph analysis framework
- Investigate parameter implementations
- Investigate connectivity strategies for:
  - Time-dependent parameters
  - Space-dependent parameters

## Aim of this thesis

- Develop simulation framework and pose-parameter graph analysis framework
- Investigate parameter implementations
- Investigate connectivity strategies for:
  - Time-dependent parameters
  - Space-dependent parameters

## Aim of this thesis

- Develop simulation framework and pose-parameter graph analysis framework
- Investigate parameter implementations
- Investigate connectivity strategies for:
  - Time-dependent parameters
  - Space-dependent parameters

## Aim of this thesis

- Develop simulation framework and pose-parameter graph analysis framework
- Investigate parameter implementations
- Investigate connectivity strategies for:
  - Time-dependent parameters
  - Space-dependent parameters

# Pose-parameter graph optimisation — Research

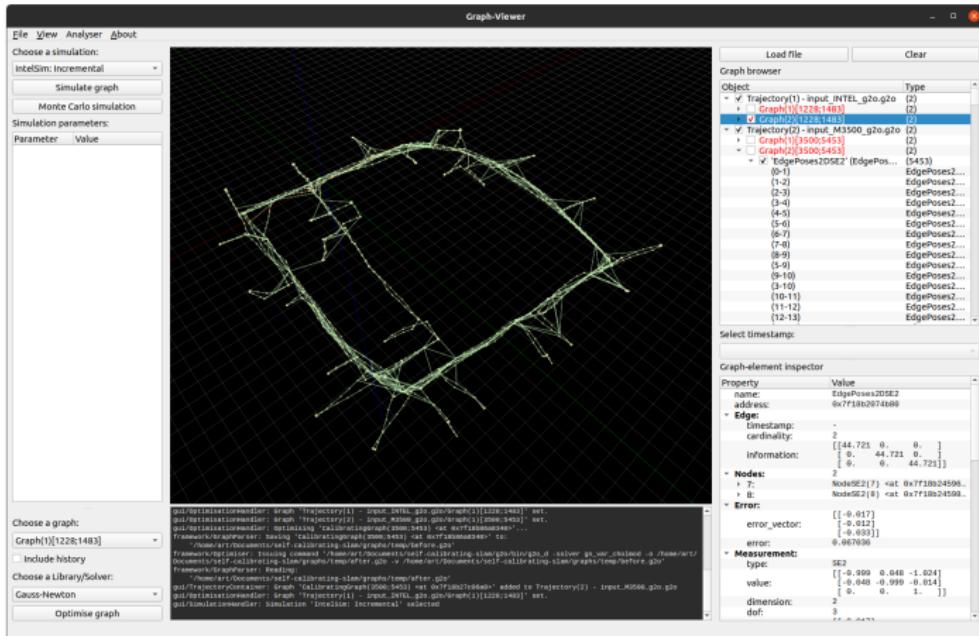


Figure: Software framework GUI

## Performance metrics

- *Absolute Trajectory Error* (ATE): average absolute translation error over all poses
- *Relative Pose Error* (RPE): average relative translation/rotation error over all poses

## Pose-parameter graph optimisation — Parameters

# Pose-parameter graph optimisation — Parameters

## *Bias* parameter

$$f_{i,j,k}^{\text{bias}}(x_i, x_j, p_k) = f_{i,j}(x_i, x_j) + p_k$$

# Pose-parameter graph optimisation — Parameters

*Bias* parameter

$$f_{i,j,k}^{\text{bias}}(x_i, x_j, p_k) = f_{i,j}(x_i, x_j) + p_k$$

*Scaling factor* parameter

$$f_{i,j,k}^{\text{scale}}(x_i, x_j, p_k) = p_k \odot f_{i,j}(x_i, x_j)$$

# Pose-parameter graph optimisation — Parameters

## *Bias* parameter

$$f_{i,j,k}^{\text{bias}}(x_i, x_j, p_k) = f_{i,j}(x_i, x_j) + p_k$$

## *Scaling factor* parameter

$$f_{i,j,k}^{\text{scale}}(x_i, x_j, p_k) = p_k \odot f_{i,j}(x_i, x_j)$$

The combination can model any affine parameter influence!

# Pose-parameter graph optimisation — Connectivity

## Time-dependent parameters

- *Sliding window* connectivity strategy
- *Timely batch* connectivity strategy

# Pose-parameter graph optimisation — Connectivity

## Time-dependent parameters

- *Sliding window* connectivity strategy
- *Timely batch* connectivity strategy

## Space-dependent parameters

- *Spatial batch* connectivity strategy

# Pose-parameter graph optimisation — Connectivity

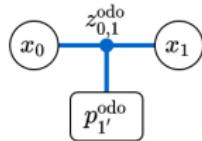
*Sliding window* connectivity strategy

Connect only recent constraints a single parameter-node

# Pose-parameter graph optimisation — Connectivity

*Sliding window connectivity strategy*

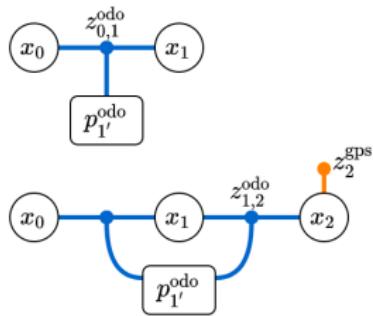
Connect only recent constraints a single parameter-node



# Pose-parameter graph optimisation — Connectivity

*Sliding window connectivity strategy*

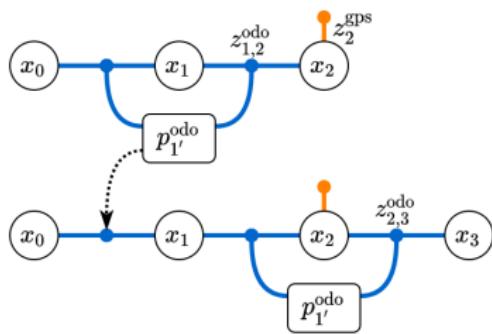
Connect only recent constraints a single parameter-node



# Pose-parameter graph optimisation — Connectivity

*Sliding window connectivity strategy*

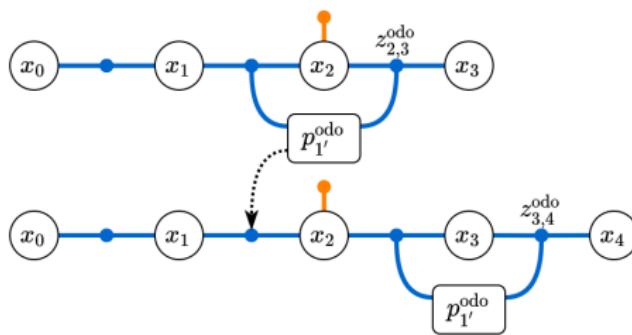
Connect only recent constraints a single parameter-node



# Pose-parameter graph optimisation — Connectivity

*Sliding window connectivity strategy*

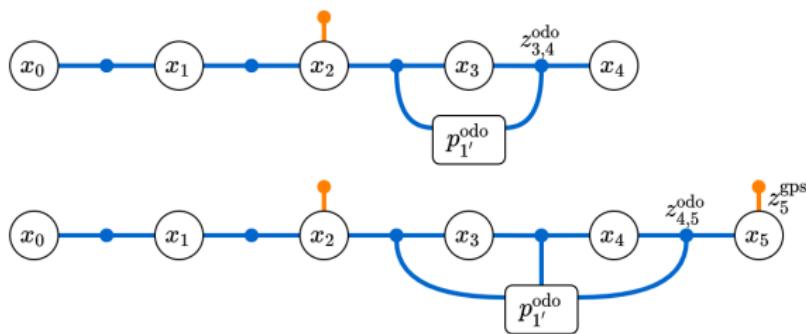
Connect only recent constraints a single parameter-node



# Pose-parameter graph optimisation — Connectivity

*Sliding window connectivity strategy*

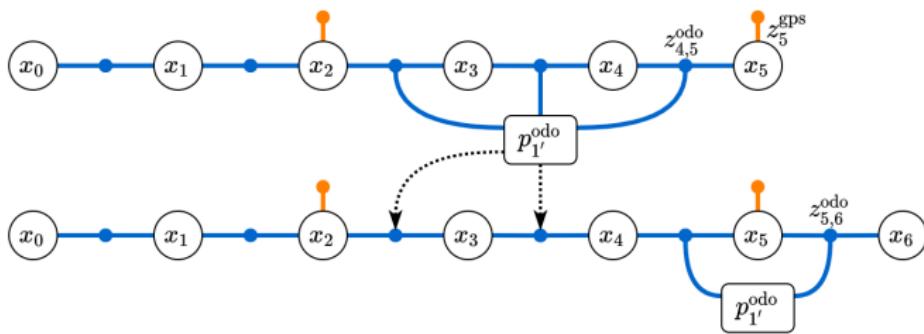
Connect only recent constraints a single parameter-node



# Pose-parameter graph optimisation — Connectivity

*Sliding window connectivity strategy*

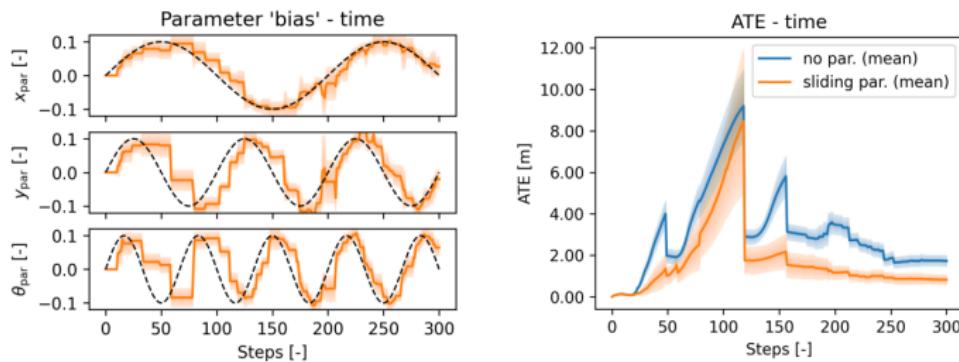
Connect only recent constraints a single parameter-node



# Pose-parameter graph optimisation — Connectivity

*Sliding window connectivity strategy*

Connect only recent constraints a single parameter-node



**Figure:** Sinusoidal bias parameter on Intel data set

# Pose-parameter graph optimisation — Connectivity

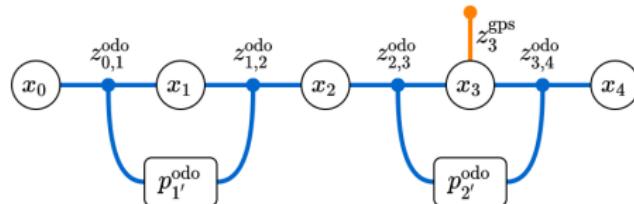
*Timely batch* connectivity strategy

Allocate constraints in time-related batches

# Pose-parameter graph optimisation — Connectivity

*Timely batch connectivity strategy*

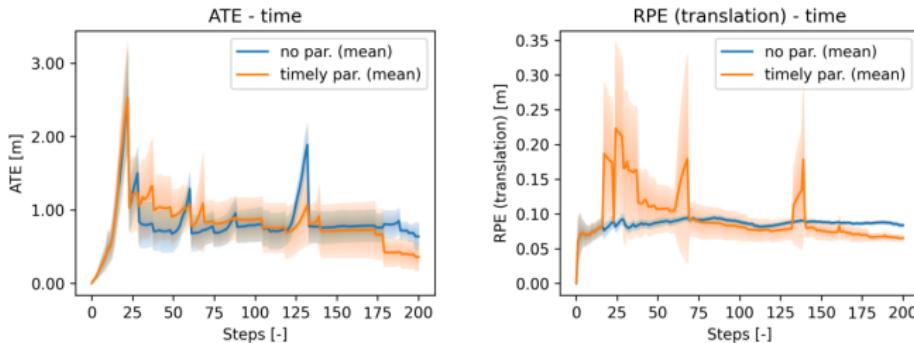
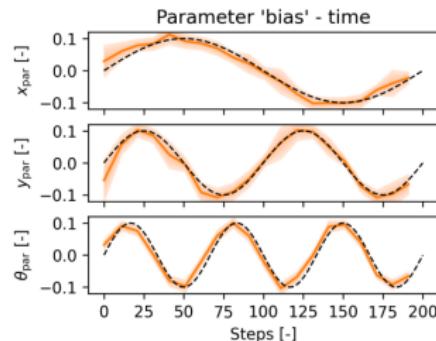
Allocate constraints in time-related batches



# Pose-parameter graph optimisation — Connectivity

*Timely batch connectivity strategy*

Allocate constraints in time-related batches



# Pose-parameter graph optimisation — Connectivity

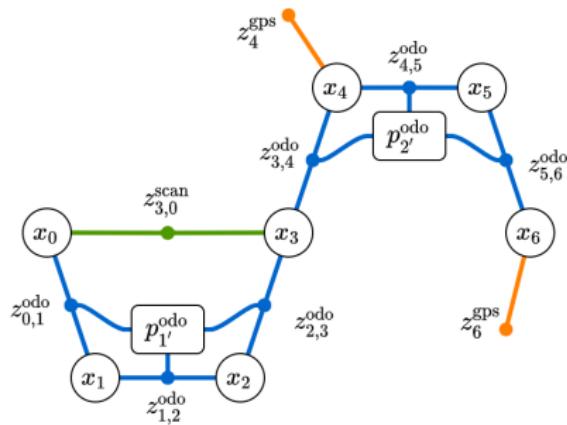
*Spatial batch* connectivity strategy

Allocate constraints in space-related batches

# Pose-parameter graph optimisation — Connectivity

## Spatial batch connectivity strategy

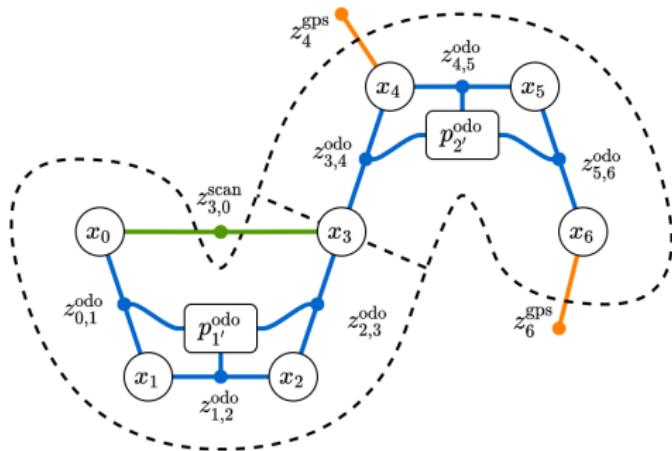
Allocate constraints in space-related batches



# Pose-parameter graph optimisation — Connectivity

## Spatial batch connectivity strategy

Allocate constraints in space-related batches



# Pose-parameter graph optimisation — Connectivity

## *Spatial batch connectivity strategy*

Allocate constraints in space-related batches

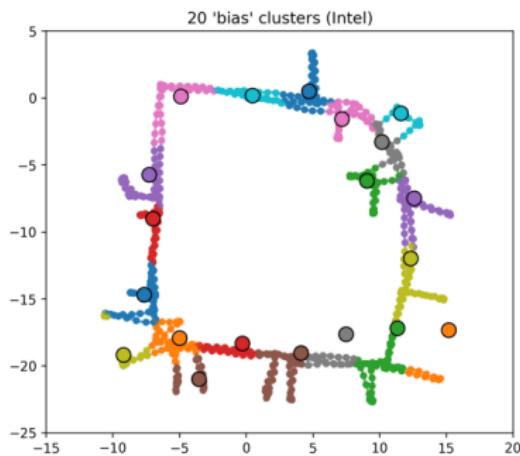
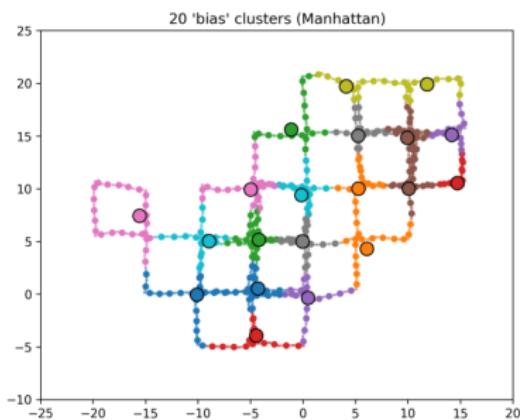


Figure: Constraint-to-batch allocation on Manhattan grid and Intel data set

# Pose-parameter graph optimisation — Connectivity

## *Spatial batch connectivity strategy*

Allocate constraints in space-related batches

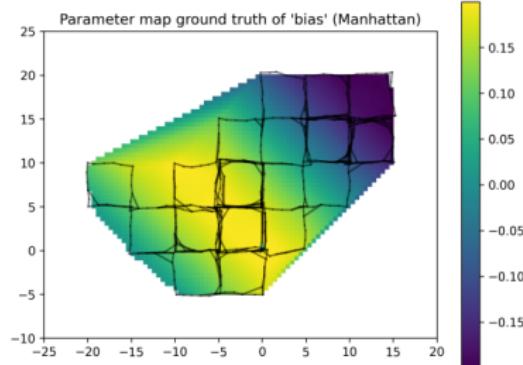
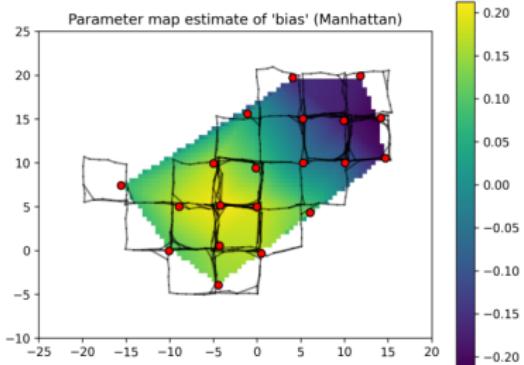


Figure: Sinusoidal parameter interpolated estimate on Manhattan grid

# Outline

- ① Introduction
- ② Pose graph optimisation
- ③ Pose-parameter graph optimisation
  - Motivation
  - Research
  - Parameters
  - Connectivity
- ④ Conclusion
- ⑤ Recommendations

# Conclusion

# Conclusion

Parameter implementations

Bias parameter and scaling factor parameter are reconstructable

# Conclusion

## Parameter implementations

Bias parameter and scaling factor parameter are reconstructable

## Time-dependent parameters

- Sliding window connectivity strategy provides instantaneous parameter estimate (with slight delay)
- Timely batch connectivity strategy best applied as post-processing step

# Conclusion

## Parameter implementations

Bias parameter and scaling factor parameter are reconstructable

## Time-dependent parameters

- Sliding window connectivity strategy provides instantaneous parameter estimate (with slight delay)
- Timely batch connectivity strategy best applied as post-processing step

All implementations improve accuracy!

# Conclusion

## Parameter implementations

Bias parameter and scaling factor parameter are reconstructable

## Time-dependent parameters

- Sliding window connectivity strategy provides instantaneous parameter estimate (with slight delay)
- Timely batch connectivity strategy best applied as post-processing step

All implementations improve accuracy!

## Space-dependent parameters

Spatial batch connectivity strategy is able to reconstruct space-dependent parameters and improve accuracy

# Outline

- ① Introduction
- ② Pose graph optimisation
- ③ Pose-parameter graph optimisation
  - Motivation
  - Research
  - Parameters
  - Connectivity
- ④ Conclusion
- ⑤ Recommendations

# Recommendations

# Recommendations

Validate results

Validate results with real-world experiments

# Recommendations

Validate results

Validate results with real-world experiments

Investigate unique parameter-nodes

Solve the under-constrained optimisation problem by relating parameter-nodes with random-walk constraints.

# Recommendations

Validate results

Validate results with real-world experiments

Investigate unique parameter-nodes

Solve the under-constrained optimisation problem by relating parameter-nodes with random-walk constraints.

Investigate combinations of parameters

Investigate e.g. the combination of bias and scaling factor

# Questions?