

Confidence indicators for ADAS functions

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Demos

1. Pedestrian detection
 - in car, real time
2. Map-matching integrity monitoring
 - in car, real time
3. Automatic detecting risk rollover situations
 - On table, real data replay

Outline of this presentation

- Motivation and scientific Interests
- The demos at a glance
 - Our experimental car: Carmen
 - What you can see on board the vehicles
- Key technologies demonstrated
 - Lidar detection, pedestrian recognition and tracking
 - Calibration of the extrinsic transformation between the lidar frame and a camera frame
 - Map-Matching integrity monitoring
 - Load Transfer Ratio

Scientific interests

- ADAS - Advanced Driver Assistance Systems
 - Techniques for Man-Machine cooperation assessment
- Perception
 - State Observation of dynamic systems
 - Multi-sensor fusion in a dynamic context
 - Ego-localization using on-board sensors and GNSS associated with GIS information
 - Dynamic behaviour (tire/road contact characterisation)

Intelligent Vehicles

- An IV is a vehicle able to perform
 - driving assistance tasks
 - autonomous navigation
 - in the presence of uncertainty and variability in its environment
- Artificial Perception and Contextual Information analysis are key issues
- Managing uncertainty in fusion processes is crucial for reliable perception

Confidence indicators

- IV embedded systems need to
 - Fuse redundant information
 - Estimate unobserved parameters
 - Monitor themselves
 - Fault detection and isolation
 - Diagnosis
 - Integrity tests
- Confidence indicators are useful for
 - The fusion processes (Input)
 - The use of the provided information (since often no high enough reliability can be reached) (Output)

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CARMEN

GPS receiver
(PolarX Septentrio)

Front scene camera
(Sony camera)



CAN bus
• Wheel Speed Sensors
• Yaw rate gyro

4-layer Lidar
(IBEO Alaska XT)

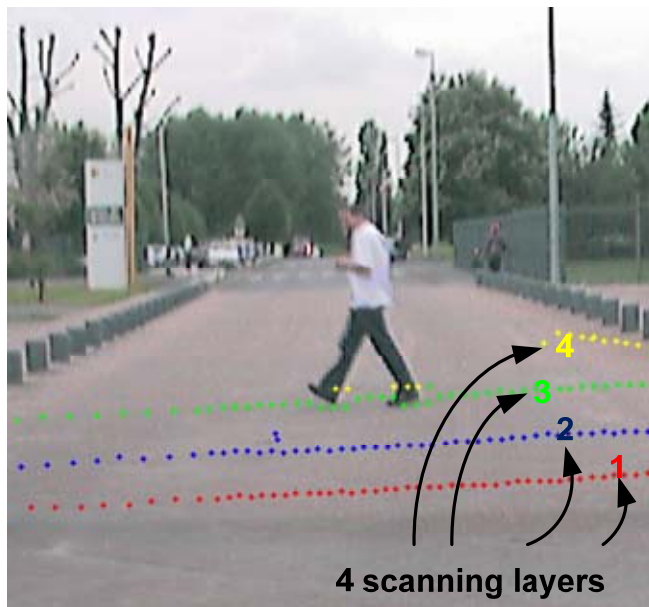
Demo 1: Pedestrian detection/recognition using lidar-only

What you can see during the demo

Projection on the image of the 4 scanning layers of a Lidar

If the recognition confidence of the lidar-only-track $> threshold$

- Projection of a corresponding rectangle (2 meters high)
- Plot of “lateral bars” to represent the confidences



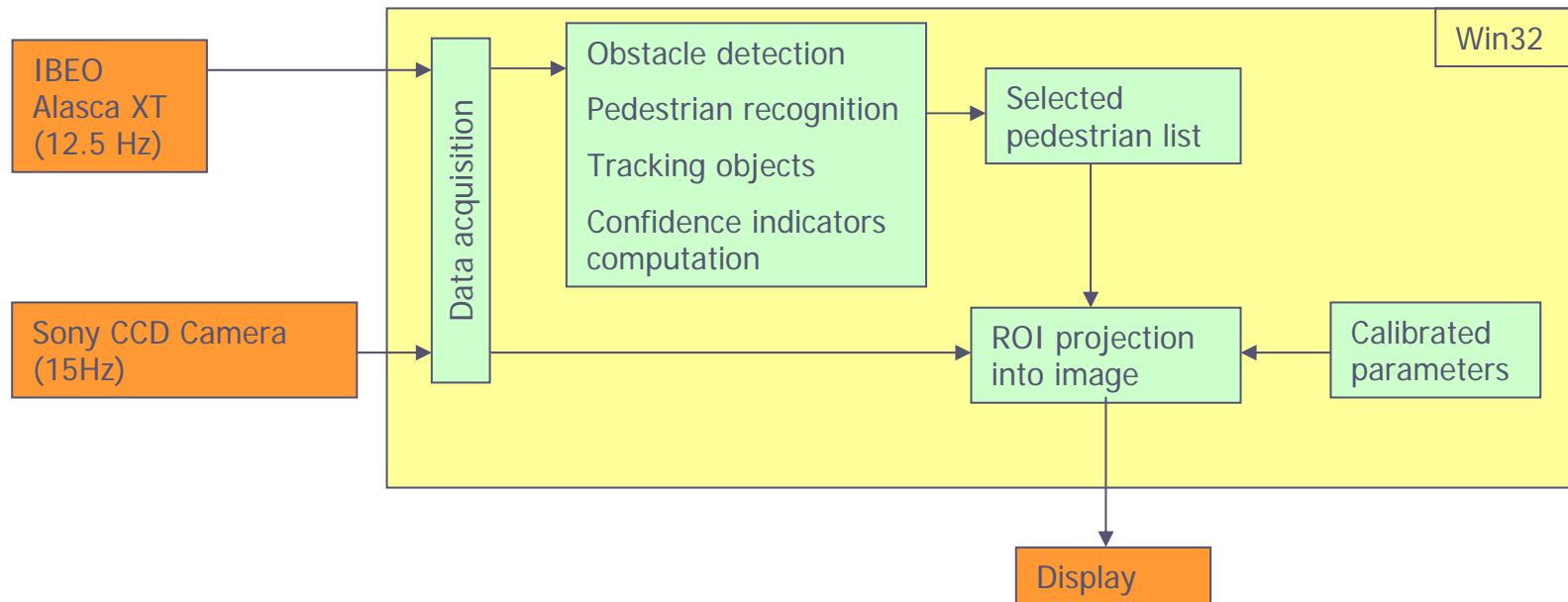
Lidar-only pedestrian detection/recognition on-board display (no gate on the confidence treshold)



Lidar-only pedestrian detection/recognition on-board display (confidence threshold=95%)



Architecture



Demo 2 : characterization of the confidence in the map matching process of a localization system

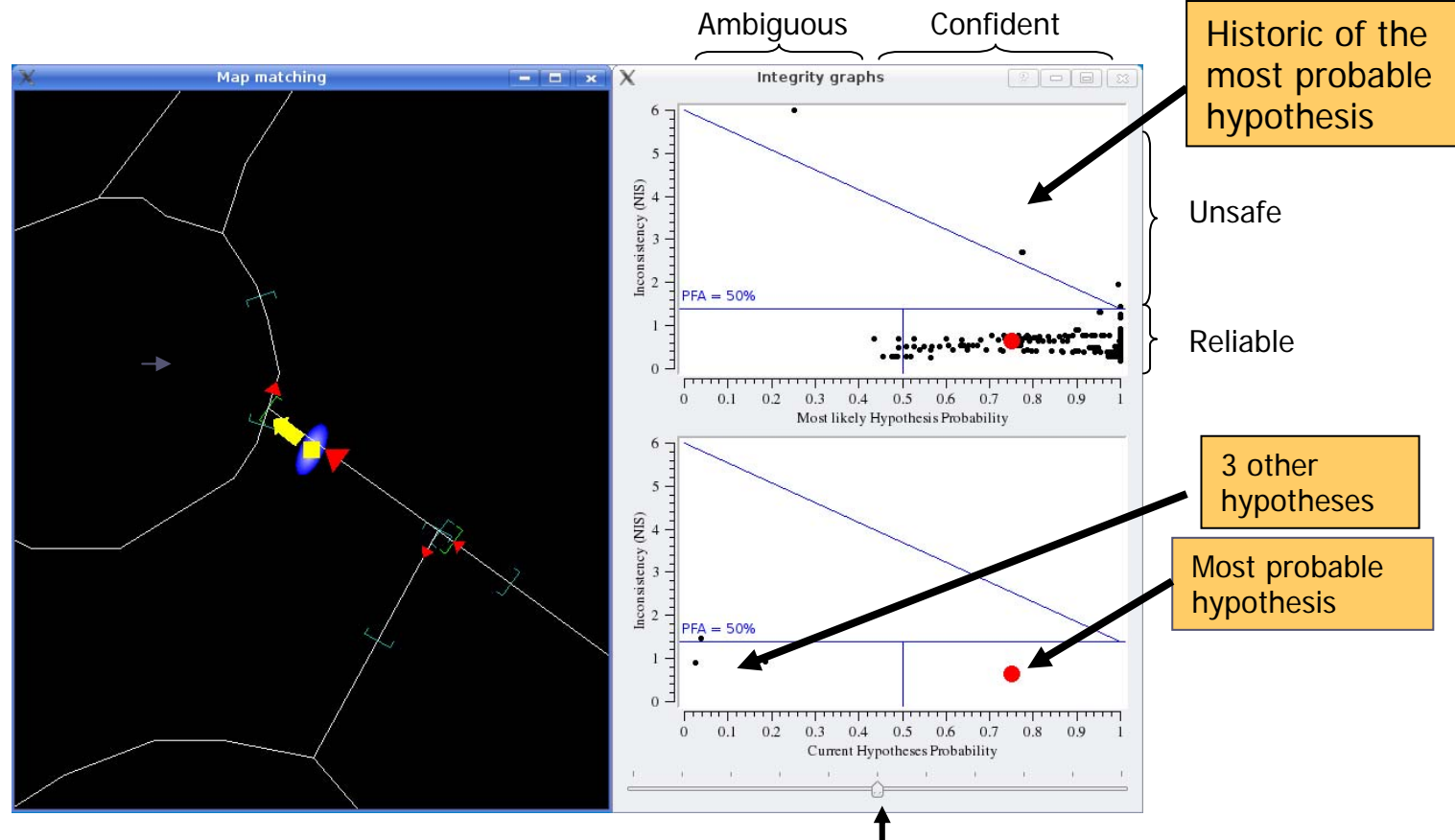
What you can see during the demo

Map display

-The yellow square and the arrow are the position and the heading of the car

-The 4 red triangles correspond to the hypotheses

-The brackets represent the confidence interval of the track

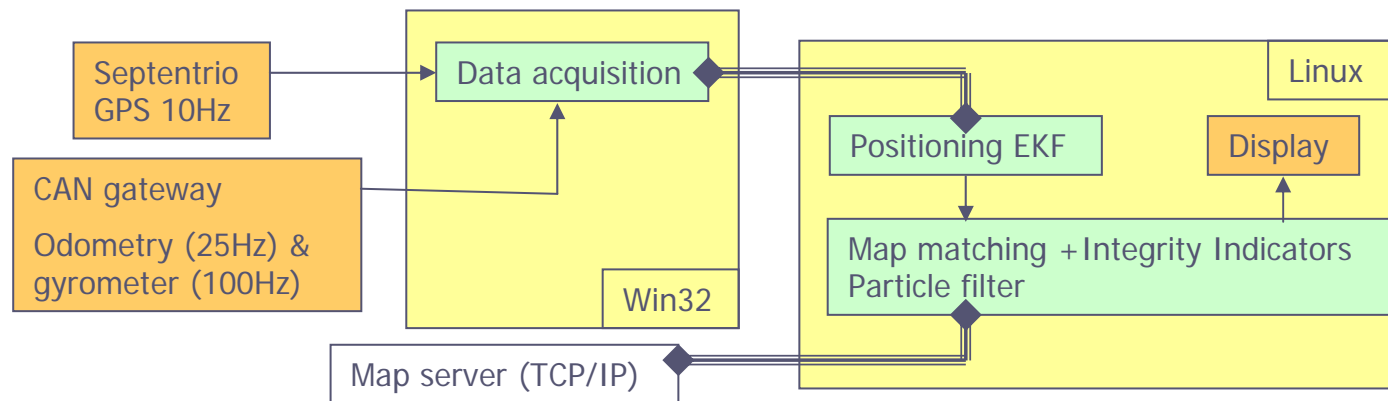


Safety level of the output : the lower the PFA (Probability of False Alarm), the more reliable the hypothesis

MM demo overview



Architecture



Two Map servers

- NavTeQ
- TeleAtlas

Outline of this presentation

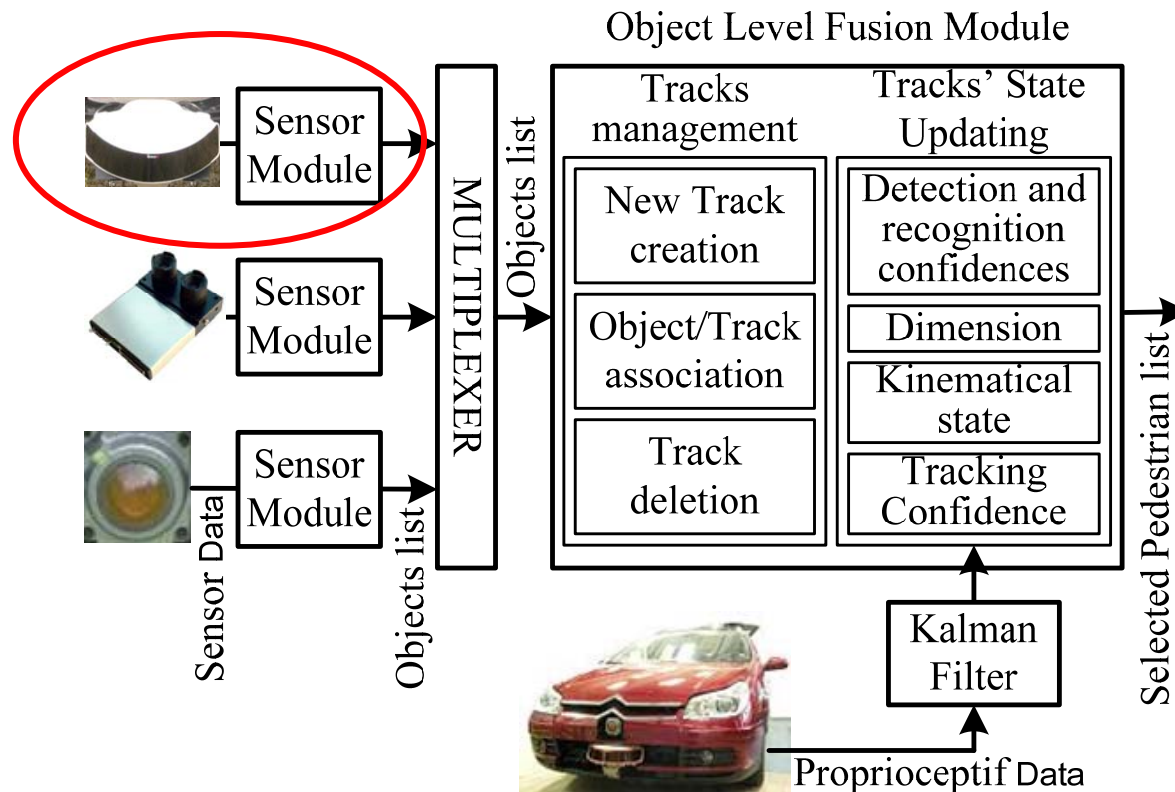
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Perception objectives

- Obstacles detection and tracking in driving situation
- Pedestrians recognition
- Confidence indicators management
 - Detection
 - Recognition
 - Tracking

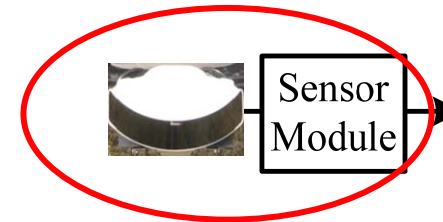
Object level fusion module

Sensor used in the demo



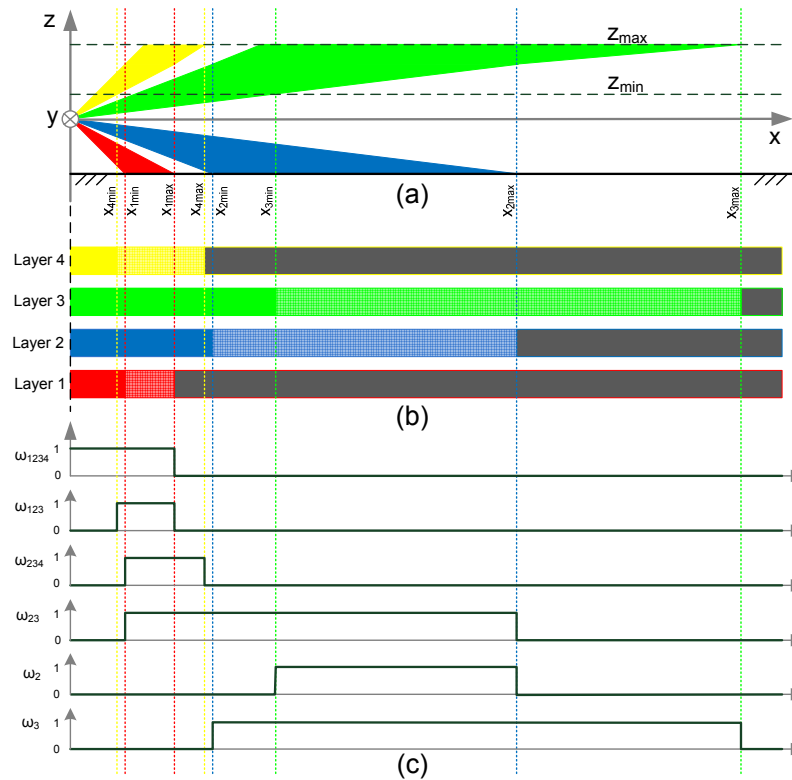
Object detection

- Four plane laser sensor
- Detecting ground
- Clustering



For each detected object

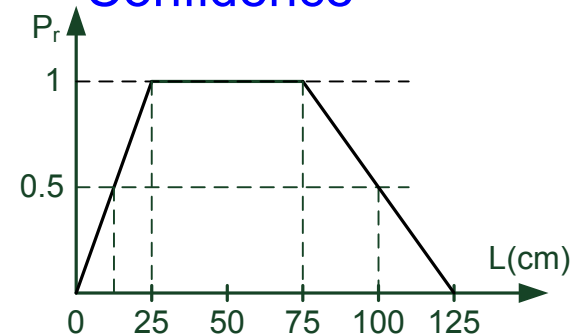
Object Detection Confidence



$$P_d = (\omega_{1234}N_{1234} + \omega_{123}N_{123} + \omega_{234}N_{234} + \omega_{23}N_{23} + \omega_2N_2 + \omega_3N_3) / N$$

$$N = \text{Round}\left(\frac{180 \times 2}{\pi \alpha} \arctan\left(\frac{L}{2D}\right)\right)$$

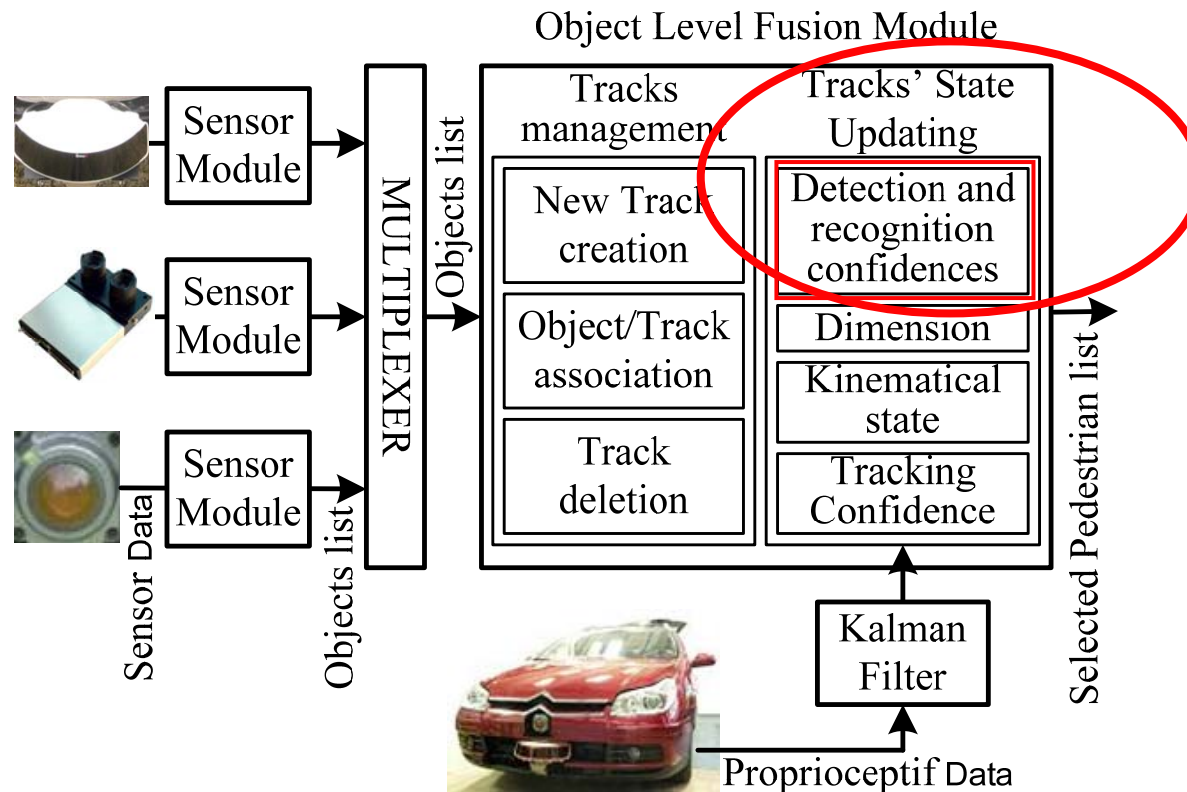
Pedestrian Recognition Confidence



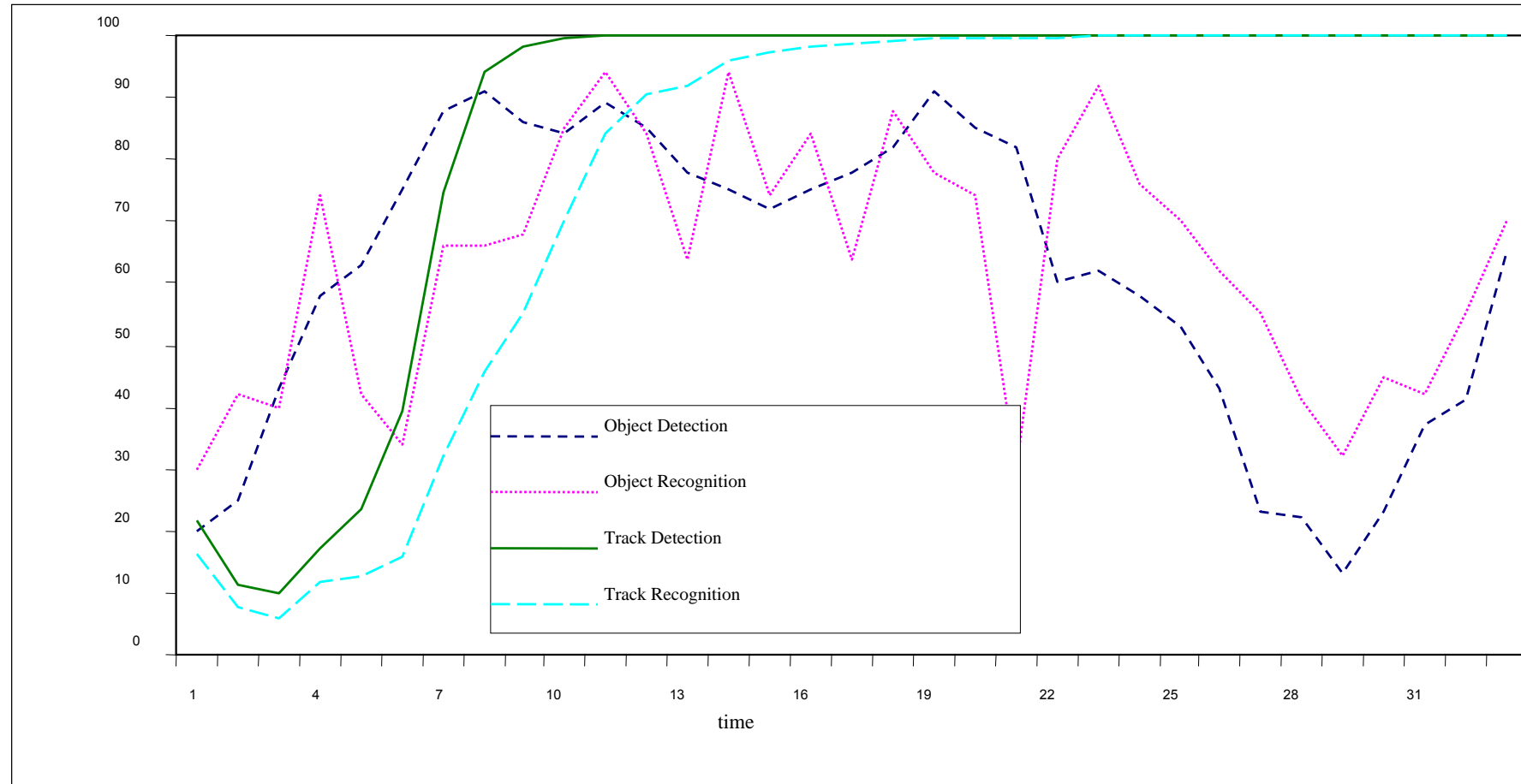
Width based Recognition function

More details in paper WeBT.27

Track's updating



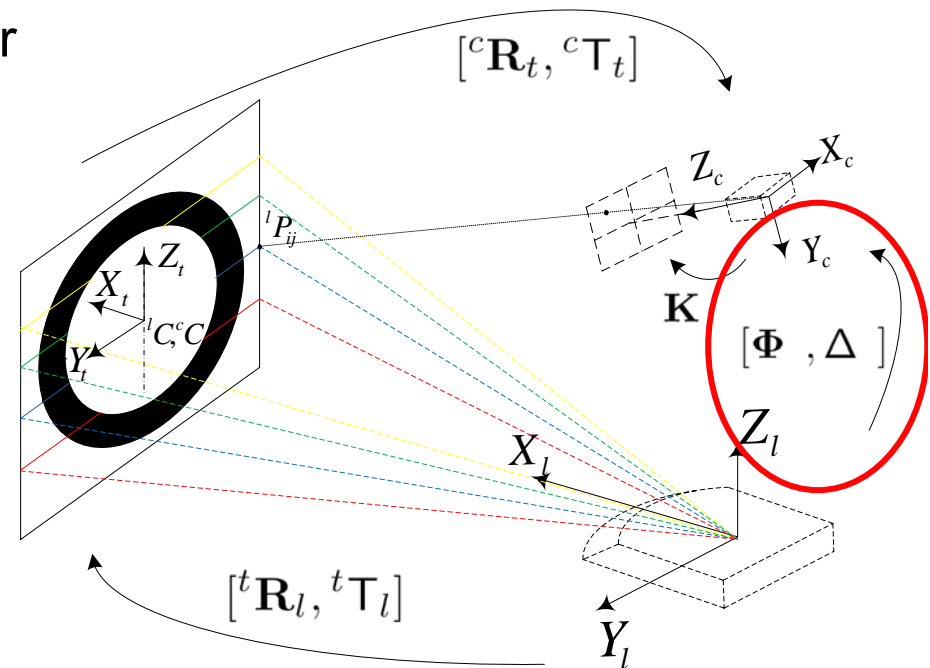
Confidences management



More details in paper WeBT.27

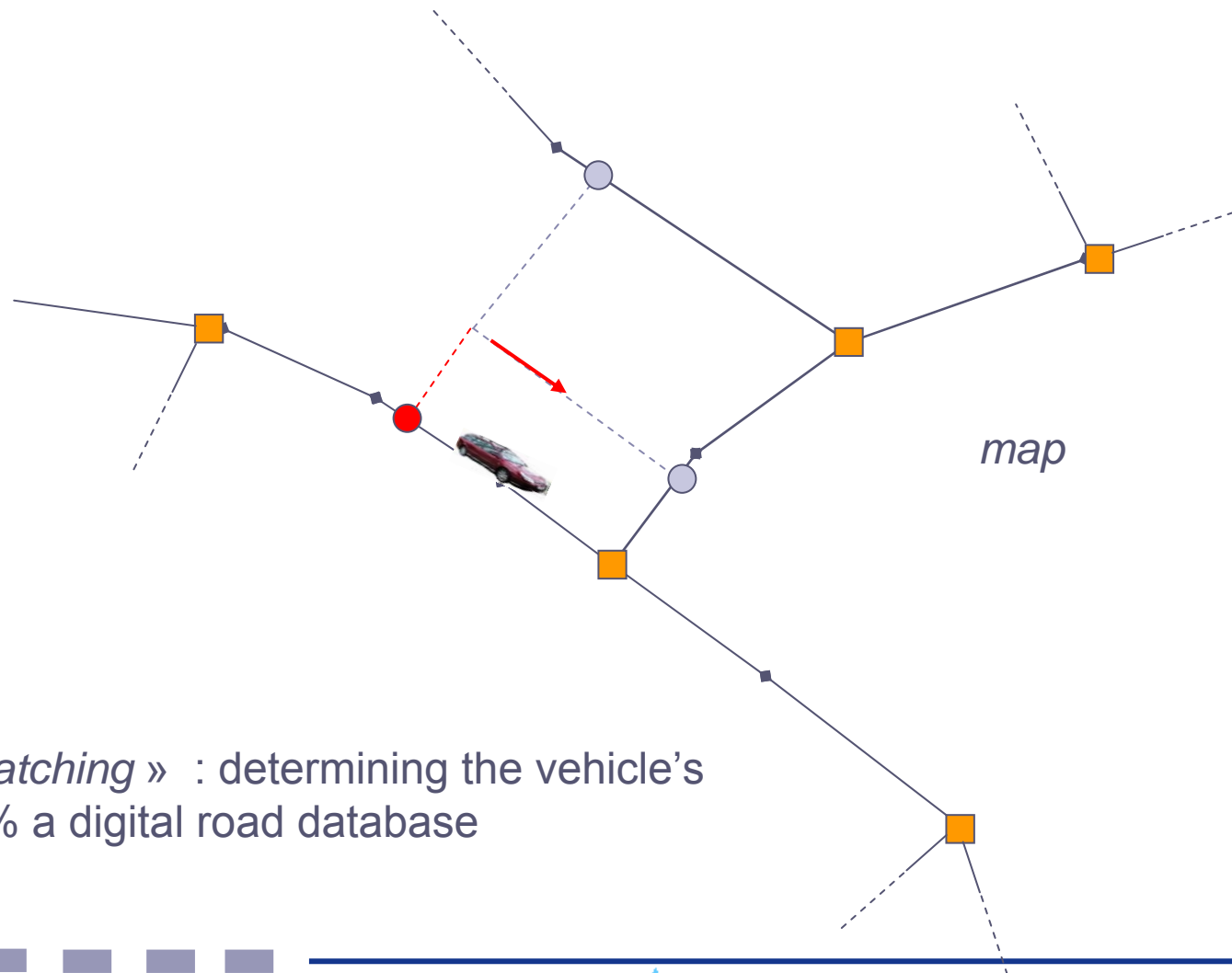
Extrinsic Calibration between a Multi-layer Lidar and a Camera

- 3D pose estimation of the calibration target from each sensor data.
 - 3D scan data (4 layers)
 - Images
- Estimation of the relative sensor position
 - 3D Robust Registration of different poses of the target
- Calibration accuracy estimation based on registration residuals



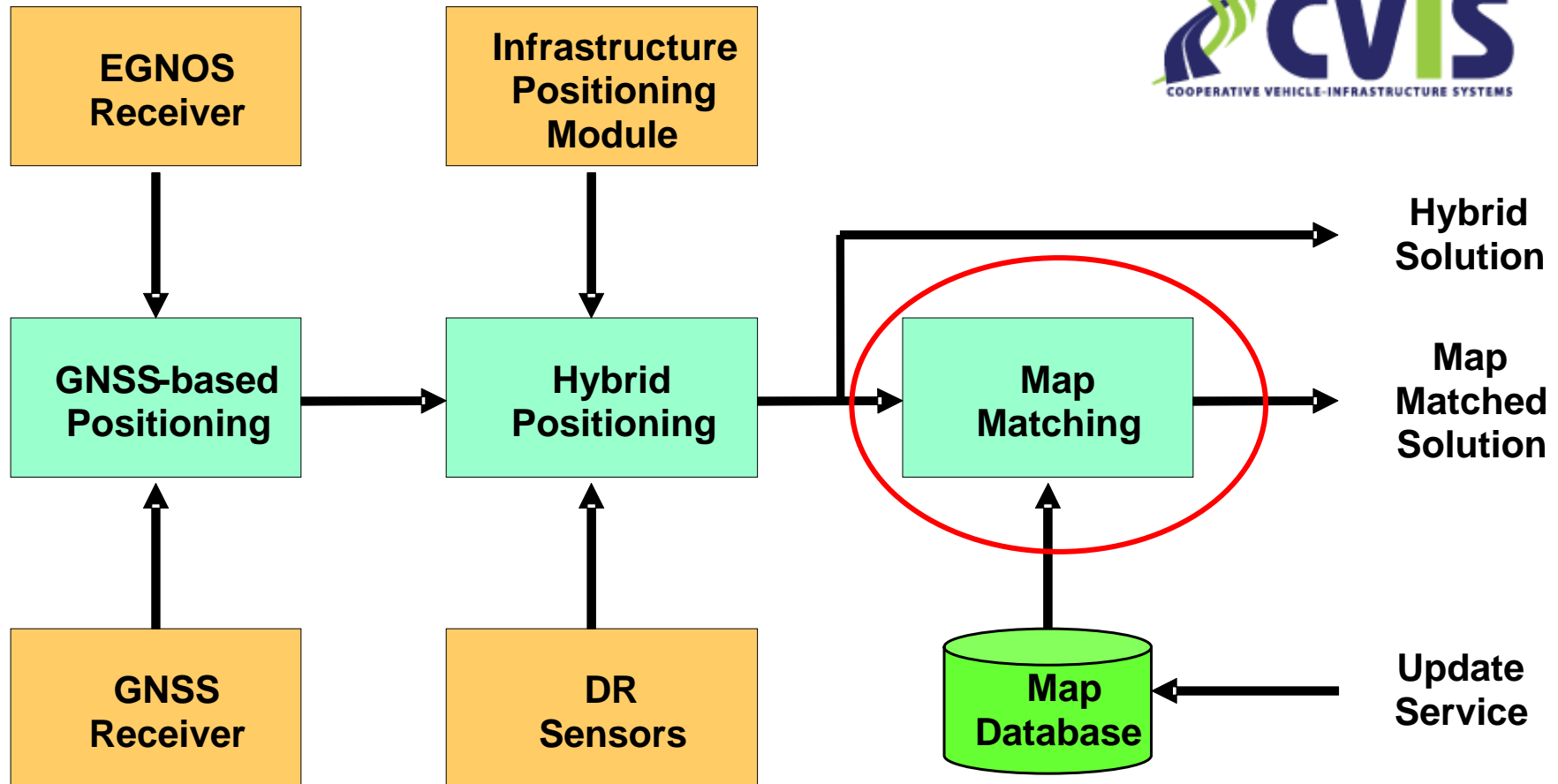
Demo 2 : characterization of the confidence in the map matching process of a localization system

Map Matching - Definition



« *map-matching* » : determining the vehicle's position % a digital road database

Main functions of the position calculation process in POMA



Modern Map-Matching Outputs

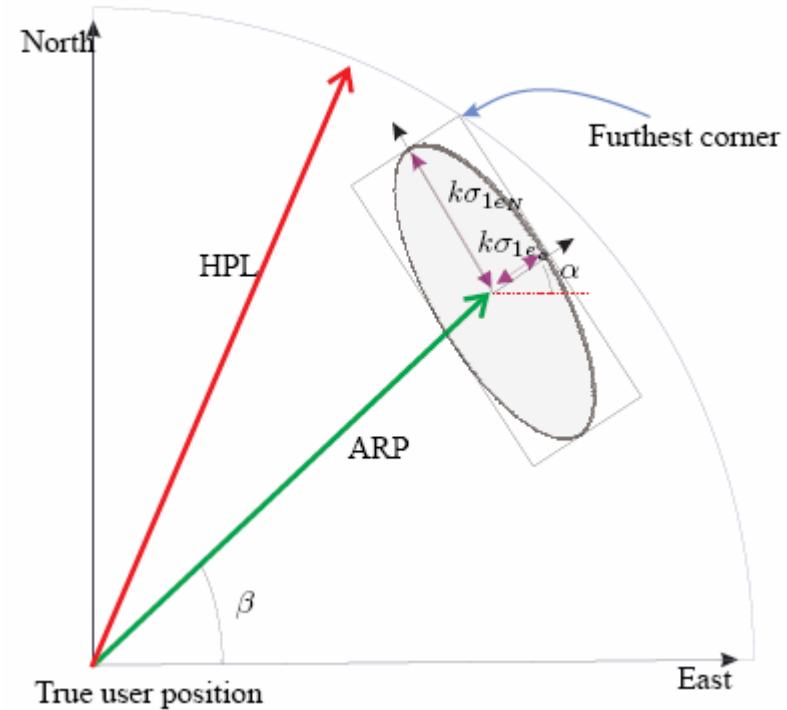
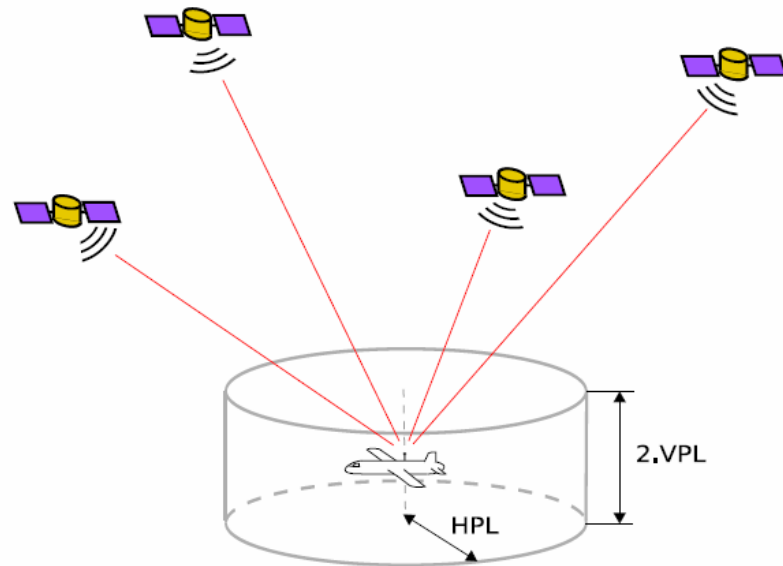
- MM outputs : up to 10 matched candidates
- Each candidate (Map-Matched hypothesis)
 - Probability with respect to the others
 - NIS – Normalized Innovation Squared
- Very often it is the hypothesis with the maximum probability that is used: for navigation tasks or fleet management applications it is acceptable. But for many other applications, like eCall or “Pay as you drive”, it is important to manage all the hypotheses.

Integrity and Localization Systems

- Integrity of a localization system: the measure of confidence that can be accorded to the exactitude of the positioning delivered by this system.
- Usual scheme
 - apply successive checks to ensure that the input information is valid
→ detect and eliminate aberrant measurements
“internal reliability”
 - estimate a positioning with a quantified inaccuracy.
“external reliability”

xPL – Protection Levels

Maximum error due to an undetected fault

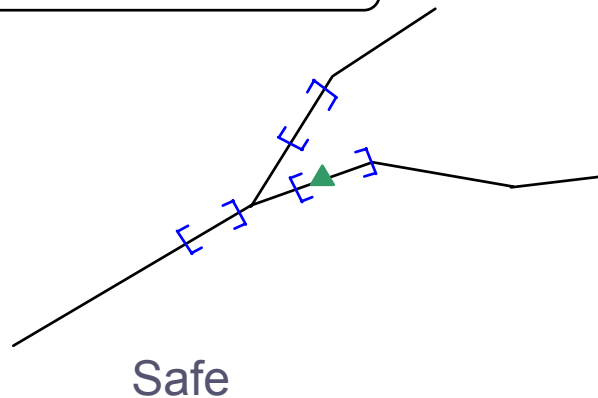


Approximate Radius of Protection (ARP)

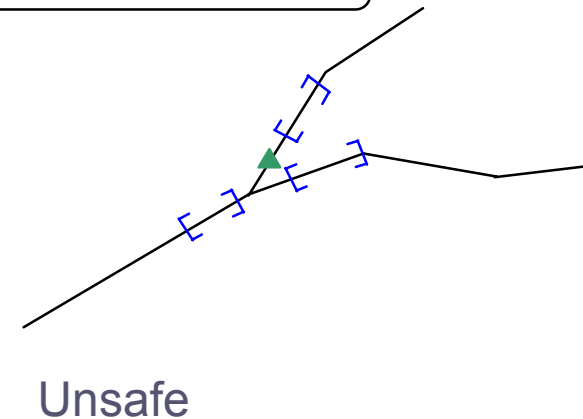
Integrity of a map-matching system

- Map-Matching Integrity definition (proposal)
 - A multi-hypothesis map-matching process is reliable (or safe) if the ground truth matched location is within the hypotheses zones provided by the system.

Real unknown matched position ▲
Candidate matched zones []



Real unknown matched position ▲
Candidate matched zones []

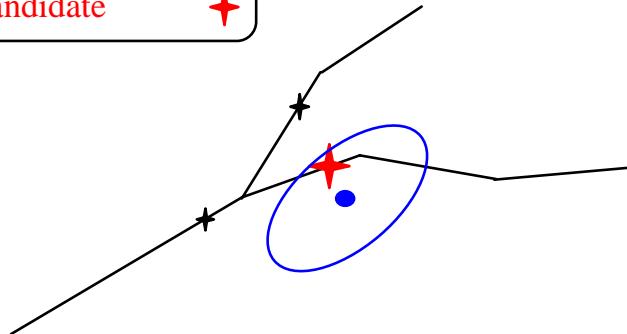


How to characterize the localization system integrity in real-time?

- The Real Map-Matched position is Unknown!
- Our proposal
 - Multi-Hypothesis Map-Matching (MHMM)
 - Estimate the probability of each hypothesis with respect to the others
 - Compute Normalized Residuals for each hypothesis
 - Apply a decision rule (depending on the application)

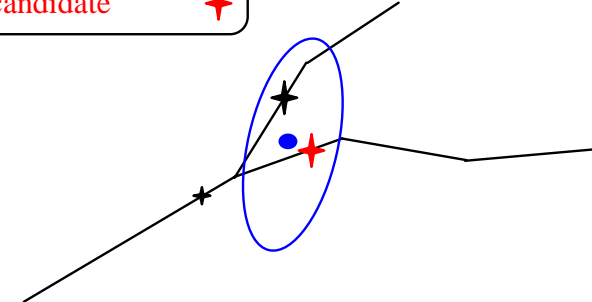
Monitoring integrity using MHMM outputs

Estimated position ●
Candidate matched position ✱
Most likely candidate ✱



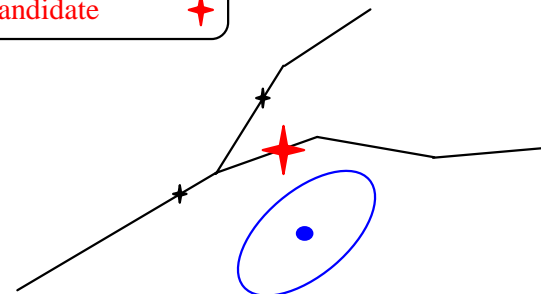
Case 1 : confident MM

Estimated position ●
Candidate matched position ✱
Most likely candidate ✱



Case 2 : ambiguous MM

Estimated position ●
Candidate matched position ✱
Most likely candidate ✱



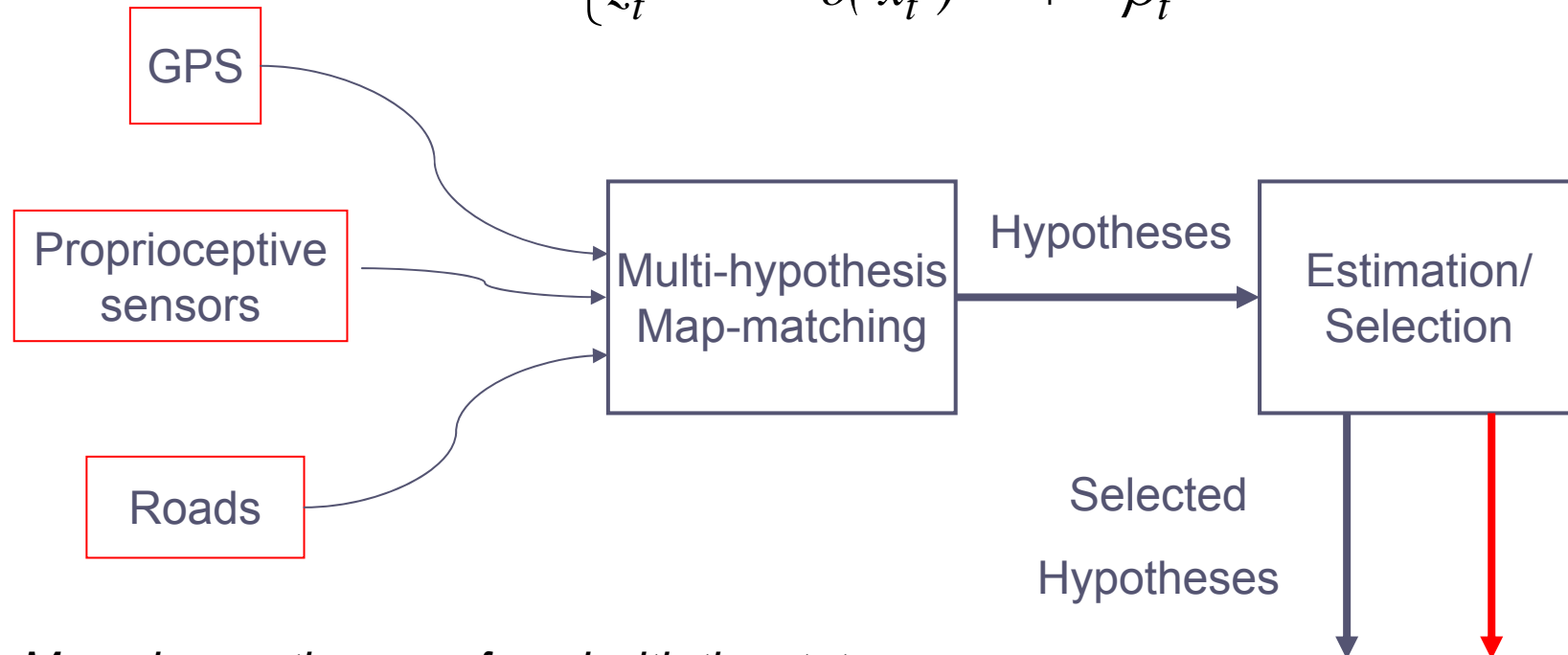
Case 3: inconsistent candidates

Bayesian MHMM using Road Tracking

MOMKF

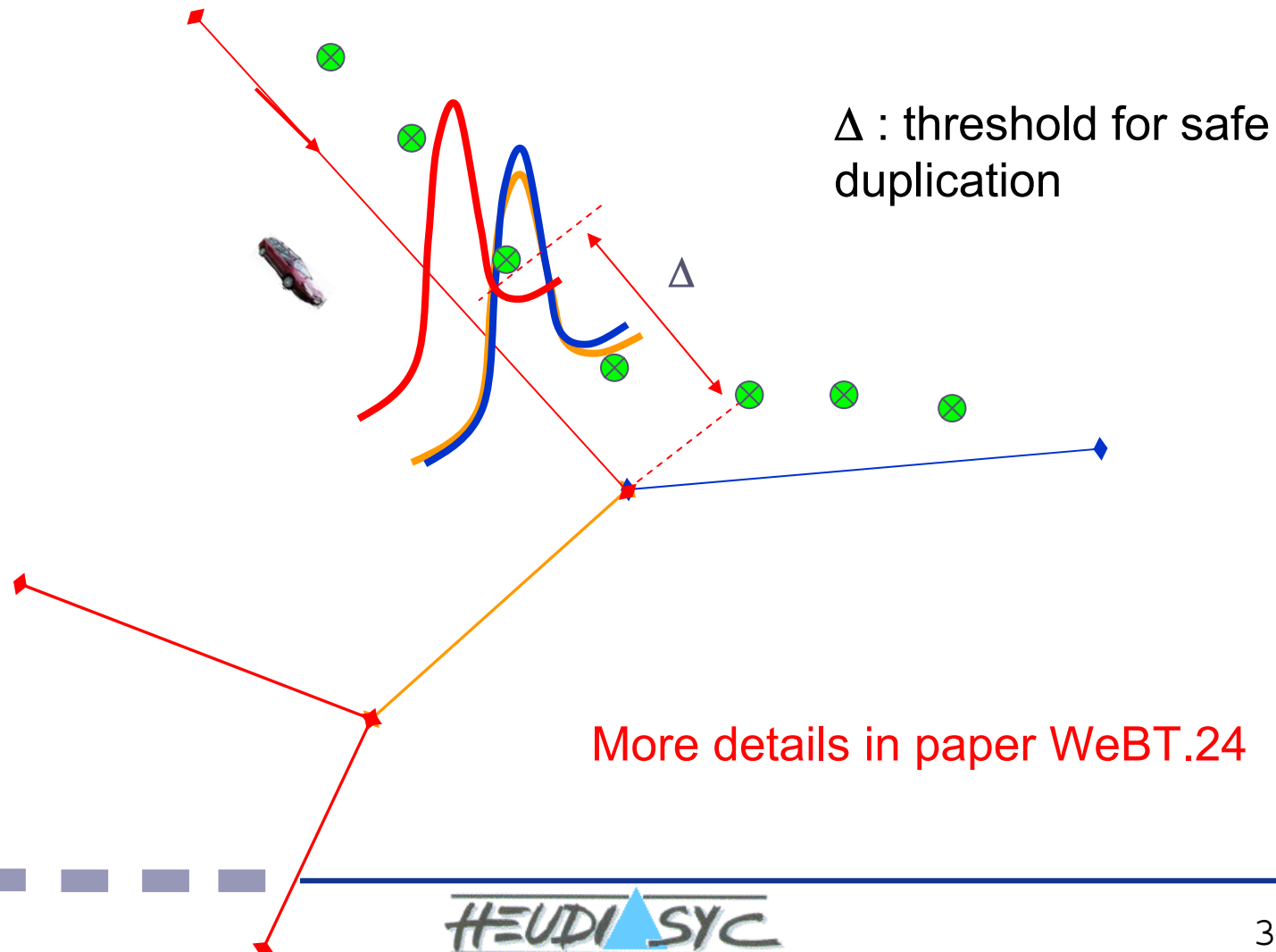
Multiple Observation Models Kalman Filter

$$\begin{cases} x_t = f(x_{t-1}) + \alpha_t \\ z_t = o(x_t) + \beta_t \end{cases}$$



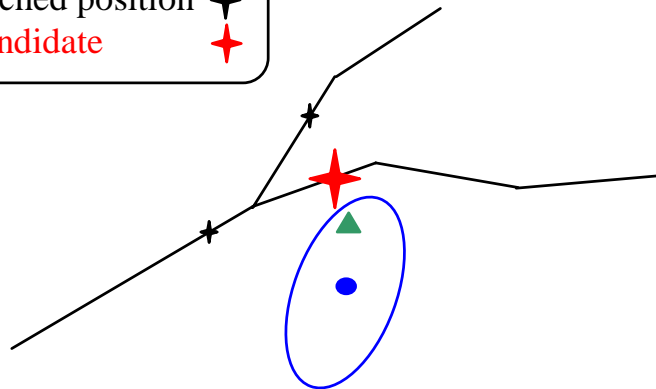
Map observations are fused with the states

MOMKF Illustration



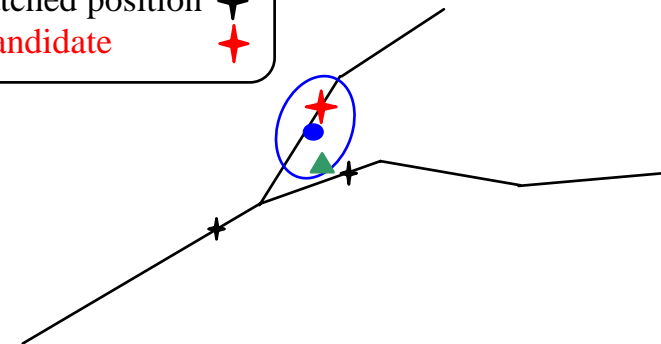
False Alarms and Missed detections

- Estimated position ●
- Real unknown position ▲
- Candidate matched position ✦
- Most likely candidate ✦



*Example of **false alarm**. The matched point is good but it is declared unsafe by the system*

- Estimated position ●
- Real unknown position ▲
- Candidate matched position ✦
- Most likely candidate ✦



*Example of **missed detection**. The most likely matched point is bad and the system is confident in its map-matching*

Managing the NIS of MHMM

- Criterion: heading + distance (for each hypothesis)
→ 2 degrees of freedom
- Gaussian hypothesis
→ NIS should follow a Chi Squared distribution
- Decision rule: compare each NIS with a Threshold
- Decision threshold depends on the probability of False Alarm
- Decision rule: accept hypothesis “i” if $NIS(i) < Th(P_{FA})$
 - $P_{FA} = 10\%$ → $Th = 4.6$
 - $P_{FA} = 1\%$ → $Th = 9.2$
 - $P_{FA} = 0.1\%$ → $Th = 13.8$
 - $P_{FA} = 0.01\%$ → $Th = 18.4$

Managing the probabilities of MHMM

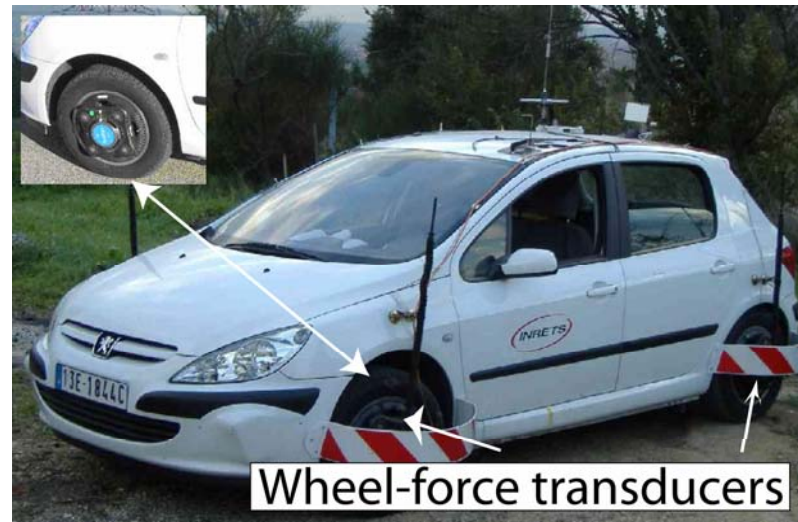
- It depends on the application!
- Navigation typical rule
 - Take the most likely hypothesis if $P_i > 0.5$
- Intelligent Speed Adaptation
 - If $P_i < 0.8$ then confirm the extracted speed limit with the one detect by the on board camera
- Road charging
 - Charge the use of the road if the less likely hypothesis j is such that $P_j < 0.1$

Demo 3 : An estimation methodology for vehicle wheel-ground contact normal forces: Automatic detecting risk rollover situations



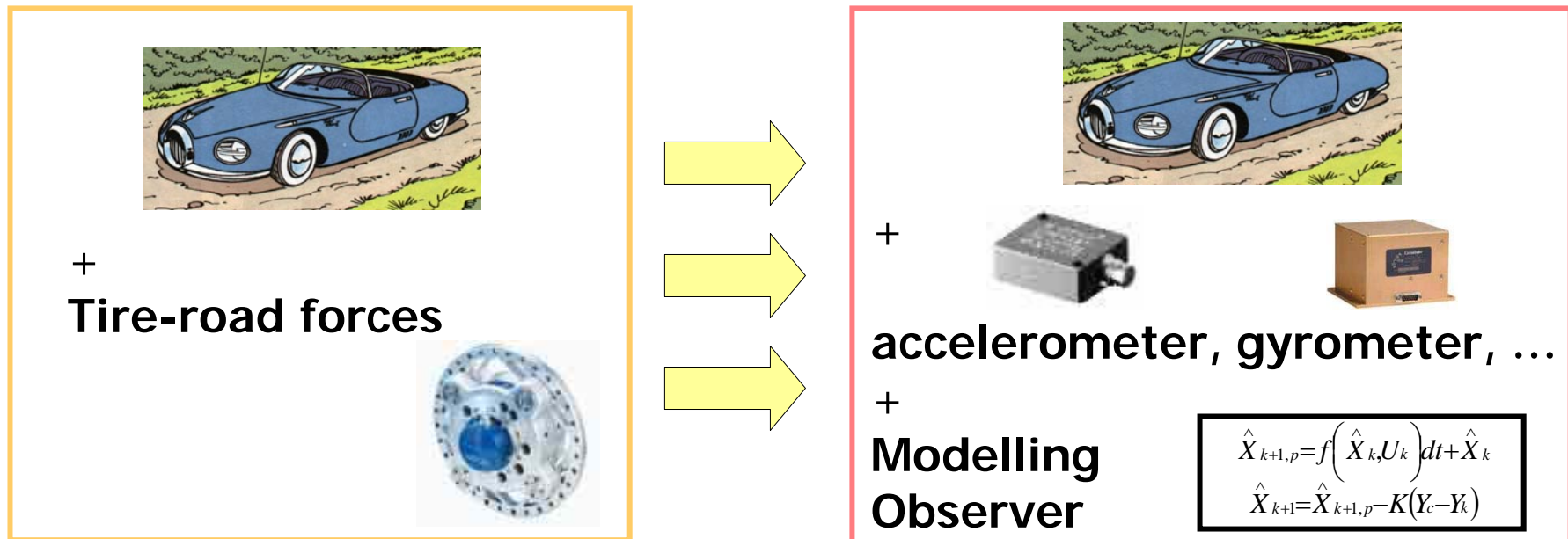
Problem

- Usual measurements: accelerations, roll rates, suspensions deflection,...
 - Missing important information
 - Dynamic variables: roll angle, tire-road forces
- high costs sensors
- > estimation



Objective

- Replace wheels transducers by virtual sensors (observers)



Why we need to estimate normal tire forces?

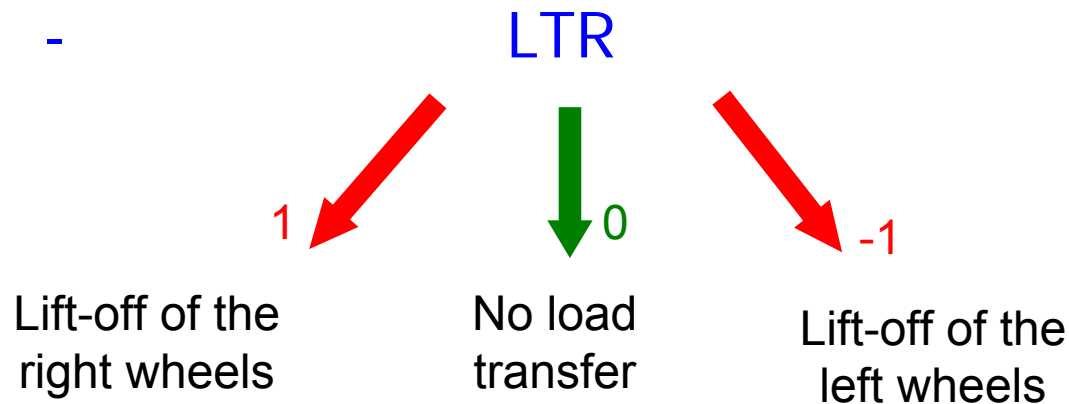
- As a result of longitudinal and lateral accelerations, the load distribution in a vehicle changes during a journey.



- Normal tire-road forces:
 - Improvement of safety systems (ABS, ESP)
 - Influence steering behavior, vehicle stability and cornering stiffness
 - Better calculation of the LTR (Load Transfer Ratio) rollover index parameter

LTR parameter definition

- LTR:
 - $LTR = (F_{zr} - F_{zl}) / (\Sigma F_z)$
 - Convenient method for supervising the vehicle's dynamic roll behavior



Estimation process

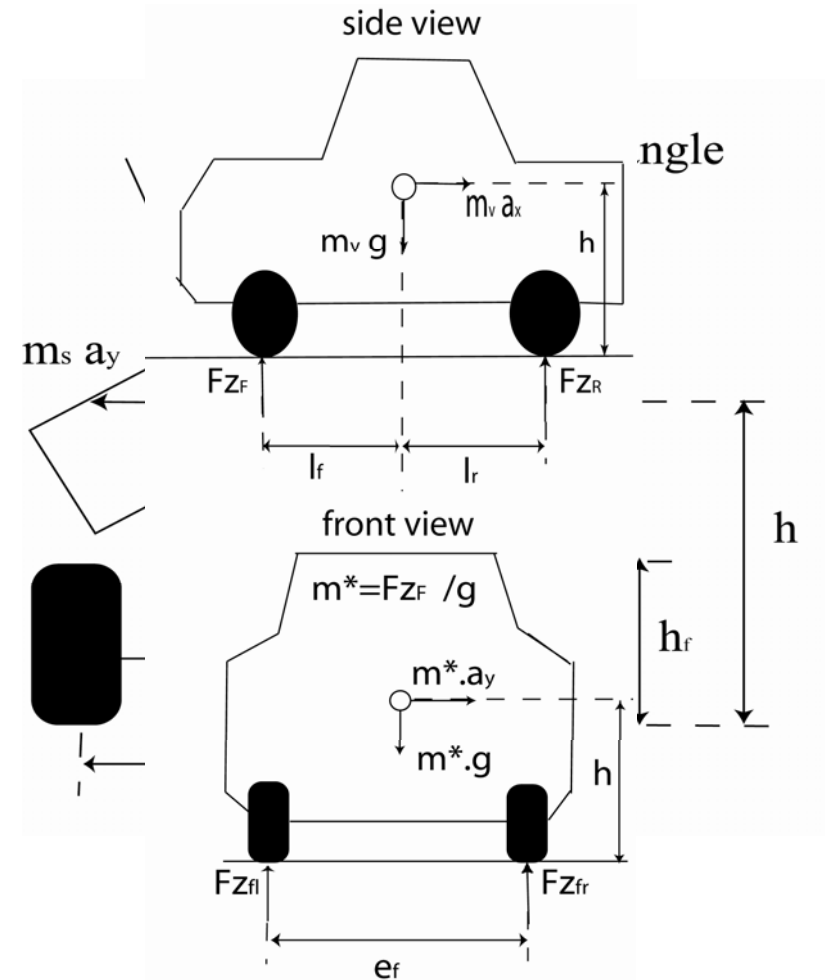
Measurements

Observer 1 (LKF)
Roll plane vehicle model

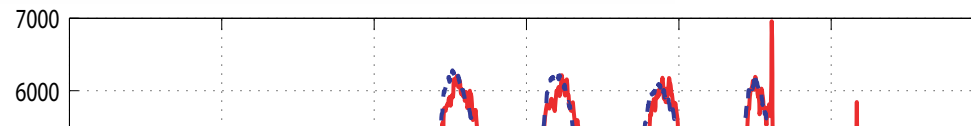
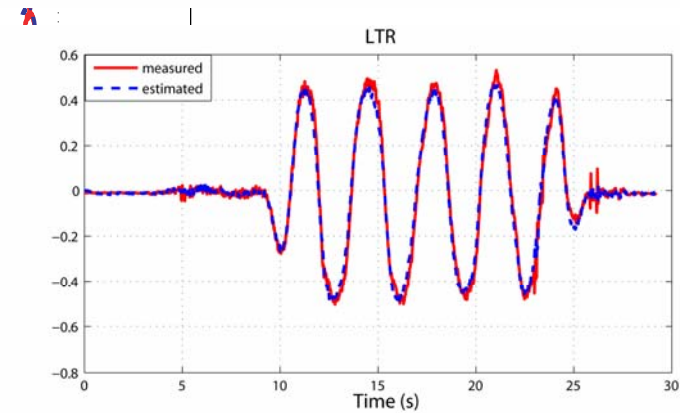
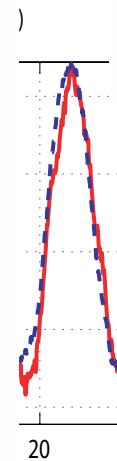
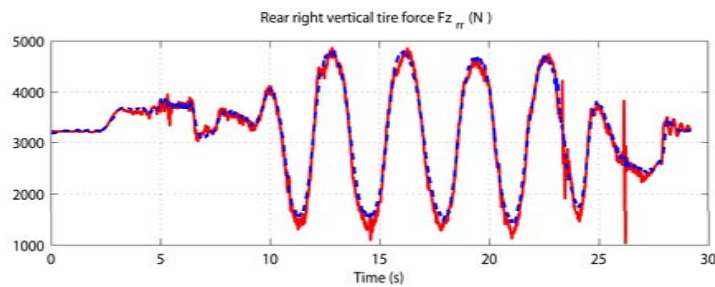
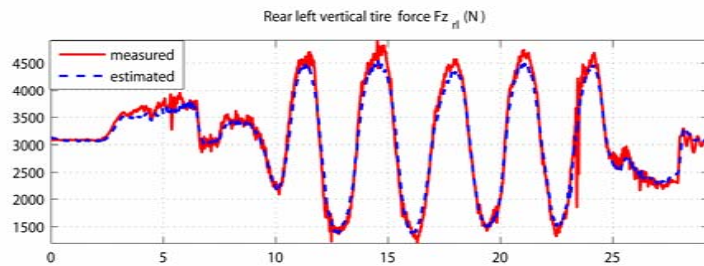
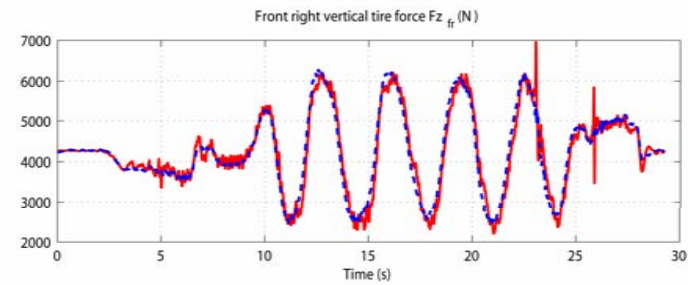
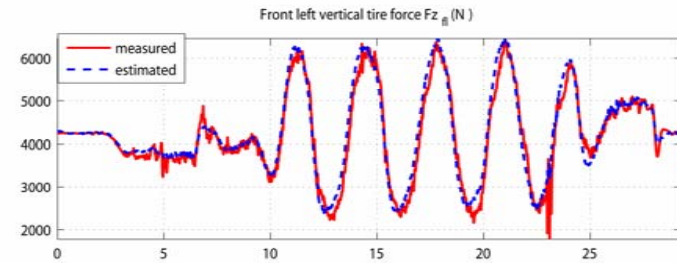
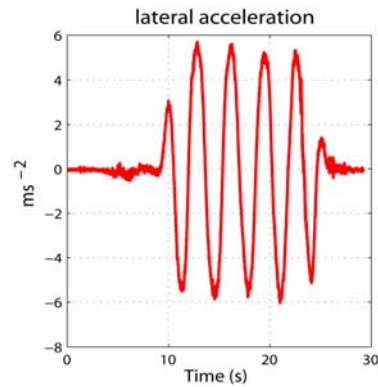
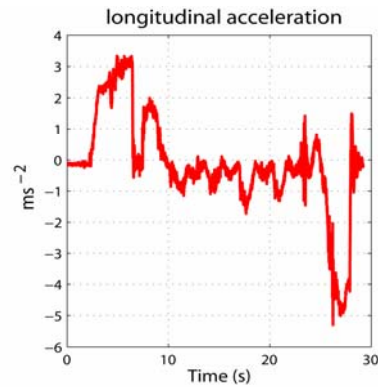
Lateral load transfer

Observer 2 (EKF)
**Nonlinear wheel ground
vertical contact force model**

Vertical forces, LTR



Some experimental results



This is the end

Have a look at our demos!

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