

# Human, Dynamic & Open Environments

## *A new challenge for Robotics*

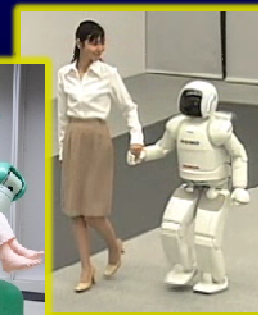
**Christian LAUGIER**

*Research Director at INRIA*

*Deputy Director of the LIG Laboratory (Grenoble France)*

*Keynote*

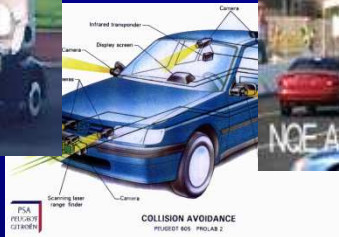
*FSR'09, Boston, July 2009*



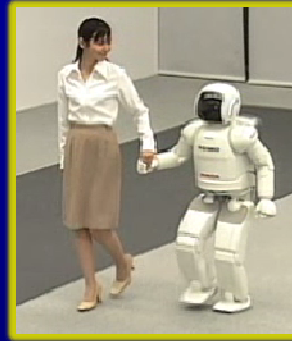
# Scientific challenge

## • 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*

# *New problems to be addressed*

*Introducing Robot in our daily lives brings new challenges to Robotics !*



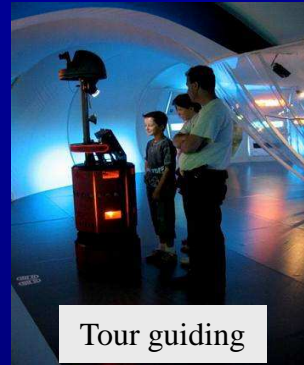
House Keeping



Personal Assistant



Care Taking



Tour guiding



Driving Assistance

## • **Robot & Human have to safely:**

- ✓ *Cooperate & Accomplish tasks together*
- ✓ *Communicate & Interact*
- ✓ *Co-exist*

**=> New concept : *Socially Acceptable Robot Motions & Behaviors***

**=> New environments : *Open & Dynamic & Uncertain***

# *Required technological breakthroughs*

- **Robust Perception & Understanding of Open, Dynamic, Uncertain (*ODU*) environments**



- **Motion Autonomy in *ODU* environments .... with a special emphasis on Safety issue**



- **Safe & Understandable Human-Robot interactions**





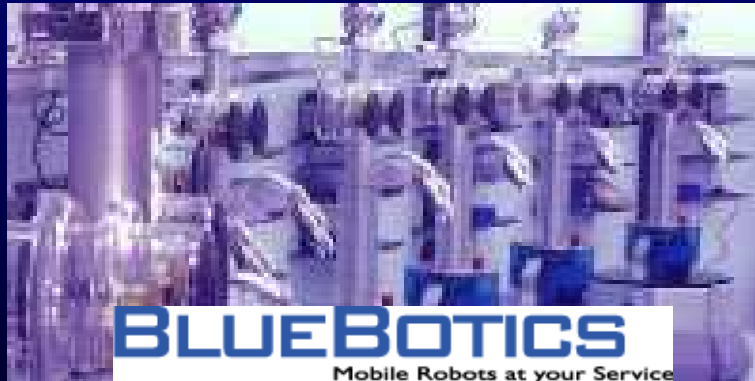
# *Some previous large experiments (1)*

## *Tour-guide robots (Swiss National Exhibition Expo.02)*

*BlueBotics SA & Autonomous Systems Lab*



- 4 Months, Daily operation, Up to 12h/day, Up to 11 robots simultaneously*
- 13 300 hours Operation time, 3 300 km Traveled distance, 680 000 Visitors*



# *Some previous large experiments (2)*

## *CyberCars Public Experiments (INRIA & EU Partners)*



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



*Shanghai Public Demo (2007)*

*Floriade 2022 (Amsterdam)*

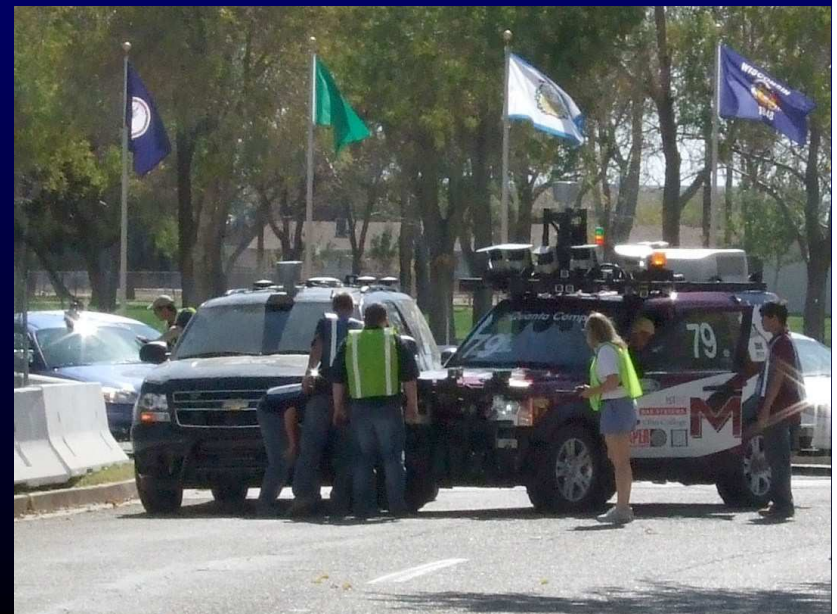
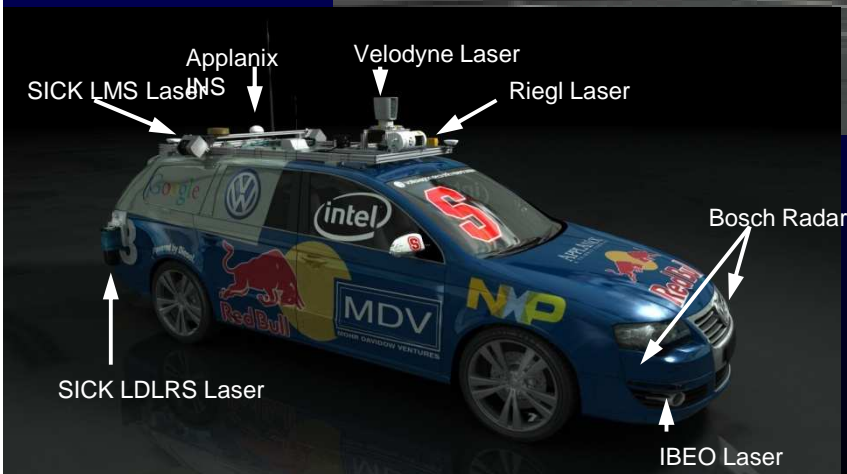


# Some previous large experiments (3)

## Urban Challenge 2007



- 96 km through an urban 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



# *Open research issues*

- **Human environment is still an open research issue for Robotics**

- ✓ *Large experiments in some human environments is a necessary step*

- ✓ *However, major issues such as “Robustness to uncertainty” and “Safety” have to be more deeply addressed*

- **Main problems to solve**

- ✓ *World & Task complexity => Scalability*

- ✓ *Reactivity & Real-time constraints => Efficiency*

- ✓ *Incompleteness & Uncertainty => Reasoning about uncertainty*

- ✓ *Human in the loop => Human factor in the decisional process & Safety*



# *General Approach*

- Revisit traditional approaches not fully adapted to the processing of *Human environments*
- Design new models & algorithms adapted to *Complex & Highly dynamic & Partly known environments*
- Focus on *Robustness & Efficiency & Safety*
- Uncertainty has to be placed at the heart of the Decisional Process. *Probabilistic models* should probably be seen as key tools.

# Key related problems for Motion Autonomy

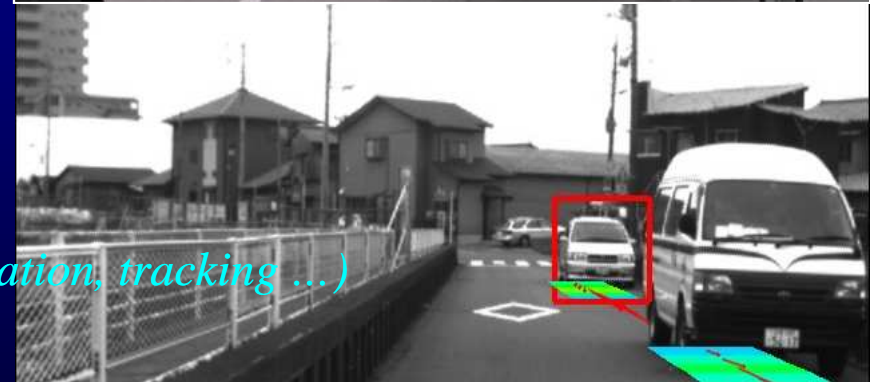
*Moving safely amidst Stationary & Moving obstacles (vehicles, pedestrians ...)  
in Open & Dynamic & Uncertain environments*

- **Continuously changing environment**

- ✓ *Continuous world modeling using sensors*
- ✓ *Space & Time have to be considered*
- ✓ *Real-time processing is required*

- **Sensed Stationary & Moving obstacles**

- ✓ *SLAM + DATMO*
- ✓ *Uncertainty is a key issue (perception, localization, tracking ...)*



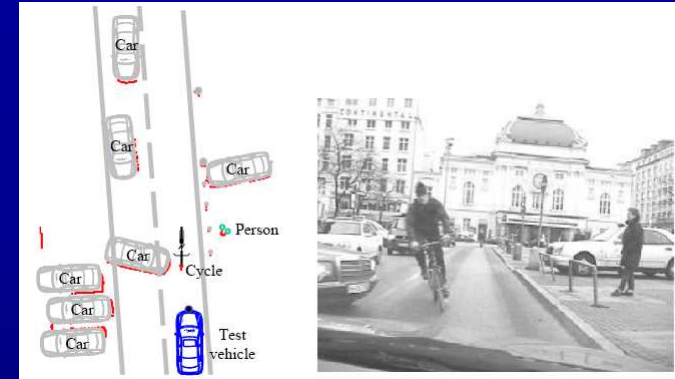
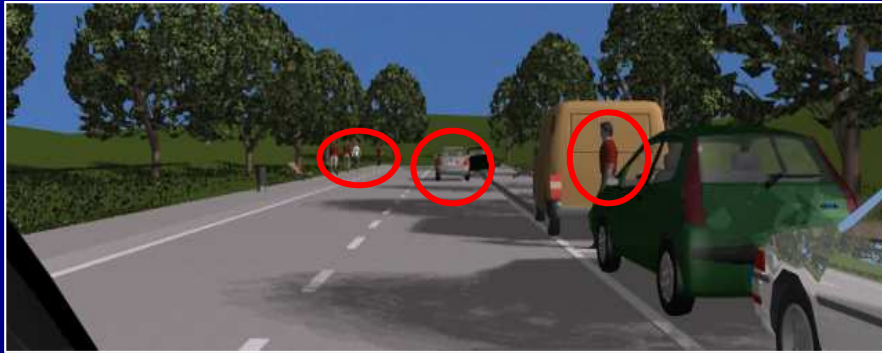
- **Uncertain & Dynamic environments**

- ✓ *World changes PREDICTION is necessary*
- ✓ *RISK based navigation decisions (based on world states Estimation & Prediction)*

# *Main Robotics issues for Open & Dynamic & Uncertain environments*

- 1. Robust detection & tracking**
- 2. Prediction & Risk assessment**
- 3. Safe goal-oriented navigation**
- 4. Human-~~Robot~~ interaction**

# Multi-Object Tracking: State-of-the-art (1)



## • Conventional approaches [Shalom88][Blackman99]

### Data Association

- 1-Scan :
  - ✓ Global Nearest Neighbor (GNN)
  - ✓ Joint Probabilistic Data Association (JPDA)
- N-Scan : Multiple Hypothesis Tracking (MHT)

### Filtering (object dynamic estimation)

- A single dynamic model :
  - ✓ Kalman Filter (KF or EKF)
  - ✓ Particle Filter (PF)
- N models: Interacting Multiple Model (IMM)

## • Tracking “point” objects (clusters)

- ✓ JPDA + PF => Tracking people, indoor [Schulz et al. 01]
- ✓ MHT+IMM => General objects, urban traffics [Wang04] [Burlet 07]

=> More robust ... but well-known problems with laser-based tracking still hold !  
(objects splitting, Appearing & disappearing targets ...)



# Multi-Object Tracking: State-of-the-art (2)

- **Model-based approaches**

- **Vision** => *More info for detection & classification, Less accurate distance for tracking*

- ✓ MCMC (1-Scan) + KF => Vehicles [Song & Nevatia. 2005]

- ✓ MCMC (1-Scan) + KF => People [Zhao & Nevatia 2008]

- ✓ MHT + EKF (stereo vision) => People [Ess et al 2008]

- **Laser** => *Less informative, Accurate distance, More robust to environment conditions*

- ✓ GNN + PF (Flexible models) => Vehicles [Petrovskya & Thrun 08]

- ✓ GNN + EKF (fixed models) => Vehicles [Urmson et al. 08]

- ✓ MCMC (N-Scan) + IMM (fixed models) => Vehicles & Peds [Vu & Aycard 09]

- **Current work: Improving robustness using Sensor Fusion**

- ✓ Some promising results for pedestrians detection using *Vision & Laser* [Broggi 07]

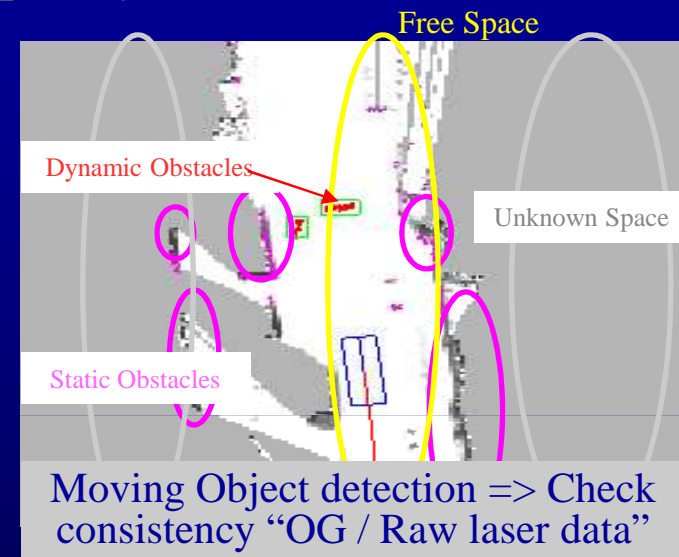
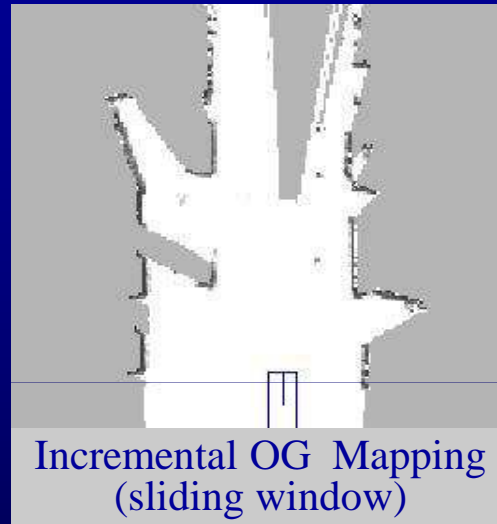
- ✓ An efficient tools Bayesian Occupancy Filter [Coue & Laugier 05]

# Laser-based Multi-Objects Detection & Tracking

“PreVent” EU project

[Burlet, Vu, Aycard 07-08]

## • Grid-based Obstacles Detection (using Occupancy Grids)



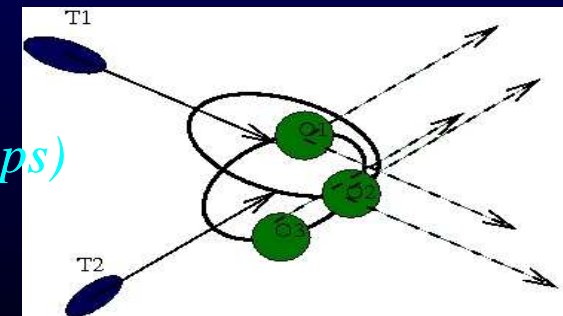
## • Multi-Objects Tracking

✓ 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 DATMO – Previous Results

“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

Multiple Hypothesis Tracking of Moving Objects  
using Grid-based Fusion

Julien Buret, Trung-Dung Vu, Olivier Aycard  
LIG & INRIA Rhône Alpes, France

Contact: [Olivier.Aycard@inrialpes.fr](mailto:Olivier.Aycard@inrialpes.fr)


## Application:

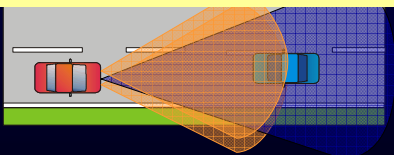
- Pre-fire  & Braking

## Sensors:

- Two short range radars
- A laser scanner ALASCA

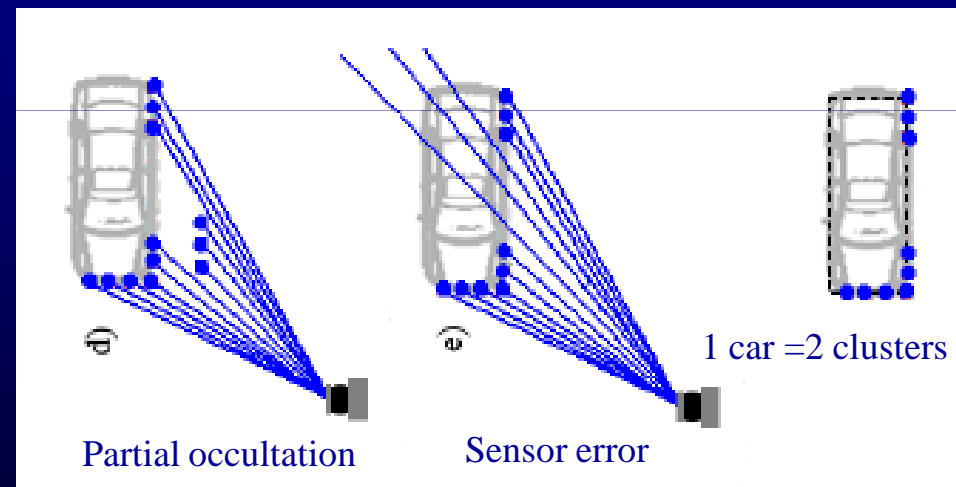
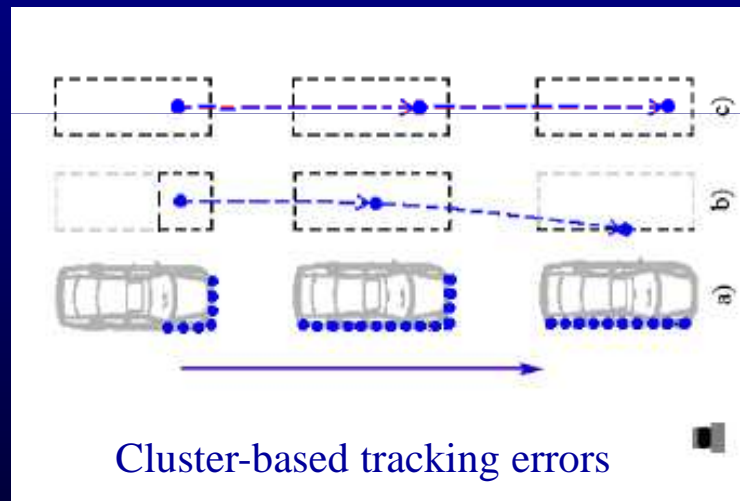
## Actuators:

- Electrical belt pre-tensioning 
- Automatic braking



# DATMO – Known problems using laser scanner

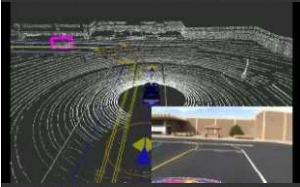
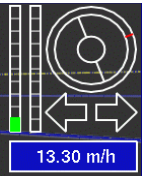
- Objects are represented by clusters of points
- Tracking clusters leads to a degradation of tracking results
- Object splitting (occlusions, glass-surfaces) makes the tracking harder



*=> Using geometric object models can help for overcoming these problems*

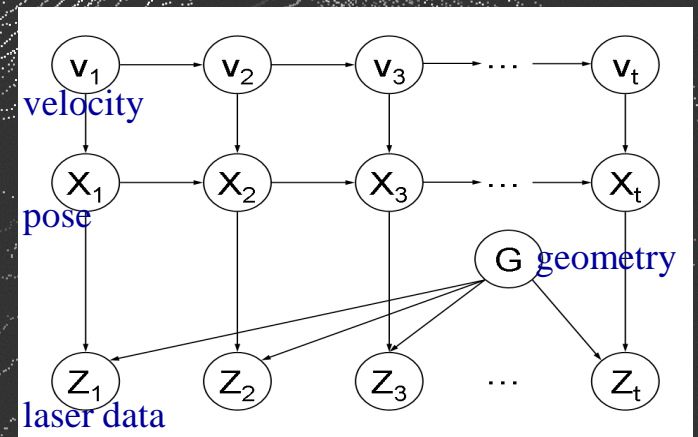
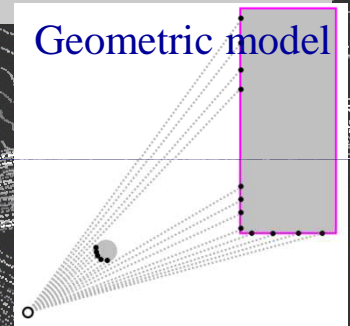
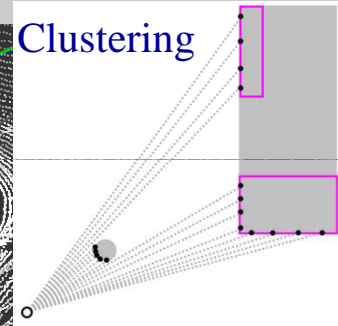


# Stanford Model-based approach



- Segment data
  - Associate data: MHT
  - Update filter: EKF
- ⇒ Bayes filter: RBPF (1 Scan)
- Model: ⇒ { dynamics, geometry }
- dynamics

Robot Junior (Stanford)



PLANNER: Switched to FORWARD\_DRIVE  
 PLANNER: OK to merge  
 PLANNER: Waiting to merge

# INRIA T-Scans Model-based Approach

Data-Driven Markov-Chain Monte-Carlo [VU & Aycard 09]

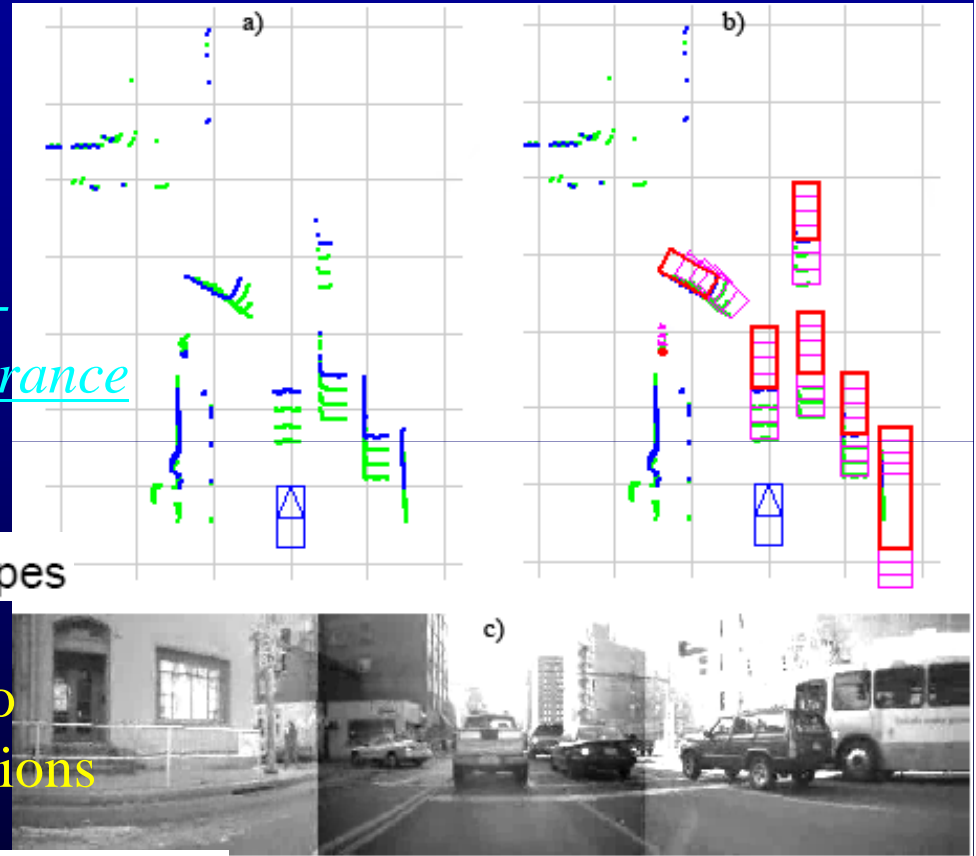
- Sliding window over  $T$ -scans (*Time Horizon*)  $Z = \{Z_1, \dots, Z_T\}$
- Find the best explanation of object trajectories (tracks) based on *Spatio-Temporal consistency in both appearance (model) & motion*

- Model Based:  $\tau_k$  is a sequence of shapes

- Sampling-based method (MCMC) to avoid enumerating all possible solutions

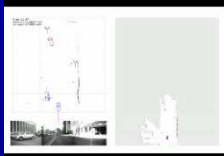
$$\omega^* = \operatorname{argmax}_{\omega} P(\omega|Z)$$

$$\omega = \{\tau_1, \tau_2, \dots, \tau_K\}$$



**=> Simultaneous Detection, Classification and Tracking**

# DDMCMC – Models & Hypotheses processing



Results Navlab

## Bus, Truck, Car, Bike

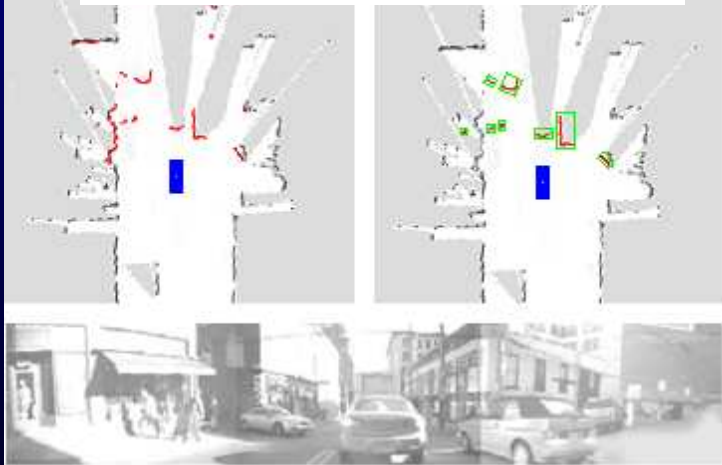
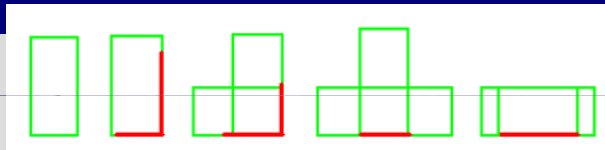
- Box model (fixed size)
- Dynamic model ( $v, a, \text{turn}, \text{stop}$ )

$$\vec{x} = (x, y, w_c, l_c, v, a, \theta, \dot{\theta})^T$$

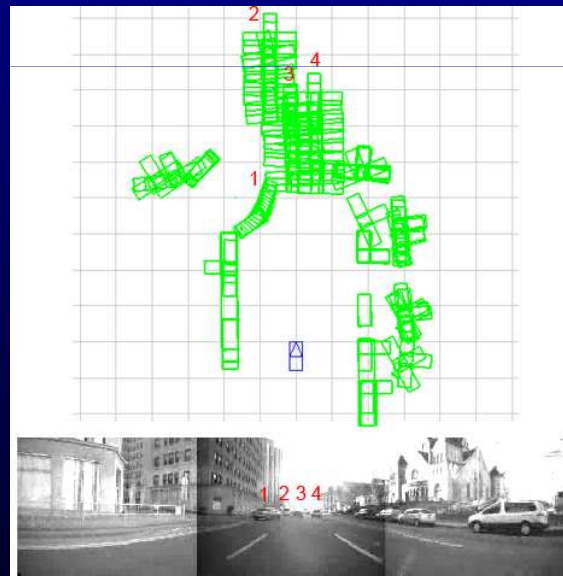
## Pedestrian

- Point model
- Dynamic model ( $v$ )

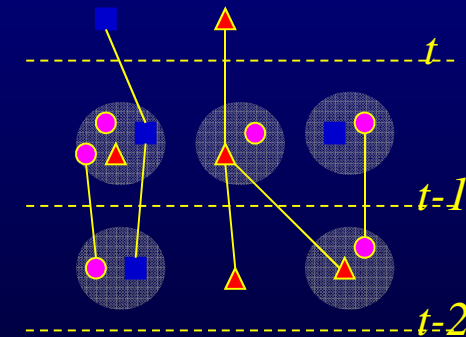
$$\vec{x} = (x, y, v_x, v_y)^T$$



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



Search of  $P(\omega | Z)$  over space of moving object hypotheses



Neighborhood graph of hypotheses







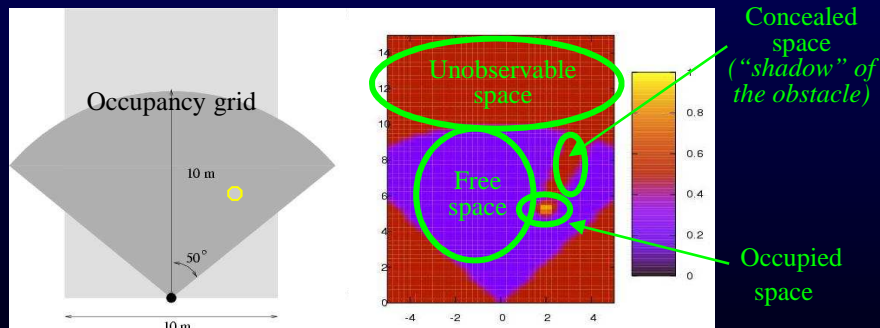
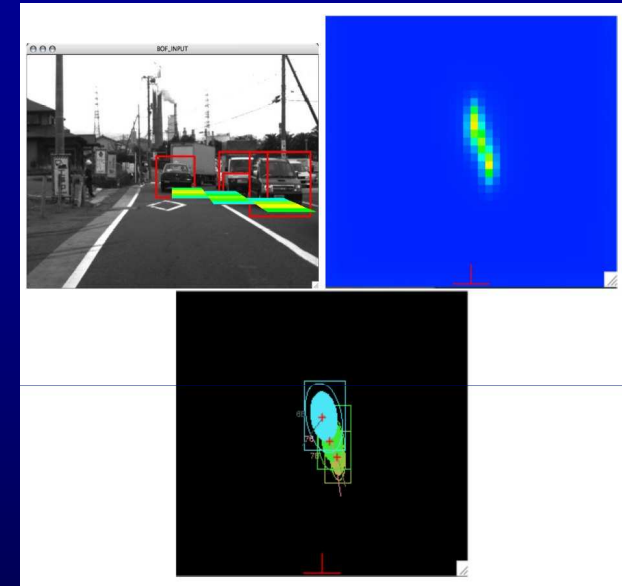
# Bayesian Sensor Fusion for “Dynamic Perception”

## “Bayesian Occupation Filter paradigm (BOF)”

Patented by INRIA & Probayes, Commercialized by Probayes

### BOF

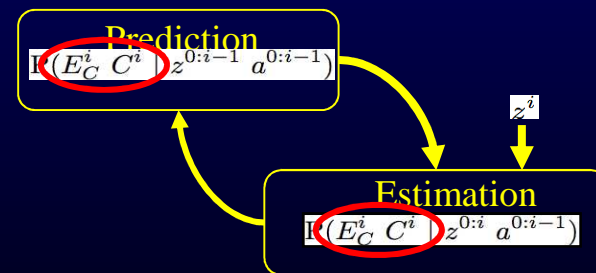
- Continuous Dynamic environment modelling
  - Grid approach based on Bayesian Filtering
  - Estimates *Probability of Occupation* & *Velocity* of each cell in a 4D-grid
  - Application to *Obstacle Detection & Tracking* + *Dynamic Scene Interpretation*
- => *More robust to Sensing Errors & Temporary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



Sensed moving obstacle

$$P([O_c=occ] | z^c)$$

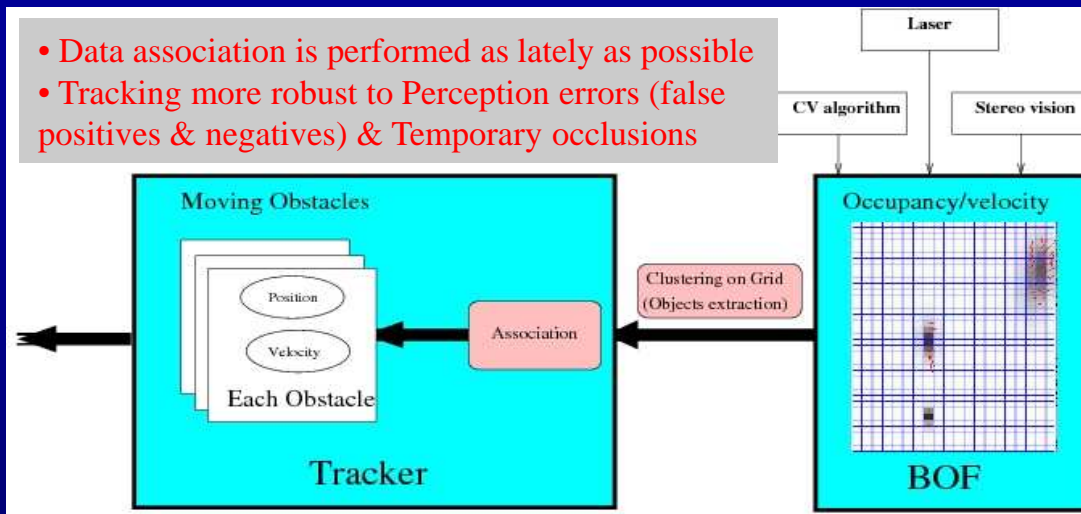
$$c = [x, y, \theta, 0] \text{ and } z=(5, 2, 0, 0)$$



[Coué & Laugier IJRR 05]

# Application to Fusion based Detection & Tracking

- Data association is performed as late as possible
- Tracking more robust to Perception errors (false positives & negatives) & Temporary occlusions



Successfully tested in real traffic conditions  
on industrial data (e.g. Toyota ...)



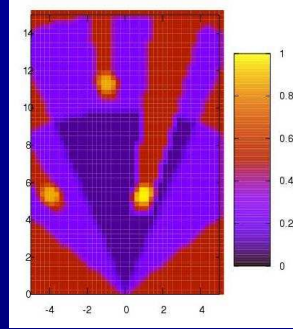
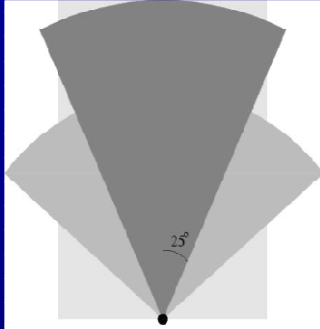
Denso Data Set

# Robustness to Temporary Occultation

Tracking + Conservative anticipation [Coué & al IJRR 05]

Autonomous Vehicle

Parked Vehicle (occultation)



Description

## Specification

- Variables :
  - $V^k, V^{k-1}$  : controlled velocities
  - $Z^{0:k}$  : sensor observations
  - $G^k$  : occupancy grid

$$P(Z^{0:k} V^k V^{k-1} G^k) = \left( \frac{P(Z^{0:k})P(V^k)}{P(G^k | Z^{0:k})P(V^k | V^{k-1} G^k)} \right)$$

- Parametric forms :
  - $P(G^k | Z^{0:k})$  : BOF estimation

Question

## Inference

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

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)

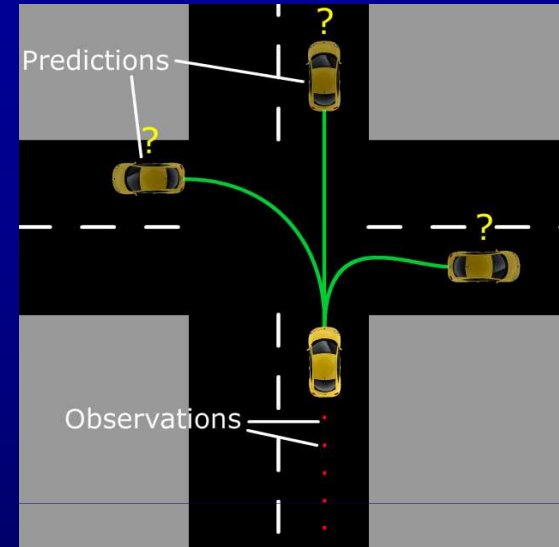
# *Main Robotics issues for Open & Dynamic & Uncertain environments*

1. Robust detection & tracking
2. Prediction & Risk assessment
3. Safe goal-oriented navigation
4. Human-~~Robot~~ interaction



# Modeling (Predicting) the Future (1)

[Vasquez & Laugier 06-08]

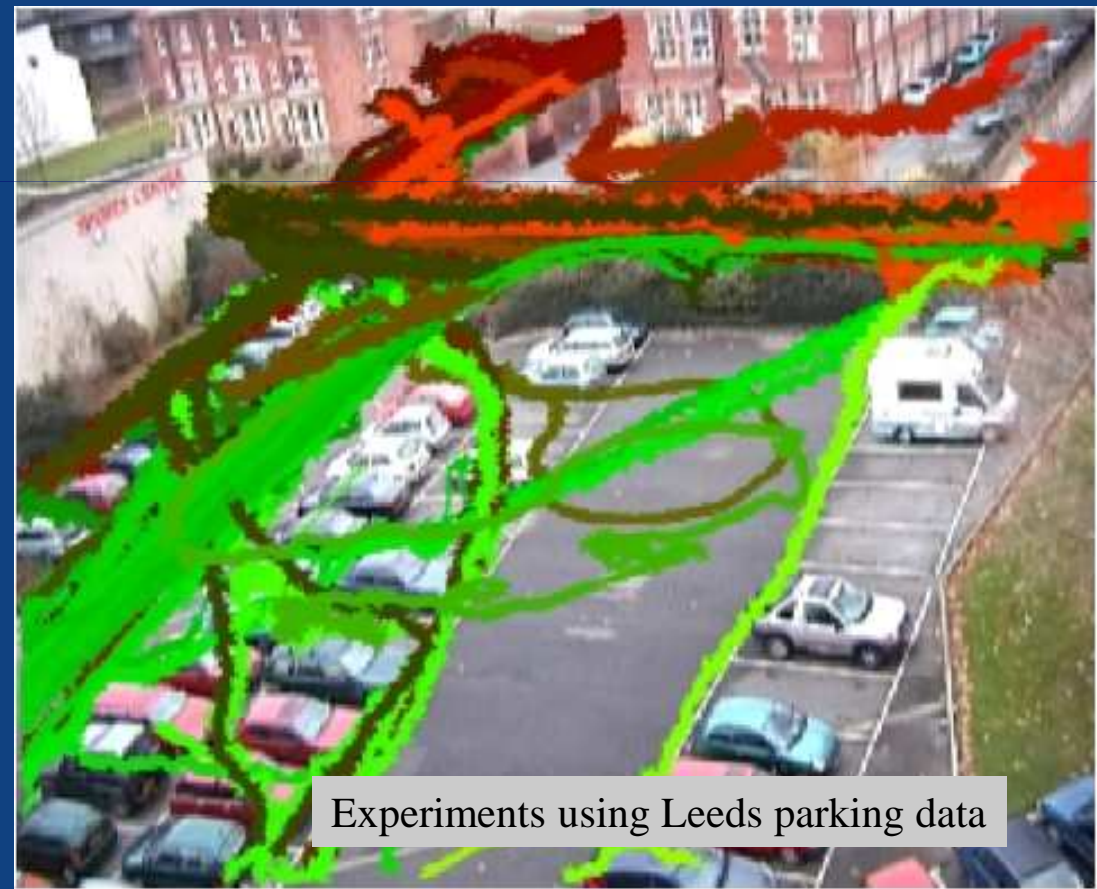
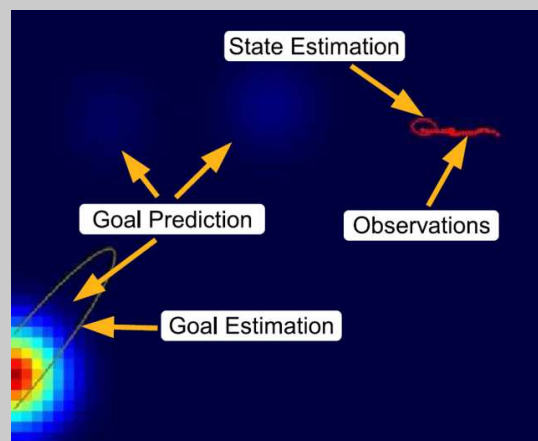
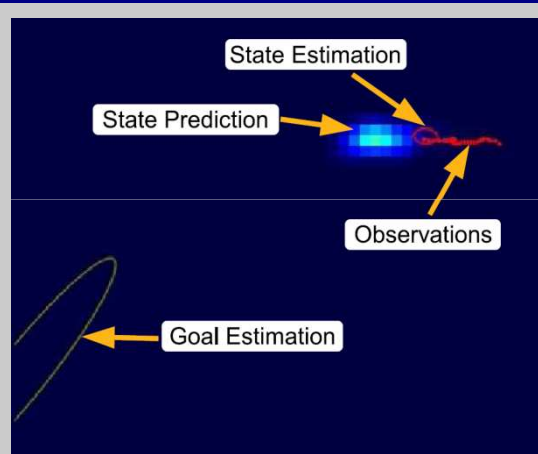


- Risk assessment requires to both *Estimate the current world state* & *Predict the most likely evolution of the dynamic environment*
- Objects motions are driven by “*Intentions*” and “*Dynamic Behaviors*” => *Goal + Motion model*
- Goal & Motion models are not known nor directly observable .... But “*Typical Behaviors & Motion Patterns*” can be learned through observations

# Modeling (Predicting) the Future (2)

Our Approach [Vasquez & Laugier & 06-09]

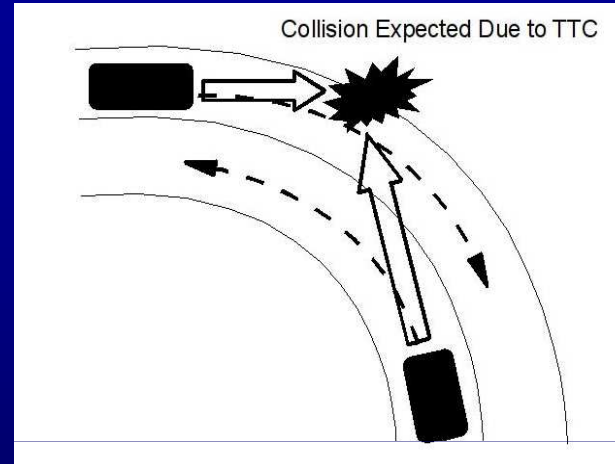
- Observe & Learn “typical motions”
- Continuous “Learn & Predict”
  - ✓ Learn => GHMM & Topological maps (SON)
  - ✓ Predict => Exact inference, linear complexity



# Collision Risk Assessment (1)

## Probabilistic Danger Assessment for Avoiding Future Collisions

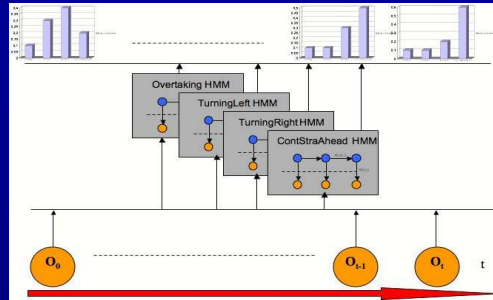
[Tay PhD thesis + Collaboration Toyota]



- Existing TTC-based crash warning assumes that motion is linear
- Simply knowing position & velocity of obstacles at each time instance is not sufficient for risk estimation
- A more accurate description of motion for PREDICTION by *Semantic (turning, overtaking ...)* and *Road Geometry (lanes, curves, intersections ...)* is necessary !!!!

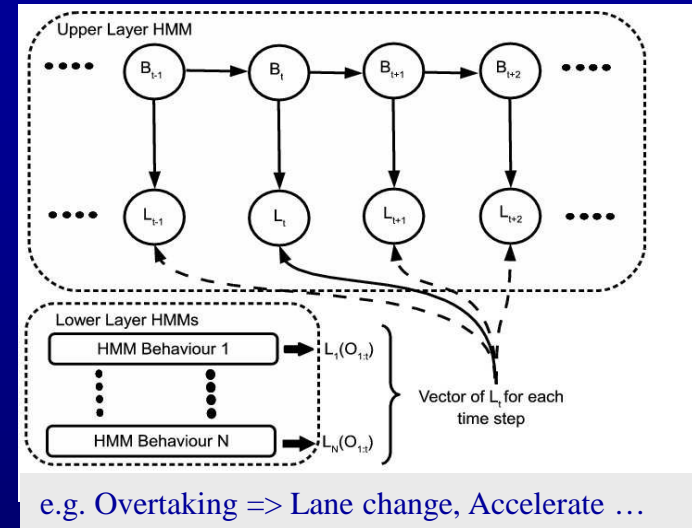
# Collision Risk Assessment (2)

- Behaviors : Hierarchical HMM (learned)**



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**

$$f(x) \sim \mathcal{GP}(m(x), k(x, x'))$$

$$m(x) = E[f(x)]$$

$$k(x, x') = E[(f(x) - m(x))(f(x') - m(x'))]$$

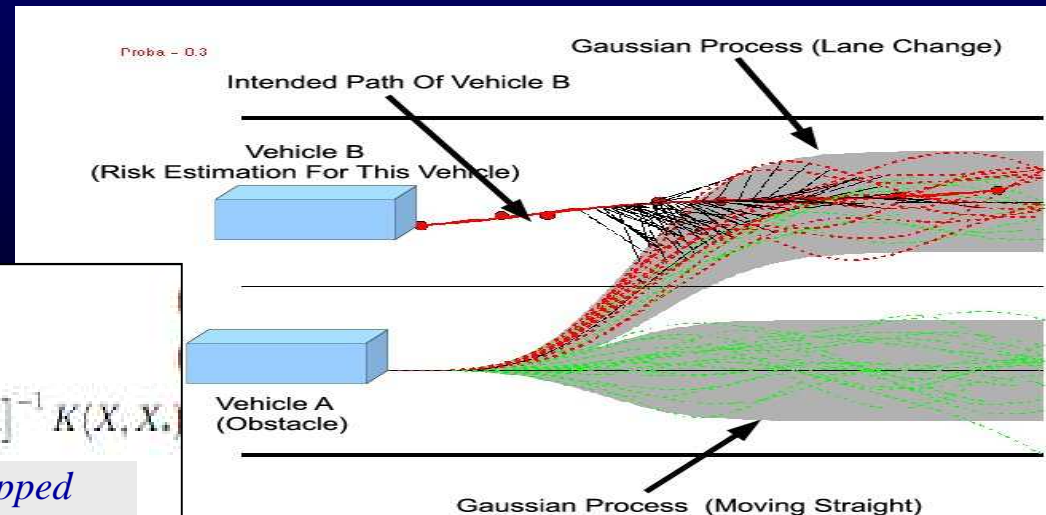
GP: Gaussian distribution over functions

$$P(Y_* | X_*, X, Y) = \mathcal{GP}(\mu_{Y_*}, \Sigma_{Y_*})$$

$$\mu_{Y_*} = K(X_*, X) [K(X, X) + \sigma^2 \mathbf{I}]^{-1} Y$$

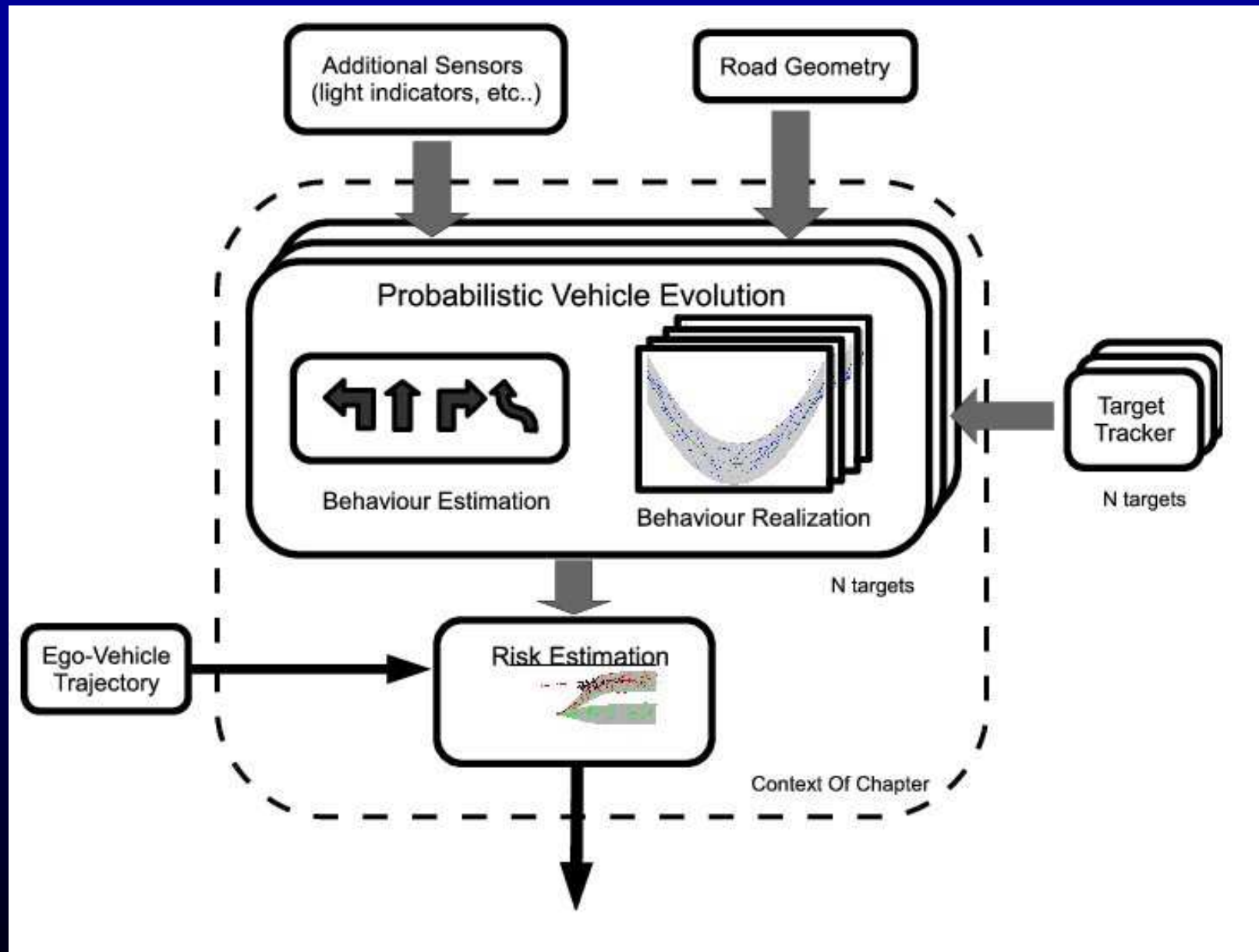
$$\Sigma_{Y_*} = K(X_*, X_*) - K(X_*, X) [K(X, X) + \sigma^2 \mathbf{I}]^{-1} K(X, X_*)$$

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

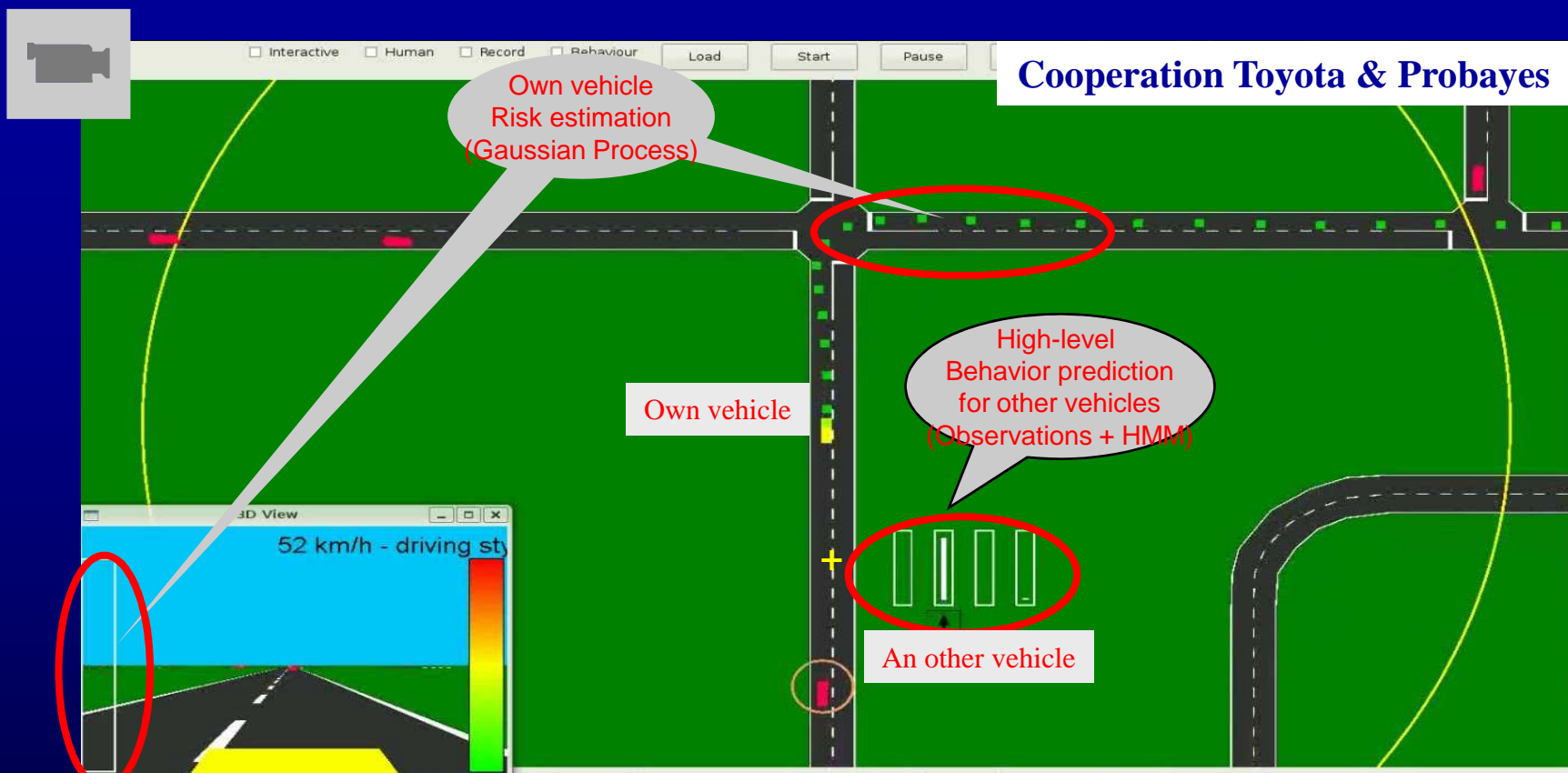




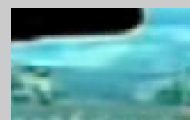
# Collision Risk Assessment (3)



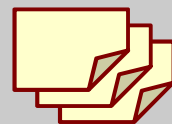
# Simulation Results



**Behavior Prediction (HMM)**



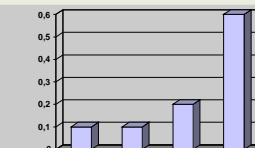
Observations



Behavior models

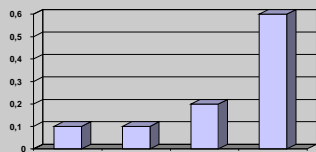


Prediction

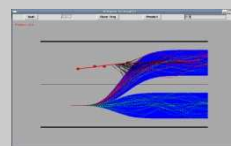


Behavior belief table

**Risk Assessment (GP)**



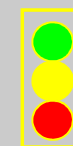
Behavior belief table for each vehicle in the scene



Road geometry (GIS) + Own vehicle trajectory to evaluate



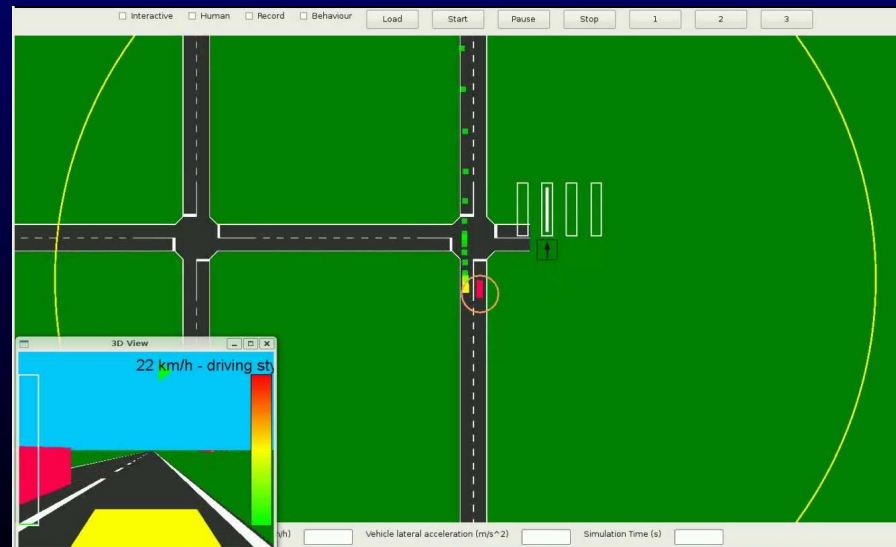
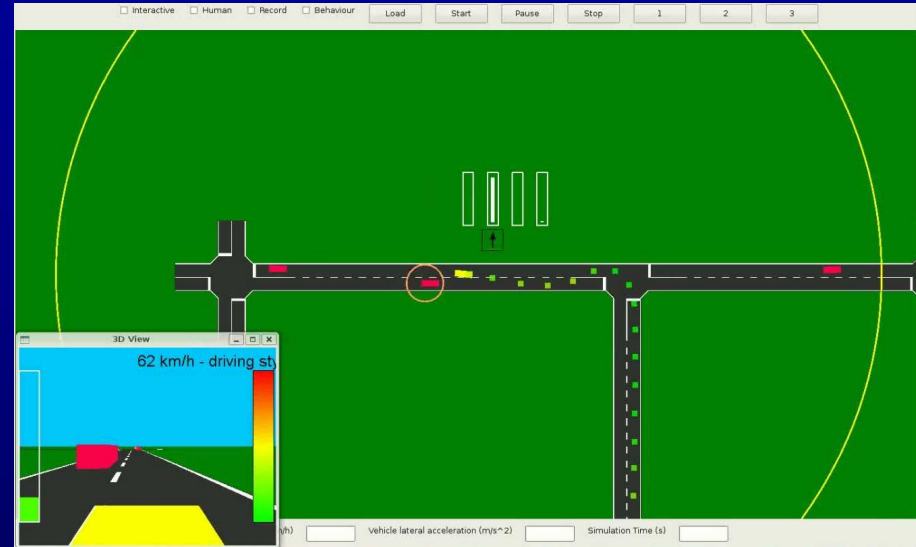
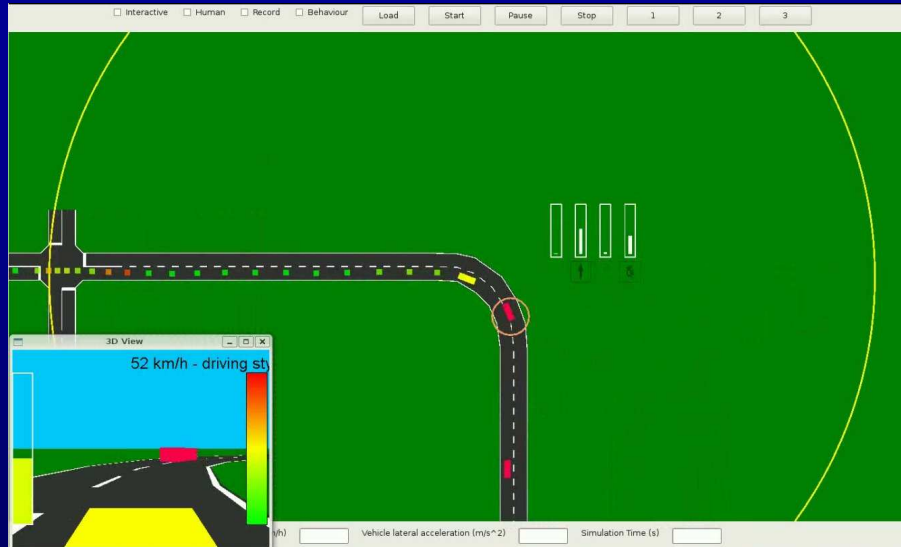
Evaluation



Collision probability for own vehicle

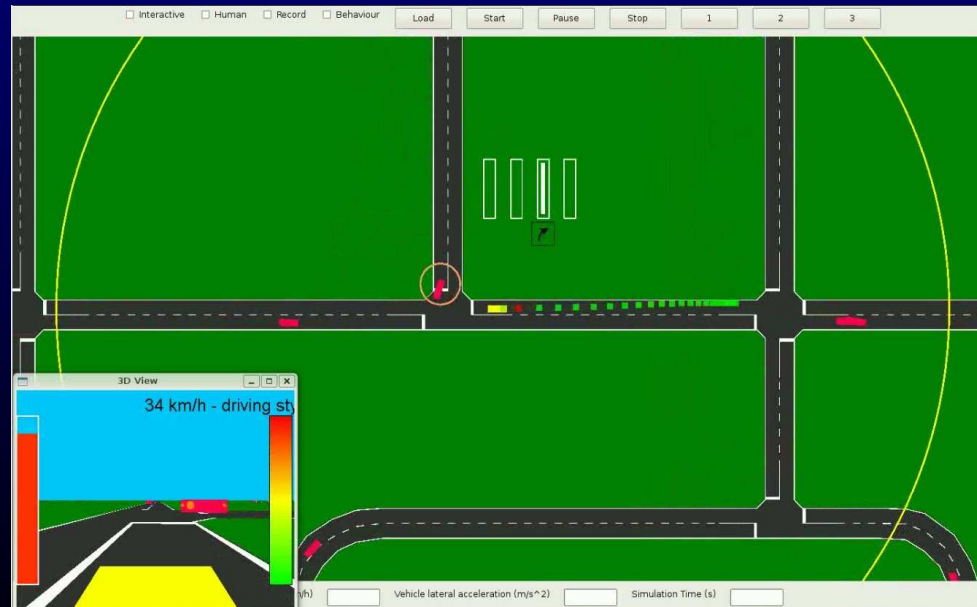
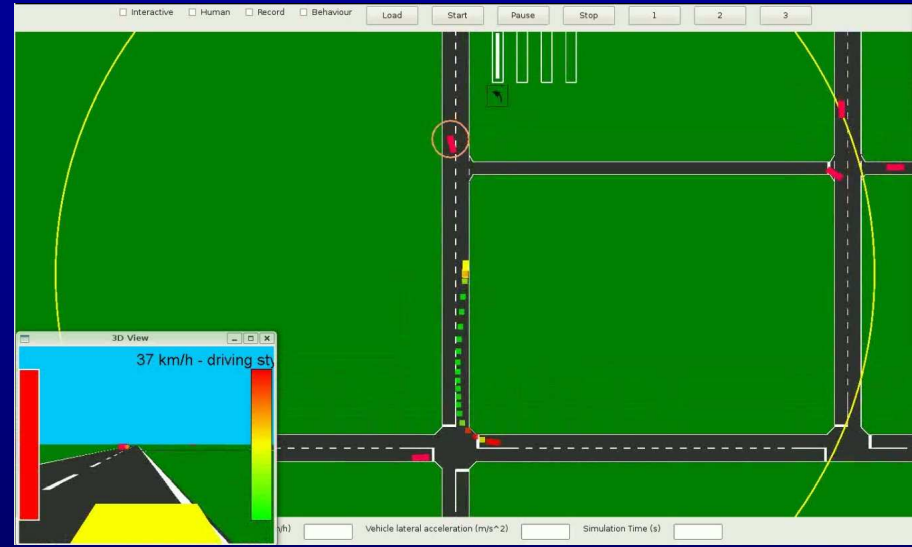
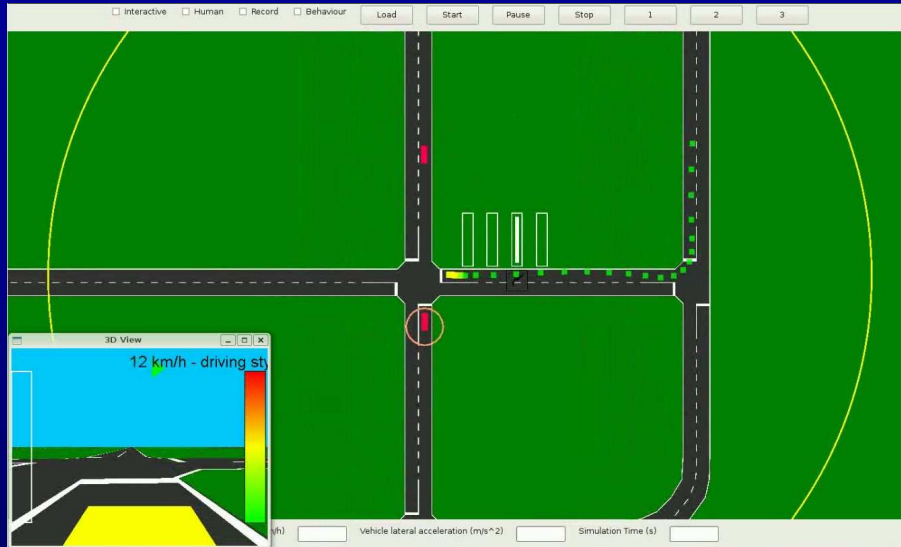
# Simulation Results - Intersection

*Good sensitivity to risks*



# Simulation Results - Intersection

*No unnecessary risk panics in intersection*





# *Main Robotics issues for Open & Dynamic & Uncertain environments*

1. Robust detection & tracking
2. Prediction & Risk assessment
3. **Safe goal-oriented navigation**
4. Human-~~Robot~~ interaction

# *Safe Goal-Oriented Navigation Decision in the Real World*



## **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*

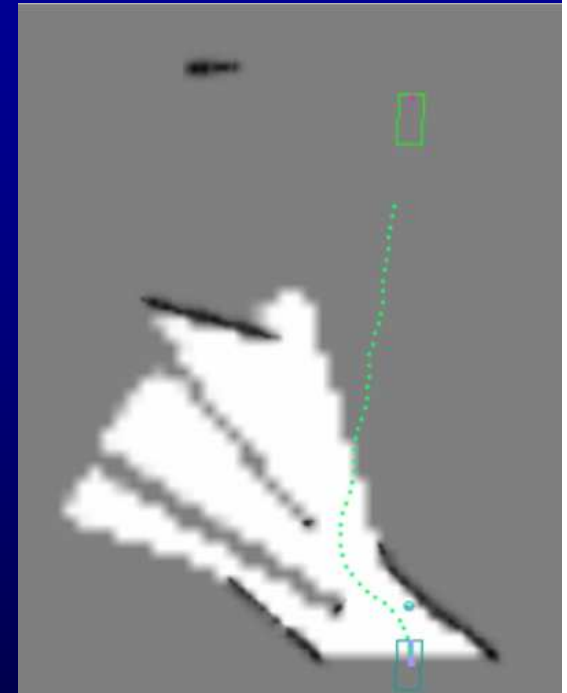
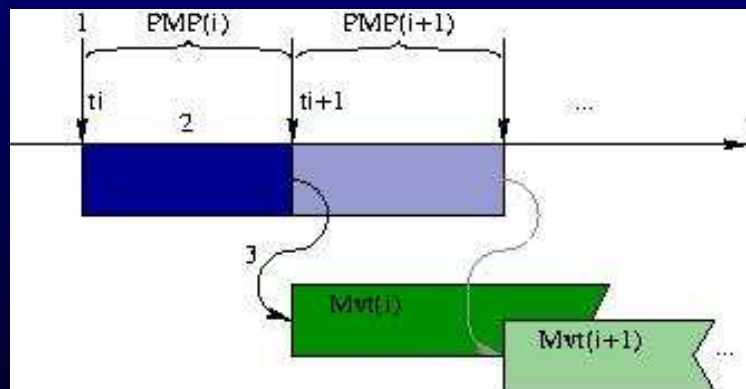
# A new framework for Motion Planning in Open & Dynamic environments (1)

[Fraichard 04] [Petti 06]

## • Partial Motion Planning (PMP)

*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  $\delta_c$  is over, Return “*best partial motion*” (e.g. *closest & safest*)

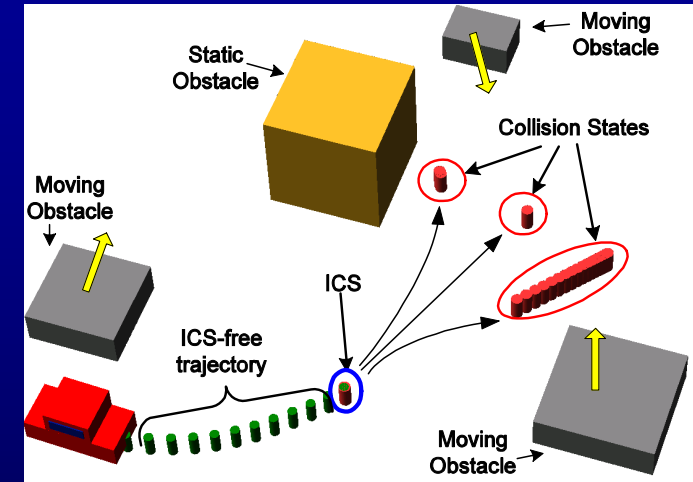


# A new framework for Motion Planning in Open & Dynamic environments (2)

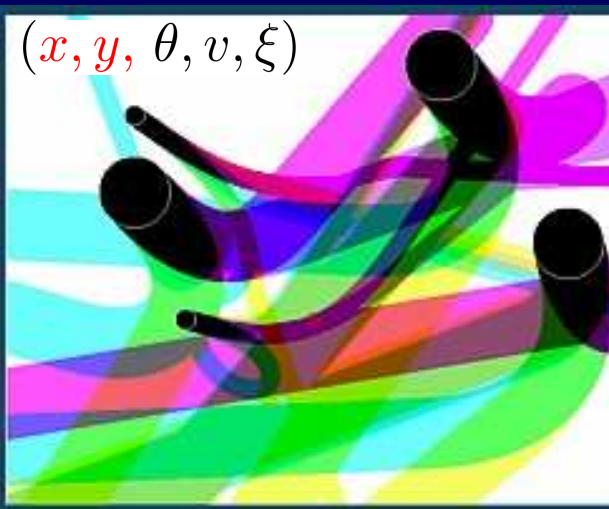
[Fraichard 04] [Martinez 08]

## • 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 !



**PMP + ICS**



- ICS-Check [Martinez 08]
- ICS-Avoid [Martinez 09]
- Prob-ICS [Bautin 09]



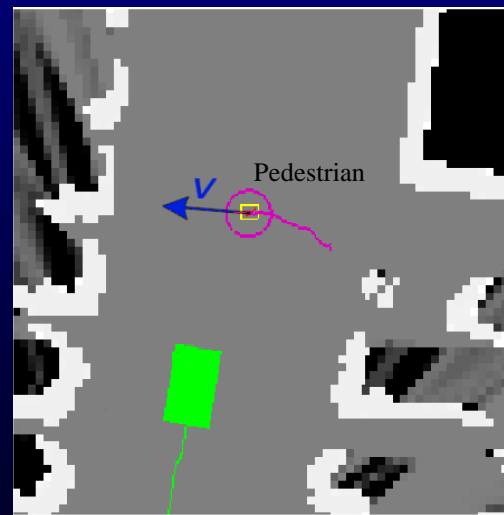
# A new framework for Motion Planning in Open & Dynamic environments (3)

[Fulgenzi & Laugier 07-09]

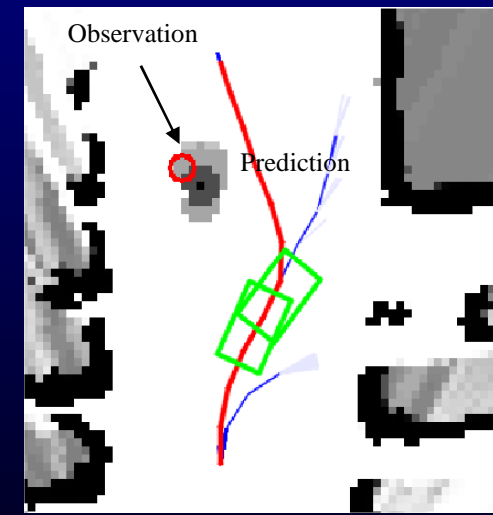
- **MP using Probabilistic Collision Risk (PCR-RRT)**
  - ✓ Integrate Obstacle Detection & Tracking
  - ✓ Risk assessment based on Behavior Prediction (HMM & GP)
  - ✓ Search function combining RRT and PMP (Previously explored states are updated on-line using new Observations & Predictions)



Real scene Processing & Recording  
(Detection & Tracking)



Reconstructed scene  
(Simulator)

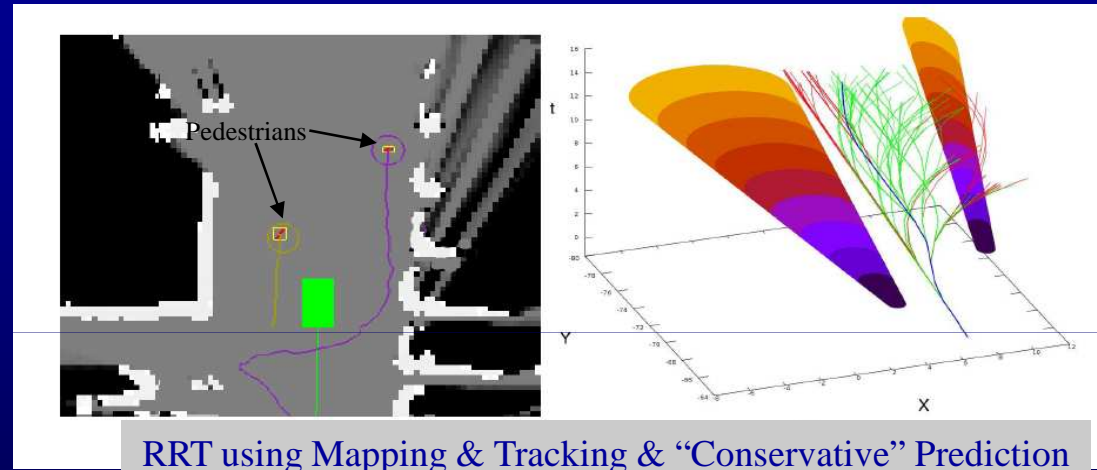


MP & Navigation  
(Simulator)

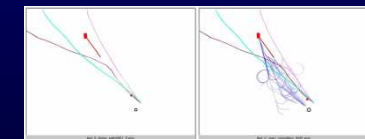
# A new framework for Motion Planning in Open & Dynamic environments (4)

[Fulgenzi & Laugier 07-09]

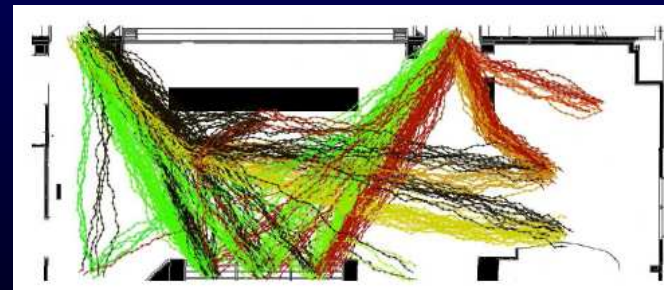
## • PCR-RRT – Real data & Simulation results



Navigation principle



Moving among peoples



Motion Prediction using GP

# Conclusion

- **Robots in Human Environments** : A new challenge for Robotics, which as recently started to be addressed by the Robotics community
- **Dynamics, Uncertainty, Scalability, Efficiency** are at the heart of the required Models & Algorithms
- Even if impressive live experiments in quite realistic human environments have successfully been achieved in the past few years, **Robustness & Safety** are major issues to be more deeply addressed in the future
- **Uncertainty** has to be placed at the heart of the Decisional process. *Probabilistic models* should probably be seen as key tools.
- **Prediction & Risk Assessment** has to be introduced at several levels of the Decisional process (for achieving *Consistent & Safe motions*)



**Thank You !  
Any questions ?**

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