

Dense Visual Odometry

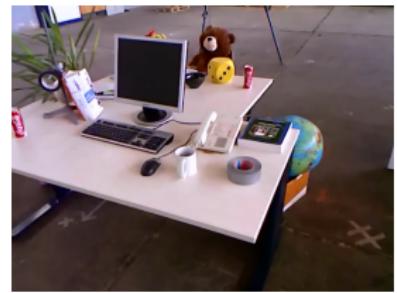
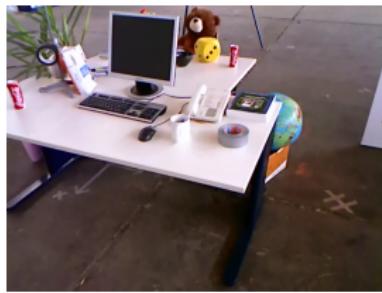
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RGB-Sequence



Depth-Sequence

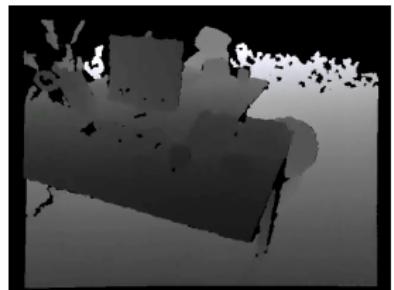
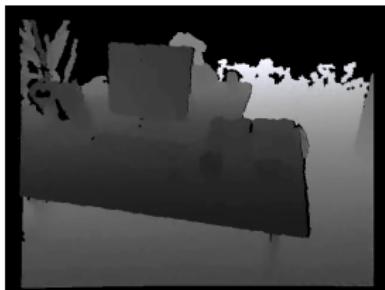
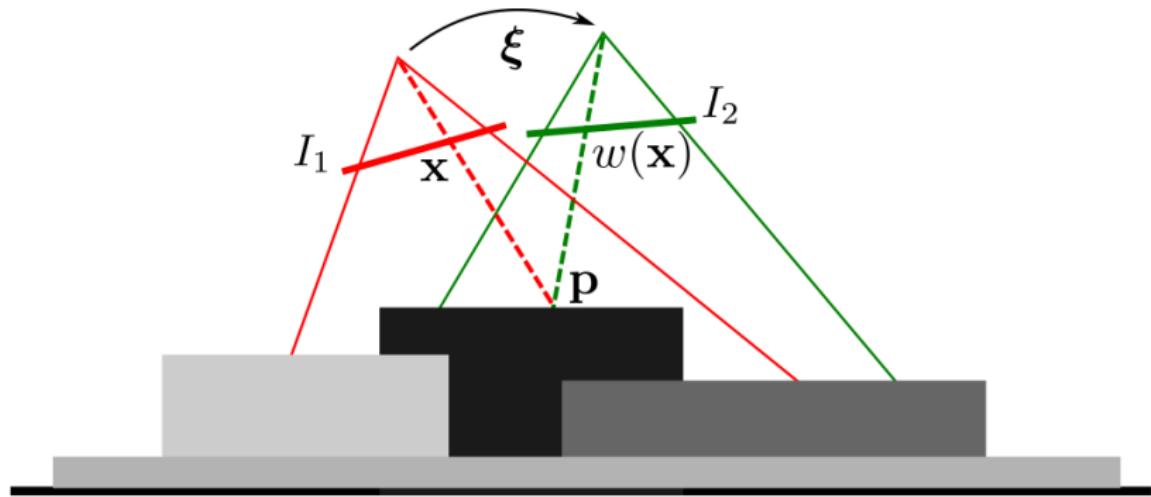
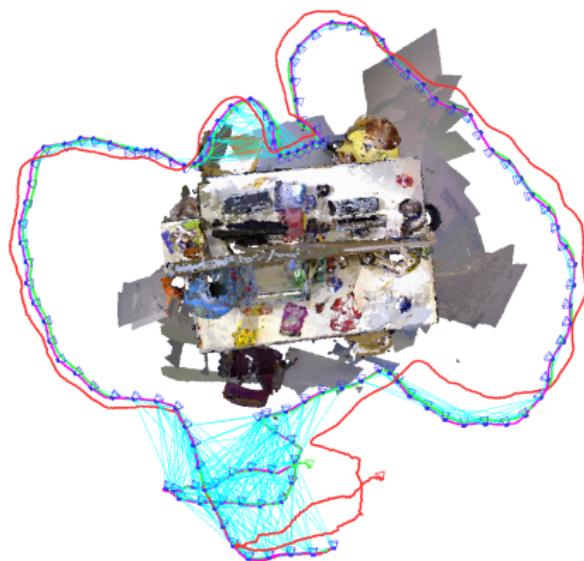


Photo Consistency Assumption

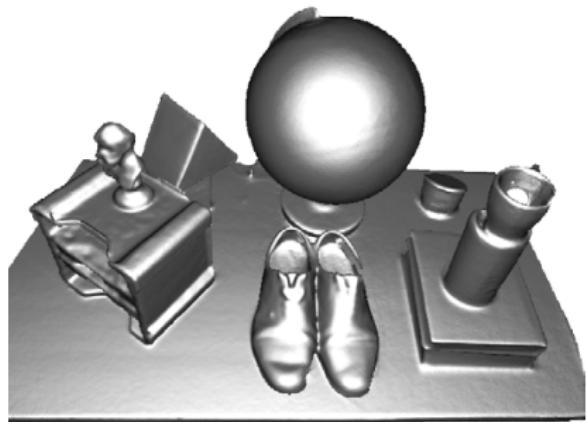
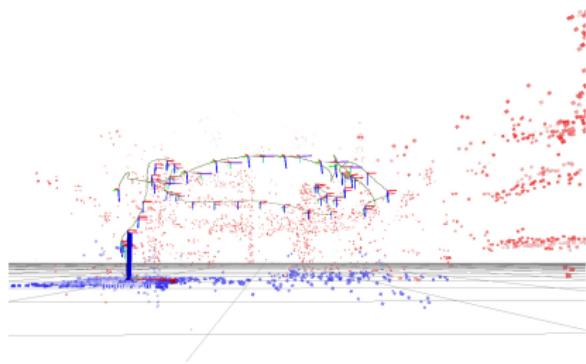


$$I_1(x) = I_2(\tau(\xi, x))$$

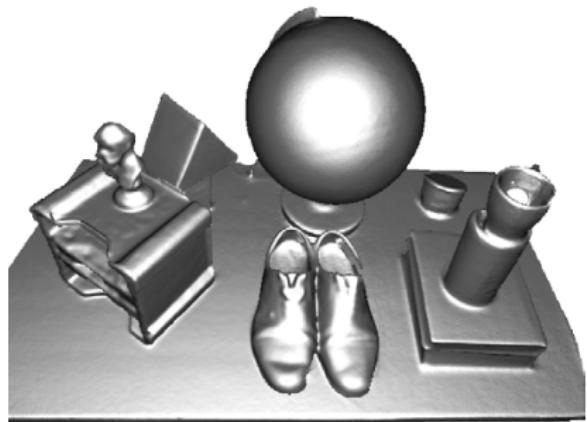
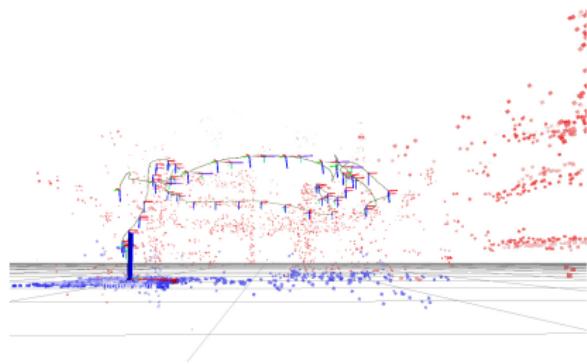
Odometry



Feature Based vs. Dense Mapping

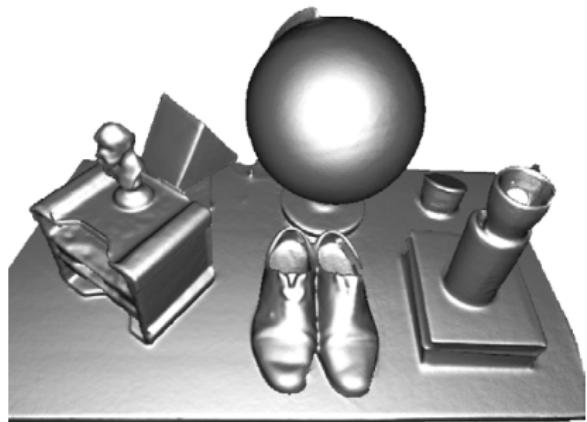
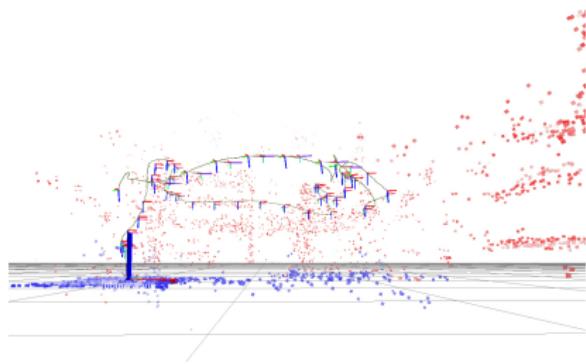


Feature Based vs. Dense Mapping



- more accuracy

Feature Based vs. Dense Mapping



- more accuracy
- the map itself is useful

Visual

Visual sensors e. g.:

- RGB camera
- IR depth sensor
- Laser scanner

Hardware



Kinect sensor

- Structured, light based depth sensor (IR-rays)
- framerate 30Hz
- $640 \times 320 \times 11$ bit

Geometric Error - Photometric Error

depth sensor data



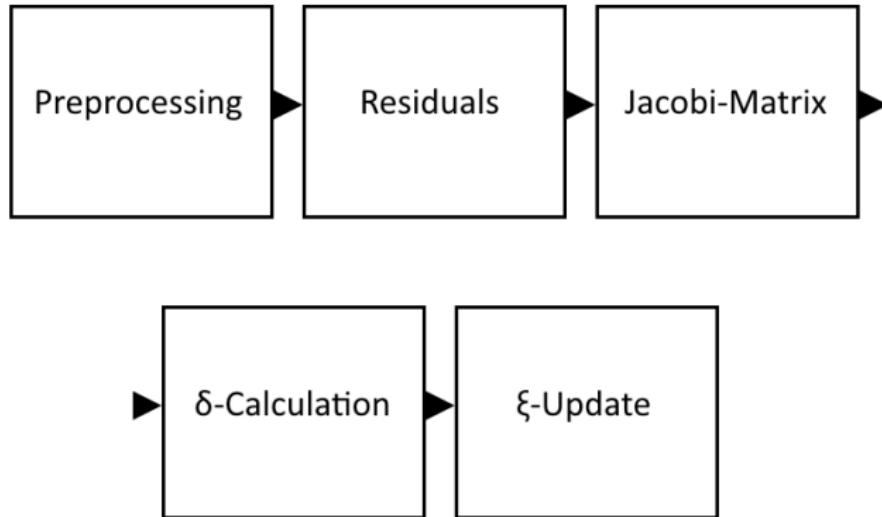
minimize geometric error

intensity sensor data
(RGB camera)

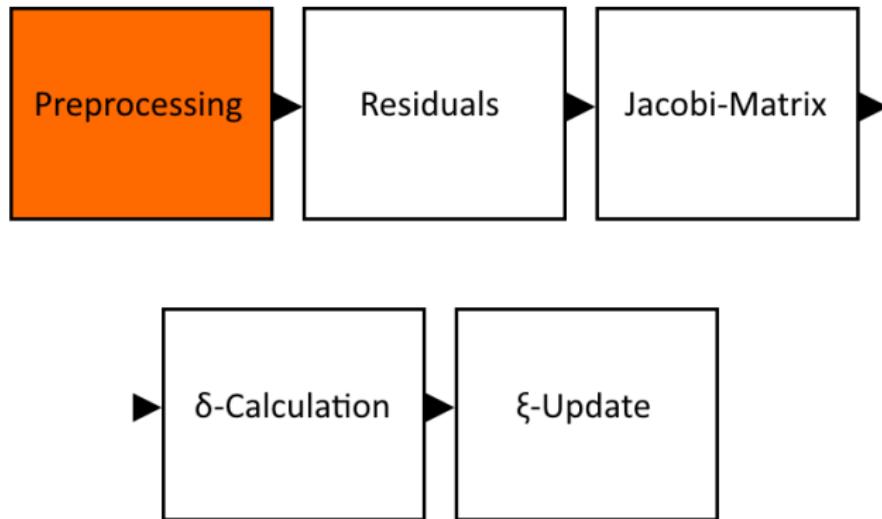


minimize photometric error

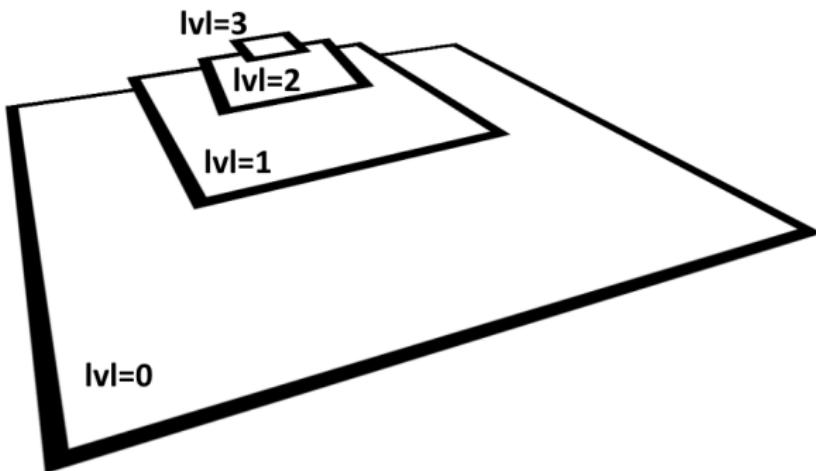
Algorithm



Algorithm

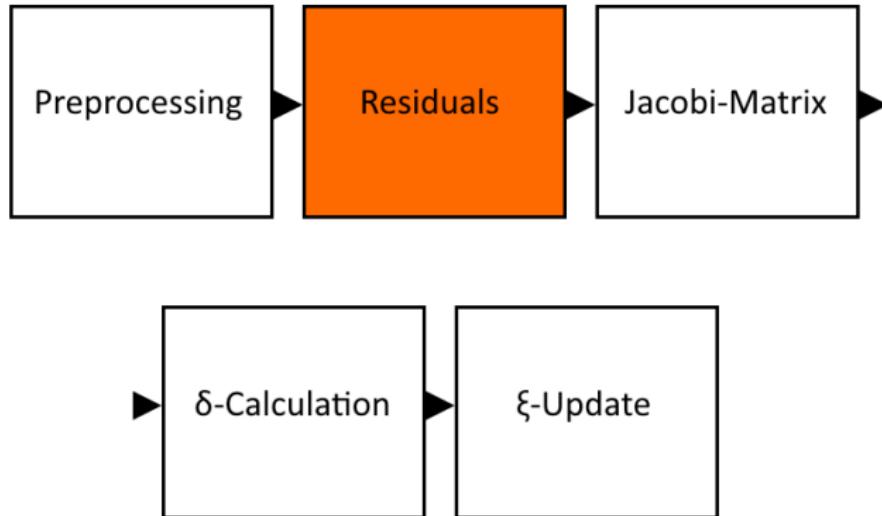


Preprocessing



- $\text{RGB} \rightarrow \text{Intensity-Image}$
- Depth-Image
- Intrinsic Calibration K
- Inverse Calibration IK

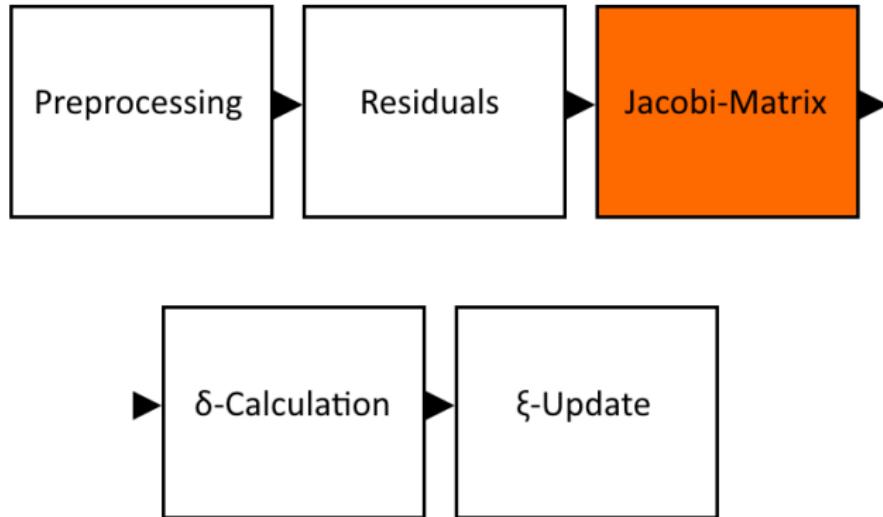
Algorithm



Residual



Algorithm

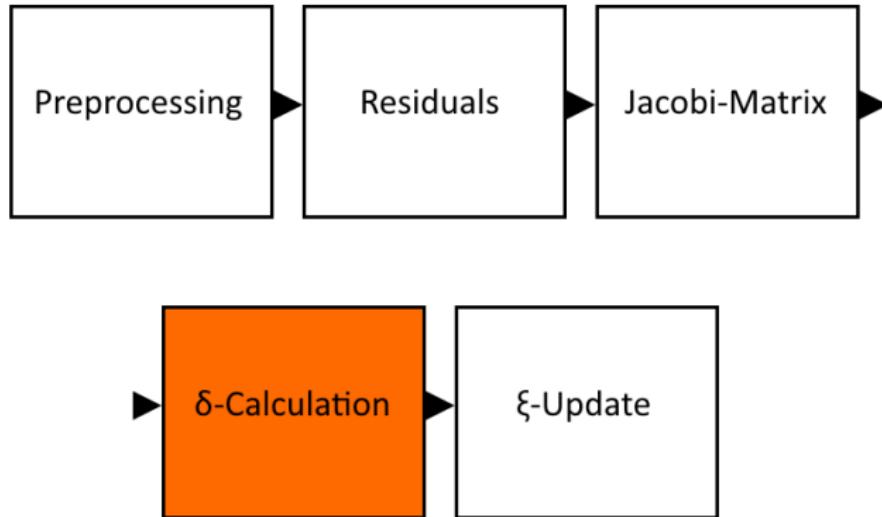


Jacobi

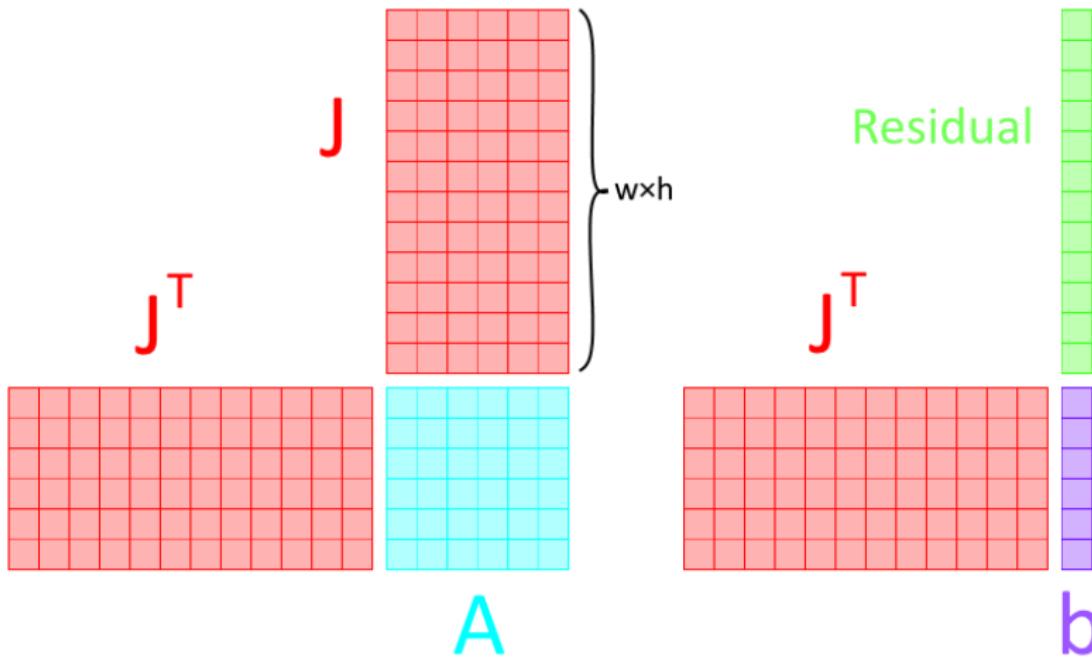
$$\left| \begin{array}{cc|ccccc} 1 & 0 & -\frac{x'}{z'} & -\frac{x'y'}{z'} & \left(z' + \frac{x'^2}{z'}\right) & -y' \\ 0 & 1 & -\frac{y'}{z'} & -(z' + \frac{y'^2}{z'}) & \frac{x'y'}{z'} & x' \\ \hline \frac{\nabla I_x f_x}{z'} & \frac{\nabla I_y f_y}{z'} & \end{array} \right|$$


1 Row of $n \times 6$ Jacobi Matrix

Algorithm



A and b

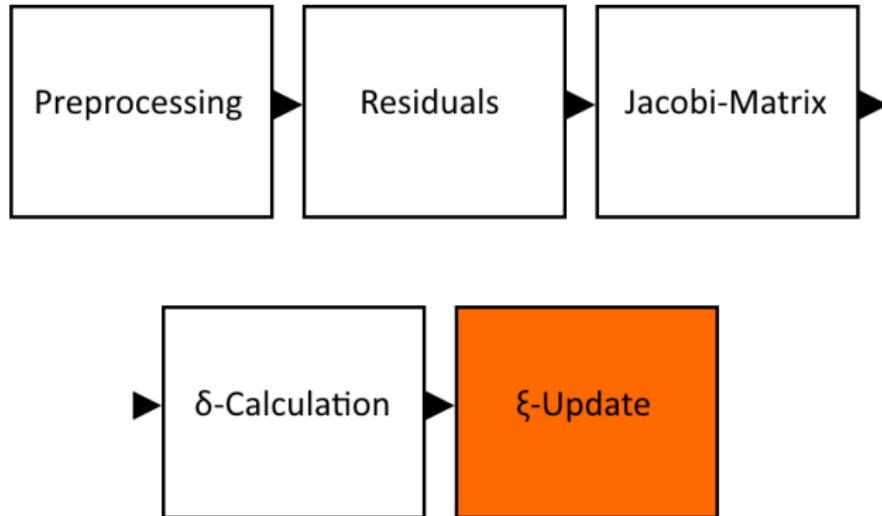


Delta - Solve Linear System

$$\delta_\xi = -(J_r^T J_r)^{-1} J_r^T \mathbf{r}_0$$

The diagram illustrates a linear system of equations. On the left, there is a large cyan square grid labeled 'A' below it. To its right is a multiplication sign '×'. To the right of the multiplication sign is an equals sign '='. To the right of the equals sign is a vertical vector labeled 'b' below it. This visual representation corresponds to the mathematical equation $\delta_\xi = -(J_r^T J_r)^{-1} J_r^T \mathbf{r}_0$.

Algorithm



Xi-Update

Apply $\xi^{(k+1)} = \delta_\xi \circ \xi^{(k)}$

 solved using the **Gauss-Newton** algorithm
using left-multiplicative increments on SE(3):
 $\xi_1 \circ \xi_2 := \log(\exp(\hat{\xi}_1) \cdot \exp(\hat{\xi}_2))^\vee \neq \xi_1 + \xi_2$
 $\neq \xi_2 \circ \xi_1$ 

```
xi = Sophus::SE3f::log(Sophus::SE3f::exp(delta)*Sophus::SE3f::exp(xi));
```

Iterate (until convergence)

Shared Memory

Parallel reduction as a part of matrix-matrix- and matrix-vector-multiplication for A and b

Constant Memory

Storage of intrinsic calibration matrix K and its inverse
(Stored once, accesses 8 times per iteration)

Saving Computation Steps

Compute only current frame's pyramids and store it as reference for next step

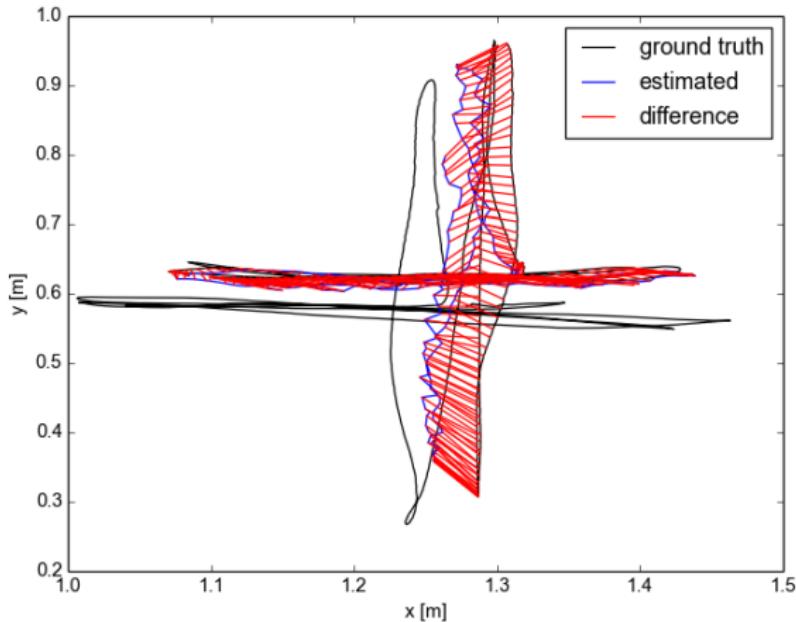
Saving Computation Steps

A is symmetric, so only 21 unique elements of 36 have to be computed

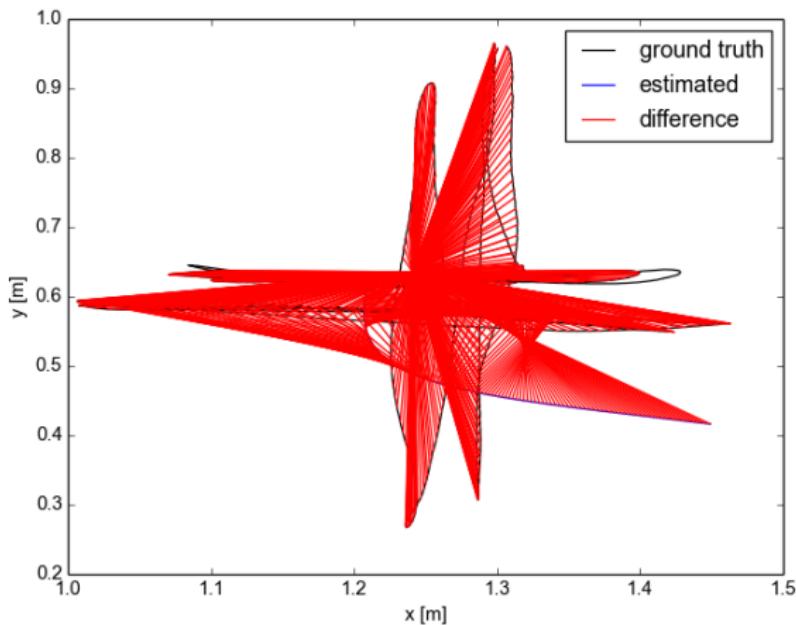
Early Break

Break out of hard coded 20 iterations if delta is below threshold

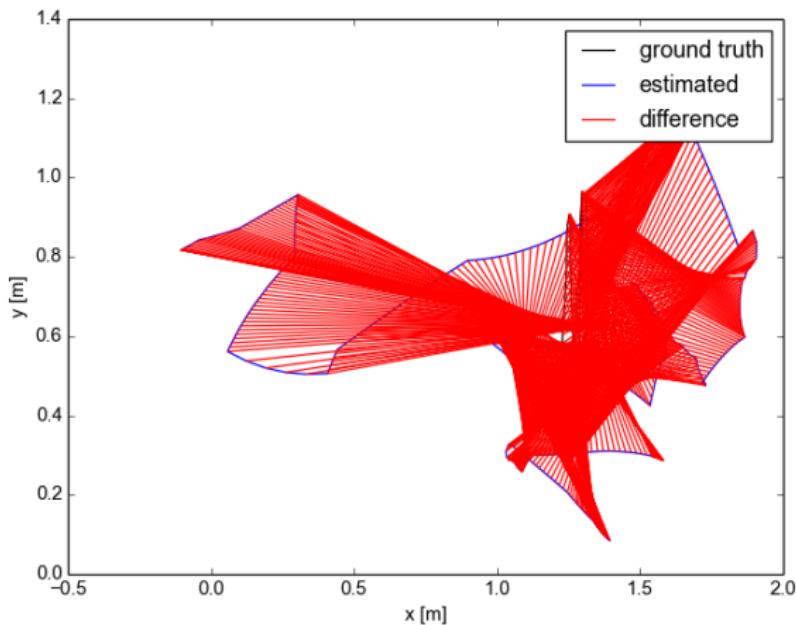
Dataset 'fr1/xyz'



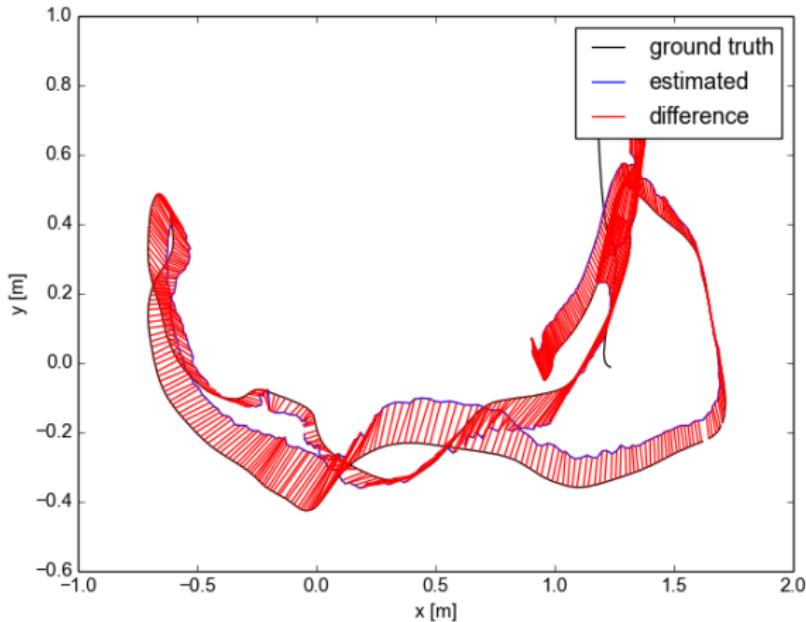
Dataset 'fr1/xyz' - threshold too high



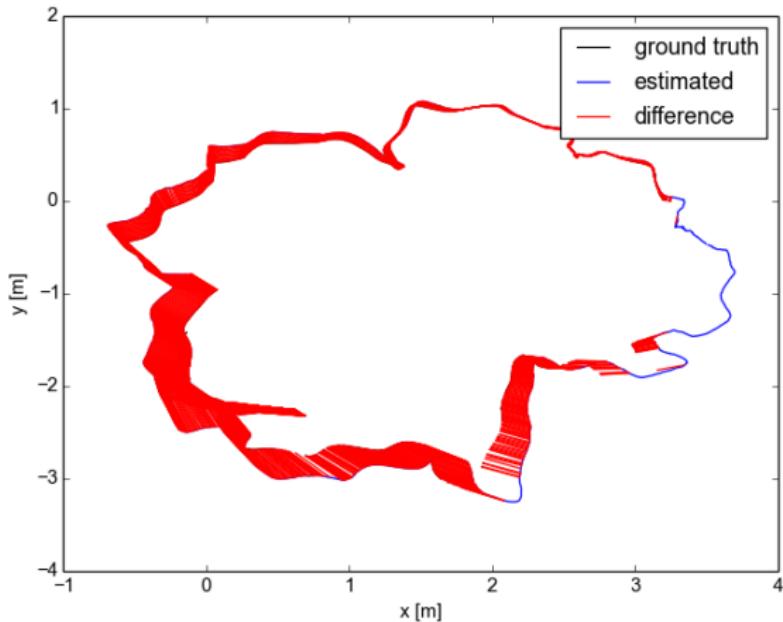
Dataset 'fr1/xyz' - too few pyramid levels



Dataset 'fr1_desk'



Dataset 'fr2_desk'



Computation Time

Alignment only (without frame loading and pyramid computations)

- naive approach: 60ms
- early break: saved 43ms
- constant K and iK: saved 1-2ms if many iterations

Further ideas

- $R, t (=x_i)$ in constant memory
- cuBLAS for multiplications

Live-Demo

Questions?

Thank you for your attention!