

Hybrid sensor fusion with dual quaternion based EKF for pose estimation

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Master thesis final presentation

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Project partner : FRAMOS GmbH

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Introduction

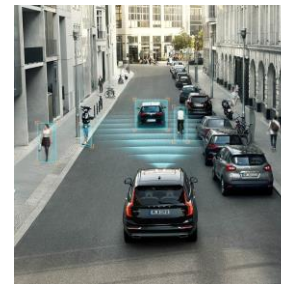
- Various tracking technologies have been developed (optical, inertial, EM sensors).
- More robust and efficient algorithms are being implemented for tracking and pose estimation.
- Many possibilities for applications to be used to (AR setups, medical robotics, autonomous flying / driving, entertainment).



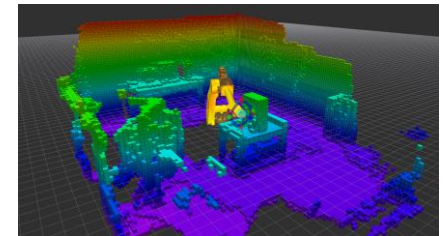
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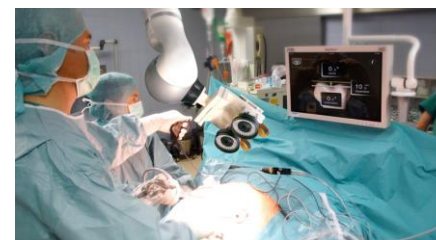
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Motivation

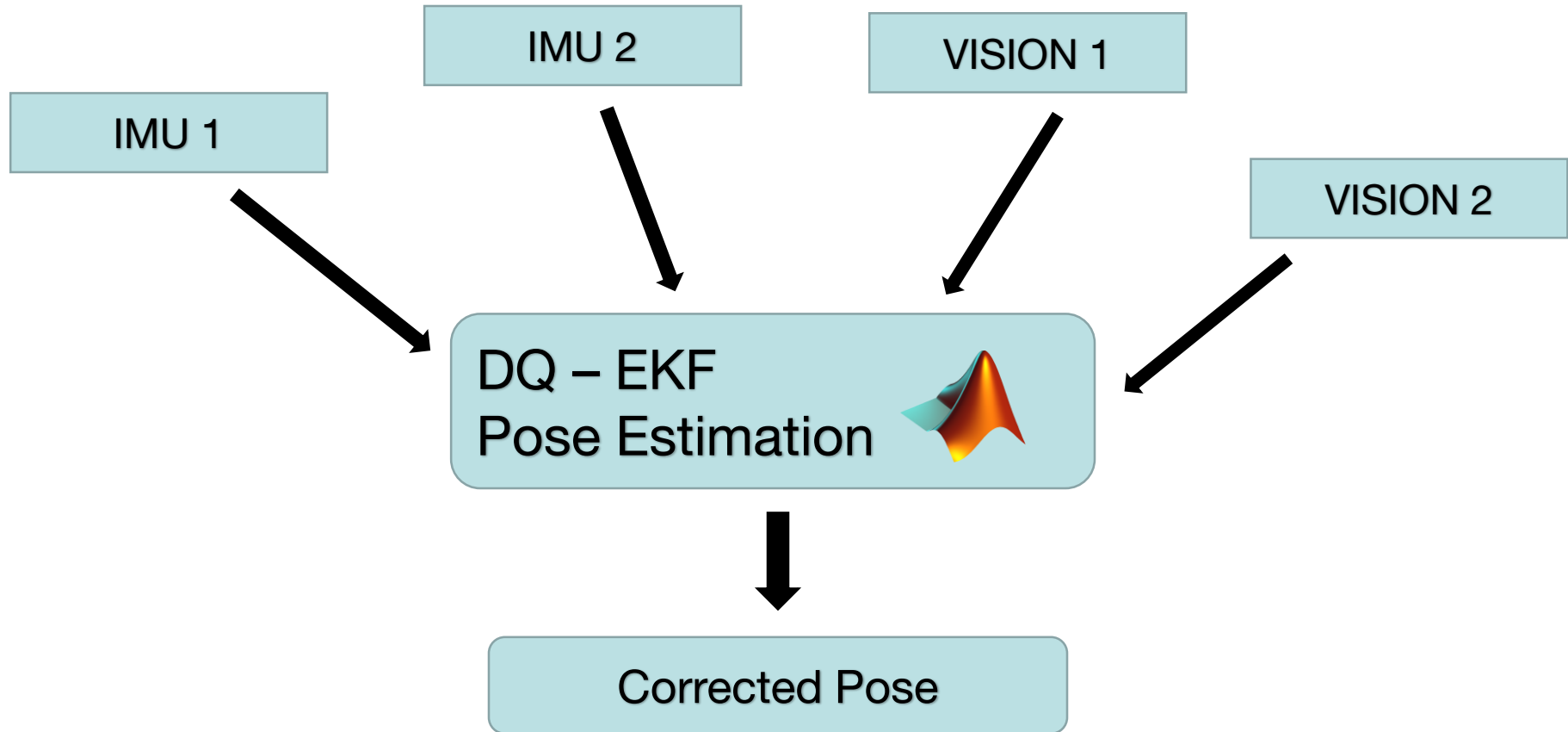
- Each sensor has strengths and weaknesses
- Need for use of more than one sensor for better precision
- Line-of-sight issues from optical tracking should be resolved
- IMU's fast sampling rate benefit the system
- More robust algorithms for improving speed and accuracy
- Real-time applications

Thesis overview

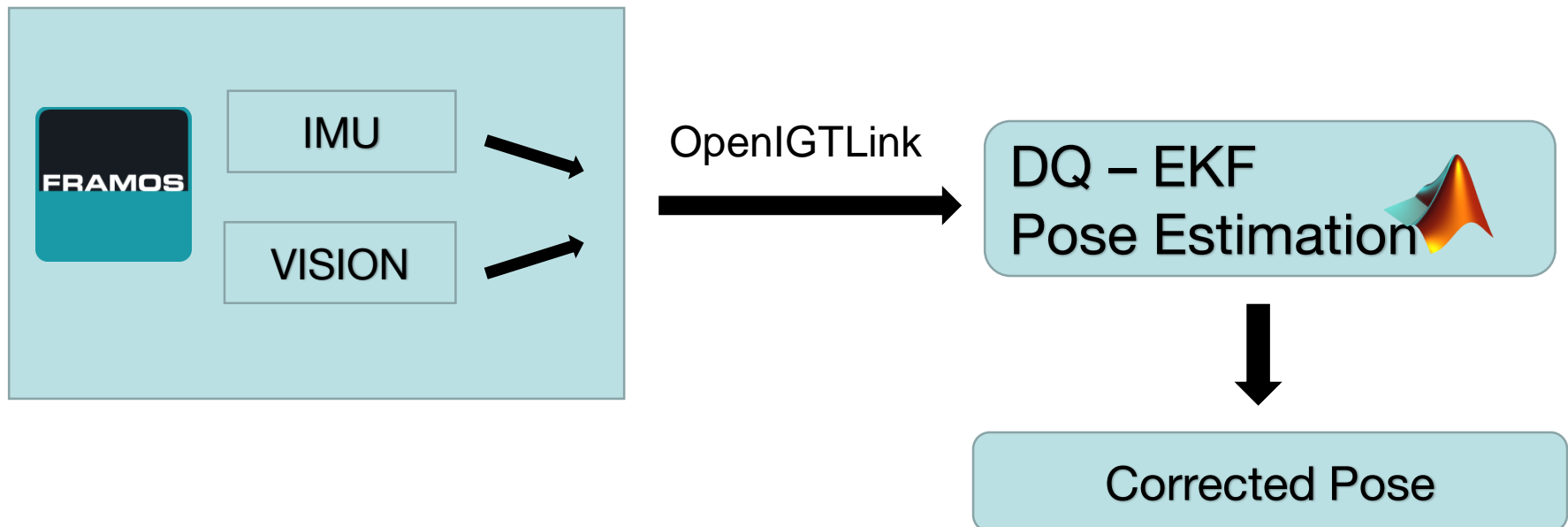
- Implementation of a generic algorithm for pose estimation with fusion of measurements from more than one sensor
- Use of dual quaternion mathematic formalization for compact and more efficient calculations
- Use of Extended Kalman filter (EKF) for tightly-coupled filtering
- Experiments for four individual cases fusing up to four sensors, using synthetic data
- Occlusion case with synthetic data
- Use data from the PennCOSYVIO dataset¹ for evaluation
- Occlusion case using the dataset
- Use of real data

1. Bernd Pfrommer, et al. Penncosyvio: A challenging visual inertial odometry benchmark. ICRA 2017.

Synthetic data & Dataset setup



Real data setup



Dual Quaternions

- General form of dual quaternions:

$$\hat{q} = q_r + \varepsilon q_d$$



property

$$\varepsilon^2 = 0$$

- Pose representation :

$$\begin{aligned}
 \hat{q} &= q_r + \varepsilon q_t \\
 &= (q_{0r} + q_{1r}\mathbf{i} + q_{2r}\mathbf{j} + q_{3r}\mathbf{k}) + \\
 &\quad \varepsilon \left(\frac{1}{2} (0 + t_x\mathbf{i} + t_y\mathbf{j} + t_z\mathbf{k}) \otimes (q_{0r} + q_{1r}\mathbf{i} + q_{2r}\mathbf{j} + q_{3r}\mathbf{k}) \right) \\
 &= (q_{0r} + q_{1r}\mathbf{i} + q_{2r}\mathbf{j} + q_{3r}\mathbf{k}) + \varepsilon (q_{0t} + q_{1t}\mathbf{i} + q_{2t}\mathbf{j} + q_{3t}\mathbf{k}).
 \end{aligned}$$

- Velocity representation :

$$\begin{aligned}
 \hat{\omega} &= q_\omega + \varepsilon q_u \\
 &= (0 + \omega_x\mathbf{i} + \omega_y\mathbf{j} + \omega_z\mathbf{k}) + \\
 &\quad \varepsilon \left(\frac{1}{2} (0 + u_x\mathbf{i} + u_y\mathbf{j} + u_z\mathbf{k}) \otimes (0 + \omega_x\mathbf{i} + \omega_y\mathbf{j} + \omega_z\mathbf{k}) \right) \\
 &= (0 + \omega_x\mathbf{i} + \omega_y\mathbf{j} + \omega_z\mathbf{k}) + \varepsilon (q_{0u} + q_{1u}\mathbf{i} + q_{2u}\mathbf{j} + q_{3u}\mathbf{k})
 \end{aligned}$$

Dual Quaternion – Extended Kalman Filter

Process
Model

$$\begin{aligned}\dot{\hat{q}} &= \frac{1}{2}\hat{q}\hat{\omega} = [q_r \otimes q_\omega + \varepsilon(q_r \otimes q_u + q_t \otimes q_\omega)] \\ \dot{\hat{\omega}} &= \frac{-1}{\tau}\hat{\omega}\end{aligned}$$

State vector

$$\hat{X} = [\hat{\omega}_0, \hat{\omega}_1, \hat{\omega}_2, \hat{\omega}_3, \hat{q}_0, \hat{q}_1, \hat{q}_2, \hat{q}_3]^T$$

Measurement vector

$$\hat{Z} = [\hat{\omega}_0, \hat{\omega}_1, \hat{\omega}_2, \hat{\omega}_3, \hat{q}_{0I}, \hat{q}_{1I}, \hat{q}_{2I}, \hat{q}_{3I}, \hat{q}_{0V}, \hat{q}_{1V}, \hat{q}_{2V}, \hat{q}_{3V}]^T$$

Dual Quaternion – Extended Kalman Filter

State
Difference

$$\Delta \hat{X}_k^- = A \Delta \hat{X}_{k-1}^-$$

with

$$A = \frac{1}{2} \cdot \begin{bmatrix} 2e^{-\frac{\Delta t}{\tau}} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 2e^{-\frac{\Delta t}{\tau}} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 2e^{-\frac{\Delta t}{\tau}} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 2e^{-\frac{\Delta t}{\tau}} & 0 & 0 & 0 & 0 \\ \hat{q}_0 \Delta t & -\hat{q}_1 \Delta t & -\hat{q}_2 \Delta t & -\hat{q}_3 \Delta t & \hat{\omega}_0 \Delta t & -\hat{\omega}_1 \Delta t & -\hat{\omega}_2 \Delta t & -\hat{\omega}_3 \Delta t \\ \hat{q}_1 \Delta t & \hat{q}_0 \Delta t & -\hat{q}_3 \Delta t & \hat{q}_2 \Delta t & \hat{\omega}_1 \Delta t & \hat{\omega}_0 \Delta t & \hat{\omega}_3 \Delta t & -\hat{\omega}_2 \Delta t \\ \hat{q}_2 \Delta t & \hat{q}_3 \Delta t & \hat{q}_0 \Delta t & -\hat{q}_1 \Delta t & \hat{\omega}_2 \Delta t & -\hat{\omega}_3 \Delta t & \hat{\omega}_0 \Delta t & \hat{\omega}_1 \Delta t \\ \hat{q}_3 \Delta t & -\hat{q}_2 \Delta t & \hat{q}_1 \Delta t & \hat{q}_0 \Delta t & \hat{\omega}_3 \Delta t & \hat{\omega}_2 \Delta t & -\hat{\omega}_1 \Delta t & \hat{\omega}_0 \Delta t \end{bmatrix}$$

Dual Quaternion – Extended Kalman Filter

A priori estimation

$$\hat{X}_k^- = \hat{X}_{k-1} + \Delta \hat{X}_k^-$$

Map to
measurement

$$\hat{Z}_k := H \hat{X}_k^-$$

Observation
matrix

$$H = \begin{bmatrix} I_4 & 0_{4 \times 4} \\ 0_{4 \times 4} & I_4 \\ 0_{4 \times 4} & I_4 \end{bmatrix}$$

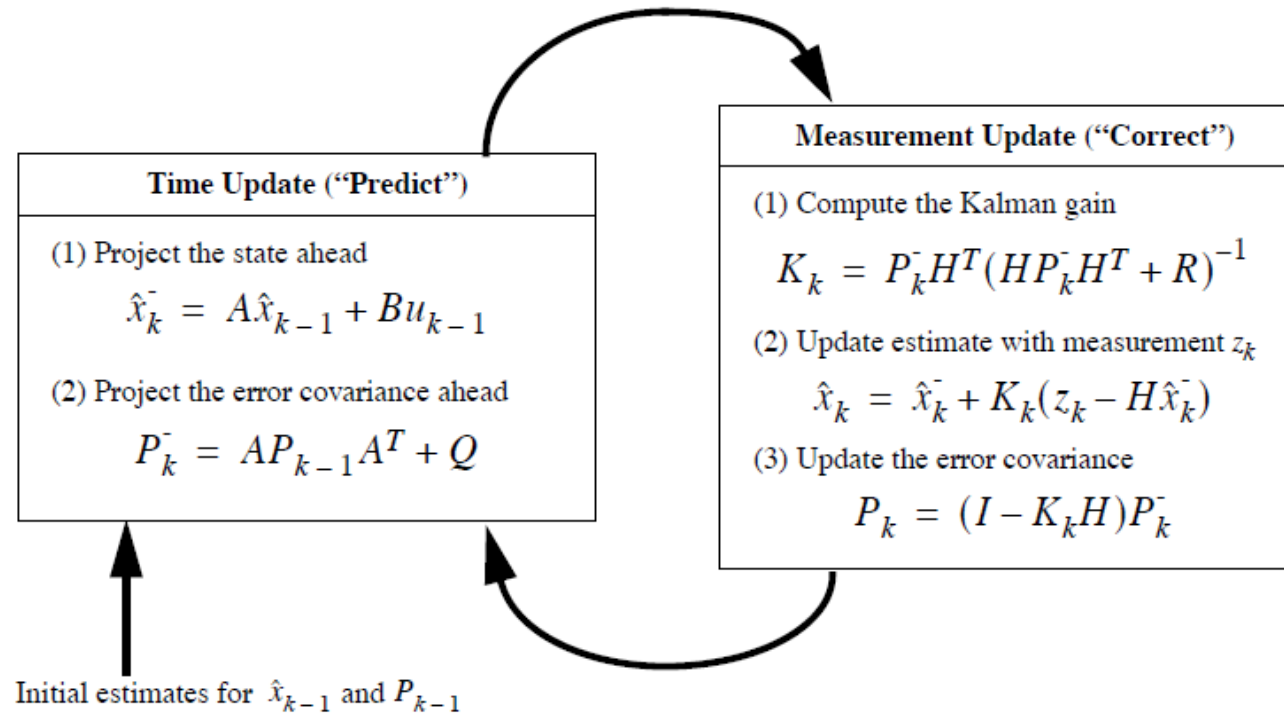
Measurement
covariance
matrix

$$R = \begin{bmatrix} I_4 \cdot \sigma_\omega^2 & 0_{4 \times 4} & 0_{4 \times 4} \\ 0_{4 \times 4} & I_4 \cdot \sigma_{qI}^2 & 0_{4 \times 4} \\ 0_{4 \times 4} & 0_{4 \times 4} & I_4 \cdot \sigma_{qV}^2 \end{bmatrix}$$

Process
covariance
matrix

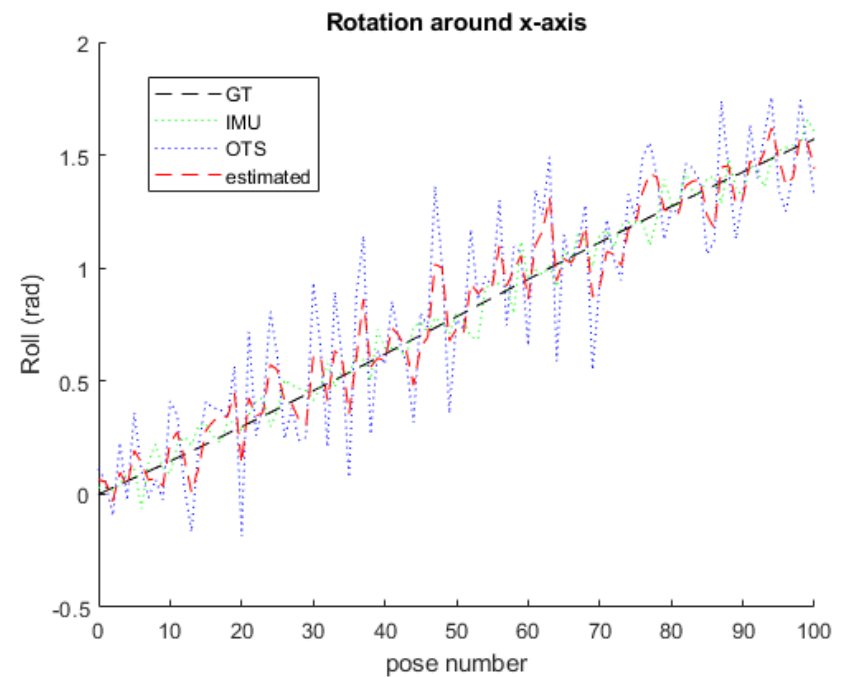
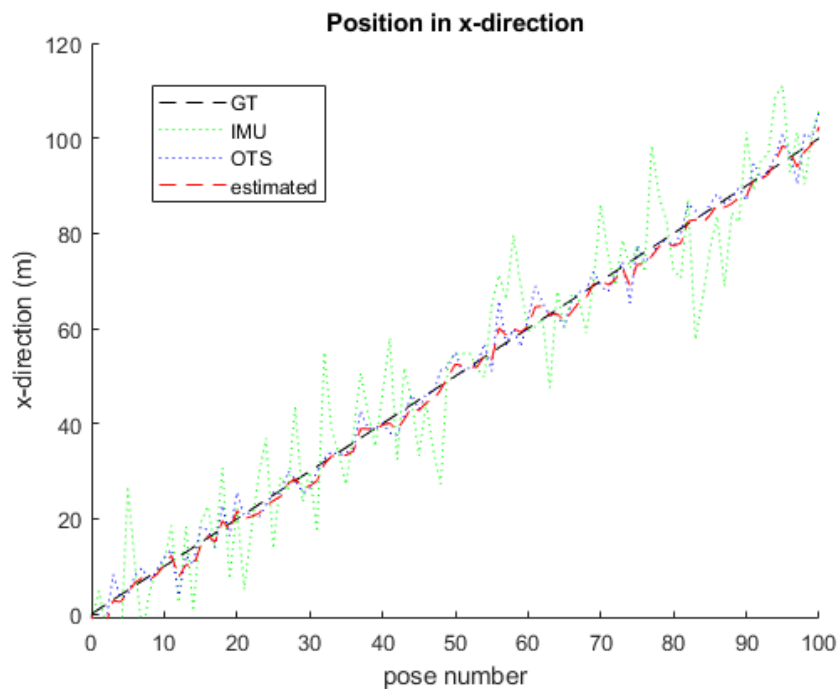
$$Q = \begin{bmatrix} I_4 \cdot p_u & 0_{4 \times 4} \\ 0_{4 \times 4} & I_4 \cdot p_q \end{bmatrix}$$

Dual Quaternion – Extended Kalman Filter

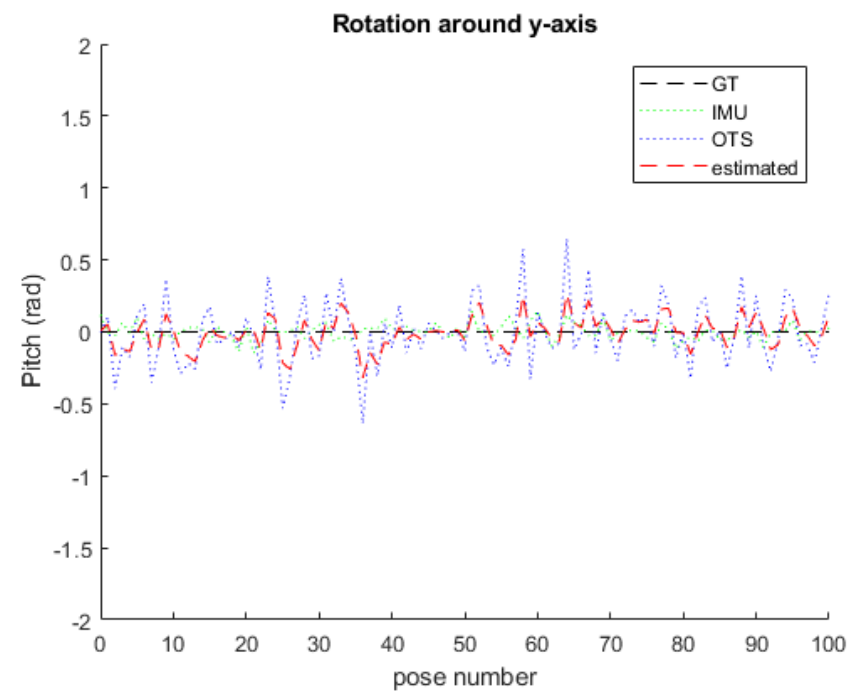
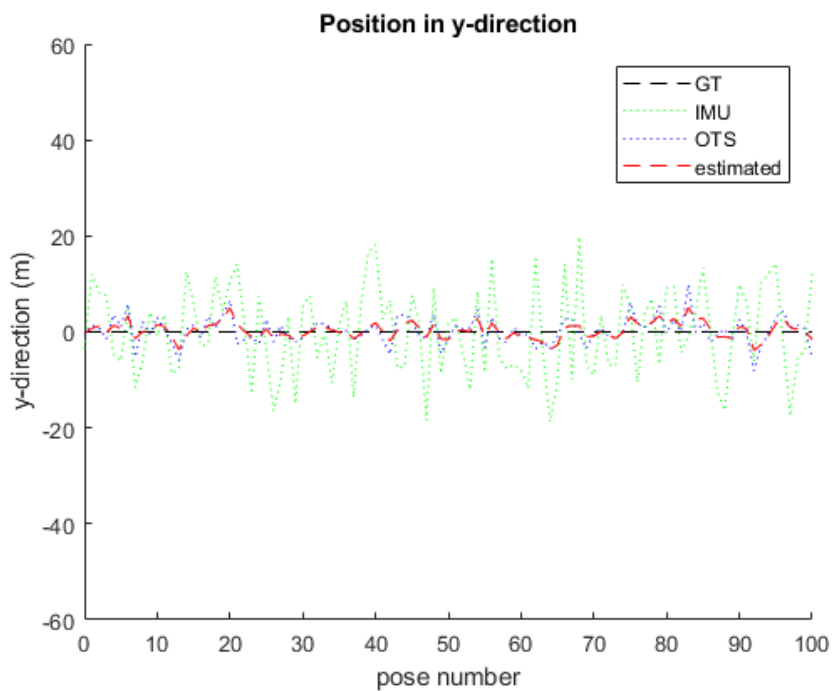


Greg Welch and Gary Bishop. An introduction to the kalman filter. Department of computer science, university of north carolina. ed: Chapel Hill, NC, unpublished manuscript, 2006.

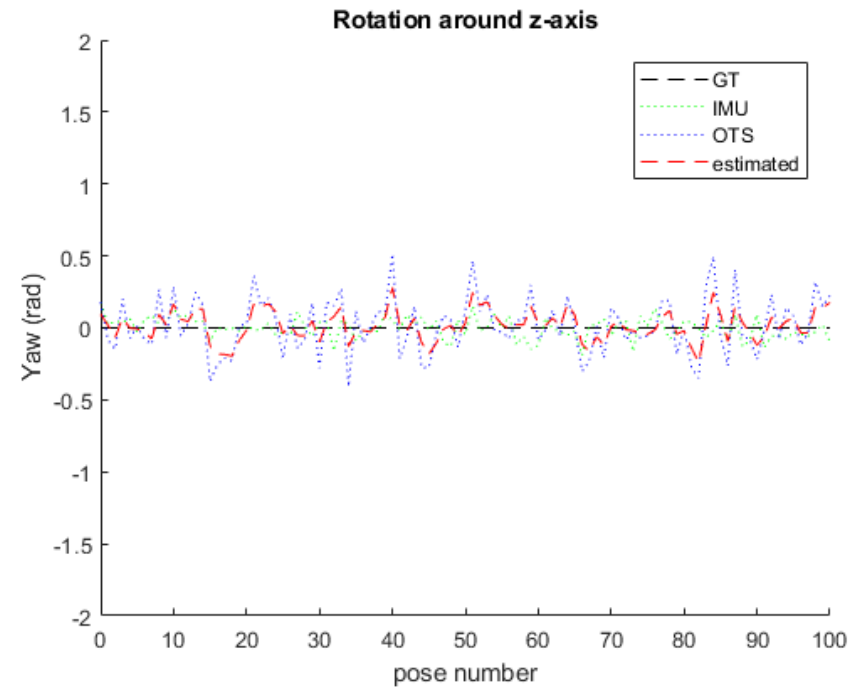
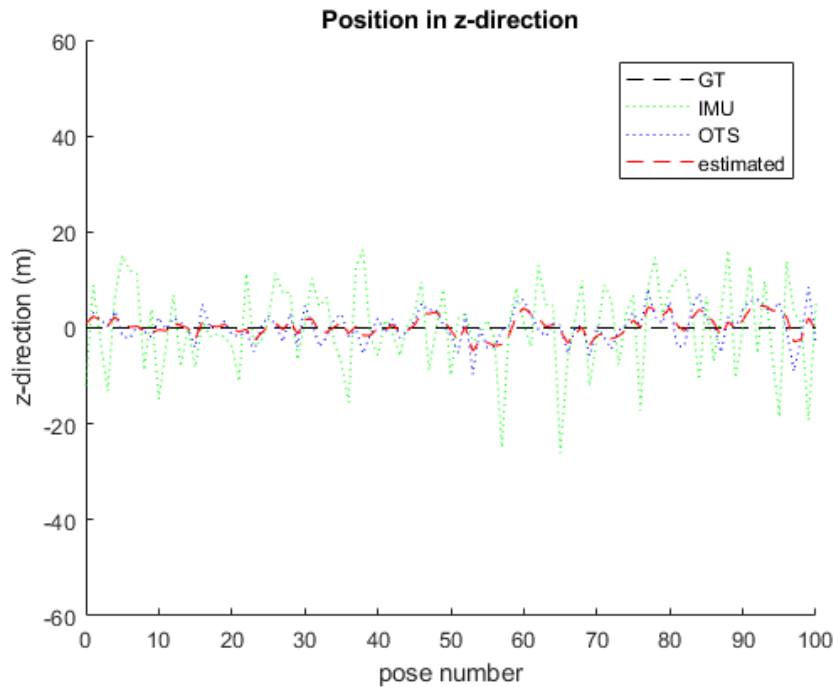
Results – Synthetic data



Results – Synthetic data



Results – Synthetic data



1 IMU & 1 VISION

Position error			
	Mean(m)	Median(m)	Std(m)
Vision	2.1480	2.1946	0.5348
IMU	3.8347	3.8244	0.7338
Fusion	1.6877	1.7131	0.4074

Angle error			
	Mean(°)	Median(°)	Std(°)
Vision	20.1310	18.4702	8.6150
IMU	5.8394	5.1448	2.7851
Fusion	10.1581	9.9927	4.0125

2 IMU & 1 VISION

Position error			
	Mean(m)	Median(m)	Std(m)
Vision	2.1480	2.1946	0.5348
IMU 1	3.8347	3.8244	0.7338
IMU 2	4.0967	4.1724	0.7657
Fusion	1.6816	1.7106	0.3963

Angle error			
	Mean(°)	Median(°)	Std(°)
Vision	20.1310	18.4702	8.6150
IMU 1	5.8394	5.1448	2.7851
IMU 2	5.9462	5.6175	2.3784
Fusion	9.6299	9.4746	3.8358

1 IMU & 2 VISION

Position error			
	Mean(m)	Median(m)	Std(m)
Vision 1	2.1480	2.1946	0.5348
Vision 2	2.2099	2.2410	0.4449
IMU	3.8347	3.8244	0.7338
Fusion	1.5689	1.5939	0.3312

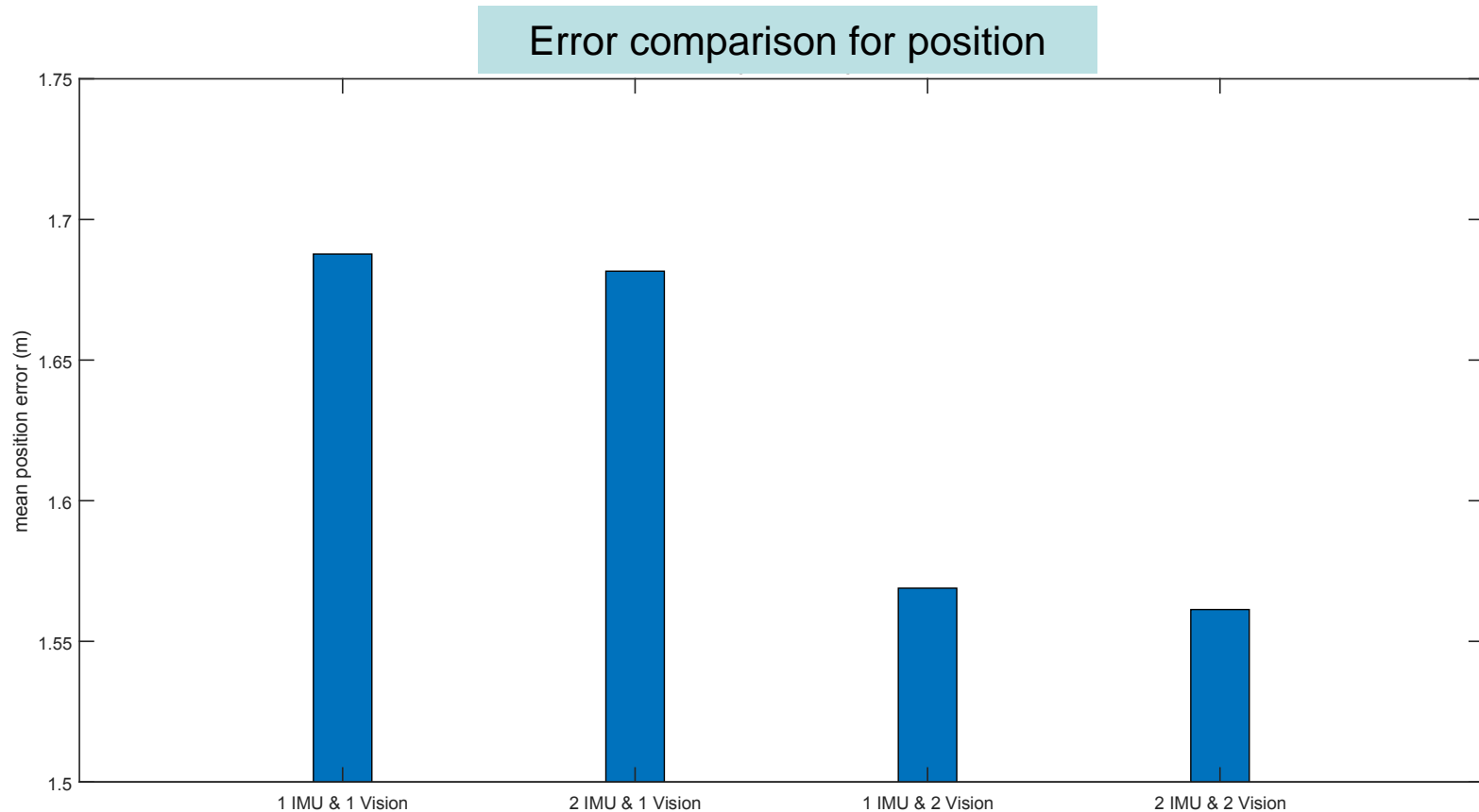
Angle error			
	Mean(°)	Median(°)	Std(°)
Vision 1	20.1310	18.4702	8.6150
Vision 2	19.3277	18.7899	7.6916
IMU	5.8394	5.1448	2.7851
Fusion	9.5670	9.6979	4.0265

2 IMU & 2 VISION

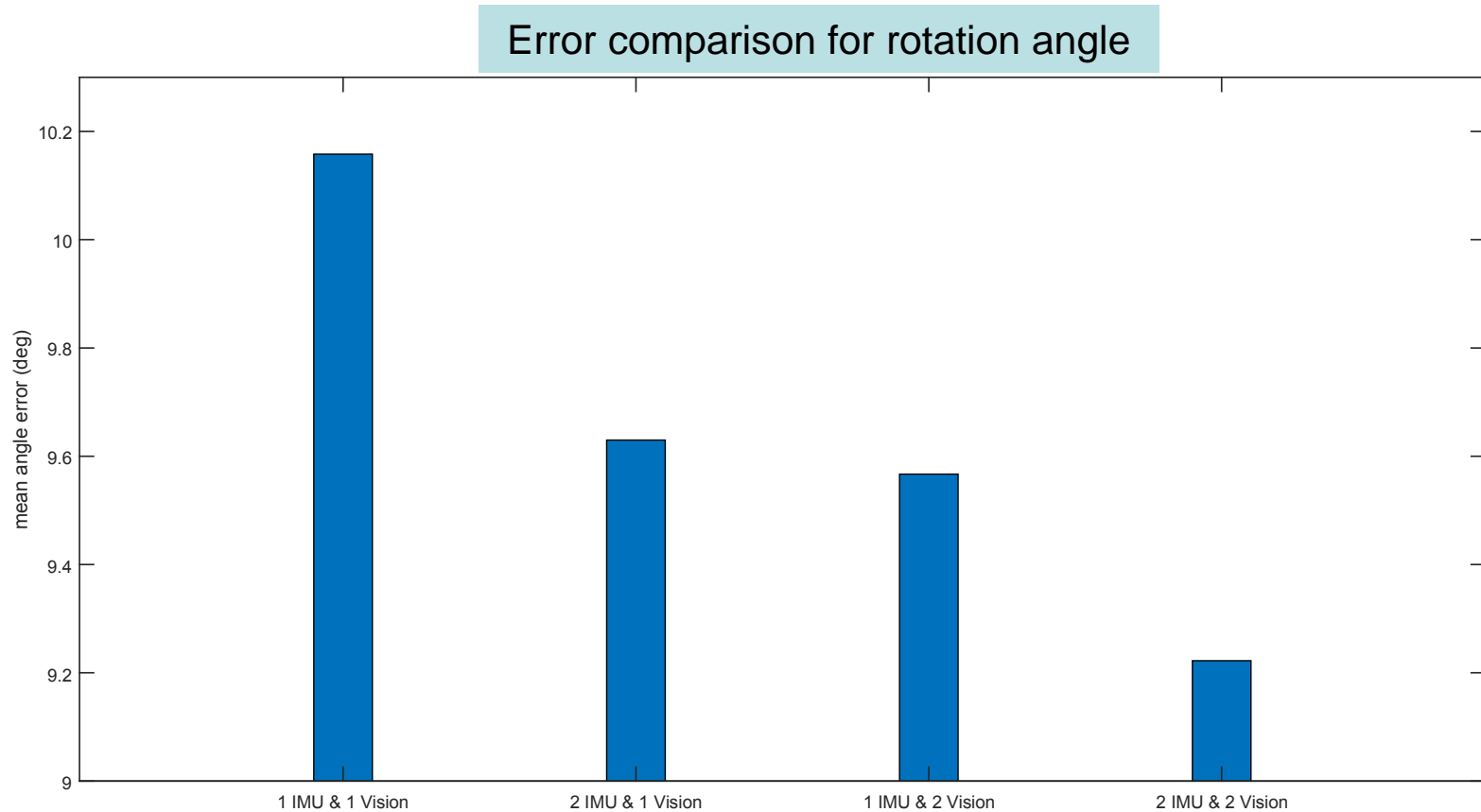
Position error			
	Mean(m)	Median(m)	Std(m)
Vision 1	2.1480	2.1946	0.5348
Vision 2	2.2099	2.2410	0.4449
IMU 1	3.8347	3.8244	0.7338
IMU 2	4.0967	4.1724	0.7657
Fusion	1.5613	1.5895	0.3351

Angle error			
	Mean(°)	Median(°)	Std(°)
Vision 1	20.1310	18.4702	8.6150
Vision 2	19.3277	18.7899	7.6916
IMU 1	5.8394	5.1448	2.7851
IMU 2	5.9462	5.6175	2.3784
Fusion	9.2223	9.4418	3.8930

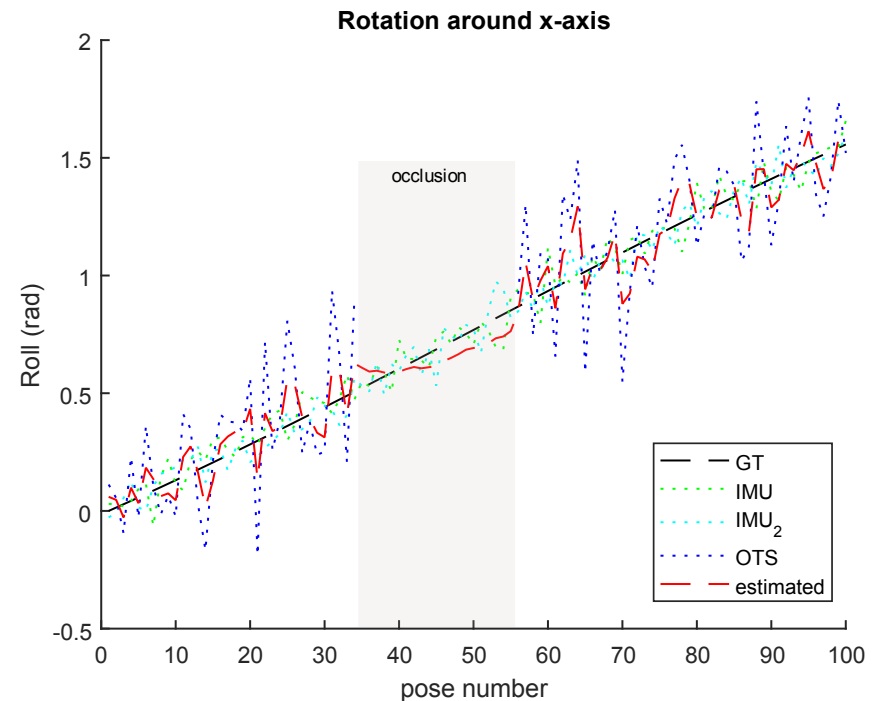
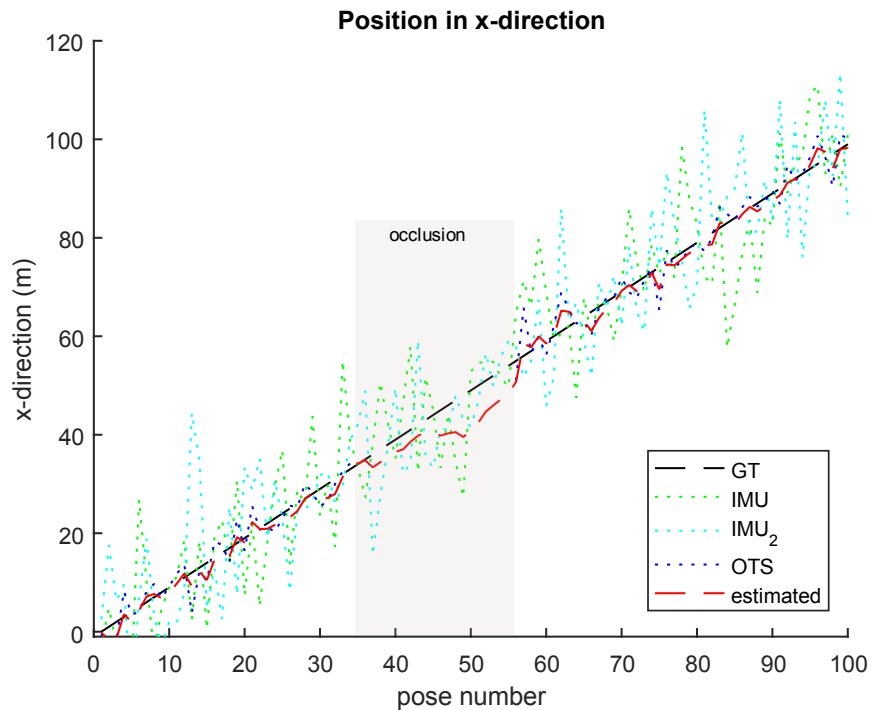
Results – Synthetic data



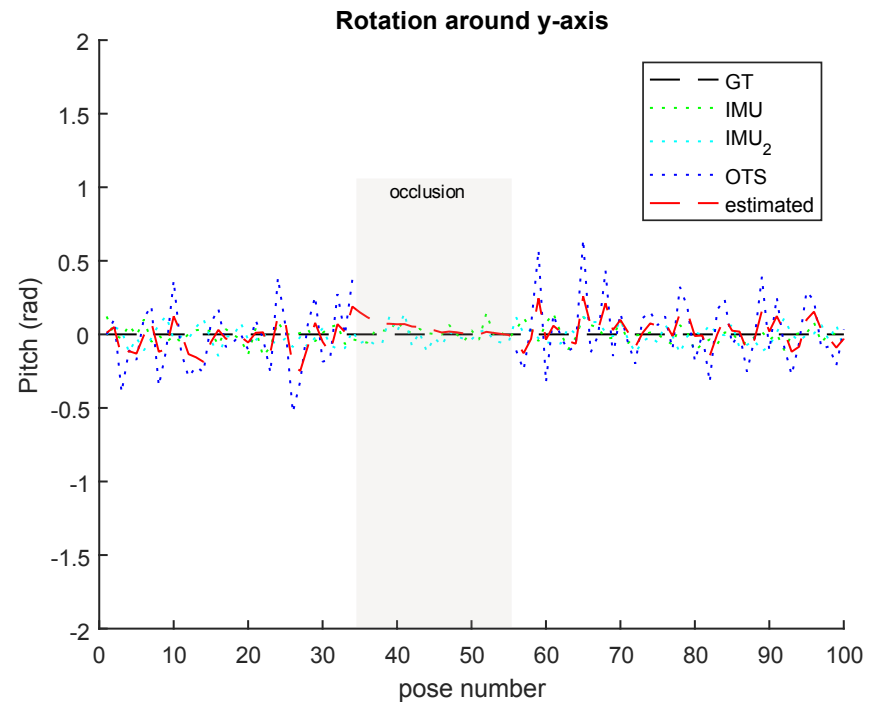
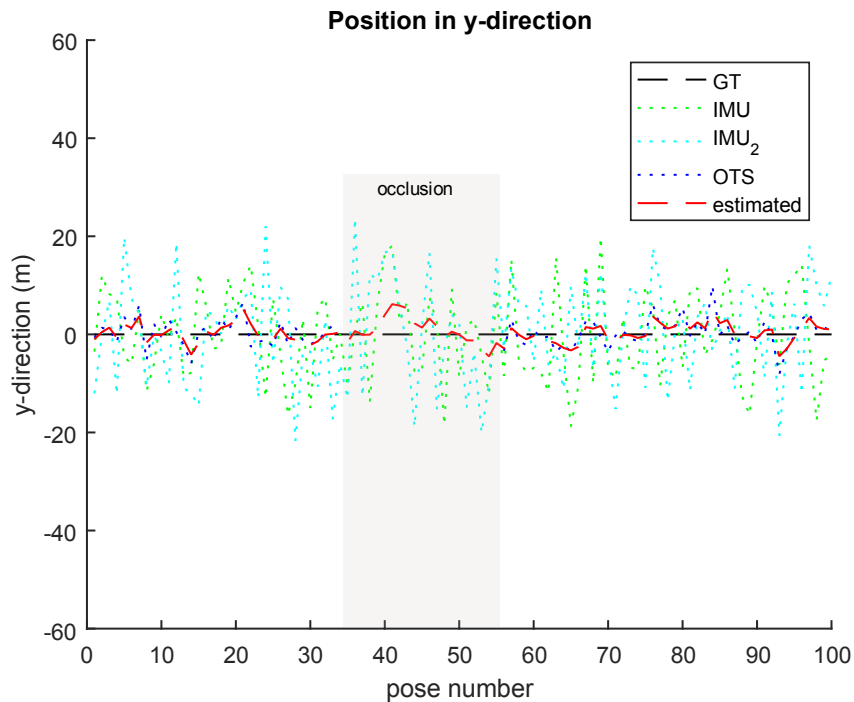
Results – Synthetic data



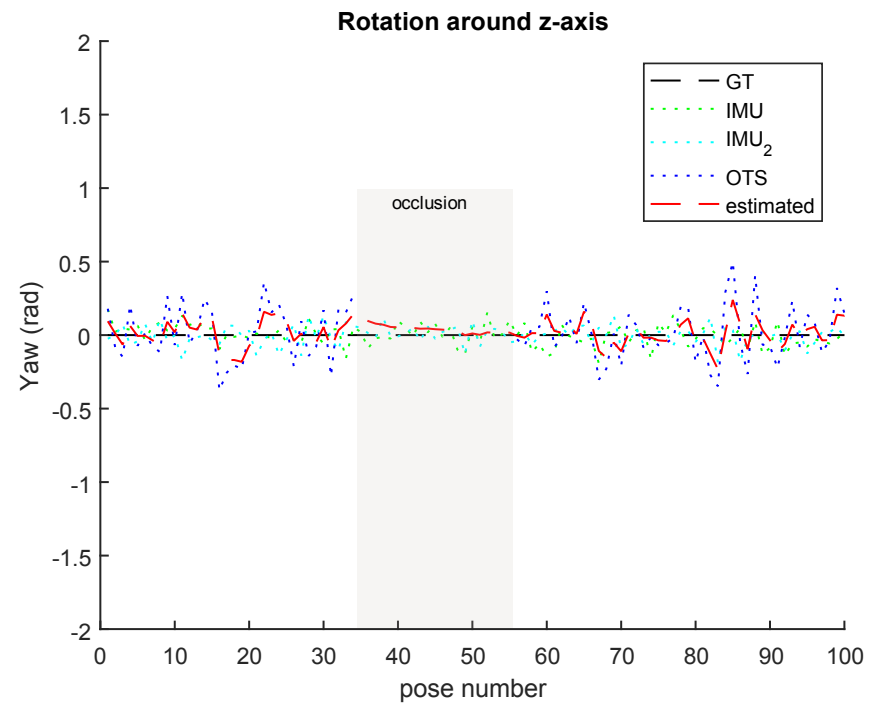
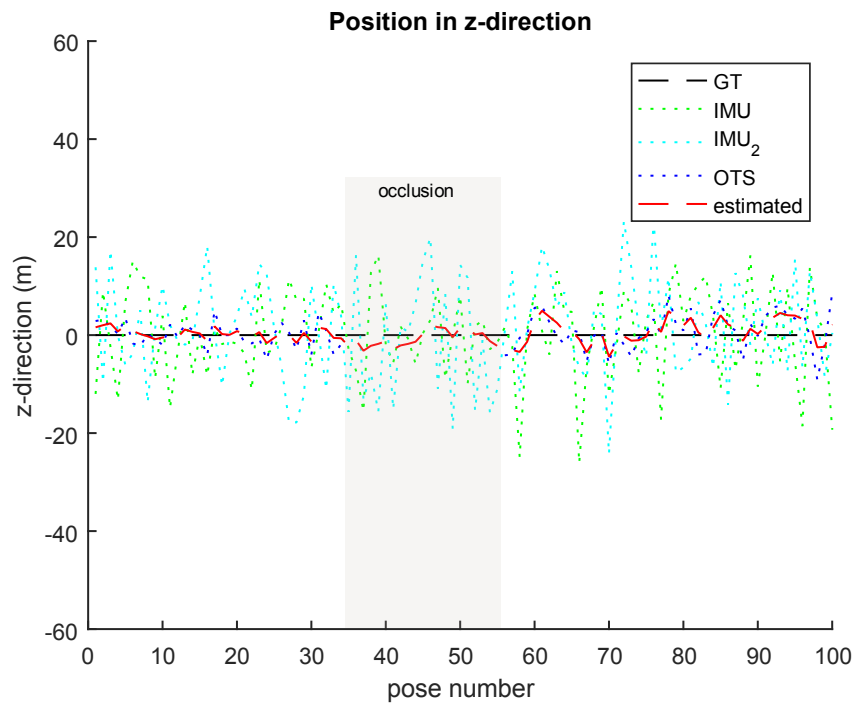
Results – Synthetic data occlusion



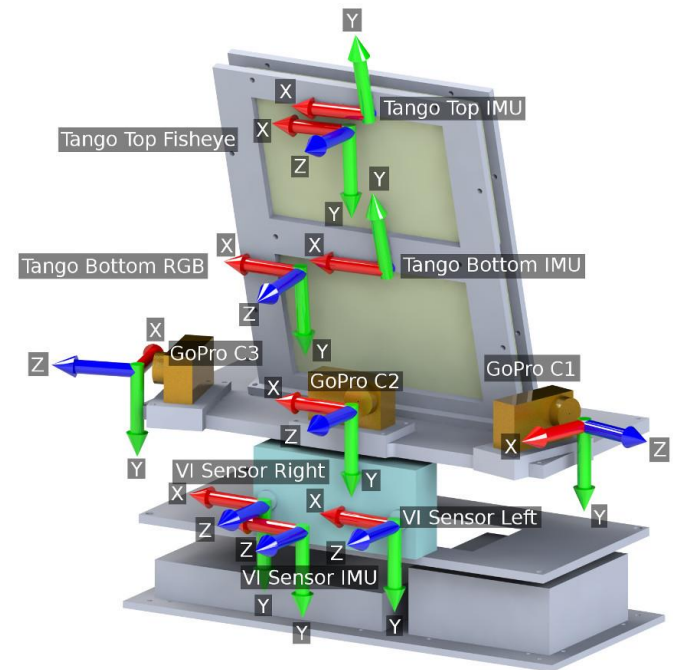
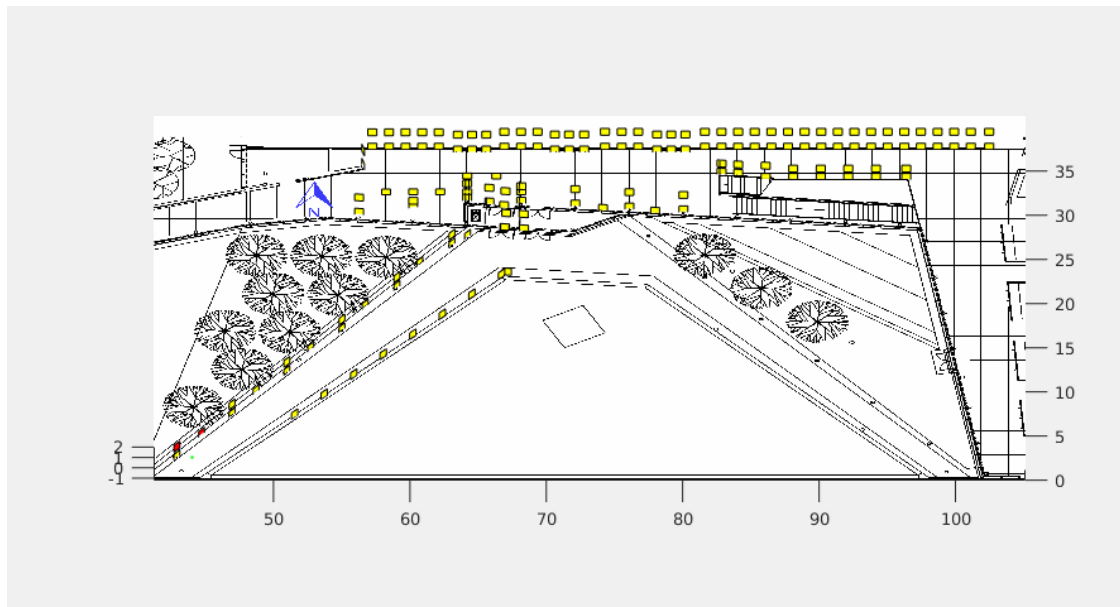
Results – Synthetic data occlusion



Results – Synthetic data occlusion



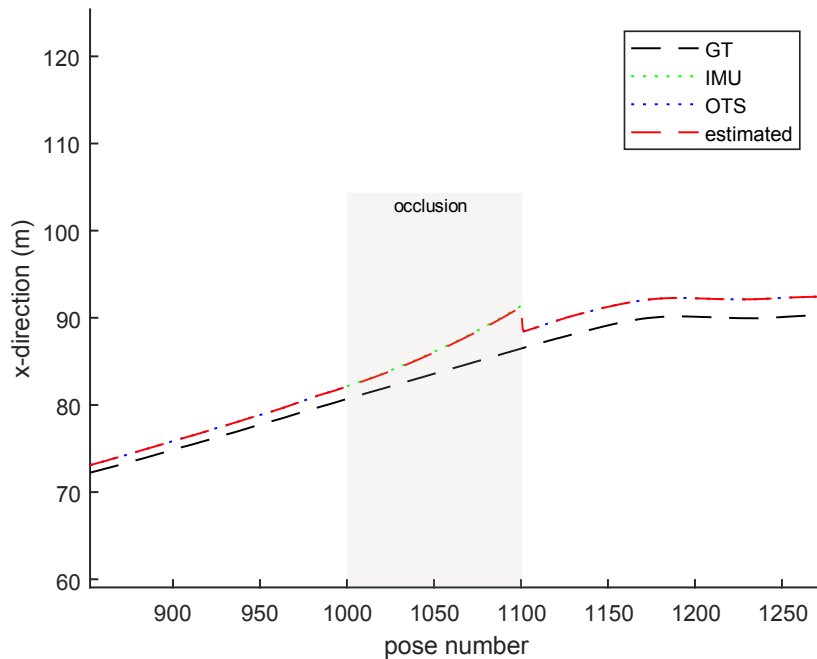
PennCOSYVIO dataset¹



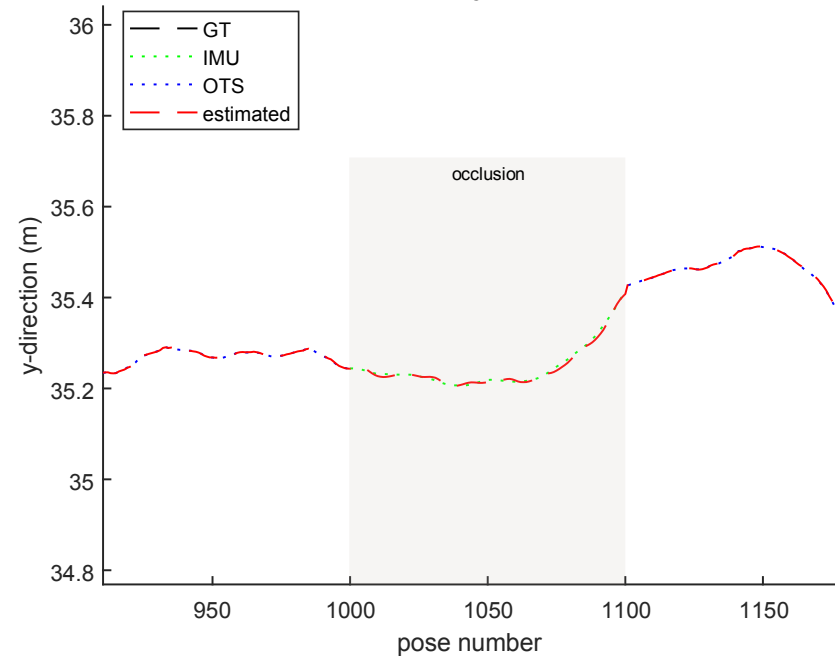
1. The PennCOSYVIO Data Set <https://daniilidis-group.github.io/penncosyvio/> access 7/6/2018.

Results – Dataset occlusion

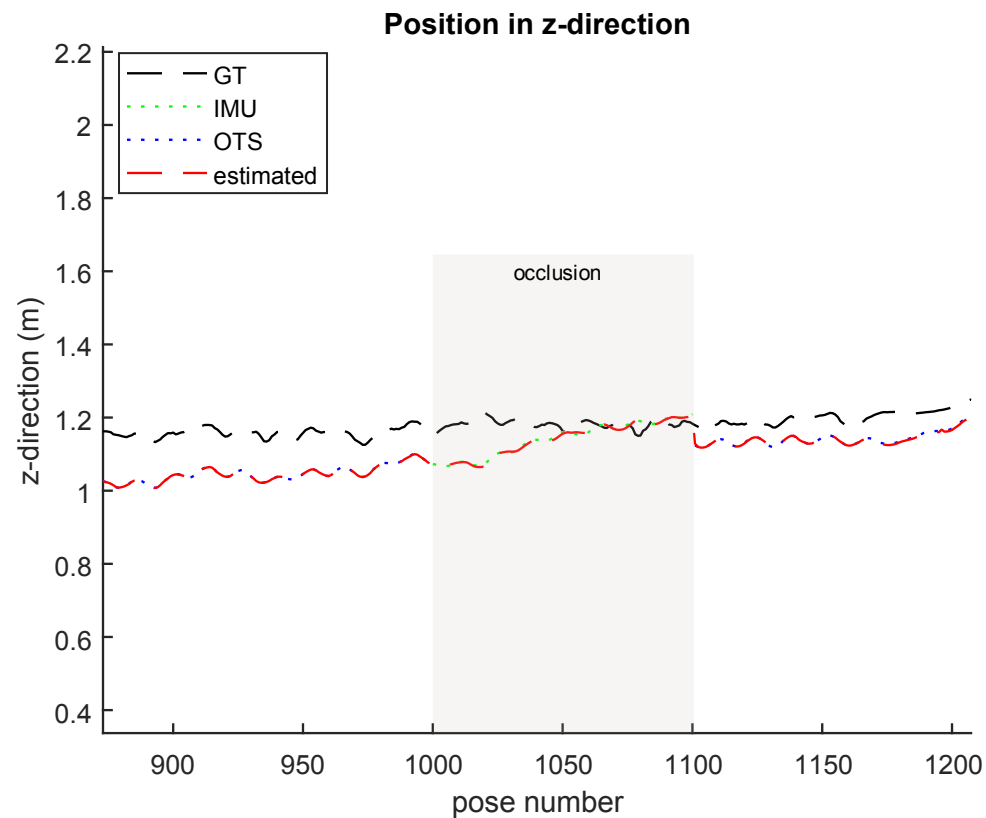
Position in x-direction



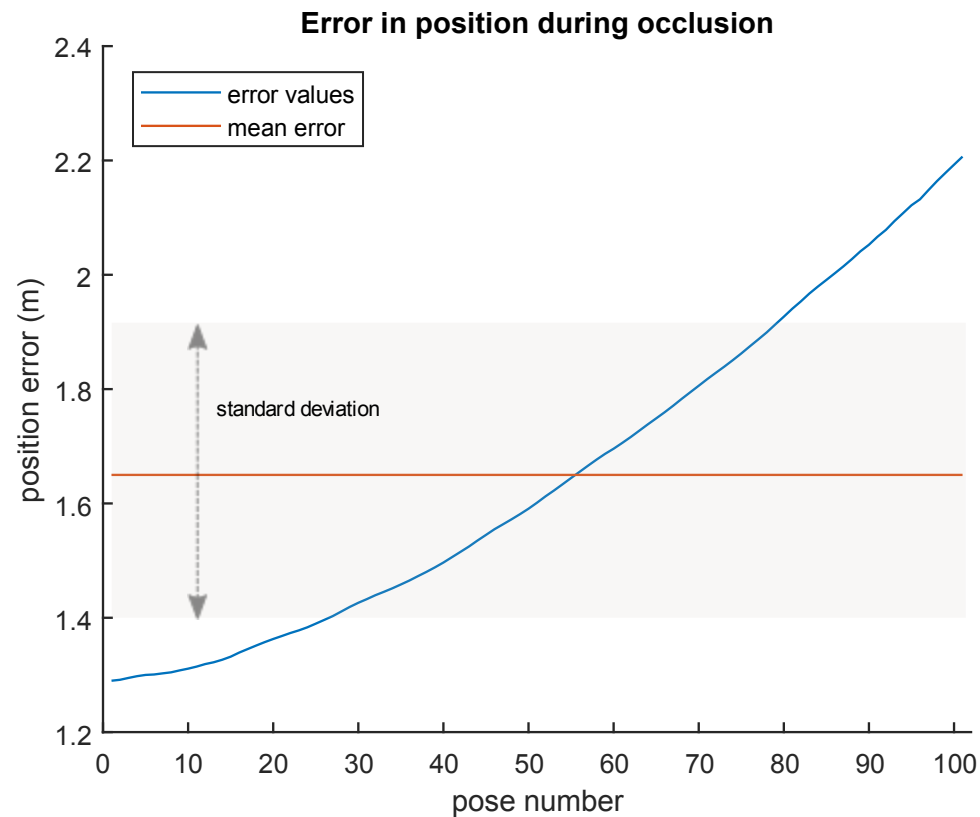
Position in y-direction



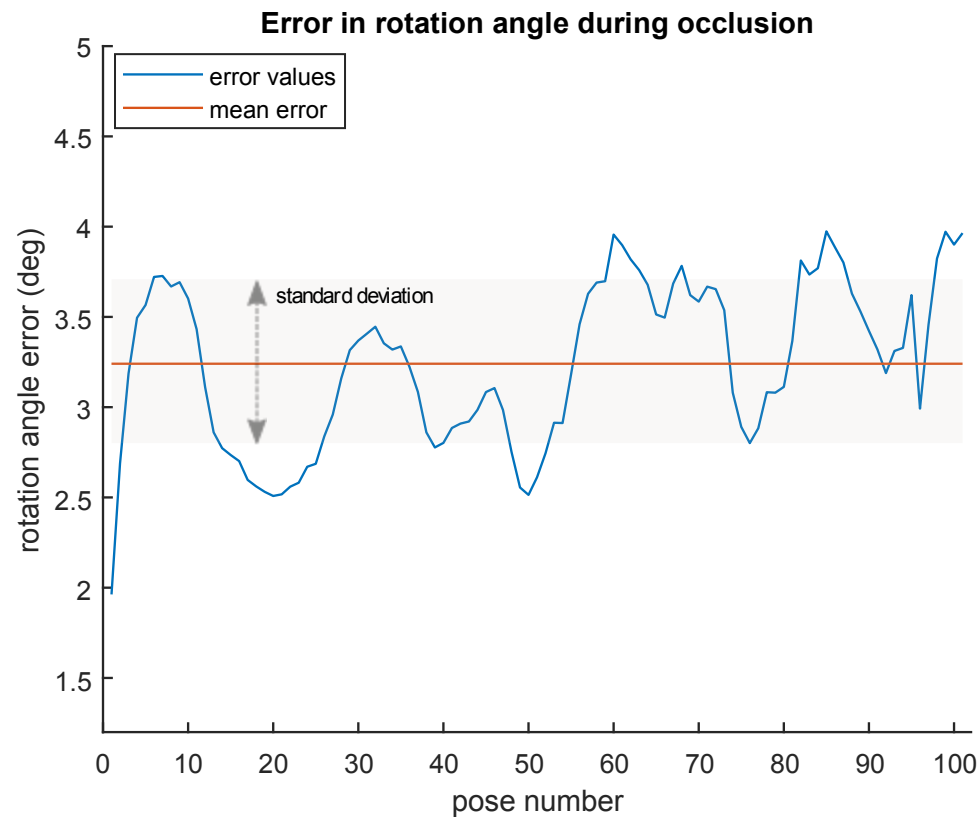
Results – Dataset occlusion



Results – Dataset occlusion

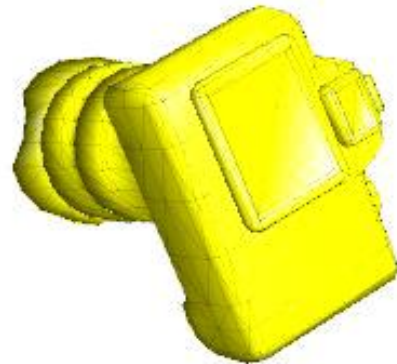


Results – Dataset occlusion

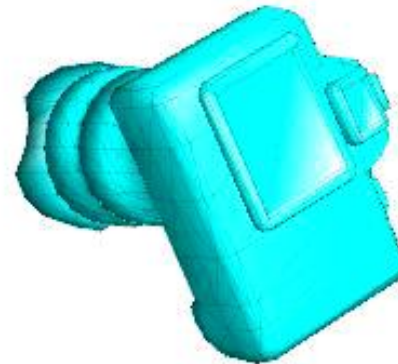


Results – Real Data

OTS

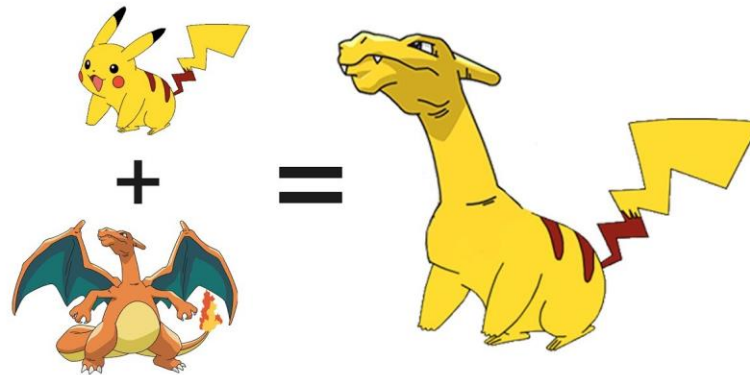


FUSION



Conclusion

- A generic implementation of the EKF fusion filter for n number of sensors is possible
- The use of dual quaternions has a compact form and can be easily integrated
- The more sensors (more information) we have as input in the system the better the accuracy
- The filter can be used in cases of loss of line of sight, in short time occlusions of each individual sensor
- Fusion of different sensor



https://i.ytimg.com/vi/Av8-QlhVOno/maxresdefault_live.jpg 6/6/18

Future work

- Adjustment of each sensor parameters that is inserted in the system according to its type
- Better estimation of the position calculation from the inertial sensor measurements will increase the accuracy during occlusion
- Frequency augmentation of the vision sensor(s)
- Implementation for real time applications



http://www.flyhigher.eu/wp-content/uploads/2013/04/aviao_Airboard-16.png 7/6/2018

Thank you
for your attention!