

# Kalman Filtering for Orientation Estimation using IMUs

## Filtrado Kalman para Estimación de la Orientación usando IMUs

Ph.D. thesis defense

Ph.D. candidate: Pablo Bernal Polo

Advisor: Humberto Martínez Barberá

UNIVERSIDAD DE  
MURCIA

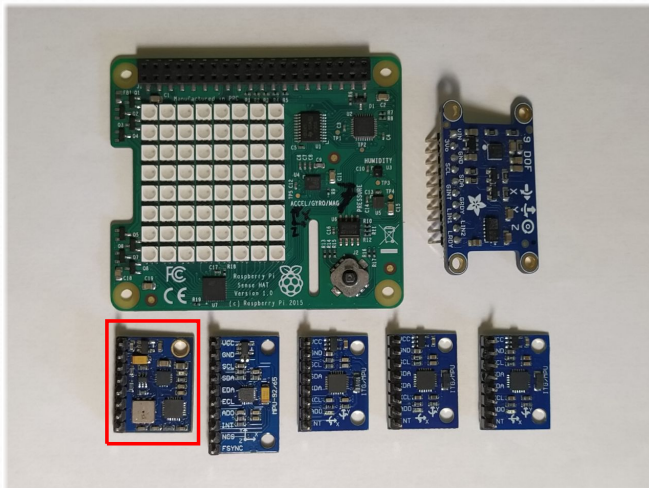


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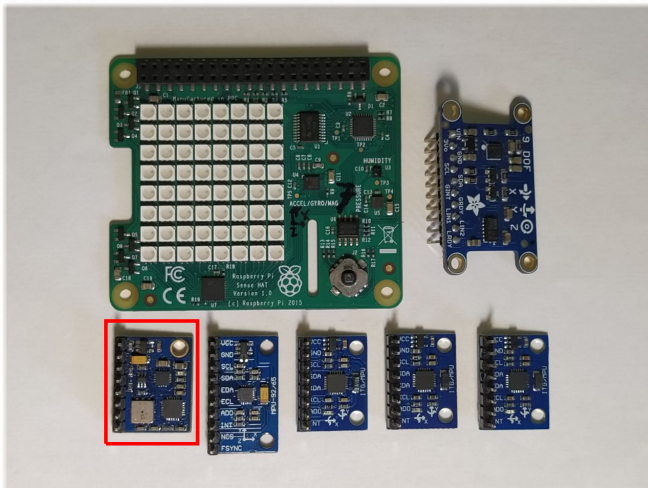
# Outline of the defense

- ▶ Motivation
- ▶ Orientation estimation
  - ▶ Kalman filters
  - ▶ Quaternions as the orientation representation
- ▶ Triaxial sensor calibration
  - ▶ Temperature dependent calibration
  - ▶ Characterization of triaxial sensors
- ▶ Future work

# Motivation

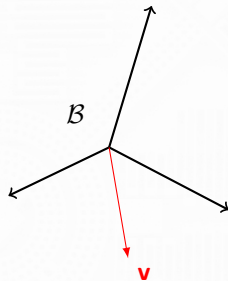
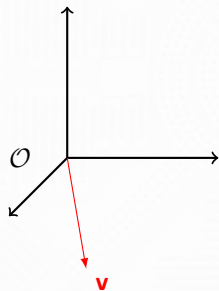


# Motivation



```
./run_show_data.sh
```

# Orientation of a system



# Kalman filter

```
./run_test_EKF.sh
```

# Orientation representation

Representation	Parameters	Continuous	Non-Singular	Linear Evolution
Euler angles	3	X	X	X
Axis-angle	3-4	X	X	X
Rotation matrix	9	✓	✓	✓
Unit quaternion	4	✓	✓	✓

# Orientation representation

Representation	Parameters	Continuous	Non-Singular	Linear Evolution
Euler angles	3	X	X	X
Axis-angle	3–4	X	X	X
Rotation matrix	9	✓	✓	✓
Unit quaternion	4	✓	✓	✓

“...it is topologically impossible to have a global 3-dimensional parametrization without singular points for the rotation group.”

John Stuelpnagel. [On the parametrization of the three-dimensional rotation group.](#)  
[SIAM review](#), 6(4):422–430, 1964



# Unit quaternions

## Complex numbers

$$\begin{aligned} z &= y + x i \equiv \\ &\equiv (y, x) \end{aligned}$$

## Quaternions

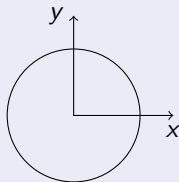
$$\begin{aligned} \mathbf{q} &= q_0 + q_1 \mathbf{i} + q_2 \mathbf{j} + q_3 \mathbf{k} \equiv \\ &\equiv (q_0, q_1, q_2, q_3) \end{aligned}$$

# Unit quaternions

## Complex numbers

$$\begin{aligned} z &= y + x i \equiv \\ &\equiv (y, x) \end{aligned}$$

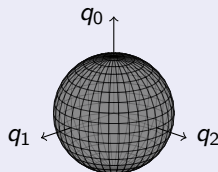
$$y^2 + x^2 = 1$$



## Quaternions

$$\begin{aligned} \mathbf{q} &= q_0 + q_1 \mathbf{i} + q_2 \mathbf{j} + q_3 \mathbf{k} \equiv \\ &\equiv (q_0, q_1, q_2, q_3) \end{aligned}$$

$$q_0^2 + q_1^2 + q_2^2 + q_3^2 = 1$$



# Kalman filter equations

- State prediction:

$$\bar{\mathbf{x}}_{n|n-1} = \mathbf{F}_n \bar{\mathbf{x}}_{n-1|n-1} + \bar{\mathbf{q}}_n$$

$$\mathbf{P}_{n|n-1} = \mathbf{F}_n \mathbf{P}_{n-1|n-1} \mathbf{F}_n^T + \mathbf{Q}_n$$

- Measurement prediction:

$$\bar{\mathbf{z}}_{n|n-1} = \mathbf{H}_n \bar{\mathbf{x}}_{n|n-1}$$

$$\mathbf{S}_{n|n-1} = \mathbf{H}_n \mathbf{P}_{n|n-1} \mathbf{H}_n^T + \mathbf{R}_n$$

- Kalman update:

$$\mathbf{K}_n = \mathbf{P}_{n|n-1} \mathbf{H}_n^T \mathbf{S}_{n|n-1}^{-1}$$

$$\bar{\mathbf{x}}_{n|n} = \bar{\mathbf{x}}_{n|n-1} + \mathbf{K}_n (\mathbf{z}_n - \bar{\mathbf{z}}_{n|n-1})$$

$$\mathbf{P}_{n|n} = (\mathbf{I} - \mathbf{K}_n \mathbf{H}_n) \mathbf{P}_{n|n-1} (\mathbf{I} - \mathbf{K}_n \mathbf{H}_n)^T + \mathbf{K}_n \mathbf{R}_n \mathbf{K}_n^T$$

# Kalman filter adaptation for unit quaternions

## Vectors

$$\mathbf{x} = \bar{\mathbf{x}} + \Delta\mathbf{x}$$

$$\Delta\mathbf{x} = \mathbf{x} - \bar{\mathbf{x}}$$

$$\mathbf{P} = \mathbb{E}[(\Delta\mathbf{x})(\Delta\mathbf{x})^T]$$

$$\Delta\mathbf{x}_n = \mathbf{K}_n (\mathbf{z}_n - \bar{\mathbf{z}}_{n|n-1})$$

$$\bar{\mathbf{x}}_{n|n} = \bar{\mathbf{x}}_{n|n-1} + \Delta\mathbf{x}_n$$

## Quaternions

$$\mathbf{q} = \bar{\mathbf{q}} * \delta$$

$$\delta = \bar{\mathbf{q}}^* * \mathbf{q}$$

$$\mathbf{e} = \varphi(\delta)$$

$$\mathbf{P} = \mathbb{E}[\mathbf{e}\mathbf{e}^T]$$

$$\mathbf{e}_n = \mathbf{K}_n (\mathbf{z}_n - \bar{\mathbf{z}}_{n|n-1})$$

$$\bar{\mathbf{q}}_{n|n} = \bar{\mathbf{q}}_{n|n-1} * \varphi^{-1}(\mathbf{e}_n)$$

# Kalman filter adaptation for unit quaternions

## Vectors

$$\mathbf{x} = \bar{\mathbf{x}} + \Delta\mathbf{x}$$

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## Quaternions

$$\mathbf{q} = \bar{\mathbf{q}} * \delta$$

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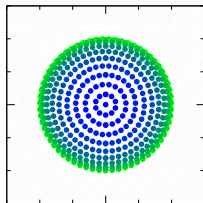
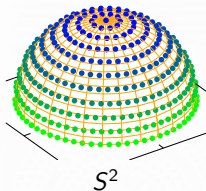
$$\mathbf{P} = \mathbb{E}[\mathbf{e}\mathbf{e}^T]$$

$$\mathbf{e}_n = \mathbf{K}_n (\mathbf{z}_n - \bar{\mathbf{z}}_{n|n-1})$$

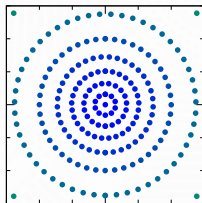
$$\bar{\mathbf{q}}_{n|n} = \bar{\mathbf{q}}_{n|n-1} * \varphi^{-1}(\mathbf{e}_n)$$

```
./run_show_charts.sh
```

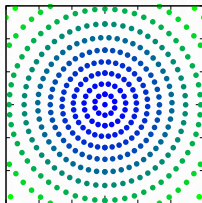
# From manifold to charts



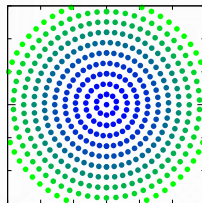
O



RP



MRP

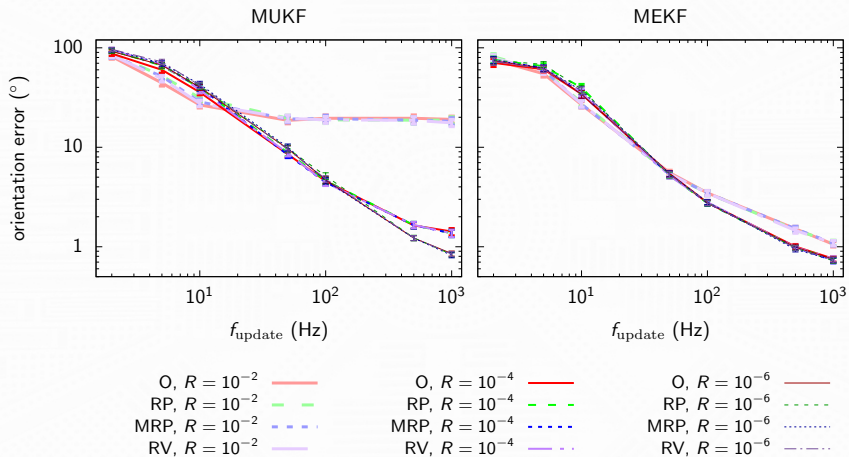


RV

# Manifold Kalman Filters

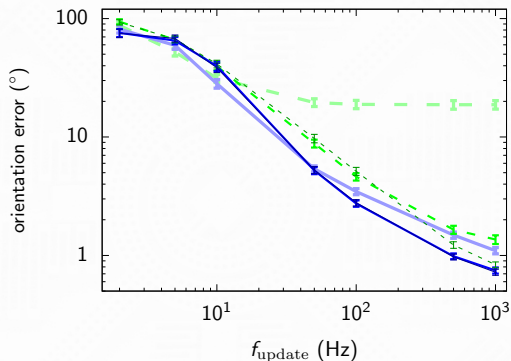
```
./run_test_MKF.sh
```

# Chart comparison





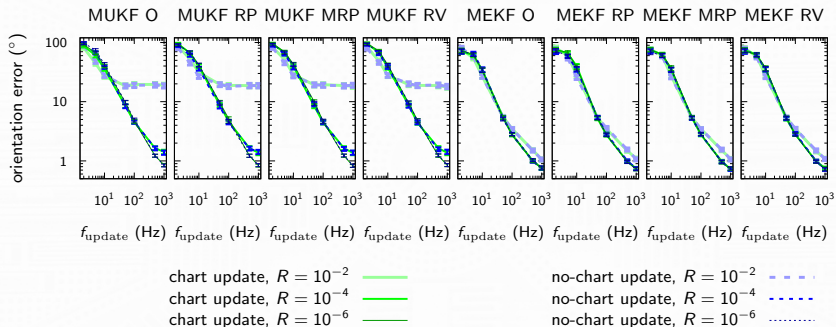
# MKF comparison



MUKF RP,  $R = 10^{-2}$  —  
MUKF RP,  $R = 10^{-4}$  - -  
MUKF RP,  $R = 10^{-6}$  . . .

MEKF RP,  $R = 10^{-2}$  —  
MEKF RP,  $R = 10^{-4}$  —  
MEKF RP,  $R = 10^{-6}$  —

# Chart update vs no-chart update



# Position estimation

```
./run_test_MKF.sh
```

# Usual steps to calibrate a scalar sensor

## Data pairs

$$\{ (x_i, y_i) \}_{i=1}^M$$

## Model

$$y = f(x, \theta)$$

## Cost function

$$C(\theta) = \sum_i (y_i - f(x_i, \theta))^2$$

## Optimization

$$\theta^* = \arg \min_{\theta} C(\theta)$$

# Usual steps to calibrate a scalar sensor

## Data pairs triplets

$$\{ (x_i, y_i) \}_{i=1}^M \longrightarrow \{ (\mathbf{x}_i, T_i, y_i) \}_{i=1}^M$$

## Model

$$y = f(\mathbf{x}, \boldsymbol{\theta})$$

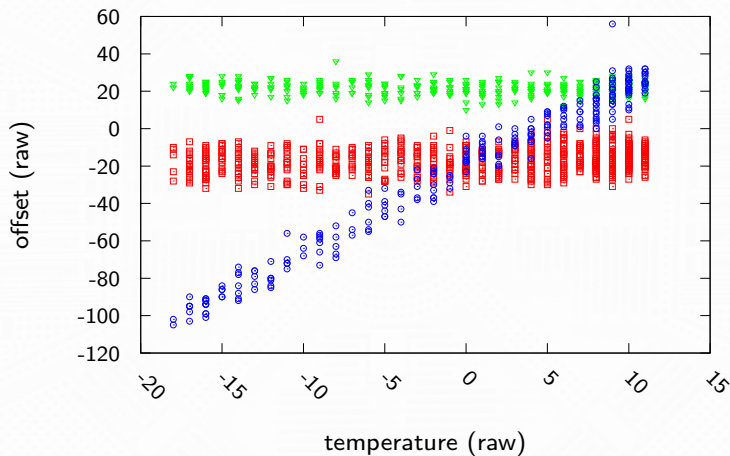
## Cost function

$$C(\boldsymbol{\theta}) = \sum_i (y_i - f(\mathbf{x}_i, \boldsymbol{\theta}))^2$$

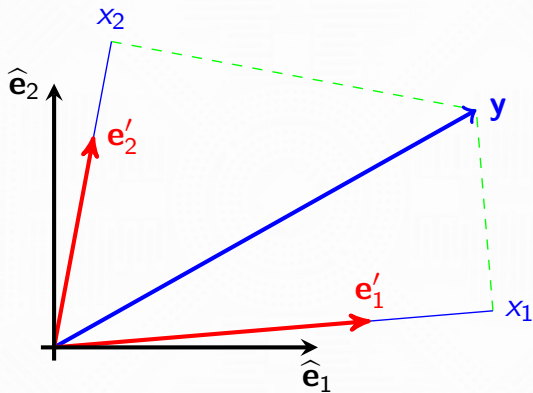
## Optimization

$$\boldsymbol{\theta}^* = \arg \min_{\boldsymbol{\theta}} C(\boldsymbol{\theta})$$

## Temperature dependence of triaxial sensors



# Triaxial sensor model



# Triaxial sensor calibration

## Sensor model

$$\mathbf{x} = \mathbf{S}(T) \mathbf{y} + \mathbf{b}(T) + \mathbf{r}$$

## Module of the vector

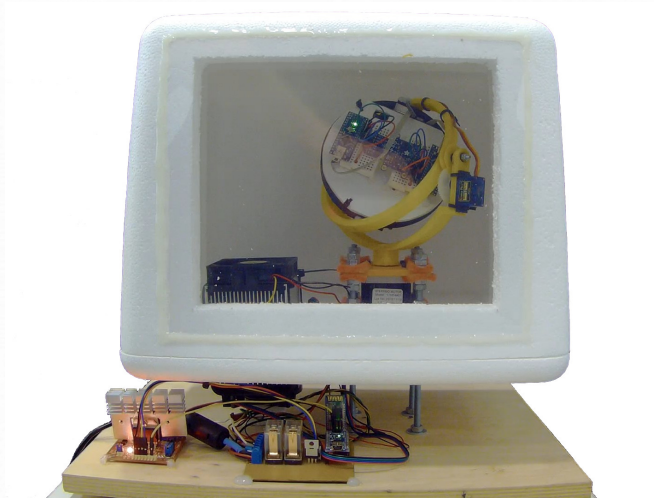
$$\begin{aligned} \|\mathbf{y}\| &= \|\mathbf{S}^{-1}(T) [\mathbf{x} - \mathbf{b}(T) - \mathbf{r}]\| = \\ &= \|\mathbf{K}(T) \mathbf{x} + \mathbf{c}(T) + \mathbf{r}'\| = \\ &= \|\mathbf{A}(T) \tilde{\mathbf{x}} + \mathbf{r}'\| \end{aligned}$$

## Cost function

$$F(\mathbf{A}) = \sum_{m=1}^M \left[ y_m^2 - \|\mathbf{A}(T_m) \tilde{\mathbf{x}}_m\|^2 \right]^2$$

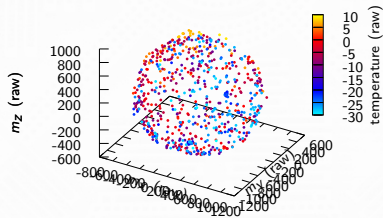
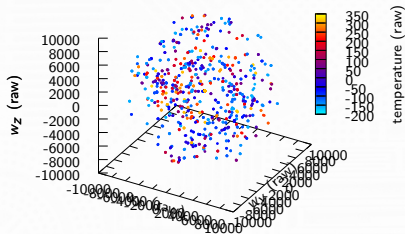
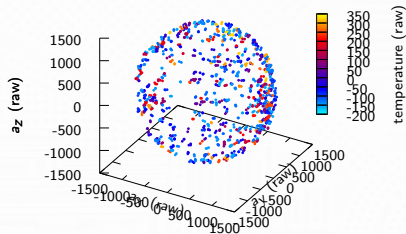


# Triaxial calibration system

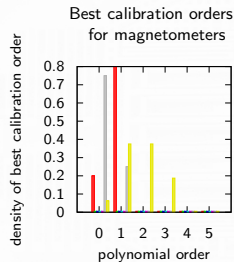
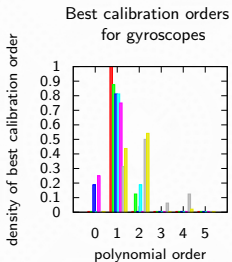
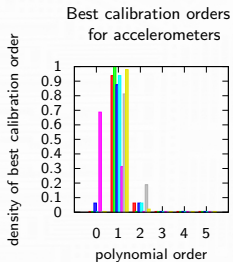


```
./show_calibrationVideo.sh
```

# Examples of calibration data

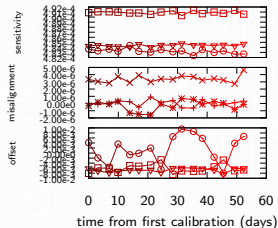


# Density of calibration orders

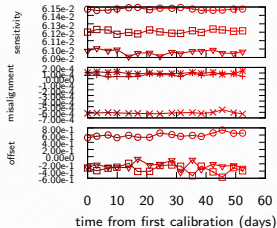


# Examples of calibration data

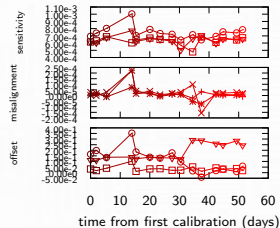
Accelerometer calibration vs time



Gyroscope calibration vs time

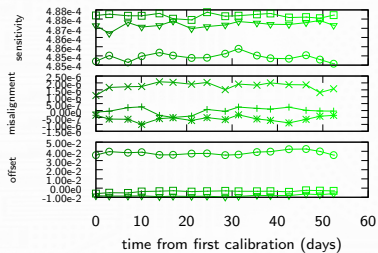


Magnetometer calibration vs time

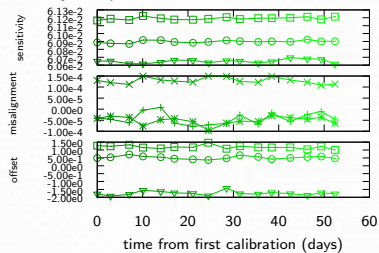


# Examples of calibration data

Accelerometer calibration vs time

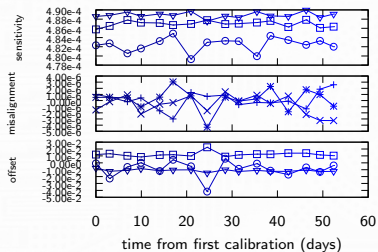


Gyroscope calibration vs time

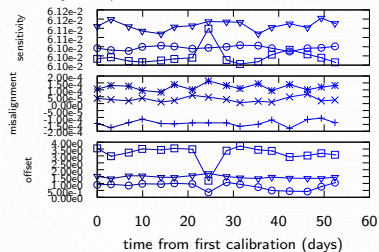


# Examples of calibration data

Accelerometer calibration vs time

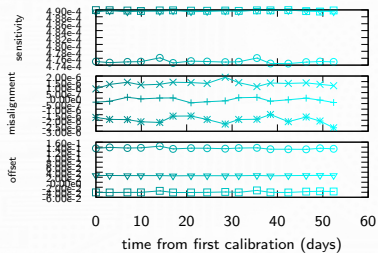


Gyroscope calibration vs time

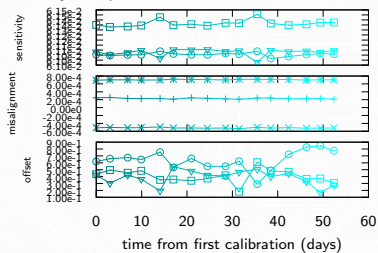


# Examples of calibration data

Accelerometer calibration vs time

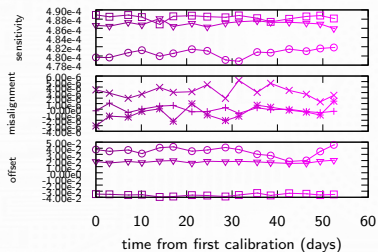


Gyroscope calibration vs time

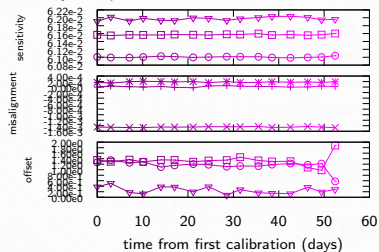


# Examples of calibration data

Accelerometer calibration vs time



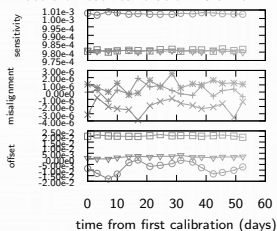
Gyroscope calibration vs time



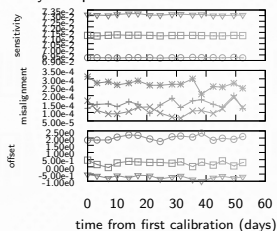


# Examples of calibration data

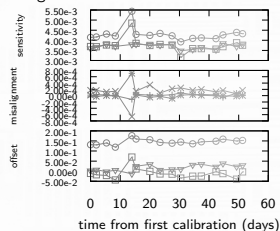
Accelerometer calibration vs time



Gyroscope calibration vs time

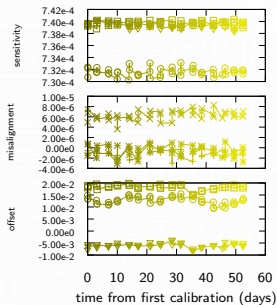


Magnetometer calibration vs time

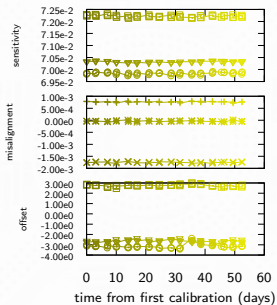


# Examples of calibration data

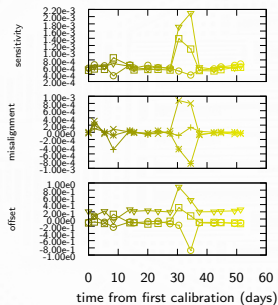
Accelerometer calibration vs time



Gyroscope calibration vs time



Magnetometer calibration vs time



# Results with calibrated sensors

```
./run_test_calibration.sh
```

# Conclusion: contributions

- ▶ Orientation estimation using the Kalman filter and quaternions to describe the orientation:
  - ▶ New perspective on the problem of orientation estimation.
  - ▶ Design of orientation estimation algorithms.
  - ▶ Solution to the problem of the “covariance correction step”.
- ▶ Temperature-dependent calibration of triaxial sensors:
  - ▶ Temperature-dependent calibration algorithm for triaxial sensors.
  - ▶ Prototype to automatically collect calibration data.
  - ▶ Characterization of real triaxial sensors.

# Conclusion: publications



(a) WAF'2016

(b) DESEi+d'2016

(c) Journal of Physical Agents; SJR: 0.176 (2016), Q4 in "Control and Systems Engineering"

(d) ROBOT'2017

(e) WAF'2018

(f) MDPI Sensors; JCR: 3.031 (2018), Q1 in "Instruments & Instrumentation"

(g) IEEE Sensors Journal; JCR: 3.076 (2018), Q1 in "Instruments & Instrumentation"

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# Future work

- ▶ Better IMUs?

```
./run_test_IMxs.sh
```

- ▶ Fusion of several IMUs

```
./run_test_IM.sh
```

- ▶ Fusion of several sensors

```
./run_test_IM.sh
```

Thank you