Dynamic perception for intelligent vehicles

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https://www.hds.utc.fr/~vberge

Motivations

Comfort	Safety	Efficiency

(Continental, wiesbaden2014)

Societal challenges

- Mobility, Urban sustainable systems
- IoT, ICT
- “Plan Nouvelle France Industrielle” : Véhicules à pilotage automatique
- H2020

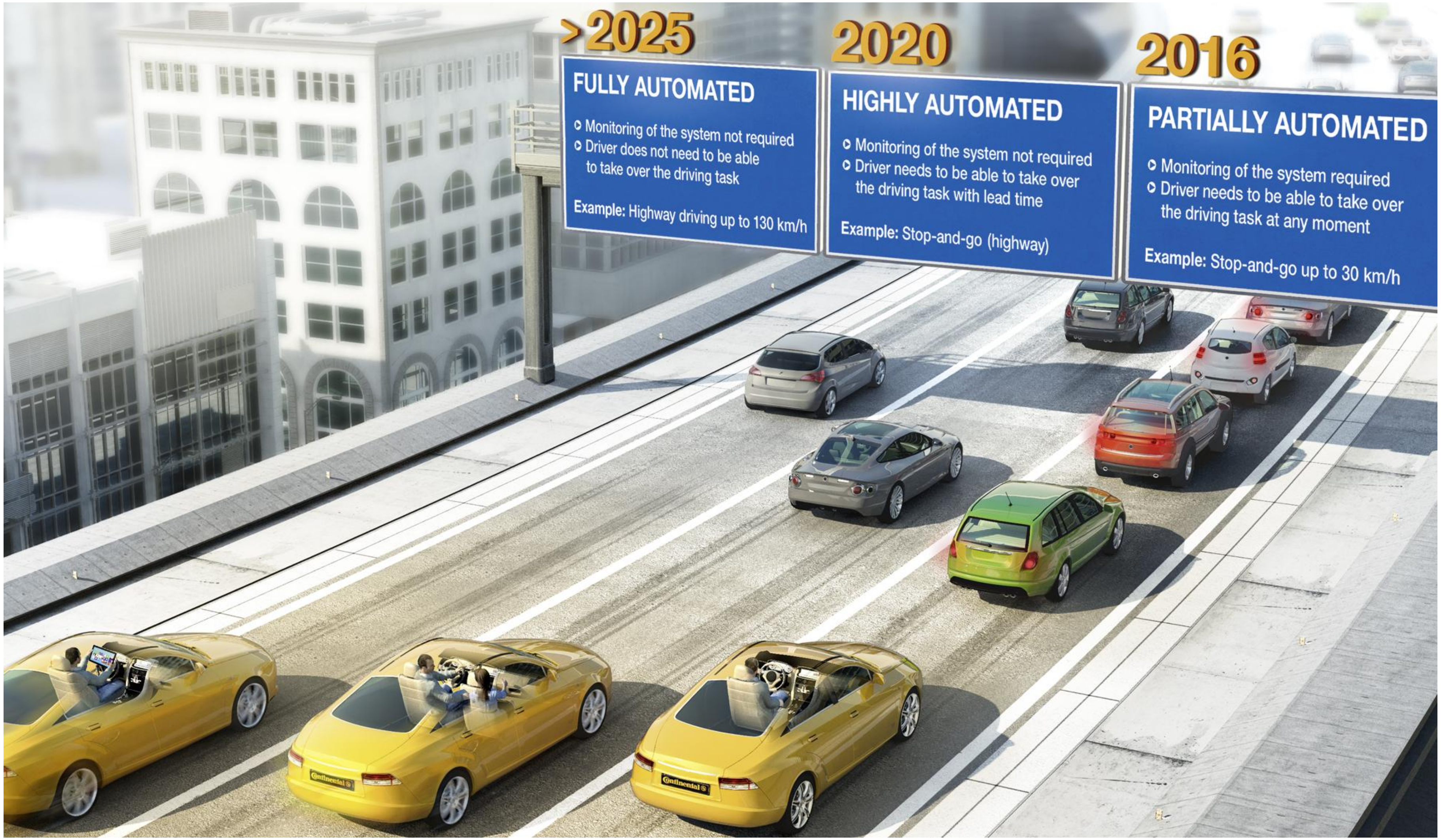
From intelligent to autonomous vehicles

SOCIETY OF AUTOMOTIVE ENGINEERS (SAE) AUTOMATION LEVELS

Full Automation

0	1	2	3	4	5
No Automation	**Driver Assistance**	**Partial Automation**	**Conditional Automation**	**High Automation**	**Full Automation**
Zero autonomy; the driver performs all driving tasks.	Vehicle is controlled by the driver, but some driving assist features may be included in the vehicle design.	Vehicle has combined automated functions, like acceleration and steering, but the driver must remain engaged with the driving task and monitor the environment at all times.	Driver is a necessity, but is not required to monitor the environment. The driver must be ready to take control of the vehicle at all times with notice.	The vehicle is capable of performing all driving functions under certain conditions. The driver may have the option to control the vehicle.	The vehicle is capable of performing all driving functions under all conditions. The driver may have the option to control the vehicle.

From intelligent to autonomous vehicles



May 2014, © Continental AG

Autonomous Vehicle Disengagement Reports 2017 [1]

Company	Autonomous Miles	Disengagements	MPD
Waymo	352,544.60	63	5,595.95
Cruise GM	128,727.31	97	1,327.09
Nissan	4,516.00	24	188.17
Zoox	2,244.60	14	160.33
Drive.ai	6,015.40	92	65.38
Baidu	1,934.84	42	46.07
Telenav	1,824.00	58	31.45
Delphi	1,819.55	81	22.46
Nvidia	505.00	109	4.63
Bosch	1,808.00	50	3.59
Valeo	574.10	215	2.67
Mercedes-Benz	1,087.70	842	1.29

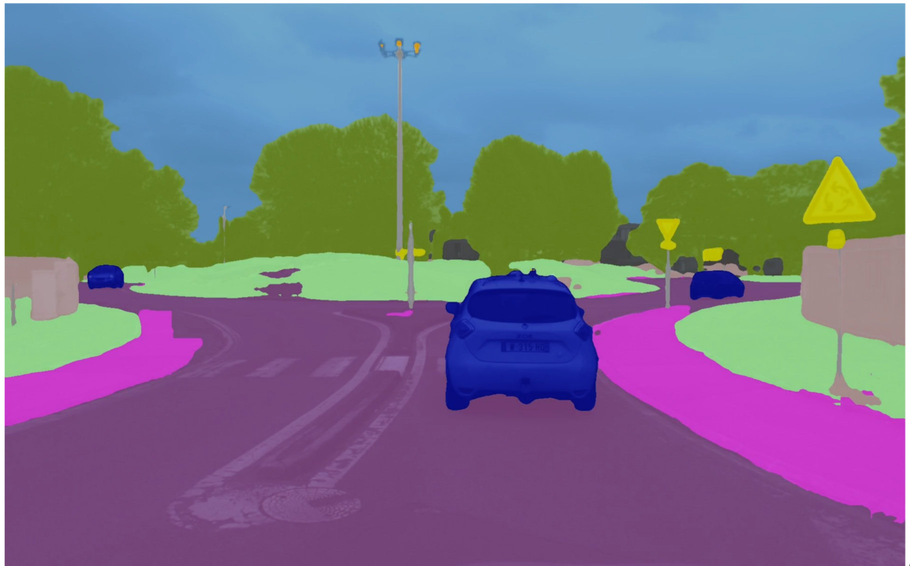
1. https://www.dmv.ca.gov/portal/dmv/detail/vr/autonomous/disengagement_report_2017

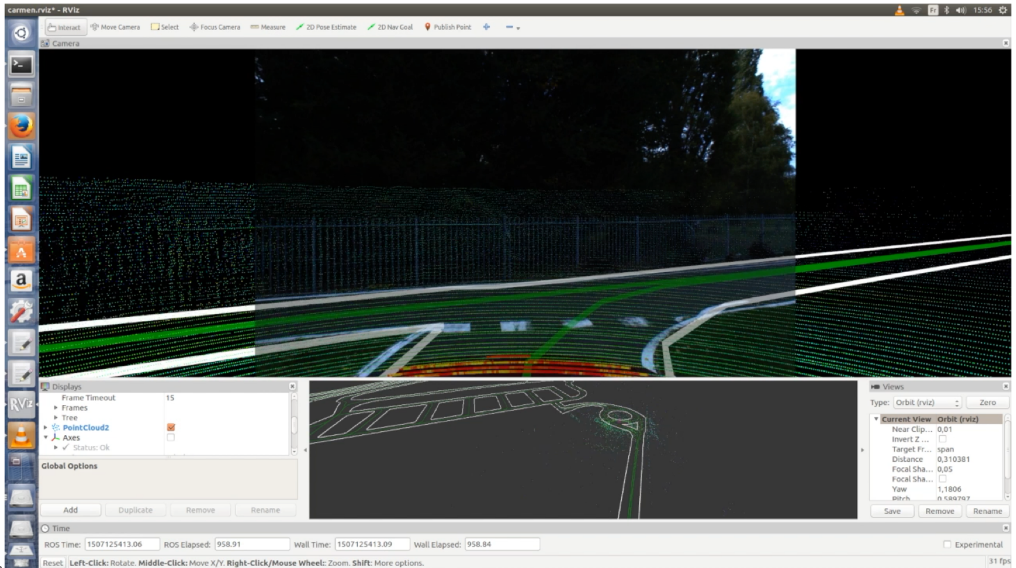
Intelligent vehicles at Heudiasyc

- 1988-1995 Prometheus, European program
- 1997 Strada, first vehicle at Heudiasyc
- 2001-2004 Arcos, French program
- 2004 CNRS platform, support of region Picardie
- 2011 Equipex Robotex
- 2016 partipation au GCDC (Eindhoven)
- 2017 SIVALab Joint laboratory with Renault, CNRS, UTC
- National and international projects (ANR, FP7, H2020…)

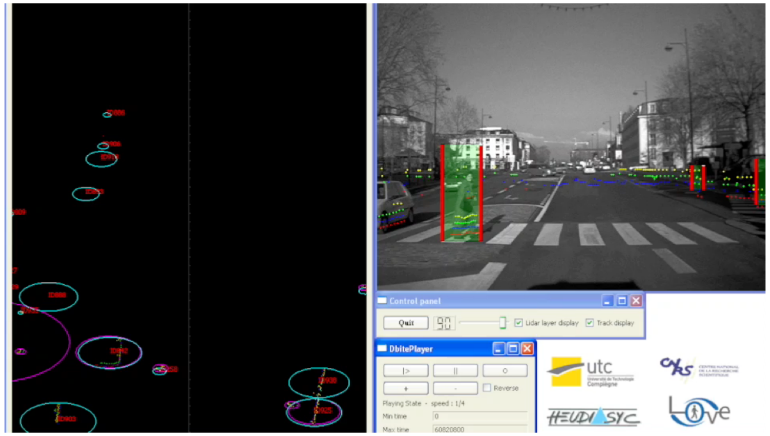
Research for autonomous vehicle

- 3D perception in dynamic environment
- Multi-sensor data fusion
- Machine learning
- Localisation
- State observation
- Control of dynamic systems
- Trajectory planning
- Cooperative systems
- HM interaction and augmented reality



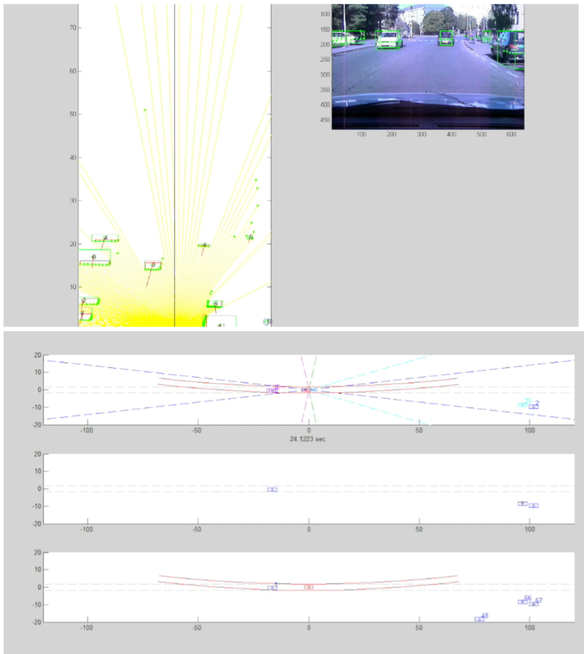


Experiments



PACPUS (vehicles)
AIRPLUG (communications V2V, V2I)
ROBOTEX (robotized electric cars and track)

National and international demonstrations
(ARCOS, IV 2008, IV2011, LOVE, CityVIP, GCDC…)



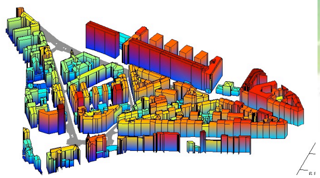
Research activities

Objectives

- Environment perception
- Sensors, digital map, V2X communications

Scientific domains

- Data fusion
    - Temporal
    - Multi-sources
- Uncertainties modelling and management in the Dempster-Shafer framework



Euca

Sensors

Camera

Low cost
Rich raw data

Emerging technologies : TOF and event camera

Smart cameras

SoC
Black box
Mobileye
Continental

Radar

Radar LRR3
Bosch

24 to 77 GHz

Up to 300m
Range and speed data, tracking

Lidar

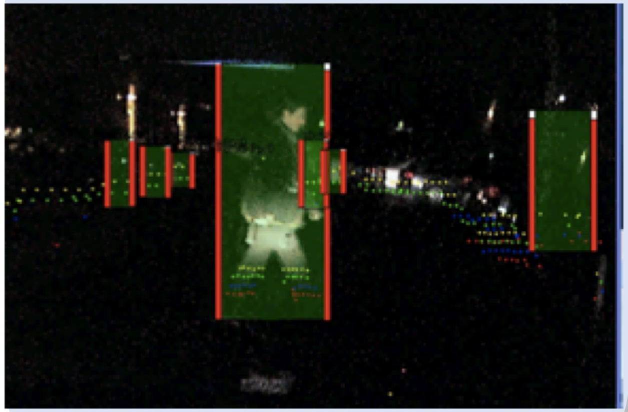
High cost
precise range data

Mechanical constraints
Up to 128 layers

Sensor data processing for object detection

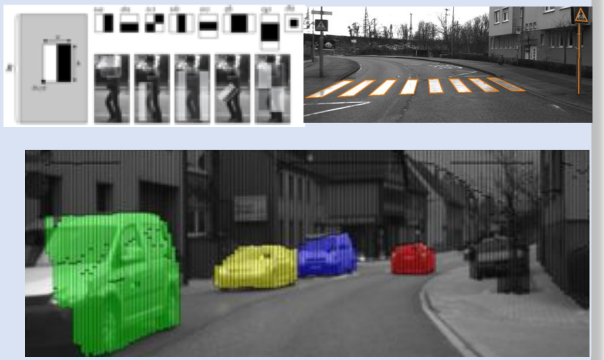
Detection

State estimation
(position, size, speed…)



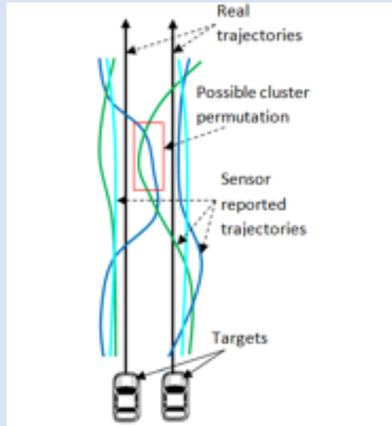
Recognition

Classification



Tracking

Trajectory estimation

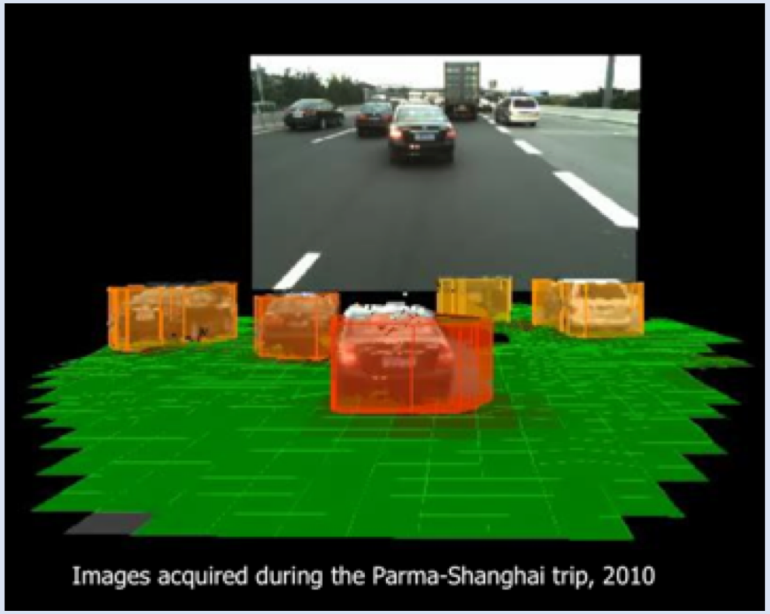


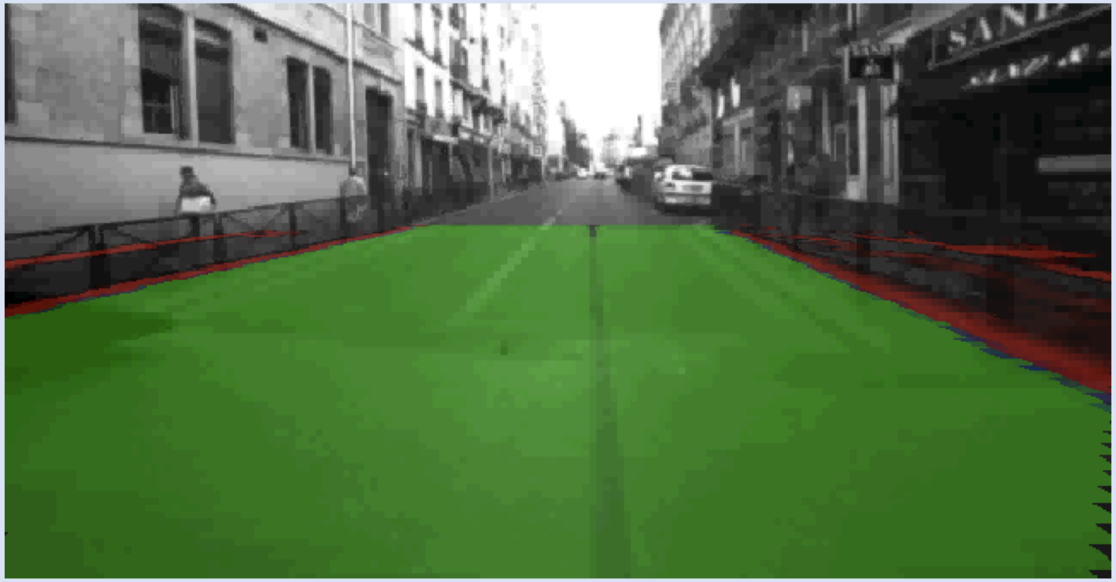
Errors :
noisy sensors, datation, calibration,imperfect detectors, classifiers, association, external conditions, dynamic scene, embedded sensors

Deep learning outperforms all classical approaches (images)

Sensor data processing

Drivable space detection





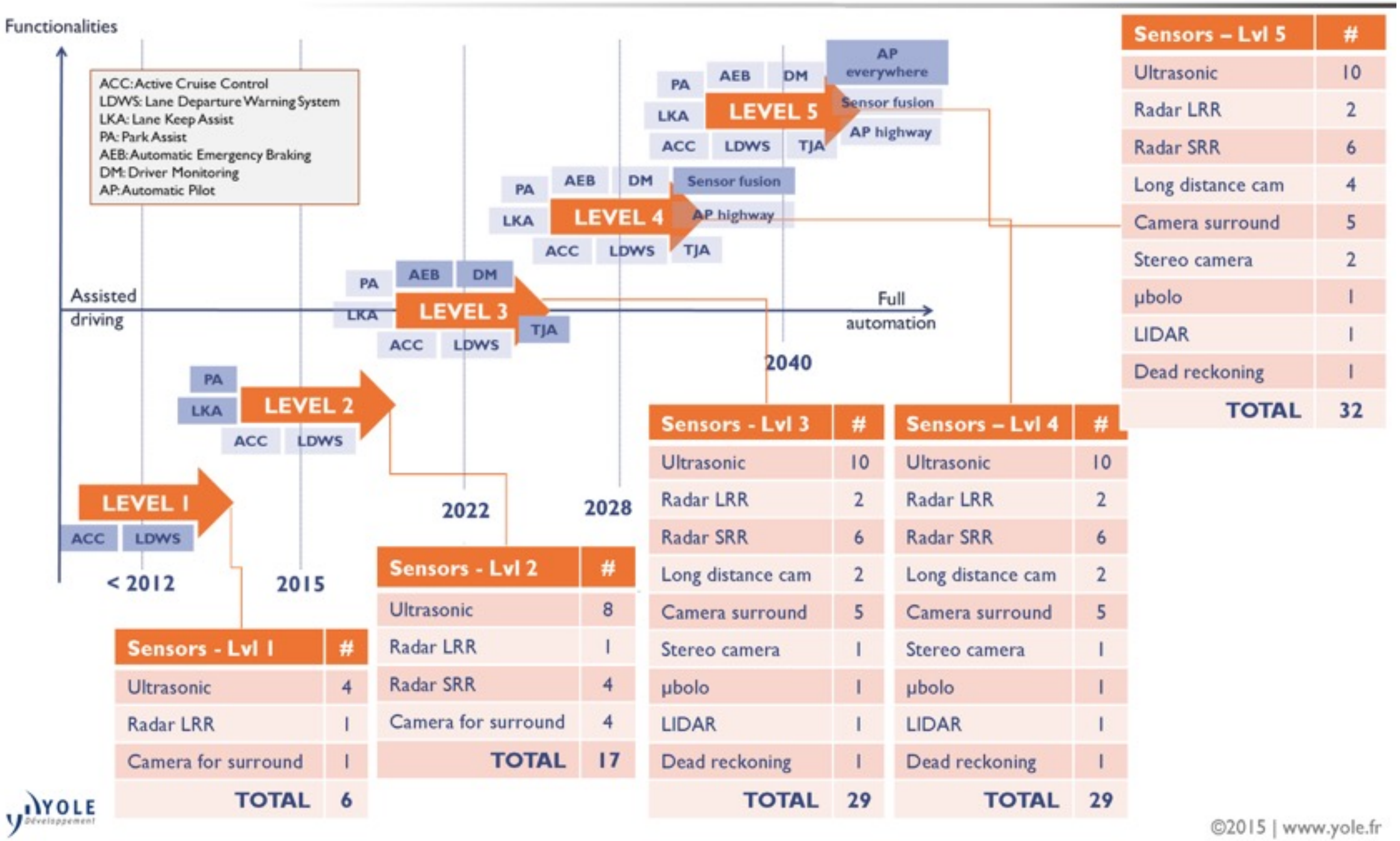
Stereovision (Vislab, 2010)

Lidar 4 layers(Heudiasyc, 2012)

Sensors

SENSOR TECHNOLOGY ROADMAP AND AUTONOMOUS FUNCTIONS ASSOCIATED

(Source: Sensors & Data Management for Autonomous Vehicles report, Oct. 2015, Yole Développement)



Sensors - Lvl 1	#
Ultrasonic	4
Radar LRR	1
Camera for surround	1
TOTAL	6

Sensors - Lvl 2	#
Ultrasonic	8
Radar LRR	1
Radar SRR	4
Camera for surround	4
TOTAL	17

Sensors - Lvl 3	#
Ultrasonic	10
Radar LRR	2
Radar SRR	6
Long distance cam	2
Camera surround	5
Stereo camera	1
µbolo	1
LIDAR	1
Dead reckoning	1
TOTAL	29

Sensors – Lvl 4	#
Ultrasonic	10
Radar LRR	2
Radar SRR	6
Long distance cam	2
Camera surround	5
Stereo camera	1
µbolo	1
LIDAR	1
Dead reckoning	1
TOTAL	29

Sensors – Lvl 5	#
Ultrasonic	10
Radar LRR	2
Radar SRR	6
Long distance cam	4
Camera surround	5
Stereo camera	2
µbolo	1
LIDAR	1
Dead reckoning	1
TOTAL	32

Multi sensor data fusion

- **Objectives**

Augmented field of view

Redundancy, Robustness

Reduce false alarms

Dependability (SdF)

- **Issues, challenges**

Synchronisation and calibration

“smart sensors” fusion

Real time computation

Variability and complexity of scenes

Integrity

reduce inaccuracy and uncertainty

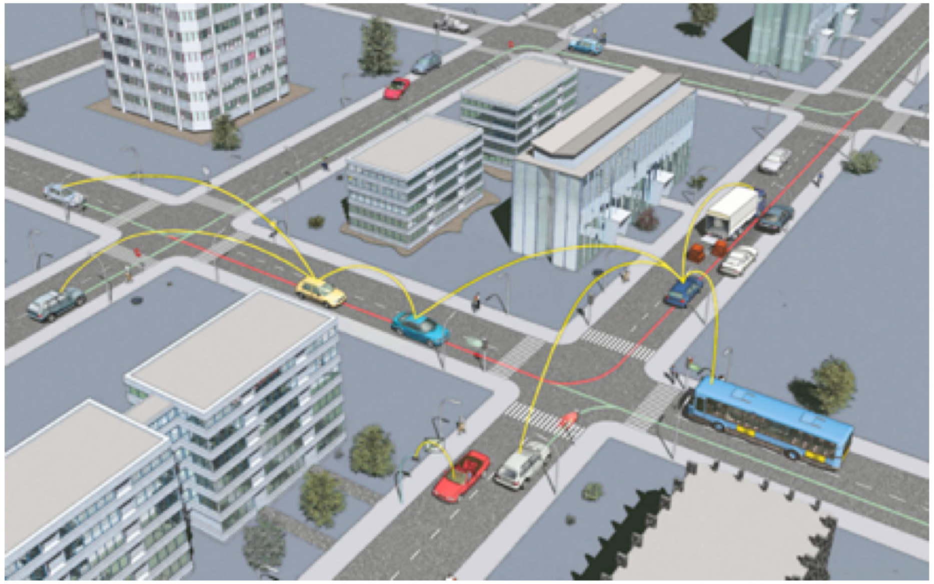
guaranteed result : ”use – not use”

Communicating vehicles

Car to car communication : V2V

Vehicle-infrastructure communication : V2I

Norme 802.11p (EU)



Useful functions

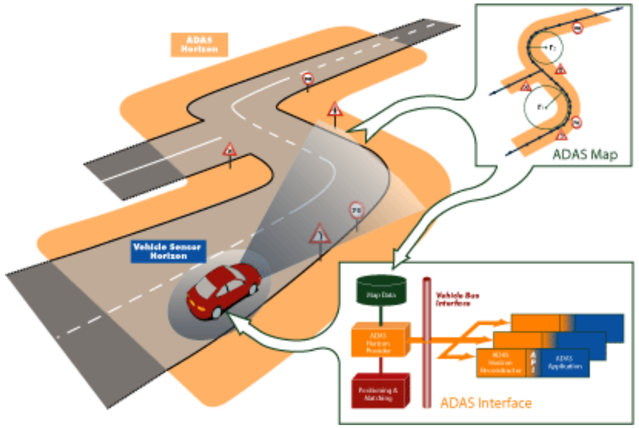
- Safety
- Traffic efficiency
- Selected *infotainment*

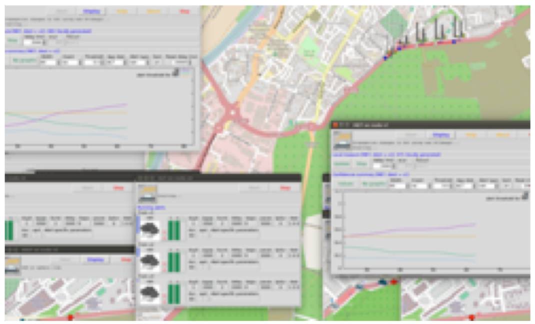
Communicating vehicles

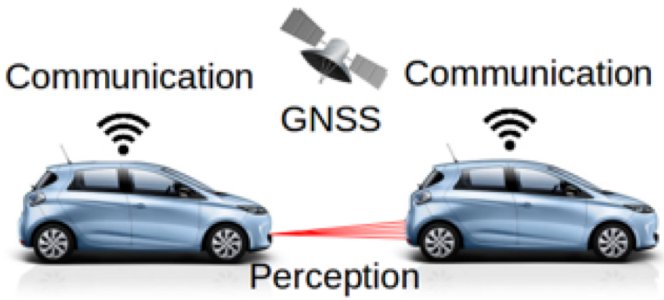
Enhanced perception

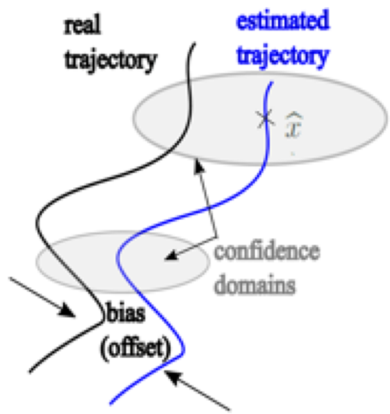
Cooperative localization

Distributed data fusion





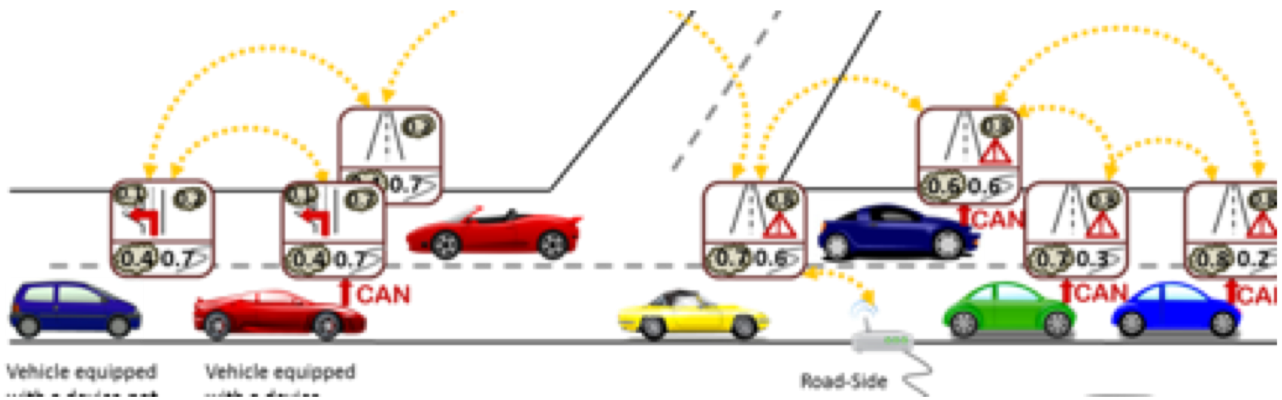




Communicating vehicles

Issues, challenges

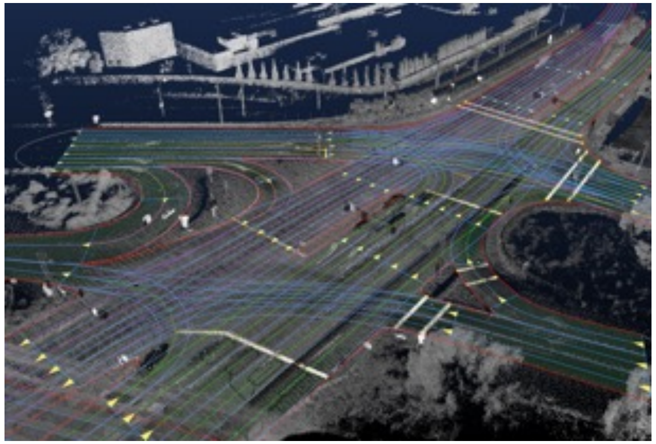
- Bandwidth limitation and dynamic networks
- Privacy, Security in ad hoc networks
- Node trust
- Cycles consideration



Digital map for intelligent vehicles

HD map

Here



OSM

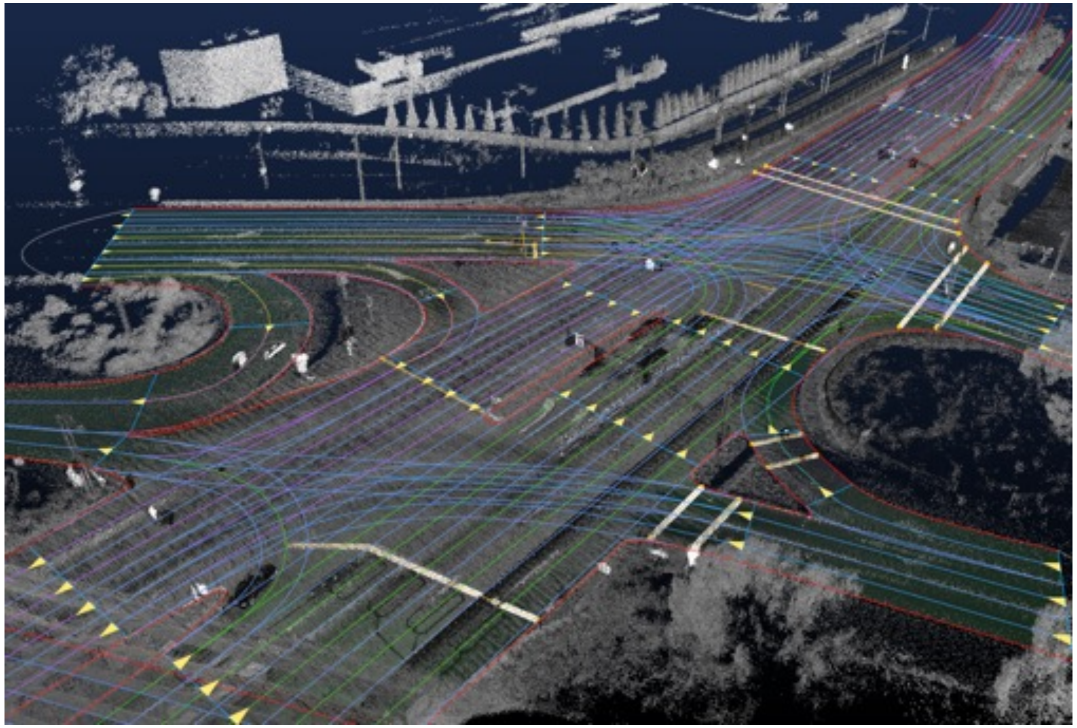
- Lane information
- Road marking
- 3D urban model
- Topology
- Semantic data
- Point cloud

IGN

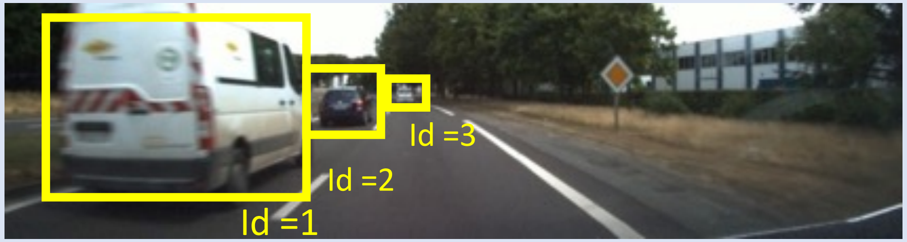
Digital map

Issues, challenges

- Accuracy of the map
- Map updating
- Map mastering
- Size of map



Perception of the IV environment

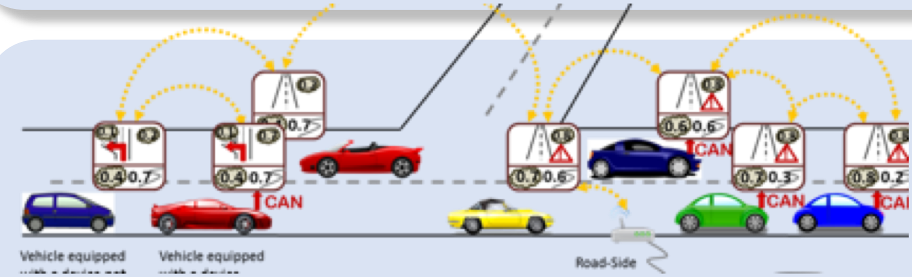


Moving objects detection and tracking

Association methods for multi-sensor data and multi objects tracking
Multi-hypothesis approaches
Track fusion and confirmation
[IEEE Trans Cyb. 2014][IROS 2013][MVA 2012]

Navigable space detection

Evidential occupancy map
Sensor models (lidars, stereo-vision)
Map-based semantic grids
Fusion operators for grids
[IEEE ITSmag 2015][IJAR 2014][ICRA 2011]



Distributed data fusion

Fusion operators study
Self stabilizing operators
Cycle consideration
[IEEE Trans ITS 2016][SRDS 2016][IV 2014]

Evidential perception grids

Evidential grid : uncertainty modelled with belief functions (Dempster-Shafer theory)

- Sensor models
- Grids fusion
- Moving objects detection
- Semantic information in perception grids
- Planning

Occupancy grid

Grid paradigm

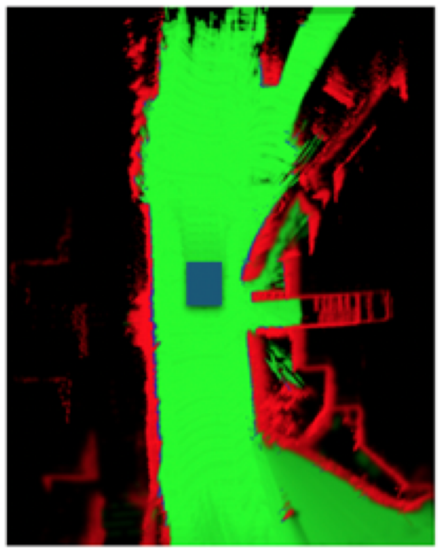
- Discrete representation 2D or 3D
- Common representation for fusion
- Tools for image processing

What for?

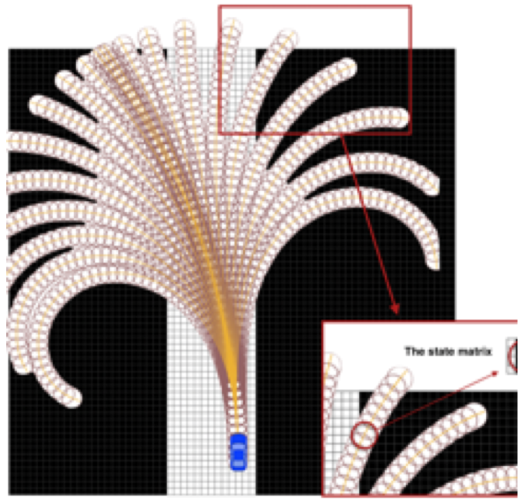
- SLAM (Localization and Mapping)
- Obstacle detection : segmentation of the grid
- Exploration : unknown area exploring
- Obstacle avoidance : reactive planning

Binary grid

Evidential grid



Reasoning for planning



Evidential occupancy grids

Discrete representation of the environment by 2D or 3D grid

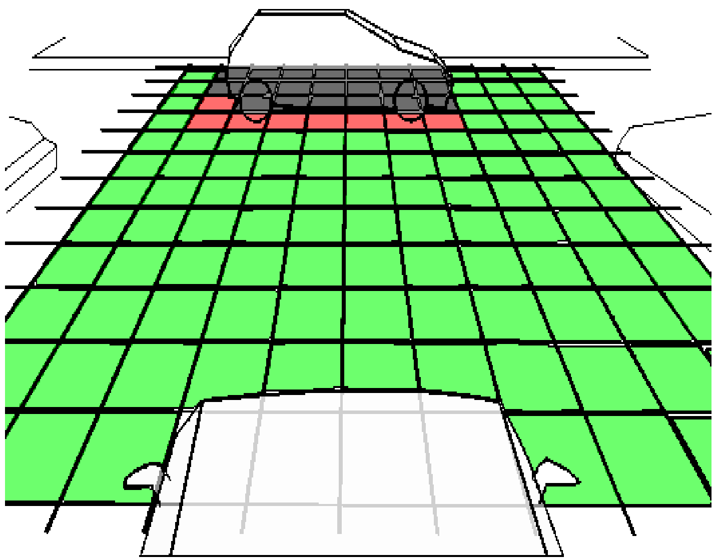
Each cell contains a part of belief of the perception system on the occupancy state : mass function on $2^{\Omega} = \{\emptyset, O, F, \Omega\}$ with $\Omega=\{O,F\}$

Free :	m(F)	green
Occupied :	m(O)	red
Unknown :	m(Ω)	dark grey

Hyp : cells are independent
vertical obstacles

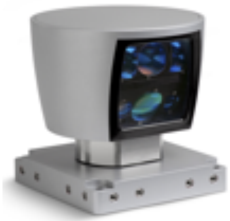
Probabilistic grid [Elfes 1989] [Coue 2005]

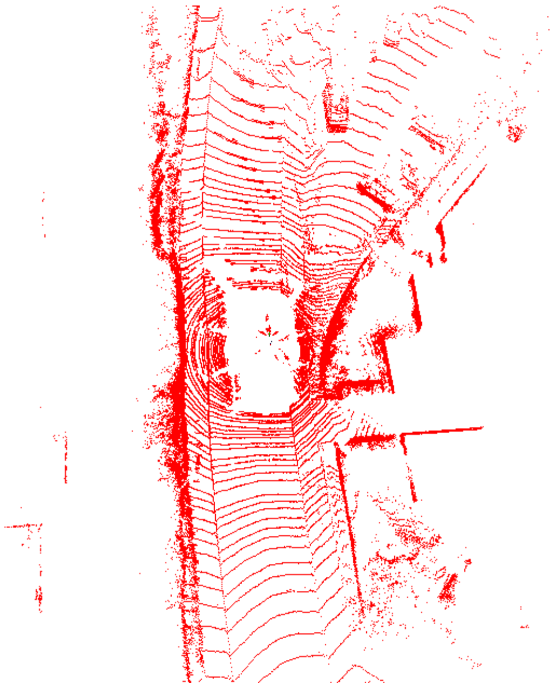
Evidential grid [Pagac 1998]



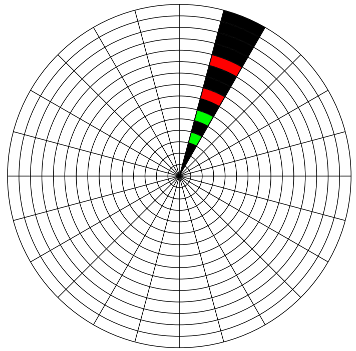
Sensor model : from sensor data to occupancy grid

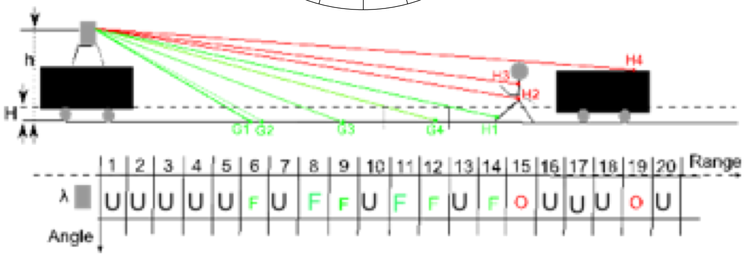
Lidar scan is 3D points cloud





Sensor model computes the belief mass assignment to cells





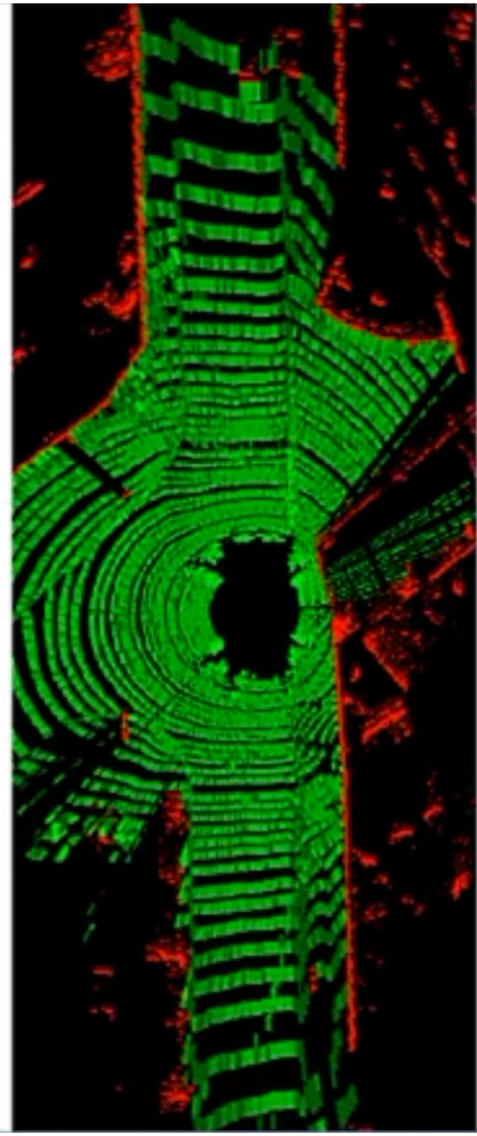
Free cell

$$m(F) = 1 - (\alpha_{MD})^{nf}$$
$$m(\Omega) = 1 - m(F)$$
$$m(O) = m(\emptyset) = 0$$

Occupied cell

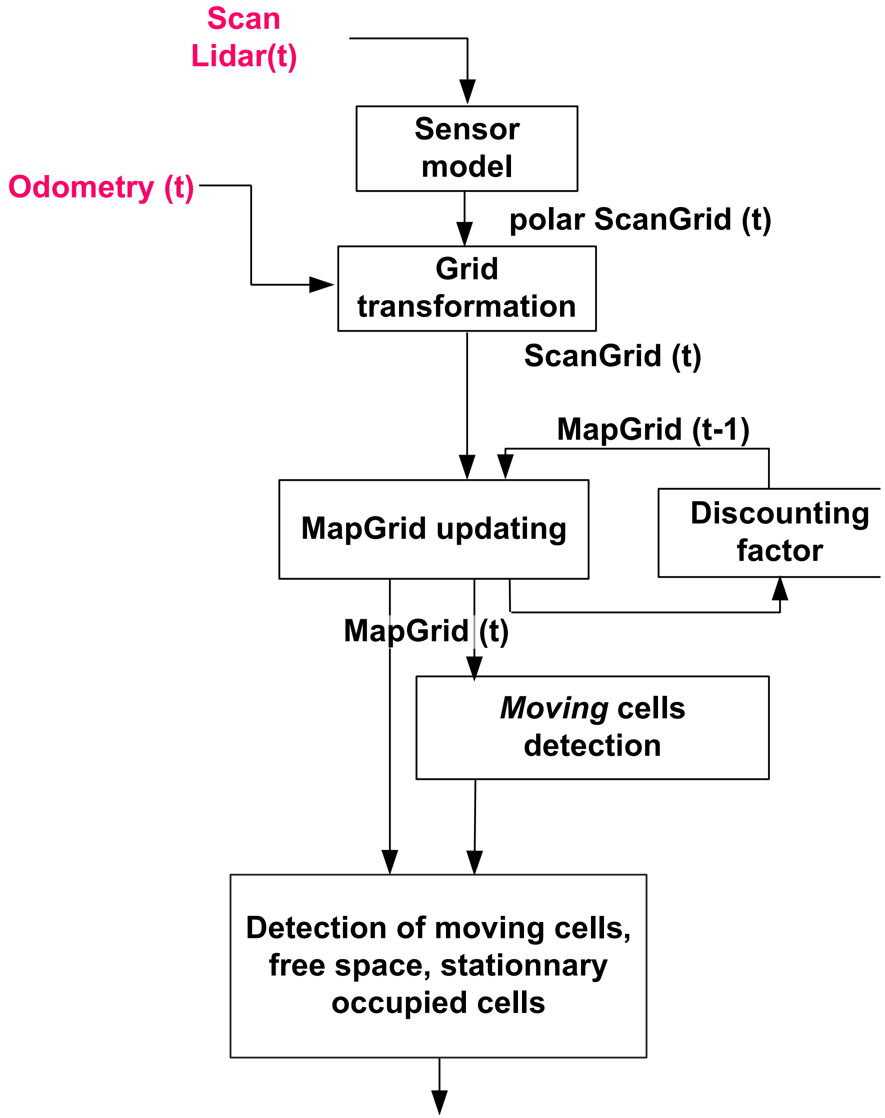
$$m(O) = 1 - (\alpha_{FA})^{no}$$
$$m(\Omega) = 1 - m(O)$$
$$m(F) = m(\emptyset) = 0$$

The result is an occupancy grid



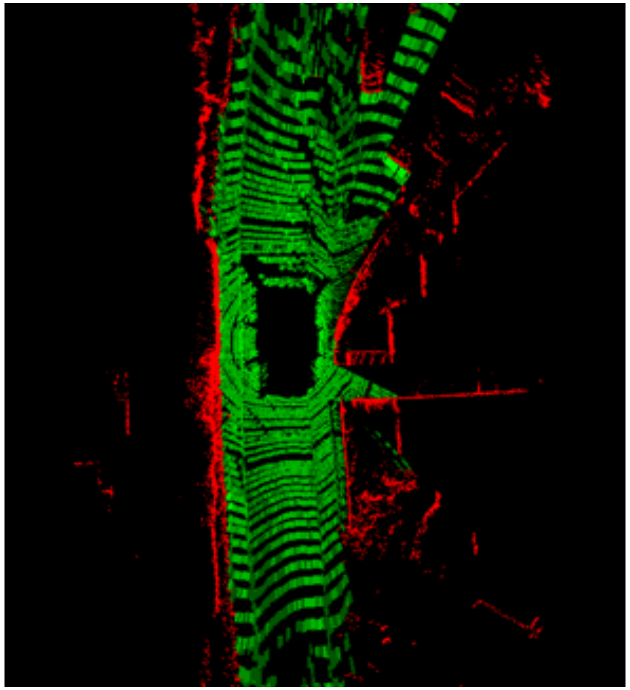
Sequential fusion to reduce uncertainties

- Multi grid approach is possible
  - Scan grid
  - Accumulation or inference grid (MapGrid)
- Cell fusion
  - Temporal Discounting
  - Conjunctive and Dempster rule
- Dynamic grid fusion enhances belief or detect conflicting data
  - Moving objects : $m(\emptyset)$

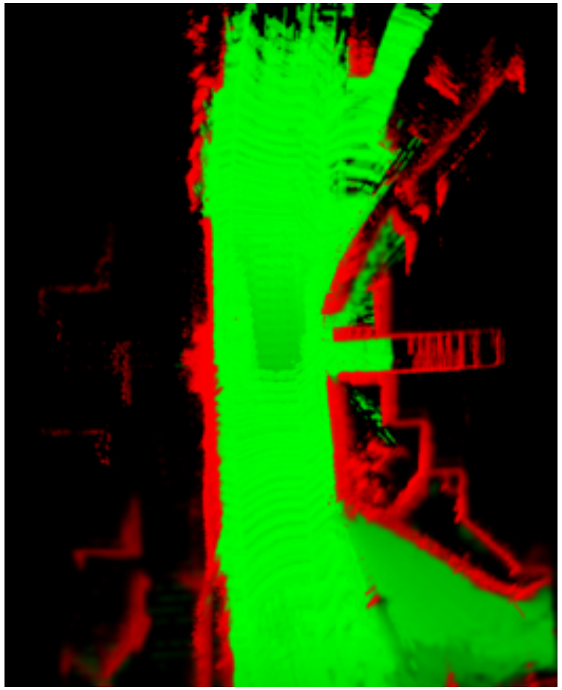


Other approaches : Slam [Reineking 2013] [Trehard 2015]

Exemples : 360 ° velodyne lidar



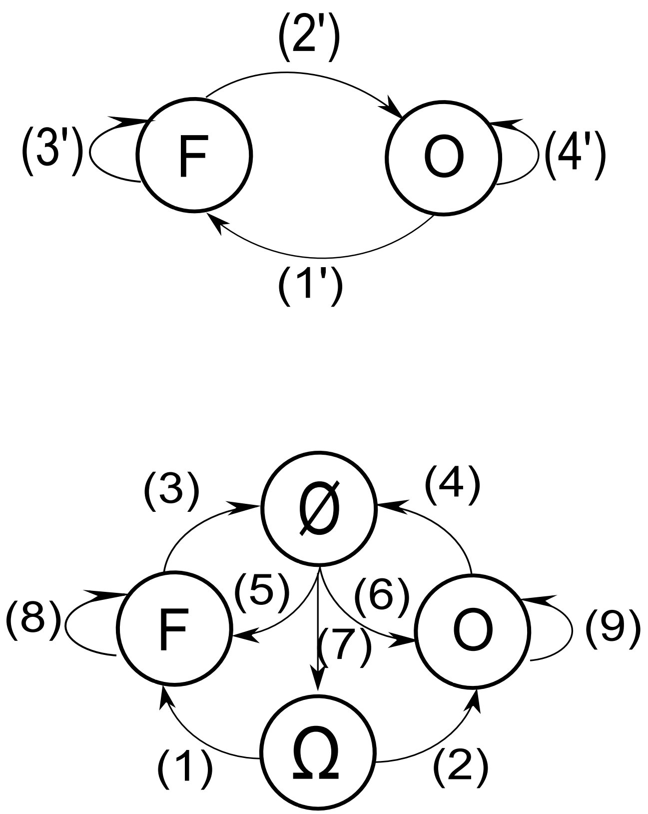
Scan grid

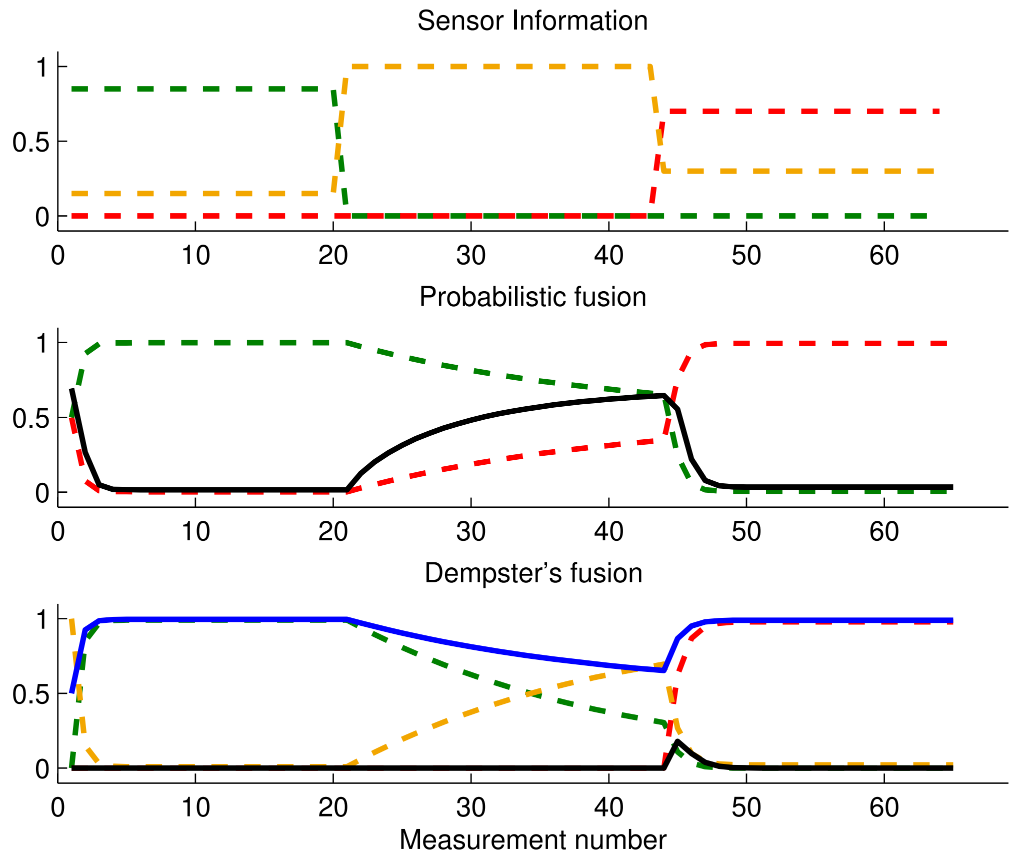


Fusion result

Exemples : a real-time implementation with 4 layers lidar

Comparison with probabilistic model





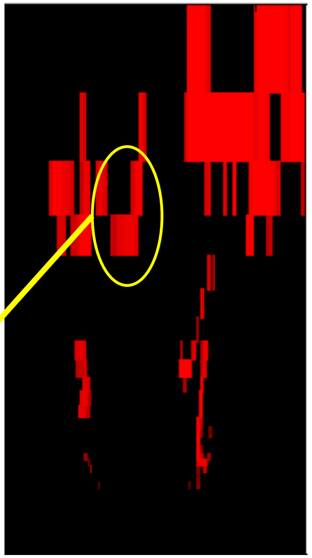
Multi-sensor grid fusion

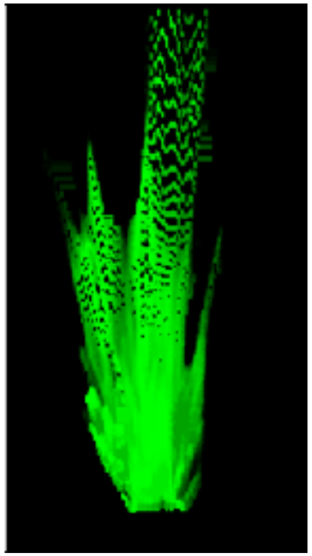
Stereo-vision :

U-disparity gives information about obstacles

V-disparity gives information about road surface

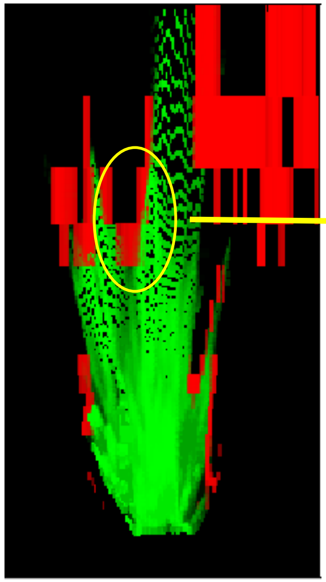
U-Grid



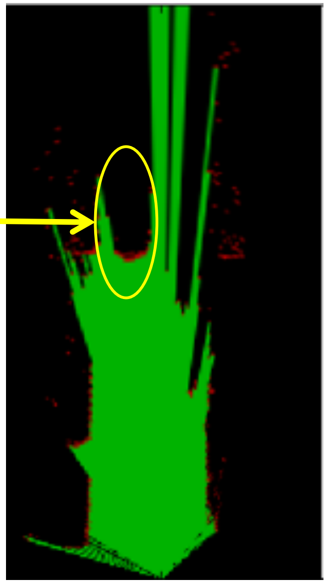


V-Grid

Stereo grid



Scan grid (lidar)



Precision decreases dramatically with distance

Obstacle information more importantly reflected

Precisely uniform information

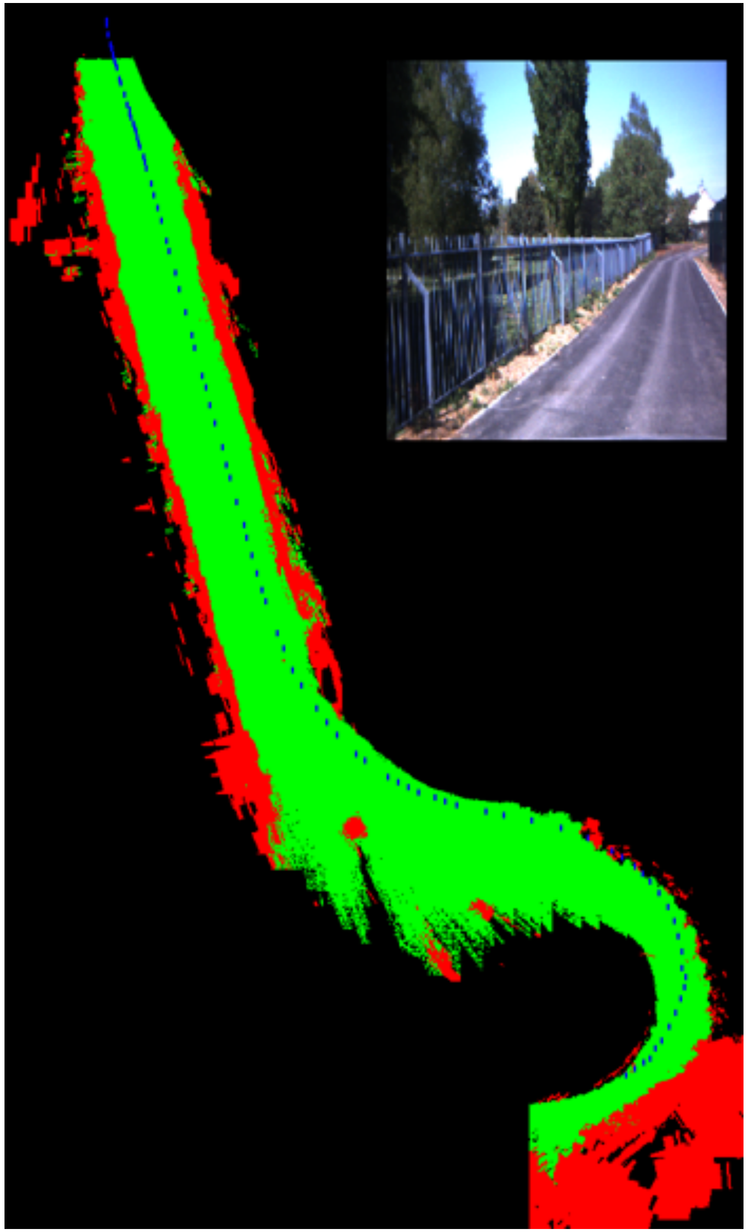
Lack of obstacle information due to sparse data points

Multi-sensor grid fusion

A mapping result :

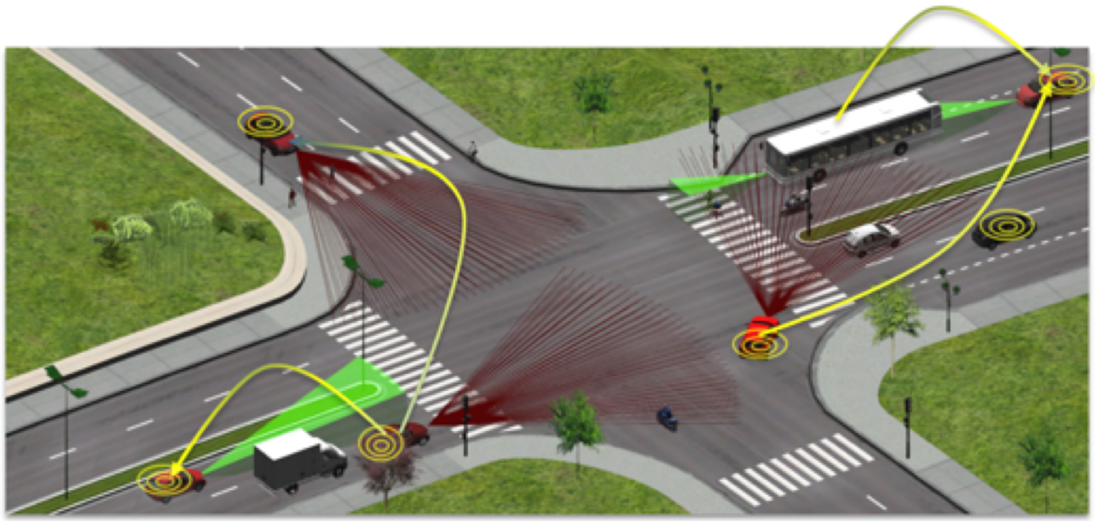
Accumulation by sequential fusion with ego-motion compensated.

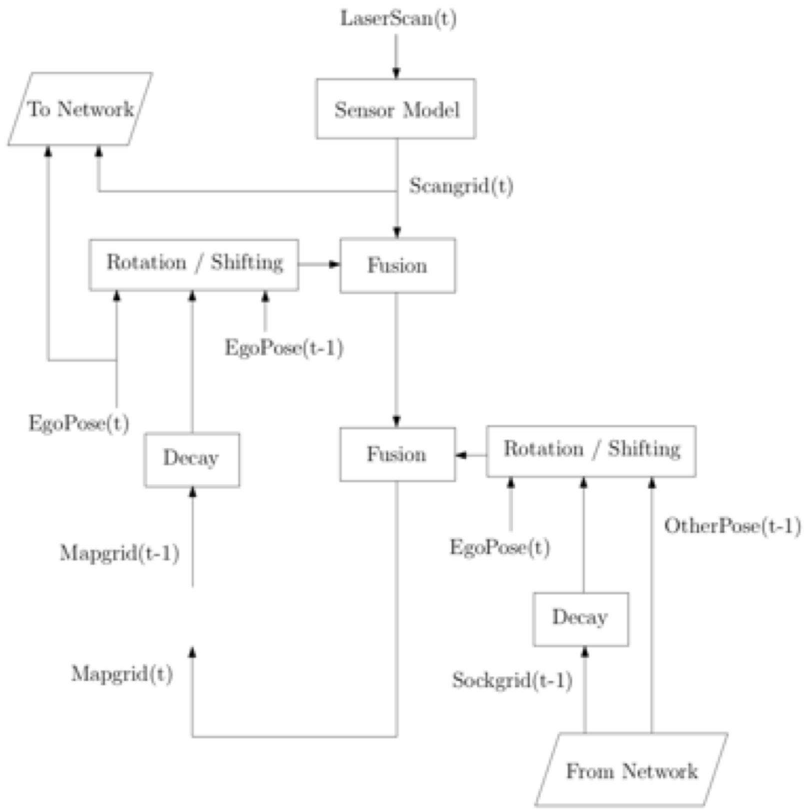
Sequential fusion with Dempster's rule.



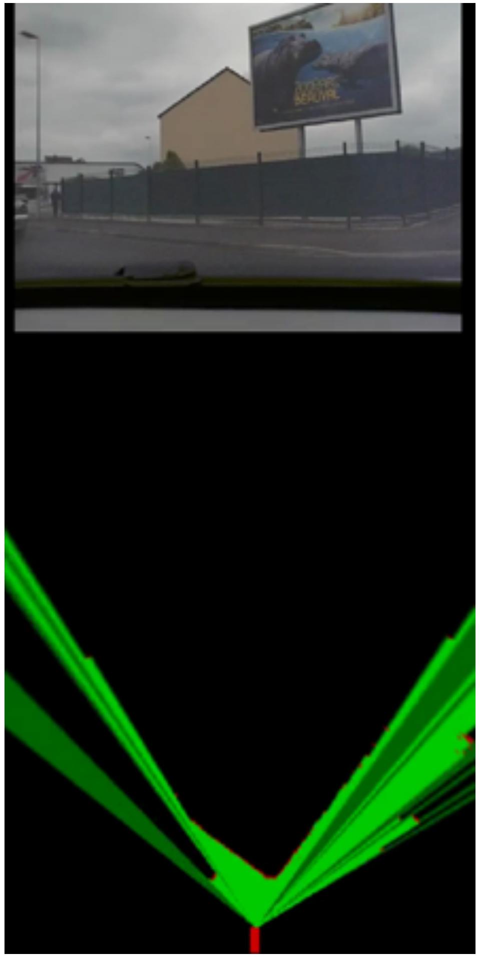
J. Moras, M. Kurdej, C. Yu
Supervised with Ph. Bonnifait

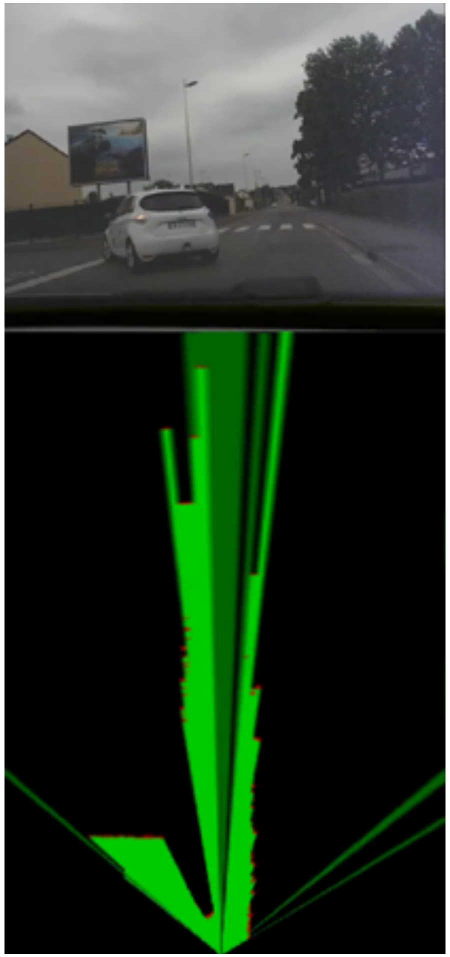
Multi-vehicle grid fusion

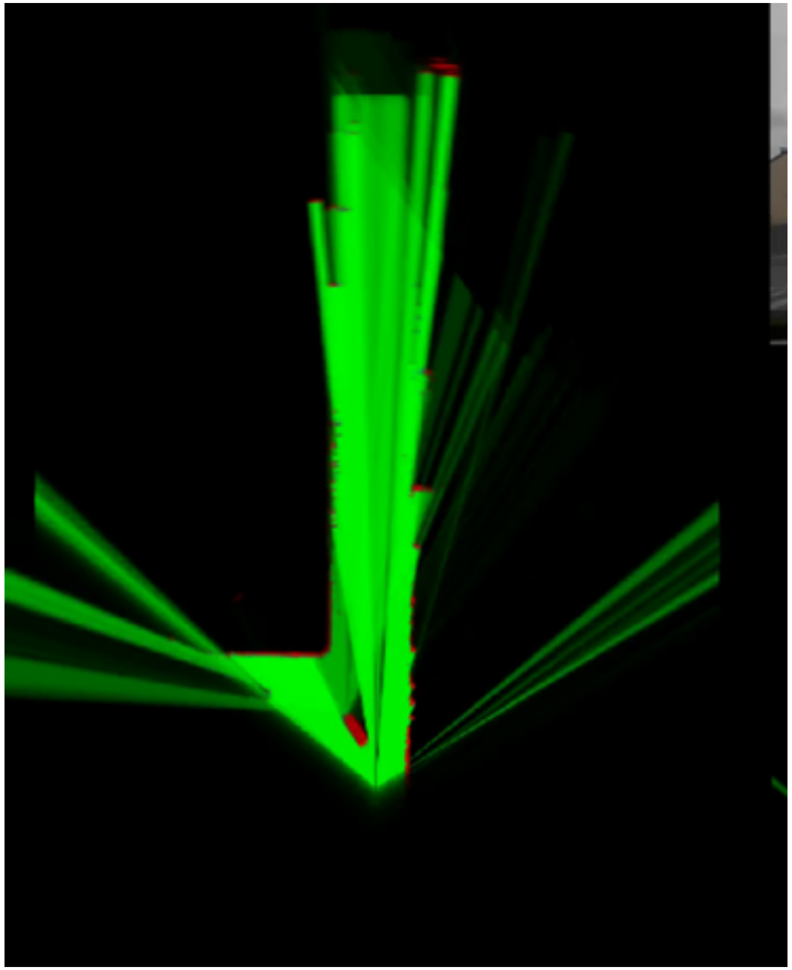




Multi-vehicle grid fusion







F. Camarda supervised with F. Davoine

Semantic information in lane grids

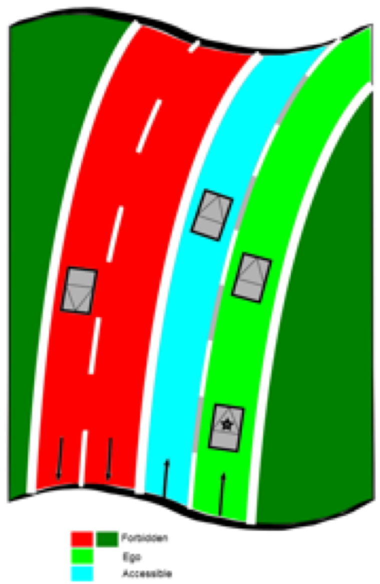
Autonomous vehicle : Traffic rules

Lane keeping

Direction of circulation

Lane grid model

Adding semantic information with prior maps for navigation and path planning



$$\Omega = \{Ego, Accessible, Forbidden\}$$

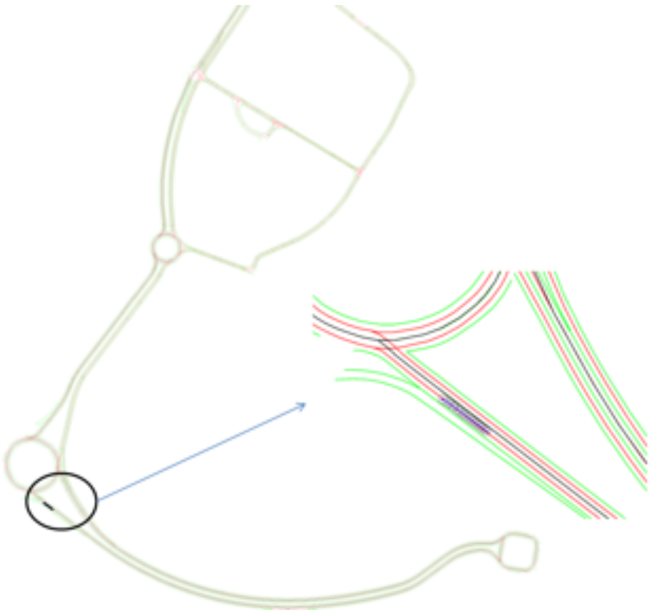
Ego

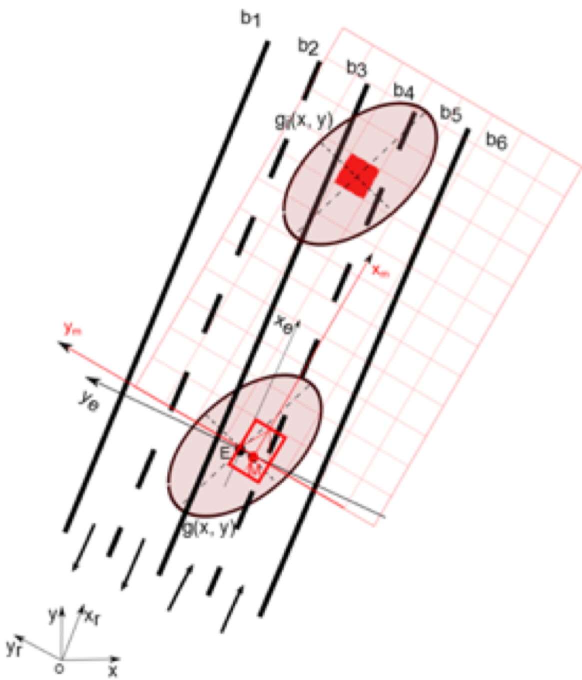
Accessible

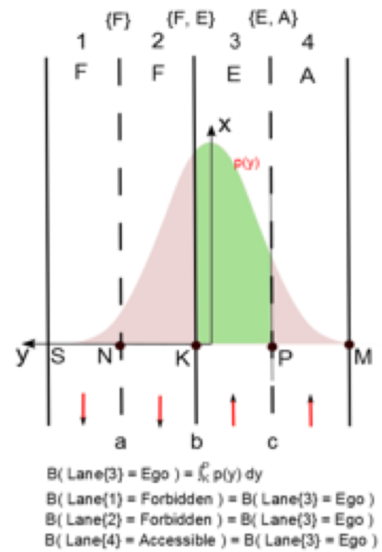
Forbidden

Semantic information in lane grids

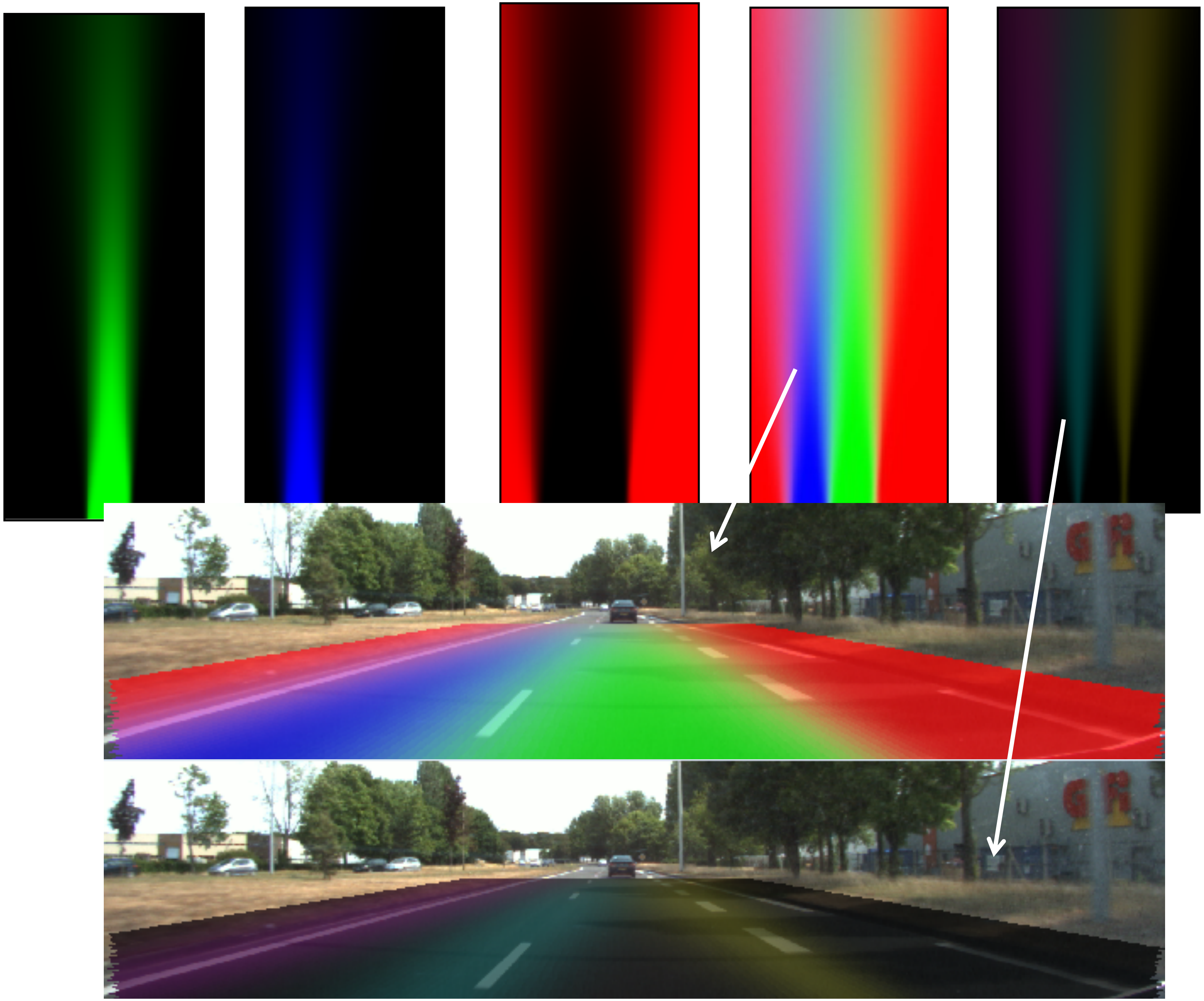
- Precise map with lane and road marking information
- Propagation of pose estimation uncertainty to the grid cells







Lane grid



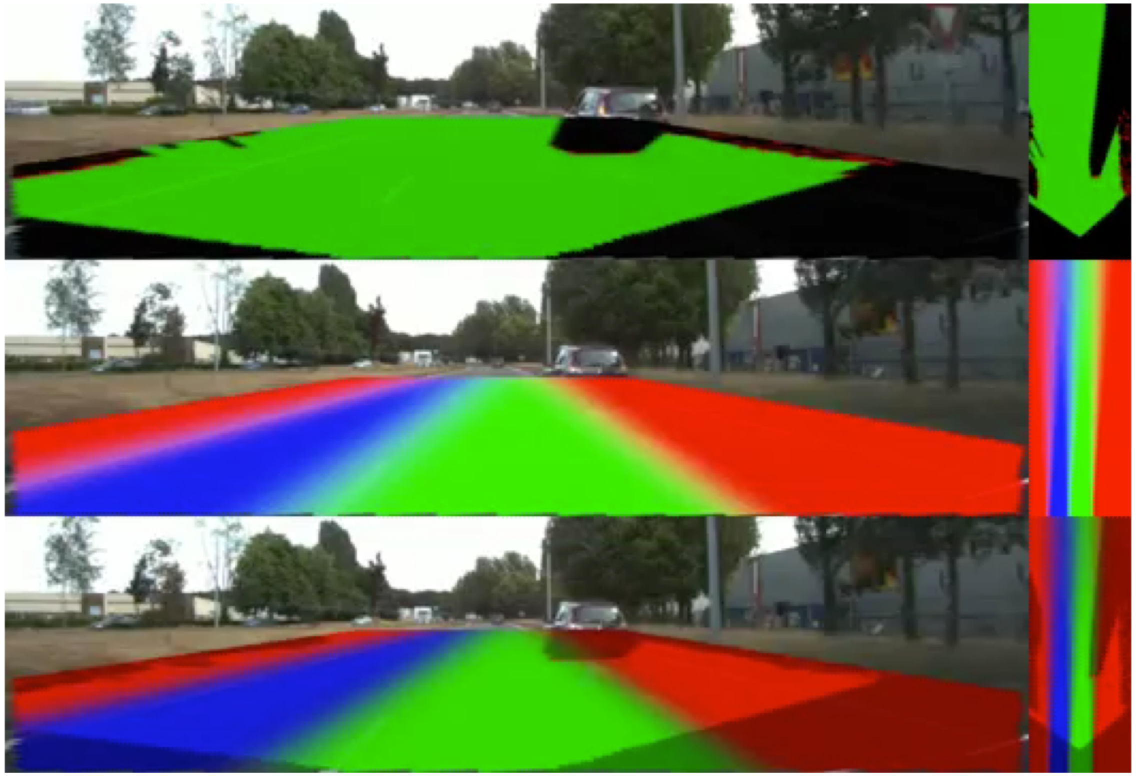
Perception grid : combination of lane grid and occupancy grid

- Validation : projection on scene image, analysis of entropy and specificity of the grid comparing with probabilistic approach

C. Yu [ITSC 2016] +Journal submitted

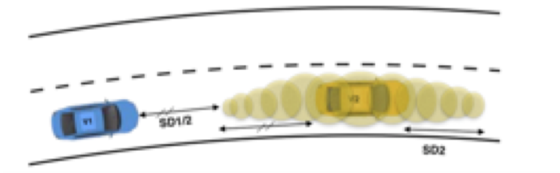
Perception grid : combination of lane grid and occupancy grid

- Validation : projection on scene image, analysis of entropy and specificity of the grid comparing with probabilistic approach

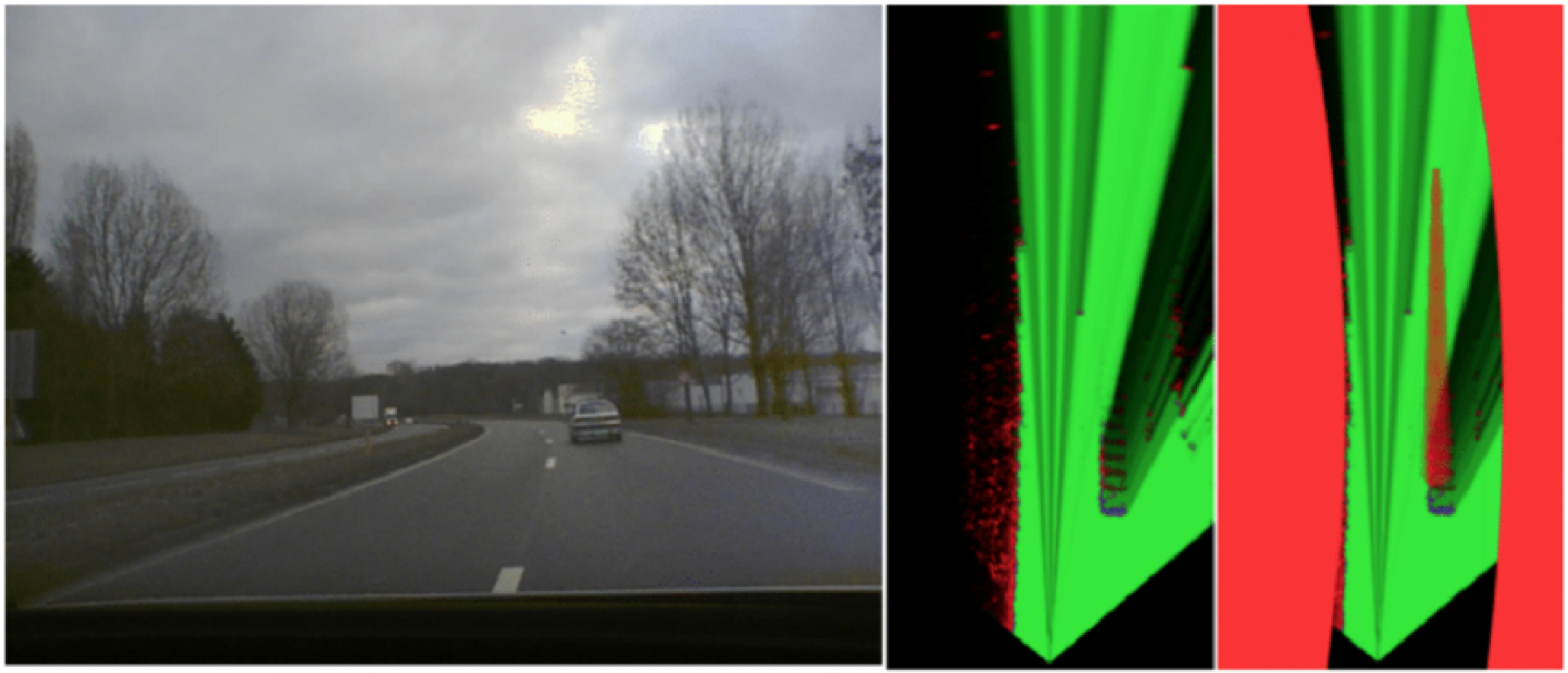


C. Yu [ITSC 2016] +Journal submitted

Safety distance

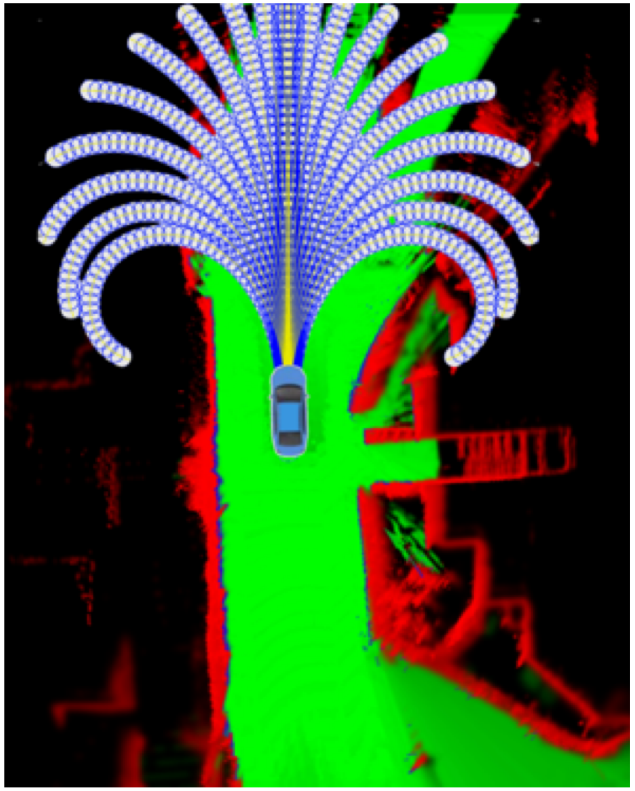


- Expansion of the dynamic obstacles to respect safety distances
- Adding speed information for each cell : amplitude, direction

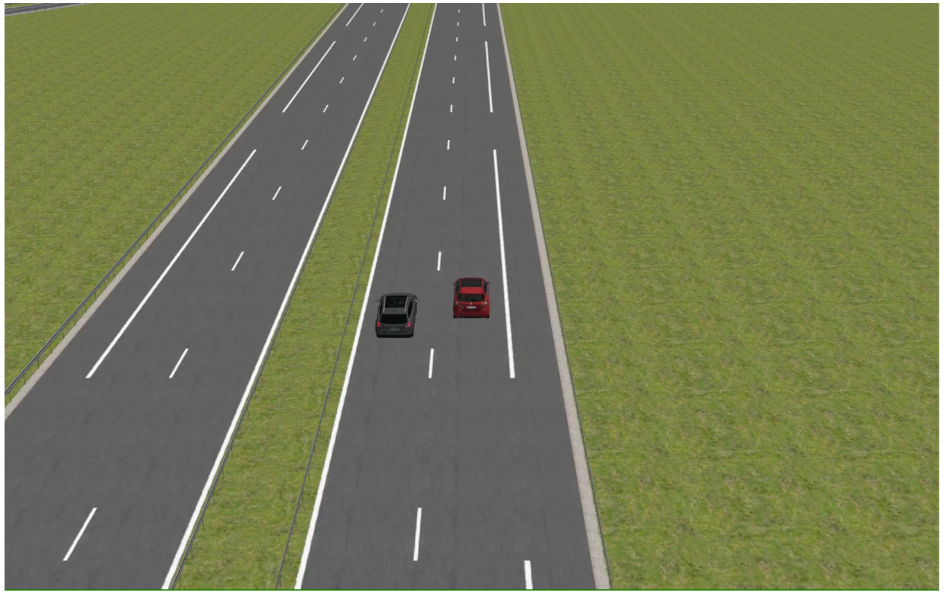


Reasoning with uncertainties : Path planning using evidential grid

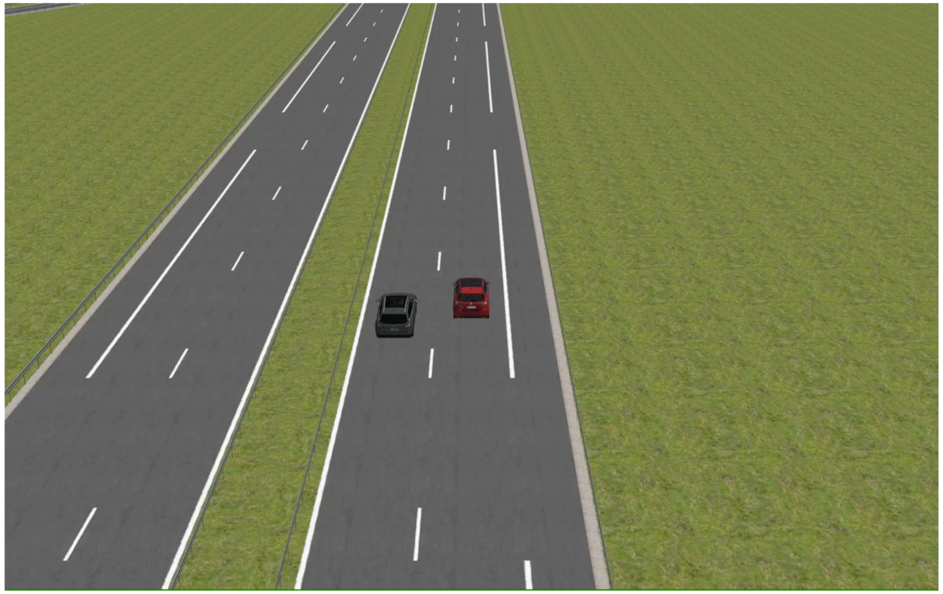
- Clothoid tentacle for path planning
- MDP-like approach to select the best tentacle
- Reward computation taking into account of uncertainties modeled by belief functions in the grid



Tested with real grids and with scanner studio



Binary grid



Evidential grid

Planning with binary grid can lead to blocking situation
A lot of parameters, some without physical meaning

H. Mouhagir co-supervised with R. Talj CIFRE PSA

Recent works

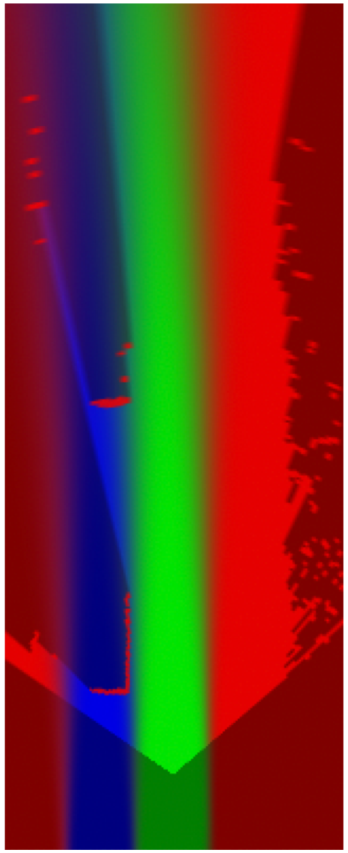
Grid paradigm

Discrete representation 2D or 3D

Common representation for fusion

Tools for image processing

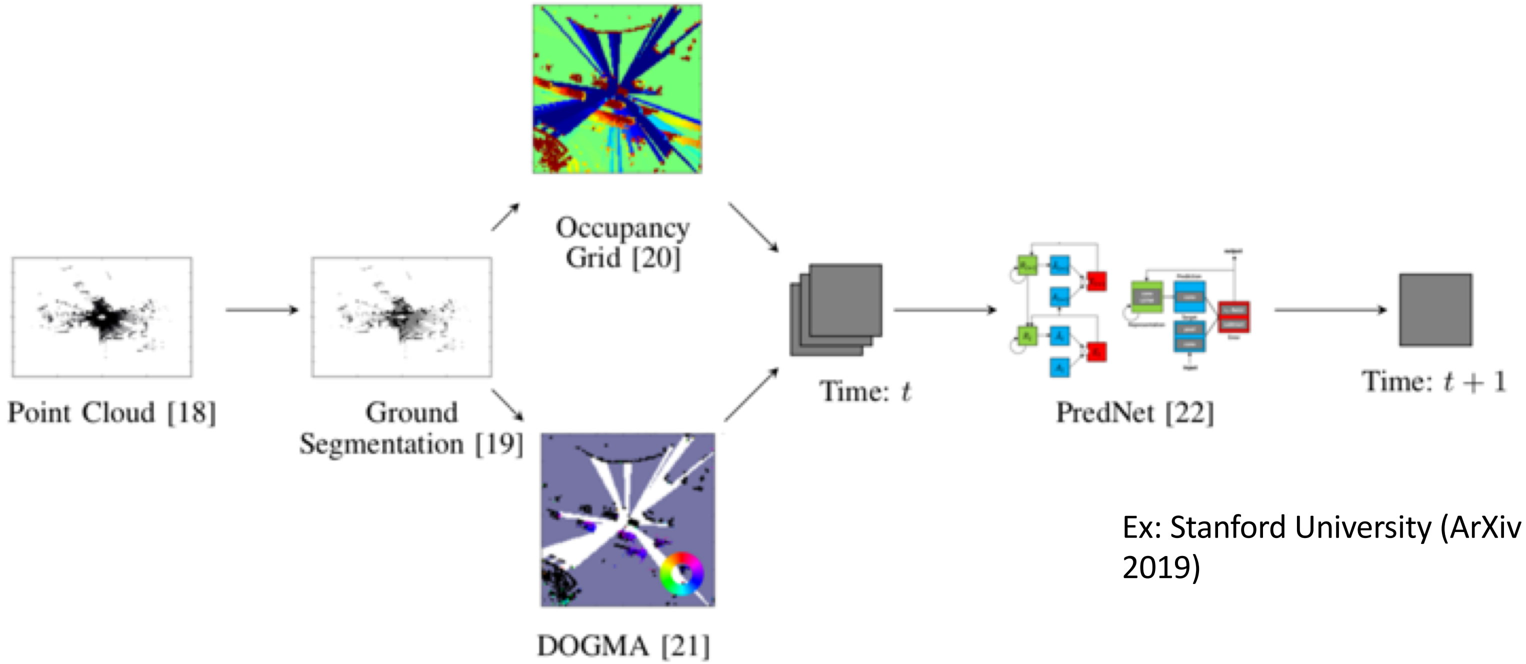
-> well adapted for machine learning



- alternative to point cloud
- pseudo-image
- (first lidar ground truth)

Recent works : Deep learning on occupancy grids

- TU ULM (K. Dietmayer) : DOGMA dynamic occupancy grid : augmented grid with velocity (2017)
- INRIA Grenoble (C. Laugier) : Deep learning on probabilistic grids
- KIT (C. Stiller): Deep Learning on 3D evidential grid for planning
- Stanford Univ : temporal learning on 2D evidential grid for prediction (2019)



Ex: Stanford University (ArXiv 2019)

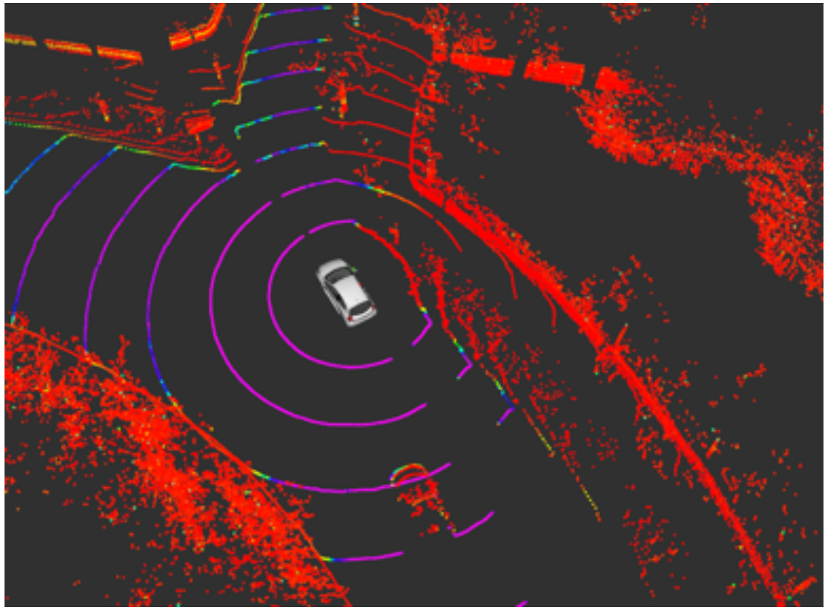
Point cloud

Lidar point segmentation

- PointNet
- SqueezeSeg

Fixed size of input data

Uncertainty is not explicitly represented



Our proposition

- reinterpretation of generalized logistic regression (GLR) classifiers as an evidential classifier
- use the output of evidential classifier for grid building

Phd E. Capellier co-supervised with F. Davoine (CIFRE Renault)

clustered point cloud

Learning stage :

A dataset of LIDAR objects was collected.

The objects were generated from a real-time range image-based clustering algorithm

Data collection platform equipped with a VLP32C LIDAR

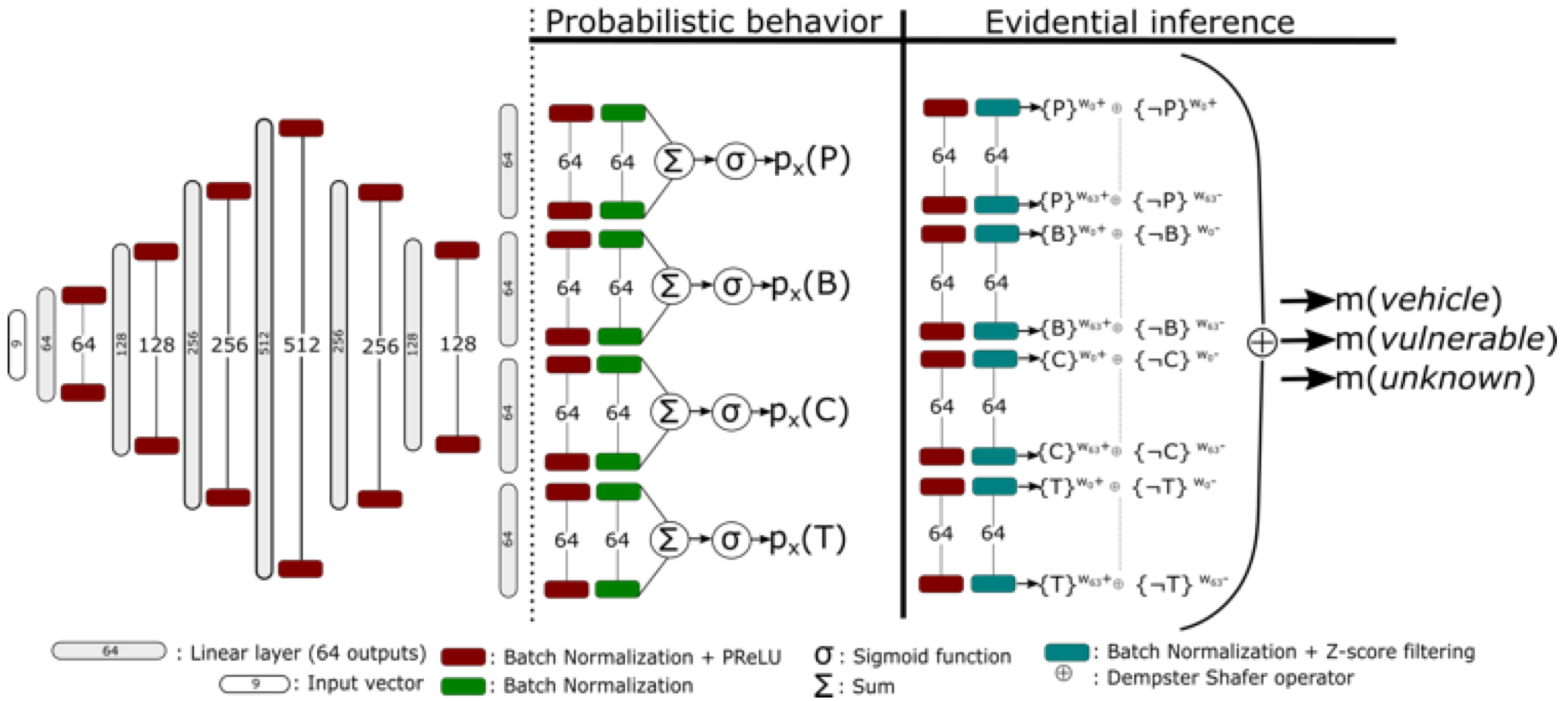
label	number of samples
Car	91297
Truck	9713
Pedestrian	3461
Bike	946

Number of LIDAR objects per class in the dataset

ML on clustered point cloud

Input : 3D bounding box (9 parameters)

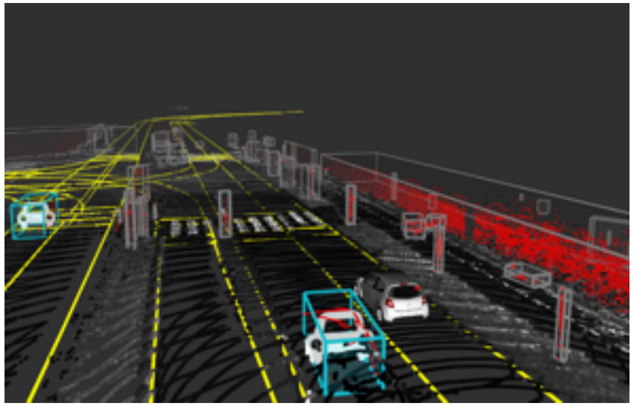
Output : mass function in evidential framework

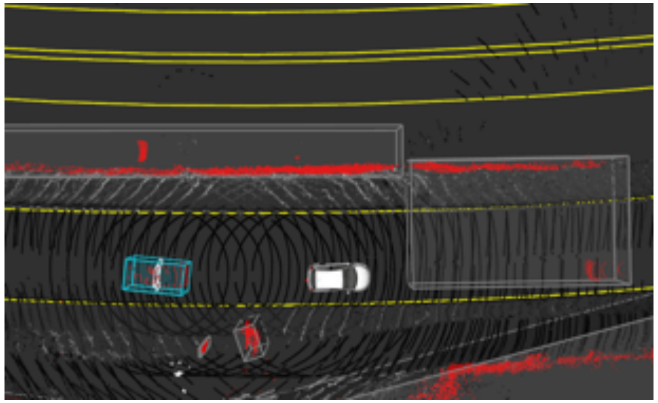


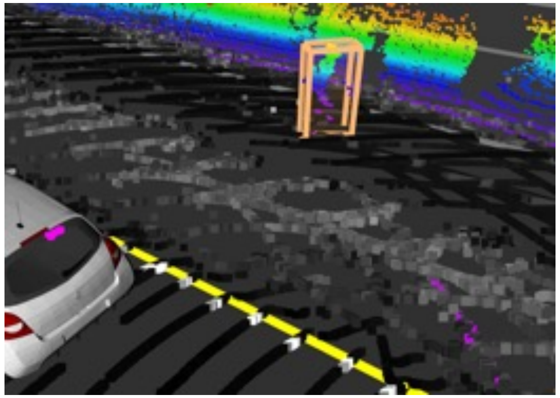
ML on clustered point cloud

Method	IoU	Accuracy	F1-score on V	F1-score on W	F1-score on Ω
Ours, probabilistic output with no Z-score filtering	0.312	0.729	0.890	0.408	0.377
Ours, evidential output with no Z-score filtering	0.320	0.733	0.890	0.412	0.388
Ours, evidential output with $ZMax = 2.58$	0.558	0.825	0.938	0.458	0.675
Ours, evidential output with $ZMax = 1.96$	0.682	0.872	**0.945**	0.570	0.786
Ours, evidential output with $ZMax = 1.65$	**0.725**	**0.897**	0.929	**0.661**	**0.825**
One-class SVMs	0.507	0.661	0.672	0.556	0.660

V stands for "vehicle",
W stands for "vulnerable road user",
Ω stands for "unknown" object







To conclude on evidential grids

- Better representation of ignorance and conflict.
- Better consideration of scene changes
- Possibility to refine the frame of discernment for adding semantic data
- Planning under uncertainty

- No ground truth

Verrous pour la perception pour les véhicules autonomes

- L'intégrité de la perception
  - Indicateurs de confiance
  - Vérité terrain
  - Sureté de fonctionnement
- S'adapter à des sources d'information différentes
- Disponibilité des cartes

Thank you for your attention

Heudiasyc, Labex MS2T, Sivalab,

Publications, Videos,

https://www.hds.utc.fr/~vberge

https://www.hds.utc.fr

https://www.labexms2t.fr

Publications

- Sensor models [IV 2011], [ICARCV 2014], [IV 2015]
- Grid fusion and moving objects detection [ICRA 2011], [IV 2012a], [IJAR 2013] , [FUSION 2013], [ITSMag2014]], [Sose 2018]
- Lane grids : [ITSC 2016] +Journal submitted
- Planification with perception grids: [IV 2015] [ITSC 2016] [IFAC WC 2017] + journal submitted
- Deep learning and grid : : [IV 2019]

Projects and collaborations

- CityVIP National project (with INRIA, univ Clermont Fd)
- PREDIMAP International project (Japan, China, Thailand)
- DGA scholarship (French dept of Army)
- CSC scholarship (China)
- PSA (Car manufacturer contract)
- DAPAD, Labex MS2T project
- SIVALab (joint lab)