Università degli Studi di Napoli Federico II

Martina Guerritore

LiDAR Systems for Advanced Assisted Driving in Tramway Sector

Supervisor: Prof. **Mauro D'Arco**
Co-Supervisor: Ingg. L.Fratelli & G.Graber, PhD

Cycle: **XXXVI**

Year: **Third**

BACKGROUND

- M.Sc. in Biomedical Engineering, Federico II University of Naples
- Research group: Electrical and Electronic Measurements (ING-INF/07)
- PhD start date: 01/11/2020 (Academic Year 2020-2021)
- Scholarship type: INPS - Dottorati Innovativi – Intersettoriali, vertenti sulle tematiche dell'iniziativa Industria 4.0
- Period abroad: European R&D centre (ERD) of HITACHI EUROPE SAS, France, under the supervision of Ing. Massimiliano Lenardi (24/10/2022 – 31/01/2023)
- Partner company: Hitachi Rail STS

THESIS OVERVIEW

*Tram-**A**dvanced **D**river **A**ssistance **S**ystem*

> *<u>Why Tram?</u>*

- Environmentally friendly
- Integration with other modes of transport and the existing urban context.

> *<u>Why T-ADAS?</u>*

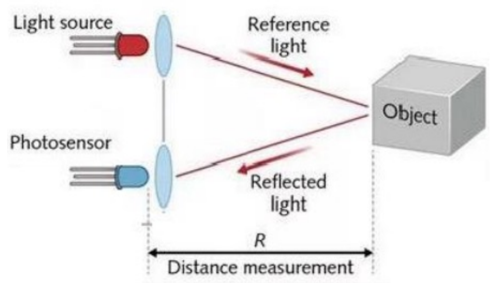
- Safety enhancement
- Reduced human error

> *<u>Existing solutions</u>*

- Dependence on visual information
- Sensitivity to environmental factors

RESEARCH AREAS

<u>What is my thesis proposing?</u>

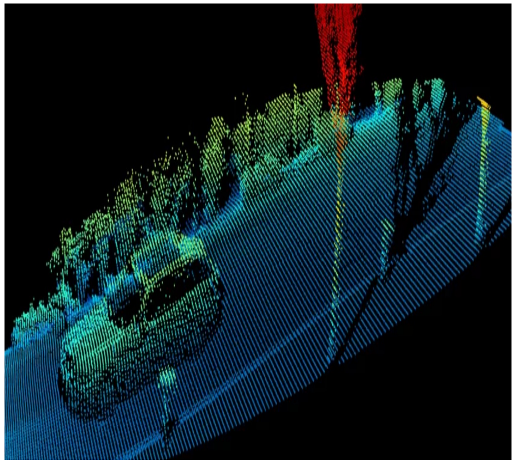


T-ADAS based on the <u>fusion</u> of <u>LiDAR and Camera</u>.

Target:

- Detection and tracking of moving objects
- Alert the driver about possible dangers/obstacles

<u>L</u>ight <u>D</u>etection <u>A</u>nd <u>R</u>anging is a technology, based on the transmission and reception of an impulse and giving back a points cloud with distance measurements of objects in the surrounding environment.



RESEARCH AREAS

T-ADAS requires the development of multiple tasks:

1. LiDAR moving object detection and tracking;
2. LiDAR localization.

I. Mauro D'Arco, Fratelli Luigi, Graber Giuseppe, Martina Guerritore. *Detection and Tracking of Moving Objects using Roadside LiDAR Sensors*. IEEE Instrumentation & Measurement Magazine.

II. D'Arco, Mauro, and Martina Guerritore. *Multi-Sensor Data Fusion Approach for Kinematic Quantities.* Energies 15.8 (2022): 2916.

III. M. D'Arco, M. Guerritore. *A new method to estimate the attitude of a LiDAR through IMU and point-cloud data analysis.* IEEE I2MTC – International Instrumentation and Measurement Technology Conference 2024 (in revision)

IV. D'Arco, Mauro, Martina Guerritore, and Annarita Tedesco. *Application Scenarios for Gait Analysis with Wearable Sensors and Machine Learning*. International Conference on 25th IMEKO TC4 Symposium and 23nd International Workshop on ADC and DAC Modelling and Testing (IWADC). DOI: 10.21014/tc4-2022.37

METHODOLOGY I

LiDAR moving object detection and tracking

Detection of moving objects
- Background filtering
- Clustering

3D Bounding box fitting
- Ellipse fitting
- Parameters estimation

Multi-object tracking
- Modeling objects kinematics
- Kalman filtering

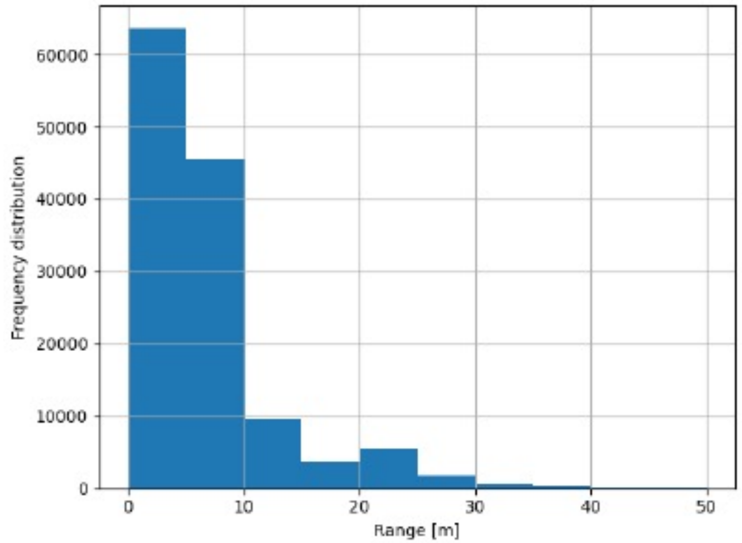
Major challenges for high-performance LiDAR:

- running in real-time
- adaptability to any scene
- accurate results

METHODOLOGY I

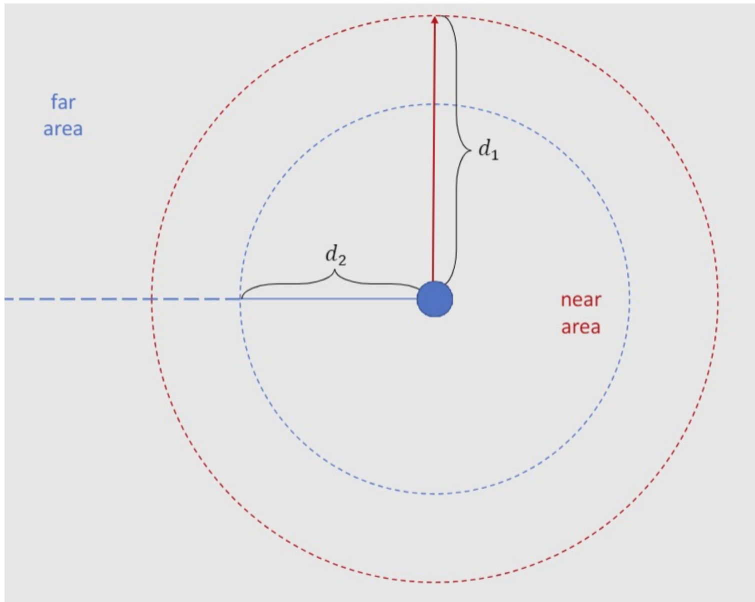
Detection of moving objects

- Background filtering
- Clustering



The proposed method exploits the DBSCAN approach, since in road monitoring:

- the number of clusters is not known in advance,
- the DBSCAN is robust to any residual noise after coarse background filtering.



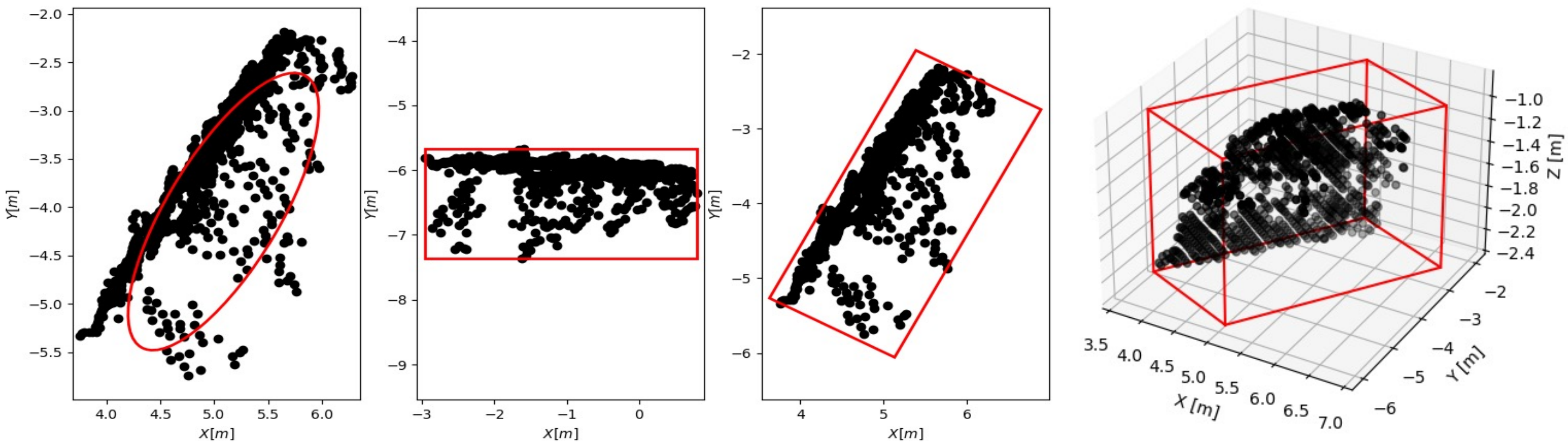
METHODOLOGY I

3D Bounding box fitting

- Ellipse fitting
- Parameters estimation

Multi-object tracking

- Modeling objects kinematics
- Kalman filtering



Experimental site and instruments set-up

San Giovanni (Naples, Italy)

1

(a) Street-view of the experimental site. (b) Set-up adopted to carry out the experiments

Urban Line (Naples, Italy)

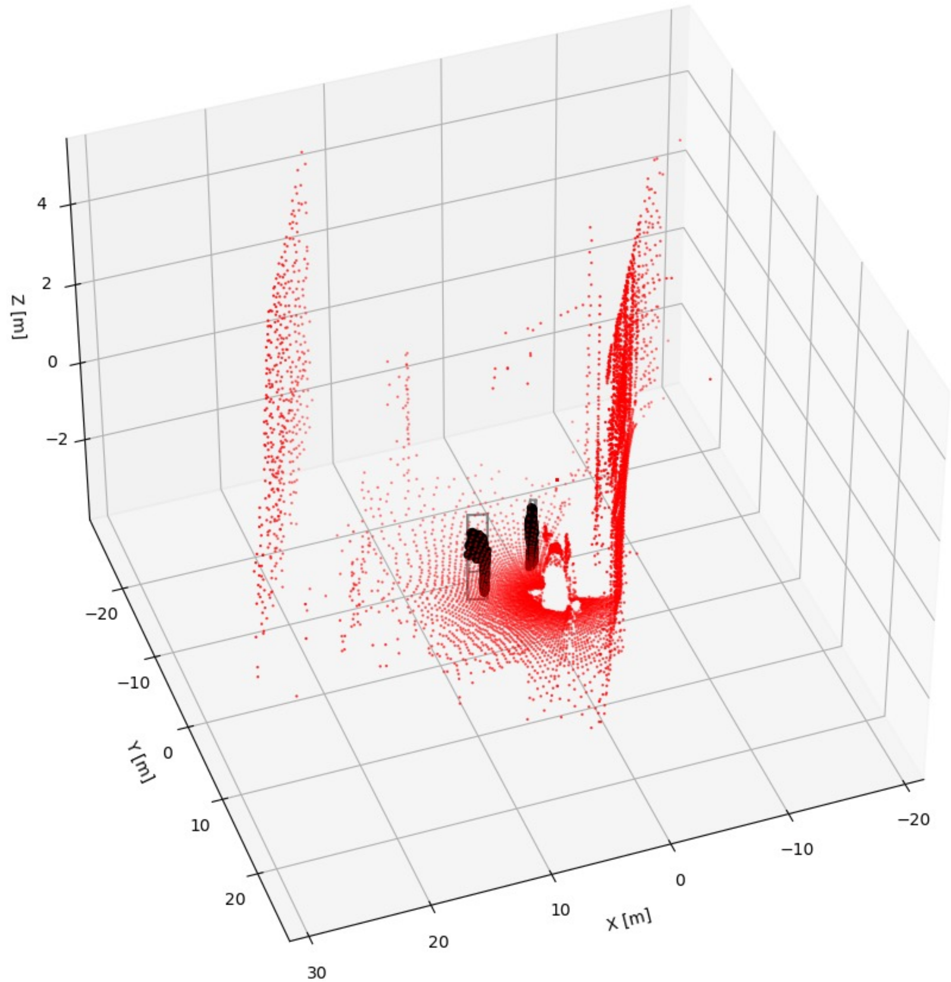
2

(a) Research team. (b) Set-up adopted to carry out the experiments

RESULTS

Results obtained by applying the proposed methodology to the data obtained from the experimental set-up:

Background	Number of detected points / the expected value	98.5%
Clustering	Number of detected clusters / the expected value	100%
Tracking	MSE	0.35 m



LOCALIZATION

Position

Orientation

OVERVIEW II

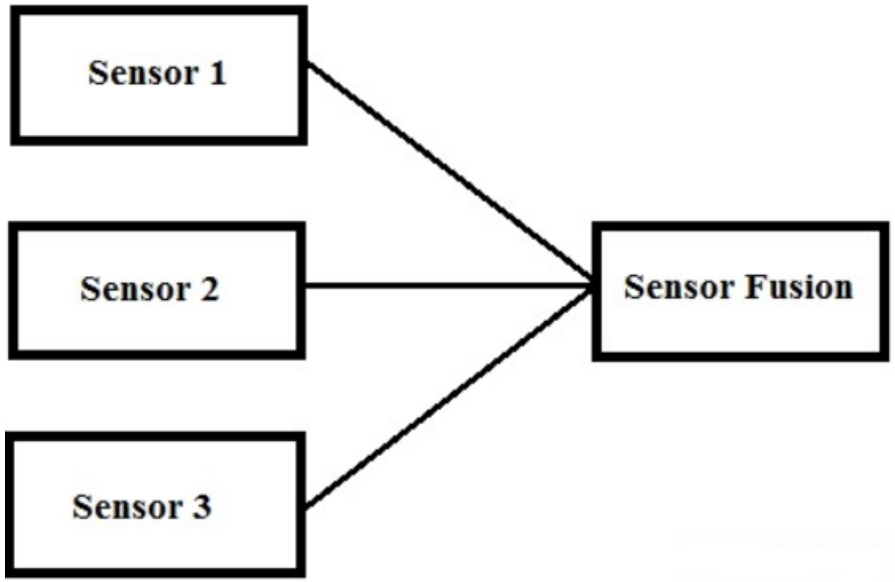
Multi-sensor data fusion method for kinematic quantities.

Why sensor fusion?

- Insensitivity to offset, drift, and flicker or random walk noise.
- Reliability if one of the sensors fails

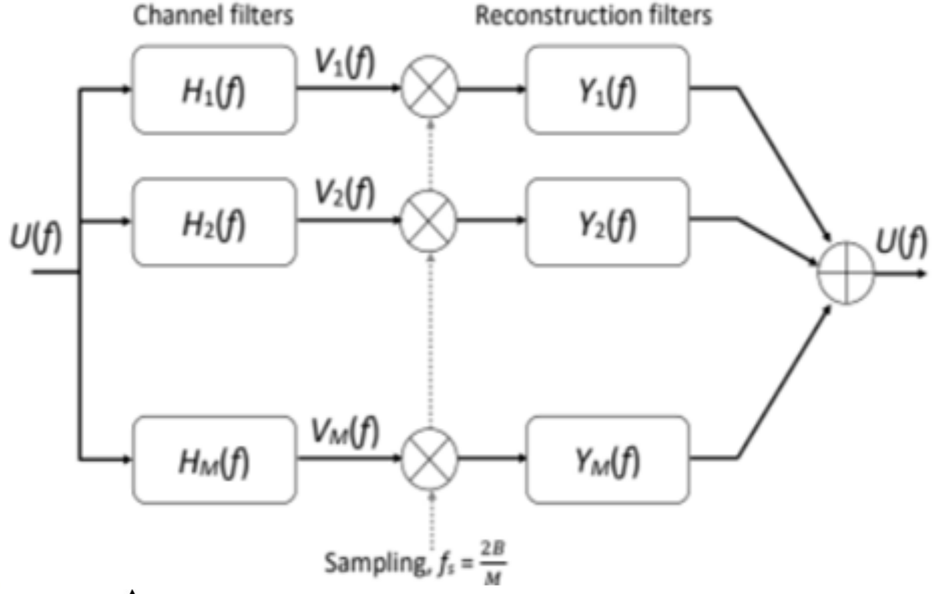
Why the proposed method?

- Absence of the mathematical model
- Knowledge of the frequency responses of the sensors
- Implementation through FIR coefficients → Low computational load
- Sampling under Nyquist → lower memory space → higher execution speed

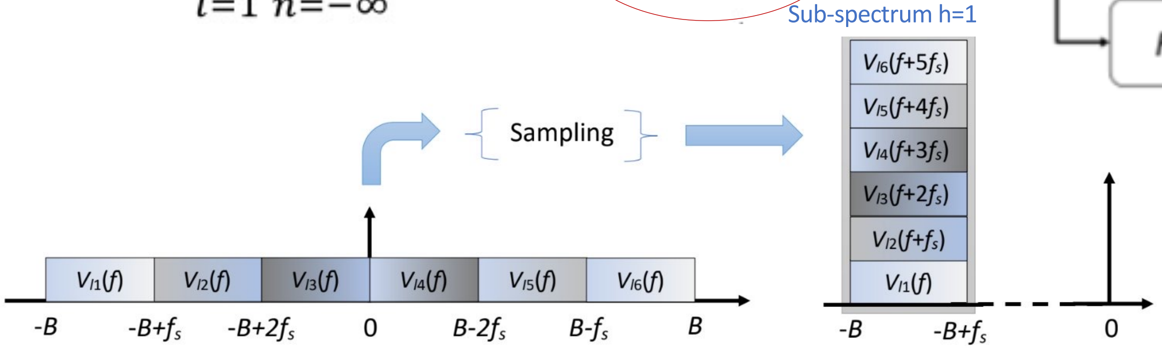


METHODOLOGY II

- Signal u(t) band limited B
- M linear, independent, and time-invariant channels.



$$u(t) = \sum_{l=1}^{M} \sum_{n=-\infty}^{+\infty} v_l(nT_s)\, y_l(t - nT_s)$$



$$U(f)\chi_h = f_s \sum_{k=-M+h}^{h-1} \left(\sum_{l=1}^{M} H_l(f - kf_s) Y_l(f) \right) U(f - kf_s)$$

$$= \frac{1}{f_s} \chi_h(f) \delta_k$$

$$\begin{bmatrix} Y_{11}(f) \\ \vdots \\ Y_{M1}(f) \end{bmatrix} = \frac{1}{f_s} \chi_1(f) \begin{bmatrix} H_1(f + (M-1)f_s) & \cdots & H_M(f + (M-1)f_s) \\ \vdots & \ddots & \vdots \\ H_1(f) & \cdots & H_M(f) \end{bmatrix}^{-1} \begin{bmatrix} 0 \\ \vdots \\ 1 \end{bmatrix}$$

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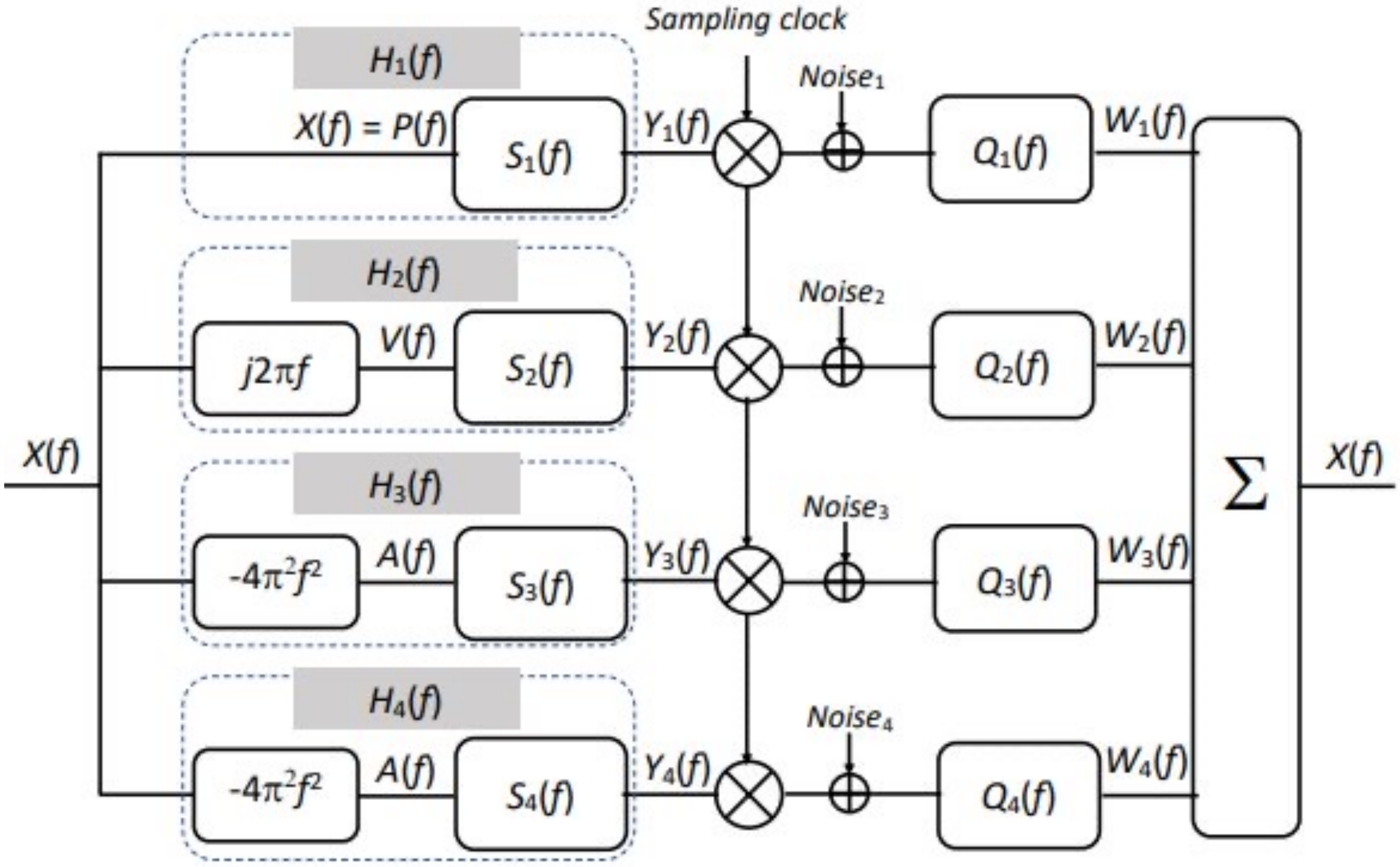
METHODOLOGY II

Position

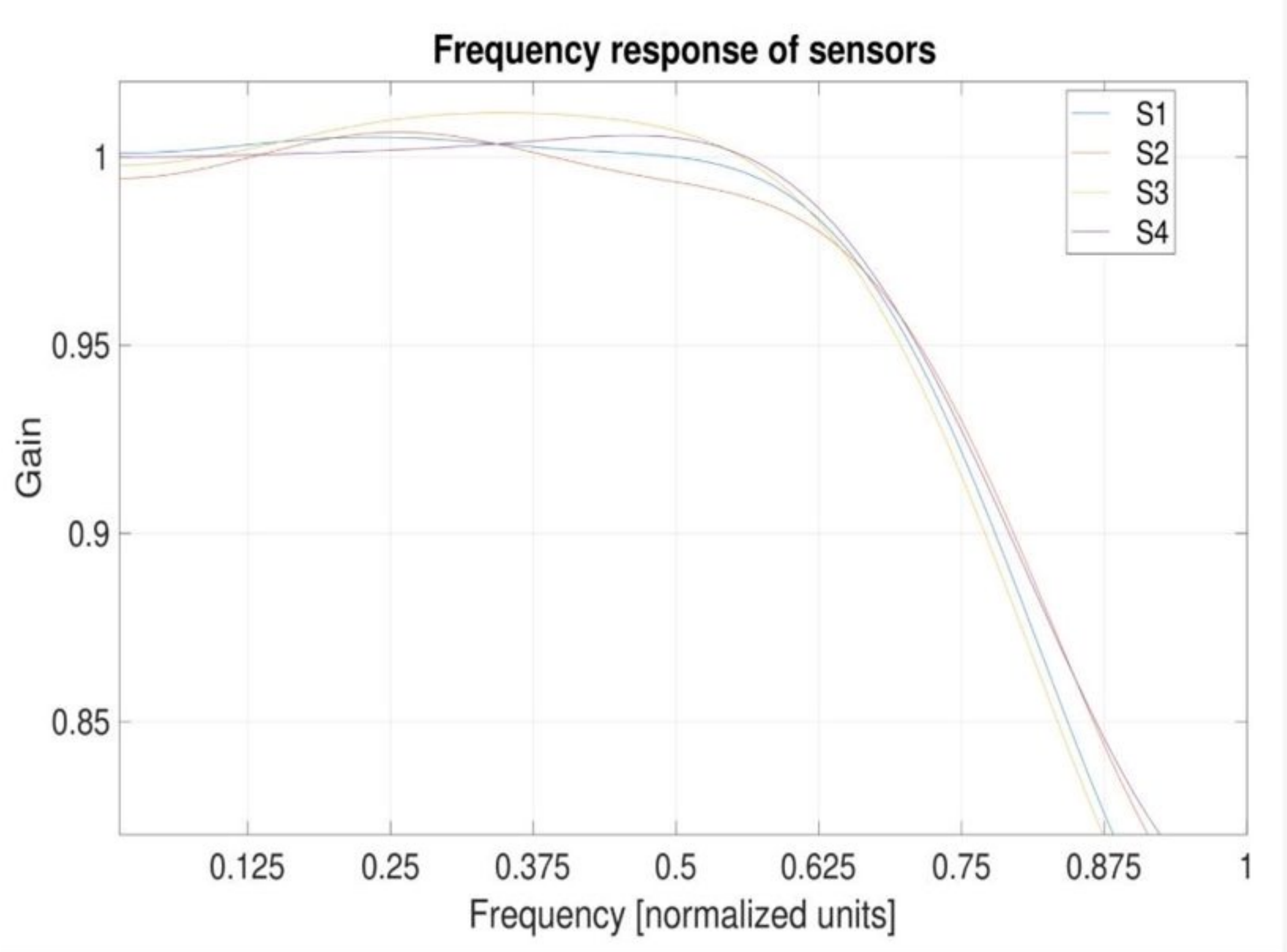
Velocity

Acceleration

Acceleration

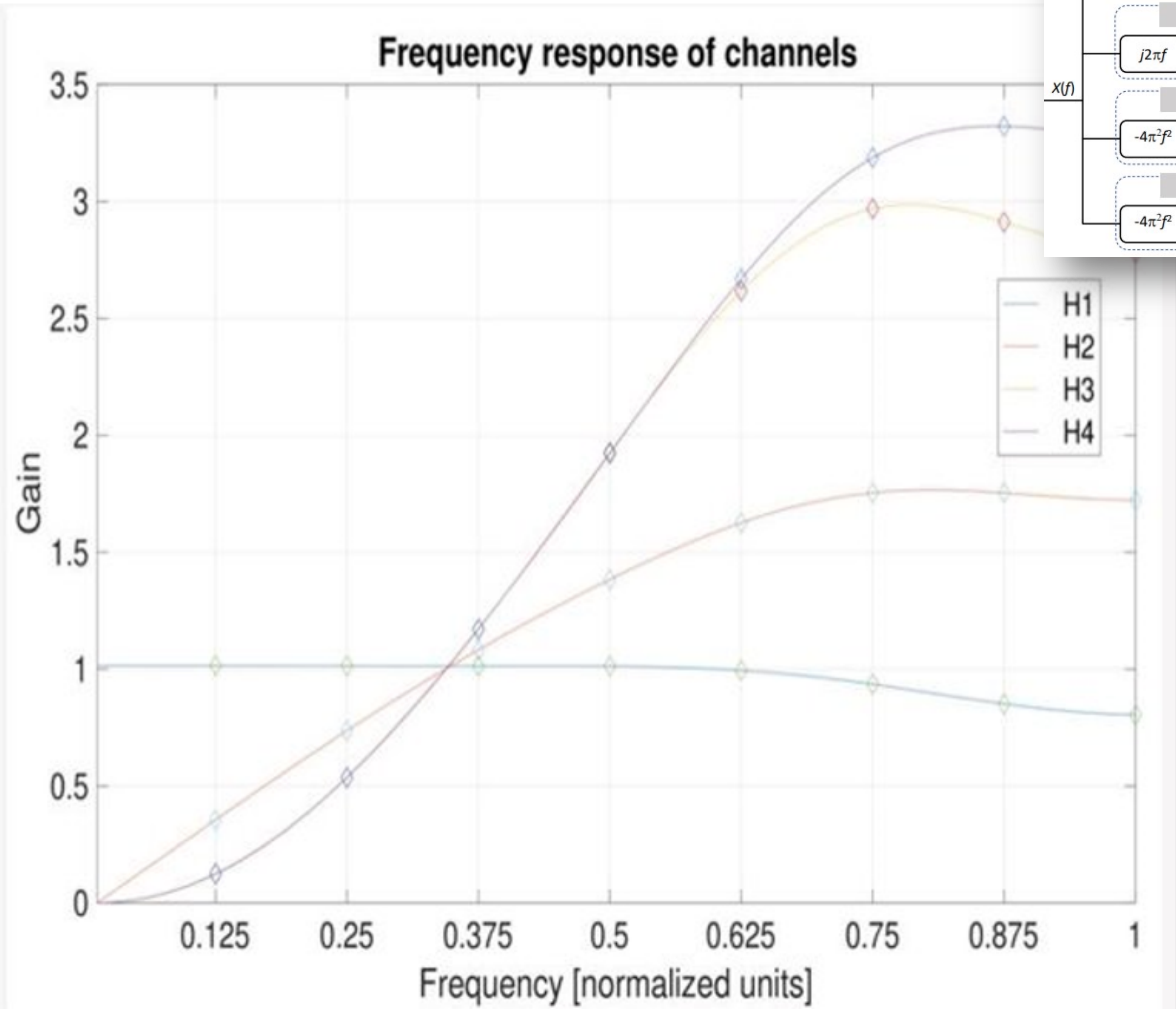


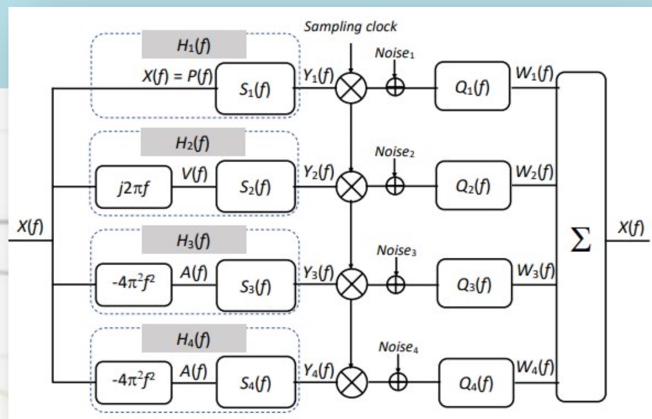
METHODOLOGY II



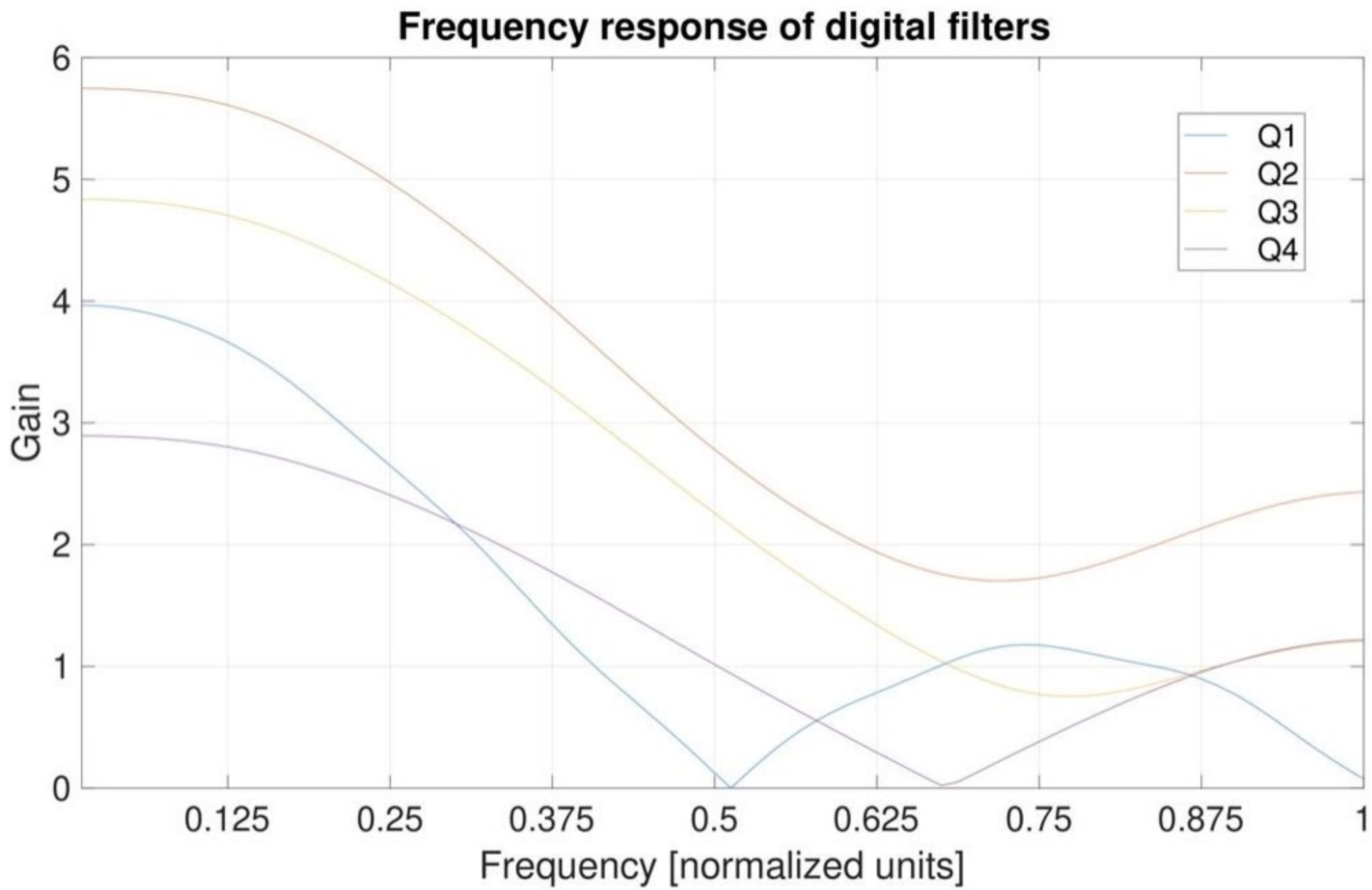
$F_{cut} \in (0,95 - 0,97)$
$Ripple < 0.18\,dB$
$2L = 16$

METHODOLOGY II





METHODOLOGY II



EXPERIMENTAL SET-UP

$$KPI = \frac{\frac{1}{N}\sum_{n=1}^{N}|x(n)|^2}{\frac{1}{N}\sum_{n=1}^{N}|x(n)-s(n)|^2}$$

Sinusoidal testing

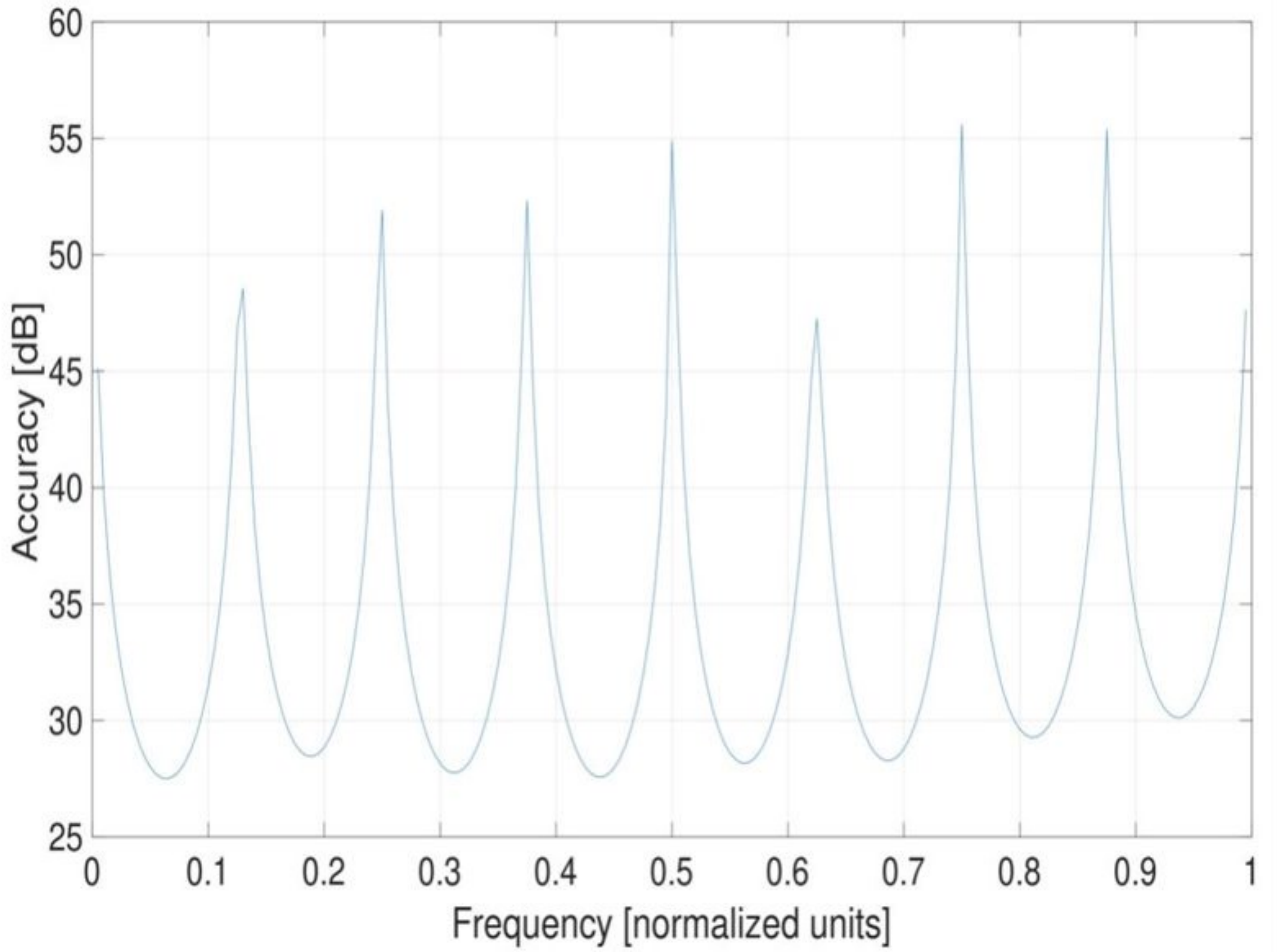
- 200 equidistant frequencies throughout the system band
- 1000 sinusoidal realizations for each frequency
- Each realization affected by broadband noise, SNR= 20dB.

Test pseudo-random signals

- 1000 pseudo-random trajectories

RESULTS II

Figure shows the mean value of the KPI, expressed in dB units, at the test frequencies.



In the presence of **non-sinusoidal test signals**, such as pseudo-random trajectories, which have spectral contents uniformly spread throughout the bandwidth of the sensors, the typical accuracy offered by the method stands within the interval (33.9–36.2) dB with a mean at 35.0 dB

LOCALIZATION

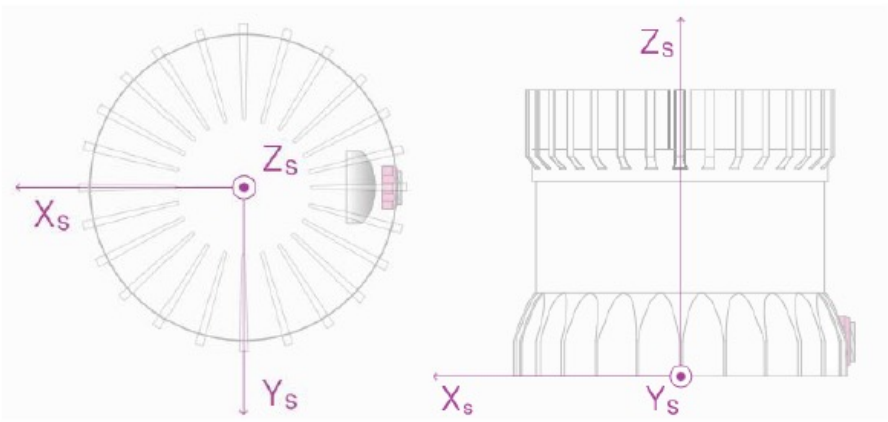
Position

Orientation

OVERVIEW III

Problem: LiDARs are mounted on a self-driving vehicle or are used for road monitoring. However, there may be deviation angles between the Main and Sensor reference systems due to the movement of the vehicle or issues in installation, vibration, and others.

- Target: The attitude estimation method aims to estimate the orientation of the vehicle by avoiding the use of the accelerometer.



Sensor Coordinate system (red). Left: top of view. Right: side of view

Existing and proposed approaches :

→ *GPS*

→ *Fusion of sensors: accelerometer and gyroscope*

→ Gyroscope → Kalman filter ← Point cloud

Disadvantages:

- Knowledge of external acceleration
- The accelerometer is sensitive to vibration.

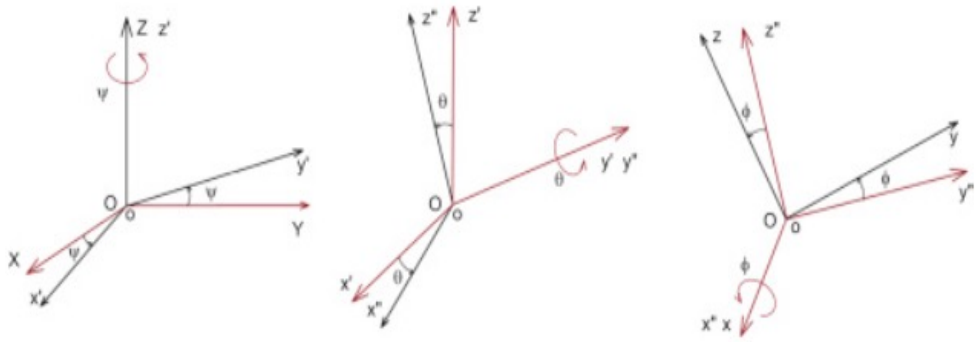
METHODOLOGY III

Modelling LiDAR configuration in the space

A common method, describing the **orientation** of a rigid body in three-dimensional space relative to a reference frame, is known as ***Euler angles***. These angles are commonly referred to as *pitch (ϑ), roll (ϕ), and yaw (ψ),* representing the rotation around the principal axes *x, y*, and *z*.

X^E Fixed reference system (ENU)

X^S Sensor reference system



The relationship:

$$X^E = RX^S$$

where represents the Z – Y – X-sequence rotation matrix

$$\mathbf{R} = \begin{bmatrix} cos\psi cos\theta & cos\psi sin\theta sin\phi - sin\psi cos\phi & cos\psi sin\theta cos\phi + sin\psi sin\phi \\ sin\psi cos\theta & sin\psi sin\theta sin\phi + cos\psi cos\phi & sin\psi sin\theta cos\phi - cos\psi sin\phi \\ -sin\theta & cos\theta sin\phi & cos\theta cos\phi \end{bmatrix}$$

$$\phi = atan\left(\frac{R_{32}}{R_{33}}\right)$$

$$\theta = atan\left(\frac{-R_{31}}{R_{32}/sin(\phi)}\right)$$

Therefore, the state vector is defined as:

$$\mathbf{x} = [R_{31}\ R_{32}\ R_{33}]^T$$

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METHODOLOGY III

IMU sensor model

An IMU sensor model is a mathematical representation describing the behavior of the IMU sensors:

$$\tilde{\boldsymbol{\omega}}(t) = \boldsymbol{\omega}(t) + \boldsymbol{b} + \boldsymbol{n}_{\omega}(t)$$
$$\tilde{\boldsymbol{a}}(t) = \boldsymbol{a}(t) + \boldsymbol{g}(t) + \boldsymbol{n}_{a}(t)$$

- $\widetilde{\omega}(t)$ gyroscope readings at time instant *t* *(*)*
- ω(t) angular rate *(*)*
- b bias which is assumed to be constant over time
- n_{ω}(t) uncorrelated zero mean white Gaussian noise *(*)*
- $\tilde{a}(t)$ accelerometer reading at a time instant *t* *(*)*
- a(t) external acceleration *(*)*
- g(t) gravitational acceleration*(*)*
- n_a(t) uncorrelated zero mean white Gaussian noise vector *(*)*

* (along x,y,z-axis)

METHODOLOGY III

Kalman filter design

The differential equation of a rotation matrix is

$$\mathbf{R}_t = \mathbf{R}_{t-1}(\mathbf{I} + \Delta t[\omega]_{t-1}) \qquad \text{(a)}$$

where $[\omega]$ denotes the skew-symmetric matrix of vector ω, $\boldsymbol{I}$ is the identity matrix 3x3, and Δt is the sampling time. Considering the state vector and model process of linear Kalman Filter eq.s:

$$\left.\begin{aligned} \mathbf{x} &= [R_{31}\ R_{32}\ R_{33}]^T \\ \mathbf{x}_t &= \Phi_{t-1}\mathbf{x}_{t-1} + \mathbf{w}_{t-1} \end{aligned}\right\} \rightarrow \text{(a)} \rightarrow \quad \mathbf{x}_t = (\mathbf{I} + \Delta t[\omega]_{t-1})\mathbf{x}_{t-1} \qquad \text{(b)}$$

The gyroscope gives in outputs an angular velocity affected by noise, so substitute the eq. of gyroscope:

$$\mathbf{x}_t = (\mathbf{I} + \Delta t\tilde{\omega}_{t-1})\mathbf{x}_{t-1} + \Delta t[\mathbf{x}]_{t-1} n_{\omega_{t-1}} \qquad \text{(c)}$$

transition matrix

white Gaussian process noise with covariance matrix

$$\mathbf{Q}_{t-1} = -\Delta t^2 \widetilde{\mathbf{x}}_{t-1} \Sigma_G^2 \widetilde{\mathbf{x}}_{t-1}$$

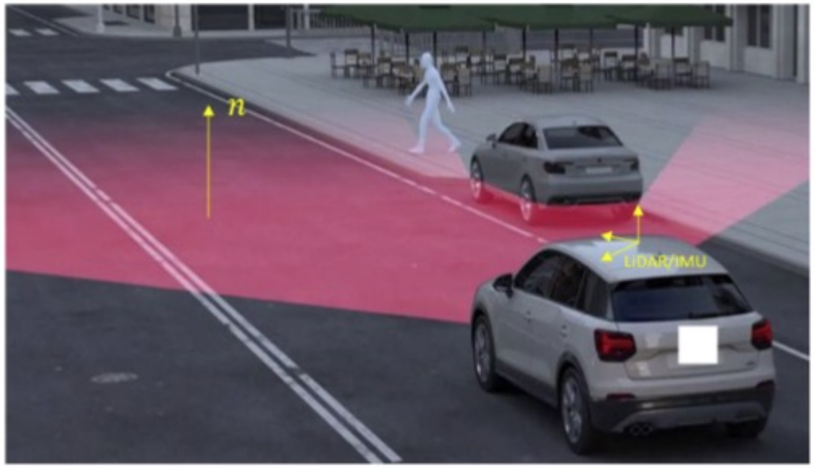
METHODOLOGY III

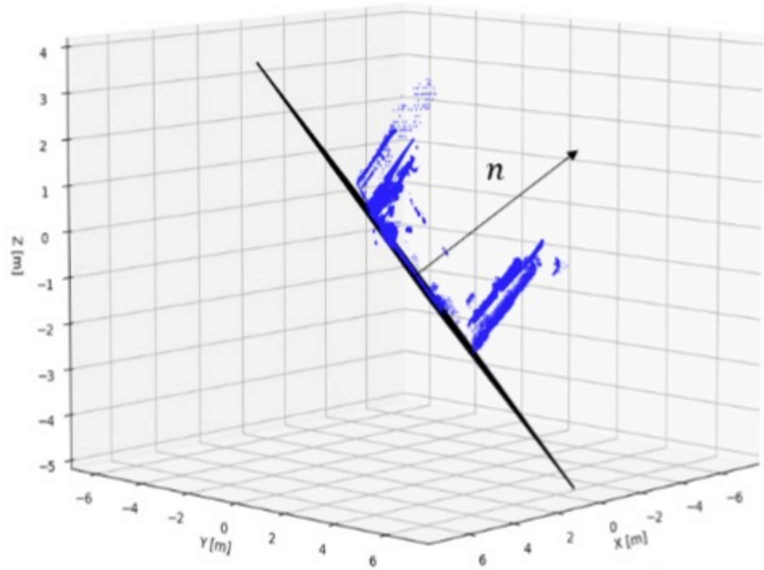
Measurement updating

The measurements updating eq. of Kalman filter is:

$$\mathbf{z}_t = \mathbf{H}\mathbf{x}_t + \mathbf{r}_M$$

where the $\mathbf{H}$ is the observation matrix and $\boldsymbol{r}_M$ is the measurement noise associated with the observation process, assuming that this noise obeys a stationary zero-mean Gaussian process.





The relationship between the vertical z–axis, named $\boldsymbol{e}_z$, and the normal with deviation $\boldsymbol{n}$ is given by:

$$\mathbf{e}_z = \mathbf{R}\frac{\mathbf{n}}{\|\mathbf{n}\|} \longrightarrow \mathbf{z}_t = \mathbf{H}\mathbf{R}^T_{3,j}$$

EXPERIMENTAL SET-UP & RESULTS

Sensor data is simulated utilizing the Driving Scenario Designer tool in MATLAB 2023

Vehicle equipped with INS and LiDAR sensor:

IMU

- sampling frequency of 100 Hz
- acceleration and angular velocity accuracy set at 0.2 m/s^2 and 0.2◦/s respectively

LiDAR

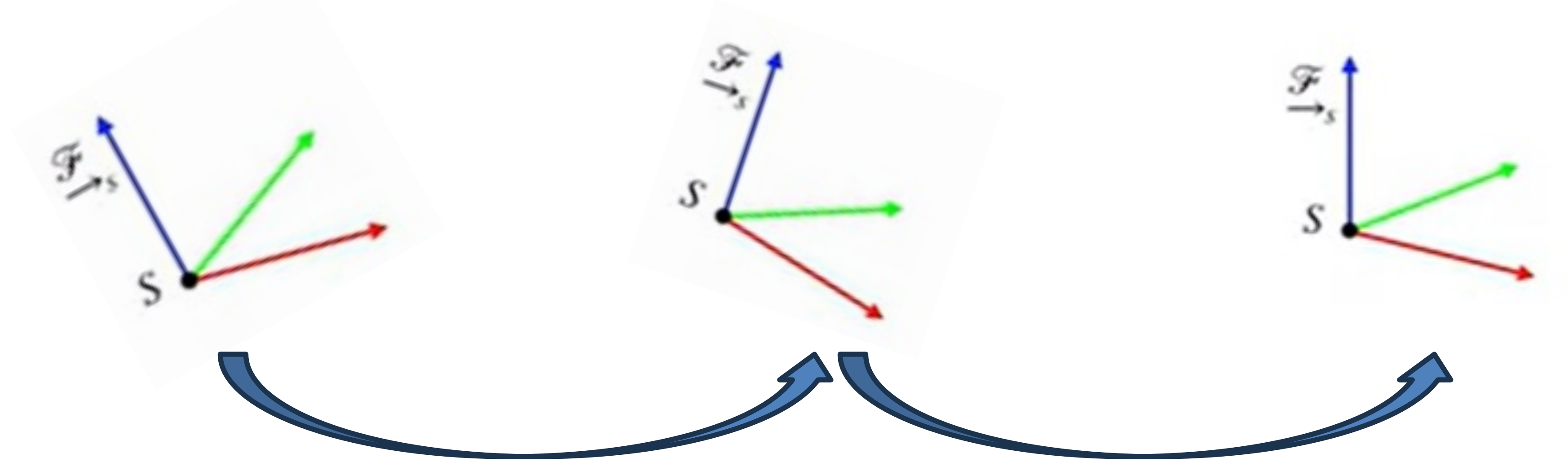
- rate frequency at 10 Hz
- azimuth resolution at 0.16°
- elevation resolution at 1.25°
- range accuracy at 0.002m
- maximum range at 100m

Test	Speed [m/s]	RMSe pitch [°]	RMSe roll [°]
1	1e-200	0.0660	0.0033
2	1e-100	0.0111	0.0205
3	10	0.0068	0.0086
4	20	0.0587	0.0200
5	30	0.0580	0.0319
6	40	0.0270	0.0083
7	50	0.0269	0.0553
8	60	0.0220	0.0144
9	70	0.0090	0.0033
10	80	0.0017	0.0035
11	90	0.0768	0.0204
12	100	0.0091	0.0146
13	110	0.0891	0.0439
14	120	0.0746	0.0089
15	130	0.0407	0.0137
16	140	0.1937	0.0145
17	150	0.0270	0.0142
18	180	0.0118	0.0031
19	200	0.0069	0.0442
20	300	0.0589	0.0380

EXPERIMENTAL SET-UP

- Experimental set-up described in previous slides.
- Inertial Measurement Unit (IMU) sensor ICM-20948, integrated within the LiDAR
- Calibration of IMU and LiDAR sensors:

IMU frame *Sensor frame* *ENU*

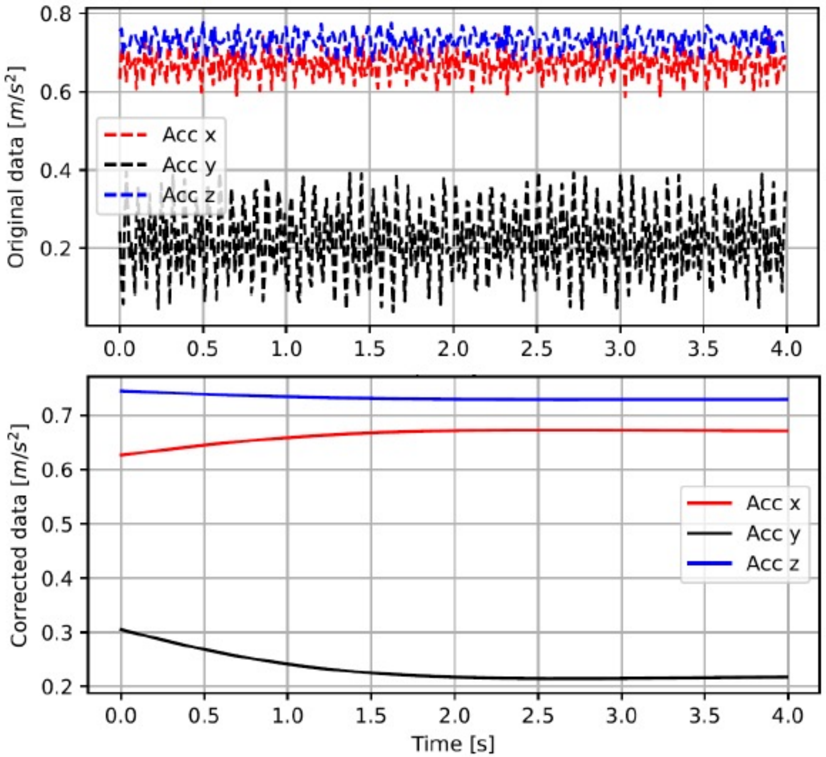


$$M_i^s = \begin{bmatrix} 1 & 0 & 0 & 6.253 \\ 0 & 1 & 0 & -11.775 \\ 0 & 0 & 1 & 11.645 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

R

EXPERIMENTAL SET-UP

The pitch and roll, used as reference values, are obtained by using the gravitational field vector. the acceleration measurements from IMUs are corrupted by noise, which significantly degrades the accuracy of the estimated reference parameters.

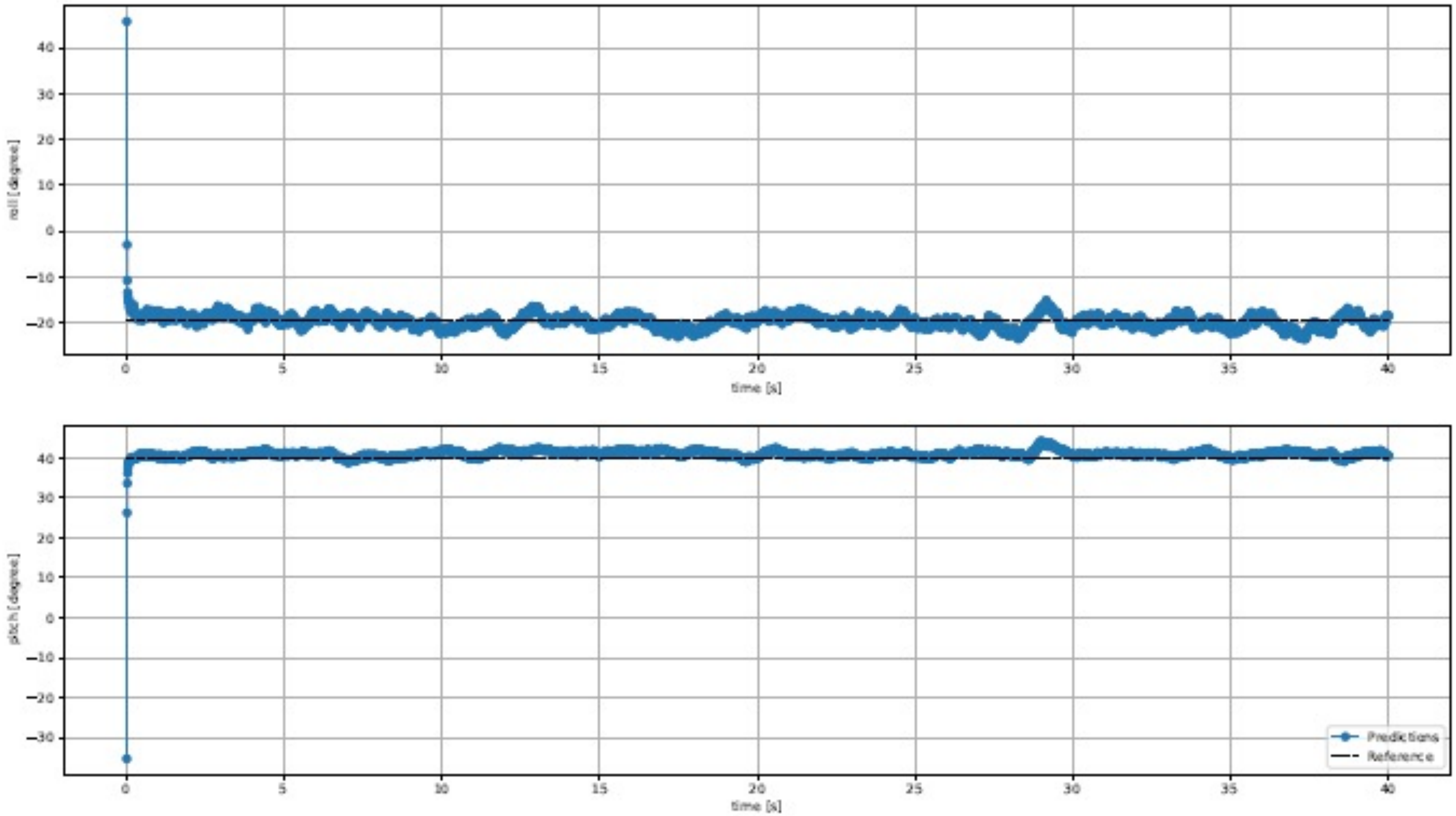


Axes	Mean $[m/s^2]$	Standard deviations $[m/s^2]$
X	0.6699	0.0385
Y	0.2189	0.0915
Z	0.7295	0.02246

Butterworth low pass filter (flat response, adequate roll-off)

Axes	Mean $[m/s^2]$	Standard deviations $[m/s^2]$
X	0.6693	0.0044
Y	0.2201	0.0087
Z	0.7298	0.0017

RESULTS III



RMS error, roll estimation: 1.306°
RMS error, pitch estimation: 1.470°

SUMMARY OF STUDY ACTIVITIES

- <u>Ad hoc courses</u>
  - Statistical data analysis for science and engineering research
  - Scientific Programming and Visualization with Python
  - Matrix Analysis for Signal Processing with MATLAB

- <u>PhD Schools</u>
  - PhD Excellence School "I. Gorini" 2021
  - PhD Excellence School "I. Gorini" 2022 - winner of BEST PROJECT AWARD
  - XR Spring School 2022 - eXtended Reality Spring School 2022

- <u>Seminars</u>
  - 68 seminars organised by the University of Naples (IEEE, ICTH) , Scuola Superiore Meridionale di Napoli, Scuola Superiore Sant'Anna di Pisa

Thank you for your attention