Final Presentation Master Thesis

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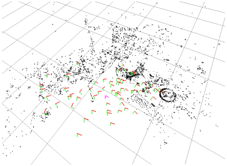
Outline

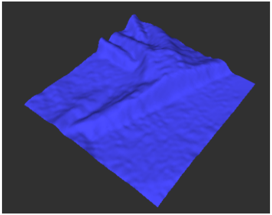
Dense SLAM with B-Splines

Motivation

Sparse SLAM (PTAM, [1])



Dense SLAM (DTAM, [2])



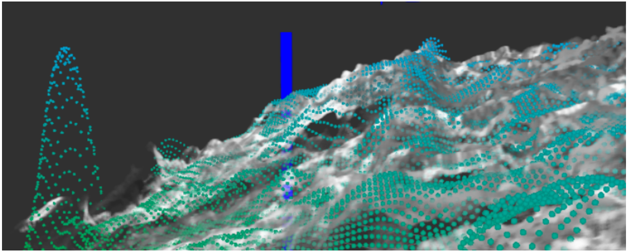
Dense SLAM with Splines [3]

Visual Terrain Estimation For Legged Robots

Project Goals

Create framework for surface reconstruction and localization using moving stereo camera

- Createing spline surface reprensentation from static stereo camera.
- Localizing new stereo camera position using obtained map.

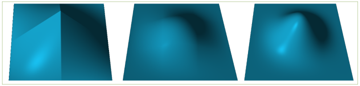


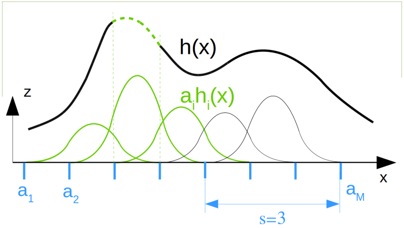
Visual Terrain Estimation For Legged Robots
Methodology

- **Simulation environment**: `ROS` with `rviz` for pointcloud and `opencv` for image handling.
- **Optimization**: own implementation of optimization algorithm using `Eigen` 's sparse matrix solvers.
- **Hardware**: `rovio` sensor for stereo camera data, *MacBook Pro* with Intel Core 2.7MHz, 4 cores.

B-Splines for Surface Representation
Methods

Splines: piecewise polynomial function of degree $<d$.
B(asis)-Splines: Specific choice of finite-support splines for basis.

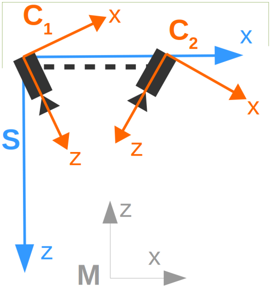




$$h(x_j) = \sum_{i=0}^{M} a_i h_i(x_j)$$
$$= \sum_{i=k}^{k+s} a_i h_i(x_j), \text{ for } j = 1 \dots N$$

Stereo Camera Setup

Methods



Camera poses described by ${}_M\boldsymbol{r}_{MC_k}$ and $\boldsymbol{C}_{C_kM}$ for $k = 1, 2$ or

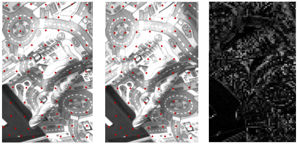
$$\boldsymbol{\xi}_{C_k} := \left[{}_M\boldsymbol{r}_{MC_k}, \boldsymbol{\Phi}_{C_kM}\right]^T$$

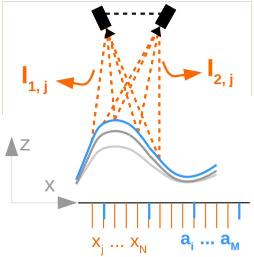
$$\boldsymbol{\xi}_{S} := \left[{}_M\boldsymbol{r}_{MS}, \boldsymbol{\Phi}_{SM}\right]^T$$

with $\boldsymbol{\Phi}_{C_kM}$, $\boldsymbol{\Phi}_{SM} \in \mathbb{R}^3$ [4]

Relative position of $\{\boldsymbol{\xi}_{C_1}, \boldsymbol{\xi}_{C_2}, \boldsymbol{\xi}_S\}$ stays fixed.

Photometric errors for mapping
Methods





Photometric error of grid point x_j, y_j:

$$r_j = I_1(\boldsymbol{u}_{j,1}) - I_2(\boldsymbol{u}_{j,2}) \ ,$$

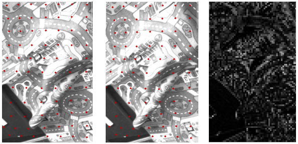
with I_1, I_2 interpolated intensities at the locations $\boldsymbol{u}_{j,k}$ in camera $k = 1$ and $k = 2$.

$$\boldsymbol{u}_{j,k} = \boldsymbol{K}_k D_k(\boldsymbol{T}_k({}_M\boldsymbol{r}_{MX_j})))$$
$$\boldsymbol{T}_k({}_M\boldsymbol{r}_{MX_j}) = \boldsymbol{\pi}(\boldsymbol{C}_{C_kM}({}_M\boldsymbol{r}_{MX_j} - {}_M\boldsymbol{r}_{MC_k}))$$

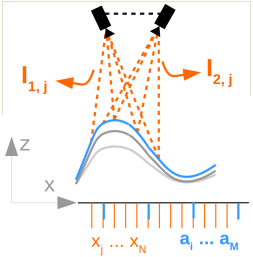
3D point given by spline map:

$${}_M\boldsymbol{r}_{MX_j} = \left[x_j, y_j, h(x_j, y_j)\right]^T$$

Photometric errors for mapping
Methods



$$\boldsymbol{J}_r(\boldsymbol{a}) = \frac{\partial \boldsymbol{r}(\boldsymbol{a})}{\partial \boldsymbol{a}} \in \mathbb{R}^{NxM}$$



$$\begin{aligned}\boldsymbol{J}_r(\boldsymbol{a}) = \big(&\boldsymbol{J}_{pixel,1}\boldsymbol{J}_{camera,1}({}_M\boldsymbol{r}_{MX_j}) \\ &- \boldsymbol{J}_{pixel,2}\boldsymbol{J}_{camera,2}({}_M\boldsymbol{r}_{MX_j})\big)\boldsymbol{J}_{splines} \,.\end{aligned}$$

$$\boldsymbol{J}_{pixel,k} = \frac{\partial I_k(\boldsymbol{u}_k)}{\partial \tilde{\boldsymbol{u}}_k}, \quad \boldsymbol{J}_{camera,k}({}_M\boldsymbol{r}_{MX_j}) = \frac{\partial \tilde{\boldsymbol{u}}_k}{\partial {}_M\boldsymbol{r}_{MX_j}}$$

$$\boldsymbol{J}_{splines} = \frac{\partial {}_M\boldsymbol{r}_{MX_j}}{\partial \boldsymbol{a}}$$

Optimization problem for mapping
Methods

$$\hat{\boldsymbol{a}} = \arg\min_{\boldsymbol{a}\in\mathbb{R}^M} f(\boldsymbol{a}) = \arg\min_{\boldsymbol{a}\in\mathbb{R}^M} \frac{1}{2}\Big(\sum_{j=0}^{N} w_j r_j(\boldsymbol{a})^2 + \beta \boldsymbol{a}^T \boldsymbol{B} \boldsymbol{a} + \gamma \boldsymbol{a}^T \boldsymbol{G} \boldsymbol{a}\Big)\ ,$$

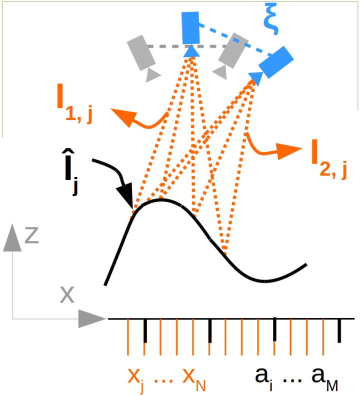
with

- bending and gradient energy regularization terms and
- weight representing the average visibility of point j.

Solved using Gauss-Newton iterations:

$$\boldsymbol{a}_{k+1} = \boldsymbol{a}_k + \alpha_k \mathbf{p}_k^{GN}$$
$$\boldsymbol{J}_f(\boldsymbol{a})^T \boldsymbol{J}_f(\boldsymbol{a}) \mathbf{p}_k^{GN} = -\boldsymbol{J}_f(\boldsymbol{a})^T \mathbf{r}_k(\boldsymbol{a})$$

Photometric errors for localization
Methods

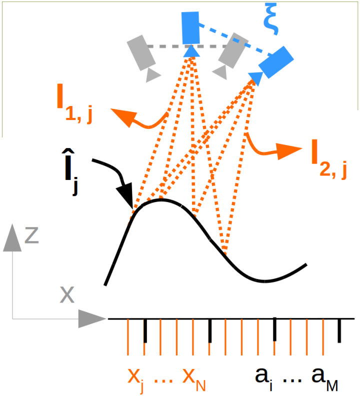


Photometric error of grid point x_j, y_j:

$$r_{j,1} = I_1(\boldsymbol{u}_{j,1}) - \hat{I}(x_j, y_j)$$
$$r_{j,2} = I_2(\boldsymbol{u}_{j,1}) - \hat{I}(x_j, y_j) \ ,$$

with I_1, I_2 interpolated intensities at pixels $\boldsymbol{u}_{j,k}$ in camera $k = 1$ and $k = 2$ and $\hat{I}(x_j, y_j)$ the estimated intensity from previous step.

Photometric errors for localization
Methods



$$J_r(\xi) = \frac{\partial \boldsymbol{r}(\xi)}{\partial \xi} \in \mathbb{R}^{Nx6}$$

$$J_r(\xi) = J_{pixel} J_{camera}(\xi)$$

with

$$J_{pixel} = \frac{\partial I(\boldsymbol{u})}{\partial \tilde{\boldsymbol{u}}}, \quad J_{camera}(\xi) = \frac{\partial \tilde{\boldsymbol{u}}}{\partial \xi}$$

Optimization problem for localization

Methods

$$\hat{\boldsymbol{\xi}} = \underset{\hat{\boldsymbol{\xi}} \in \mathbb{R}^6}{\arg\min} \frac{1}{2} \sum_{j=0}^{N} r_j(\boldsymbol{\xi})^2$$

Solved using Gauss-Newton iterations:

$$\boldsymbol{\xi}_{k+1} = \boldsymbol{\xi}_k \boxplus \alpha_k \mathbf{p}_k^{GN}$$
$$\boldsymbol{J}_r(\boldsymbol{\xi})^T \boldsymbol{J}_r(\boldsymbol{\xi}) \mathbf{p}_k^{GN} = -\, \boldsymbol{J}_r(\boldsymbol{\xi})^T \mathbf{r}_k(\boldsymbol{\xi})$$

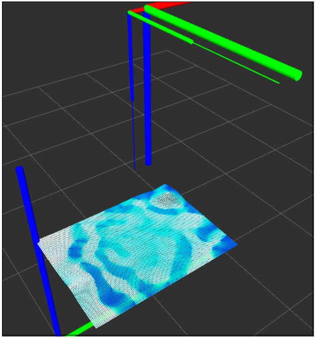
Overview

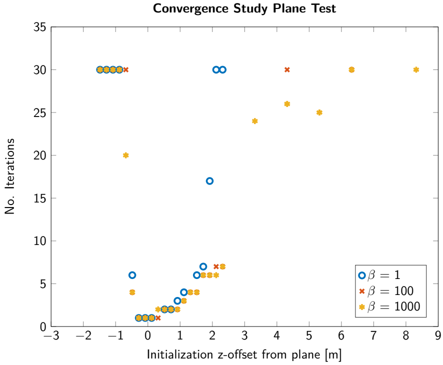
Mapping And Localization Datasets

Dataset	Plane test	Middlebury [5]	Inhouse
Ground truth	analytical	structured light	pattern matching
Images	rectified	rectified	non rectified
Calibration	+++	++	+
Mapping	yes	yes	yes
Localization	yes	no	no
Map dimensions [m]	0.9 x 1.2	1.5 x 2.0	
Spline resolution	20 x 20	75 x 100	
Residuals resolution	90 x 120		

Plane Test

Mapping Results

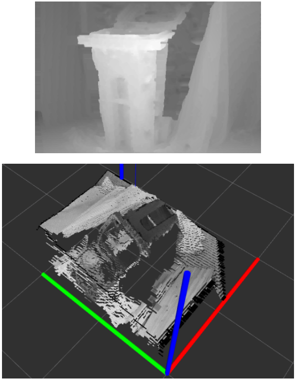




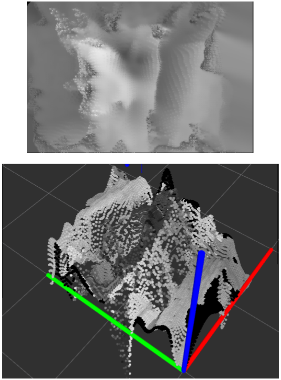
Middlebury Dataset

Mapping Results

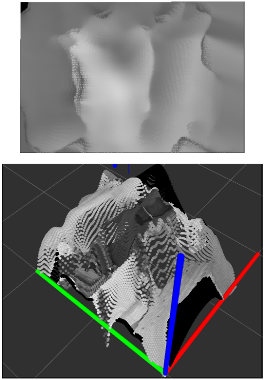
groundtruth



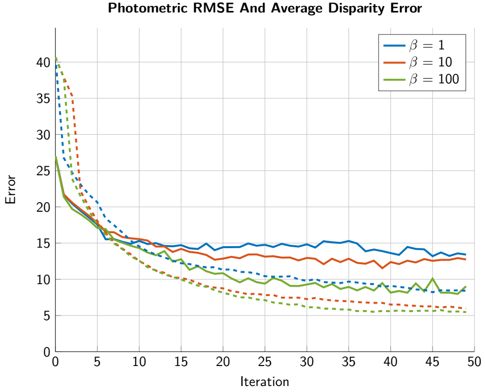
$\beta = 1$

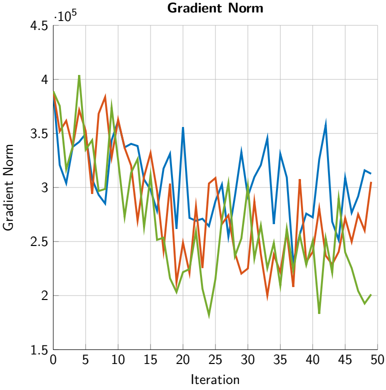


$\beta = 10$



Middlebury Dataset
Mapping Results

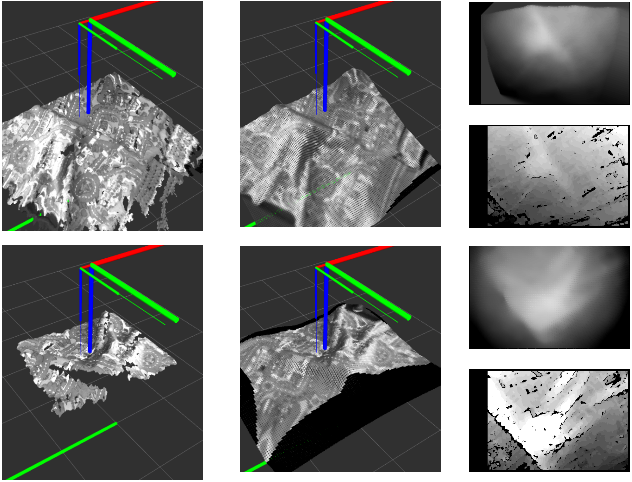




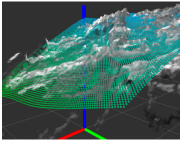
Inhouse Dataset
Mapping Results

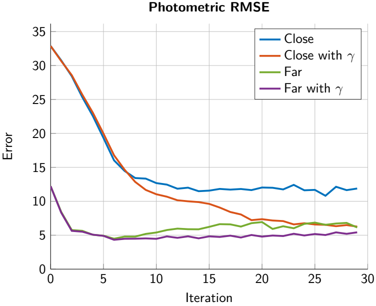
“far ”
$\beta = 10$
$\gamma = 1e6$

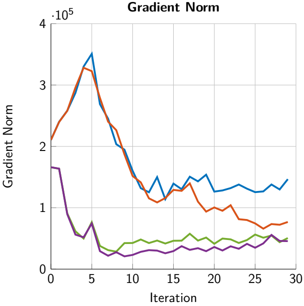
“close”
$\beta = 10$
$\gamma = 1e5$



Inhouse Dataset
Mapping Results

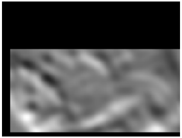


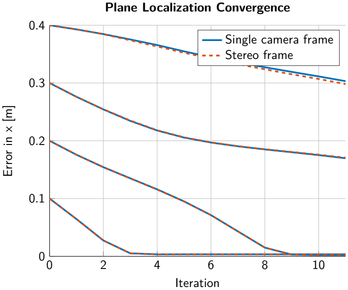


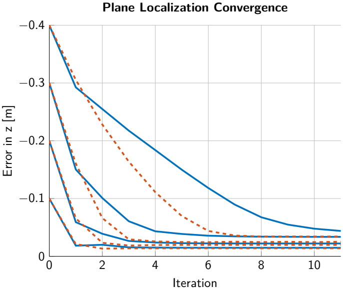


Plane Test

Localization Results







Achievements

- Created versatile `stereo surface reconstruction` package for
  - variable spline degrees and resolution,
  - entirely customizable optimization parameters and
  - rectified and unrectified images.
- Implemented photometric localization algorithm based on one stereo measurement.
- Tested functionalities on real and simulated datasets.

Future Work

- Implement sequence of mapping and localization steps to improve map accuracy by solving recursively over multiple measurements.
- Integrate measurements to extend map and create wider camera baseline.
- Test framework in realistic sceneries.

Questions?

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