Multi-Sensor Fusion for High Integrity Localization: how to bound estimation errors?

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Outline

1. The concept of integrity
2. Localization with multi-lane camera measurements
3. Data fusion architecture for high-integrity localization
4. Bounding estimation error
5. Parameters tuning using a data-driven approach
6. Experimental results

The concept of integrity

A high integrity system is a system that provides miss-leading information with a very low rate

For systems operating in complex environments, integrity needs redundancy

Integrity definition (Navipedia):

- a measure of trust that can be placed on the correctness of the information supplied by a navigation system
- integrity includes the ability of the system to provide timely warnings to users when the system should not be used for navigation

Accuracy is characterized by statistical metrics, while integrity is intended to serve as a **real-time decision-making** criterion for the use or non-use of the system

The probability of hazardous situations (that would possibly put at risk human lives) is in general very small (e. g. 10^{-6})

Integrity in terms of error bounds

A Protection Level (*PL*) is a statistical bound of the error

The Integrity Risk (*IR*) is the probability that the position error *e* exceeds a *PL* without providing a warning:

$$\Pr(e > PL) = IR$$

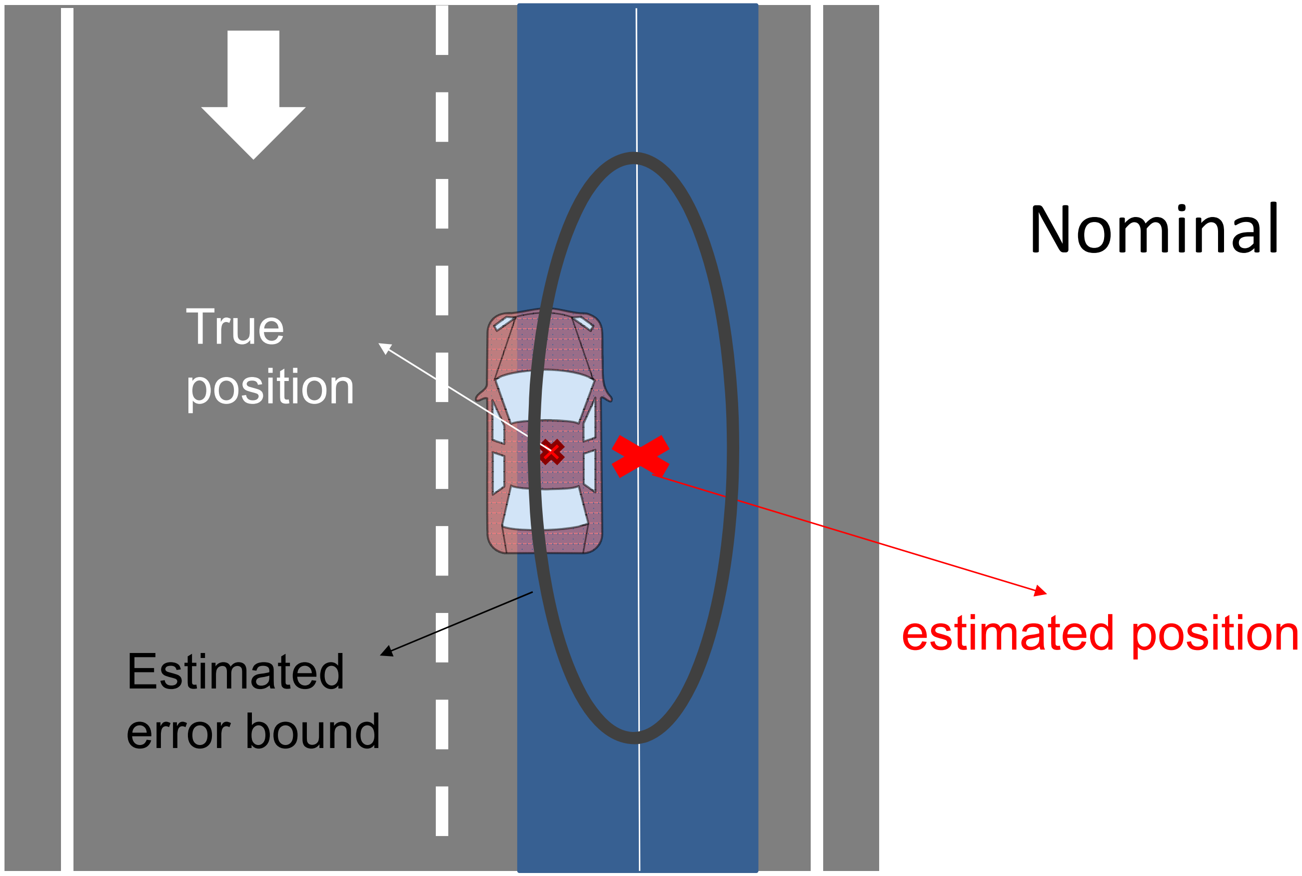
A Target Integrity Risk (*TIR*) is defined by the application

The *TIR* is used to tune the parameters of the models and filters to compute the *PL* in real-time

A system is considered as satisfying the integrity requirement at a given *TIR* , if the relation $IR < TIR$ is empirically verified

$$\Pr(e > PL(TIR)) \leq TIR$$

Bounding errors for autonomous driving



1

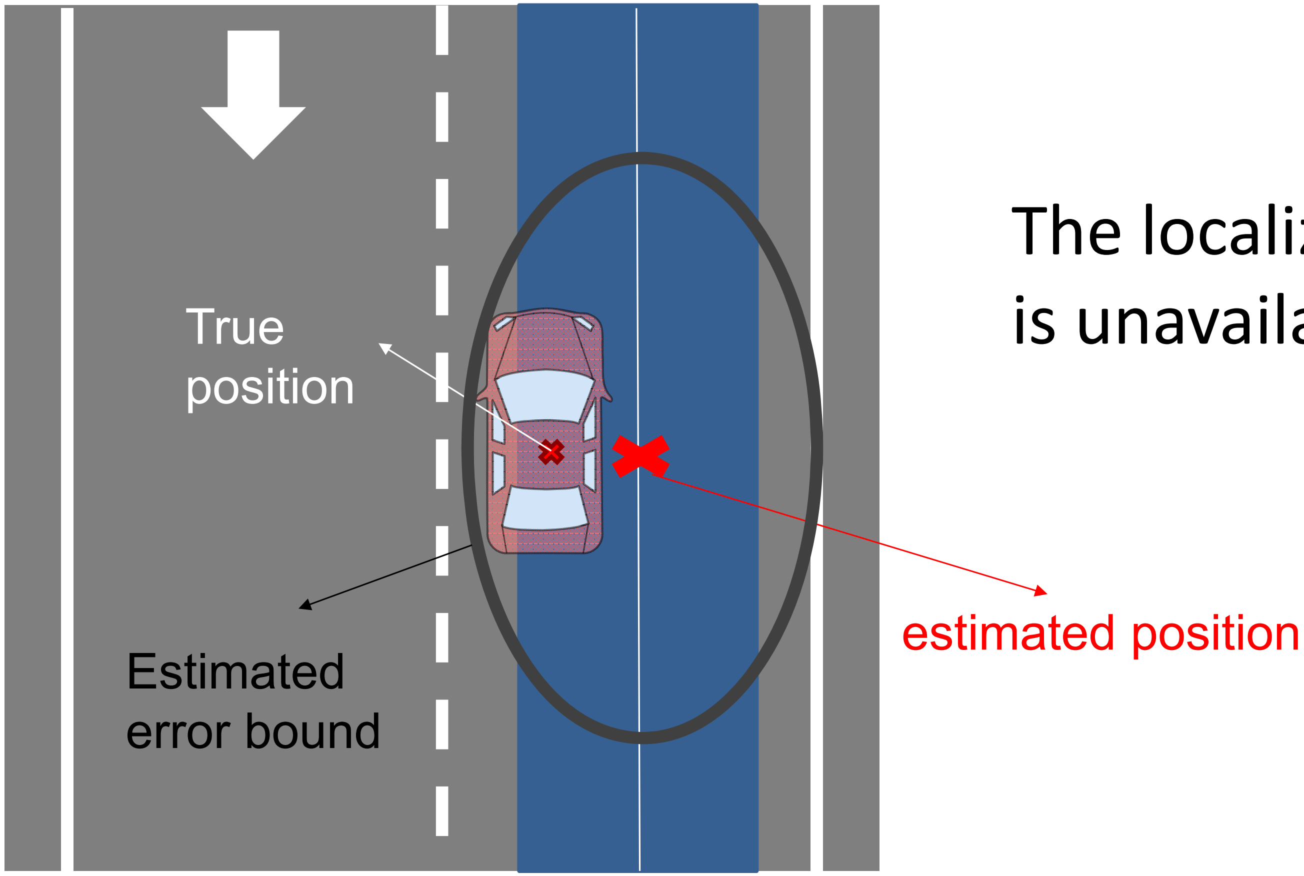
Nominal case e<PL<AL

The error is correctly bounded. OK!

The bound is in the limit ➔ use

Bounding errors for autonomous driving

2

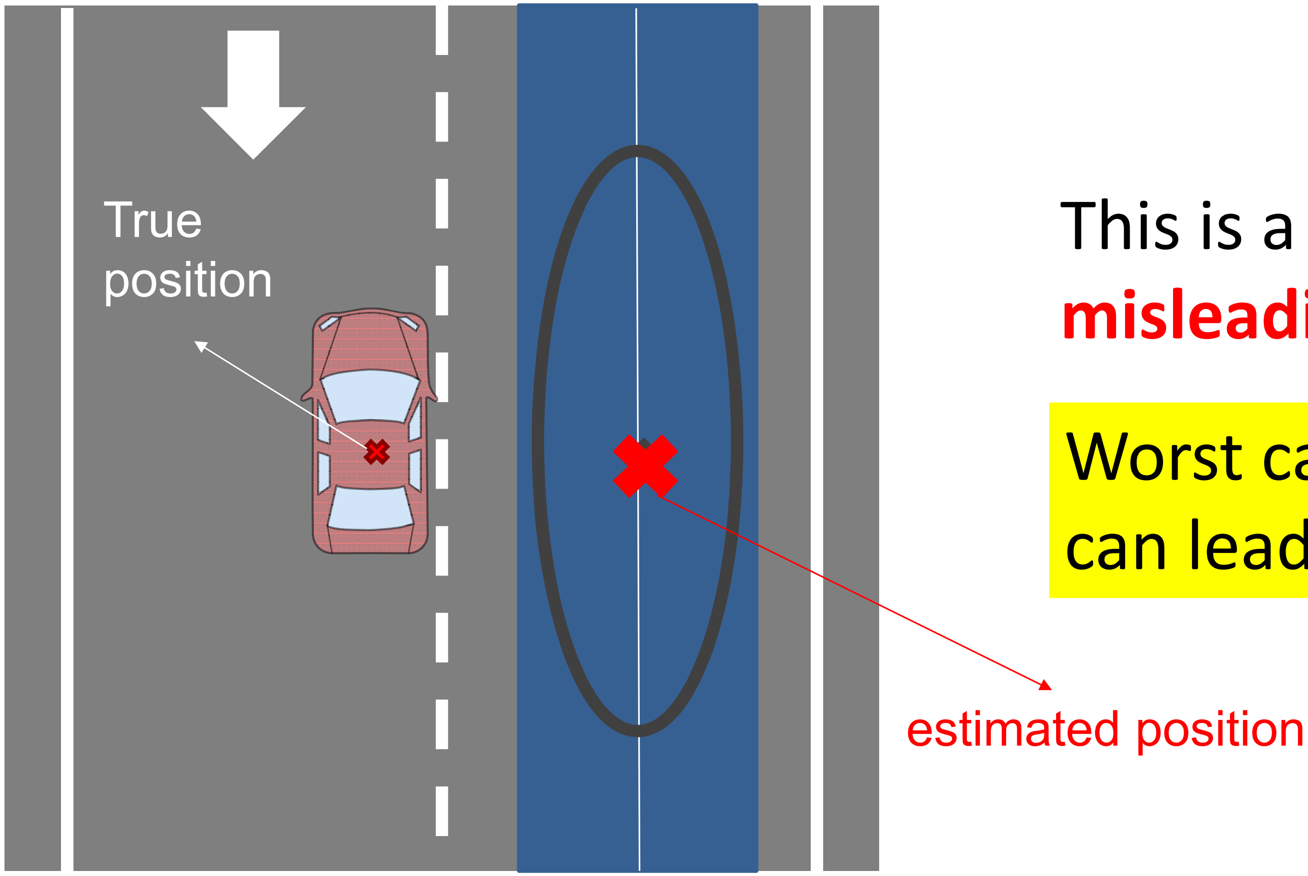


The localization system is unavailable

The error is correctly bounded. OK!

The bound is out of the limit → Don't use

Bounding errors for autonomous driving



3

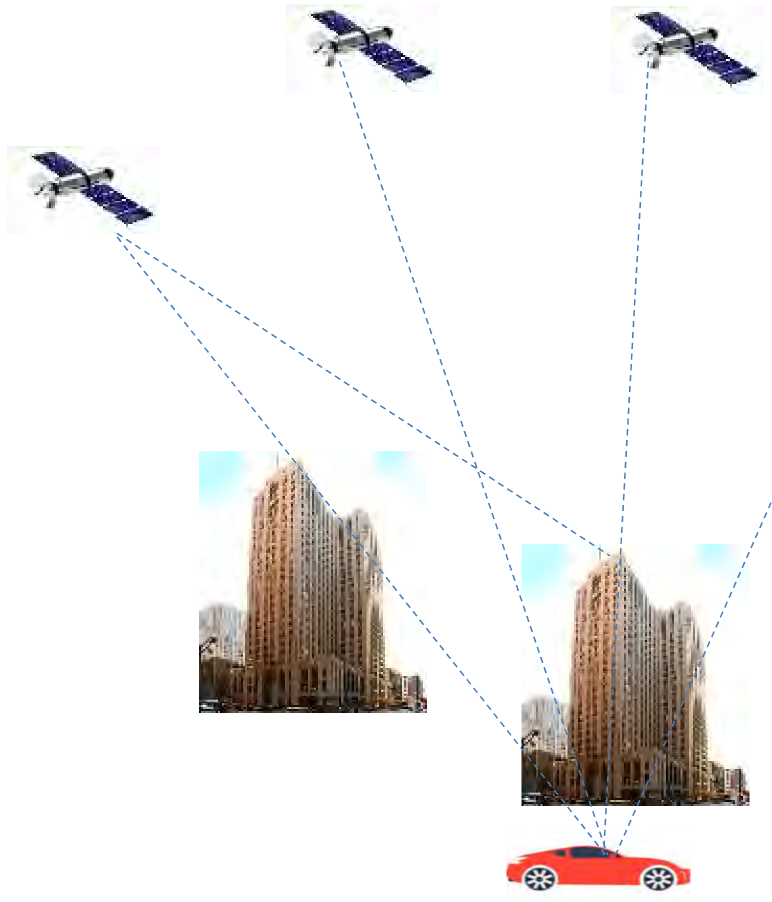
This is a situation of **misleading information**

Worst case scenario that can lead to an accident

The error is NOT correctly bounded

The bound is in the limit → use

Classification of integrity methods for GNSS based localization systems



Integrity methods

- Measurement rejection approach
- Error characterization approach

Avionics integrity applied to road vehicles

1st approach: Receiver autonomous integrity monitoring RAIM

- Measurement rejection approach
- Hypothesis : one faulty satellite at a time
- Decision test = Least Squares Residuals (LSR)
- The missed fault hypothesis on the satellite which has the greatest impact on the error is used to bound the error (maximum slope)

$$PL = HSLOPE_{max}\sigma\sqrt{\lambda}$$

Extension to simultaneous faults difficult to do.

Avionics integrity applied to road vehicles

2nd approach: Satellite-based augmentation systems (SBAS)

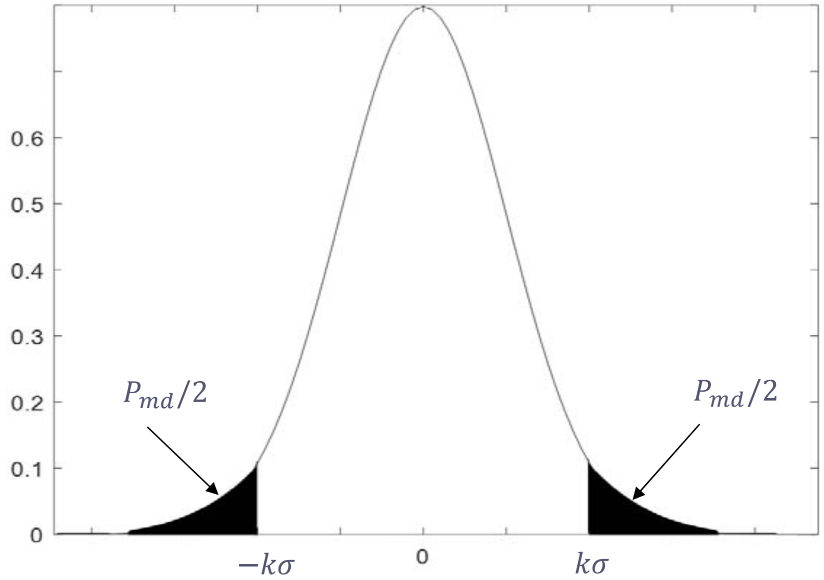
— Error characterization approach

— Hyp:

- Faulty satellites are detected and removed thanks to SBAS
- Error distribution supposed to be zero mean Gaussian

$$\sigma = HDOP.\sigma_{UERE}$$

$$PL = k_H \sigma$$



k_H = factor that propagates the position variance to a given integrity requirement

Limitations of GNSS avionics integrity when applied to road vehicles

Not applicable to road vehicles in complex environments

Rejection of faults approaches

- assumption of one fault at a time
- unrealistic in urban environments since the main error sources are multipath and NLOS

Error characterization approach

- assumption of a zero mean Gaussian distribution
- unrealistic because of multipath, NLOS and limited satellite visibility

PL calculation methods for road vehicles have to take into account actual measurements

- And not only satellite-user geometry and *a priori* distribution of the error

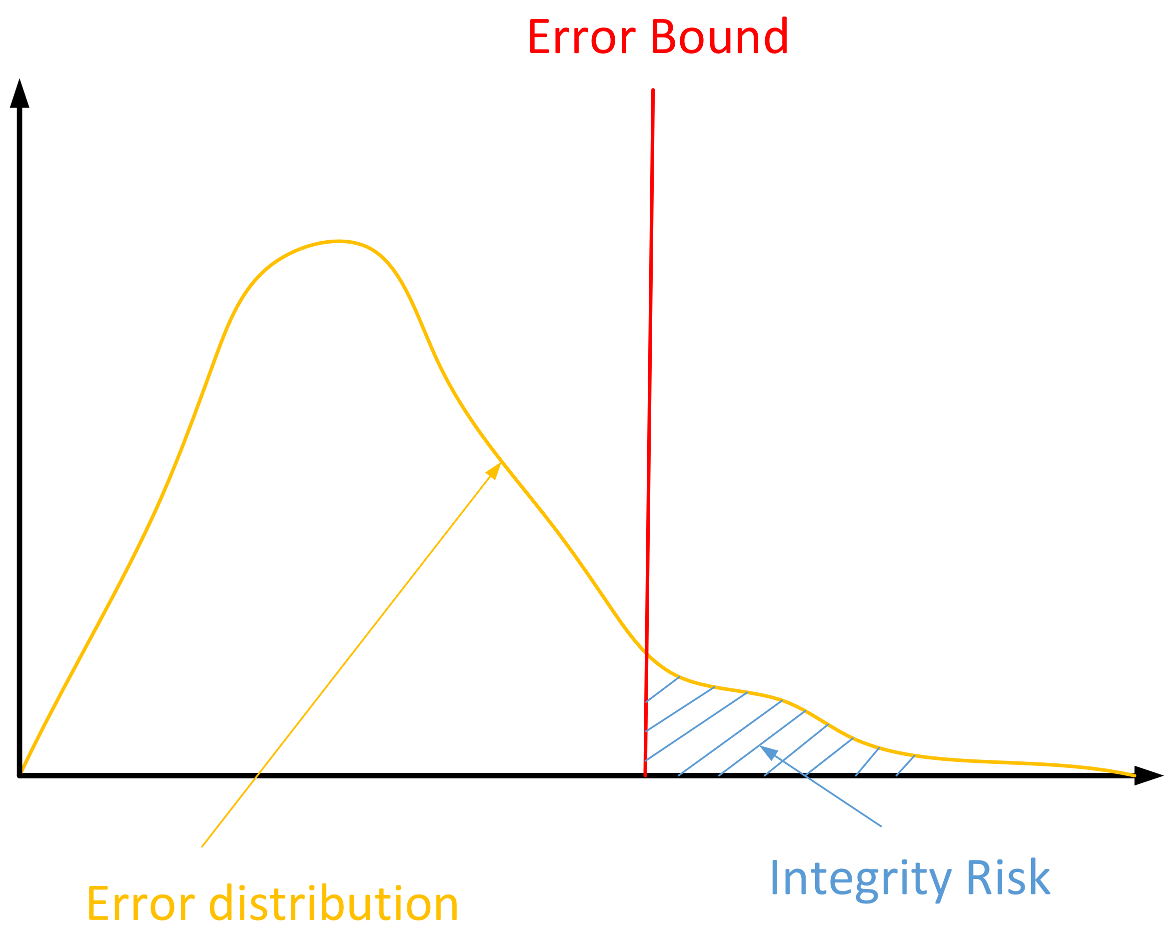
Workshop FRCA-IAV Formal Methods vs. Machine Learning approaches for reliable navigation

This workshop aims to focus on the advantages and limitations of using different kinds of innovative control architectures for autonomous vehicles based on formal approaches or/and based on machine learning

Keywords: reliability guarantees, risk assessment and management, model-based approaches, data-driven approaches

Key issue that remains opened for the localization of autonomous car: How to bound estimation errors with a low probability risk?

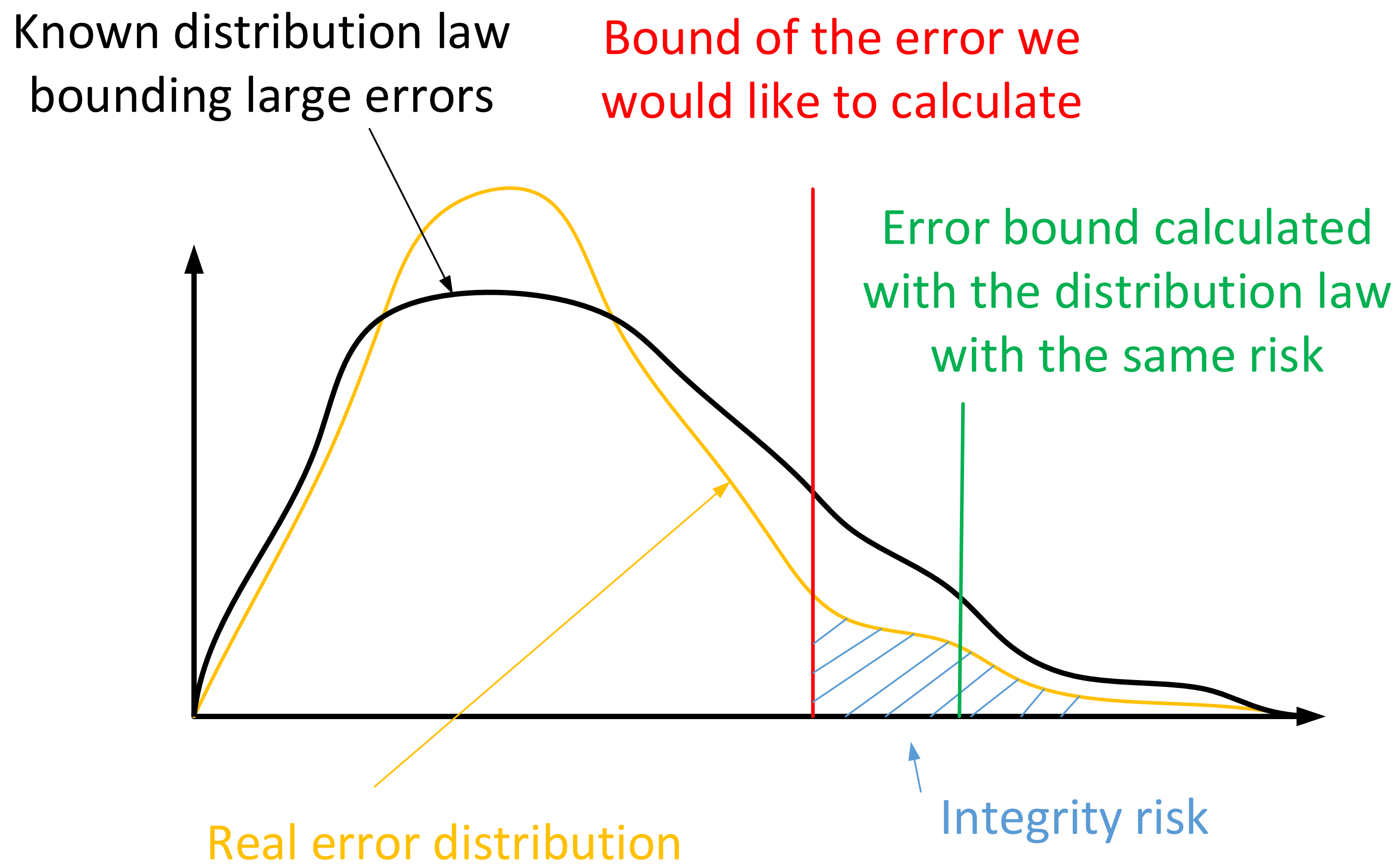
Problem illustration



For a chosen target integrity risk, how to find the error bound?

Proposed approach

We choose a heavy tail distribution with a known and easy to manipulate mathematical expression that bounds the actual error of the localization system, especially for small risks



Localization with multi-lane camera measurements

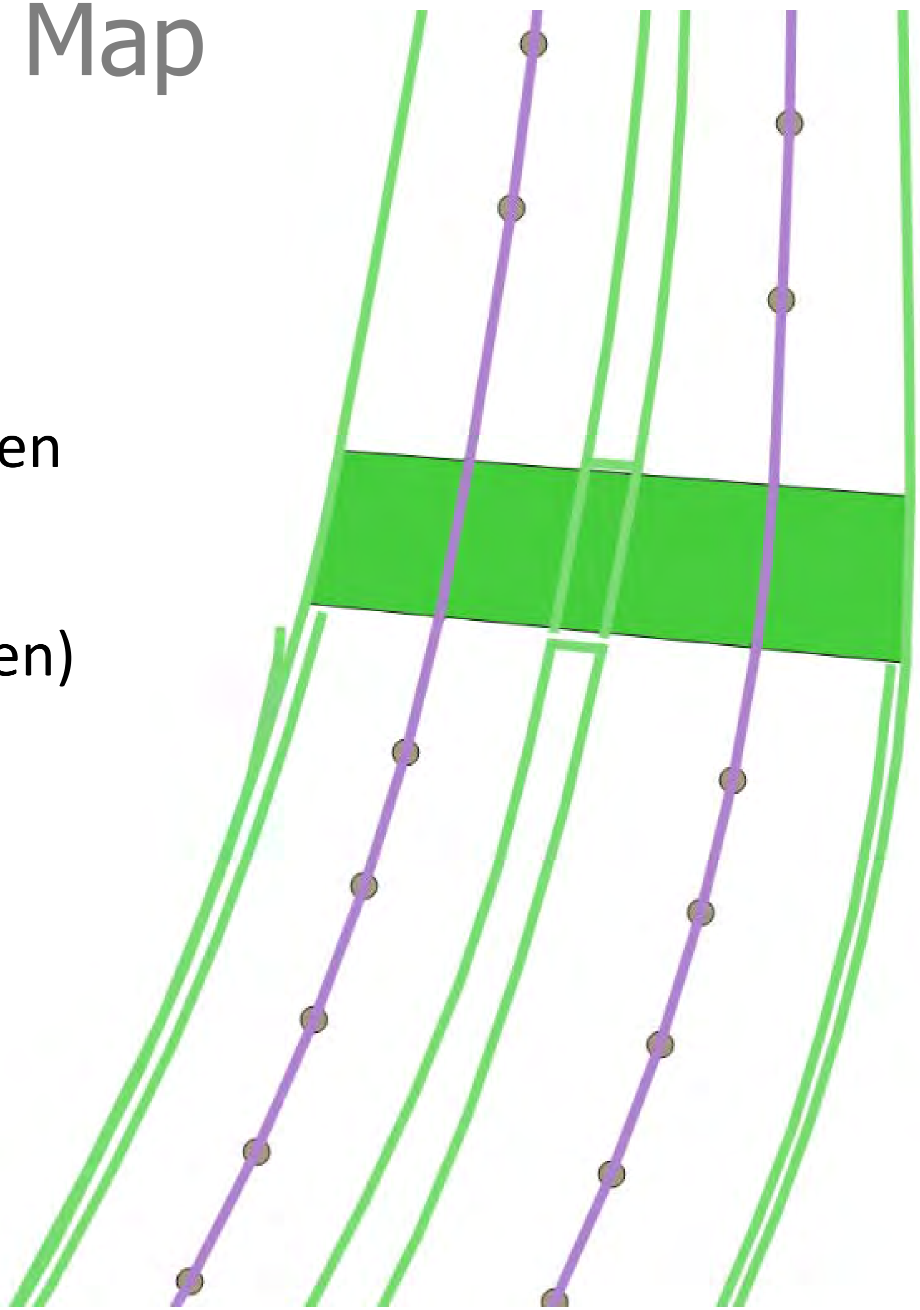
Part 2

HD Map

Lane markings and road edges in green

Centerline in purple

Pedestrian crossing (rectangle in green)

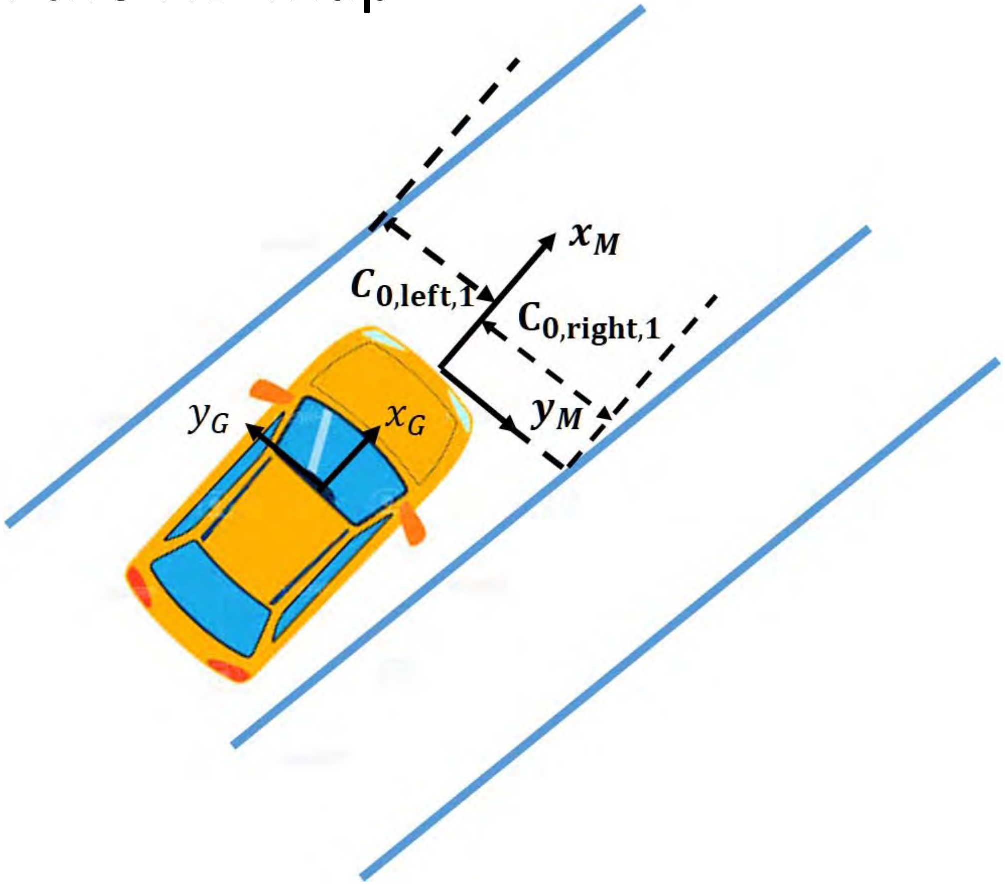


Multi-Lane Camera Measurements

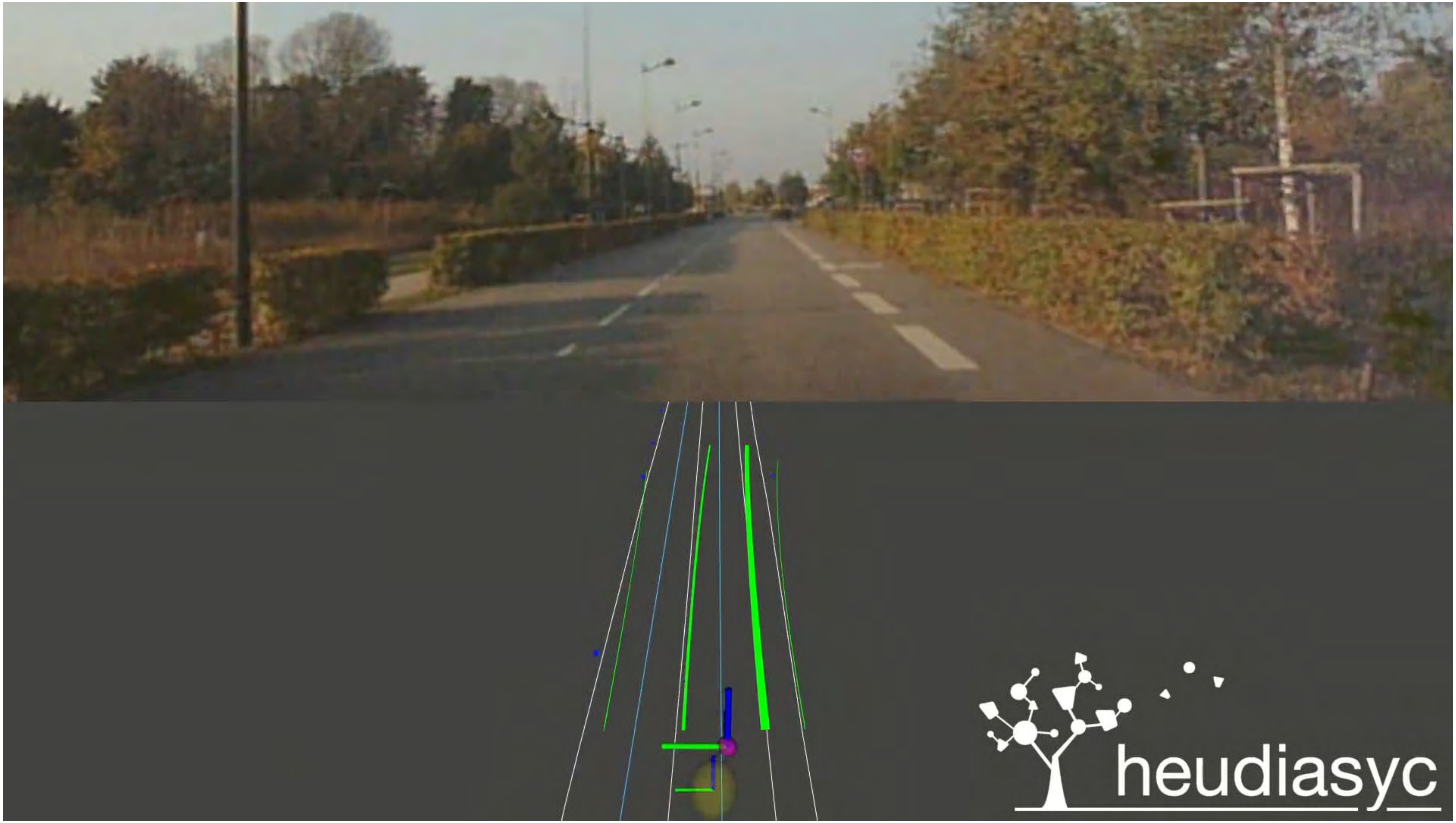
Camera able to detect up to two markings/edges on each side

Up to 4 lateral distance measurements simultaneously

Each one is map-matched with the HD map



Video



Data fusion architecture for high-integrity localization

Part 3

Classical techniques

System Modeling (State Space)

$$X_{k+1} = f(X_k, u_k) + v_k$$

$$Z_k = h(X_k) + w_k$$

X is the state vector
u_k is the input vector (for instance speed or acceleration)
Z is the observation vector (typically exteroceptive sensors measurements)

Data fusion solver: Kalman Filter (KF)

Data fusion with Information Form of the KF

Also called "Inverse-Covariance Form"

Prediction

$$X_{k+1/k} = f(X_{k/k}, u_k)$$

Information and covariance matrices

$$Y_{k+1/k} = {P_{k+1/k}}^{-1}$$

Information vector

$$y_{k+1/k} = Y_{k+1/k} X_{k+1/k}$$

Data fusion with Informational Form of the KF

Update

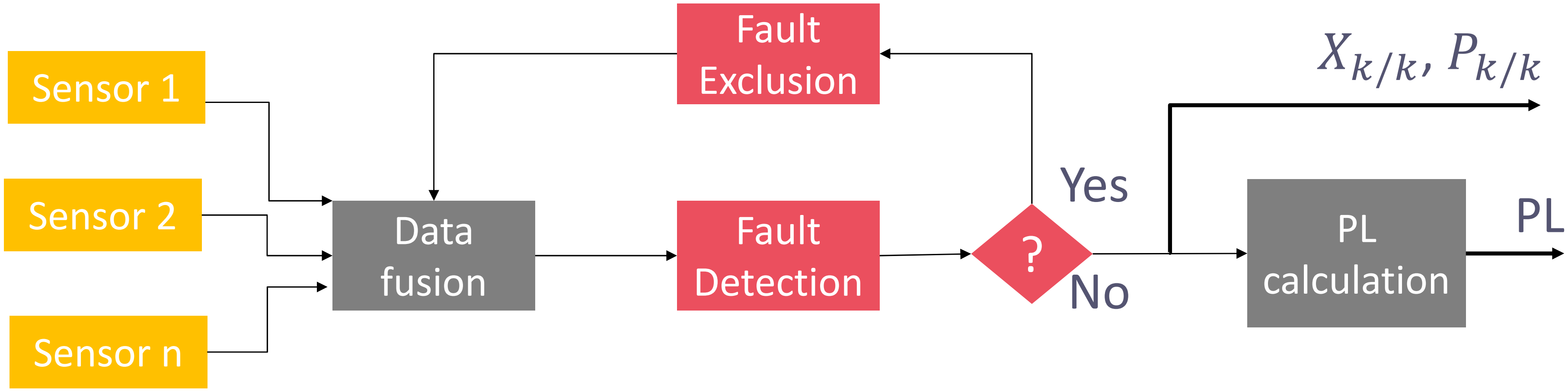
$$I_i(k) = H_{i,k}^T R_{i,k}^{-1} H_{i,k}$$ Jacobian matrix

$$i_i(k) = H_{i,k}^T R_{i,k}^{-1} [Z_{i,k} - (\hat{Z}_{i,k} - H_{i,k} X_{k/k-1})]$$

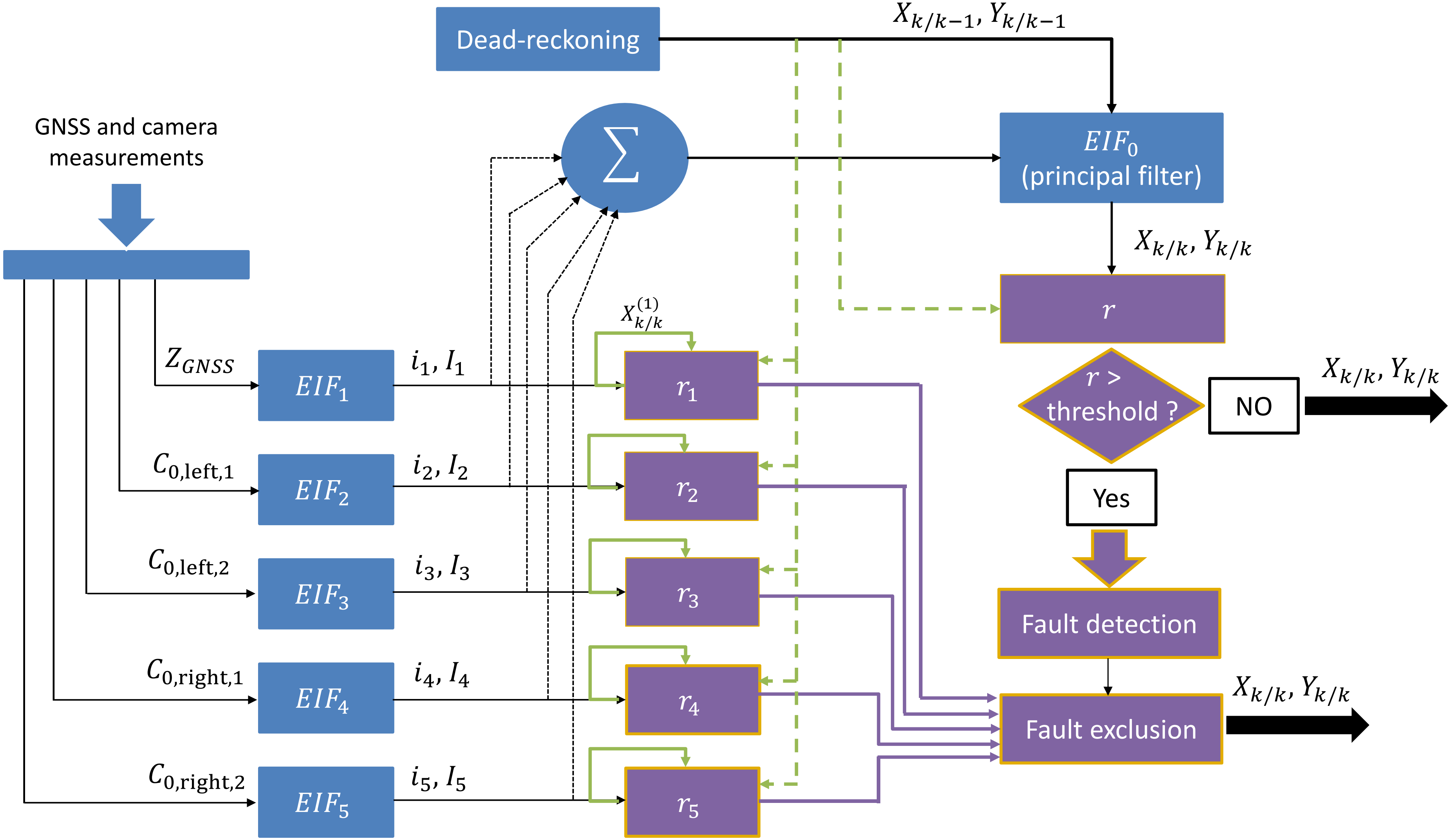
$$Y_{k/k} = Y_{k/k-1} + \sum_{i=1}^{n} I_i(k)$$

$$y_{k/k} = y_{k/k-1} + \sum_{i=1}^{n} i_i(k)$$

Multi-sensor data fusion with FDE and PL computation



Implementation with the Informational Form



Advantage of the Informational Form

The IF is well adapted to

— decentralized multi-sensor data fusion

— multi-sensor data fusion with many sensors to merge

— multiple Fault Detection and Exclusion (FDE) thanks to its update step that is modeled as a simple summation of the information contributions of the different observations
➔ **faulty measurements are quickly and easily suppressed from the update stage**

Bounding estimation error

Protection level computation

Part 4

Problem statement

After having removed the detected faulty measurements, the objective is now to bound the errors

The aim is to avoid an underestimation of the PL that may be due to

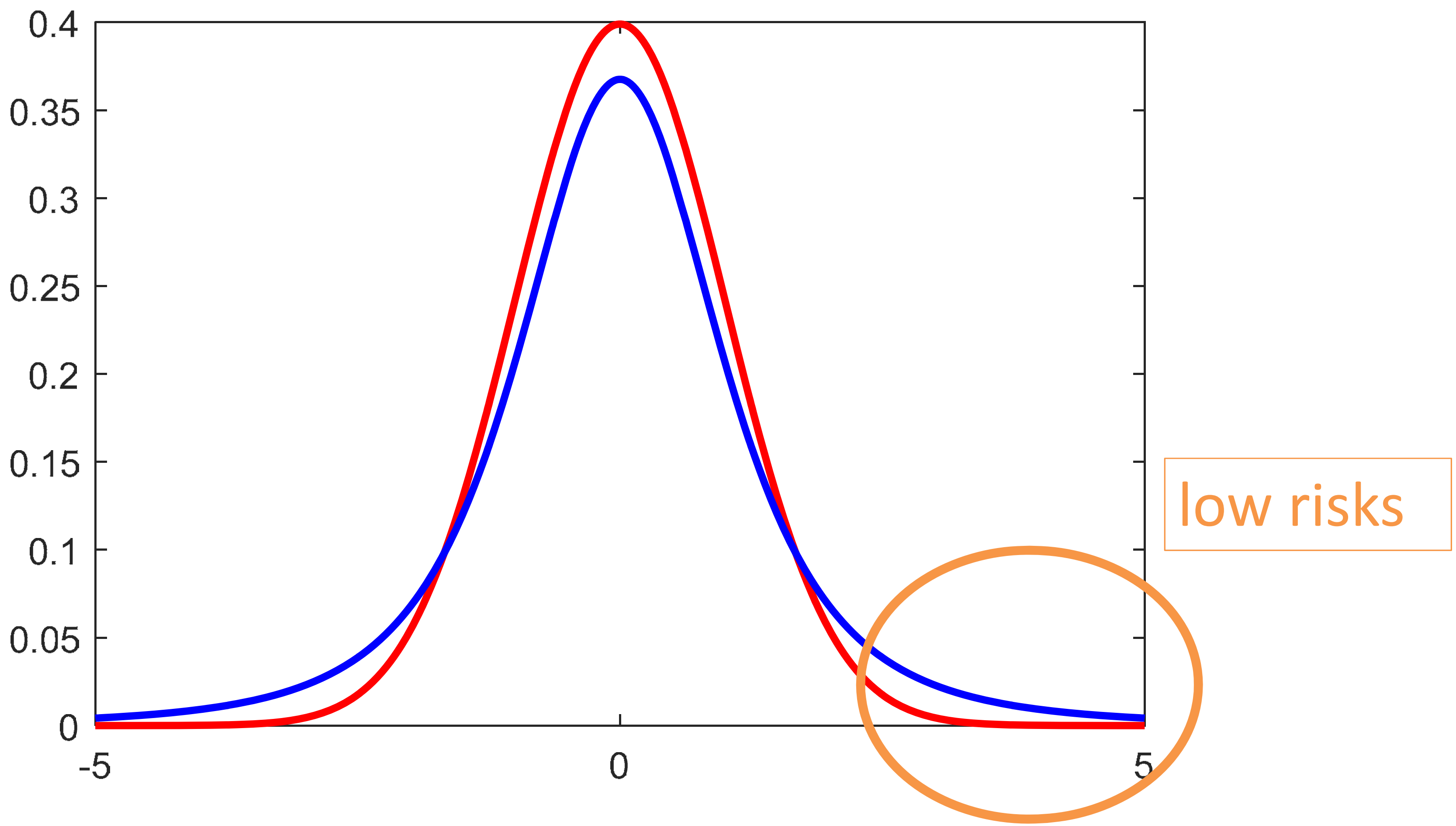
— an undervaluation of the covariance matrix of the filter

— undetected faults

while trying not to be too pessimistic (because this degrades the availability of the system).

Student's t distribution

More conservative for error bounding for low risks than a Gaussian



Student's t distribution

A random variable X that follows a multivariate t distribution with mean vector μ, scale matrix P and dof ν is denoted as:

$$X \sim St(\mu, P, \nu)$$

The covariance of the t distribution is defined only if $\nu > 2$

In this case it can be written as

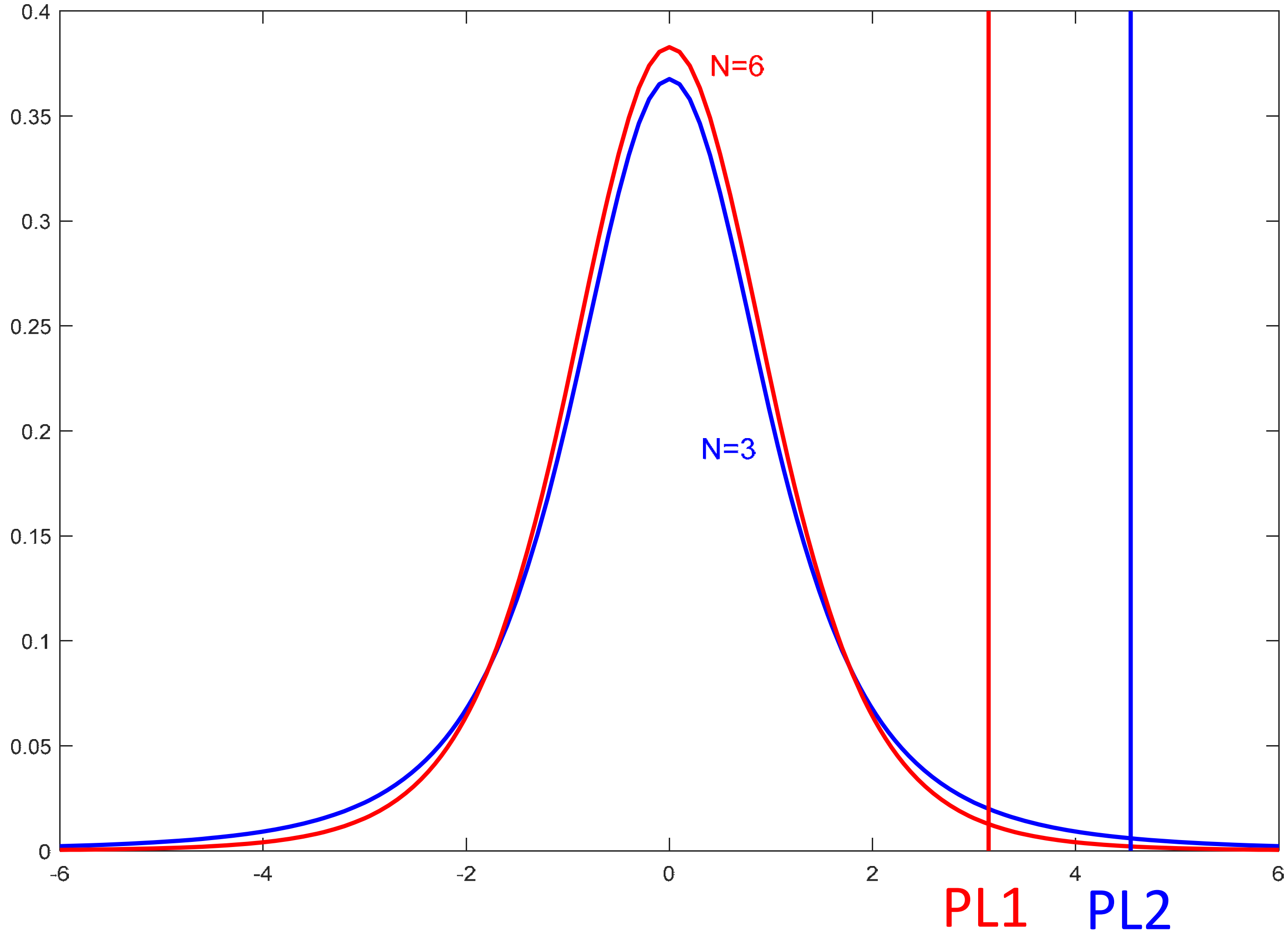
$$\Sigma = \frac{\nu}{\nu - 2} P$$

If $\nu \to \infty$, the t distribution converges to a Gaussian one.

If $\nu \to 2$, the covariance matrix tends to infinity which leads to infinitely large confidence domain.

This guarantees a consistent bounding of the error as long as the dof is well computed

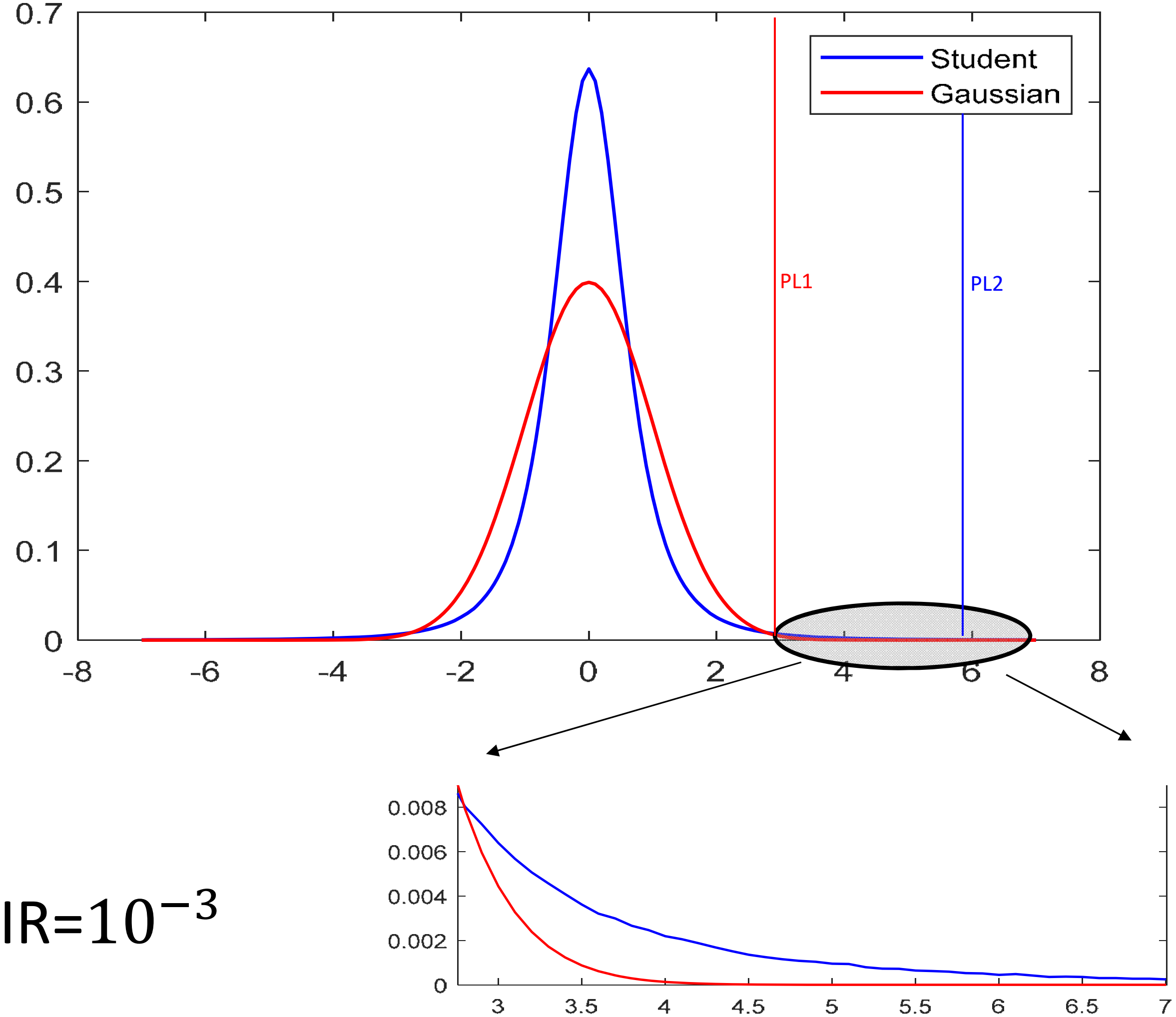
Student’s t degree of freedom



For a TIR $\alpha = 0.01$: PL2>PL1

Student’s t distribution choice

For a given dof, the covariance of the t distribution is chosen to be the covariance of the Gaussian one



TIR=10^{-3}

Protection levels computation

$$PL = K(\alpha, N)\sqrt{N-2}\sqrt{\max(\text{eigenvalue}(P_{k/k}))}$$

α =TIR, N= dof

K can be computed by solving numerically an integral equation

For road vehicles, we are interested by protection levels in the Along-Track (AT) and Cross-Track (CT) directions

$$PL_{AT} = K(\alpha, N).\sqrt{N-2}\sqrt{[\text{eigenvalue}(P_{k/k,proj})]_1}$$

$$PL_{CT} = K(\alpha, N).\sqrt{N-2}\sqrt{[\text{eigenvalue}(P_{k/k,proj})]_2}$$

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Parameters tuning using a data-driven approach

Part 5

Problem statement

Every navigation filter has parameters to tune

— Model parameters (e.g. position of the camera in the body frame)

— Noise variances

— Fault detection thresholds

— Degree of freedom of the Student’s t distribution

— …

The idea is

— to calibrate all parameters that can be calibrated

— to carry out real tests under the vehicle's navigation conditions with a ground truth to tune the filter and choose the dof

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Choice of the degree of freedom

Example of experimental results with DR/GNSS only

N	Empirical Integrity Risk (IR)
3	0
5	0
6	5.65×10^{-4}
8	1.1×10^{-3}
10	2.3×10^{-3}
100	1.7×10^{-2}

$$TIR = 10^{-3}$$

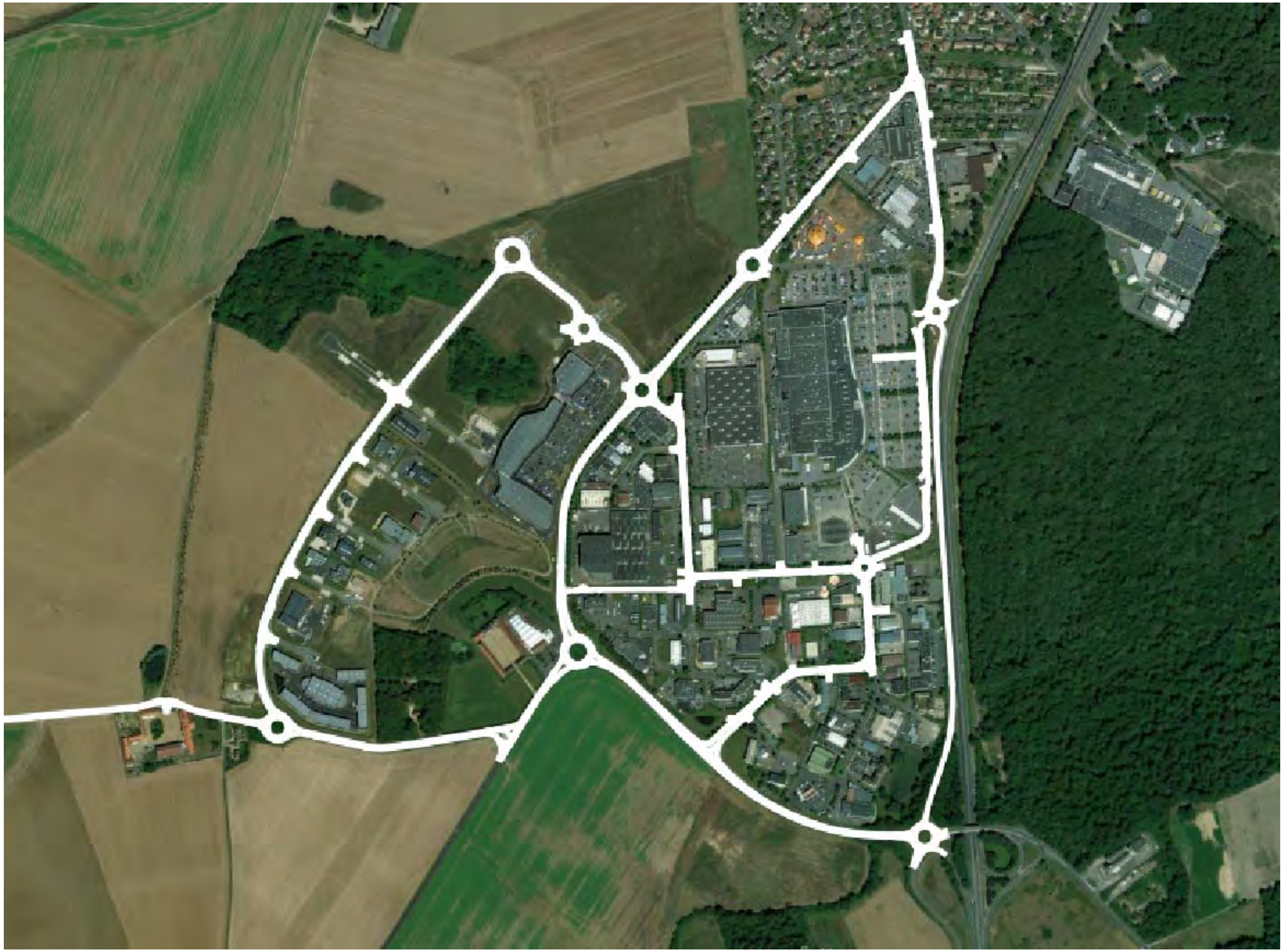
Experimental results

Part 6

Experimental set-up

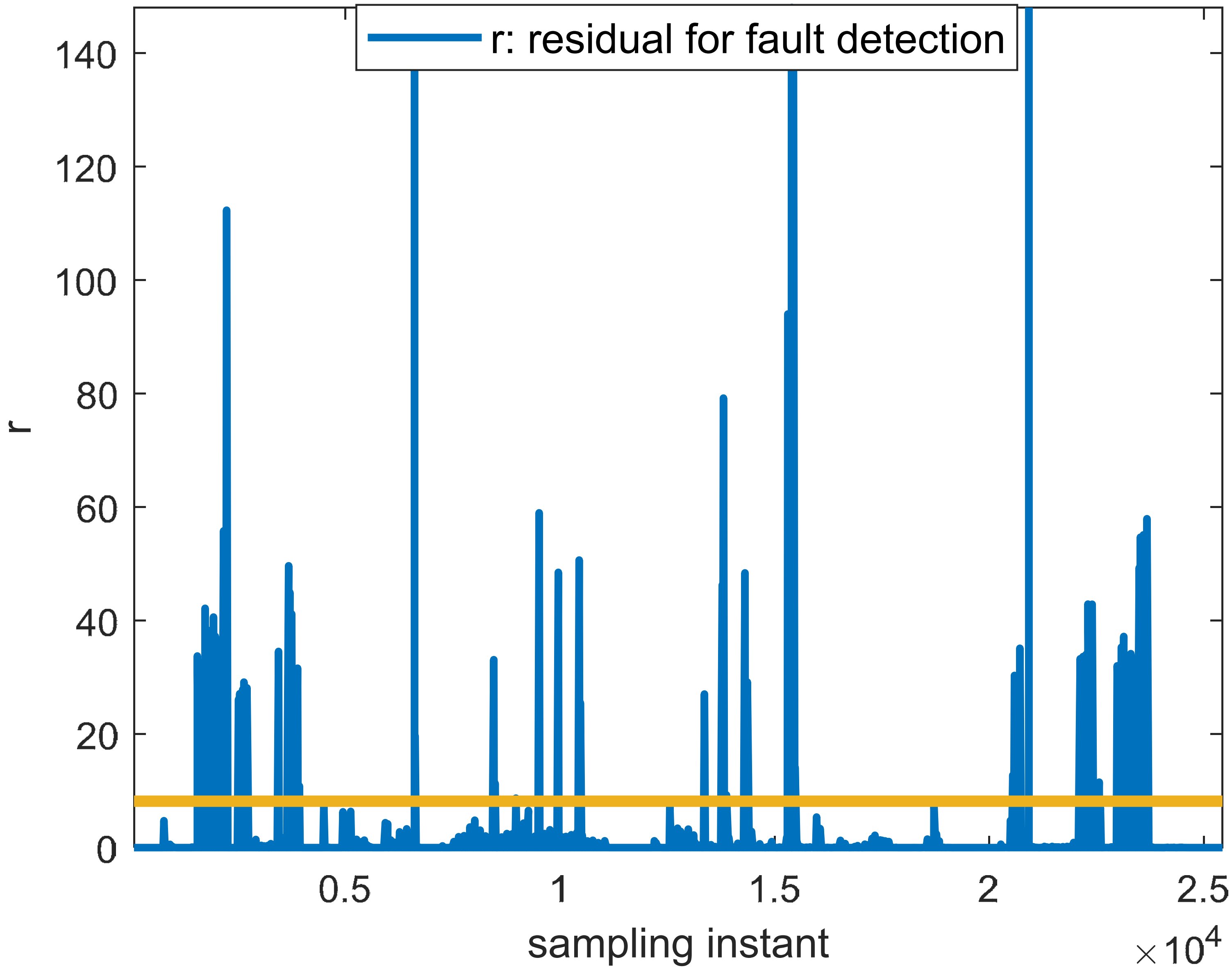
- Ublox 8T (single frequency multi-constellation GPS/GLONASS)
- NovAtel SPAN-CPT with RTK corrections (ground truth)
- Mobileye camera for lane marking detections

Experimental environment

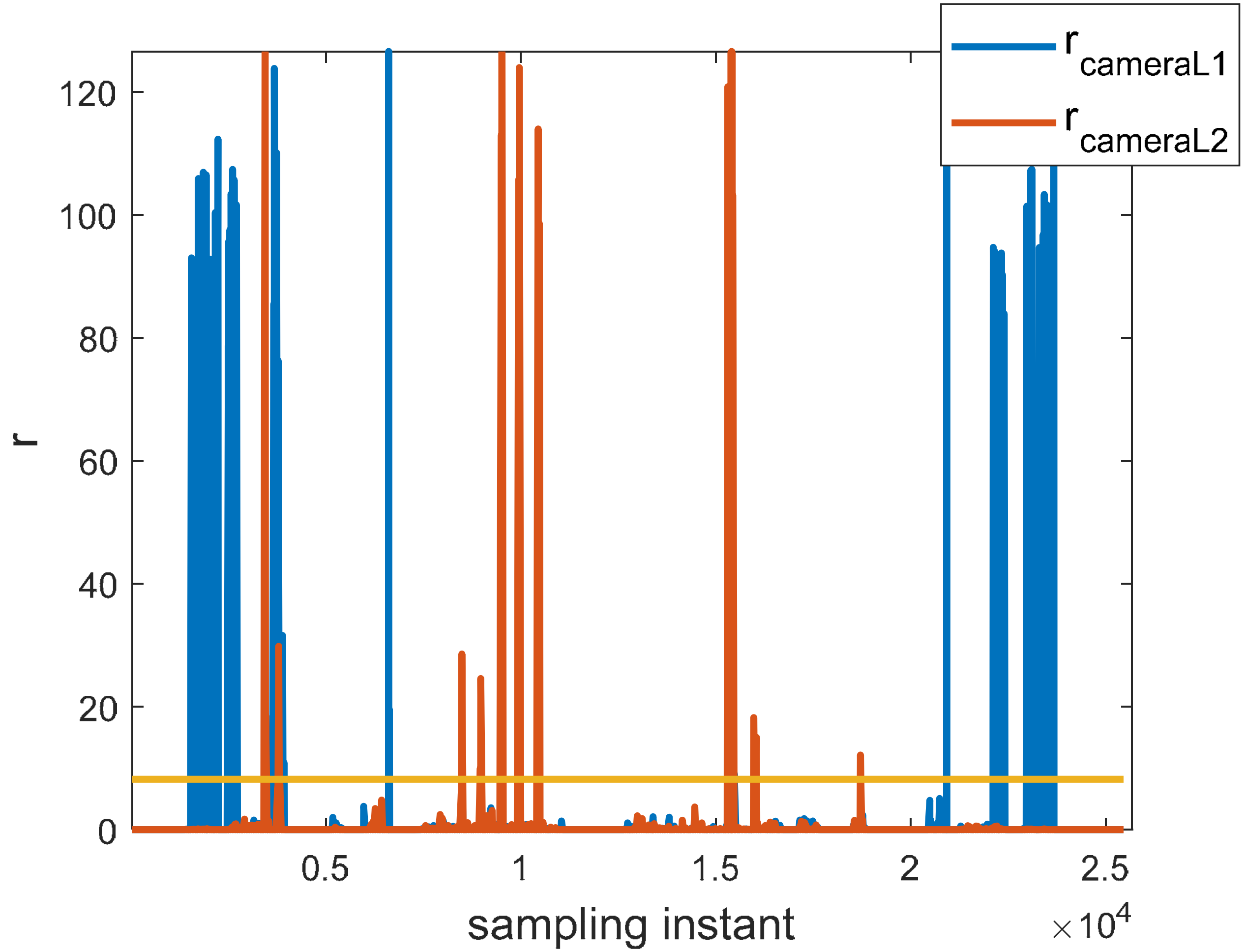


Rambouillet, France

Residual for fault detection



Camera residuals



Residuals associated with the camera left (used for fault exclusion).

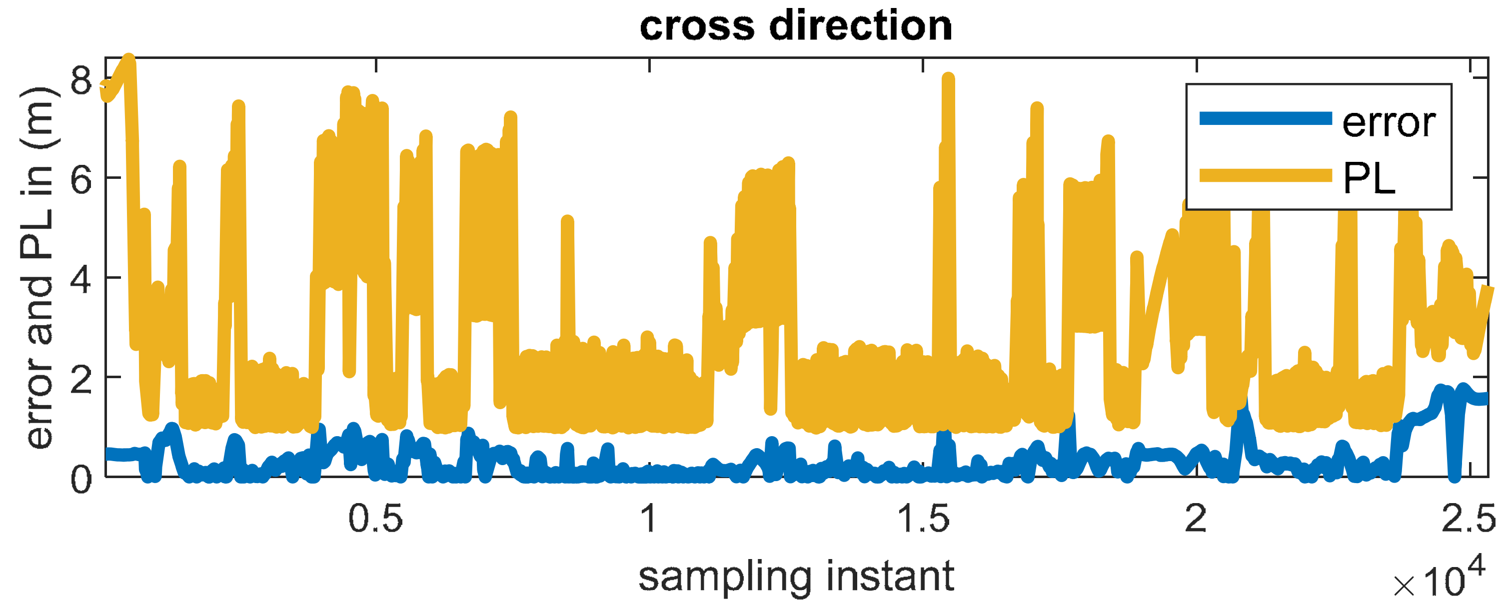
Increased accuracy with FDE

Max Error (m)	CT	AT
Before FDE	4.34	3.54
After FDE	1.76	1.80

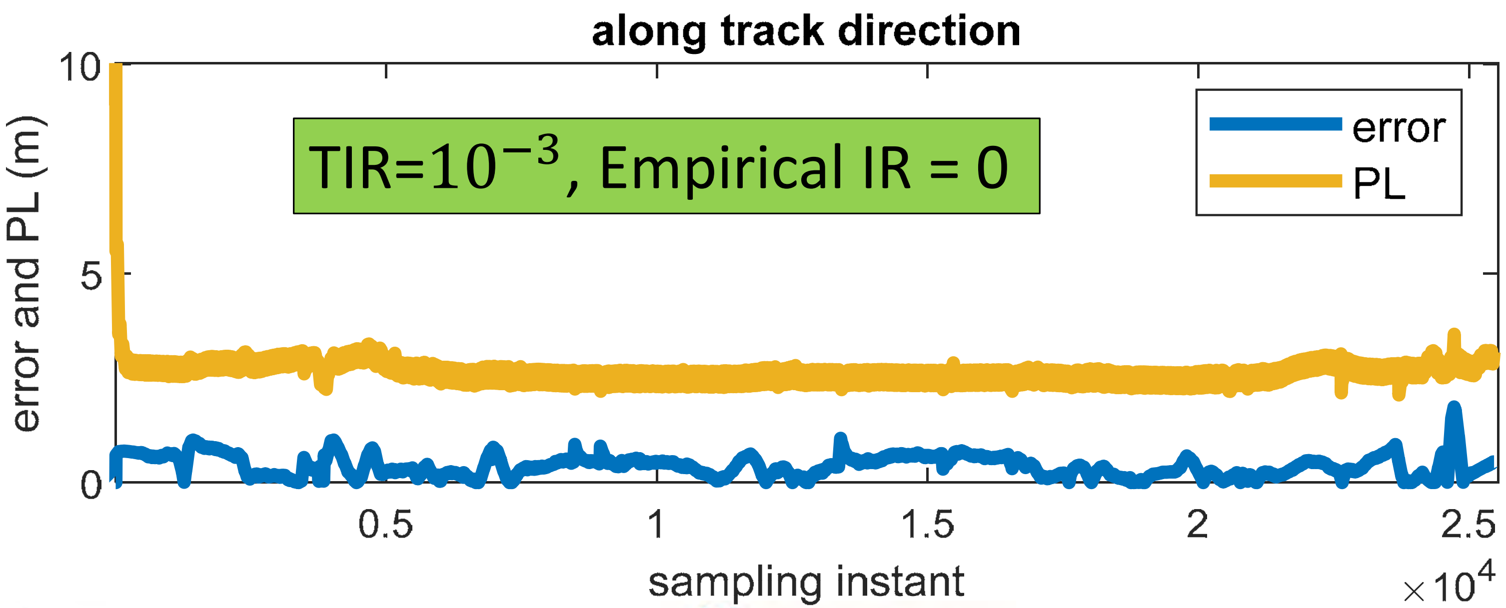
Statistical values of the errors

Errors and PLs in the AT and CT directions

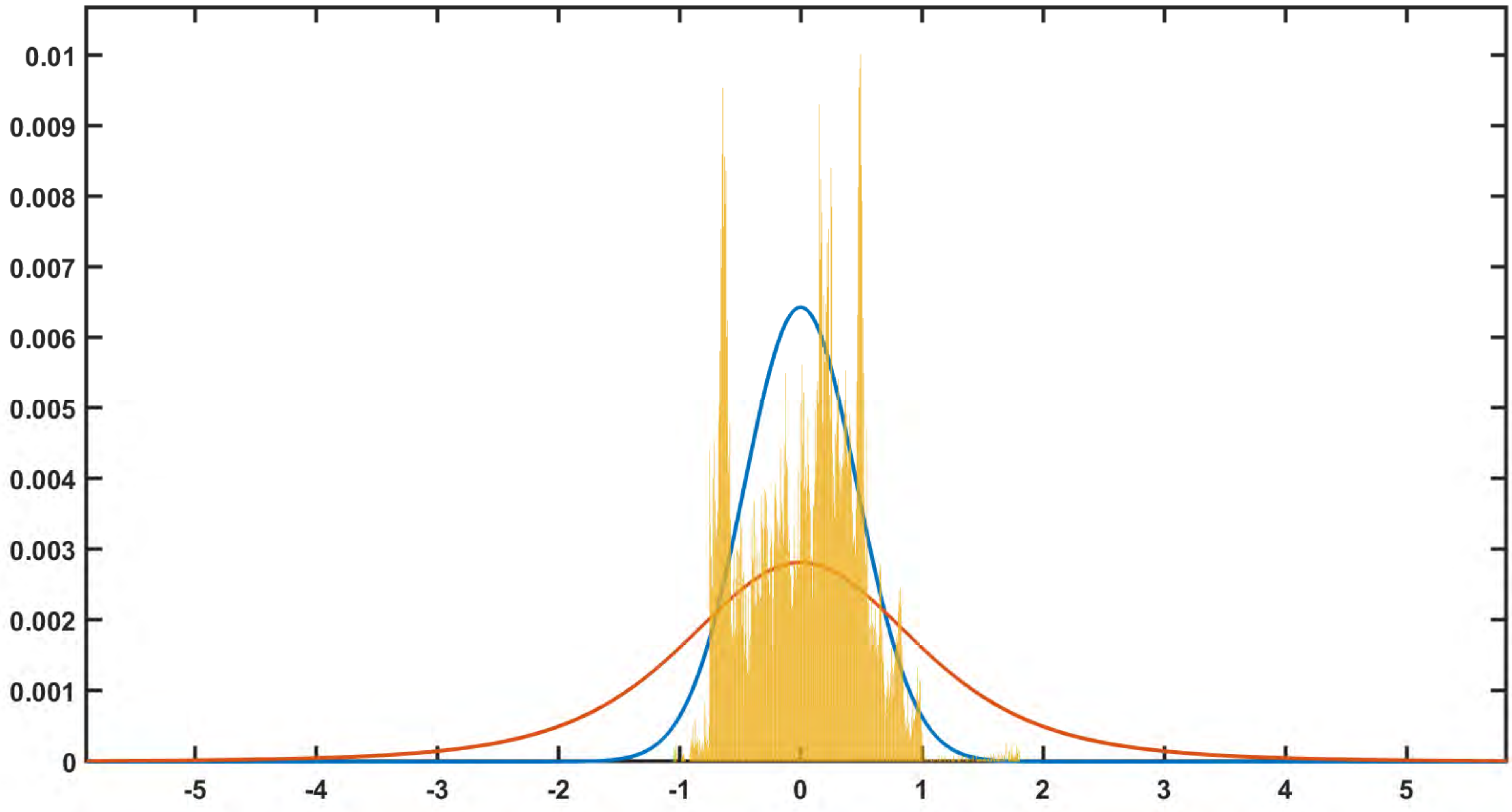
$PL_{CT,\,min}$=1m



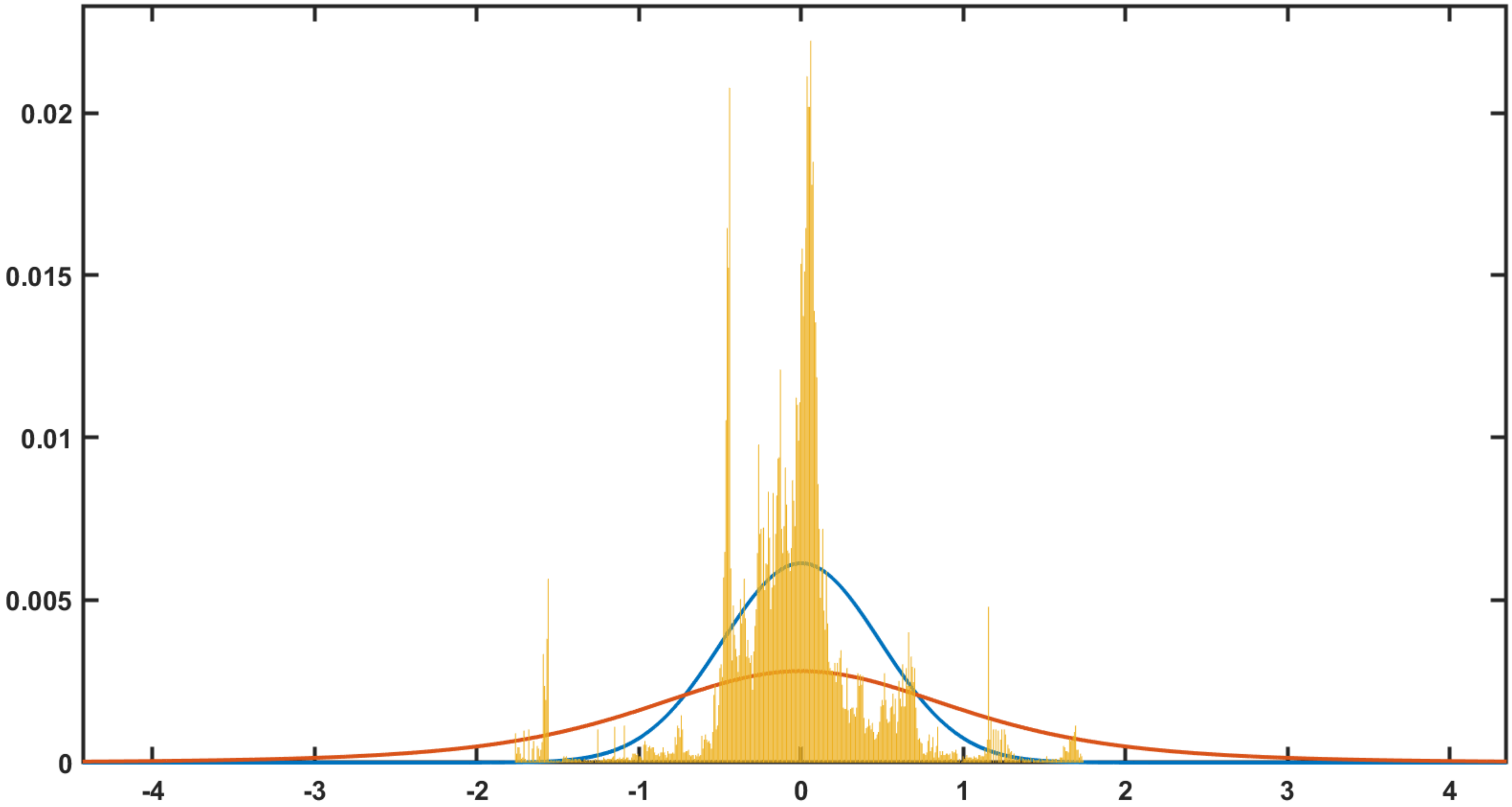
$PL_{AT,\,min}$=2m



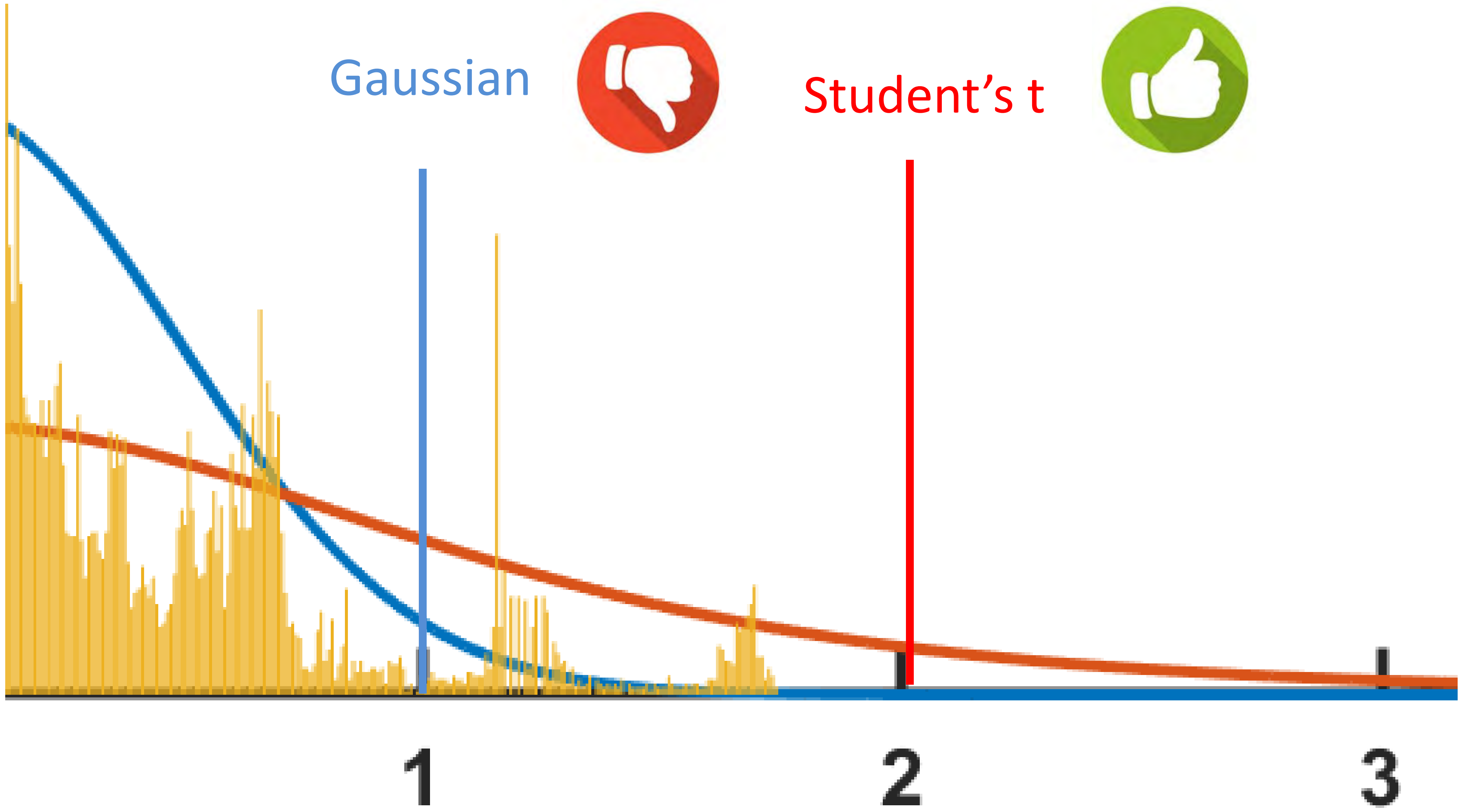
Error distribution Along-Track



Error distribution Cross-Track



Error distribution Cross-Track



Conclusion

Method for PL calculation adapted to road vehicles

Use of an information filter that rejects the main faulty measurements

— The FDE step improves significantly the localization accuracy

Error bound with a heavy tailed multivariate Student's t-distribution

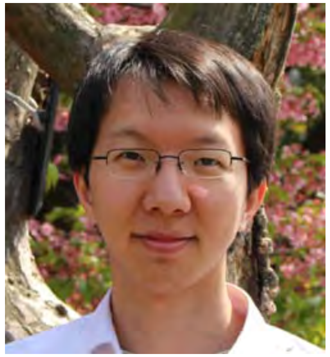
— The computed PL are consistent

We tune the method in a learning stage with a ground truth

The proposed method has to be tested in different land navigation environments.

Thank you for your attention!

Associated publications



1. *Bounding Localization Errors With Student Distribution For Road Vehicles*. J. Al Hage, Ph. Xu and Ph. Bonnifait, ITSNT 2018, Toulouse
2. *High Integrity Localization with Multi-Lane Camera Measurements*. J. Al Hage, Ph. Xu and Ph. Bonnifait, 30th IEEE Intelligent Vehicles Symposium 2019
   Poster 2: Mapping and Localization, Monday 16:00-17:30, Room 9
3. *Student's t Information Filter with Adaptive Degree of Freedom for Multi-Sensor Fusion*, J. Al Hage, Ph. Xu and Ph. Bonnifait, International Conference on Information Fusion, Ottawa, Canada, July 2-5, 2019