Tuesday, October 21th – INRIA, Rocquencourt

EGO-LOCALIZATION FOR AUTONOMOUS DRIVING, A REMAINING ISSUE

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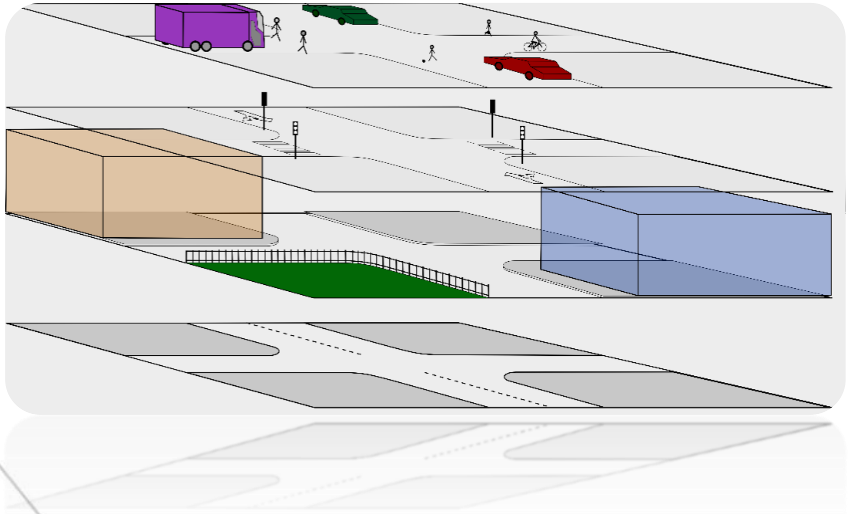
Presentation:

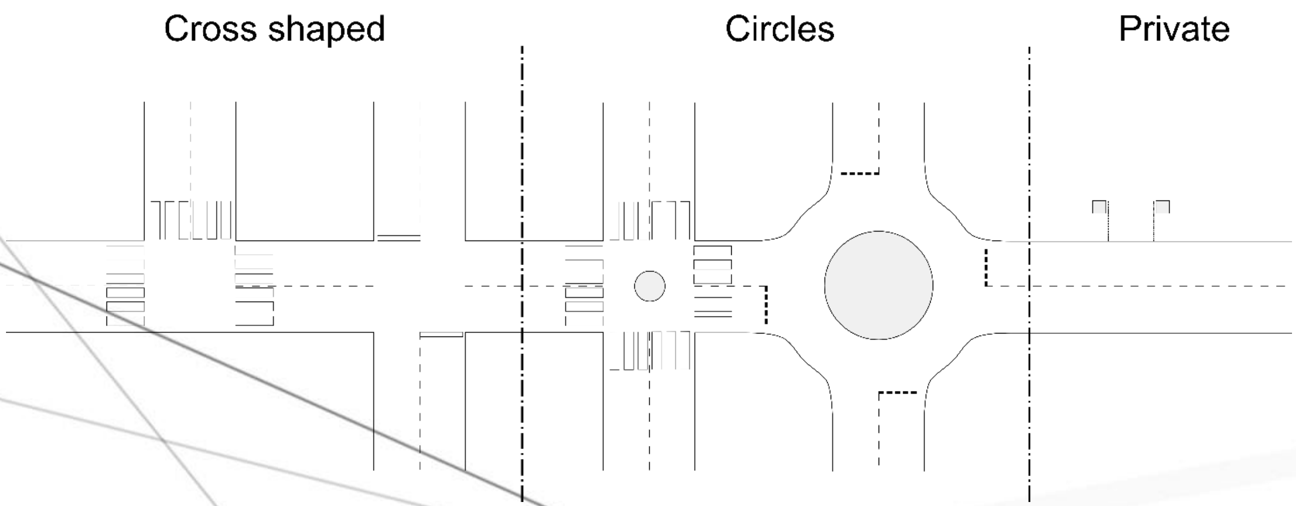


- PhD student
- RITS team (Robotics & Intelligent Transport System)
- Valeo project V50
- Working in autonomous driving and especially in perception

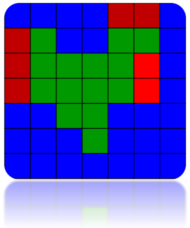
Intersection management in urban environment for autonomous driving

Ego-localization and intersection

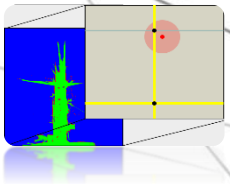
- Intersection is an open area
- Urban context can interfere with GPS systems
- A lot of cases possible



I. Localization for autonomous driving



II. Credibilist simultaneous localization and mapping



III. Toward a link between local and semantic map

LOCALIZATION FOR AUTONOMOUS DRIVING

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Sensors for localization:

➔ Global localization:

GPS-RTK (centimeter precision) ; DGPS (~1m precision) ; Classic GPS (~10m precision)

➔ Relative localization:

Vision ; Laser scanner (LIDAR) ; Odometry (speed and orientation) ; Inertial Measurement Unit (IMU)

II

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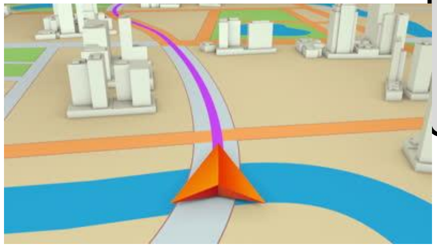
Localization requirements:

→ References: Vehicle / Global

→ Map correspondences: Semantic map; Dense map



→ Performances: Rate; Precision; Cost

→ Robustness: Dense urban; motorway

II

III

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The google car example:

- ➔ High precision and dense pre-recorded map
- ➔ Supported by GPS-RTK/IMU/LIDAR localization system

Concept of a virtual and dense railroad of data

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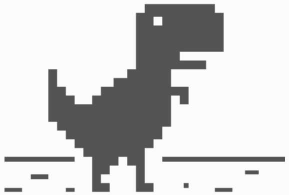

Impossible to address your request : Destination out of range

Another approach: Vislab example

- ➔ Online reconstruction of the drivable area with vision technics
- ➔ Supported by D-GPS/IMU system

Concept of on-line mapping with poor known information

Road network detection advantages:

- The road network is already a constrained environment
- Detecting it could avoid costly off-line mapping and enable robust localization
- Global semantic information are a lot more usable and sharable than dense data map

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Our approach:

- ➔ Drivable area can be detected by a SLAM solution:

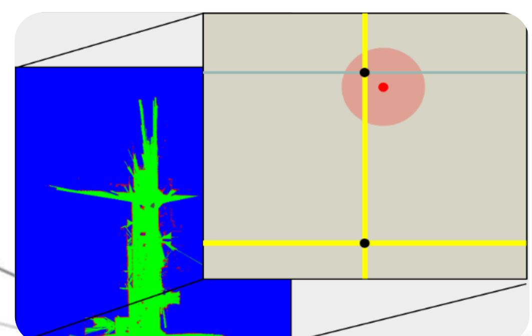
credibilist SLAM based on a LIDAR

- ➔ Link with geo-referenced position must be approached with classic GPS

~10m precision GPS solution

- ➔ Correspondence between surrounding map and semantic map must be achieved

For data-sharing and map enrichment



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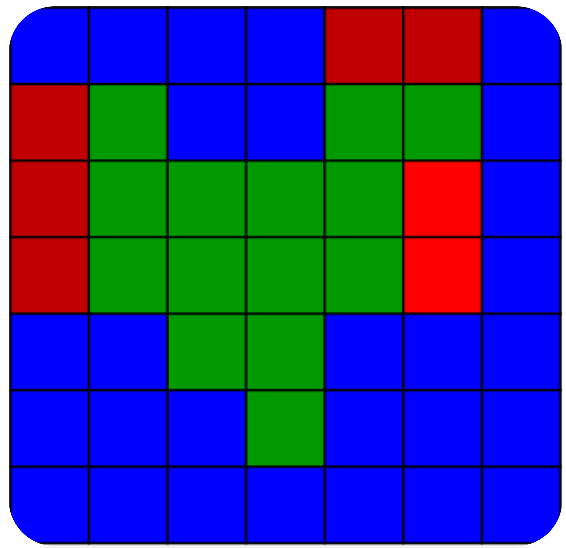
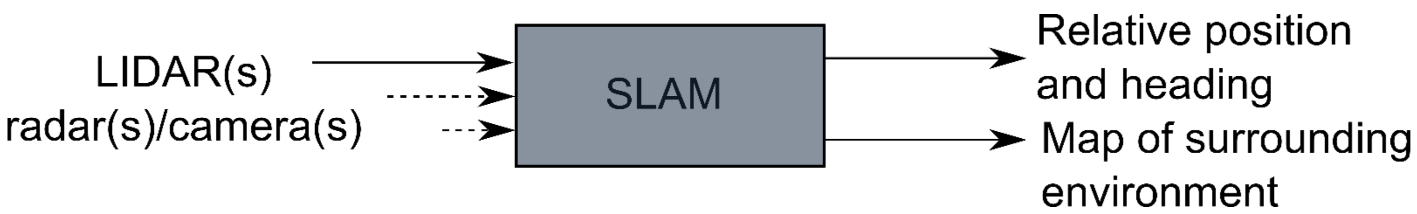
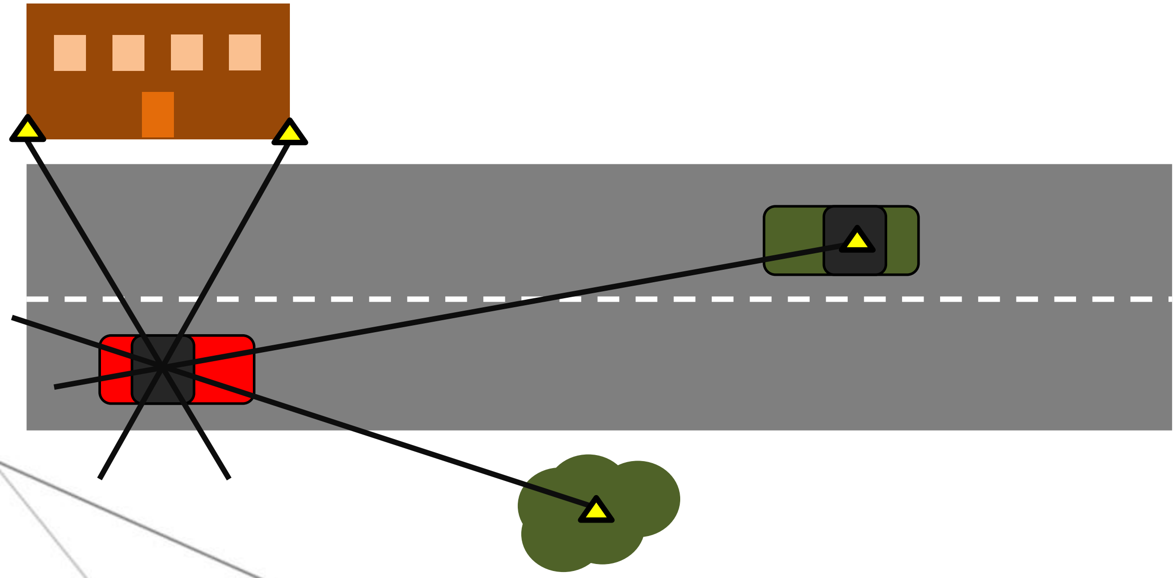
CREDIBILIST SIMULTANEAOUS LOCALIZATION AND MAPPING



SLAM in general:





➔ By tracking beacons on successive scan, both the “map” and the displacement are computed in a static world assumption

SLAM limits in our situation:

Urban context

Without prior-knowledge

Autonomous driving

Grid map based SLAM with LIDAR

Urban scenarios can be highly crowded

SLAM algorithms assume static landmarks as inputs

-> To bypass the static world assumption, the proposition is to use the Transferable Belief Model framework (TBM)

Transferable Belief Model Framework:

- An other way to represent the knowledge

The belief of each singleton event is computed along with all their possible combination.

Hypothesis : h1, h2

probability	credibility
$\Omega = \{h1, h2\}$	$\Omega = \{h1, h2, h1 \cup h2, h1 \cap h2\}$
$p(h1), p(h2)$	$m(h1), m(h2), m(h1 \cup h2), m(h1 \cap h2)$

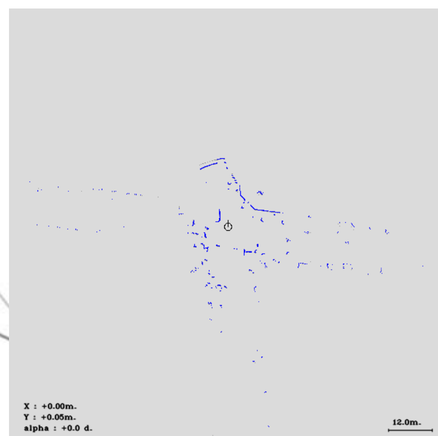
- Each hypothesis then have a mass, updated with measures

The sum of masses is normalized at one.

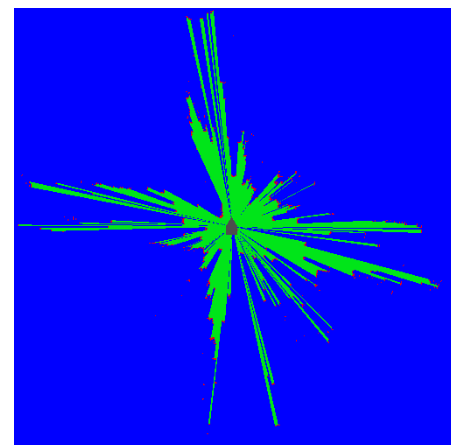
$$\sum_{A \subset \Omega} m(A) = 1$$

Probabilities vs Credibilities for grid maps:

- An explicit representation of not-known information, well adapted for LIDAR input
- A management of incoherent information (Conflict) through the time



From 2 probabilities to 4 masses



TBM framework provides a way to weight the impact of dynamic obstacles all along the SLAM process

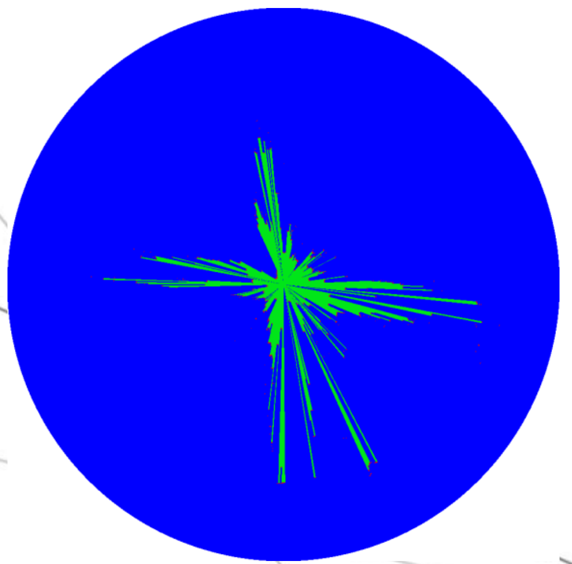
Grid map based SLAM solution:

- Unknown
- Free
- Occupied

360° LIDAR

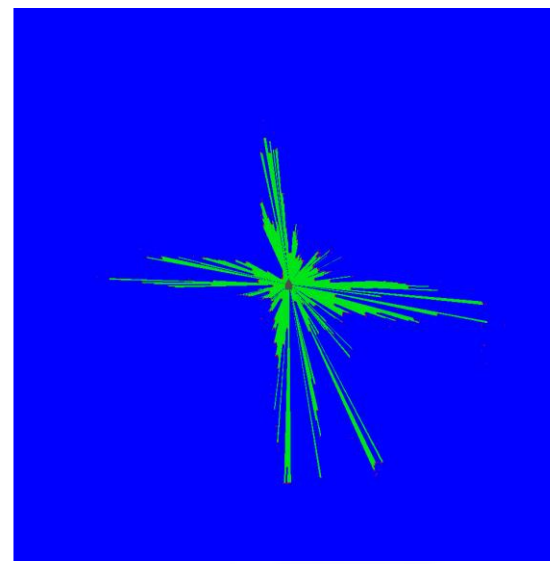
Speed and yaw rate of the vehicle

Representation of laser data



Search fort the best match

Fusion with the recorded map



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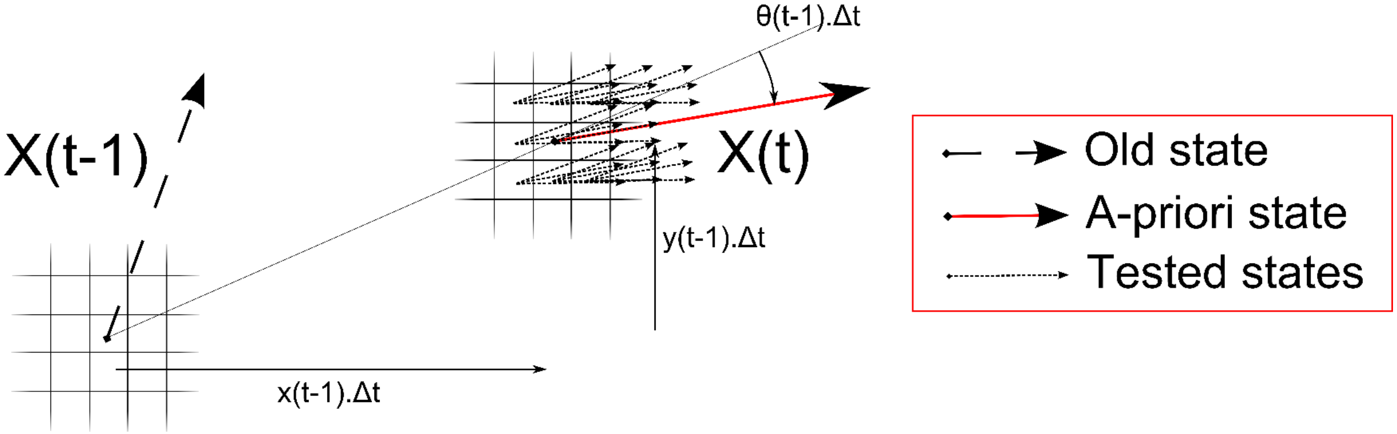
Matching:

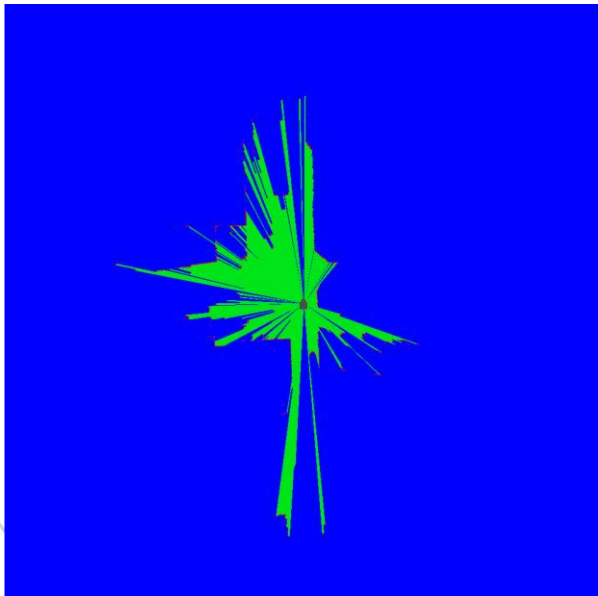
- An a-priori state is computed given a constant speed model

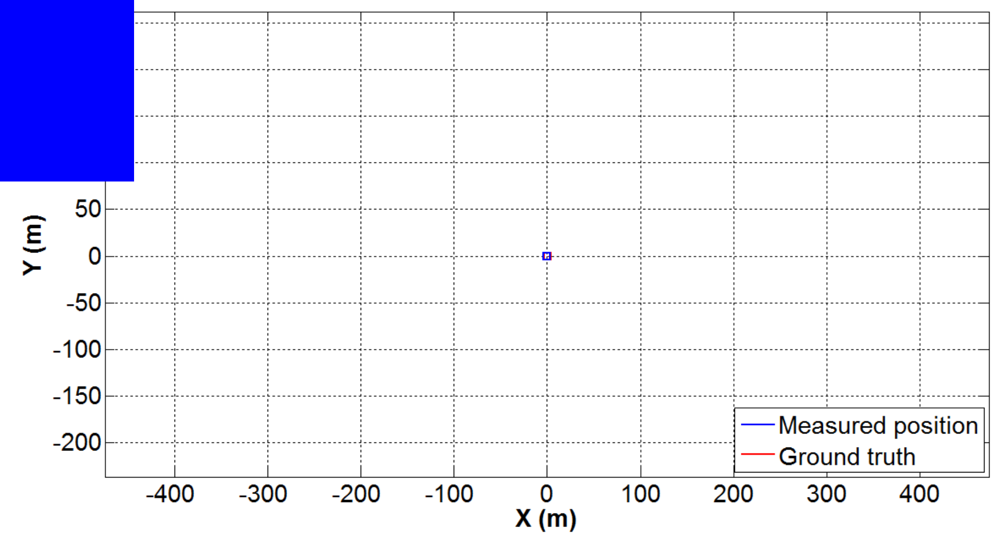


- Candidates around this a priori are tested with a credibilist operator

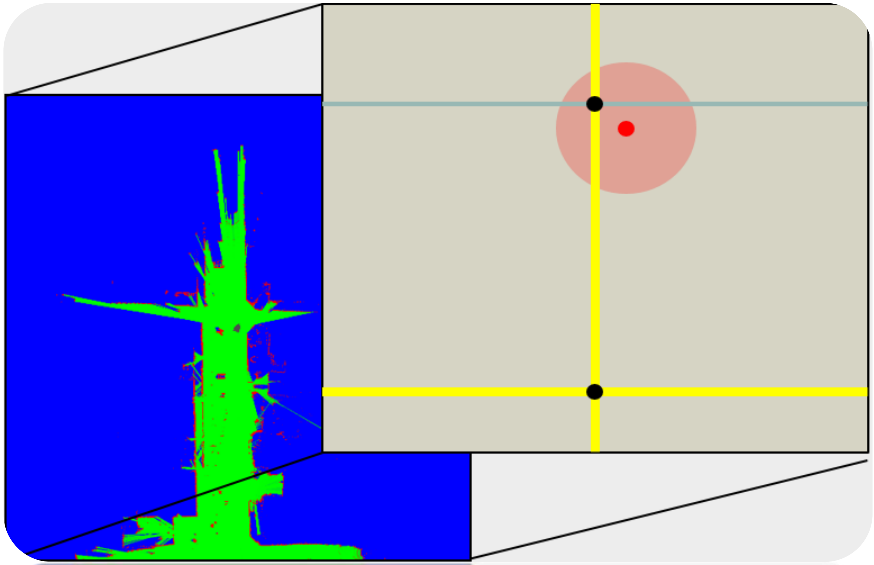
$$Op\left(\hat{m}^{\Omega}_{i,j,t-1}, \tilde{m}^{\Omega,C}_{i,j,t}\right) = \sum_{cells} \frac{(\hat{m}^{\Omega}_{i,j,t-1} \cup \tilde{m}^{\Omega,C}_{i,j,t})(O)}{1 - (\hat{m}^{\Omega}_{i,j,t-1} \cap \tilde{m}^{\Omega,C}_{i,j,t})(\emptyset)}$$

Example of result:





TOWARD A LINK BETWEEN LOCAL AND SEMANTIC MAP



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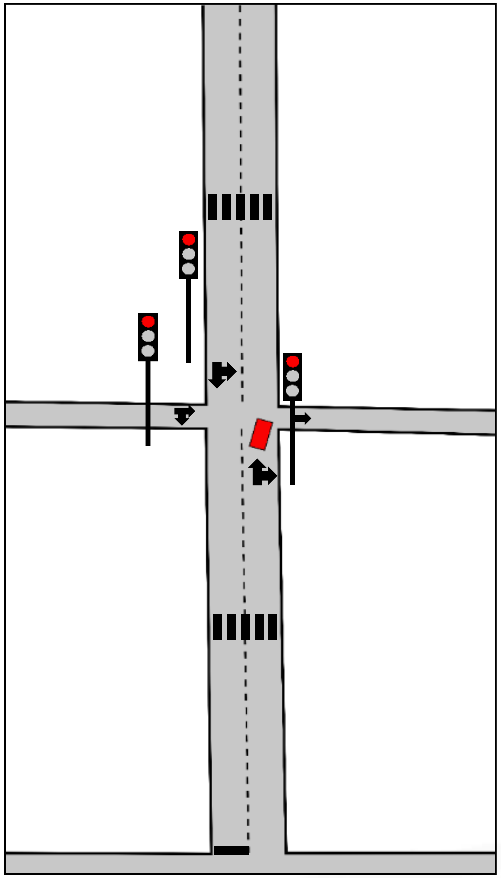
Linking with semantic navigation map:

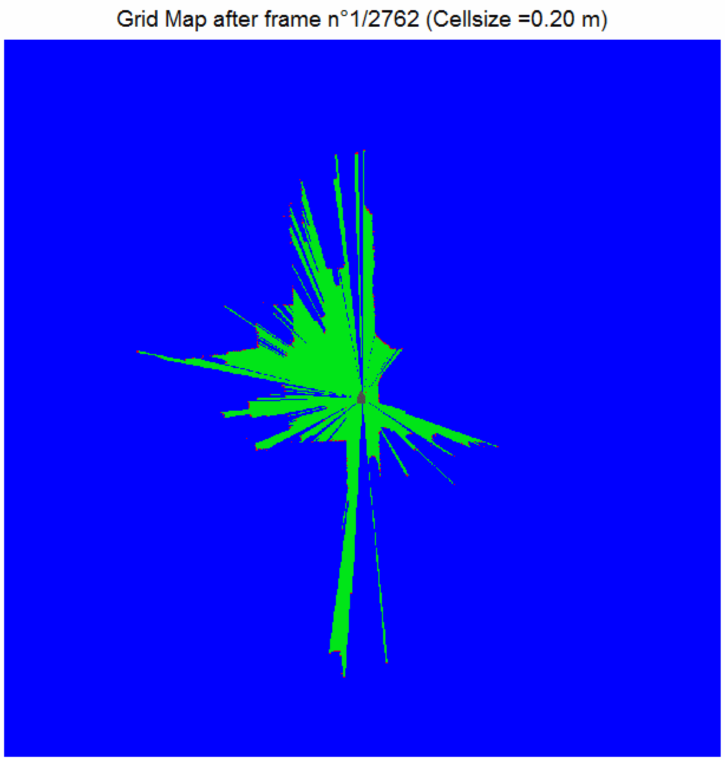
- Leads to correct the natural drift of the SLAM alone
- Enriches the surrounding map of the environment with pre-recorded semantic information
- Enables to share perceived data with other vehicles

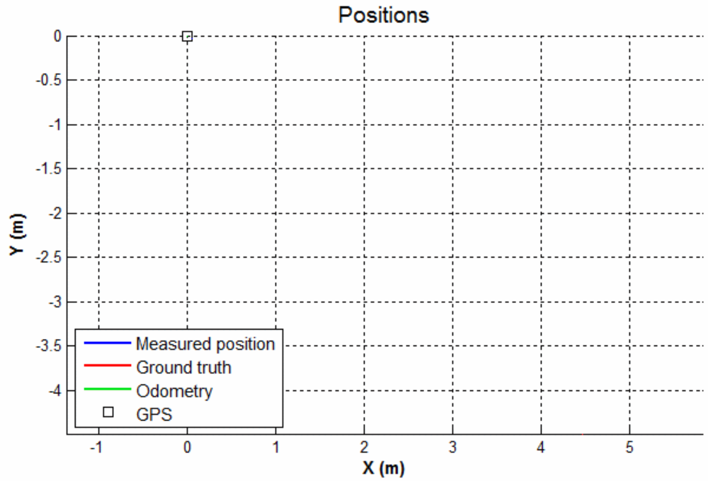


Fusion between SLAM and a classic GPS (~10m precision)

Fusion with classic GPS system:

- Without any prior knowledge, initialization is done using the first GPS position (particular filter running 5000 samples)





CONCLUSION

Conclusion:

- Current ego-localization system are based on high definition map or lacks robustness in urban context
- The proposed solution is based on a credibilist SLAM and so afford a more robust solution in crowded situations
- A solution to link this SLAM with a global semantic map has been started by fusion of GPS and SLAM data
- Semantic information could then be added in the local SLAM map and so enrich the autonomous car knowledge with reasonable costs

THANKS FOR YOUR ATTENTION

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