EuRoC Project

UAV control application for an European Challenge

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What is EuRoC

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Reconfigurable Interactive Manufacturing Cell

Shop Floor Logistics and Manipulation

Plant Inspection And Servicing

European Robotics Challenges

KUKA
DLR
ASCENDING TECHNOLOGIES
Fraunhofer IPA
LAAS-CNRS
ETH zürich
ALSTOM Inspection Robotics
INNOCENTIVE

Stages of the Challenge

European Robotics Challenges

- **Stage I – QUALIFYING: Simulation Contest**

  The simulation contests are ranked according to objective metrics (criteria and grading system). The best 45 contestants (3 × 15) are selected based on their scores in the tests, and they become **Perspective Challengers**.
  Prospective challengers are given an opportunity to form teams with system integrators and end users and submit short proposals, of which the best 3 x 5 will be selected to become the official Challenger Teams (03/2015).

- **Stage II – REALISTIC LABS: Benchmarking, free-style and showcase**

  Round A (benchmarking + free-style).
  Round B (showcase).
  Challenger Teams will be ranked according to objective metrics (criteria and grading system). 3 x 2 Challenge Finalists will be selected for the Field Tests stage of each challenge (12/2016).

- **Stage III – FIELD TESTS: Pilot Experiments**

  This last stage involves much engineering effort because the general solutions developed during the Realistic Labs stage will be customised for end users and tested on the field. A EuRoC Winner will be selected by the BoJ (12/2017).

Challenge 3 Contestants

- **35 partecipants (9 italian Universities/Laboratories)**
  - ACTLAB (*Università di Parma*)
  - ARS (*Università del Salento*)
  - CASY (*Università di Bologna*)
  - Laborics PSI (*private*)
  - PEGASUS (*Scuola Superiore Sant'Anna*)
  - Polibrì (*Politecnico di Milano*)
  - Robo-Team *(Campus-Bio-Medico di Roma)*
  - RomaUno *(Università La Sapienza di Roma)*
  - UNIPI (*Università di Pisa*)

- **21 of them submitted a solution**

Challenge 3 Contestants

1. ACTLAB
2. Attempto Tuebingen
3. CVG-UPM
4. Eiffel Team
5. Eyefly
6. First ROS Team of Kosice
7. Graz Griffins
8. GRVC-CATEC
9. LEO
10. MIRIAMM
11. NimbRo Copter
12. Polibrì
13. proaut-autec
14. Robo-Team
15. RomaUno
16. RPG
17. TUM Flyers
18. Unikorn
19. UNIPI
20. UNIZG-FER
21. Vicomtech-IK4

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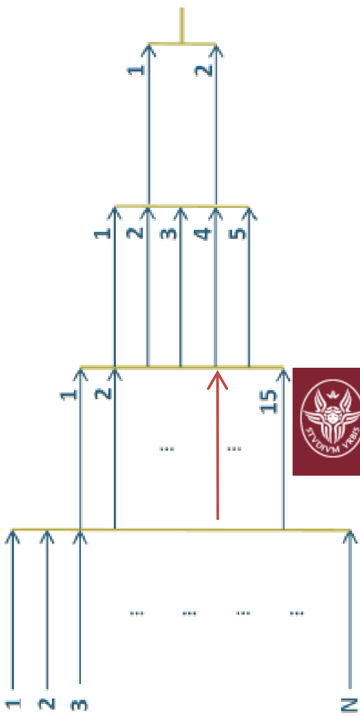
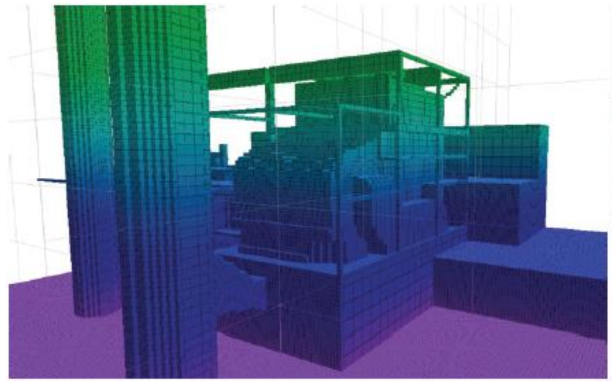
The Challenge Chart

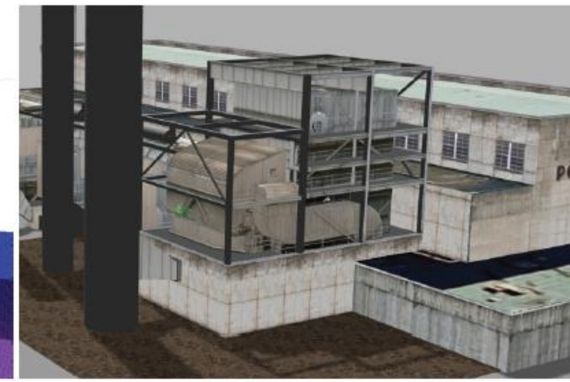


Challenge 3

Rank	Team Name	Total Score
1	TUM Flyers	90.5
2	UNIZG-FER	82.5
2	Eiffel Team	82.5
4	NimbRo Copter	77.0
5	RPG	75.0
6	Graz Griffins	74.5
7	MIRIAMM	73.5
8	Attempto Tuebingen	73.0
9	GRVC-CATEC	46.5
10	TU-Chemnitz Proaut	45.0
11	RomaUno	43.0
12	LEO	37.5
13	Polibrì	37.0
14	Unikorn	35.0
15	ACTLAB	25.0

Challenge 3: Plant Servicing and Inspection





- Type of robot: Hexacopter MAV
- Track 1: Vision-based localization and reconstruction
  - Task 1
  - Task 2
- Track2: State estimation, control and navigation
  - Task 3
  - Task 4

Task 3

- Subtask 3.1: simply keep **hovering** at the starting point
- Subtask 3.2: keep hovering with a **constant wind** applied
- Subtask 3.3: keep hovering with a **wind gust** applied

- ❑ Some **benchmarks** are defined in each subtask, in order to assign a **score** to the designed solution

- ❑ Contestants' solutions are designed under **ROS framework** (**R**obot **O**perating **S**ystem)

ROS

Outlines

- MAV System Analysis
- Designed Solution Description
- Simulations & Results

- The robot architecture provided for the Challenge is an **Hexacopter MAV**
- Structure and model comparable to the well-known Quadcopter (**six** blades instead of **four** ...)
  - **Control inputs** are the same: **Thrust** + **torques** on RPY angles
  - **Motor velocities mapping** differs because of the number of blades:

Quadcopter

$$f_i = b\,\omega_i^2$$

$$\tau_{R,i} = d\,\omega_i^2$$

$$T = f_1 + f_2 + f_3 + f_4$$

$$\tau_\varphi = l(f_2 - f_4)$$

$$\tau_\vartheta = l(f_1 - f_3)$$

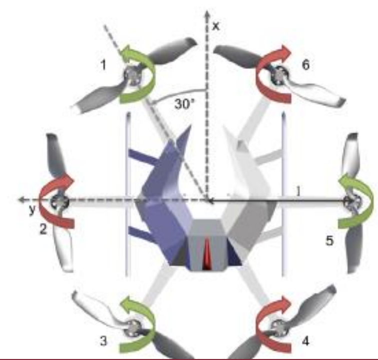
$$\tau_\psi = -\tau_{R,1} + \tau_{R,2} - \tau_{R,3} + \tau_{R,4}$$

Hexacopter

$$\begin{bmatrix} \tau_\phi \\ \tau_\theta \\ \tau_\psi \\ T \end{bmatrix} = \mathrm{diag}\left(\begin{bmatrix} b \cdot l \\ b \cdot l \\ d \\ b \end{bmatrix}\right) \cdot \begin{bmatrix} s & 1 & s & -s & -1 & -s \\ -c & 0 & c & c & 0 & -c \\ -1 & 1 & -1 & 1 & -1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 \end{bmatrix} \cdot \begin{bmatrix} \omega_1^2 \\ \omega_2^2 \\ \omega_3^2 \\ \omega_1^2 \\ \omega_5^2 \\ \omega_6^2 \end{bmatrix}$$

$$s = \sin(30°);\ c = \cos(30°)$$

$$l = 0.215\,\mathrm{m}$$



MAV Sensory Equipment

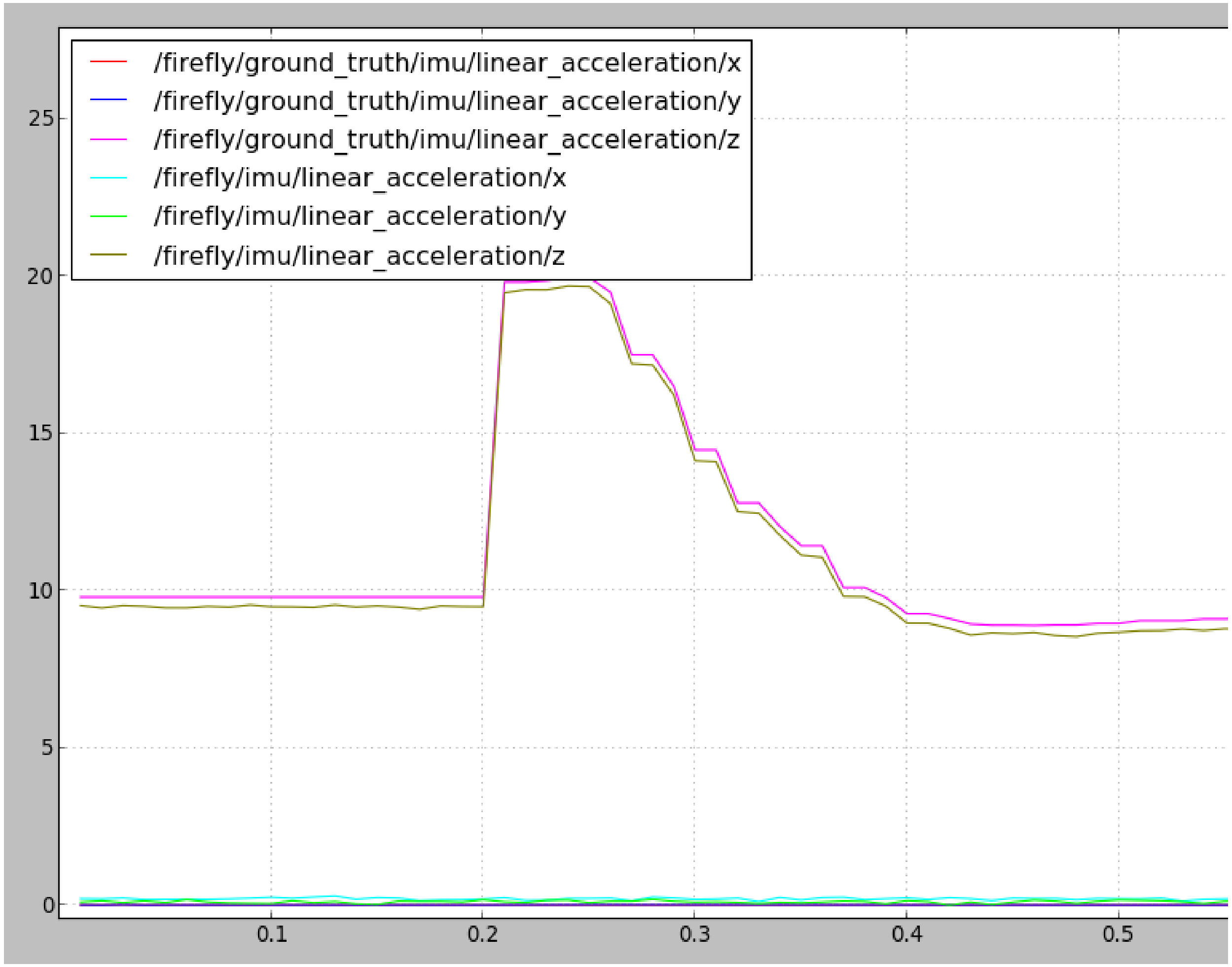
- The MAV model provided is equipped with two **sensors**:
  - A **noisy IMU sensor** providing:
    - *MAV Orientation*
    - *MAV linear acceleration*
    - *MAV angular rate*
  - A **6-DoF Pose sensor** providing:
    - Sensor position
    - Sensor orientation

*Not a **real** sensor! It abstracts a vision-based localization approach*

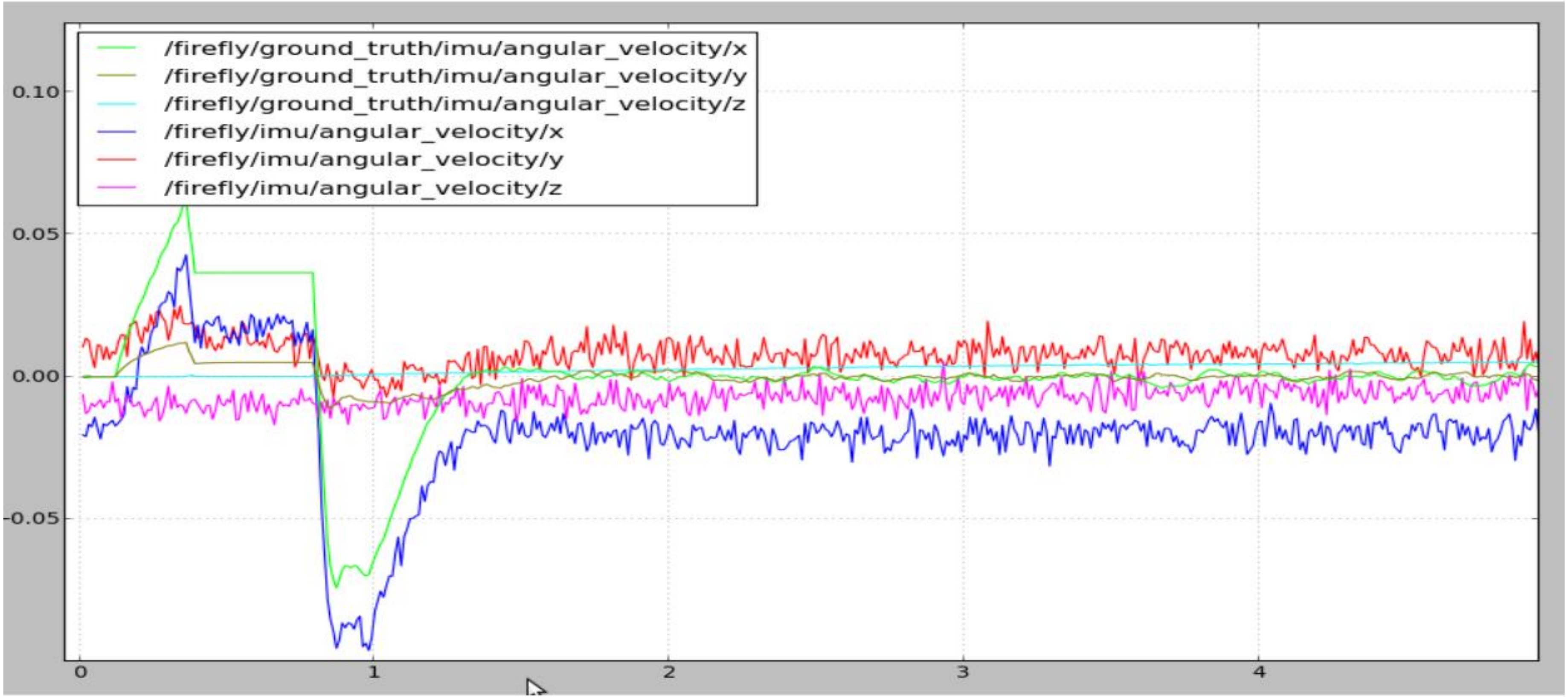
*MAV and Sensor frames do **not** coincide!*

Sensor Noise Corruption

- IMU sensor: *MAV linear acceleration*



- IMU sensor: *MAV angular rate*



Sensor Noise Corruption

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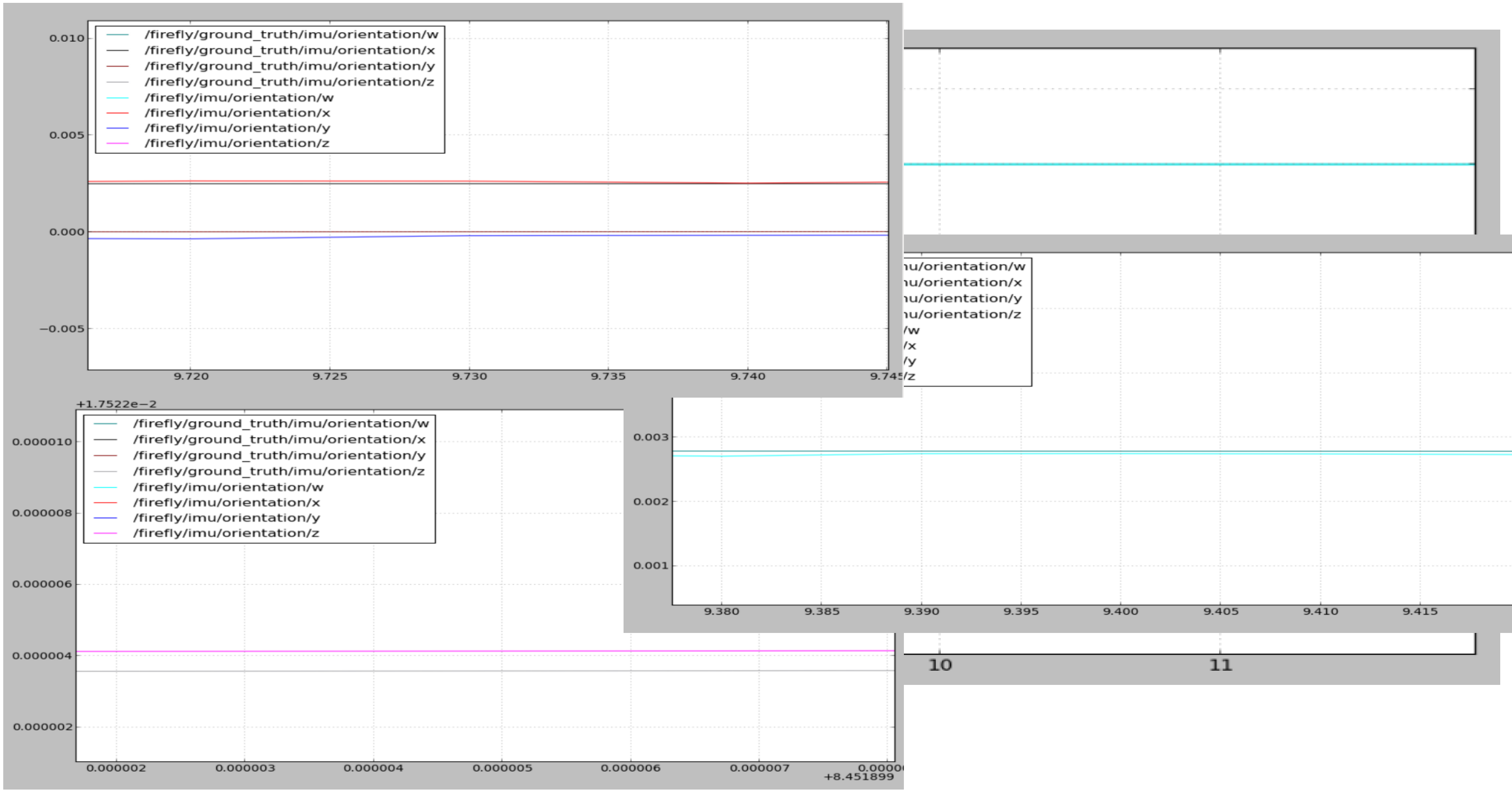
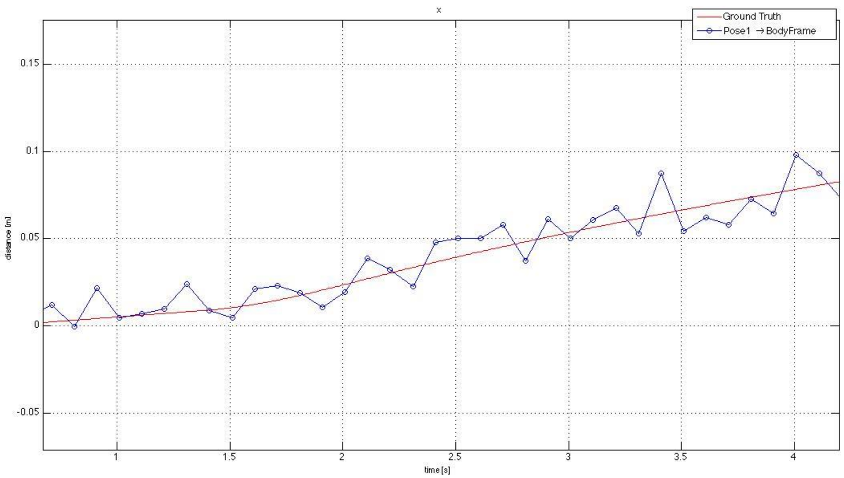
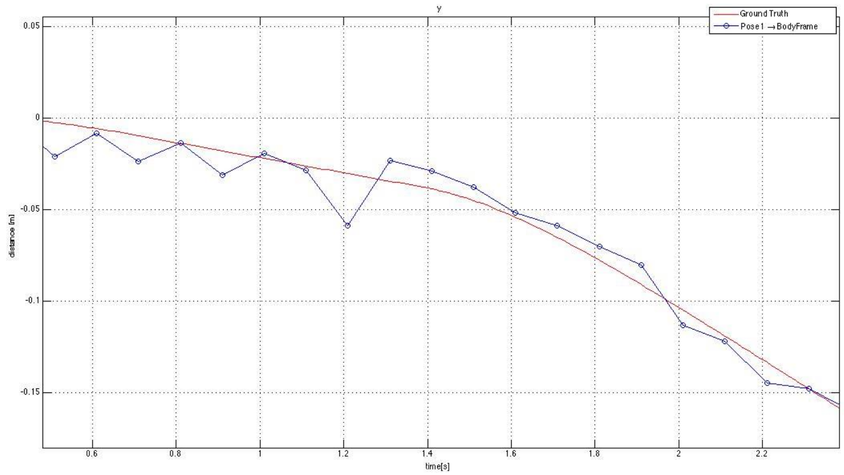
- IMU sensor: *MAV orientation*

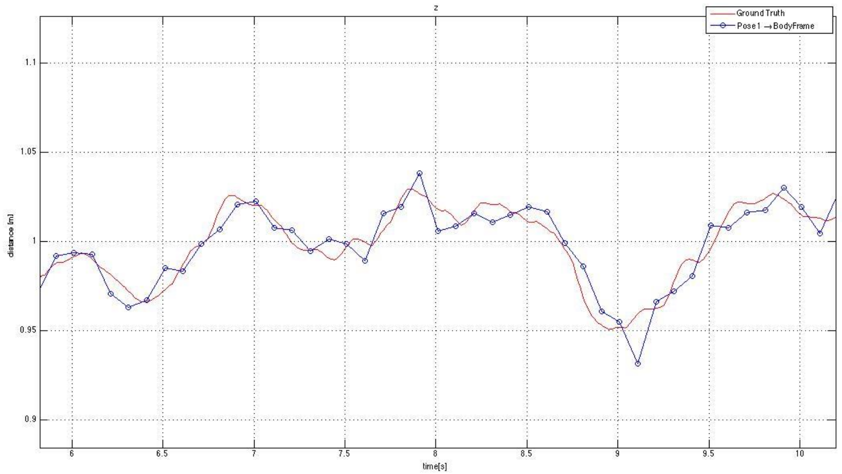


Sensor Noise Corruption

- Pose Sensor







Outlines

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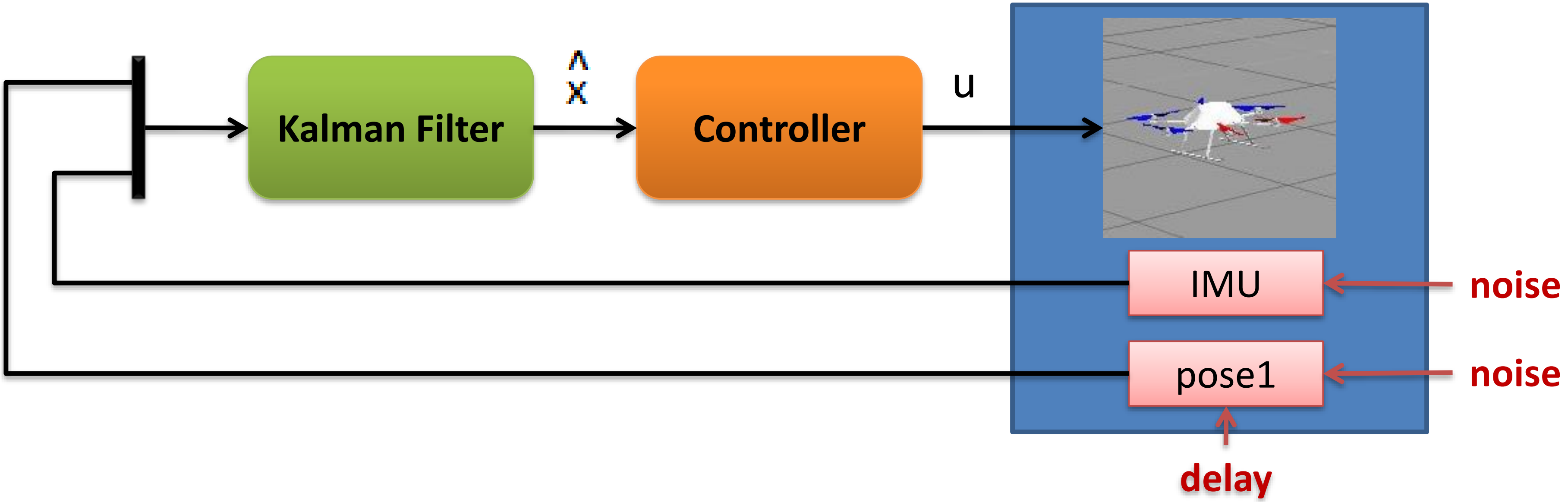
Filtering to reject noise

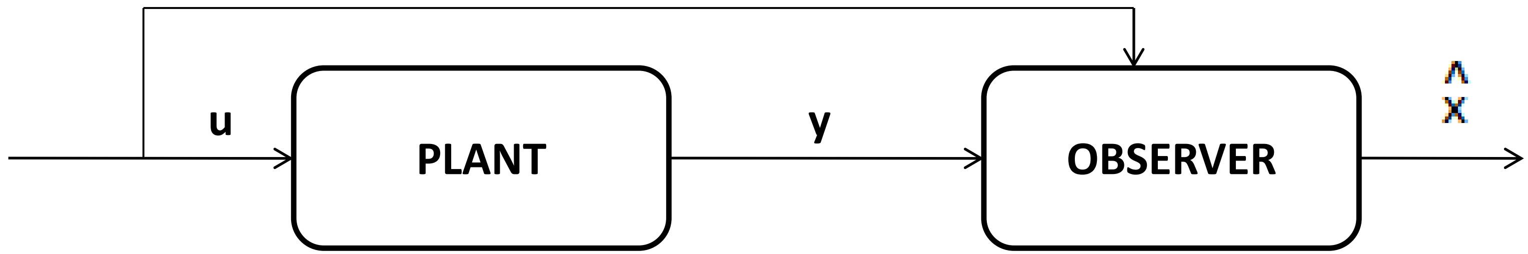
- The highly noisy nature of the sensor data prevents us to rawly use them in order to accomplish the assigned control tasks

- A **filter** is usually adopted in order to reject noise coming with corrupted data, so that the control modules are fed with more reliable inputs
- We choose to implement an **Extended Kalman Filter**



Kalman Filter

- A **Kalman Filter** is an observer that **estimates** the state of a dynamic system, if not directly available



- Built in two steps:
  Prediction step: *process dynamics* is used in order to generate an intermediate estimate of the state
  Update step: the intermediate estimate is corrected according to the *measured output*

Extended Kalman Filter

- An **Extended Kalman Filter (EKF)** is an observer for a **non-linear discrete-time system with noise**, with dynamics:

$$\begin{cases} \mathbf{x}_{k+1} = \mathbf{f}_k(\mathbf{x}_k, \mathbf{u}_k) + \mathbf{v}_k \\ \mathbf{y}_k = \mathbf{h}_k(\mathbf{x}_k) + \mathbf{w}_k \end{cases} \qquad \begin{aligned} \mathbf{v}_k &\sim \mathcal{N}(0, \mathbf{V}_k) \\ \mathbf{w}_k &\sim \mathcal{N}(0, \mathbf{W}_k) \end{aligned}$$

- **State and Covariance Prediction**:

$$\hat{\mathbf{x}}_{k+1|k} = \mathbf{f}_k(\hat{\mathbf{x}_k}, \mathbf{u}_k)$$
$$\mathbf{P}_{k+1|k} = \mathbf{F}_k \mathbf{P}_k \mathbf{F}_k^T + \mathbf{V}_k$$

$$\mathbf{F}_k = \left. \frac{\partial \mathbf{f}_k}{\partial \mathbf{x}} \right|_{\mathbf{x} = \hat{\mathbf{x}}_k}$$

- **State and Covariance Update:**

$$\hat{\mathbf{x}}_{k+1} = \hat{\mathbf{x}}_{k+1|k} + \mathbf{R}_{k+1} \nu_{k+1}$$
$$\mathbf{P}_{k+1} = \mathbf{P}_{k+1|k} - \mathbf{R}_{k+1} \mathbf{H}_{k+1} \mathbf{P}_{k+1|k}$$

$$\mathbf{H}_{k+1} = \left. \frac{\partial \mathbf{h}_{k+1}}{\partial \mathbf{x}} \right|_{\mathbf{x} = \hat{\mathbf{x}}_{k+1|k}}$$

innovation $\nu_{k+1} = \mathbf{y}_{k+1} - \mathbf{H}_{k+1} \hat{\mathbf{x}}_{k+1|k}$

Kalman Gain $\mathbf{R}_{k+1} = \mathbf{P}_{k+1|k} \mathbf{H}_{k+1}^T (\mathbf{H}_{k+1} \mathbf{P}_{k+1|k} \mathbf{H}_{k+1}^T + \mathbf{W}_{k+1})^{-1}$

EKF in our problem

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- The state to be estimated for the hexacopter system is given by:

$$\mathbf{x} = [{}^w\mathbf{p}, {}^w\mathbf{v}, \mathbf{b}_a]^T$$

where:

- ${}^w\mathbf{p}$ is the *MAV position in the world frame;*
- ${}^w\mathbf{v}$ is the *MAV velocity in the world frame;*
- $\mathbf{b}_a$ is the *accelerometer bias*

- **Initialization**:

$$\mathbf{x}_0 = \Big[\underbrace{0, 0, 0.08}_{{}^w\mathbf{p}}, \underbrace{0, 0, 0}_{{}^w\mathbf{v}}, \underbrace{0.2, 0.1, -0.3}_{\mathbf{b}_a}\Big]^T$$

$$\mathbf{H}_k = \begin{bmatrix} \mathbf{I}_{3\times3} & \mathbf{0}_{3\times6} \\ \mathbf{0}_{6\times3} & \mathbf{0}_{6\times6} \end{bmatrix}$$

$$\mathbf{P}_{0|0} = \mathbf{0}_{9\times9}$$

$$\mathbf{W}_k = \begin{bmatrix} 0.0001 & 0 & 0 \\ 0 & 0.0001 & 0 \\ 0 & 0 & 0.0001 \end{bmatrix}$$

$$\mathbf{V}_k = diag(0.00000000016 * \mathbf{I}_{3\times3}, diag(0.0000000016 * \mathbf{I}_{3\times3}), diag(0.00000016 * \mathbf{I}_{3\times3}))$$

Prediction

- An **IMU-based propagation model** has been used: *IMU linear acceleration* and *angular rate* are used as *system inputs* in the **prediction step** (actually only linear acceleration)

$$a = a_{imu} - \hat{\mathbf{b}}_a$$

State Prediction

$$\hat{\mathbf{x}}_{k+1|k} = \mathbf{f}_k(\hat{\mathbf{x}_k}, \mathbf{u}_k)$$

$${}^w\hat{\mathbf{p}}_{k+1|k} = {}^w\hat{\mathbf{p}}_k + T_{imu}\,{}^w\hat{\mathbf{v}}_k + \frac{1}{2}T_{imu}^2(R(\mathbf{q})a + g)$$

$${}^w\hat{\mathbf{v}}_{k+1|k} = {}^w\hat{\mathbf{v}}_k + T_{imu}(R(\mathbf{q})a + g)$$

$$\hat{\mathbf{b}}_{ak+1|k} = \hat{\mathbf{b}}_{ak}$$

$\mathrm{R}(\mathbf{q})$ is the **Rotation matrix** expressing the orientation of the **body frame** wrt the **world frame**

$\mathbf{F}_k$ **non-zero entries**

$$T_{imu} = 0.01s$$

$$\frac{\partial^w\hat{\mathbf{p}}_{k+1|k}}{\partial^w\hat{\mathbf{p}}_k} = \mathbf{I}_{3\times3}, \quad \frac{\partial^w\hat{\mathbf{p}}_{k+1|k}}{\partial^w\hat{\mathbf{v}}_k} = T_{imu}\mathbf{I}_{3\times3}, \quad \frac{\partial^w\hat{\mathbf{p}}_{k+1|k}}{\partial^w\hat{\mathbf{b}}_{ak}} = \text{-}\ \frac{1}{2}T_{imu}^2\mathbf{R}(\mathbf{q}),$$

$$\frac{\partial^w\hat{\mathbf{v}}_{k+1|k}}{\partial^w\hat{\mathbf{v}}_k} = \mathbf{I}_{3\times3}, \quad \frac{\partial^w\hat{\mathbf{v}}_{k+1|k}}{\partial^w\hat{\mathbf{b}}_{ak}} = -T_{imu}\mathbf{R}(\mathbf{q}), \quad \frac{\partial^w\hat{\mathbf{b}}_{ak+1|k}}{\partial^w\hat{\mathbf{b}}_{ak}} = \mathbf{I}_{3\times3},$$

Covariance Prediction

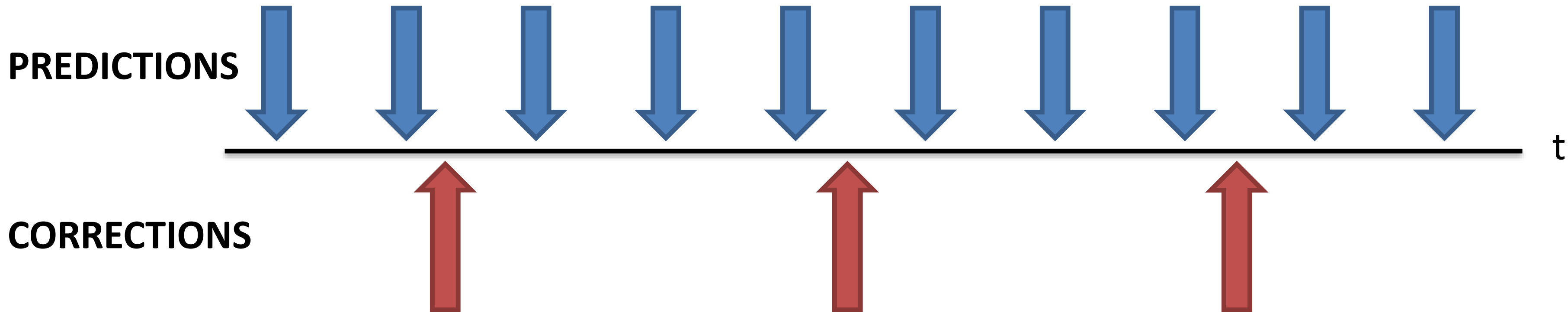
$$\mathbf{P}_{k+1|k} = \mathbf{F}_k\mathbf{P}_k\mathbf{F}_k^T + \mathbf{V}_k$$

Correction

- The Correction step is performed with data coming from the Pose Sensor, where

$$T_{pose} = 0.1s \quad (\neq T_{imu} = 0.01 \ !!!)$$

- The Prediction and Correction steps rates are clearly different: the result is that the filter applies a certain number of **predictions** before a new measurement arrives (and so, a **correction** is performed)



- The equations shown before (see State and Covariance Update) are then applied whenever a new Pose sensor message arrives

Filter Validation

- In this way, **noise** and **low-rate** issues can be handled in the sensors...
- ... but Pose Sensor is still **delayed**!!
- In fact, Pose Sensor messages contain a *timestamp* field referring to a previous time instant, so the corresponding correction has to be applied on a properly previous prediction

- This does not cause so many troubles while working *off-line*, since a simple *timestamp comparison* is enough in order to apply the correction to the proper intermediate estimate

- On the other hand, when everything needs to work *on-line*, the **validation** on the virtual environment **Gazebo** has to include a **synchronization mechanism ...**

Synchronisation

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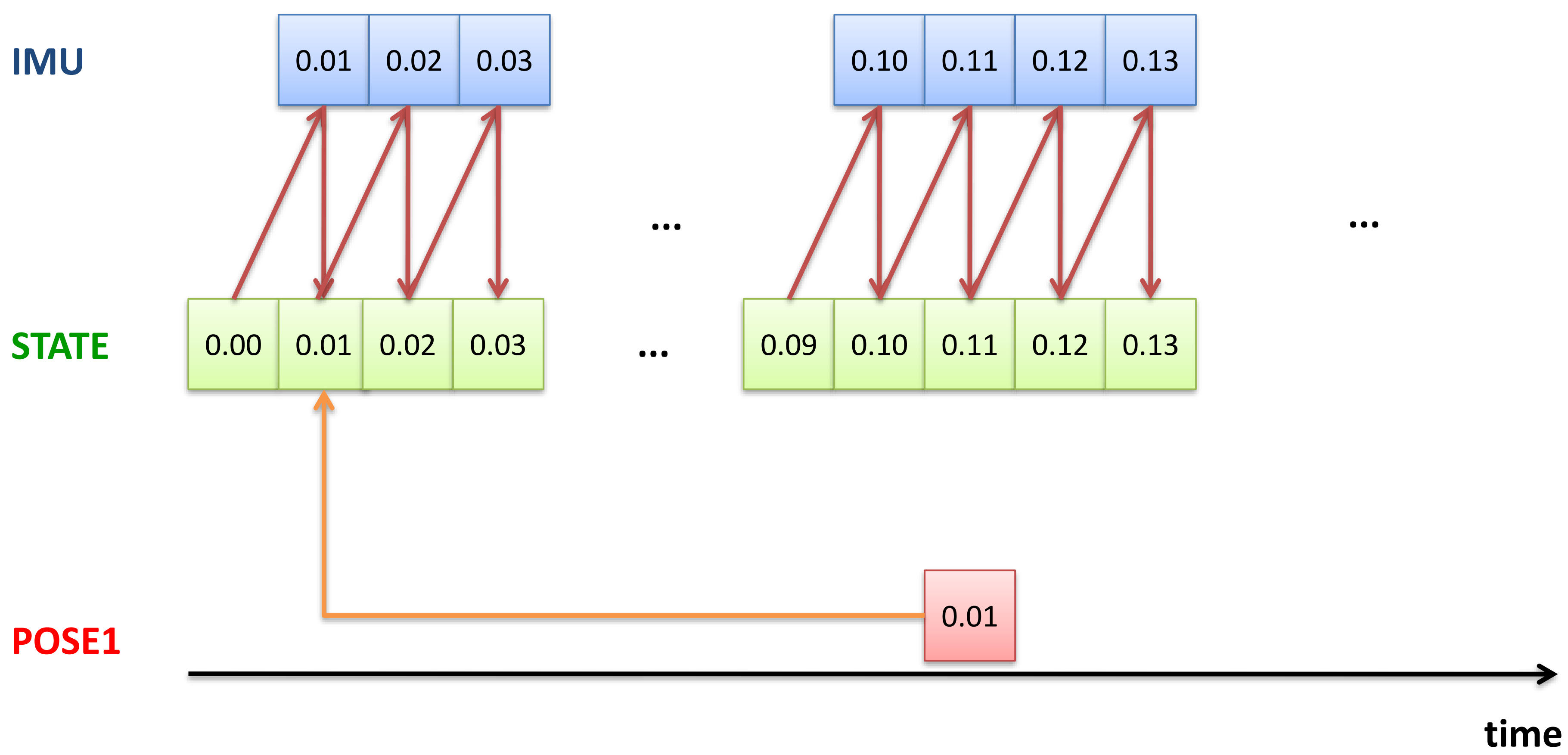
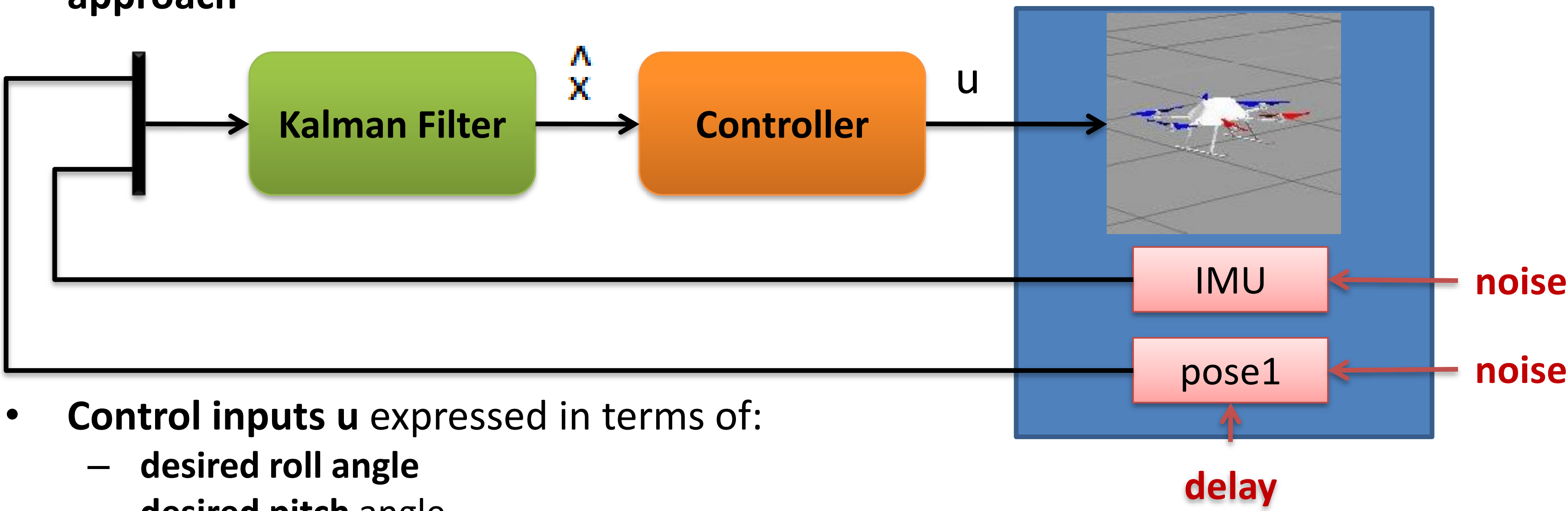


From filter ...
To control

- Data coming from the Kalman Filter module are more reliable to be managed than noisy sensor data
- These data are used in order to feed the **Controller** module that allows the MAV to behave in a desired way by computing proper **control inputs**
- The chosen control paradigm for this application is an **Integral Backstepping approach**



- **Control inputs u** expressed in terms of:
  - **desired roll angle**
  - **desired pitch** angle
  - **desired yaw rate**
  - **Thrust**

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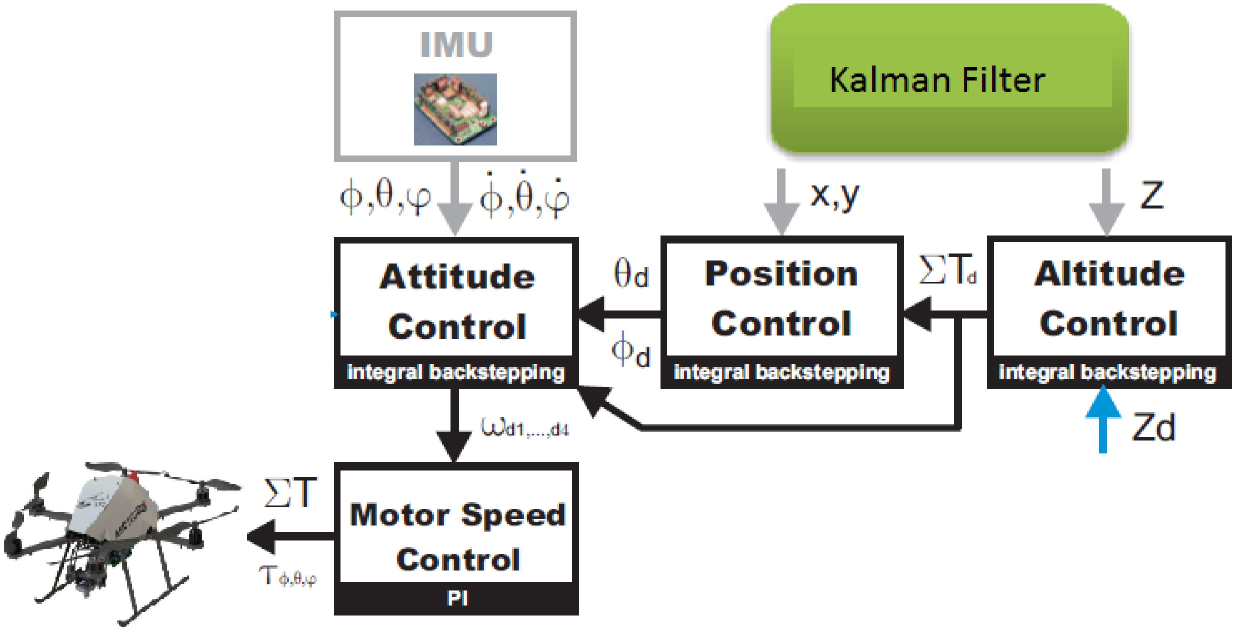
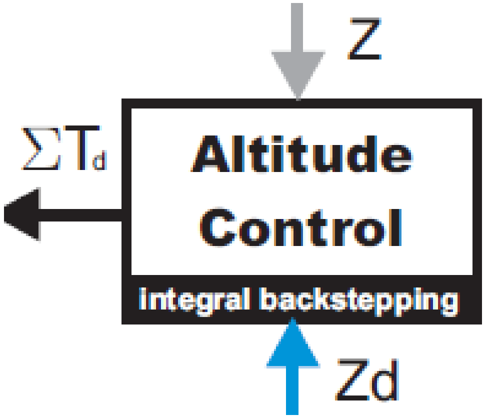
- **Integral Backstepping** paradigm differentiates three **control modules** for **altitude**, **position** and **attitude**
- In our node:
  - **Altitude** and **Position controller** have been implemented
  - **Attitude controller** is an inner module of the MAV provided by the organizers



Altitude Controller



- Altitude tracking error

$$e_z = z_d - z$$

- Altitude speed tracking error

$$e_{\dot{z}} = c_z e_z + \dot{z}_d + \lambda_z \chi_z - \dot{z}$$

$$\chi_i = \int_0^t e_i(\tau)\, d\tau$$
$$c_z, c_{\dot{z}}, \lambda_z > 0$$

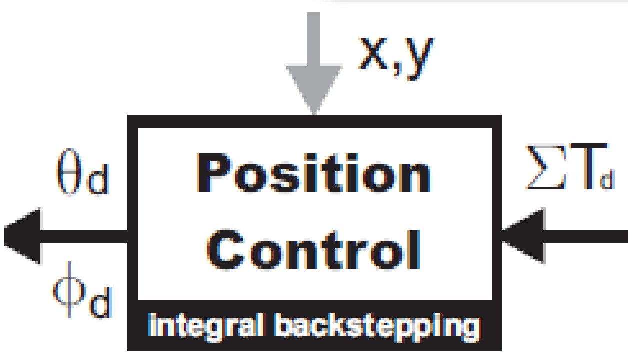
- Thrust control input

$$T = \frac{m}{\cos\phi\cos\theta} = \left[g + \left(1 - c_z^2 + \lambda_z\right) e_z + \left(c_z + c_{\dot{z}}\right) e_{\dot{z}} - c_z \lambda_z \chi_z\right]$$

Position Controller

- x- and y-tracking errors

$$e_x = x_d - x$$
$$e_y = y_d - y$$



- Speed tracking errors

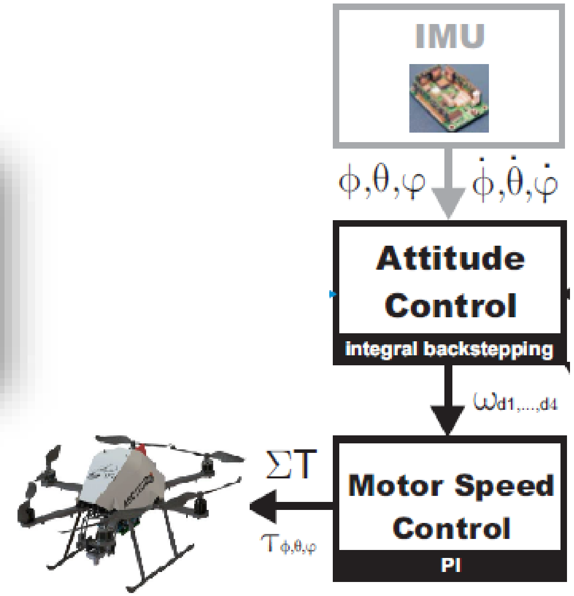
$$e_{\dot{x}} = c_x e_x + \dot{x}_d + \lambda_x \chi_x - \dot{x}$$
$$e_{\dot{y}} = cy e_y + \dot{y}_d + \lambda_y \chi_y - \dot{y}$$

- desired roll and pitch angles control inputs

$$\theta_d = \frac{m}{T}\left[\left(1 - c_x^2 + \lambda_x\right) e_x + \left(c_x + c_{\dot{x}}\right) e_{\dot{x}} - c_x \lambda_x \chi_x\right]$$
$$\phi_d = -\frac{m}{T}\left[\left(1 - c_y^2 + \lambda_y y\right) e_y + \left(c_y + c_{\dot{y}}\right) e_{\dot{y}} - c_y \lambda_y \chi_y\right]$$

Attitude Controller

- Attitude Controller has been used as provided in the Simulation VM
- **Inputs:** $T, \phi_d, \theta_d, \dot{\psi}_d$



Parameter Initialization

K_p: attitude gain

K_d: angular rate gain

I: inertia matrix

$$b = 8.54858 \cdot 10^{-6} \left[\frac{kg \cdot m}{s^2}\right]$$

$$d = 1.3677 \cdot 10^{-7} \left[\frac{kg \cdot m^2}{s^2}\right]$$

This makes gain tuning independent of inertia matrix

$$K_p \leftarrow K_p / I$$
$$K_d \leftarrow K_d / I$$

$$A = \begin{bmatrix} s & 1 & s & -s & -1 & -s \\ -c & 0 & c & c & 0 & -c \\ -1 & 1 & -1 & 1 & -1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 \end{bmatrix} : \text{allocation matrix}$$

$$u = \begin{bmatrix} \tau_\phi \\ \tau_\theta \\ \tau_\psi \\ T \end{bmatrix} \quad K = diag\left(\begin{bmatrix} b \cdot l \\ b \cdot l \\ d \\ b \end{bmatrix}\right)$$

$$u = KA\omega^2 \rightarrow \omega^2 = (KA)^{-1}u = (KA)^{-1} \begin{bmatrix} I & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} a_\tau \\ T \end{bmatrix}$$

$$\omega^2 = A^T(AA^T)^{-1}K^{-1}\bar{I}a_\tau = \tilde{A}\begin{bmatrix} a_\tau \\ T \end{bmatrix}$$

Attitude Controller

Compute Angular Acceleration

1. $\psi \rightarrow R\left(\mathbf{q}\right).\mathrm{get\_yaw}()$

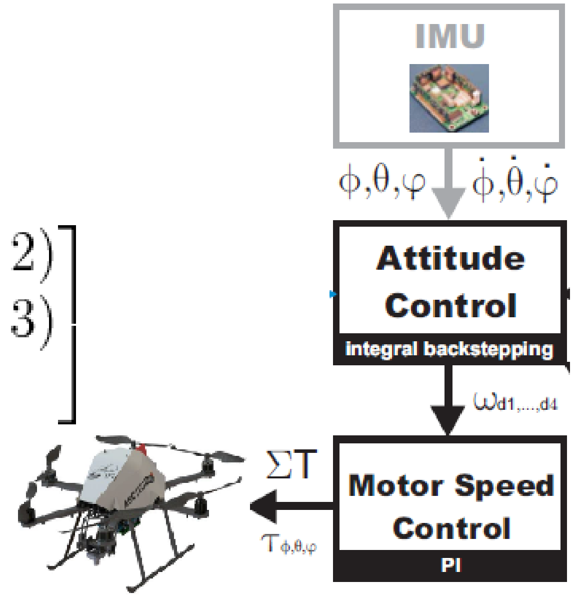
2. $R_d = R(\psi, \vec{z})R(\phi_d, \vec{x})R(\theta_d, \vec{y})$

3. $e_R = \frac{1}{2}\left(R_d^T R - R^T R_d\right) \rightarrow e_{angle} = \begin{bmatrix} e_R(3,2) \\ e_R(1,3) \\ 0 \end{bmatrix}$

4. $\omega_d = \begin{bmatrix} 0 \\ 0 \\ \dot{\psi}_d \end{bmatrix}$

5. $e_\omega = \omega - R^T R_d \omega_d$

6. $a_\tau = -K_p e_{angle} - K_d e_\omega + \omega \times \omega$



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Provided Infrastructure for Challenge 3

- **Two virtual machines** (running Ubuntu 12.04) are provided to each Contestant:
  - A **Simulation VM**, containing the virtual environment (**Gazebo**) for simulations.
  - A **Contestant VM**, containing the Contestant's solution for the assigned tasks.
- The VMs communicate via **Client/Server Protocol**:
  - The **Simulation VM** acts as a **Server** and must not be modified
  - The **Contestant VM** acts as a **Client** submitting the solution to the Server
- **ROS** is installed on both VMS

ROS in a nutshell

- ROS framework is an Operating System for robots (a *meta-operating system*)
  - **standard OS functionalities** offered:
    - Hardware abstraction
    - Processes handling and message-passing mechanism
    - ...
  - Development environments provided, with client **API libraries**:
    - C++
    - Python
    - Java
    - Lisp

further info: www.wiki.ros.org

ROS in a nutshell (2)

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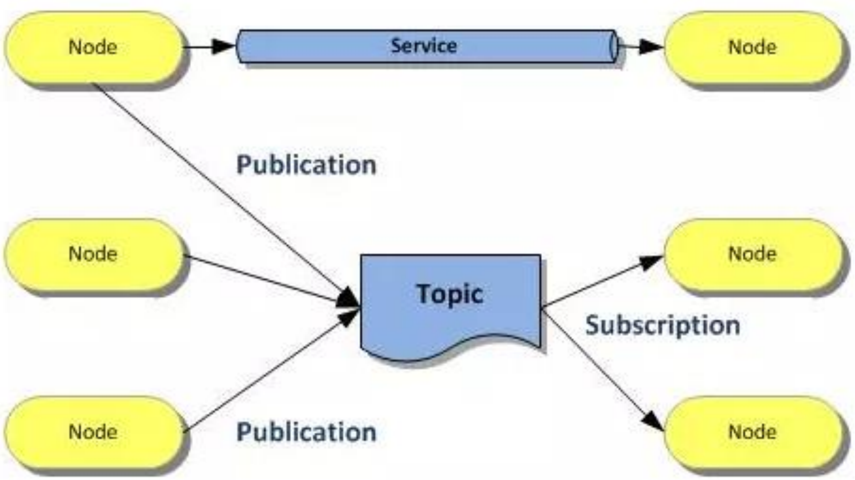
- Processes running under ROS are called **nodes**
- **Nodes** communicate through **message-passing mechanism**
- A **message** is a data structure with some designed typed fields (integer, float, boolean, array, ...)
- Nodes can write a message and **publish** it on a **topic**, or it can **subscribe** to a topic in order to read the corresponding message
- A special node, called ***roscore***, acts as a **master node** and needs to be run first before any other node.



- ROS usually works on a single machine; but so ...
- ... How can we make VMs to communicate between them?

- EuRoC partners have set a “*network bridging*” mechanism between the two machines, so that the ***roscore*** master node of the Server machine is shared with the Client Machine
- On the Contestant VM:

```
  i. <host machine’s IP>            eurocsimserv
 ii. <Contestant VM adapter 3 IP>   eurocsimclient
```

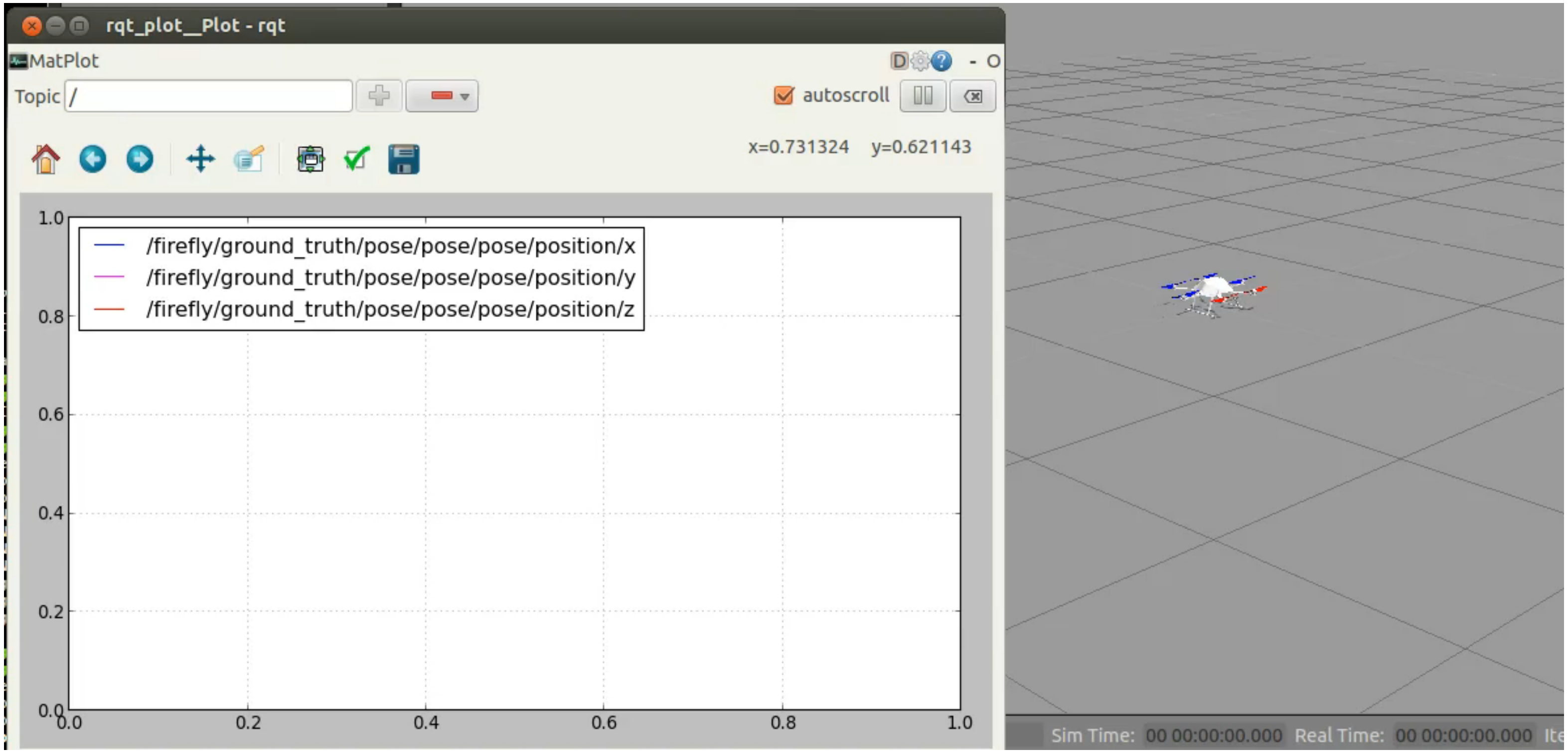
```
  i. export ROS_MASTER_URI=http://eurocsimserv:11311
 ii. export ROS_HOSTNAME=eurocsimserv
```

Launch files

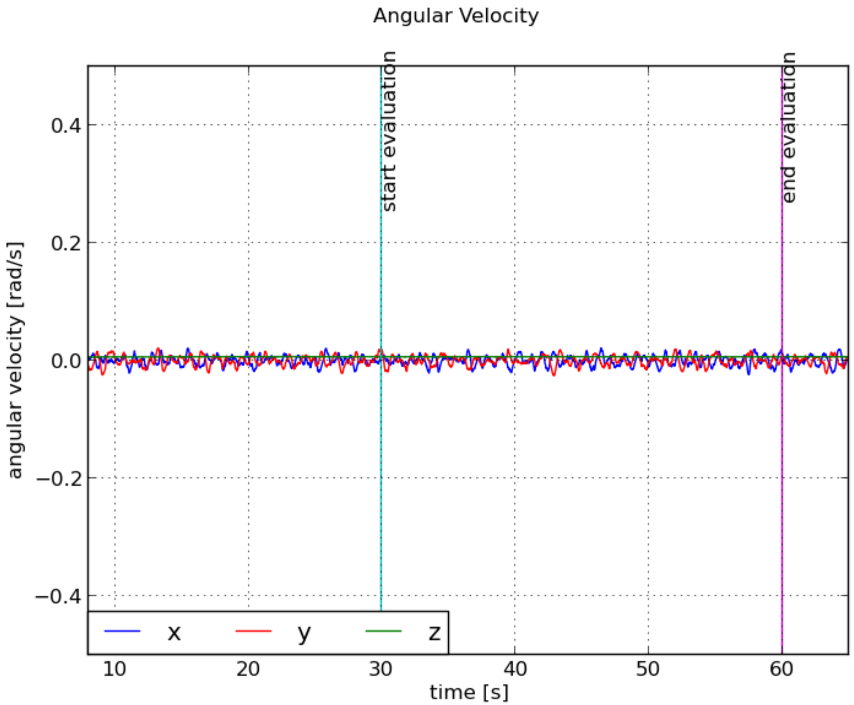
- The source code is the same for each subtask...
- ... But virtual scenarios change!
- Some common parameters need to be modified so that each subtask can be properly satisfied (mainly **control gains** and **flags**)
- These parameters may be set by defining a **launch file** for each subtask
- Solution node can then be run through the ROS command *roslaunch*

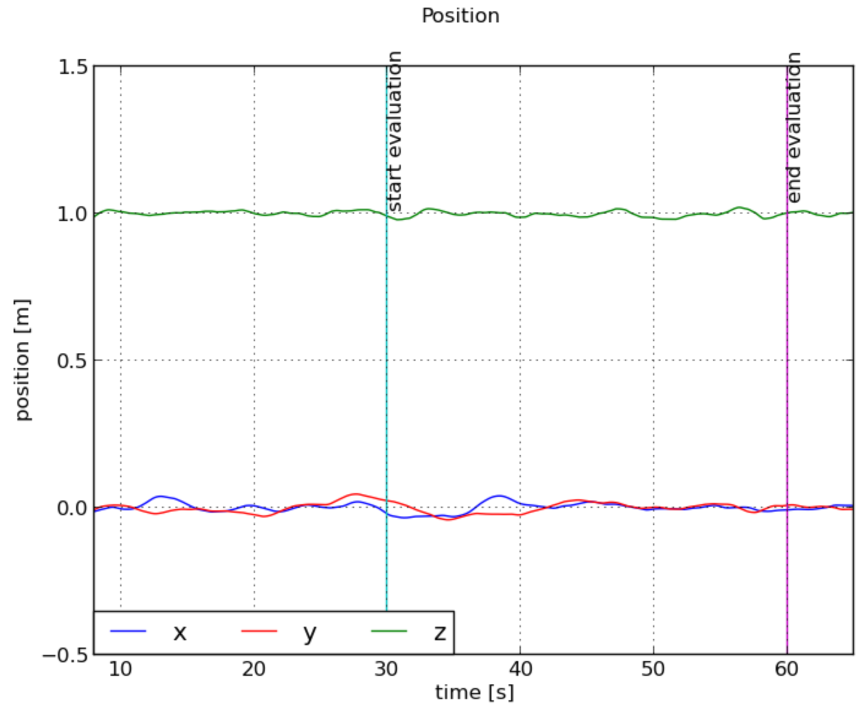
```
<launch>
  <group ns="firefly">

    <!-- Launch your nodes here. Extend / adapt for the subtask at hand, if necessary.-->

    <node name="euroc_solution_t3"  pkg="euroc_solution_t3" type="euroc_solution_t3" output="screen"/>
  <param name="c10" value="0.5"/>
  <param name="c12" value="0.5"/>
  <param name="alfa" value="0.3"/>
  <param name="beta" value="1.5"/>
  <param name="lambda4" value="1.0"/>
  <param name="lambda5" value="1.0"/>
  <param name="lambda6" value="1.0"/>
  <param name="sub_task2or3" value="1"/>
  </group>
</launch>
```

Task 3.1: results



Task 3.1: results





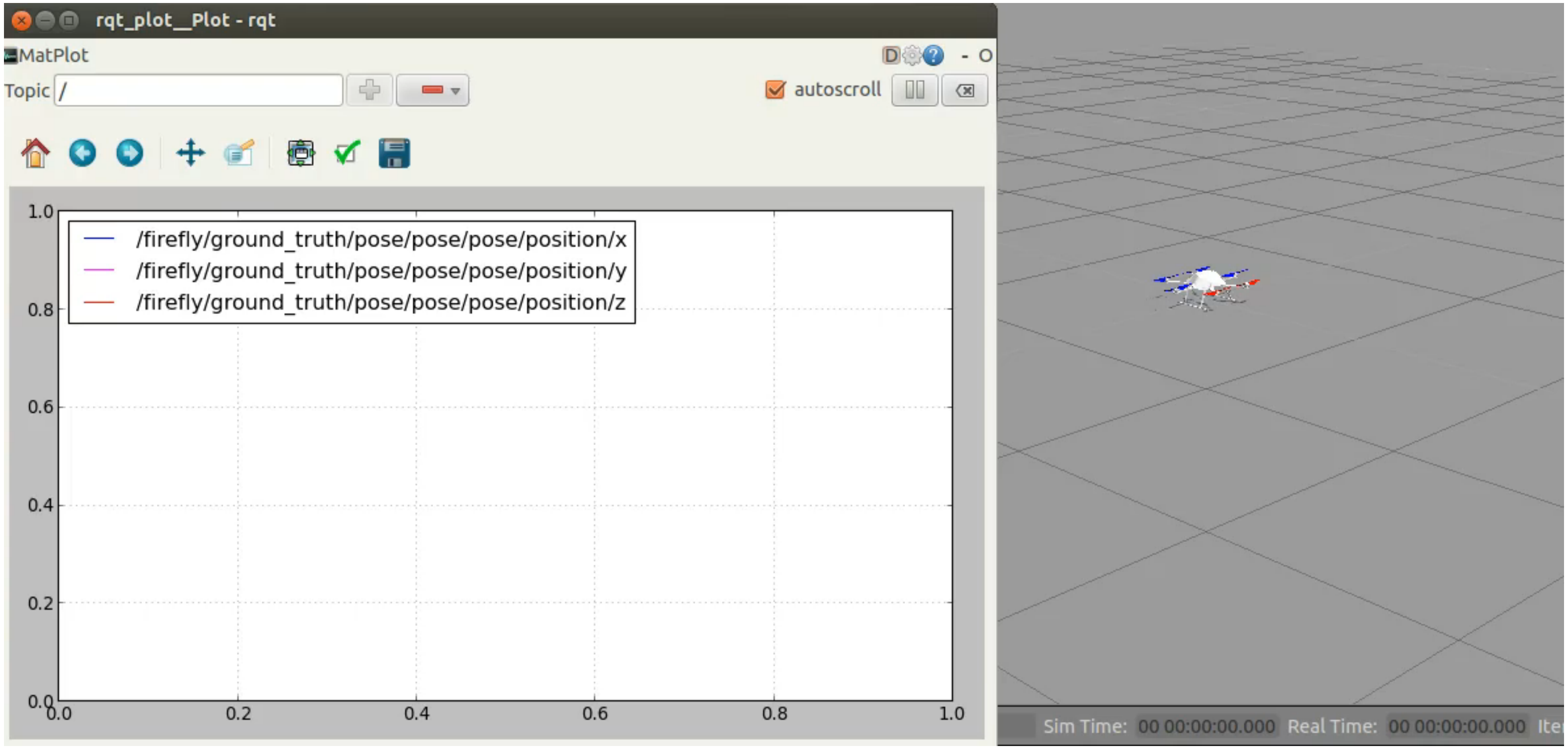
Position RMS error: 0.027 m

Angular velocity RMS error: 0.014 rad/s

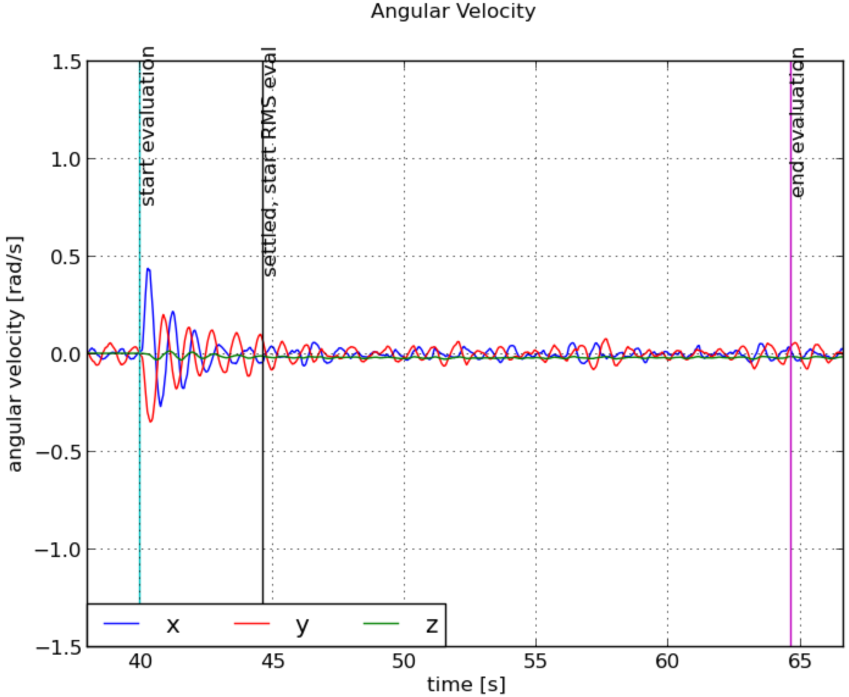
Scores: 3.0, 4.5

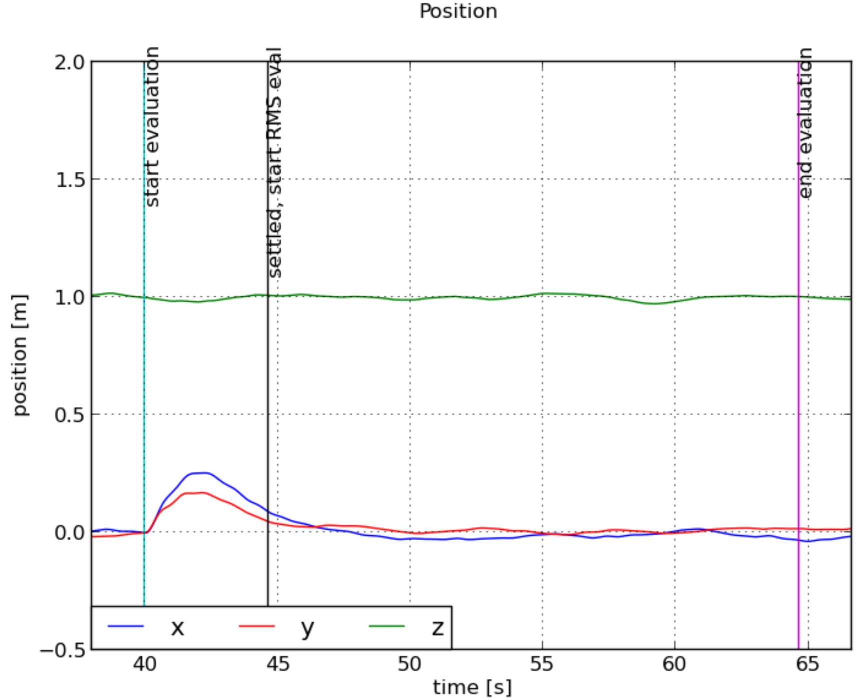
Total Score for Task 3.1 is: **7.5**

Task 3.2: results



Task 3.2: results





Settling time: 4.630 s

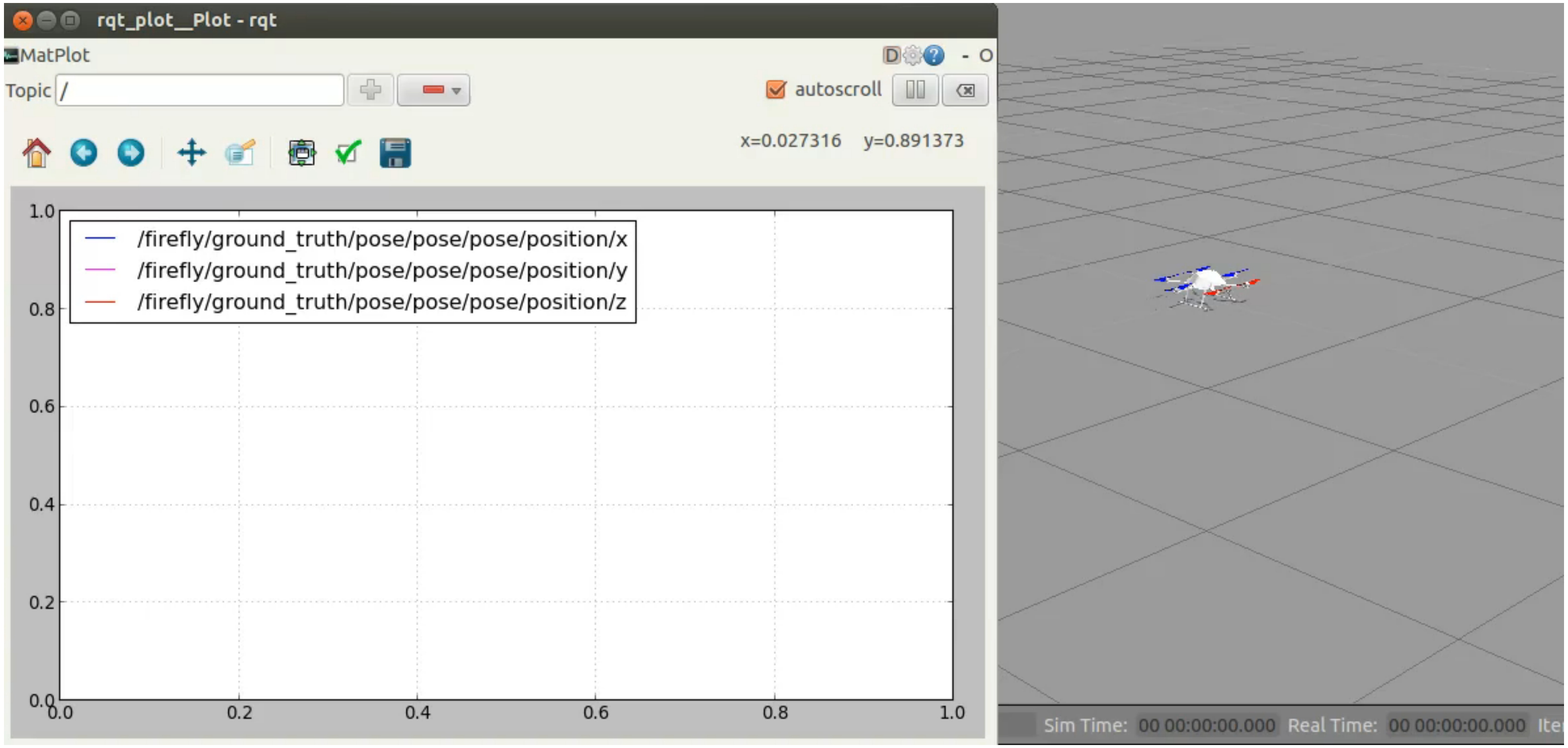
Position RMS error: 0.031 m

Angular velocity RMS error: 0.041 rad/s

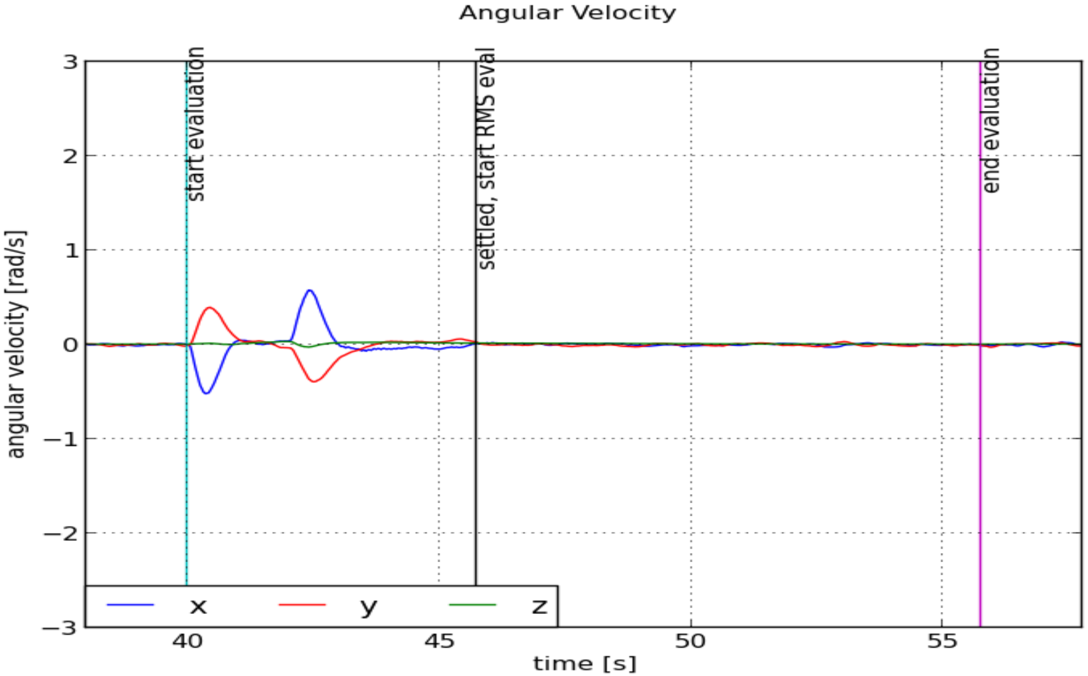
Scores: 1.0, 1.0, 1.0

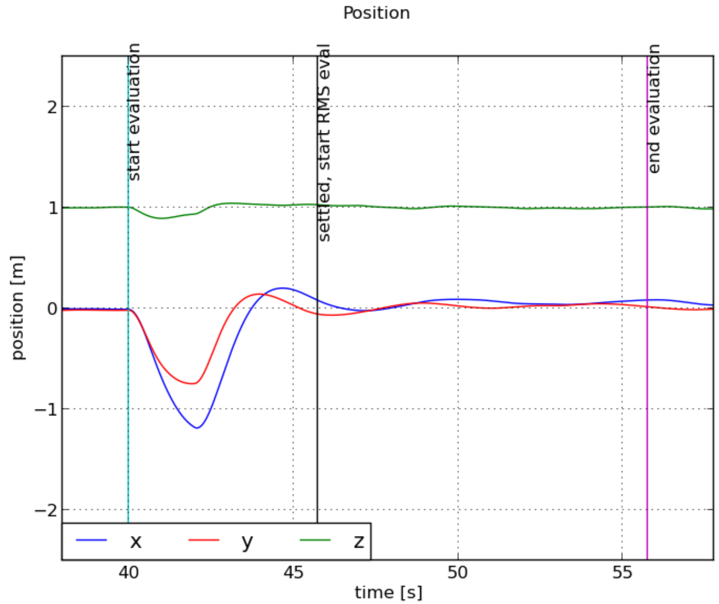
Total Score for Task 3.2 is: **3.0**

Task 3.3: results



Task 3.3: results





Settling time: 5.760 s

Position RMS error: 0.070 m

Angular velocity RMS error: 0.017 rad/s

Scores: 2.0, 2.0, 3.0

Total Score for Task 3.3 is: **7.0**

Questions?