

## **High Integrity Localization of Intelligent Vehicles** with Student's t filtering and Fault exclusion

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# Localisation integrity

### Information has to be

- Accurate enough for the task to be performed
- Available at a sufficiently high rate
- Non-misleading and trustworthy

Integrity involves combining and merging data from complementary, diversified and redundant sources



The error is correctly bounded. OK! The bound is in the limit (AL)  $\rightarrow$  use



### Nominal case e<PL<AL



# Typical localization system for Intelligent Vehicles



Research questions addressed in this paper:

- 1. How to achieve the optimal accuracy (given a set of information sources)?
- 2. How to achieve high integrity without being too pessimistic?
- 3. How to achieve simultaneously high integrity and high accuracy?





Pose & Uncertainty

<sup>F</sup> information sources)? ssimistic? igh accuracy?



## Sensors used in this study





### HD map with georeferenced lane markings







### **GPS** and Galileo pseudoranges







## Classical multi-sensor data fusion



### Faults are due to:

- GNSS multipath and NLOS
- Poor camera measurements
- Data association errors with the HD map \_\_\_\_
- Errors in georeferenced features



### Common approach:

- White Gaussian errors
- Kalman Filtering



 $X_{k/k}, P_{k/k}$ 



### There are many methods

- Parameter =
  - Target Integrity Risk (TIR)



## Student's t distribution for integrity

 $X \sim St(\mu, P, \nu)$ : follows a Student's t distribution with mean  $\mu$ , scale matrix P and degree of freedom (dof)  $\nu$ .

The covariance matrix is defined as  $(\nu > 2)$ :

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

If  $\nu \to \infty$ : The t distribution converges to a Gaussian distribution

Well adapted to model the measurements with some outliers and to compute PL with small TIR





## **Dead-reckoning Modeling**

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

 $u_k = [\Delta_k, \Omega_k]$  input vector contains the elementary displacement and rotation obtained from the wheel-speed sensors and the gyro

 $v_k \sim St(0, Q_k, \gamma_k)$ 

If the dof  $\gamma$  is high, this a Gaussian distribution







# GNSS observations modeling

### Measurements:

 $\rho_k$ = pseudoranges =  $R_i + cdt$ 

Euclidean distance between the receiver and the satellite

Receiver clock offset

Observation model:  $\rho_k = h_G(X_k) + \omega_k$   $\omega_k \sim St(0, R_k, \delta_k)$ 





# Camera observations modeling

### Measurements:

 $C_{0,k}$  = lateral offset between  $R_M$  and L(up to 4 simultaneous meas.)

$$C_{0,k} = h_{C}(X_{k}) + \omega_{k}$$

$$\omega_k \sim St(0, R_k, \delta_k)$$

Improve the integrity in presence of poor perception data



![](_page_8_Picture_7.jpeg)

![](_page_8_Picture_10.jpeg)

# End-to-End Student's t Filter (StF)

Student's t distributions are used to :

- Estimate the state
- To model any error or uncertainty

If the DoF is not controlled, it tends to infinity and the StF becomes a KF

- Often, the DoF is fixed to a chosen value —
- Here, the DoF is adaptive in a given interval and it depends on a residual computed by a Fault Detection and Exclusion (FDE) stage
- Based on the Kullback-Leibler divergence in the state space

Jacobian matrices are used for linearization (Extended Student's t Filter) An Information StF has been implemented (for efficient FDE)

![](_page_9_Picture_9.jpeg)

![](_page_9_Picture_14.jpeg)

![](_page_10_Figure_0.jpeg)

$$v_{k-1}, v_{k-1}'$$

## **Experimental Results**

![](_page_11_Picture_1.jpeg)

![](_page_11_Picture_2.jpeg)

### Compiègne, trajectory of 6km

![](_page_11_Picture_4.jpeg)

![](_page_11_Figure_6.jpeg)

![](_page_11_Picture_7.jpeg)

![](_page_12_Figure_0.jpeg)

![](_page_12_Picture_3.jpeg)

# **Experimental Results**

	Without FDE		With FDE	
	StF	KF	StF	K
Mean absolute error[m]	0.76	0.74	0.71	0.7
$IR_{AT} \times 10^{-3}$	1.1	3.9	1.5	1.
$IR_{CT} \times 10^{-3}$	6.8	22	0.9	1

### **Conclusions**:

- StF is as accurate as KF (with or without FDE) -
- StF is much more consistent is terms of integrity (with or without FDE) —

![](_page_13_Picture_5.jpeg)

![](_page_13_Figure_8.jpeg)

IR = P(e > PL)

AT: Along Track **CT: Cross Track**  $TIR = 10^{-3}$ 

![](_page_13_Picture_12.jpeg)

## Green: KF Red: StF with adaptive DoF Blue: StF with fixed DoF = 3

DoF dynamic adaptation is therefore important to reduce pessimism

## **Protection Levels**

![](_page_14_Figure_3.jpeg)

**CT direction** 

![](_page_14_Figure_5.jpeg)

![](_page_14_Picture_6.jpeg)

![](_page_14_Figure_7.jpeg)

![](_page_14_Picture_9.jpeg)

## Conclusion

## Student't filtering for:

- Raw data fusion and PL computation
- Fault detection and exclusion based on KLD
- DOF adaptation according to the quality of the observations

### **Experimental evaluation:**

- Gives the same level of accuracy compared to Kalman filtering
- Improves external integrity while maintaining non pessimistic uncertainty values
- StF parameter setting is more complex than KF
- Future work: Use data driven techniques to simplify this issue

![](_page_15_Picture_10.jpeg)

![](_page_15_Picture_15.jpeg)

![](_page_16_Picture_0.jpeg)

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![](_page_16_Picture_5.jpeg)

![](_page_16_Picture_8.jpeg)