Robots in Human Environments
The Intelligent Vehicle Context

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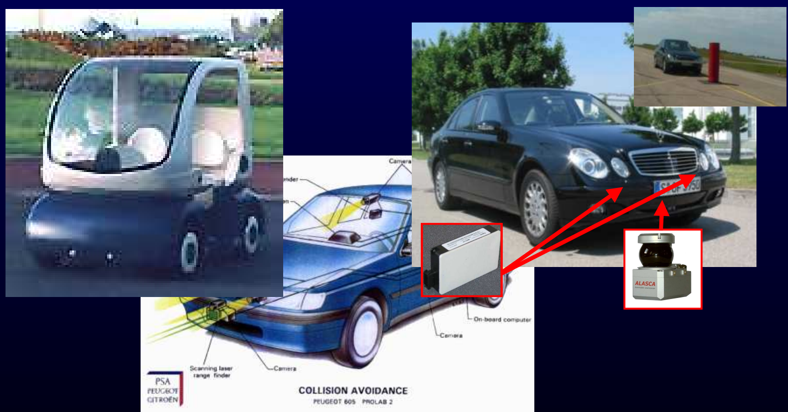
Invited talk
AMS'09, Karlsruhe, December 2009



Structure of the talk

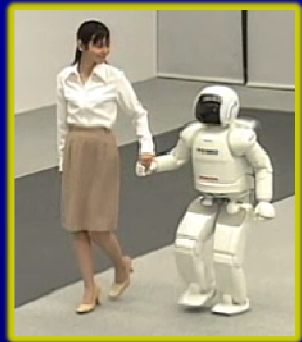
1. **Introduction & Challenges**
2. **Perceiving & Understanding the physical world**
3. **World change Prediction & Risk Assessment**
4. **Safe navigation decisions**
5. **Share Control & Human-Robot Interaction**

Context & Scientific Challenge

- **Overall challenge**

Robots in Human Environments

ITS for improving Safety & Comfort & Efficiency



Personal Assistant & House Keeping & Rehabilitation

- **Main Motivations**

  ✓ Important socio-economic perspectives *=> Transport, Aging society, Medical care & Rehabilitation, Human assistance, Intelligent home …*

  ✓ Increasing interest of industry *=> Automotive industry, Robots, Health sector, Services …*

  ✓ Challenging research topics *=> Dynamic world, Robust perception, Safety, Human Aware Motion, Complex Human-Robot interactions …*

  ✓ Robotics state-of-the-art **+** Progress in ICT Technologies *(computers, sensors, micro-nano technologies, energy …)* *=> Challenge potentially reachable*

The main Technical Challenge

- **Current robots are often "Unsafe"**

DARPA Grand Challenge 2004
✓ *Significative step towards Motion Autonomy*
✓ *…. But still some "Uncontrolled Behaviors"*

Requirement: Machines that "know" what they do !

✓ *Perceiving & Understanding the physical world*

✓ *Behave Safely*

✓ *Share decisions with human beings*

✓ *Include Adaptive capabilities & Learning capabilities*

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Autonomous Vehicles – Large scale experiments

CyberCars Public Experiments (INRIA & EU Partners)

- *Several successful large scale experiments in "protected" public areas*
- *Some CyberCars products in commercial use for private areas (e.g. Robosoft, Frog …)*

Shanghai Public Demo 2007

Floriade 2002 (Amsterdam)

Autonomous Vehicles – Large scale experiments

CyberCars Public Experiments (INRIA & EU Partners)

- *Several successful large scale experiments in "protected" public areas*

Some technologies are almost ready for use in "protected" public areas

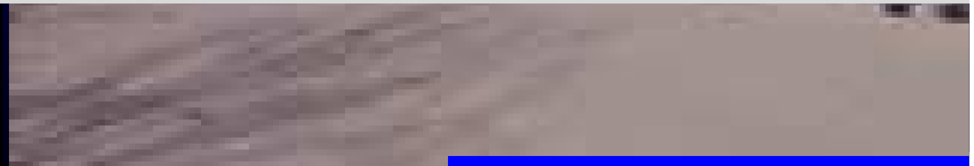
…. But ….

Open Urban environments are still beyond the State of the Art

&

"Full autonomy" is easier than "Share control"

Shanghai Public Demo 2007

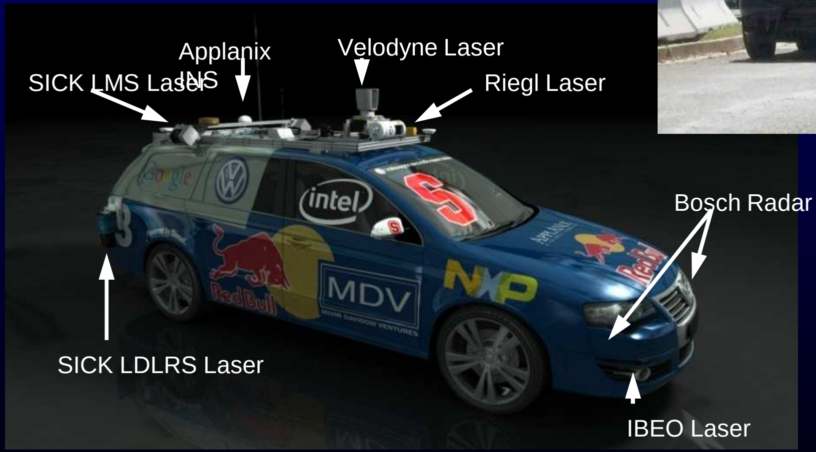


Floriade 2002 (Amsterdam)

Autonomous Vehicles – Large scale experiments

Urban Challenge 2007

- 96 km through an urban like environment, 50 manned & unmanned vehicles
- 35 teams for qualification (NQE during 8 days), 11 selected teams, 6 vehicles finished the race
- Road map provides a few days before the race, Mission (checkpoints) given 5 mn before the race
- Several incident/accidents during the event



Autonomous Vehicles – Large scale experiments

Urban Challenge 2007

- 96 km through an urban like environment, 50 manned & unmanned vehicles
- 35 teams for qualification (NQE during 8 days),

Big step towards Autonomous Vehicles

…. But …

Safety is still not guaranteed

&

Too many costly sensors are required

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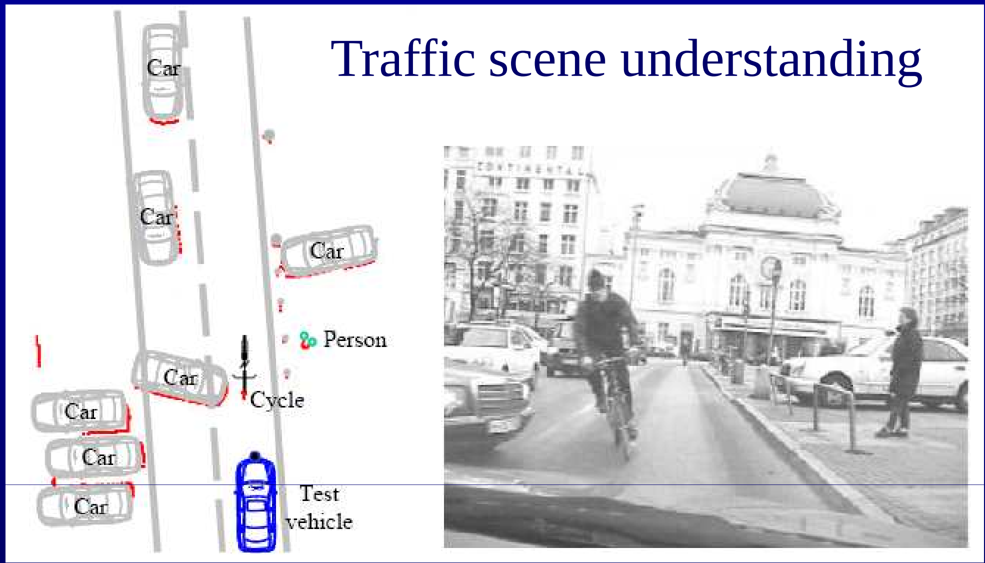
Perceiving & Understanding the physical world

A World full of Uncertainty & Continuously changing



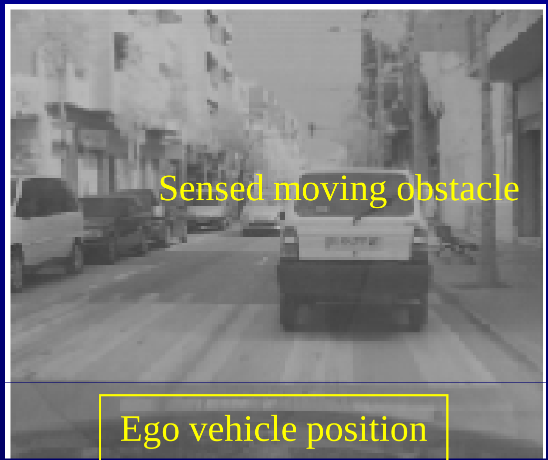
- Dealing with the physical world constraints – *Dynamicity, Space & Time, Real-time*
- Reasoning under Uncertainty & Partial information – *Probabilistic Reasoning*
- Sensing Stationary & Moving entities – *SLAM , DATMO, Classification*
- Sensing is not sufficient ! *We also need to Reason about Contextual information*
- Future world changes have to be taken into account – *Predictions & Risk assessment*

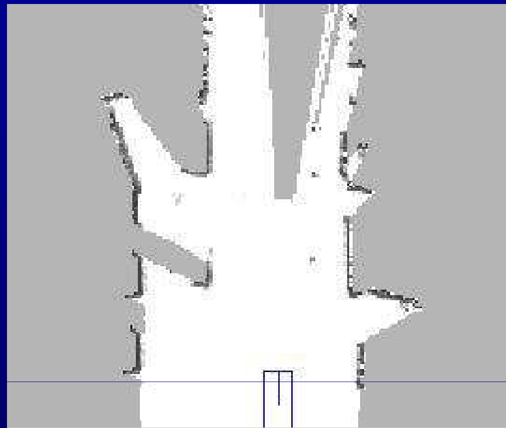
Multi-Objects Detection & Tracking

Traditional Laser-Based Approach

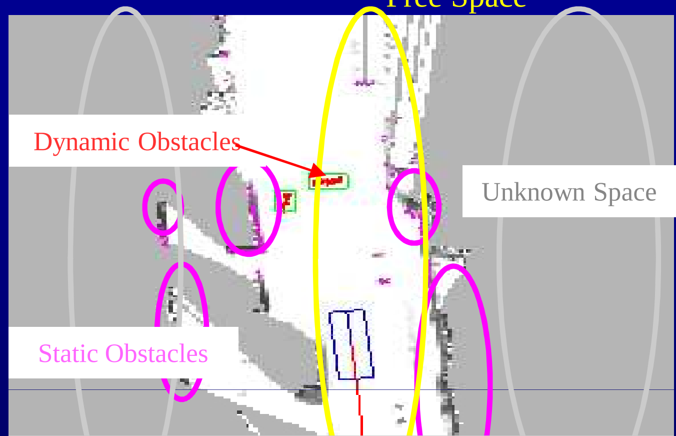
[Burlet, Vu, Aycard 07-08]

- **Grid-based Obstacles Detection (using Occupancy Grids)**





Incremental OG Mapping (sliding window)



Moving Object detection => Check consistency "OG / Raw laser data"

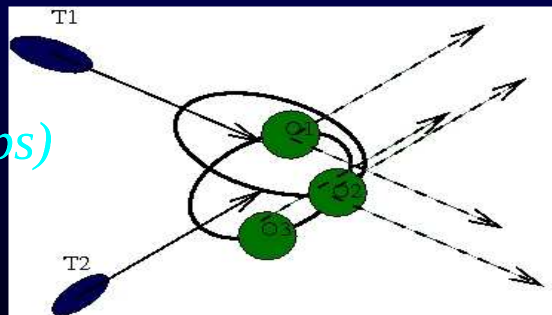
- **Multi-Objects Tracking**

  ✓ *Mapping & localization: Scan matching*

  ✓ *Data Association: Multiple Hypotheses (for n time steps)*

  ✓ *Filtering : Interacting Multiple Models*

  Inspired from [Blakman 98] (radar) & [Wang 04] (laser + ICP)



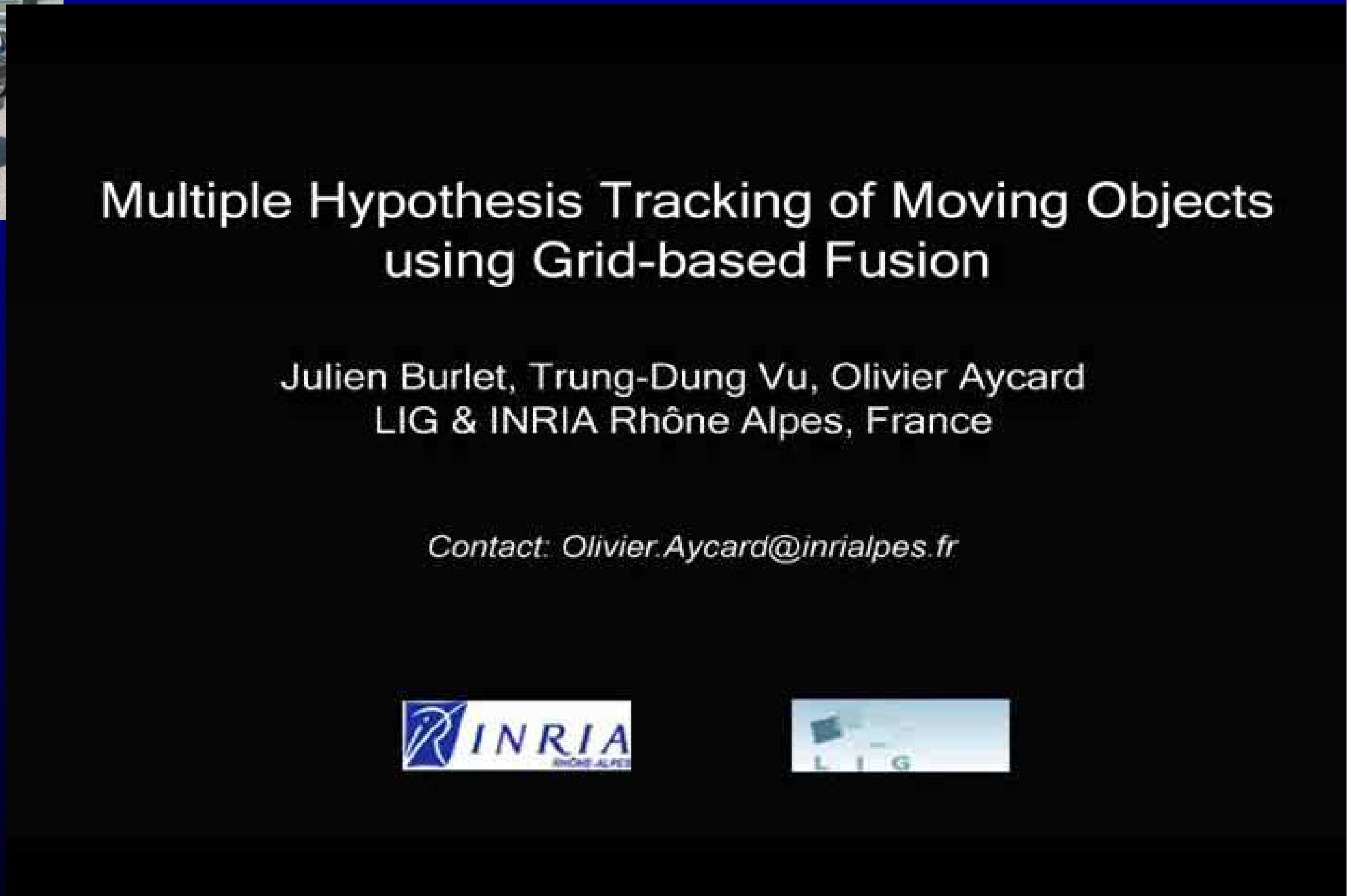
Multi-objects Detection & Tracking

"PreVent" EU project, Versailles demo 2007 (Daimler-Chrysler & Ibeo test vehicle)

Mercedes E-Class 350

Grid-Based approach
Multiple Hypotheses & Interacting Multiple Models

Computational time ~ 10 ms



Application:

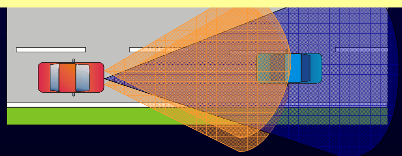
- **Pre-fire & Braking**

Sensors:

- Two short range radars
- A laser scanner ALASCA

Actuators:

- Electrical belt pre-tensioning
- Automatic braking



Multi-objects Detection & Tracking

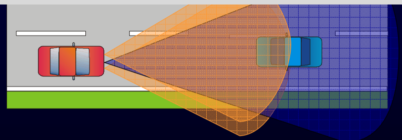
"PreVent" EU project, Versailles demo 2007 (Daimler-Chrysler & Ibeo test vehicle)

Grid-Based approach
Multiple Hypotheses & Interacting Multiple Models

Computational time ~ 10 ms

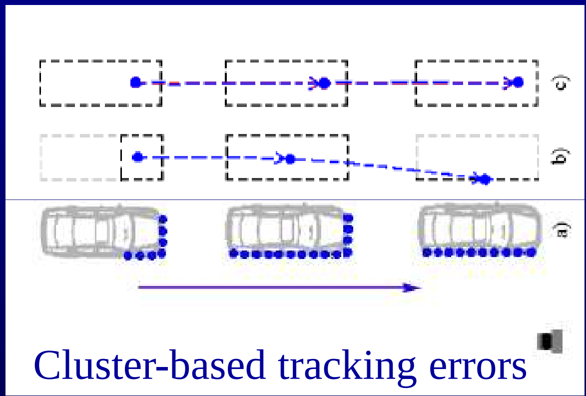
Quite good results … But well known robustness problems have still to be solved (for reducing false positives & negatives)

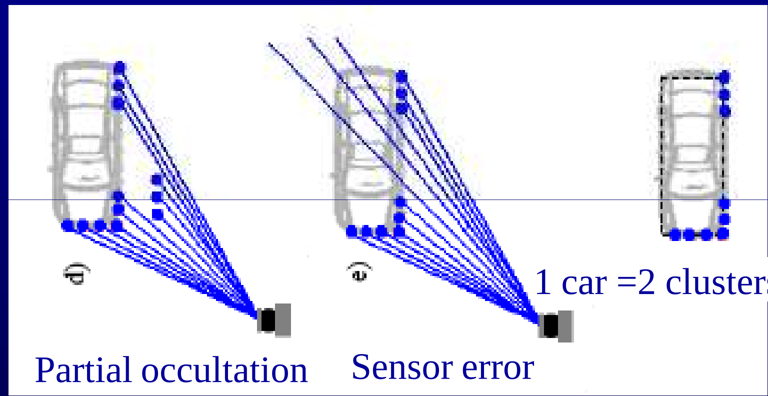
- ***Appearance & Geometric / Dynamic models***
- ***Sensor Fusion***



Improving Detection & Tracking using
Geometric & Dynamic models

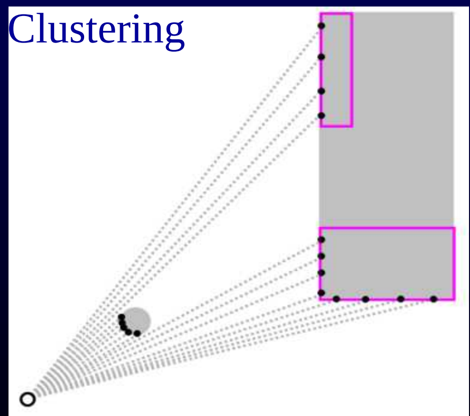
- Laser sensed objects are represented by clusters of points
- Tracking clusters often leads to a degradation of tracking results
- Object splitting (occlusions, glass-surfaces) makes the tracking harder

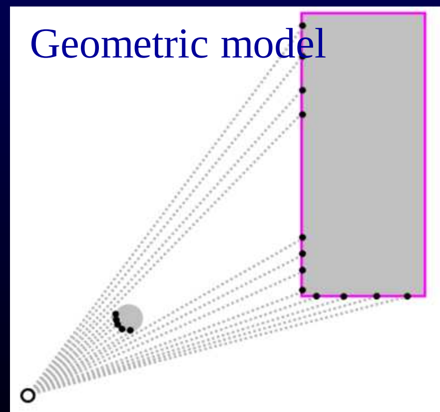




Geometric models help in overcoming these problems

[Thrun & Petrovskaya 08]





INRIA T-Scans Model-based Approach

Data-Driven Markov-Chain Monte-Carlo (DDMCMC)

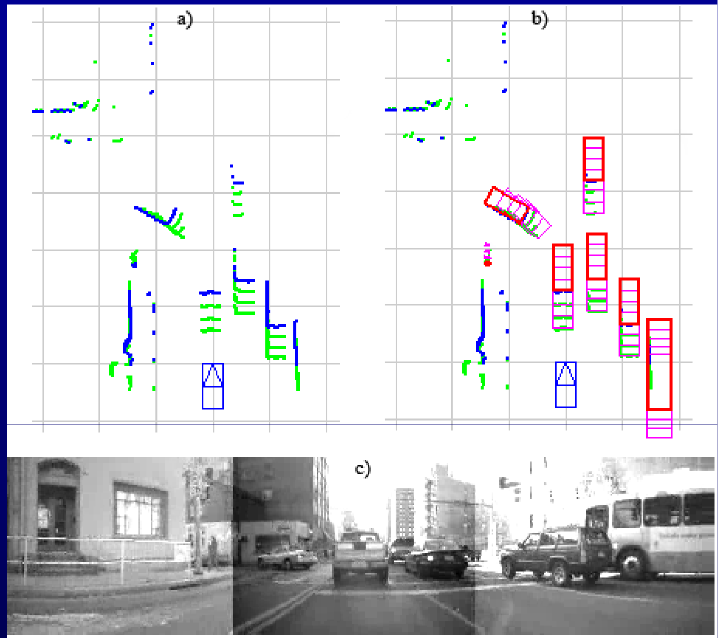
[Vu & Aycard 09]

- Sliding window over *T*-scans *(Time Horizon)*

  $Z = \{Z_1, ..., Z_T\}$

- Find the best explanation of object trajectories (tracks) based on *Spatio-Temporal consistency in both Appearance (model) & Motion*
- Model Based: τ_k is a sequence of shapes
- Sampling-based method (MCMC) to avoid enumerating all possible solutions

$$\omega^* = \underset{\omega}{\operatorname{argmax}}\, P(\omega|Z) \qquad \omega = \{\tau_1, \tau_2, \ldots, \tau_K\}$$



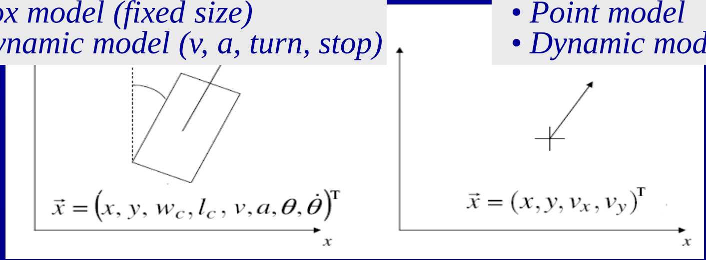
⇒ More Robust thanks to the

"Simultaneous Detection – Classification –Tracking" process

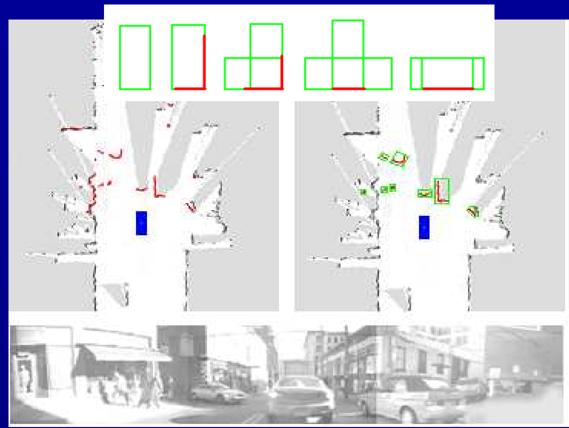
DDMCMC – Models & Hypotheses processing

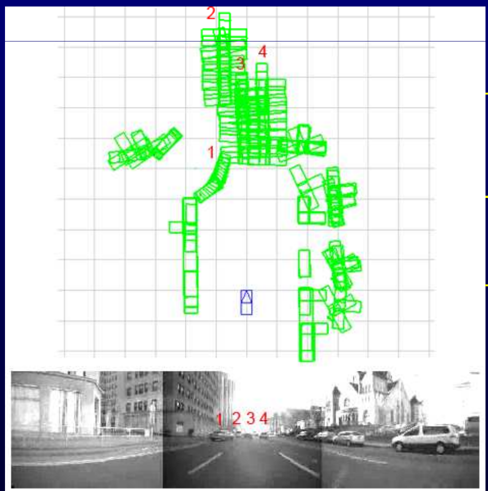
Bus, Truck, Car, Bike
- *Box model (fixed size)*
- *Dynamic model (v, a, turn, stop)*

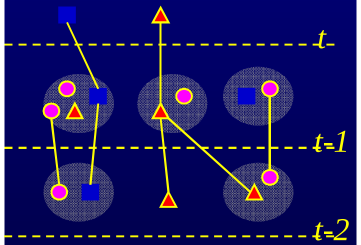
Pedestrian
- *Point model*
- *Dynamic model (v)*



L-shape & I-shape => *Box model*
Else wise => *Point object*

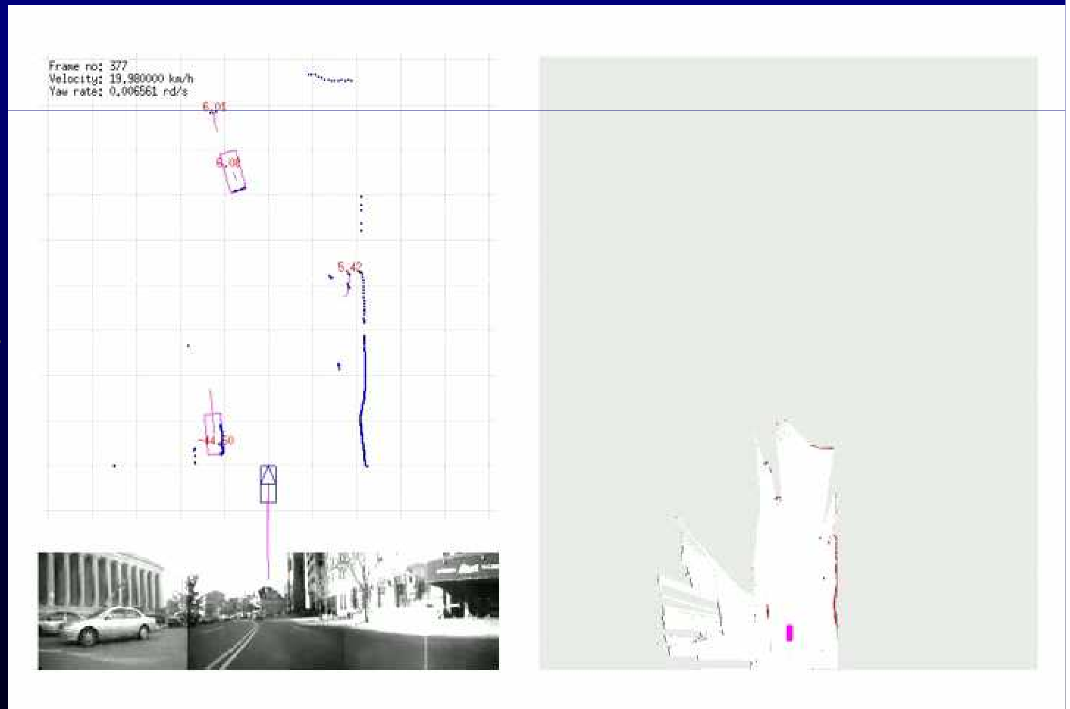






Neighborhood graph of hypotheses

Search of *P(ω | Z)* over space of moving object hypotheses



Results using Navlab dataset

Improving Perception *– Bayesian Filtering*

"Bayesian Occupation Filter paradigm (BOF)" *[Coué & Laugier IJRR 05]*

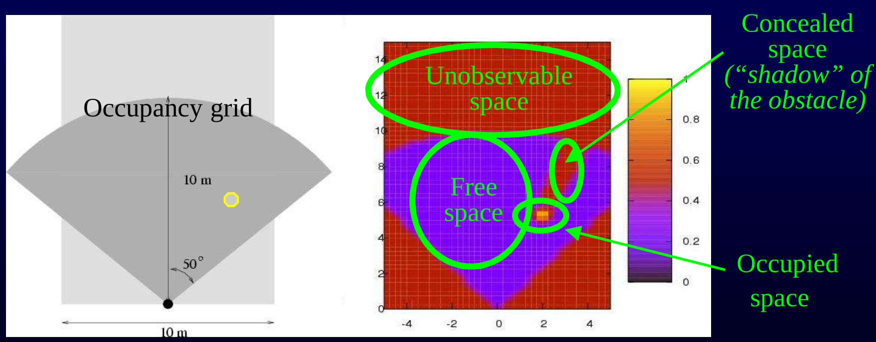
Patented by INRIA & Probayes, Commercialized by Probayes

BOF

- Continuous Dynamic environment modelling
- *Grid* approach based on *Bayesian Filtering*
- Estimates *Probability of Occupation* & *Velocity* of each cell in a 4D-grid
- Application to *Obstacle Detection & Tracking + Dynamic Scene Interpretation*

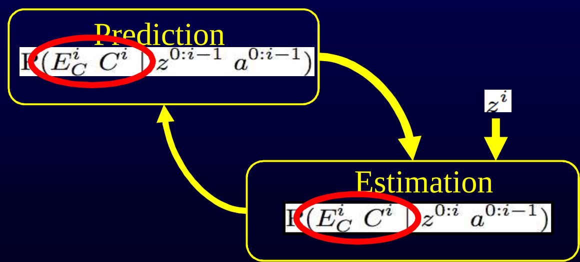
=> More robust to Sensing Errors & Temporary Occultation

Successfully tested in real traffic conditions using industrial dataset (e.g. Toyota, Denso, ANR LoVe)



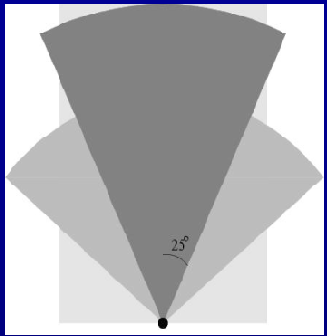
Sensed moving obstacle

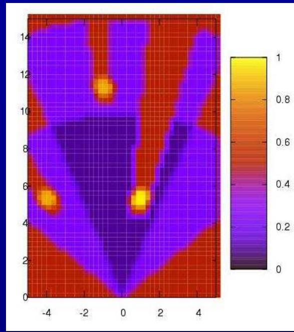
P($[O_c = occ]$ | z c)
$c = [x, y, 0, 0]$ and z=(5, 2, 0, 0)



Improving Perception *– Dealing with Temporary Occultation (Tracking + Conservative anticipation)*

[Coué & al IJRR 05]





Description

Specification

- Variables :
  - V^k, V^{k-1} : controlled velocities
  - $Z^{0:k}$: sensor observations
  - G^k : occupancy grid
- $P(Z^{0:k}\ V^k\ V^{k-1}\ G^k) = \left(\begin{array}{l} P(Z^{0:k})P(V^{k-1}) \\ P(G^k \mid Z^{0:k})P(V^k \mid V^{k-1}\ G^k) \end{array} \right)$
- Parametric forms :
  - $P(G^k \mid Z^{0:k})$: BOF estimation
  - $P(V^k \mid V^{k-1}\ G^k)$: Given or learned

Question

Inference

$P(V^k \mid z^{0:k}\ v^{k-1})$

Thanks to the prediction capability of the BOF, the Autonomous Vehicle "anticipates" the behavior of the pedestrian and brakes (even if the pedestrian is temporarily hidden by the parked vehicle)

Improving Perception – *Bayesian Sensor Fusion*

ANR project "LoVe"

Sensor Model → Observation grid
Sensor Model → Observation grid

Projection

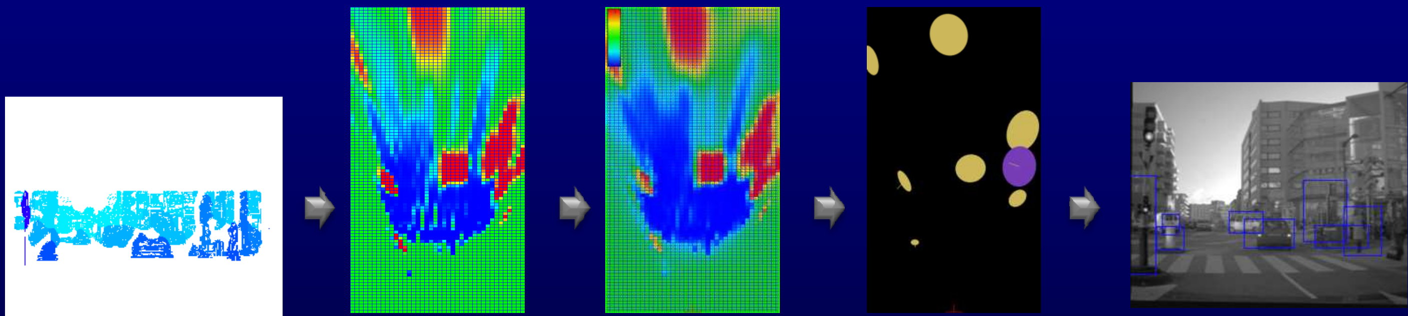
→ Bayesian Occupancy Filter (BOF) → Occupancy & Velocity Grids

Fusion & Estimation

→ Fast Clustering / Tracking Algorithm (FCTA) → obstacles

Detection & Tracking

Stereo-vision data processing



Disparity data | Observation grid | Estimated grid | Tracks | Results in image

Laser data processing

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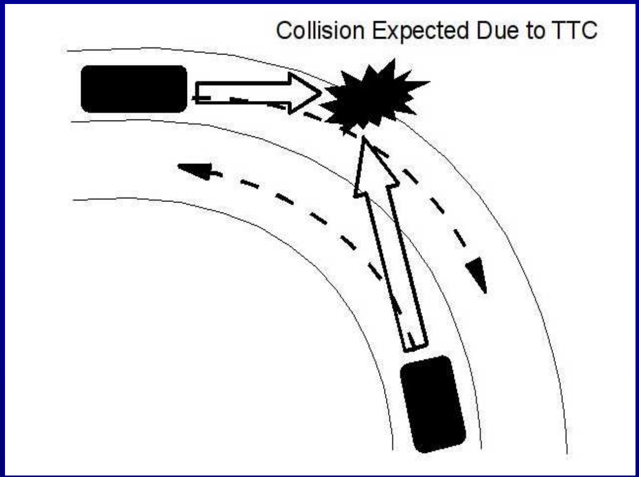
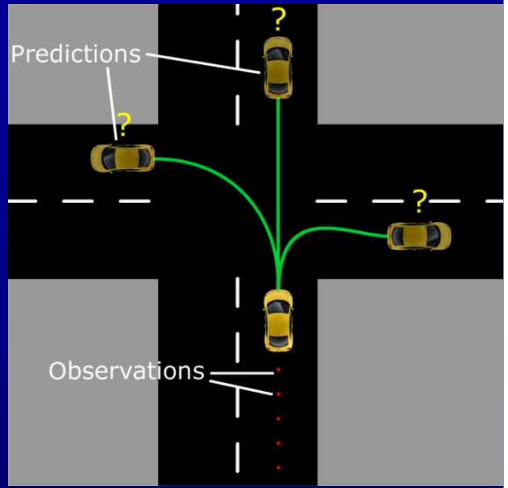
Prediction & Collision Risk Assessment



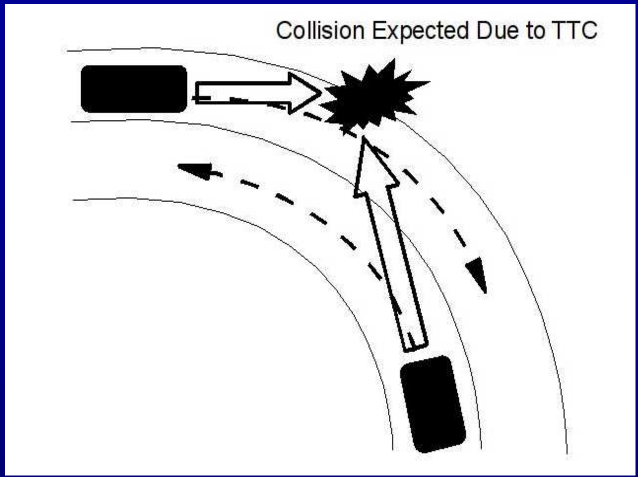


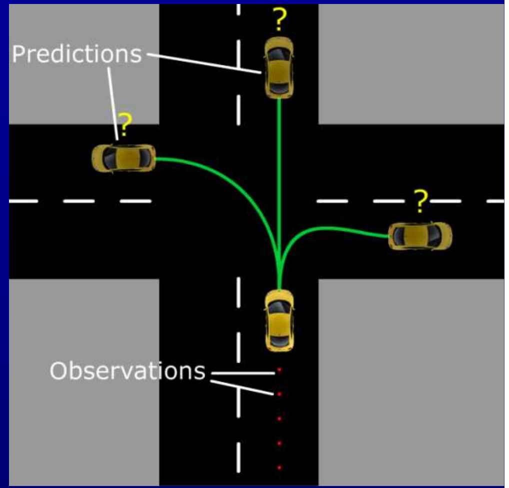
• Existing TTC-based crash warning assumes that motion is linear

• Knowing instantaneous Position & Velocity of obstacles is *not sufficient* for risk estimation !

• Consistent *Prediction & Risk Assessment* also require to reason about "Obstacles behaviors" *(e.g. turning, overtaking ...)* and "Road geometry" *(e.g. lanes, curves, intersections … using GIS)*

Step 1 – Modeling (Predicting) the Future





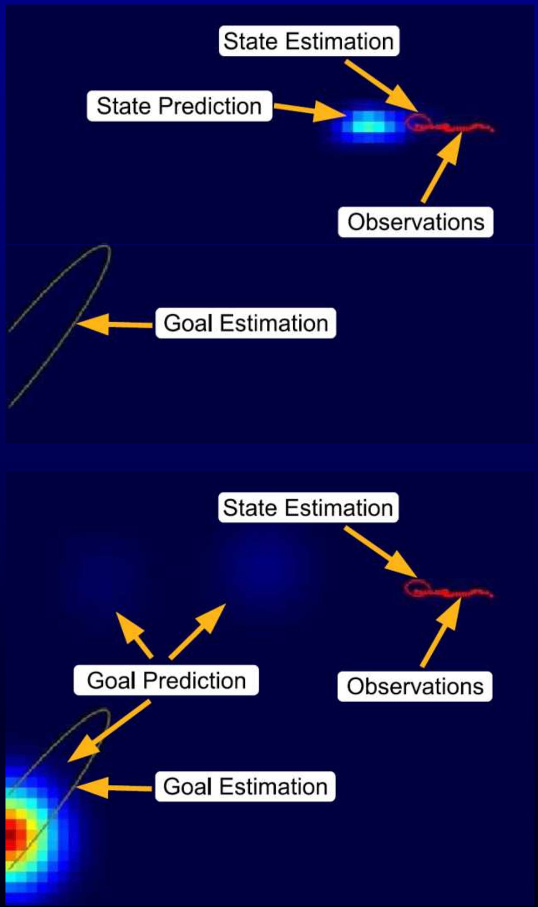
- Objects motions are driven by *"Intentions"* and *"Dynamic Behaviors"* *=> Goal + Motion model*

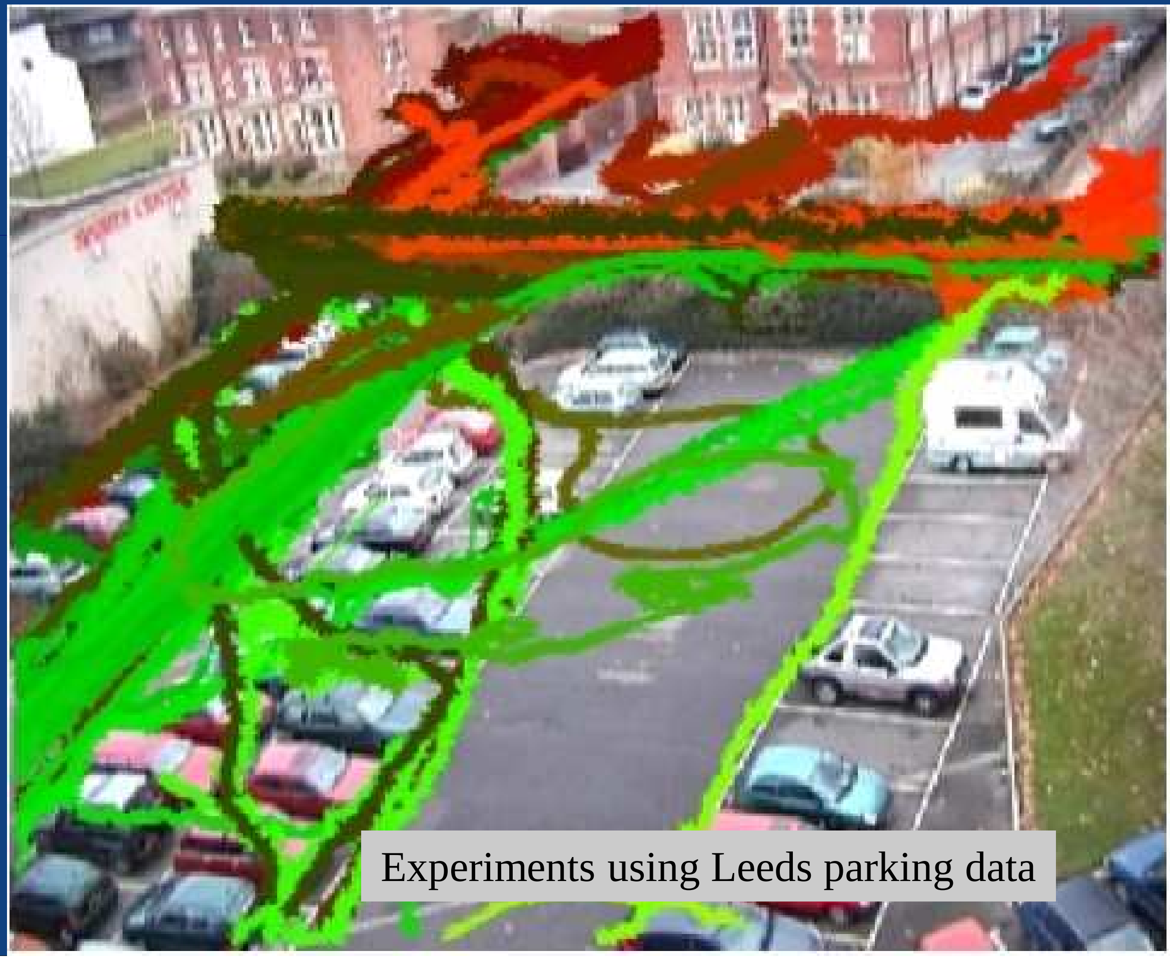
- Goal & Motion models are not known nor directly observable …. But *"Typical Behaviors & Motion Patterns"* can be learned through observations

Learn & Predict paradigm

[Vasquez & Laugier & Fraichard 06-09]

- *Observe & Learn "typical motions"*
- *Continuously "Learn & Predict"*
  - ✓ *Learn => GHMM & Topological maps (SON)*
  - ✓ *Predict => Exact inference, linear complexity*

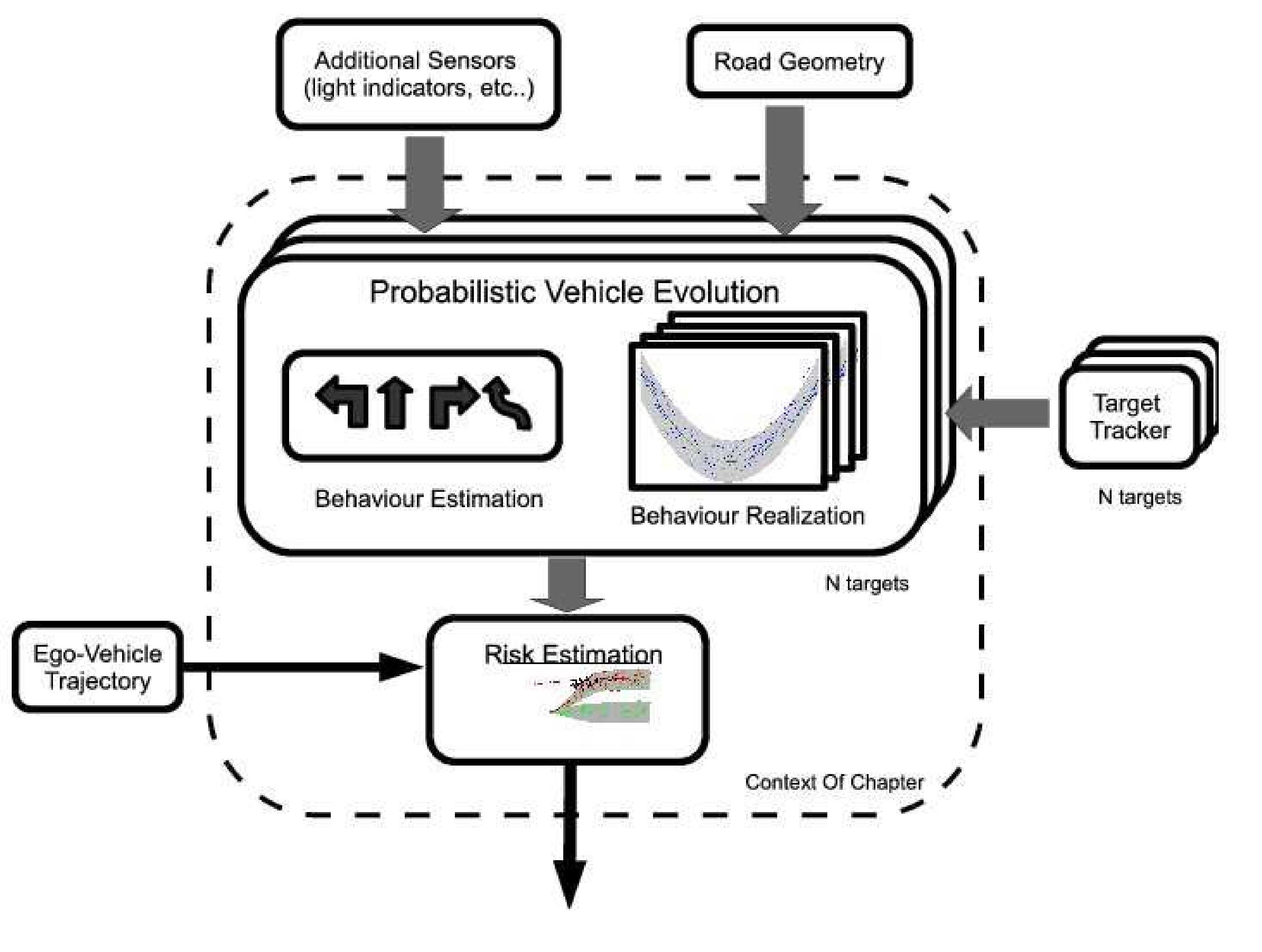




Experiments using Leeds parking data

Step 2 – Probabilistic Collision Risk

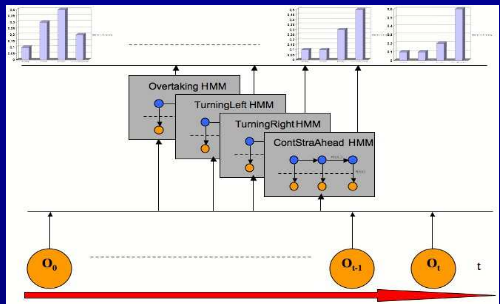
Patent Inria & Toyota 2009

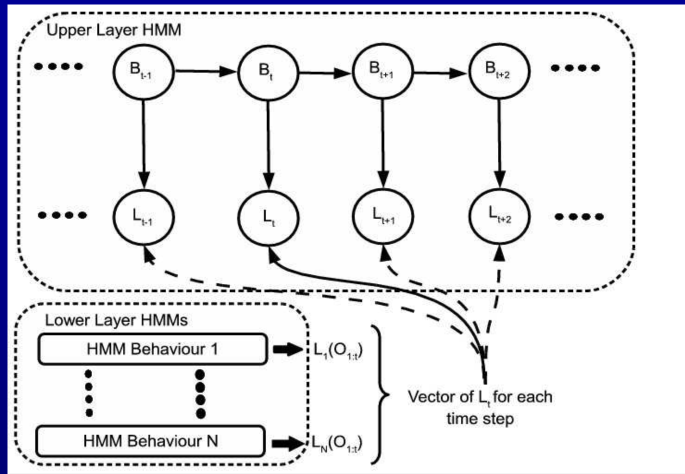


Probabilistic Collision Risk Assessment

[Tay & Laugier 08-09]

- **Behaviors :** *Hierarchical HMM (learned)*





e.g. Overtaking => Lane change, Accelerate …

Behavior Prediction

$$P(B_t|O_{1:t}) = L_{B_t}(O_{1:t}) \sum_{B_{t-1}} P(B_{t-1}) P(B_t|B_{t-1})$$

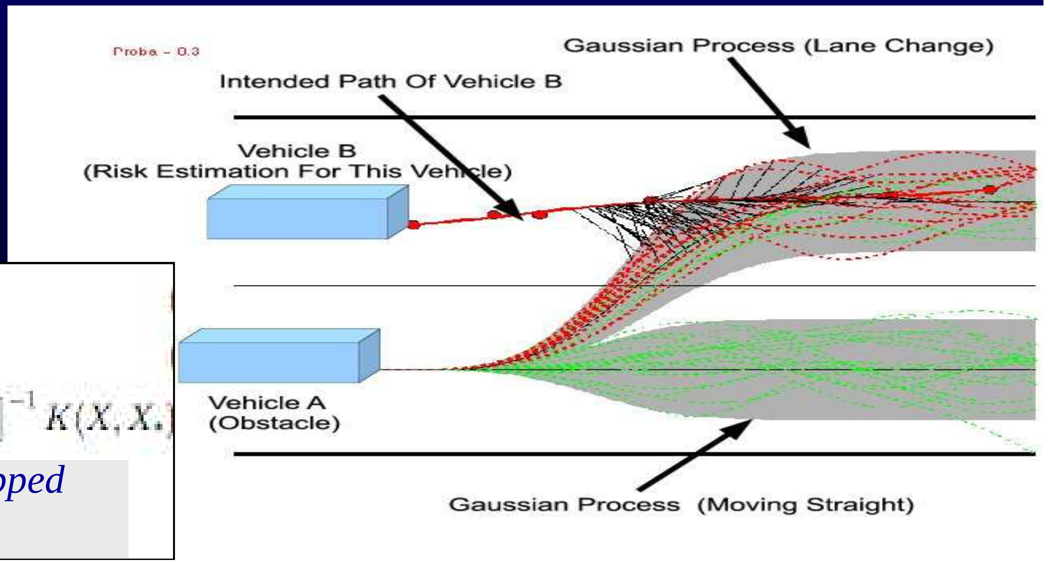
- **Motion Execution & Prediction :** *Gaussian Process*

$$\begin{aligned} f(x) &\sim \mathcal{GP}(m(x), k(x, x')) \\ m(x) &= E[f(x)] \\ k(x, x') &= E[(f(x) - m(x))(f(x') - m(x'))] \end{aligned}$$

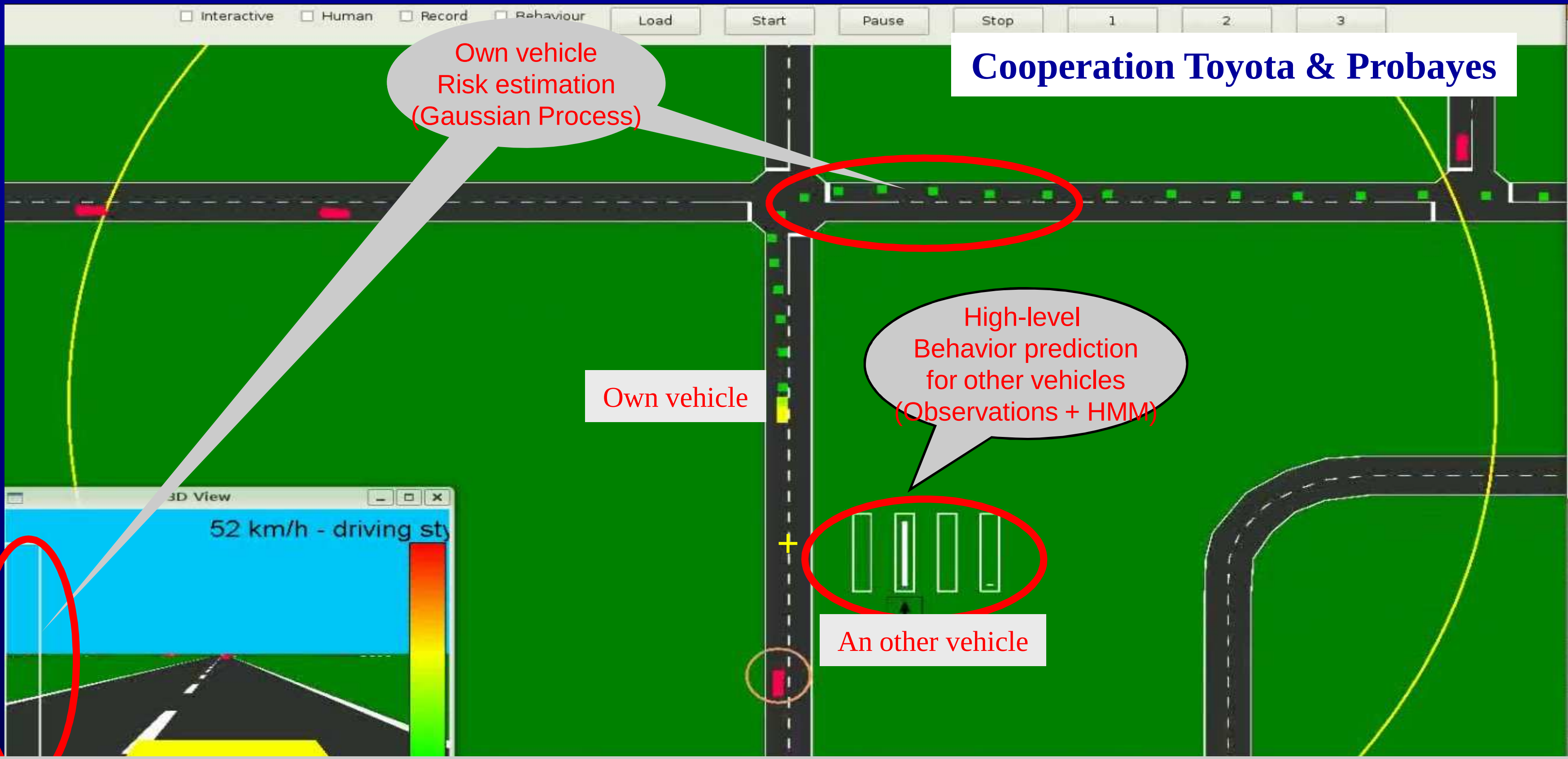
GP: *Gaussian distribution over functions*

$$\begin{aligned} P(Y_*|X_*, X, Y) &= \mathcal{GP}(\mu_{Y_*}, \Sigma_{Y_*}) \\ \mu_{Y_*} &= K(X_*, X)\left[K(X, X) + \sigma^2 \mathbf{I}\right]^{-1} Y \\ \Sigma_{Y_*} &= K(X_*, X_*) - K(X_*, X)\left[K(X, X) + \sigma^2 \mathbf{I}\right]^{-1} K(X, X_*) \end{aligned}$$

Prediction: *Probability distribution (GP) using mapped past n position observation*

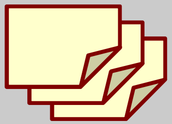


Experiments – Toyota Simulator & Driving Device



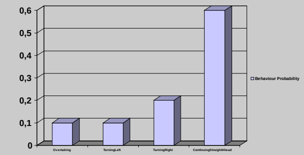
Behavior Prediction (HMM)

Observations +



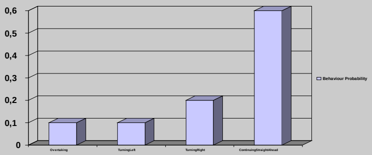
Behavior models

Prediction

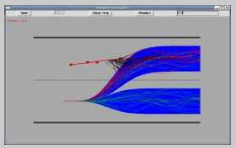


Behavior belief table

Risk Assessment (GP)

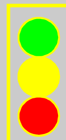


Behavior belief table for each vehicle in the scene +



Road geometry (GIS) + Own vehicle trajectory to evaluate

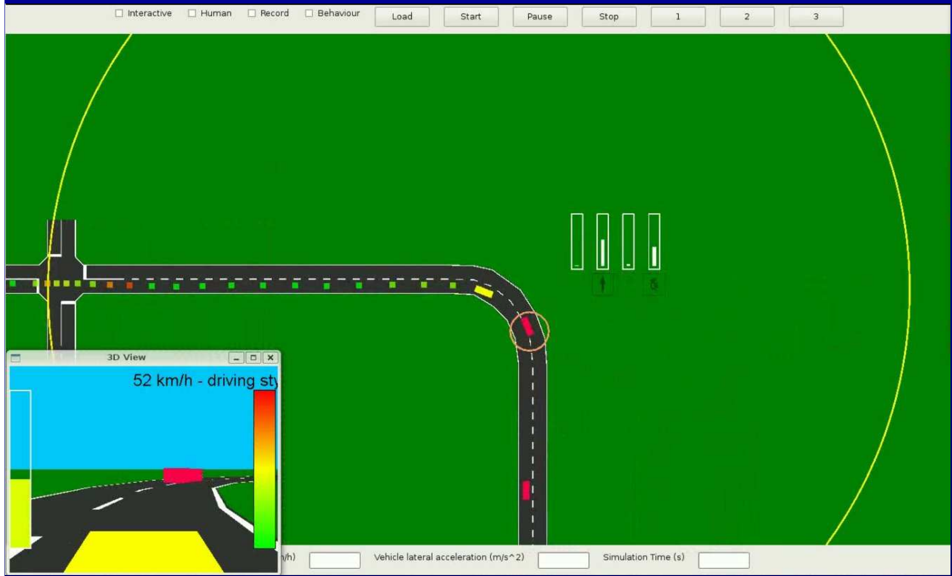
Evaluation

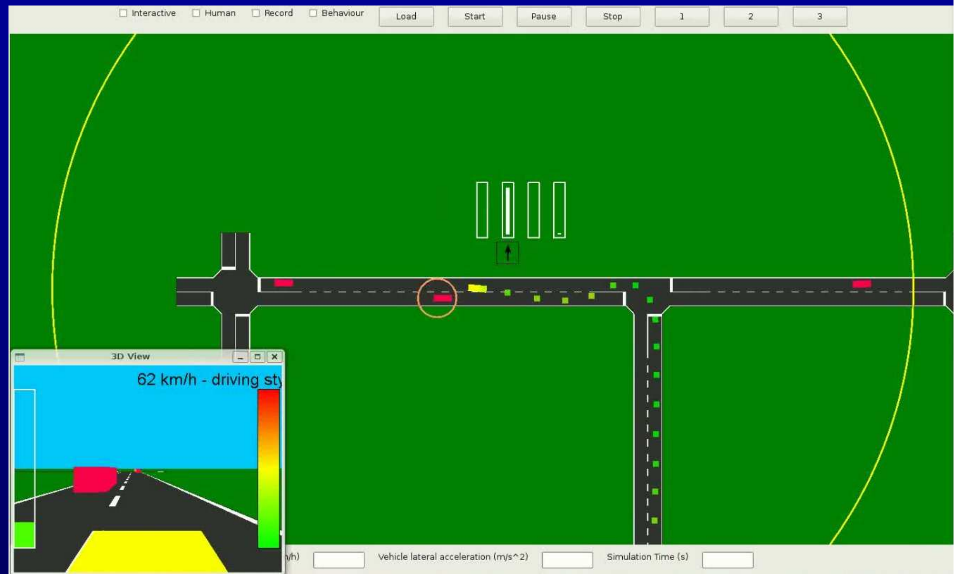


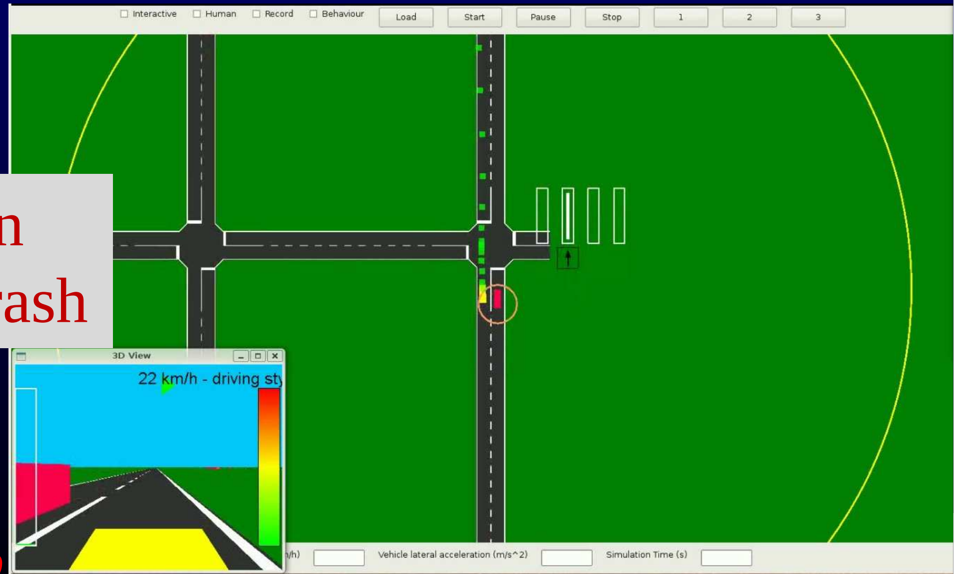
Collision probability for own vehicle

Simulation Results - Intersection

Good sensitivity to risks



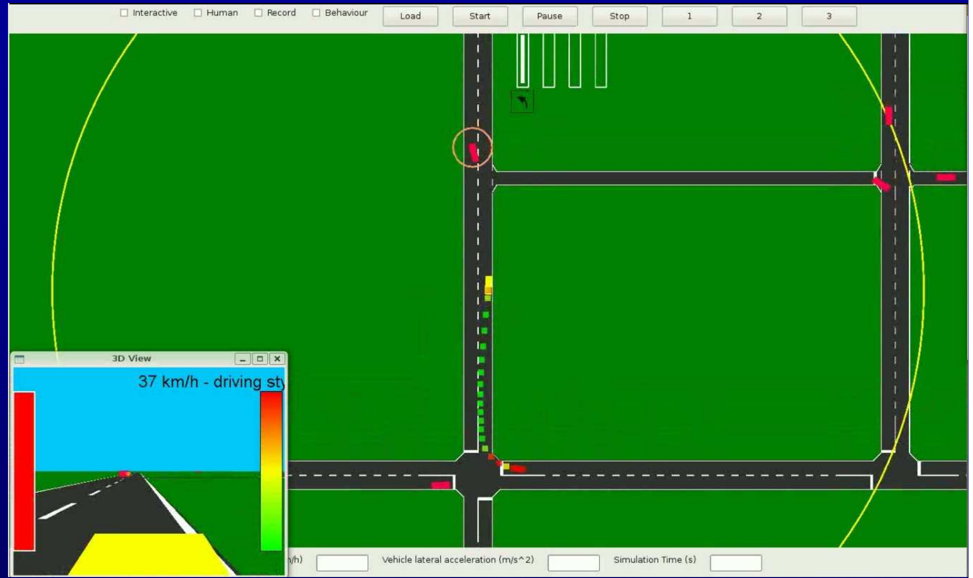


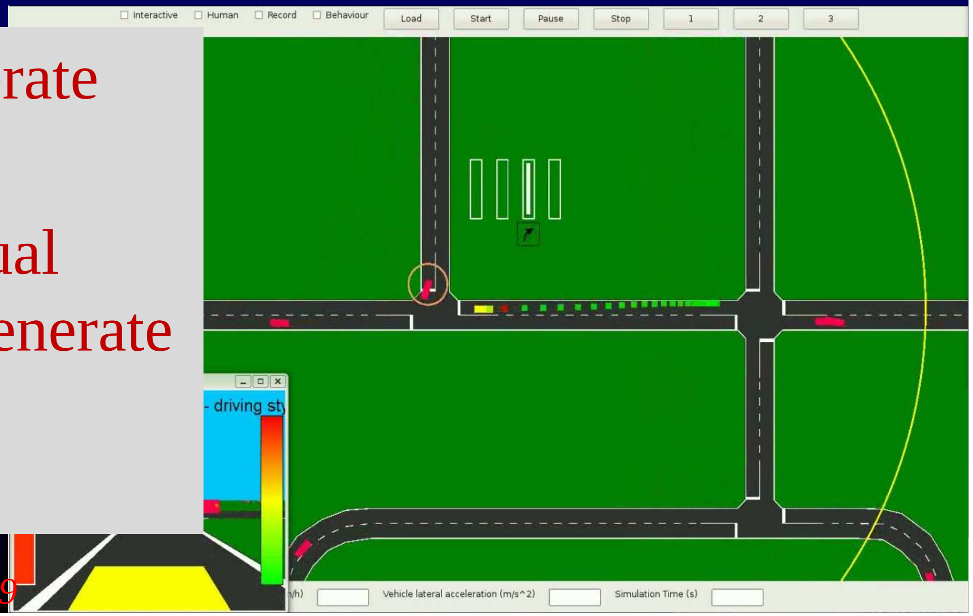


All collisions have previously been predicted 2 - 3 seconds before the crash

Simulation Results - Intersection

No unnecessary risk panics in intersection





- Traditional approaches would generate false alerts in such situations
- Since it takes into account contextual information, our approach doesn't generate unnecessary risk panics

Structure of the talk

1. **Introduction & Challenges**
2. **Perceiving & Understanding the physical world**
3. **World change Prediction & Risk Assessment**
4. **Safe navigation decisions**
5. **Share Control & Human-Robot Interaction**

Safe Navigation Decisions in the Real World

On-line Predictive Motion Planning & Motion Safety

New constraints:

- ✓ *Upper-bounded decision time*
- ✓ *System's dynamics*
- ✓ *Moving Objects' future behavior*
- ✓ *Look-ahead*
- ✓ *Uncertainty*

Positioning:

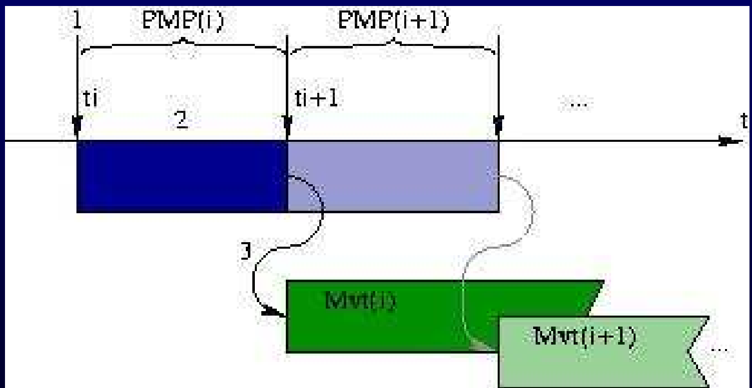
- ✓ *Few contributions in the literature*
- ✓ *Taking into account all the constraints coming from the Real World*
- ✓ *A new framework based on Iterative safe motion decisions*
- ✓ *Focus on motion Safety*

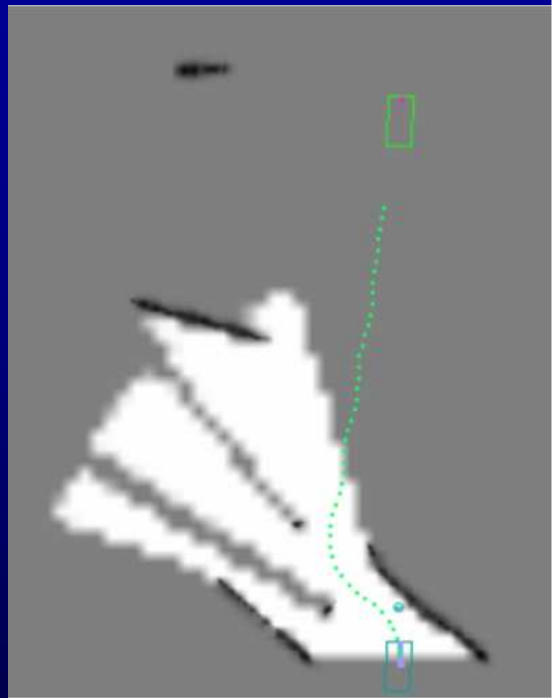
Safe Navigation Decisions in the Real World
Partial Motion Planning Paradigm (PMP)

[Fraichard 04] [Petti 06]

Repeat until goal is reached

1. Get model of the future *(Observation & Prediction)*
2. Built tree of partial motions towards the goal
3. When time δ_c is over, Return *" Best partial motion " (e.g. closest & safest)*





Safe Navigation Decisions in the Real World

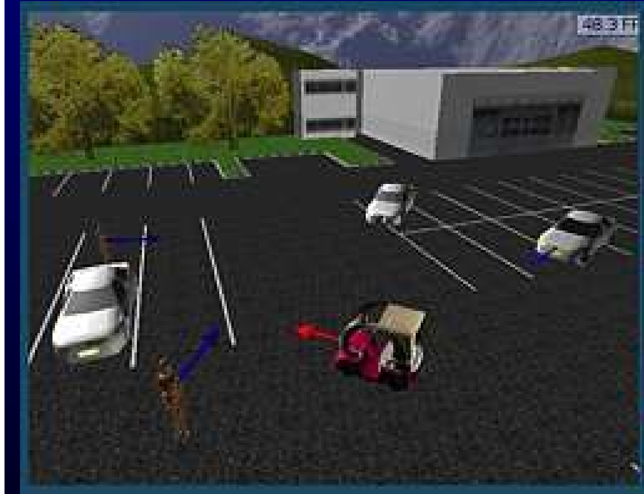
Avoiding Future Collisions

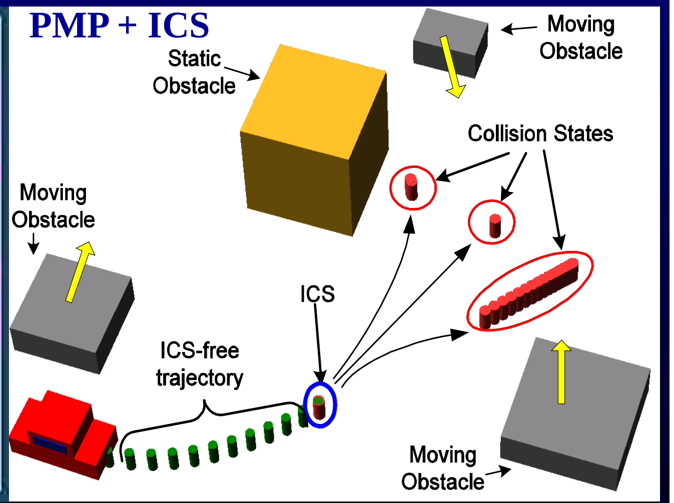
[Fraichard 04] [Martinez 08]

Concept of "Inevitable Collision States" (ICS)

✓ Avoiding instantaneous collision is not enough ! *We also have to avoid STATES leading to inevitable collisions in the near future*

✓ Doing nothing may also be dangerous ! *e.g. Stopping in the center of an intersection increase the collision risk*





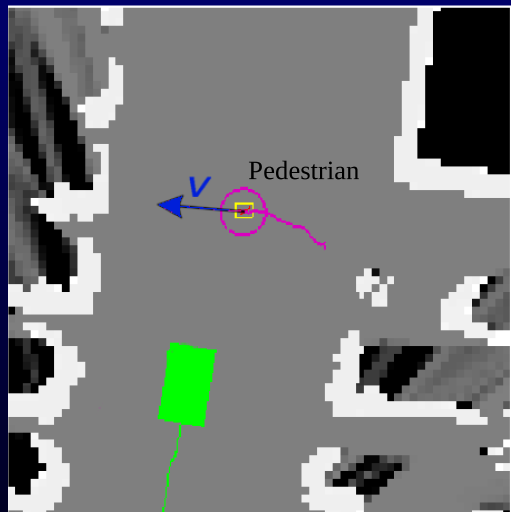
Safe Navigation Decisions in the Real World
Navigation Decisions & Probabilistic Collision Risk

[Fulgenzi & Laugier & Spalanzani 07-09]

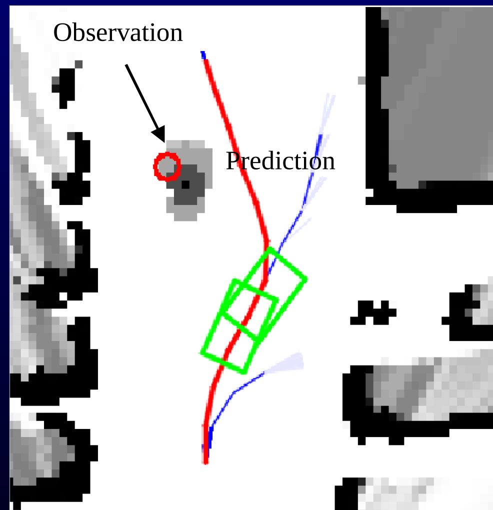
Probabilistic Collision Risk & Partial Motion Planning (PCR-PMP)

- ✓ *Integrate Obstacle Detection & Tracking in the Decisional Process*
- ✓ *Risk assessment based on Behavior Prediction (HMM & GP)*
- ✓ *Search function combining "Perception, PMP, and RRT" => Previously explored states are updated on-line using new Observations & Predictions*

Real scene Processing & Recording
(Detection & Tracking)



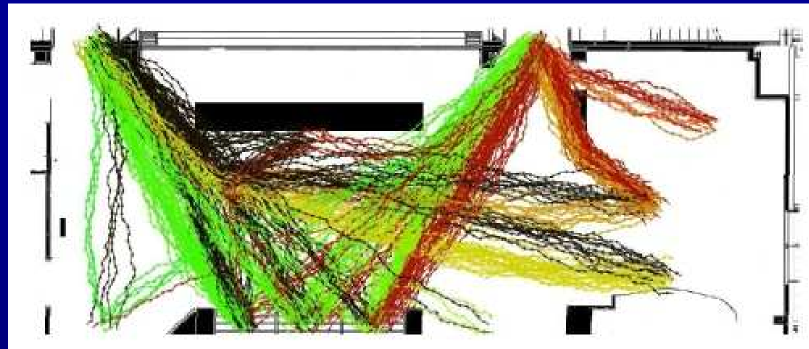
Reconstructed scene
(Simulator)

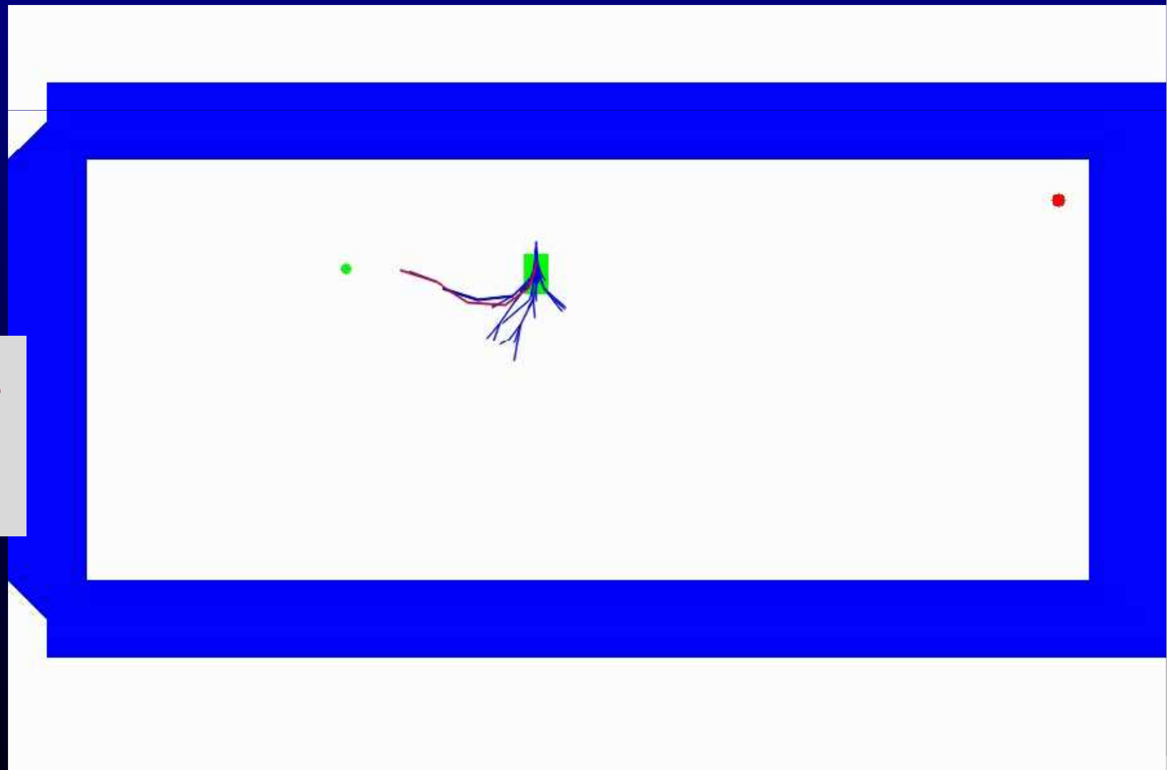


Prediction & MP & Navigation
(Simulator)

Safe Navigation Decisions in the Real World
Real data & Simulation results

[Fulgenzi & Laugier & Spalanzani 07-09]





- No collision when the robot is moving
- Some collision when the robot stop to move *(pedestrian generated collisions)*

Structure of the talk

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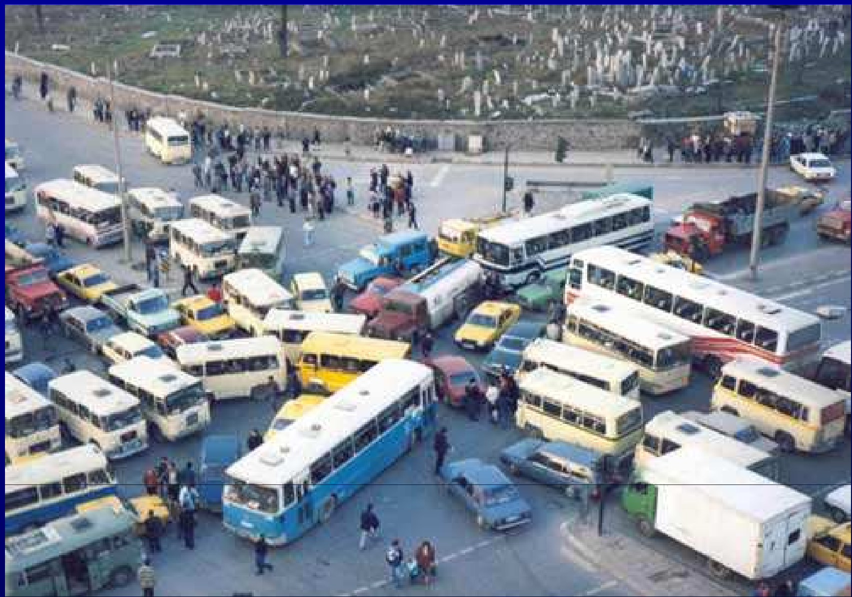
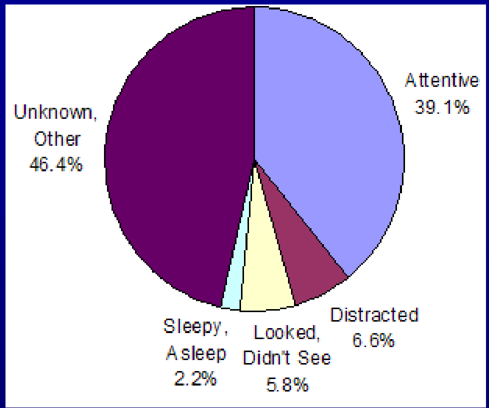
Share Control & Human-Robot Interactions



- *Human beings are unbeatable in taking decisions in complex situations*
- *Technology is better for "simple" but "fast" control decisions (ABS, ESP …)*
- ***Human driver is a potential danger for himself** (inattention, wrong reflexes ..) ! => Monitoring & Understanding Human Actions & Intentions is mandatory*

Human Driver Inattention

- **Driver inattention is a major cause of accident**



Distribution of
driver attention status

Distraction
(visual, auditory, cognitive …)

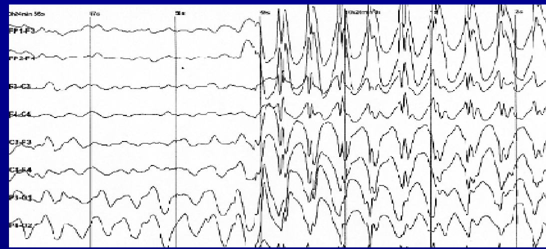
Fatigue
(physical, nervous, mental …)

When necessary, bring back the
Human Driver to the Attentive State !

Courtesy Zhencheng James HU
Kumamoto University

Monitoring Driver Actions & Intentions

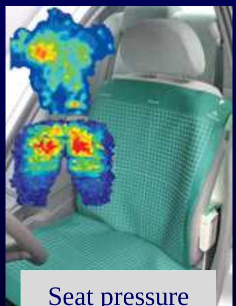
- **Detecting Driver Inattention** – *Biological signal processing*

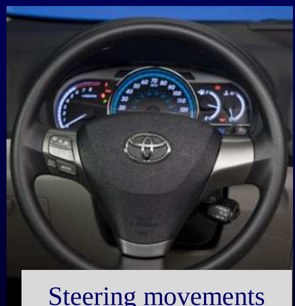


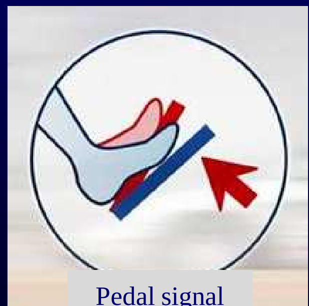
Example of EEG signal

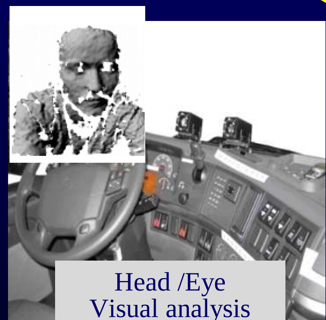
Clearly not appropriate for Car Driving !

- **Detecting Driver Inattention** – *Behavior signal processing*

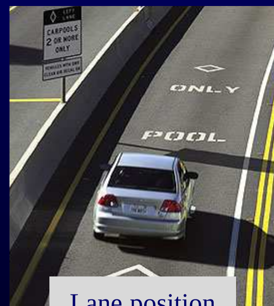


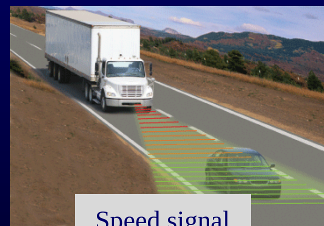






Driver Behavior Perception





Car Behavior Perception

Courtesy Zhencheng James HU, Kumamoto Univ

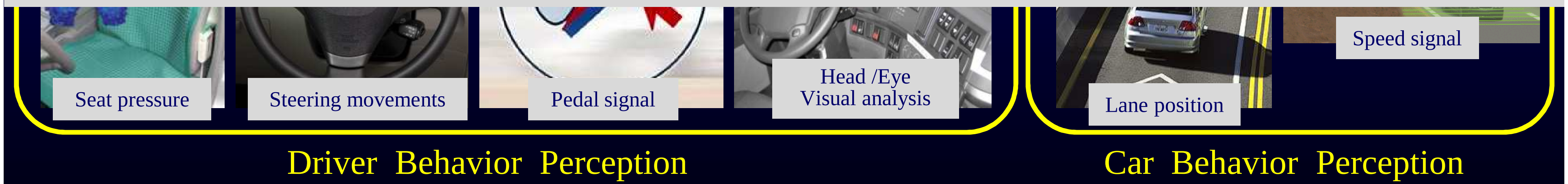
Monitoring Driver Actions & Intentions

Even if some pioneer commercial systems exist for Fatigue detection

(e.g. Zelinky's company in Australia)

…. This is still an open issue

- *Driver model*
- *Learning behaviors & skills*
- *Driver behavior assessment from multiple sensors*



Conclusion & Future Research Avenues

- **Robots in Human Environments** is a new challenge for both Robotics Systems and Future Applications *(service robots, aging society, automobile …)*
- **Dynamics, Uncertainty, Robustness, Efficiency and Safety** are major issues to be more deeply addressed
- **Probabilistic models** are clearly key tools for addressing these issues
- **Prediction & Risk Assessment** have also to be introduced at several levels of the Decisional process *for obvious Safety reasons.*

INRIA RHÔNE-ALPES

Conclusion & Future Research Avenues

Intelligent Vehicle issue

• Thanks to the recent progress in Robotics & ICT, Automobile & Transportation systems will drastically changes in the next 15-20 years *(Driving assistance, Autonomous driving capabilities, V2V & I2V communications, Green technologies …)*

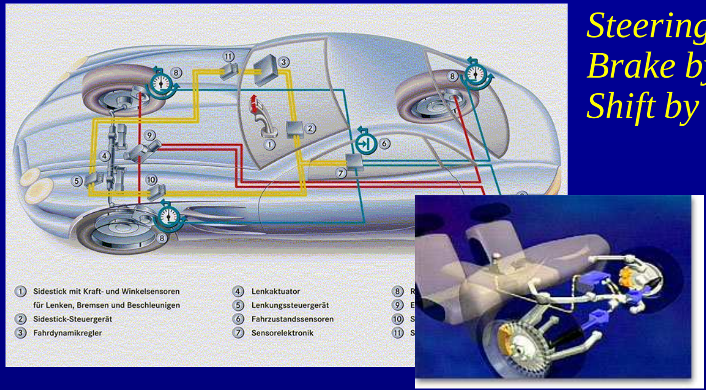
• **ICT-Car concept** is gradually becoming a reality … *But cooperative research is still needed for solving the above-mentioned problems (Robustness, Safety, Efficiency, Car-Driver interaction)*


Parking Assistant


Night Perception


Enhanced interface devices

Current & Future car equipments

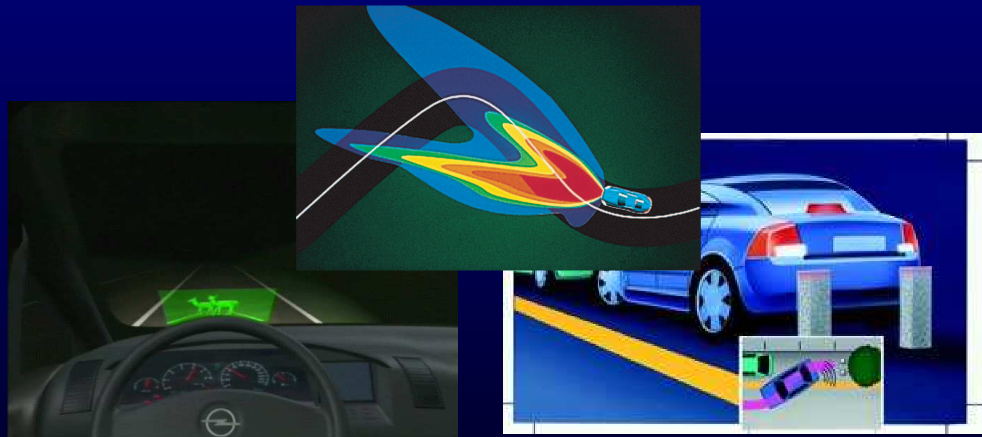


Steering by wire
Brake by wire
Shift by wire

Virtual dash-board
Modern "wheel"

Navigation system

Wireless Communication
Speech Recognition & Synthesis

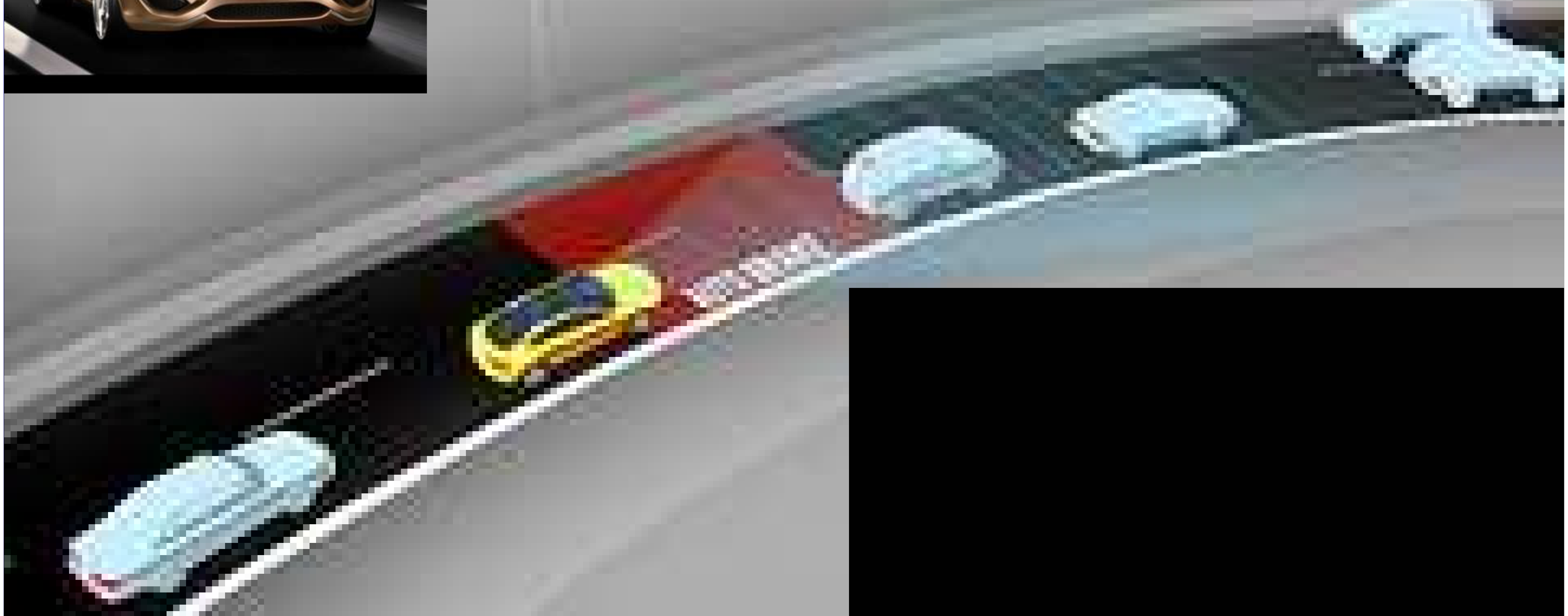


Radar, Cameras, Night Vision, Various sensors
…. Cost decreasing & Efficiency increasing (future mass production, SOC, embedded systems …) !!!!

New technology appearing on the market

Volvo Pedestrian collision avoidance system

- *In 2010, the Volvo S60 will be equipped with automatic braking system for avoiding collisions with pedestrians (below 25km/h)*
- *Pedestrian detection is realized by fusing Camera & Radar data*



Thank You !
Any questions ?

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