Proprioceptive Visual Tracking of a Humanoid Robot Head Motion

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The Problem

- Develop a balance algorithm based on the motion of the head;
- Measure the motion of the head;
- Improve measurements accuracy by merging different sources of data.

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Experimental Setup

- Inertial sensors;
- Visual sensors;
- Processing Unit.

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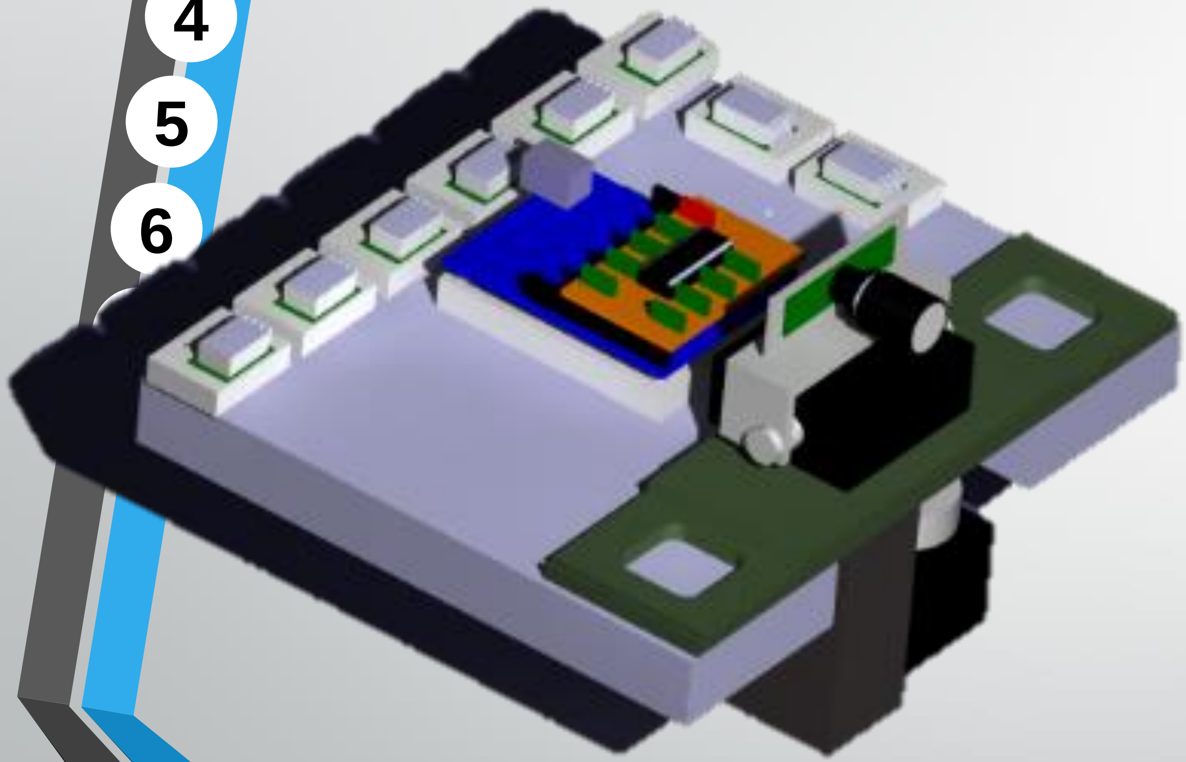
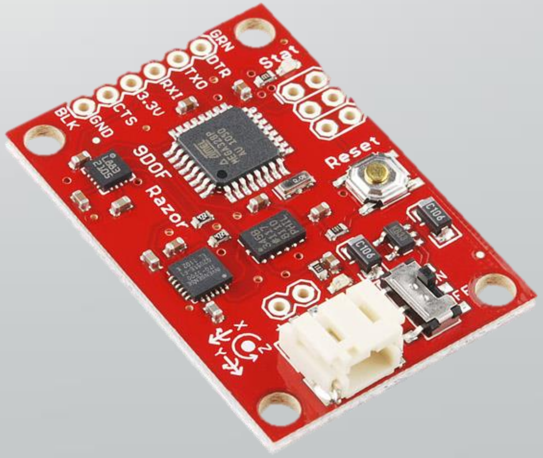
Experimental Setup

- **Sensor A**
- Sensor B
- Processing Unit
- Fire-wire Camera

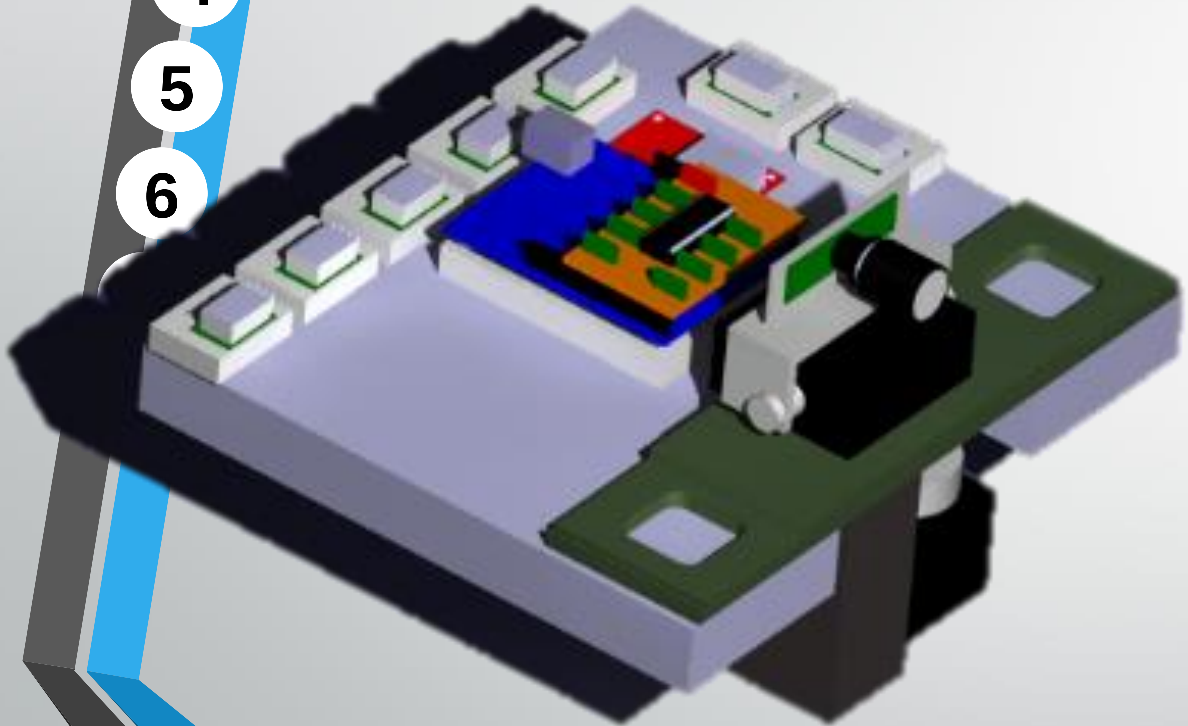


RAZOR 9DOF - SEN 10736



Experimental Setup

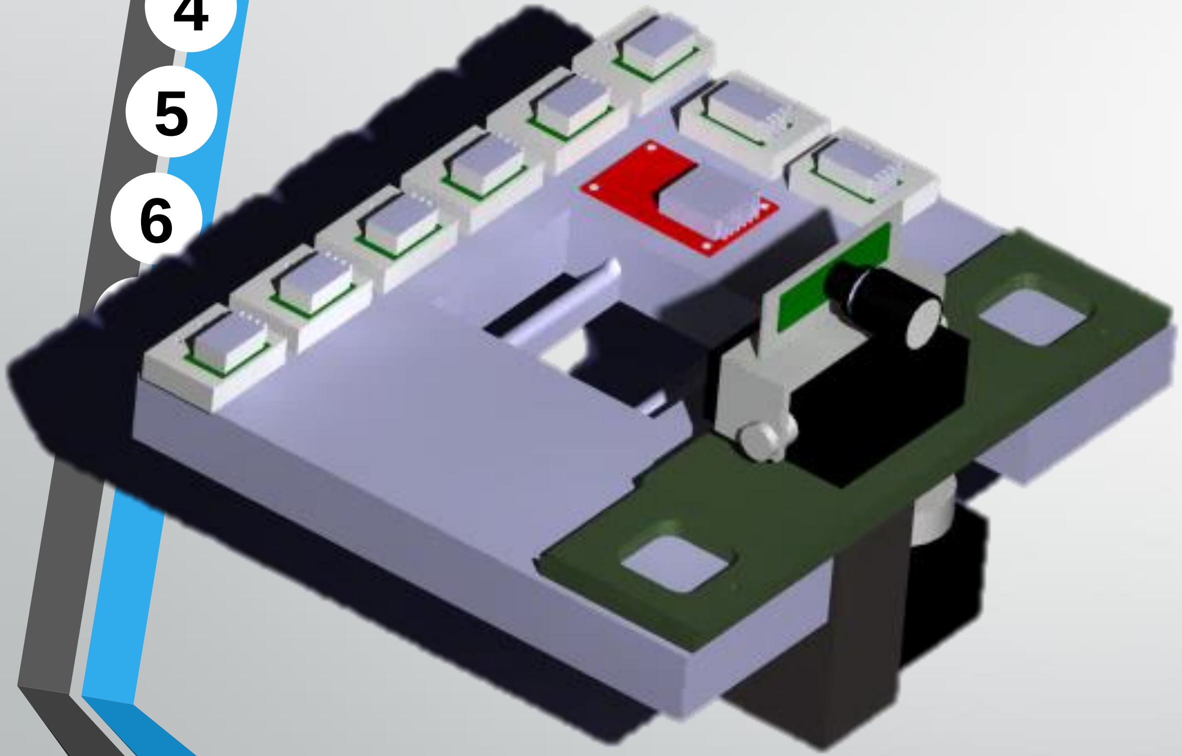
- Sensor A
- **Sensor B**
- Processing Unit
- Fire-wire Camera

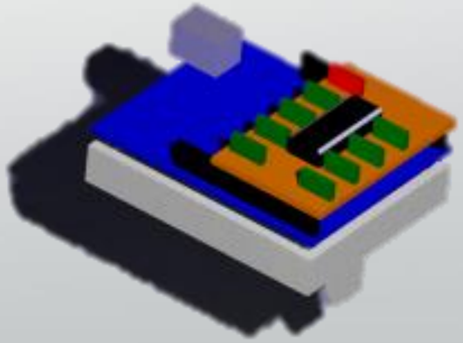


POLOLU - MinIMU9DOF v2

Experimental Setup

- Sensor A
- Sensor B
- **Processing Unit**
- Fire-wire Camera

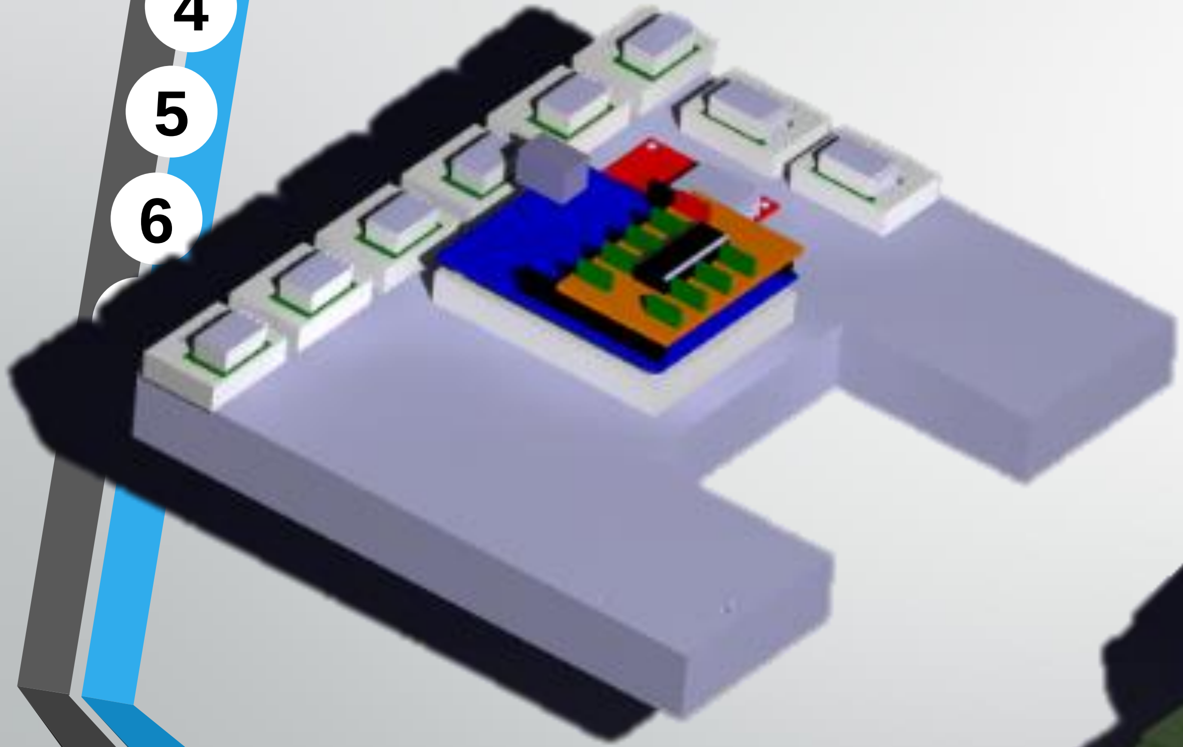


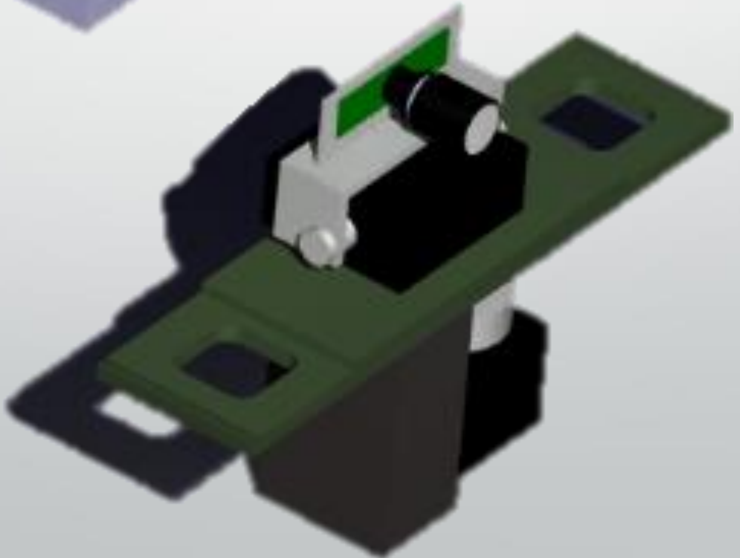


Arduino UNO R3

Experimental Setup

- Sensor A
- Sensor B
- Processing Unit
- **Fire-wire Camera**





Firefly MV-03MTC - Pointgrey

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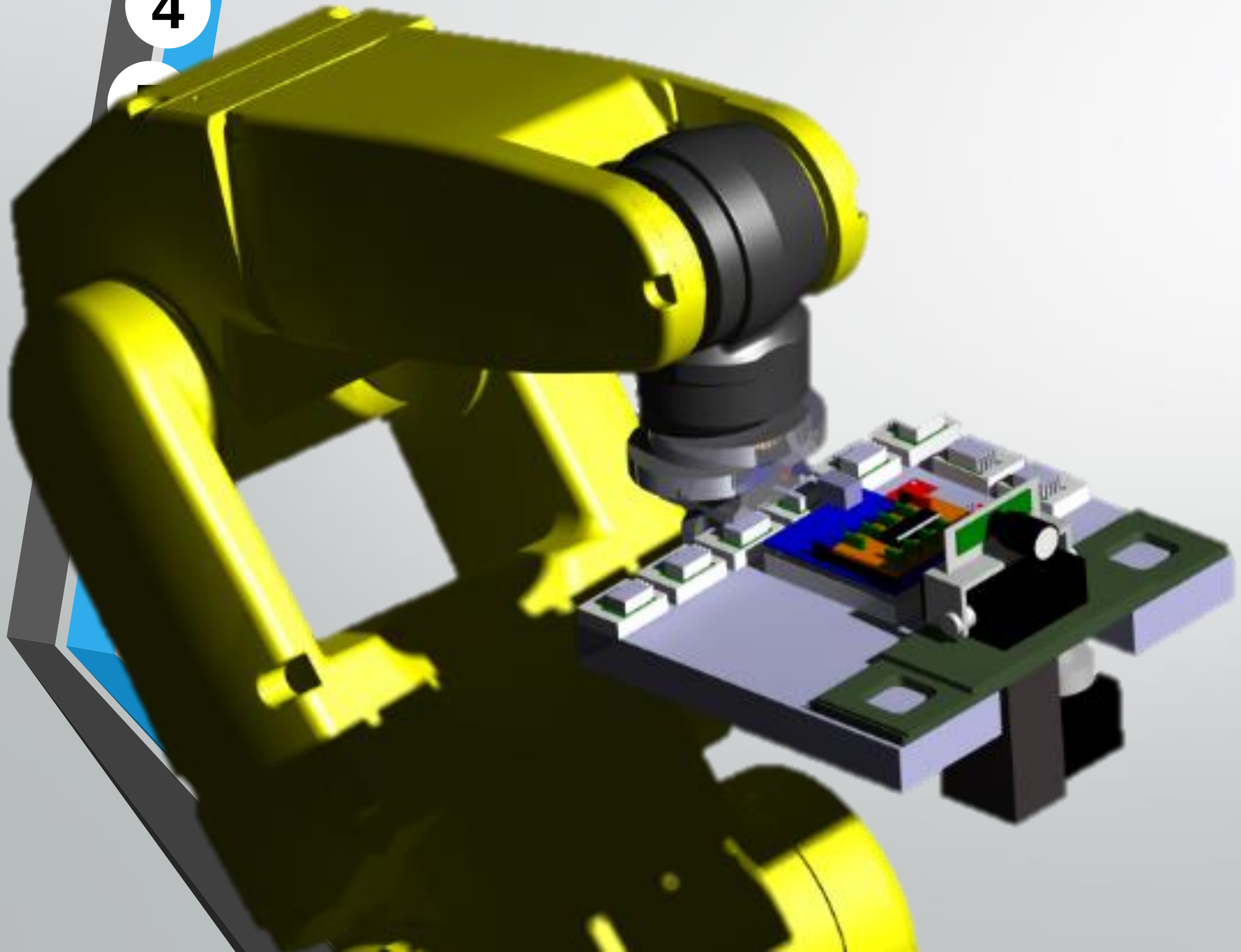
Experimental Setup

- Experiment design problem:
  - Lack of accurate ground truth.

Experimental Setup



FANUC LR Mate 200iB

- High repeatability;
- High end-effector position accuracy;
- Reliable ground truth;
- Easy experiment design.

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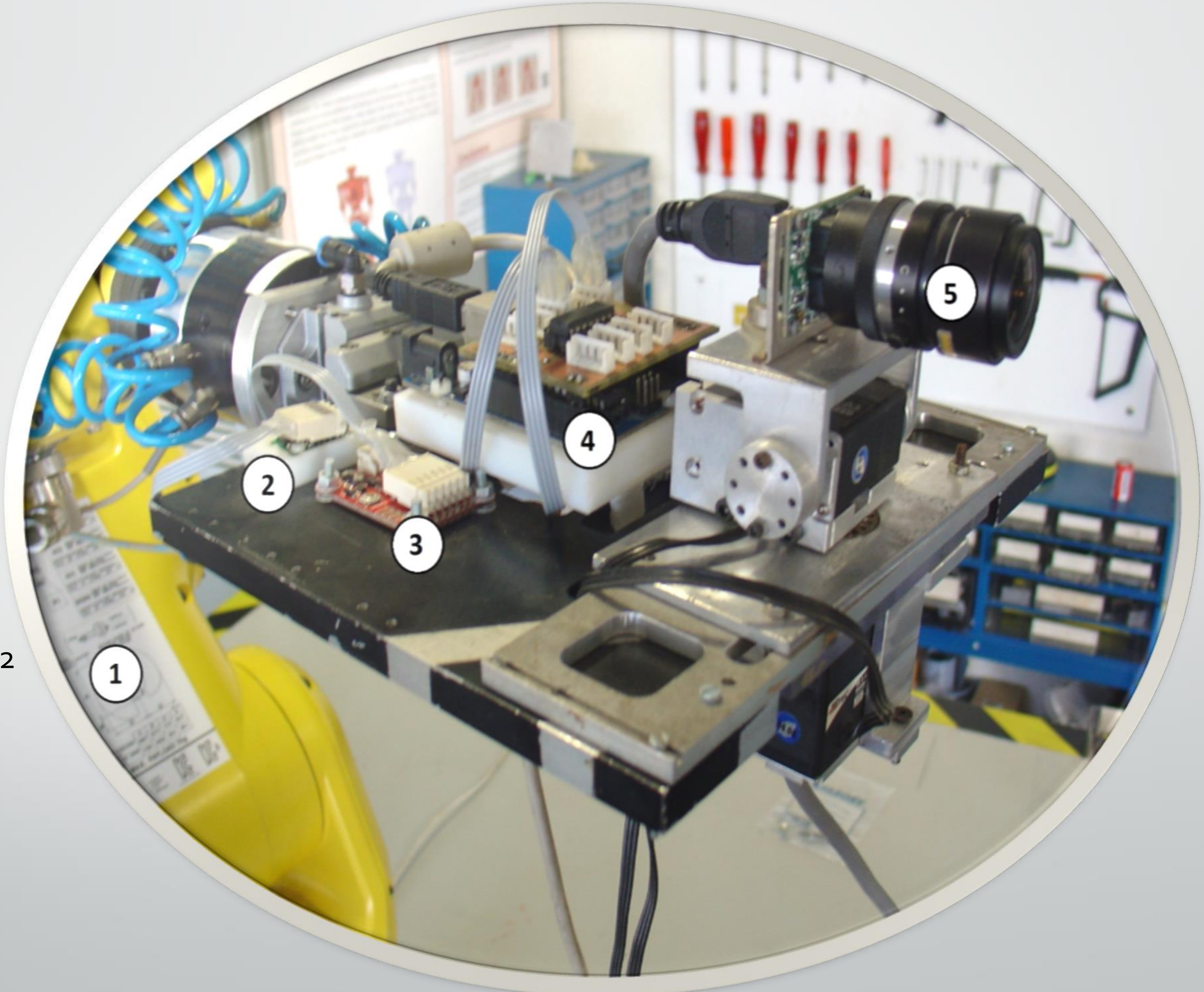
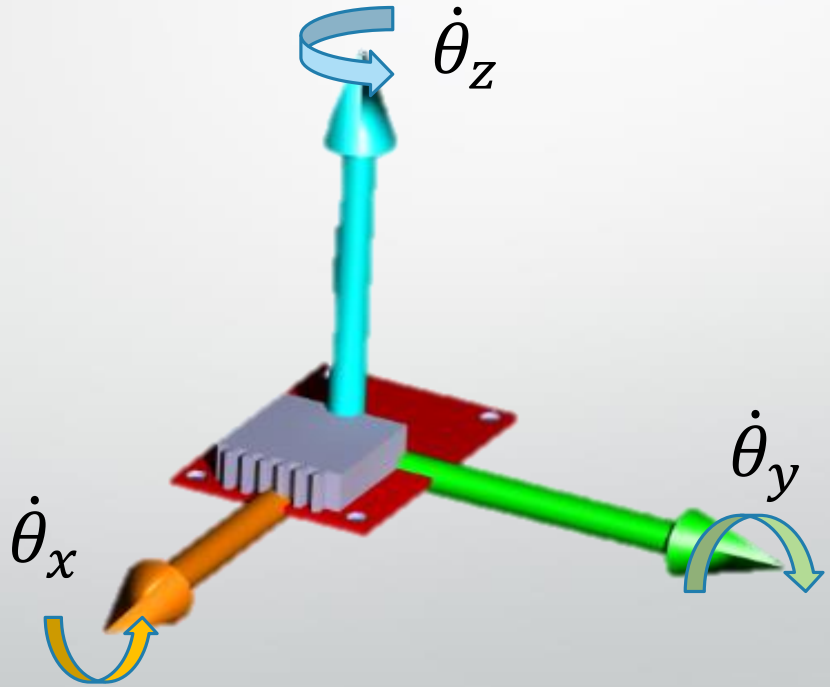
1) Fanuc 200iB
2) POLOLU - MinIMU9DOF v2
3) RAZOR 9DOF - SEN 10736
4) Arduino UNO R3
5) Fire-wire Camera

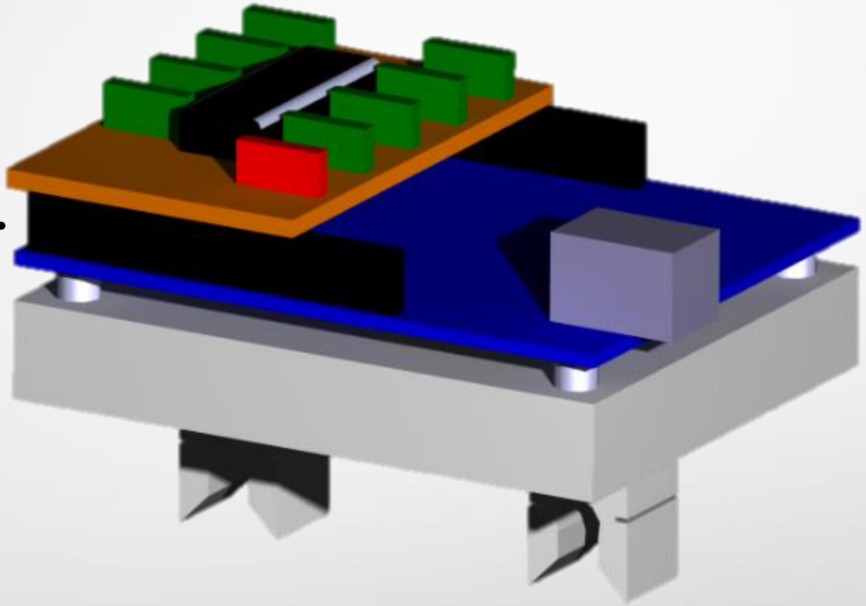


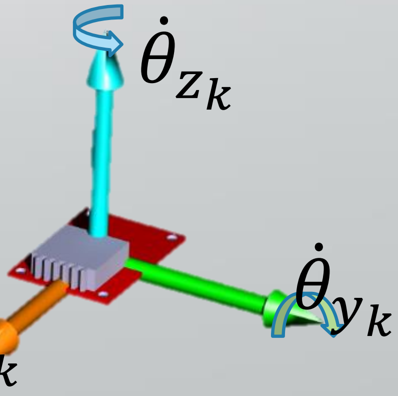
Obtaining Inertial Data



Obtaining Inertial Data

θ_x
θ_y
θ_z

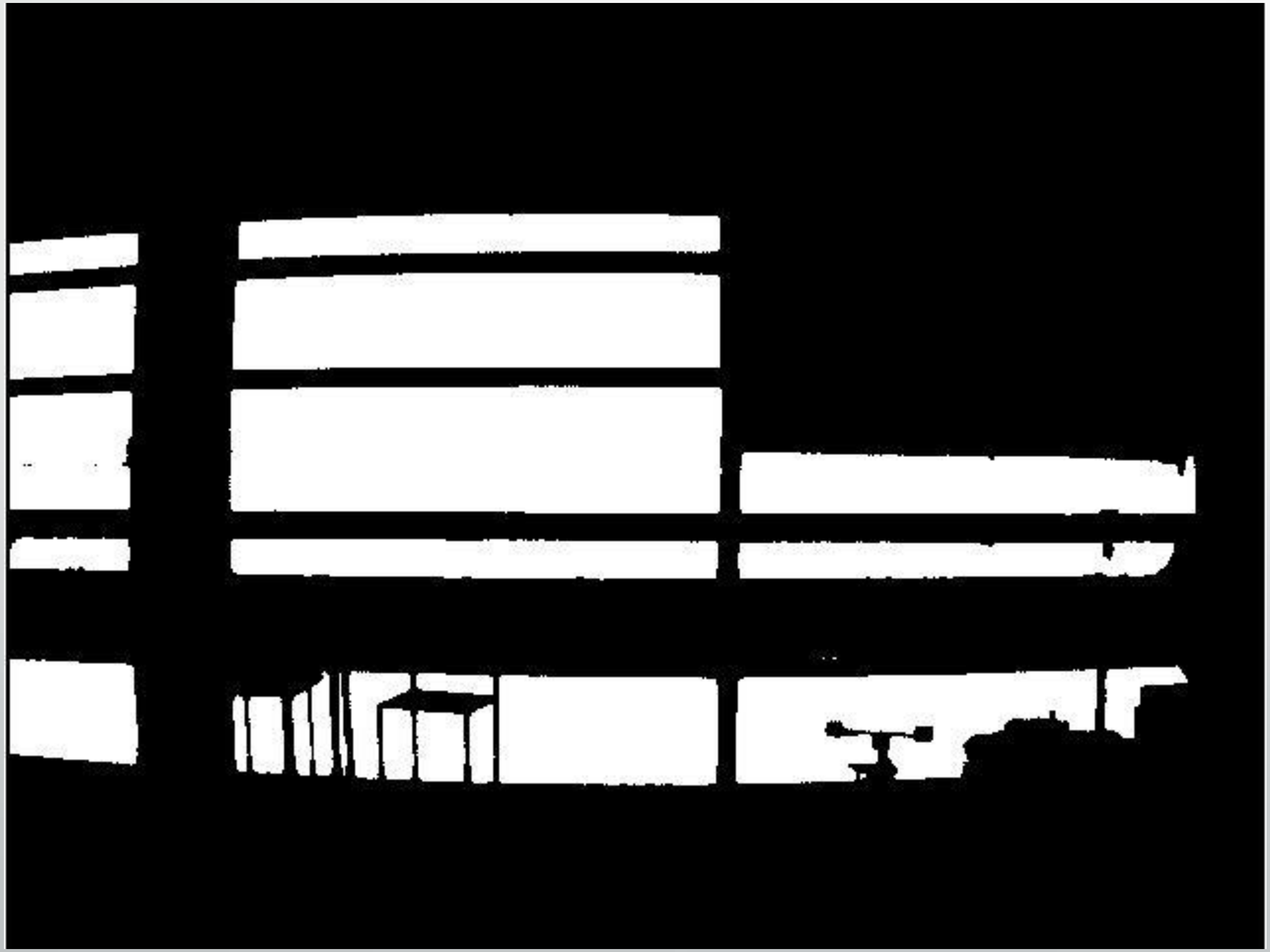




Obtaining Visual Data

- Blob Detection Method;
- Feature Extraction Method.

Blob Detection



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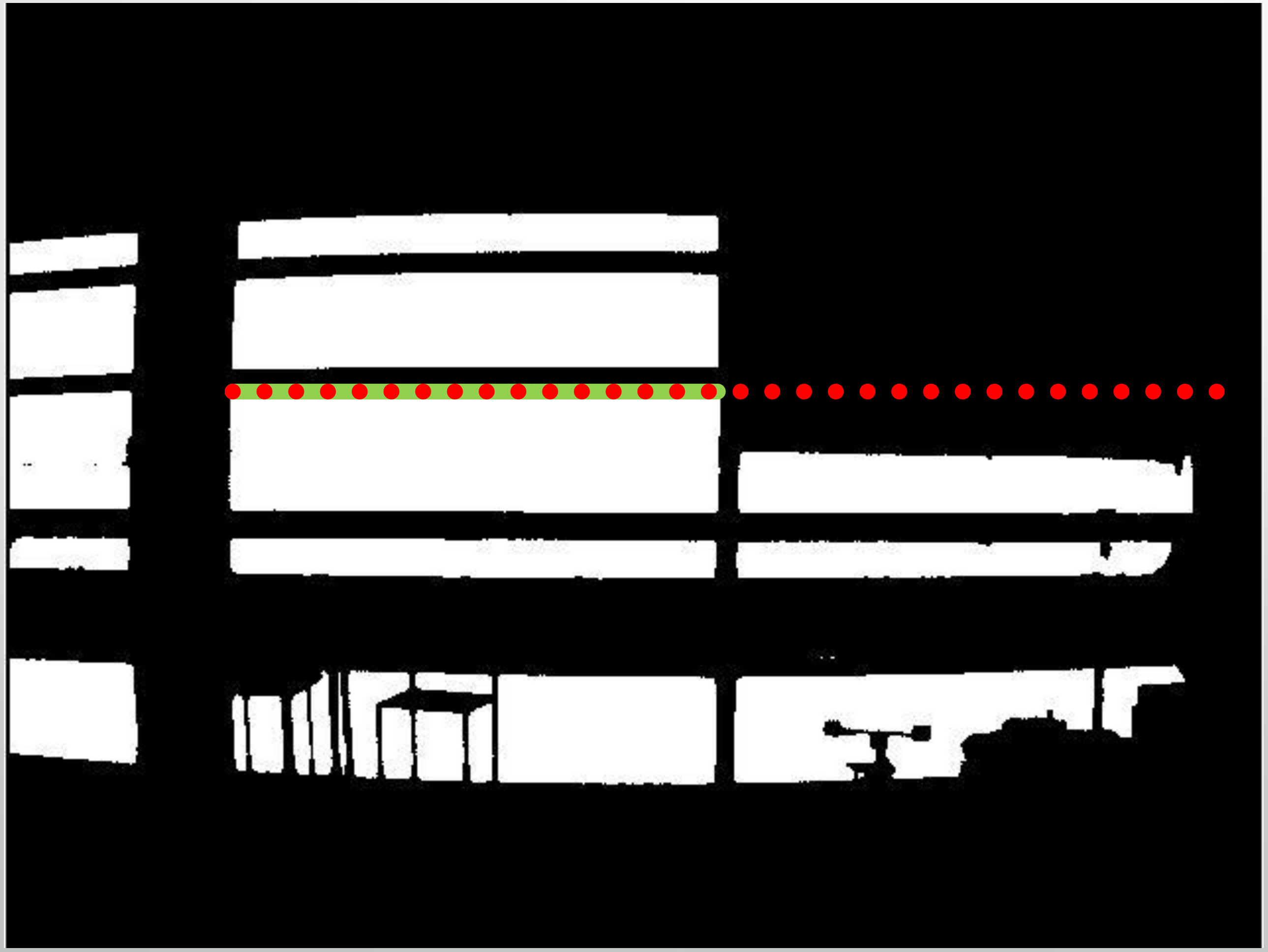
Blob Detection

$\theta_y = 0\ (°)$



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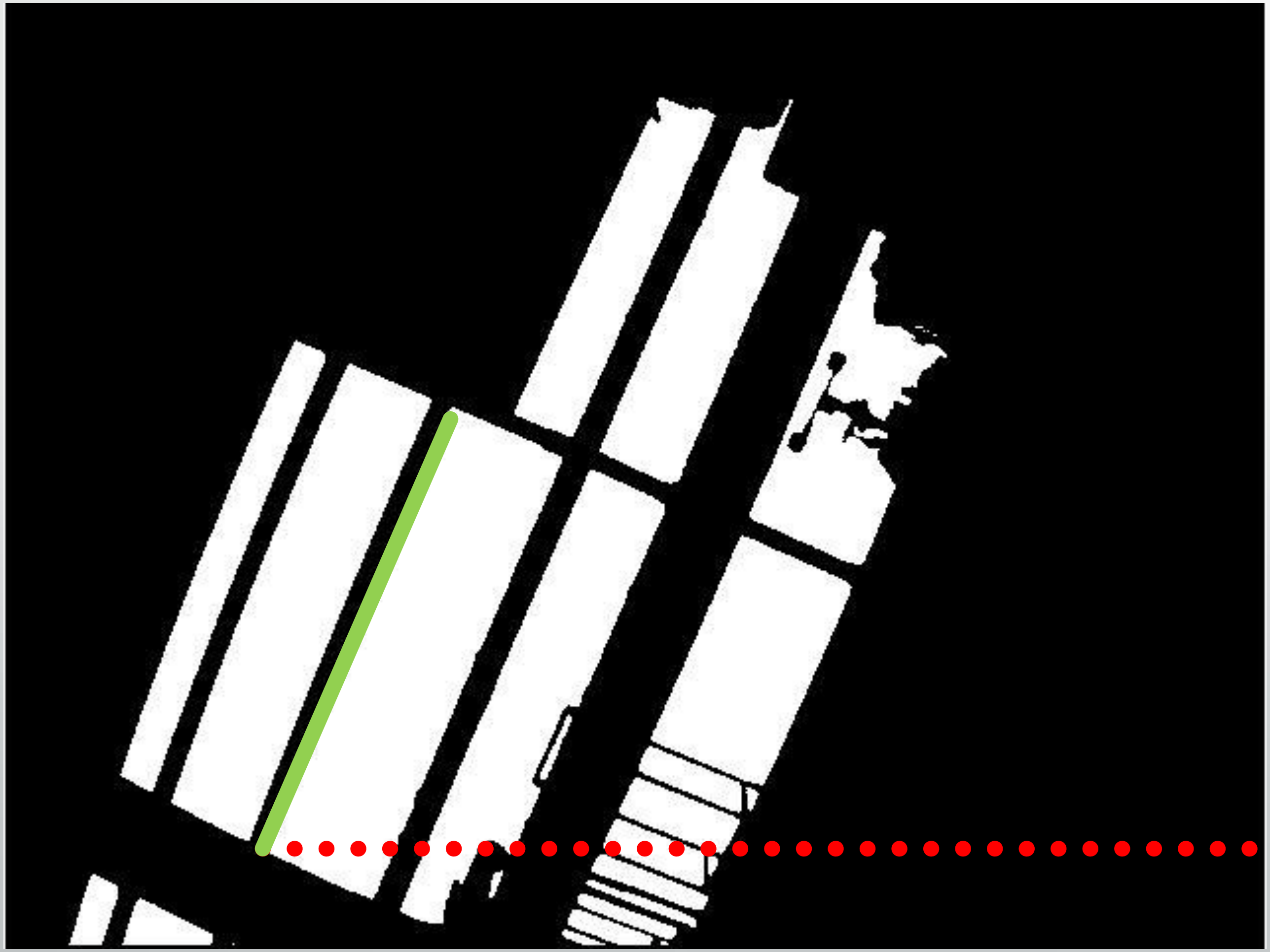
Blob Detection

$\theta_y = 55\ (°)$



Blob Detection

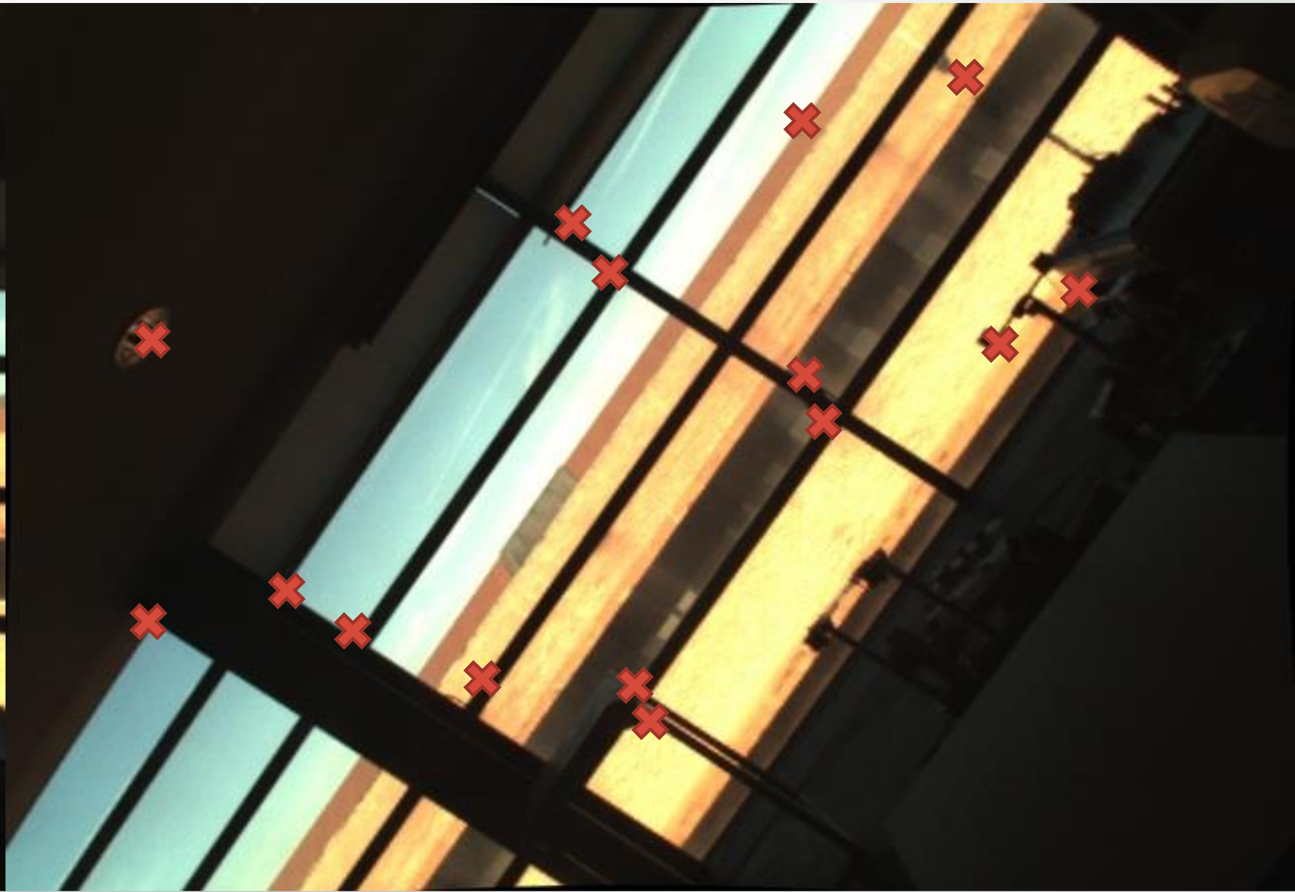
Advantages

- Direct measure of angular position;
- Not dependent of previous measures.

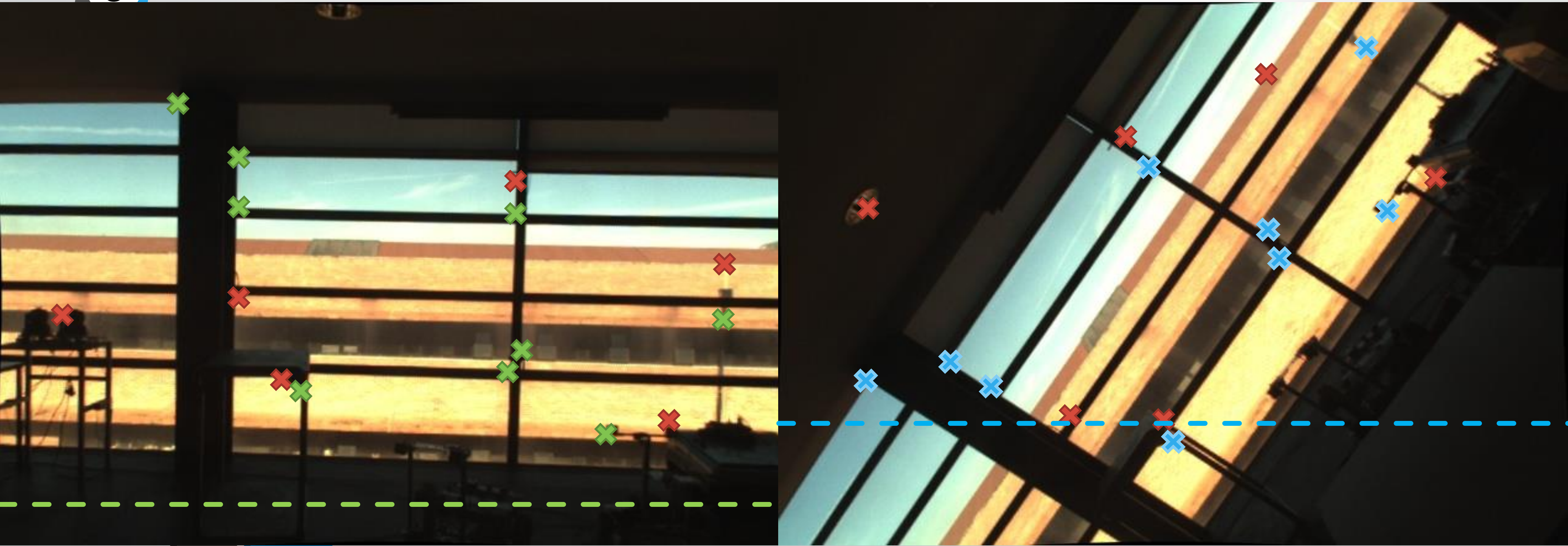
Disadvantages

- Lack of robustness

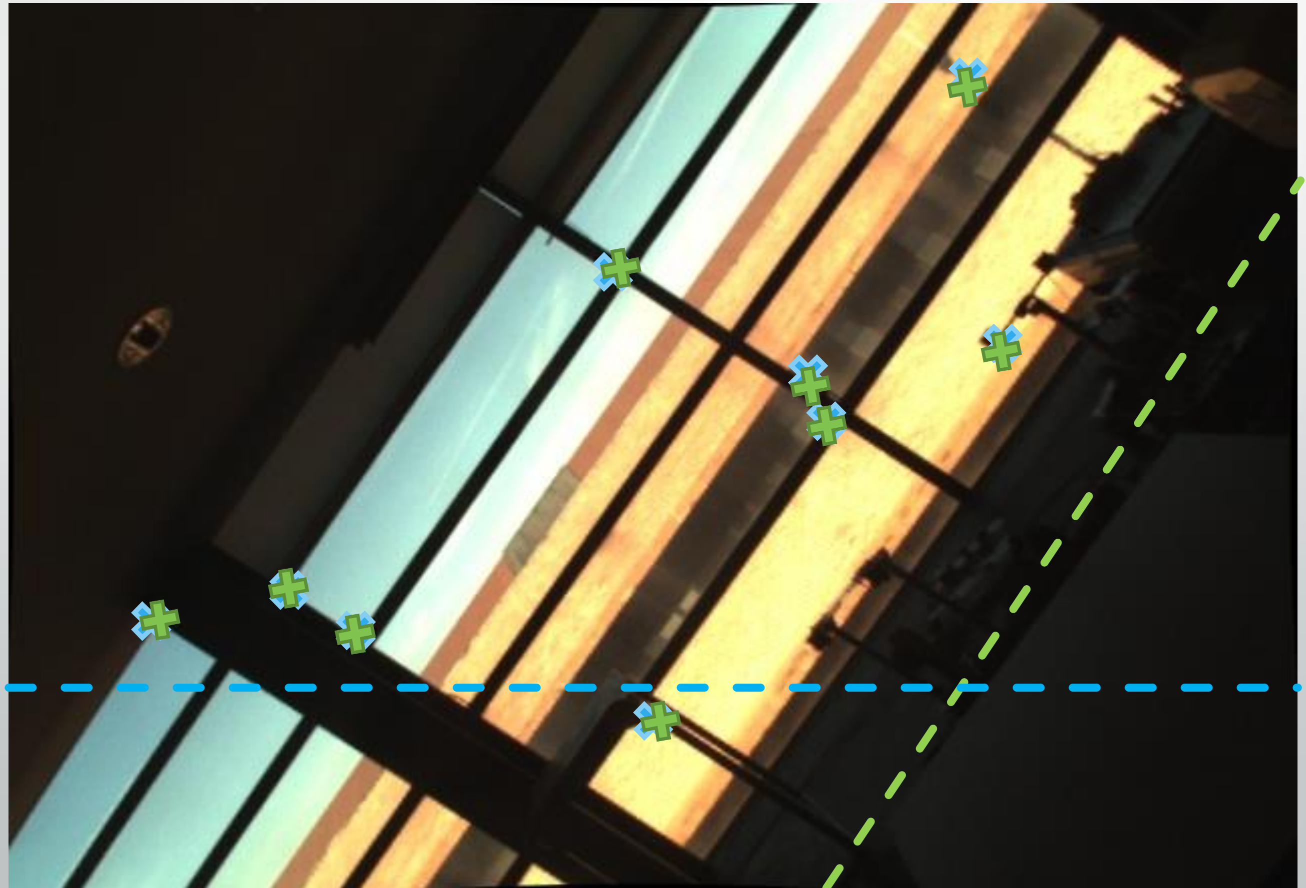
Feature Extraction



Feature Extraction



Feature Extraction



$\rightarrow [T]$

Feature Extraction

$$[T] = \begin{bmatrix} cos\theta_T & -sin\theta_T & d_z \\ sen\theta_T & cos\theta_T & d_x \\ 0 & 0 & 1 \end{bmatrix}$$

$$\theta_{T_k} - \theta_{T_{k-1}} = \boxed{\Delta\theta_{T_k}}$$

$$\theta_{y_k} = \Delta\theta_{T_k} + \theta_{y_{k-1}}$$

$$\dot{\theta}_{y_k} = \frac{\Delta\theta_{T_k}}{\Delta t_k} + \dot{\theta}_{y_{k-1}}$$

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Feature Extraction

Advantages

- More robust method, which can operate in several environments;
- Can be used for various tasks, like mapping or scene recognition.

Disadvantages

- Relies on previous measurements

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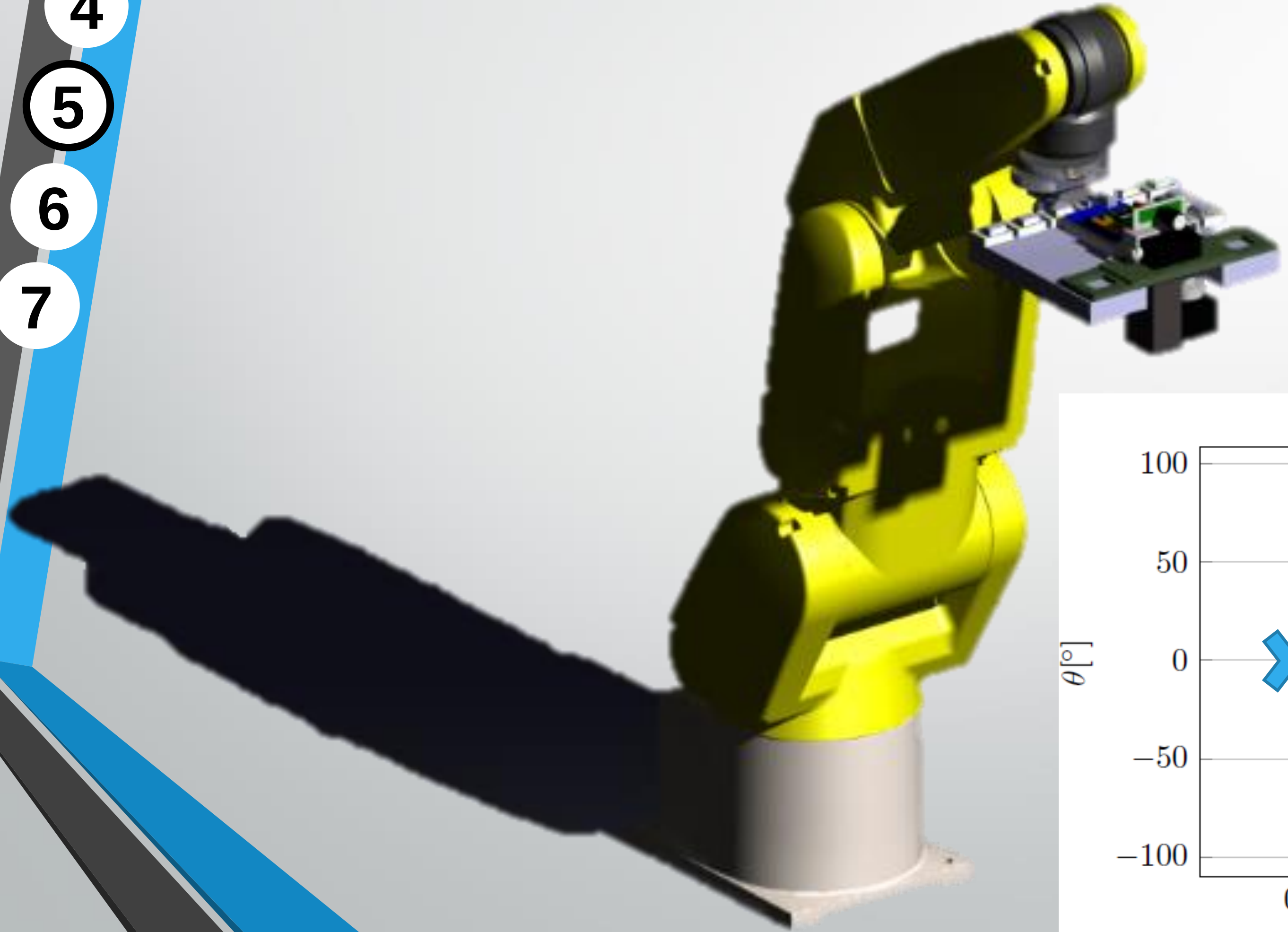
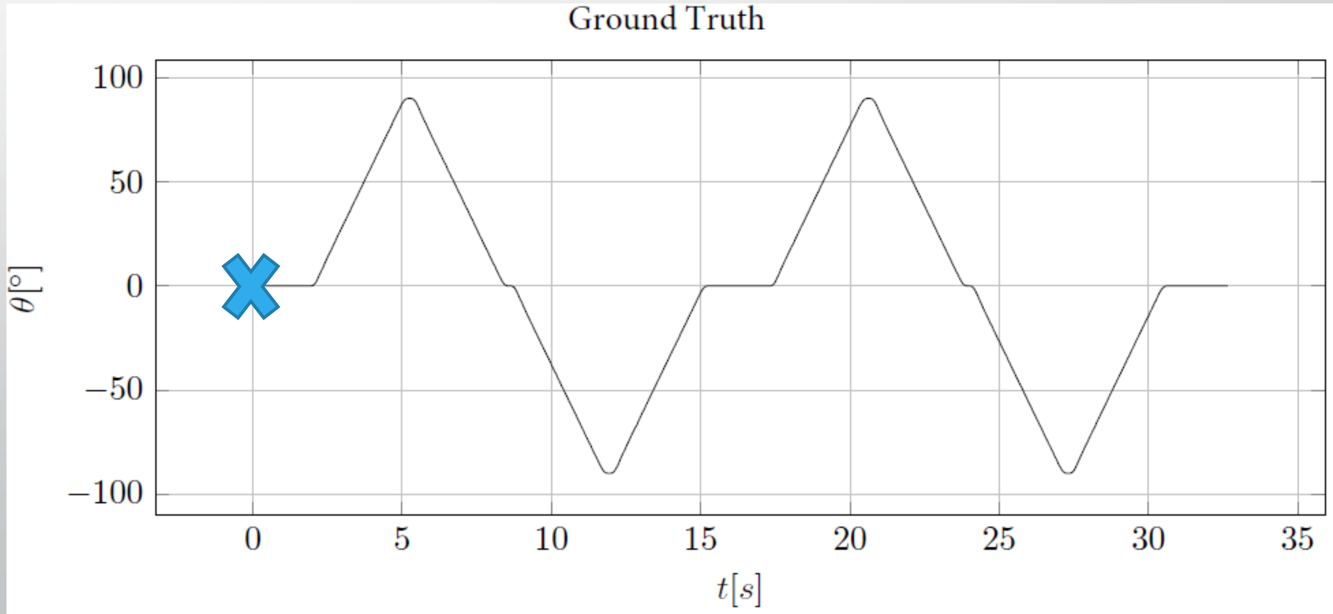
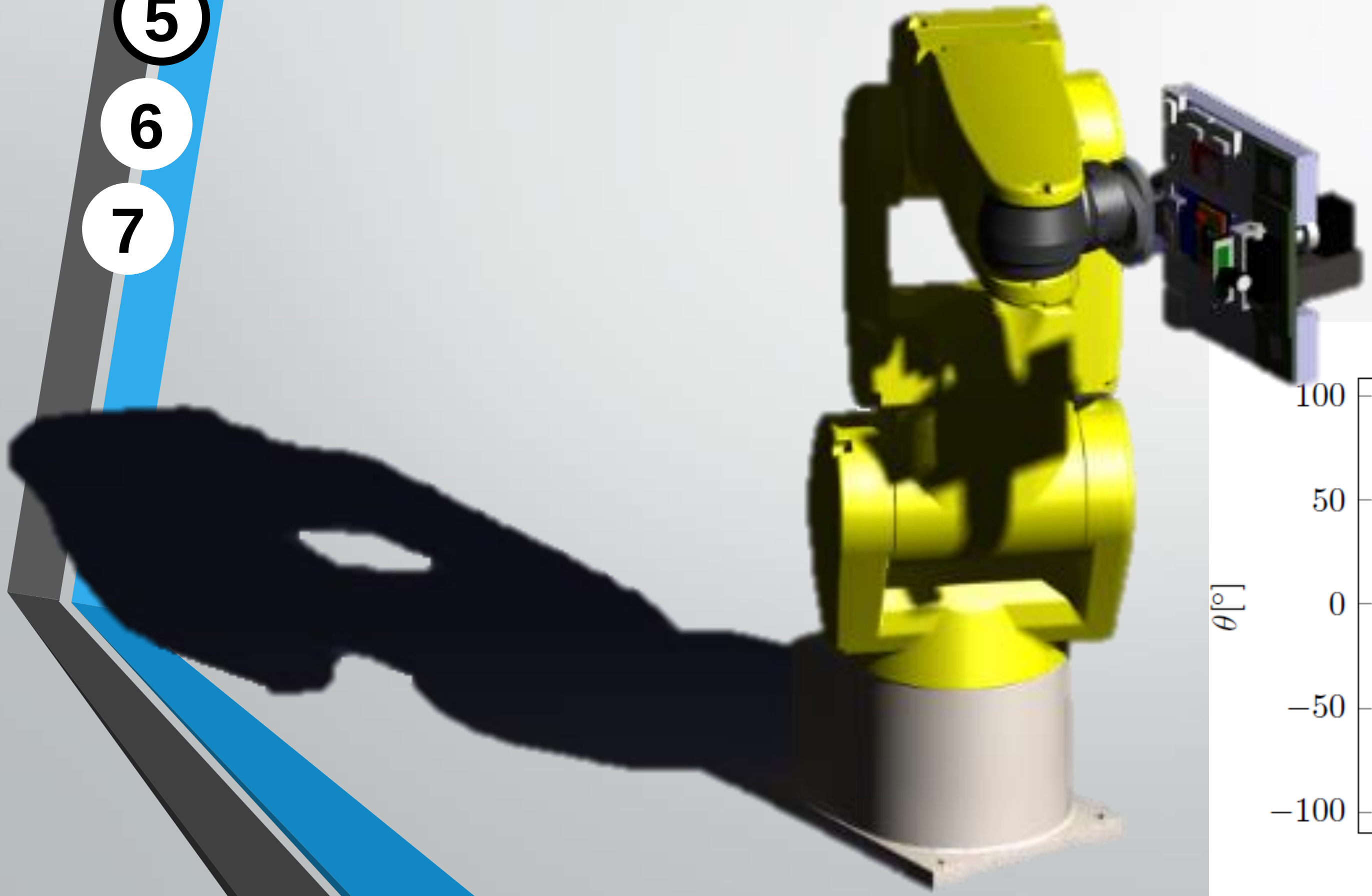
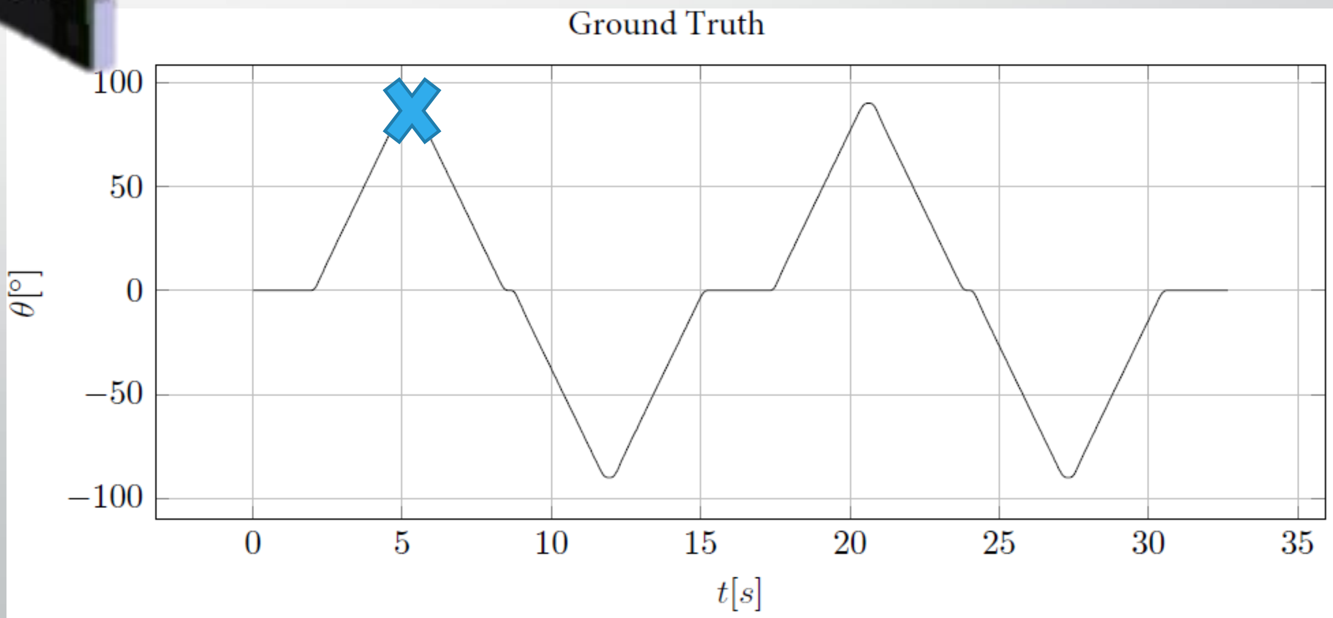
Visual Tracking



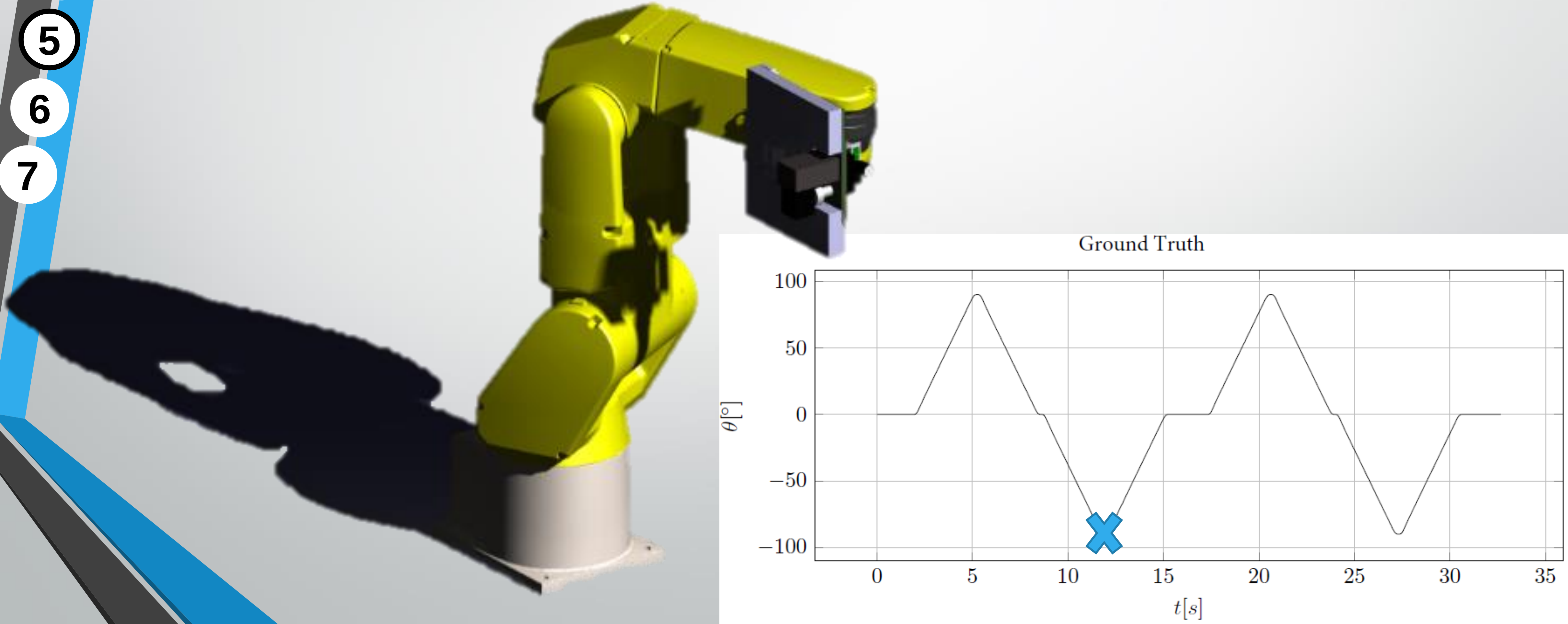


Visual Tracking





Results



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Kalman Filter

$$x_k = A.x_{k-1} + B.u_{k-1} + w_k$$
$$y_k = C.x_k + v_k$$

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Data Merging Using Kalman Filter

$$x_k = A.x_{k-1} + B.u_{k-1} + w_k$$
$$y_k = C.x_k + v_k$$

$\boldsymbol{State\ Variables}$:

$$x_k = \begin{bmatrix} \theta_x \\ \theta_y \\ \theta_z \\ \dot{\theta}_x \\ \dot{\theta}_y \\ \dot{\theta}_z \end{bmatrix}$$

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Data Merging Using Kalman Filter

$$x_k = A.x_{k-1} + B.u_{k-1} + w_k$$
$$y_k = C.x_k + v_k$$

$\boldsymbol{Model\ Definition}$:

$$\theta_k = \theta_{k-1} + \dot{\theta}_{k-1}.\Delta_t + 0{,}5.\ddot{\theta}_{\mathrm{k-1}}.\Delta \mathrm{t}^2$$
$$\dot{\theta}_k = \dot{\theta}_{k-1} + \ddot{\theta}_{\mathrm{k-1}}.\Delta t$$

$$\ddot{\theta}_{k-1} = u_k = \begin{cases} \mathbf{0} \\ \cancel{\left(\dot{\theta}_{k-1} - \dot{\theta}_{k-2}\right)\big/\Delta t_k} \end{cases}$$

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Data Merging Using Kalman Filter

$$x_k = A.x_{k-1} + B.u_{k-1} + w_k$$
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$\boldsymbol{Model\ Definition}$:

$$\theta_k = \theta_{k-1} + \dot{\theta}_{k-1}.\Delta_t + 0{,}5.\ddot{\theta}_{\mathrm{k-1}}.\Delta \mathrm{t}^2$$
$$\dot{\theta}_k = \dot{\theta}_{k-1} + \ddot{\theta}_{\mathrm{k-1}}.\Delta t$$

$$A = \begin{bmatrix} 1\ 0\ 0\ \Delta_t\ 0\ 0 \\ 0\ 1\ 0\ 0\ \Delta_t 0 \\ 0\ 0\ 1\ 0\ 0\ \Delta_t \\ 0\ 0\ 0\ 1\ 0\ 0 \\ 0\ 0\ 0\ 0\ 1\ 0 \\ 0\ 0\ 0\ 0\ 0\ 1 \end{bmatrix} \quad B = \begin{bmatrix} 0{,}5\Delta \mathrm{t}^2 \\ 0{,}5\Delta \mathrm{t}^2 \\ 0{,}5\Delta \mathrm{t}^2 \end{bmatrix}$$

Data Merging Using Kalman Filter

$$\boldsymbol{x_k} = \boldsymbol{A}.\boldsymbol{x_{k-1}} + \boldsymbol{B}.\boldsymbol{u_{k-1}} + \boldsymbol{w_k}$$

$$y_k = C.x_k + v_k$$

$$\begin{bmatrix} \theta_{x_i} \\ \theta_{y_i} \\ \theta_{z_i} \\ \dot{\theta}_{x_i} \\ \dot{\theta}_{y_i} \\ \dot{\theta}_{z_i} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & \Delta_t & 0 & 0 \\ 0 & 1 & 0 & 0 & \Delta_t & 0 \\ 0 & 0 & 1 & 0 & 0 & \Delta_t \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} . \begin{bmatrix} \theta_{x_{i-1}} \\ \theta_{y_{i-1}} \\ \theta_{z_{i-1}} \\ \dot{\theta}_{x_{i-1}} \\ \dot{\theta}_{y_{i-1}} \\ \dot{\theta}_{z_{i-1}} \end{bmatrix} + \begin{bmatrix} 0{,}5\Delta t^2 \\ 0{,}5\Delta t^2 \\ 0{,}5\Delta t^2 \end{bmatrix} \begin{bmatrix} \ddot{\theta}_{x_{i-1}} \\ \ddot{\theta}_{y_{i-1}} \\ \ddot{\theta}_{z_{i-1}} \end{bmatrix}$$

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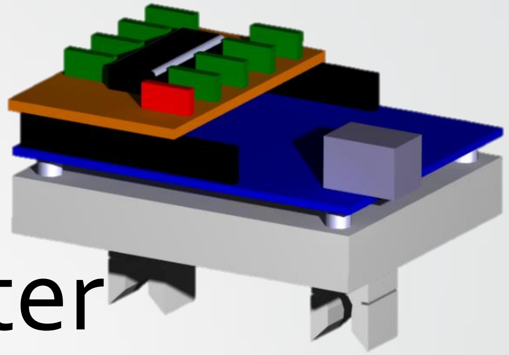
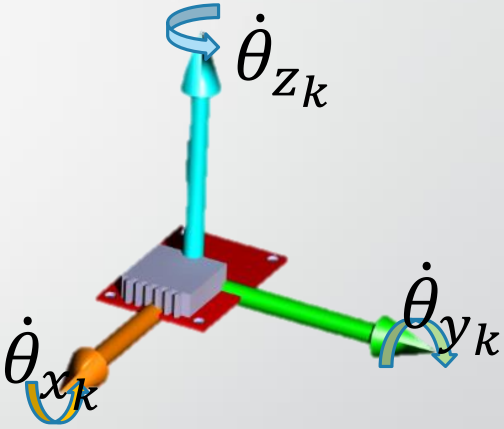
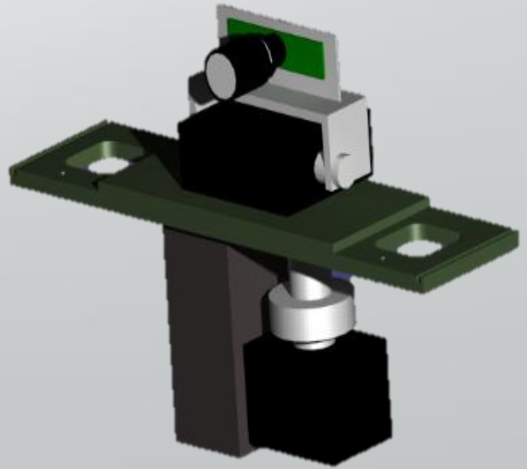
Data Merging Using Kalman Filter

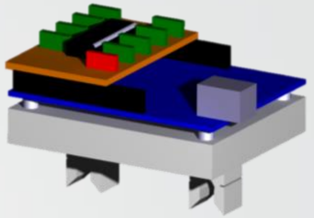




$$x_k = A.x_{k-1} + B.u_{k-1} + w_k$$
$$y_k = C.x_k + v_k$$

$$y_k = \begin{bmatrix} \\ \end{bmatrix}$$

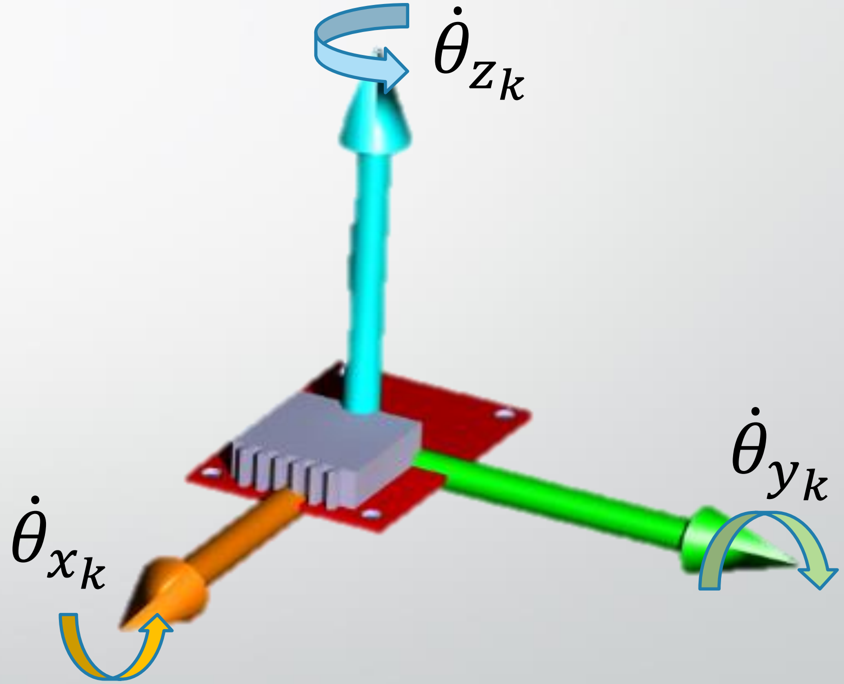


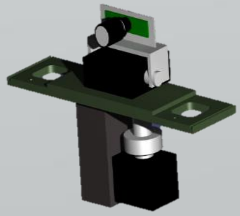


Data Merging Using Kalman Filter

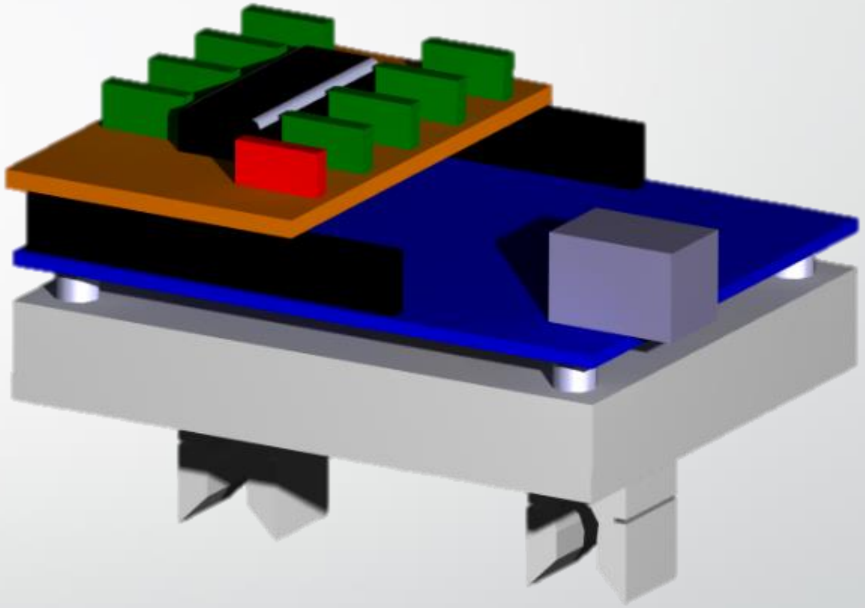
$$x_k = A.x_{k-1} + B.u_{k-1} + w_k$$
$$y_k = C.x_k + v_k$$

$$y_k = \begin{bmatrix} \dot{\theta}_x \\ \dot{\theta}_y \\ \dot{\theta}_z \end{bmatrix}$$



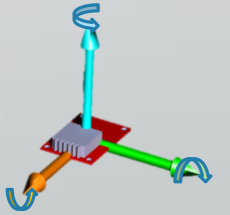


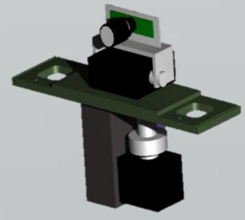
Data Merging Using Kalman Filter

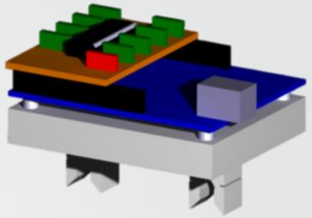


$$x_k = A.x_{k-1} + B.u_{k-1} + w_k$$
$$y_k = C.x_k + v_k$$

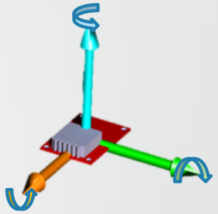
$$y_k = \begin{bmatrix} \theta_x \\ \theta_y \\ \theta_z \\ \dot{\theta}_x \\ \dot{\theta}_y \\ \dot{\theta}_z \end{bmatrix}$$







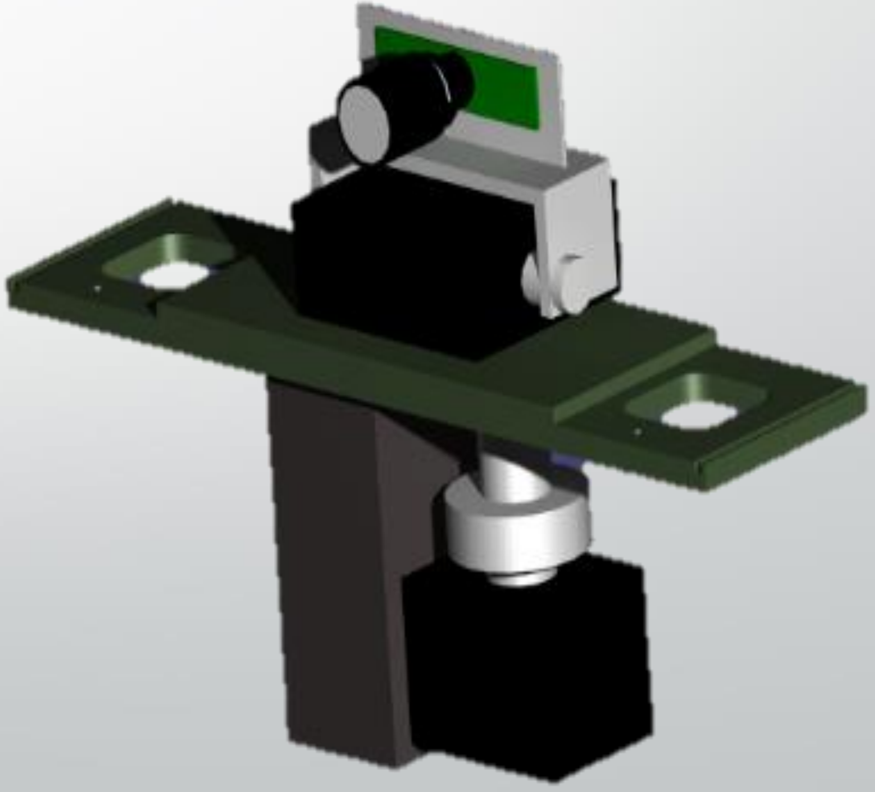
Data Merging Using Kalman Filter



$$x_k = A.x_{k-1} + B.u_{k-1} + w_k$$

$$y_k = C.x_k + v_k$$

$$y_k = \begin{bmatrix} \theta_x \\ \theta_y \\ \theta_z \\ \dot{\theta}_x \\ \dot{\theta}_y \\ \dot{\theta}_z \\ \theta_{c_y} \\ \dot{\theta}_{c_y} \end{bmatrix} \cdots$$



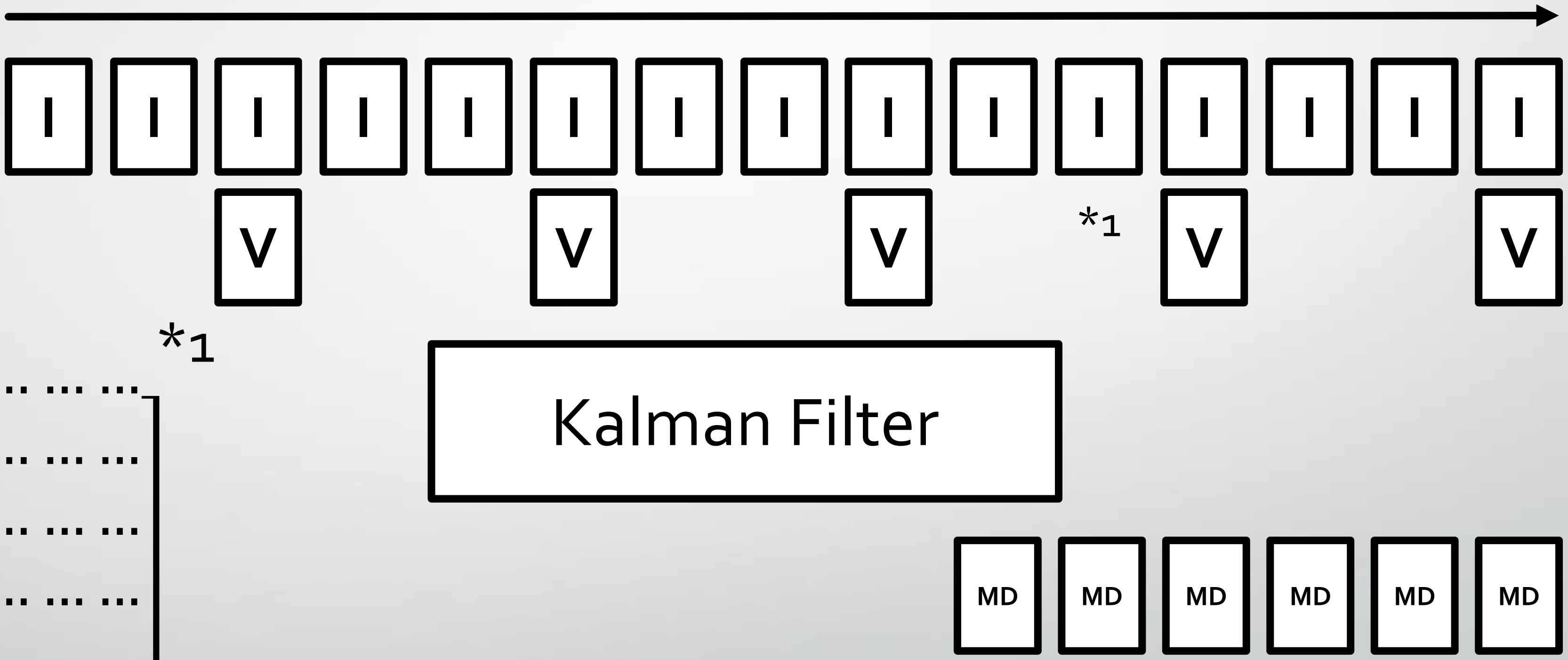
Data Merging Using Kalman Filter

$$x_k = A.x_{k-1} + B.u_{k-1} + w_k$$

$$y_k = C.x_k + v_k$$

$$y_k = \begin{bmatrix} \theta_x \\ \theta_y \\ \theta_z \\ \dot{\theta}_x \\ \dot{\theta}_y \\ \dot{\theta}_z \\ \theta_{c_y} \\ \dot{\theta}_{c_y} \\ \dots \end{bmatrix} \quad C = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ \hdashline 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ & & \dots & & & \end{bmatrix} \quad x_k = \begin{bmatrix} \theta_x \\ \theta_y \\ \theta_z \\ \dot{\theta}_x \\ \dot{\theta}_y \\ \dot{\theta}_z \end{bmatrix}$$

Data Merging Using Kalman Filter



$$G_k = \begin{bmatrix} \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}^{*1}$$

Results

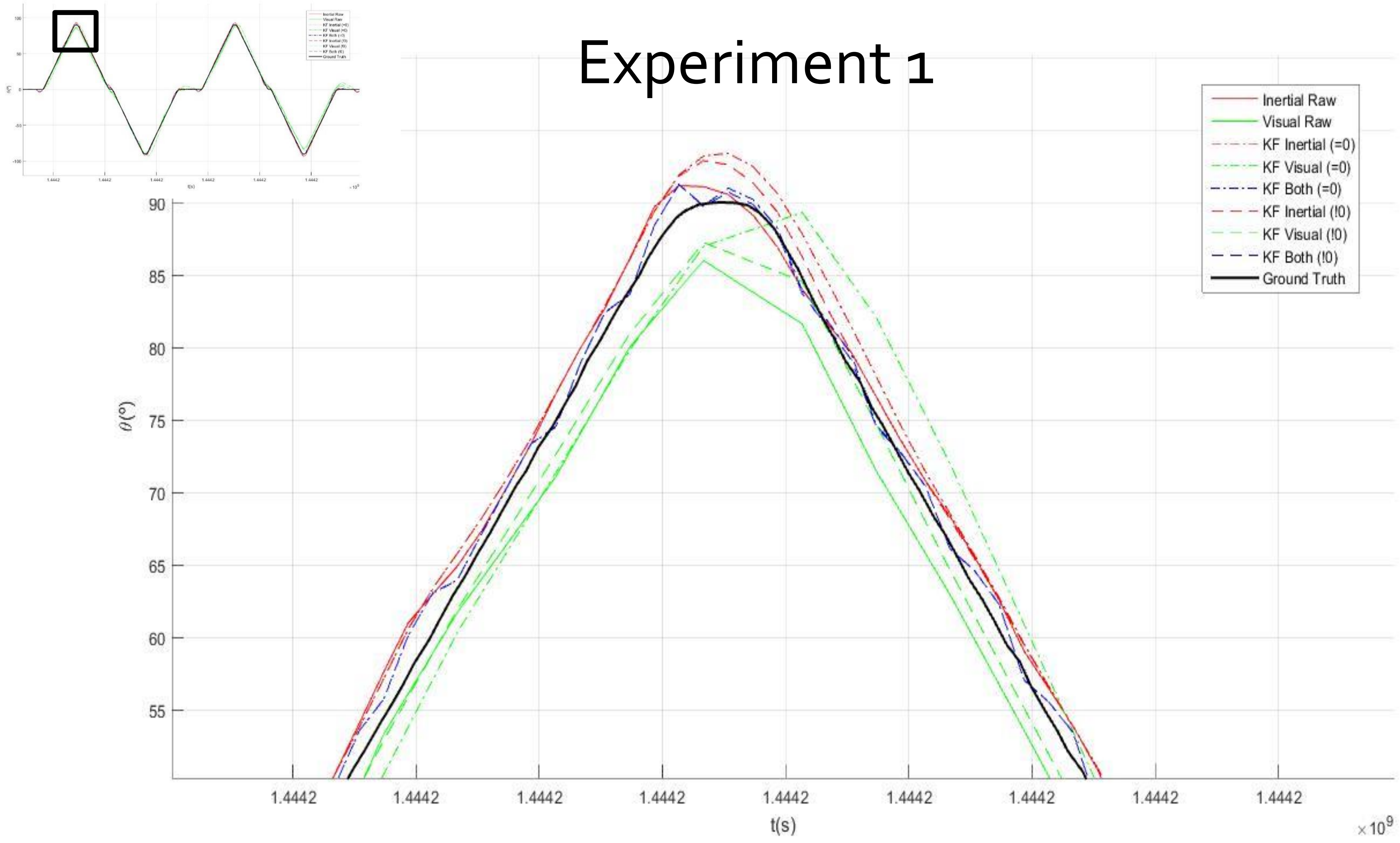
Results

	Exp1	Exp2	Exp1 (noise)	Exp2 (noise)
Inertial	1.58°	2.80°	8.82°	8.73°
Visual	2.26°	4.68°	2.26°	4.68°
Inertial Kalman ($\ddot{\theta} = 0$)	1.56°	2.52°	5.03°	4.35°
Visual Kalman ($\ddot{\theta} = 0$)	2.42°	6.16°	2.43°	3.80°
Both Kalman ($\ddot{\theta} = 0$)	1.09°	2.43°	2.15°	2.47°
Inertial Kalman ($\ddot{\theta} \neq 0$)	1.49°	2.57°	4.86°	3.87°
Visual Kalman ($\ddot{\theta} \neq 0$)	1.96°	3.79°	1.99°	2.86°
Both Kalman ($\ddot{\theta} \neq 0$)	1.00°	2.49°	2.08°	2.37°

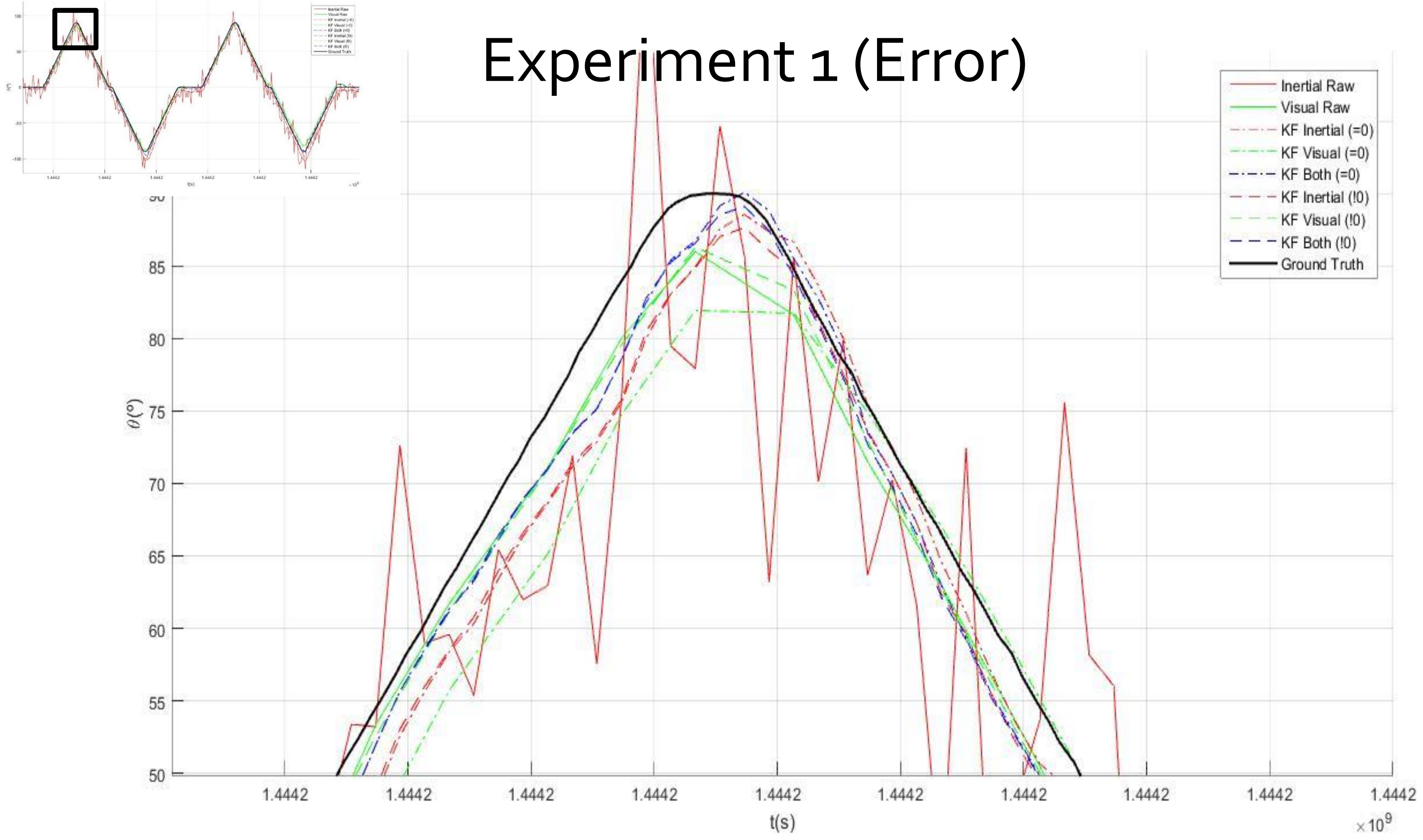
Results

	No Treatment	Kalman Filter $u_k = 0$	Kalman Filter $u_k = {(\dot{\theta}_{k-1} - \dot{\theta}_{k-2})}/{\Delta t_k}$
Inertial Data			
Visual Data			
Merged Data			
Ground Truth			

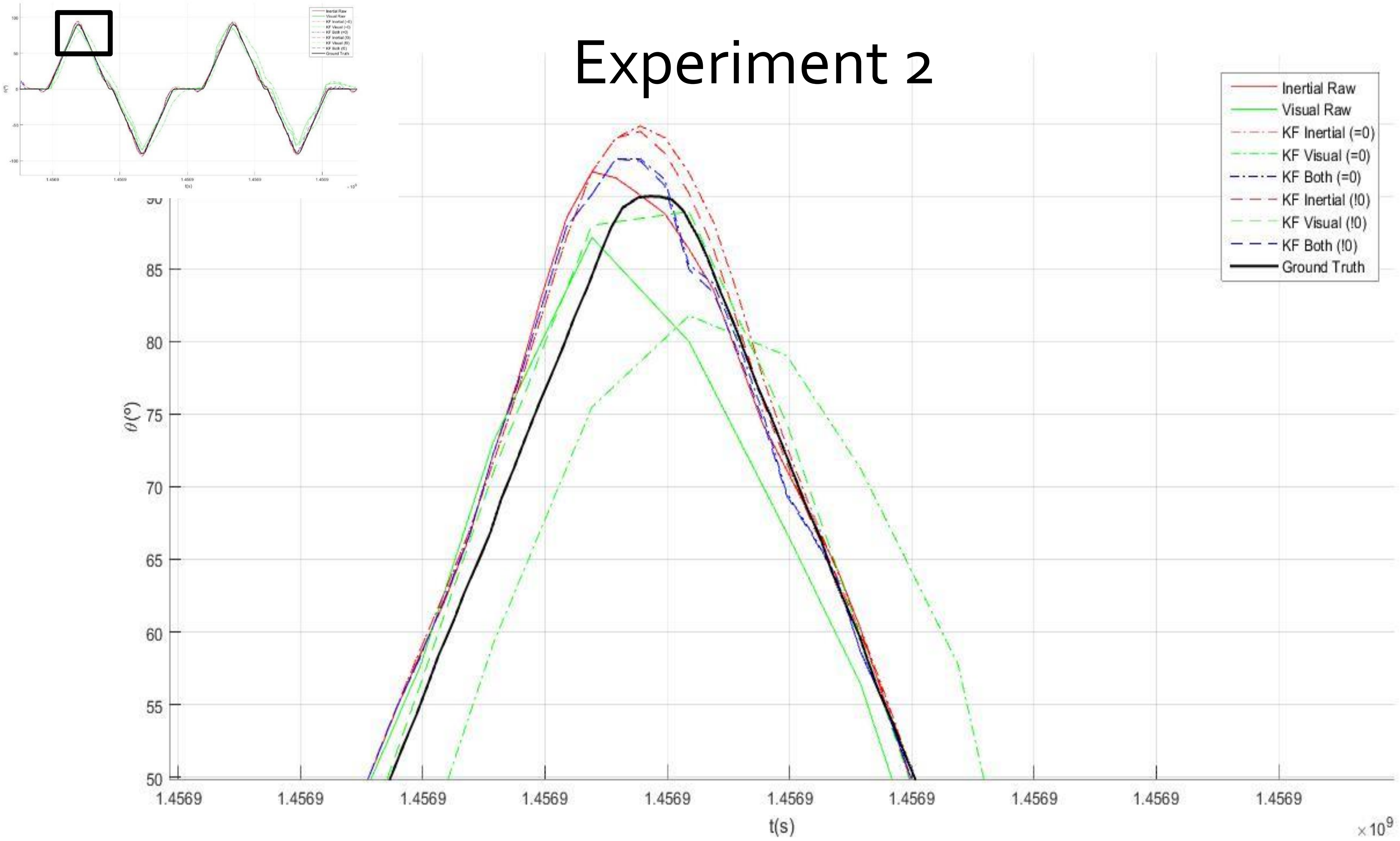
Experiment 1

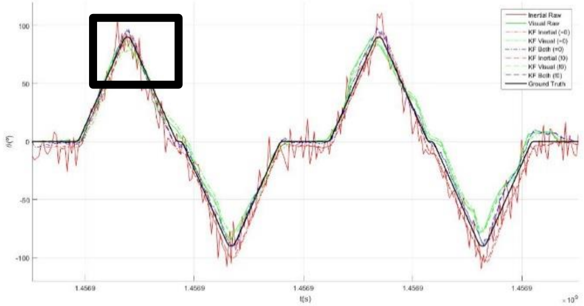


Experiment 1 (Error)

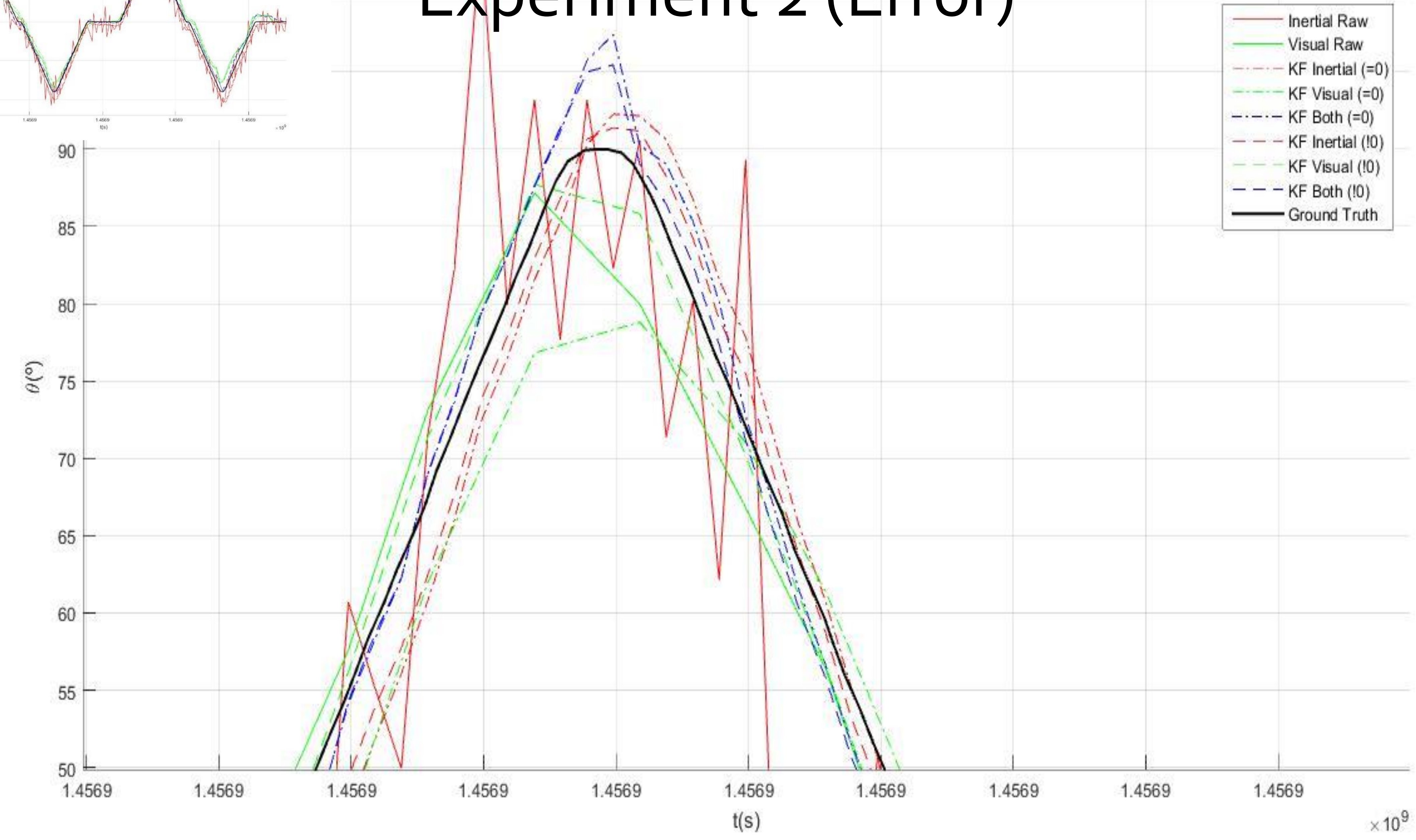


Experiment 2





Experiment 2 (Error)



Conclusions

- FANUC 200iB provides accurate and reliable ground truth;
- Merging inertial and visual data will wield better results than the original data by itself;
- Kalman Filter is robust to noise;
- Worst cases will have better improvement;
- Extensible tool/approach.