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Accident avoidance by active intervention for Intelligent Vehicles

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Grid based SLAM & DATMO

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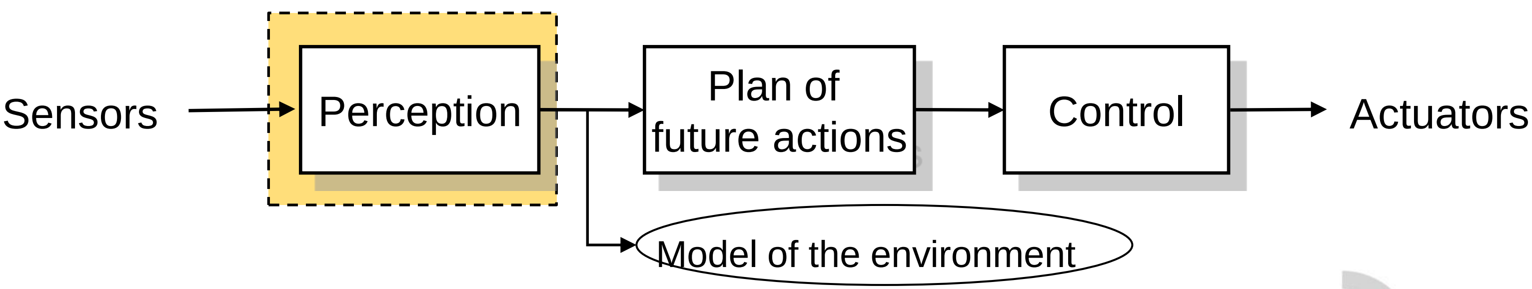
SCIENCES.TECHNOLOGIE.SANTÉ

GRENOBLE 1

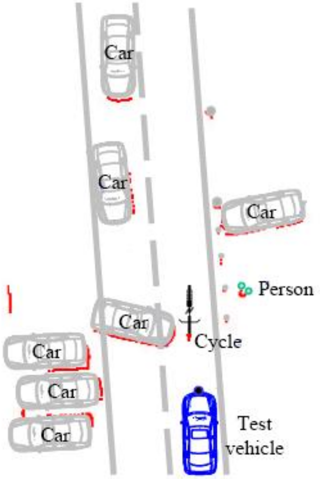
What is an intelligent vehicle ?

- An Intelligent Vehicle is a vehicle designed to:
  - monitor a human driver and assist him in driving;
  - drive automatically.
- Need of sensors to perceive the environment



Introduction

- **Goal**
  - Vehicle perception in open and dynamic environments
  - **Laser scanner**
  - Speed and robustness



- **Present Focus: interpretation of raw and noisy sensor data**
  - Identify static and dynamic part of sensor data
  - Modeling static part of the environment
    - Simultaneous Localization And Mapping (SLAM)
  - Modeling dynamic parts of the environment
    - Detection And Tracking of Moving Objects (DATMO)

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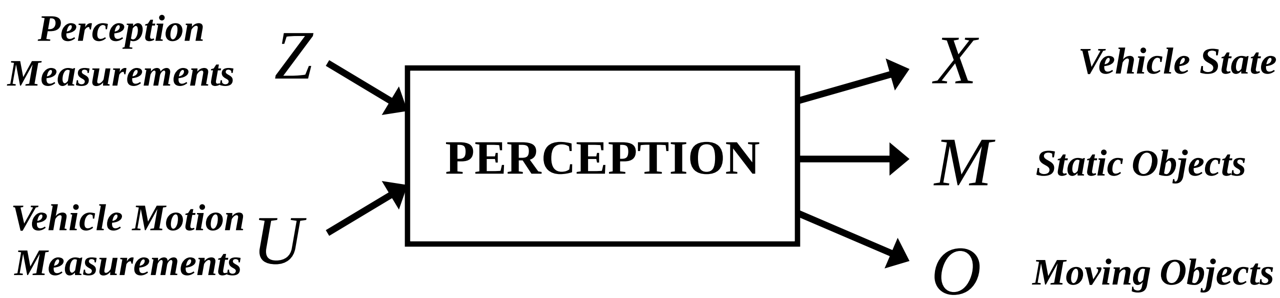
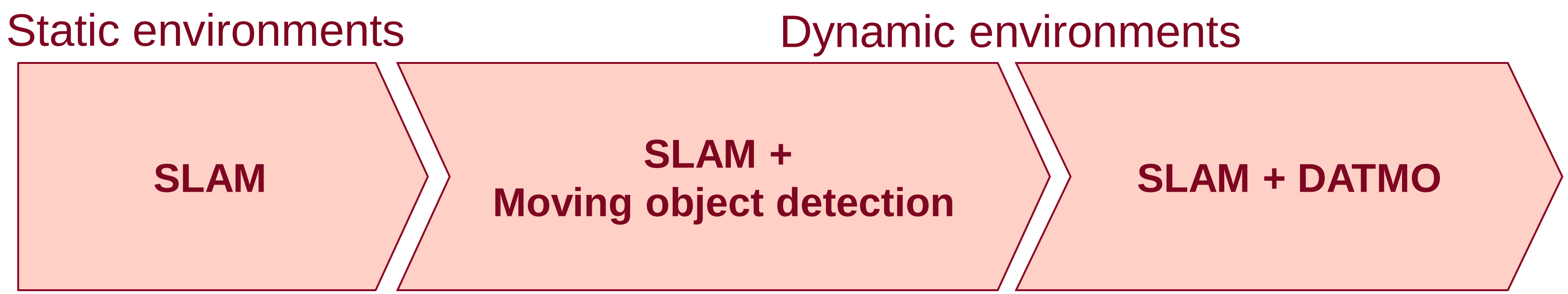
Problem statement





$$\underline{P(X,M \mid Z,U)}$$

$$\begin{cases} \underline{Z = Z^{(s)} + Z^{(d)}} \\ P(X,M \mid Z^{(s)},U) \end{cases}$$

$$\underline{P(X,M,O \mid Z,U)}$$

$$\begin{cases} P(X,M \mid Z^{(s)},U) \\ P(O \mid Z^{(d)}) \end{cases}$$

Outline

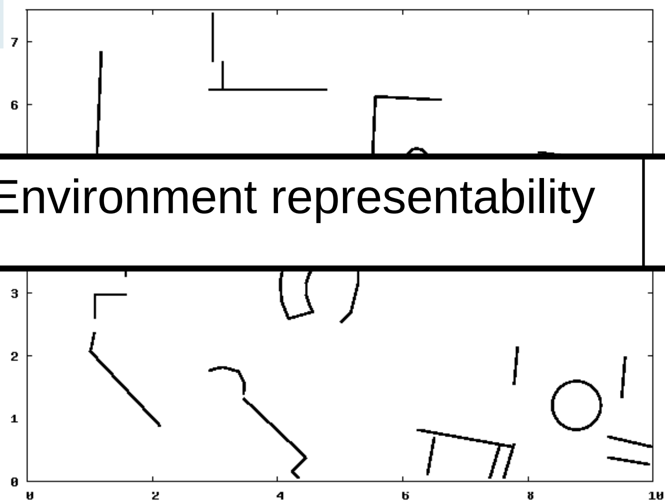
Introduction
- Part I -

SLAM with
Moving object detection
- Part II -

SLAM + DATMO
- Part III -

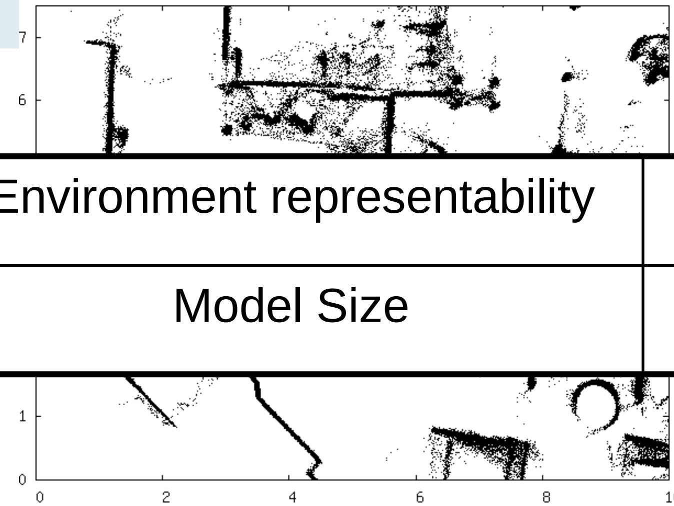
Experimental results on real vehicles will illustrate SLAM+DATMO theoretical contributions

Map representation



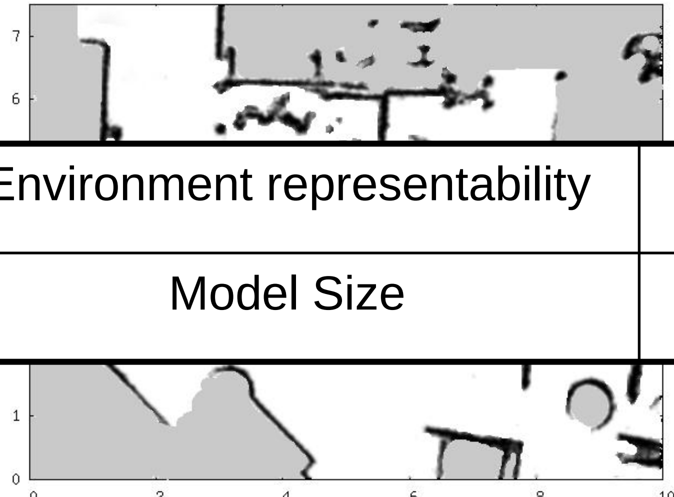
Environment representability	-

Feature-based map [Leonard’91]



Environment representability	+
Model Size	-

Point cloud map [Lu’97]



Environment representability	+
Model Size	+

Occupancy Grid(OG)-based map [Elfes’89]

SLAM

$$P(C_t = c \mid x_{1:t}, z_{1:t})$$

Incremental mapping [Elfes'89,Thrun'00]

$$\log O(C_t = c \mid x_{1:t}, z_{1:t}) = \log O(C_{t-1} = c \mid x_{1:t-1}, z_{1:t-1}) + \log O(\underbrace{C_t = c \mid x_t, z_t}_{\text{inverse sensor model}}) - \log O(\underbrace{C_0 = c}_{\text{a priori map}})$$

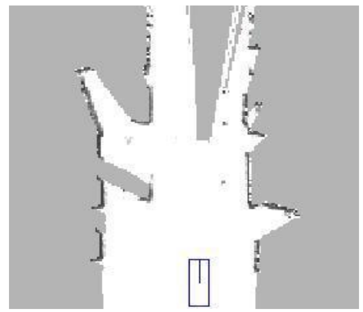
where $O(a \mid b) = odds(a \mid b) = P(a \mid b) \ / \ (1 - P(a \mid b))$

Maximum Likelihood Localization [Vu'07]

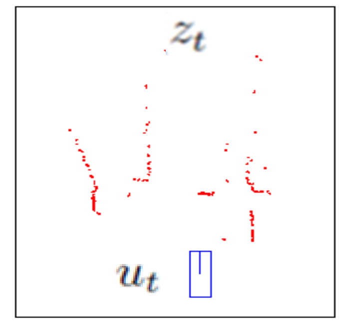
Example of Maximum Likelihood Localization [Vu'07]

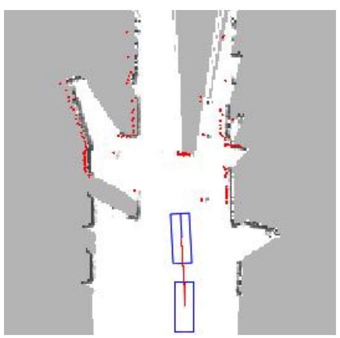
$$\begin{cases} \hat{x}_t = \underset{x_t}{\operatorname{argmax}}\{P(z_t|x_t, \hat{M}_{t-1})\,P(x_t|u_t, \hat{x}_{t-1})\} \\ \hat{M}_t = \hat{M}_{t-1} \cup \{\langle \hat{x}_t, z_t \rangle\} \end{cases}$$

$\hat{M}_{t-1}$

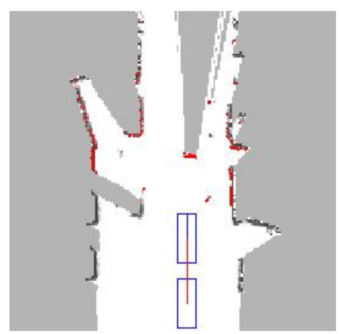


$\hat{x}_{t-1}$

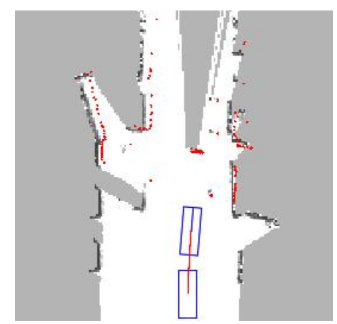




$P(.) = 0.21$



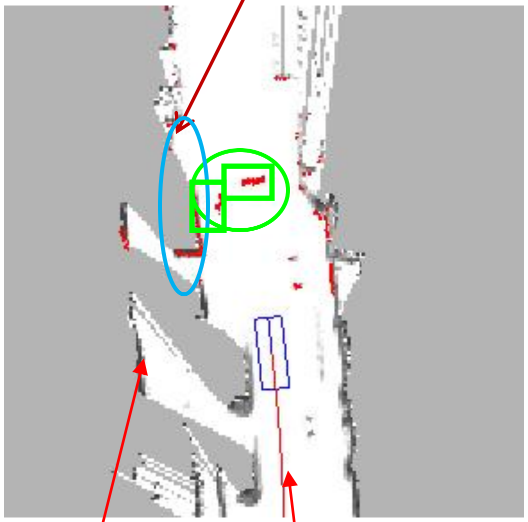
$P(.) = 0.92$



$P(.) = 0.17$

SLAM

$$P(C_t = c \mid x_{1:t}, z_{1:t})$$



Incremental mapping [Elfes'89,Thrun'00]

$$\log O(C_t = c \mid x_{1:t}, z_{1:t}) = \log O(C_{t-1} = c \mid x_{1:t-1}, z_{1:t-1}) + \log \underbrace{O(C_t = c \mid x_t, z_t)}_{\text{inverse sensor model}} - \log \underbrace{O(C_0 = c)}_{\text{a priori map}}$$

where $O(a \mid b) = odds(a \mid b) = P(a \mid b) \,/\, (1 - P(a \mid b))$

Maximum Likelihood Localization [Vu'07]

$$\begin{cases} \hat{x}_t = \underset{x_t}{\operatorname{argmax}} \{ P(z_t | x_t, \hat{M}_{t-1}) \, P(x_t | u_t, \hat{x}_{t-1}) \} \\ \hat{M}_t = \hat{M}_{t-1} \cup \{ \langle \hat{x}_t, z_t \rangle \} \end{cases}$$

Moving object Detection

- Inconsistency between OG and observations allows deciding a measurement belonging to a static or dynamic object
- Close points are grouped to form objects

Experiments

- **Daimler demonstrator (IP PReVENT)** [Vu'07]
  - Laser scanner
  - Velocity, steering angle
  - High speed (>120km/h)
  - Camera for visual reference
  - Different scenarios: city streets, country roads, highways

- **Volkswagen demonstrator (STREP Intersafe2)** [Baig'09]
  - Laser scanner
  - Odometry: rotational and translational speed
  - Camera for visual reference
  - Urban traffics

Results: SLAM + moving objects detection

Execution time: ~20ms on a PIV 3.0GHz PC 2Gb RAM

Daimler demonstrator

DATMO

Introduction

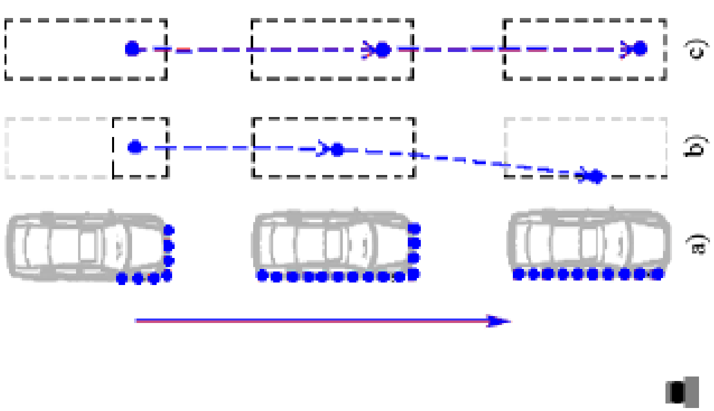
SLAM with
Moving object detection

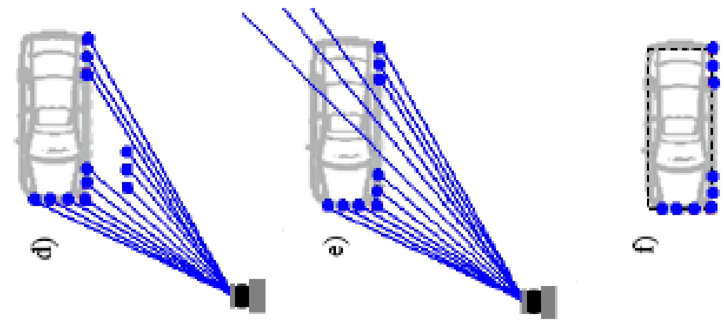
SLAM + DATMO

Conclusion & Perspectives

DATMO – known problems using laserscanner

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





=> Using object models to overcome these problems

DATMO: our approach

- Interpretation of moving objects and their trajectories from a laser sequence

- Considering data sequence over a sliding window of time

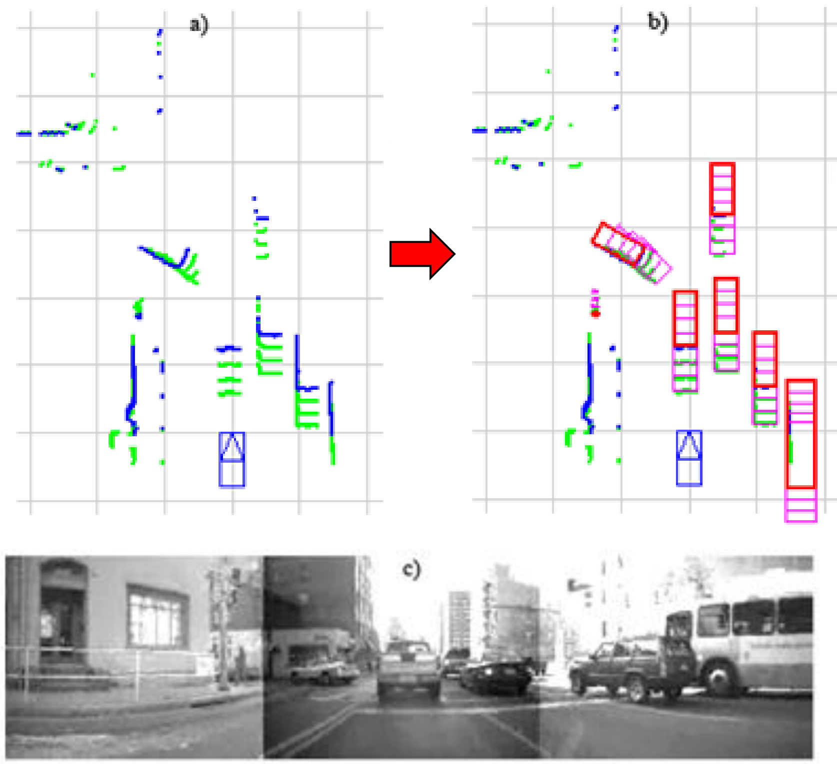
$$Z = \{Z_1, \ldots, Z_T\}$$

- Maximizing a posterior probability

$$\boxed{\omega^* = \underset{\omega}{\operatorname{argmax}}\, P(\omega \mid Z)}$$

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

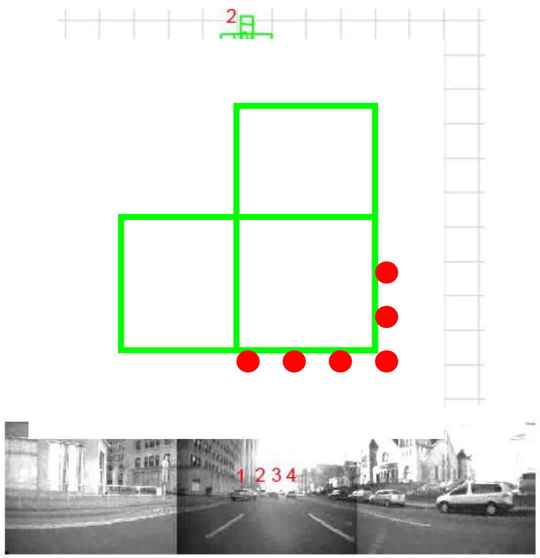
τ_k is a trajectory of object models



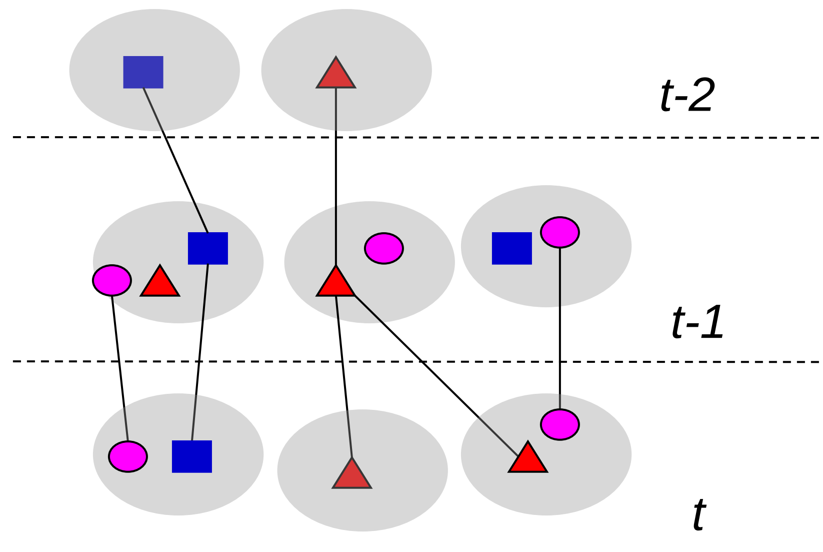
=> Simultaneous Detection, Classification and Tracking of Moving Objects

Representation and exploration of space of moving objects hypothesis

- **Define object model**
  - Box model to represent cars, trucks or bus and motorcycle
  - Point model to represent pedestrian
- **Incremental build of the graph of hypothesis**



Moving object hypothesis generated over a sliding window of time



Incremental graph of hypothesis

- **Exploration of the graph**
  - Use of sampling techniques (MCMC)

Evaluation of a hypothesis knowing observations

- MAP estimate: $\omega^* = \underset{\omega}{\operatorname{argmax}} P(\omega|Z)$

$$P(\omega|Z) \propto P(\omega)P(Z|\omega)$$

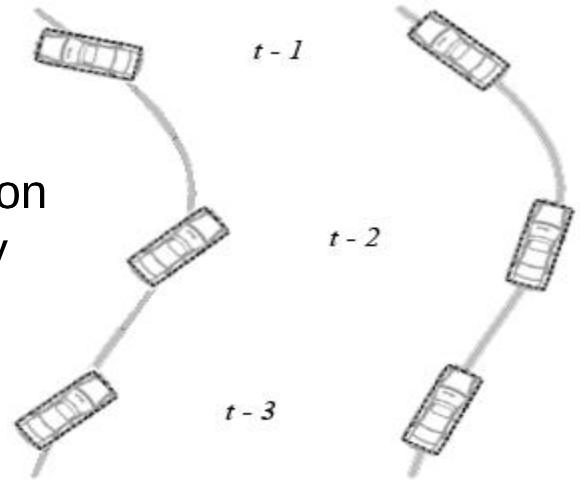
Prior model:

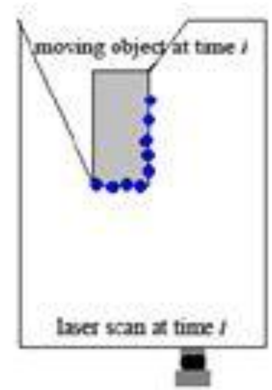
=> Add some *apriori* constraints on individual objects

Likelihood model:

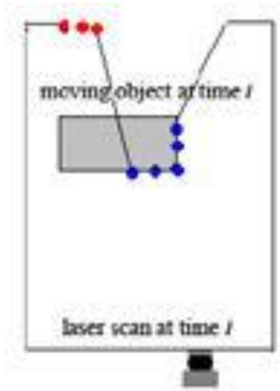
=> Evaluate likelihood of observations knowing hypothesis

temporal motion consistency





Reward



Penalyze

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Experiments

- Navlab Dataset (CMU) [Vu'09]
  - SICK laser scanner: resolution: 0.5^0, range: 50m, FOV: 180^0, freq: 37.5Hz
  - Odometry: rotational and translational speed
  - Camera for visual reference
  - Real-life urban traffics

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Results: SLAM + DATMO

- Execution time: ~120ms on a PIV 3.0GHz PC 2Gb RAM

Conclusion & perspectives

Introduction

SLAM with Moving object detection

SLAM + DATMO

Conclusion & Perspectives
- Part IV -

Conclusion

- **Modeling static part of the environment**
  - 2D OG to model open environment
  - Particle filter to perform localization
  - Moving object detection

[Vu'07] T.D. Vu, O. Aycard and N. Appenrodt. *Online Localization and Mapping with Moving Object Tracking in Dynamic Outdoor Environments.* In IEEE International Conference on Intelligent Vehicles (IV). **2007**.

- **Modeling dynamic part of the environment**
  - Simultaneous detection, **classification** and tracking moving objects
    - Using object models overcomes existing problems of laser-based tracking
    - Data-driven MCMC helps to search for the optimum solution in the spatio-temporal space in real-time

[Vu'09] T.D. Vu, O. Aycard. *Laser-based Detection and Tracking Moving Objects using Data-Driven Markov Chain Monte Carlo.* In IEEE International Conference on Robotics and Automation (ICRA), **2009**.

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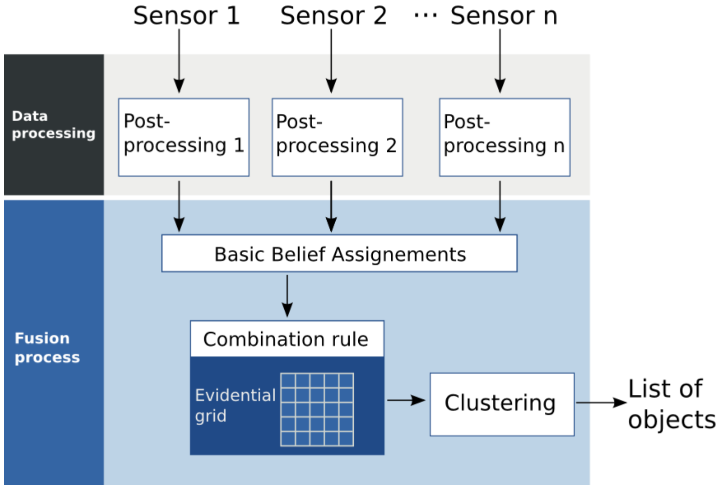
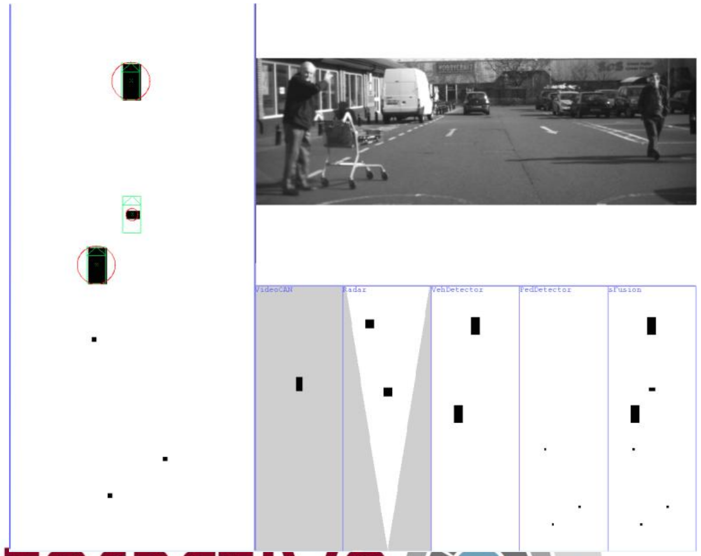
Perspectives

- CRF/TRW demonstrator car (European InteractIVe project) [Chavez'12]
  - Data available: 2D laser, radar, camera
  - Generic perception platform for active safety

- Sensor data fusion based on Occupancy Grid and Evidential theory to improve detection performance [Chavez'12]





- Vision based classification

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Accident avoidance by active intervention for Intelligent Vehicles

Thank you.

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by the European Commission

SEVENTH FRAMEWORK
PROGRAMME

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