Improving Monte Carlo Localization using Reflective Markers: An Experimental Analysis

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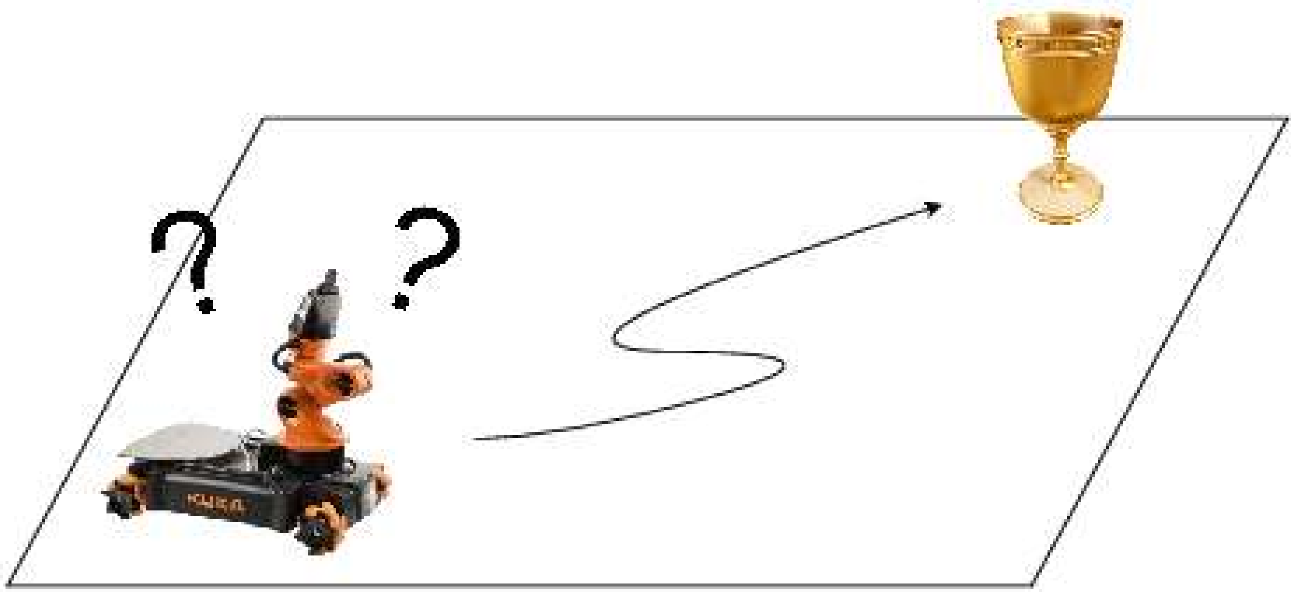
Context and Motivations

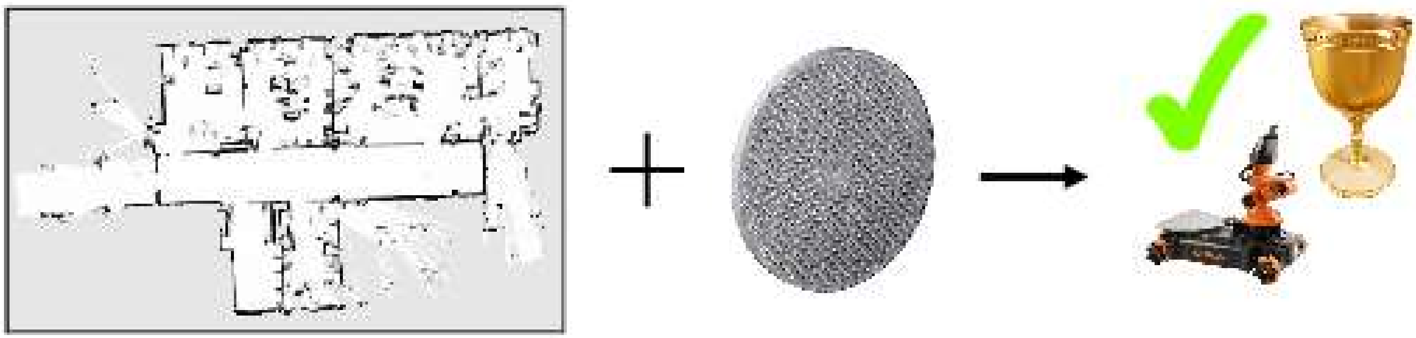
Robust localization is a basic requirement for many applications in mobile robotics.



BUT Symmetrical or featureless environments represent a problem!

Objectives

During this presentation, we will show how artificial landmarks can be used to reduce the chances of failure of the localization process.



More specifically, an experimental analysis of a probabilistic sensor model designed to employ reflective markers is presented.

Localization

Augmented Monte Carlo

1. Given a map of the environment

2. A particle filter represents the distribution of likely states

$$\mathcal{X}_t = x_t^{[1]}, \ldots, x_t^{[M]}$$

3. Estimate the pose of the robot as this moves

Augmented Monte Carlo

4. Using sensor readings compute the likelihood of the estimate carried by particles

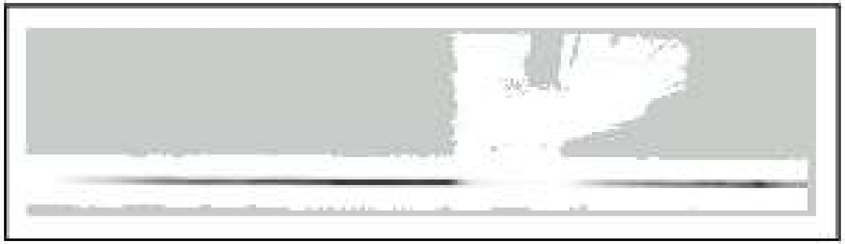
5. Likelihood Field Model:

   ⇝ end points of a sensor scan z_t are projected into the global coordinate space;

   ⇝ for each measurement z_t^k

$$p_{hit}(z_t^k) \sim \mathcal{N}(d_{hit}, \sigma_{hit}^2) \quad (1)$$

Problem:
featureless and symmetrical environments lead to failure!



Implementation of a new sensor model

IDEA: $\rightsquigarrow$ use artificial markers to provide additional information

Some constraints had to be considered when devising the new model

1. The model must be general:
- $\rightsquigarrow$ not related to a specific environment
- $\rightsquigarrow$ working for different layouts of the markers
- $\rightsquigarrow$ different sensors could be used

2. What markers should we use? They might be occluded due to the presence of moving obstacles and operators

3. Due to the characteristics of the environment, geometrical reasoning may not be well suited.

4. Probabilistic reasoning is to be used:
- $\rightsquigarrow$ uncertainties in readings
- $\rightsquigarrow$ occlusions

Implementation of a new sensor model

IDEA: $\rightsquigarrow$ use reflective markers at known location to reduce ambiguity

Step 1: compute likelihood field

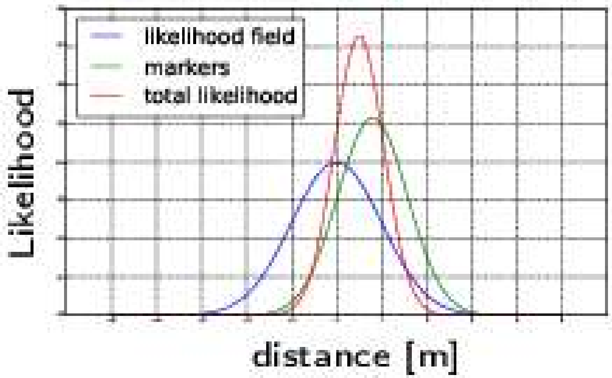
$\rightsquigarrow$ $p_{hit}(z_t^k) \sim \mathcal{N}(d_{hit}, \sigma_{hit}^2)$

Step 2: apply correction based on markers

$\rightsquigarrow$ $p_b(z_t^k) \sim \mathcal{N}(d_b, \sigma_b^2)$

Step 3: the resulting likelihood is

$\rightsquigarrow$ $$p(z_t \mid x, m) = \prod_{k=1}^{N} p_{hit}(z^k) \prod_{k=1}^{N} \gamma p_b(z^k)$$



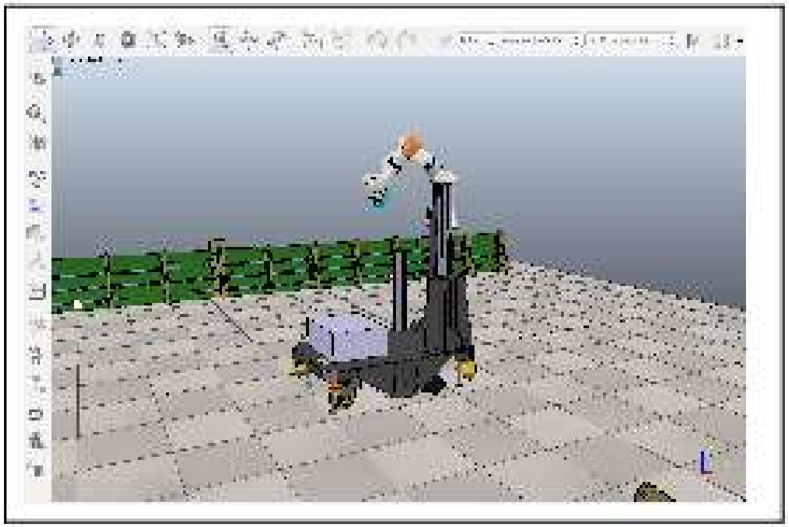
Tests and Results

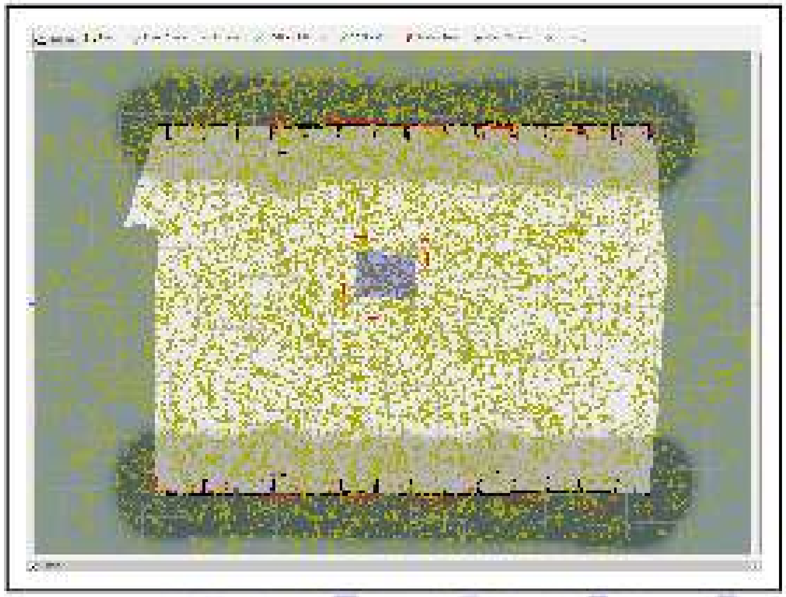
Building a simulation in V-REP

A simulation has been implemented using the robot simulator V-REP

The simulation is fully compatible with ROS AMCL and Navigation stack:

- ⇝ Real model of the robot
- ⇝ *tf* available
- ⇝ Odometry and sensor outputs
- ⇝ Laser readings (with intensity)



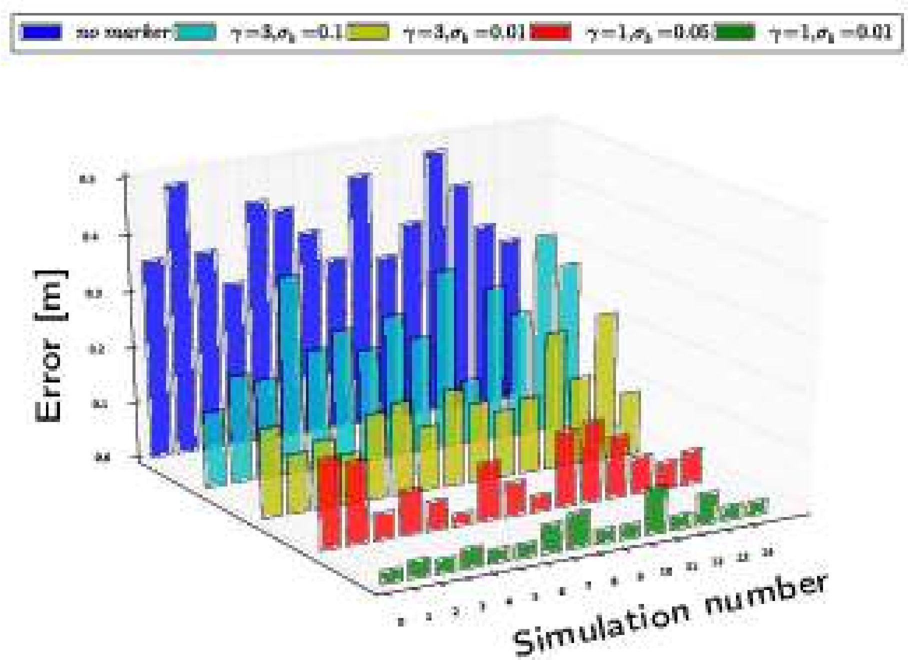


Tests and Results

Simulation

A preliminary evaluation of the sensor model was carried out using simulations in which the robot had to move along a fixed trajectory in the environment.

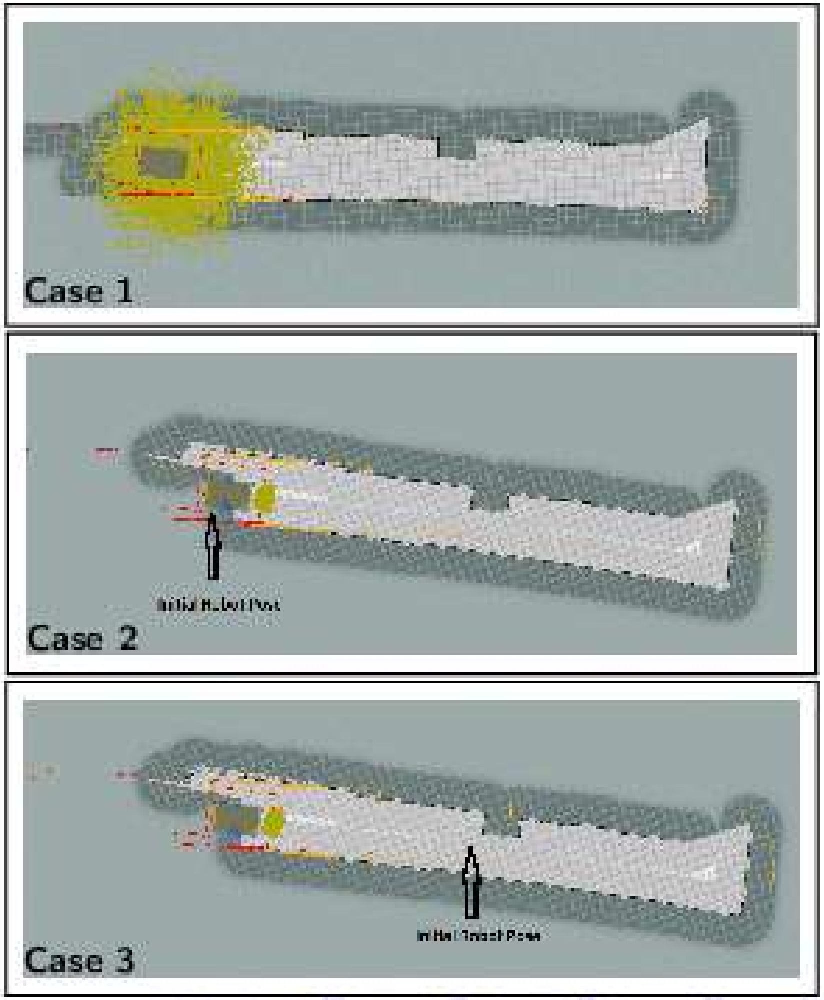
The error on the final position was recorded, for different values of the parameters γ and σ_b , and different parameter choices were then compared.



Tests and Results

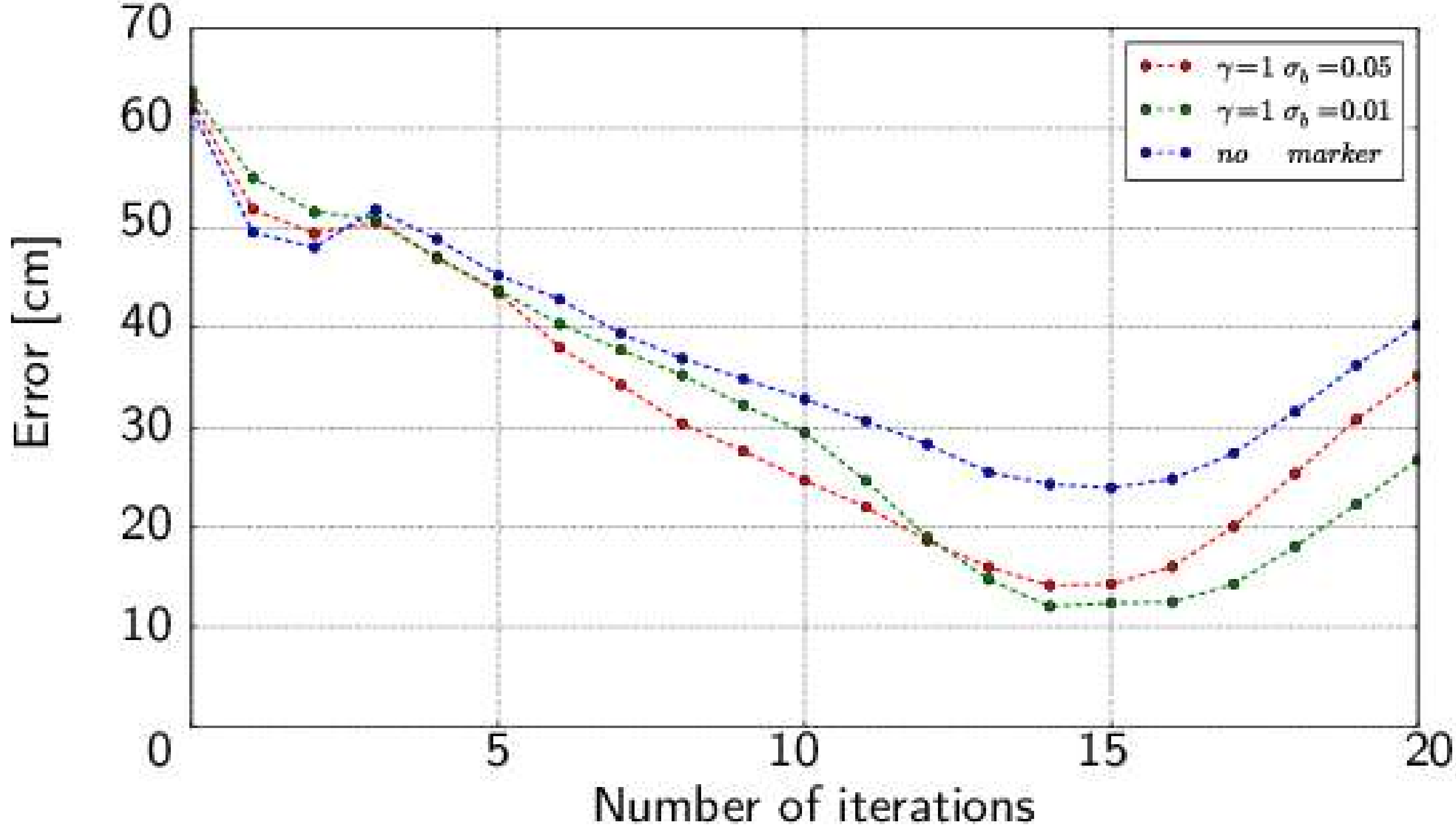
Real Experiments

- Data collected with *PMA0* robot equipped with two SICK S300 Expert CMS lasers
- Experiments carried out in a corridor of $\sim 12 \times 2m$ size
- Robot moved along fixed trajectories on the major axis of the corridor
- AMCL executed 10 times per set of parameters, using 10000 particles
- Odometry used as ground truth



Tests and Results

Case 1 - Standard Gaussian



Average localization error with and without reflectors, and for different values of γ and σ_b. The marker is visible until iteration 15 approximatively.

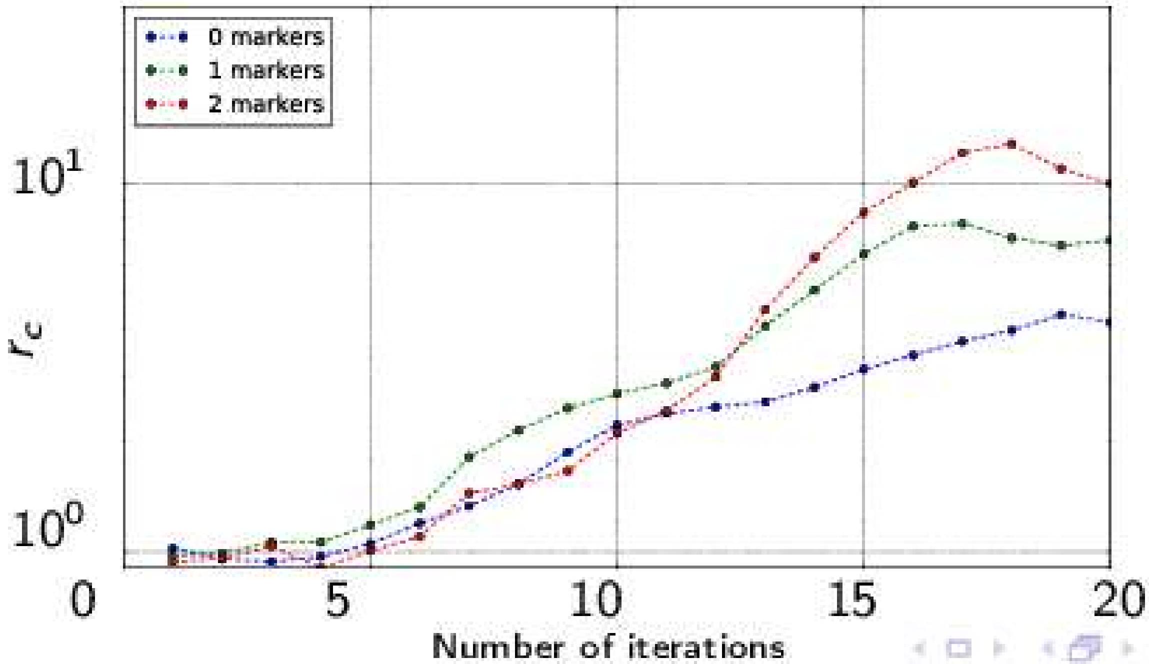
Tests and Results

Case 2 - Three Clusters

The evolution of the weights of the three particle clusters was monitored. A performance index r_c has been defined as:

$$r_c = \frac{\omega_{first}}{\omega_{second}} \tag{2}$$

where ω_{first} is the weight of the cluster centred in the correct position, and ω_{second} is the second most weighted cluster.



Tests and Results

Case 3 - Kidnapped Robot

The presence of markers helps reducing the error the initial estimate.

Conclusions and Future Directions

Conclusions:

- a sensor model based in indistinguishable artificial landmarks has been proposed to reduce the overall ambiguity of featureless environments.
- a simulation has been developed to study the performances of the model, for different configurations of the landmarks, and for different parameter values.
- we evaluated the model for various environments using real data demonstrating that the model yields to considerable improvements in the localization performance.

Future developments

Investigate more sophisticated models, maybe taking into account angles of incidence.
Study how location and number of markers might affect localization.

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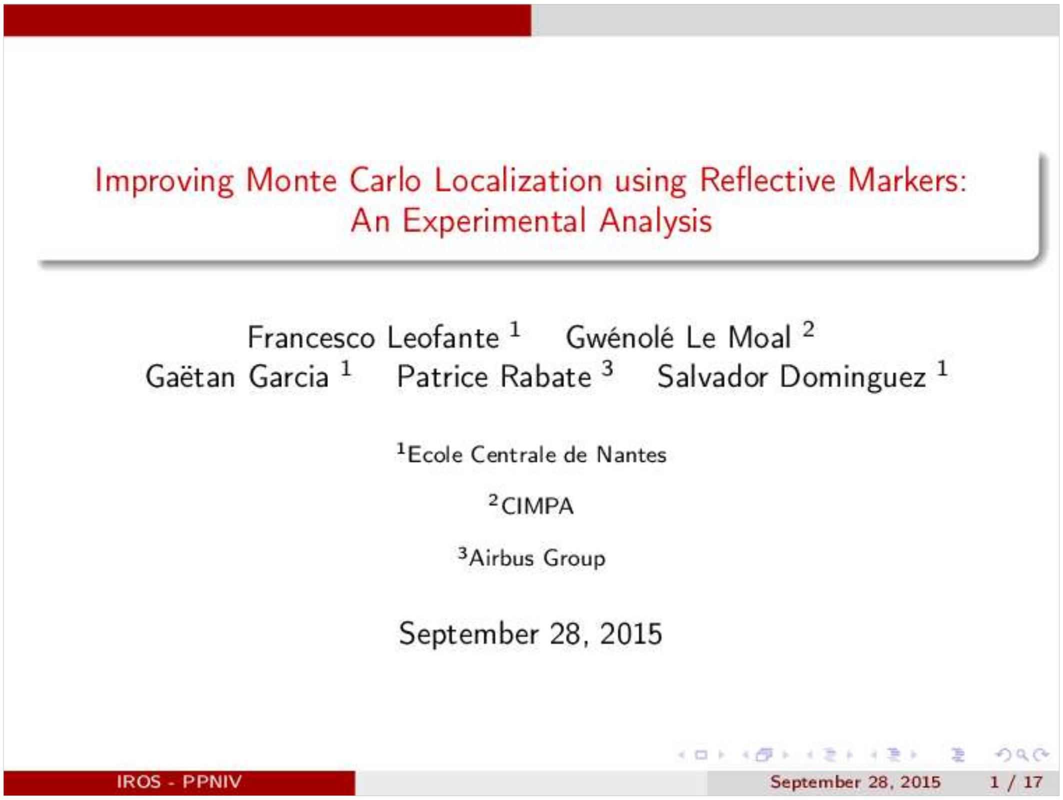
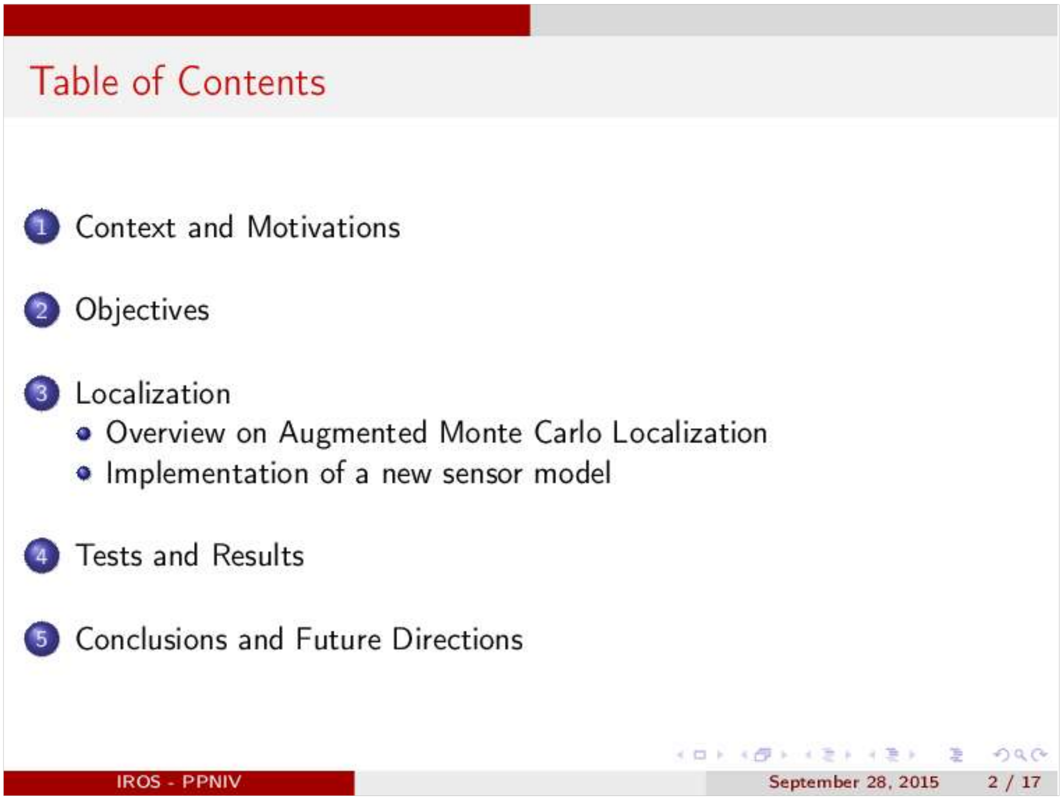


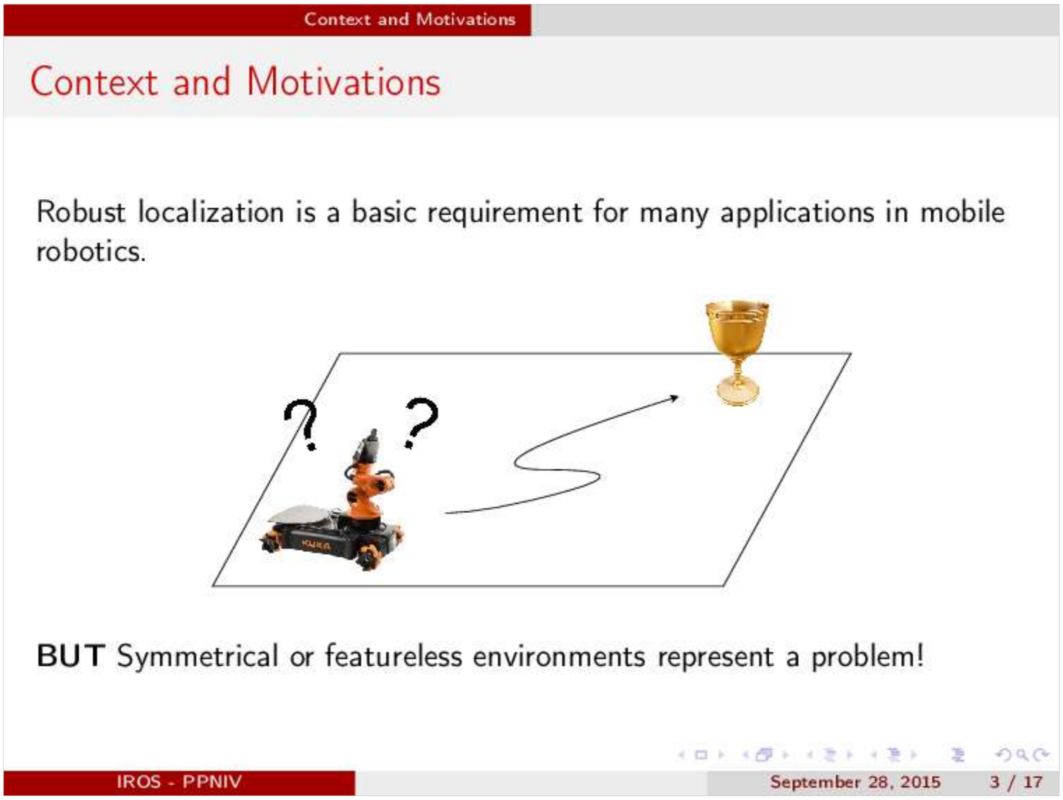
Good afternoon. My name is Salvador Dominguez, I am a research engineer at IRCCyN, Ecole Centrale de Nantes. I come in representation of Francesco Leofante who is the main author and could not come to the workshop to present his paper.

This presentation is about: “Improving Monte Carlo Localization using Reflective Markers: An Experimental Analysis”

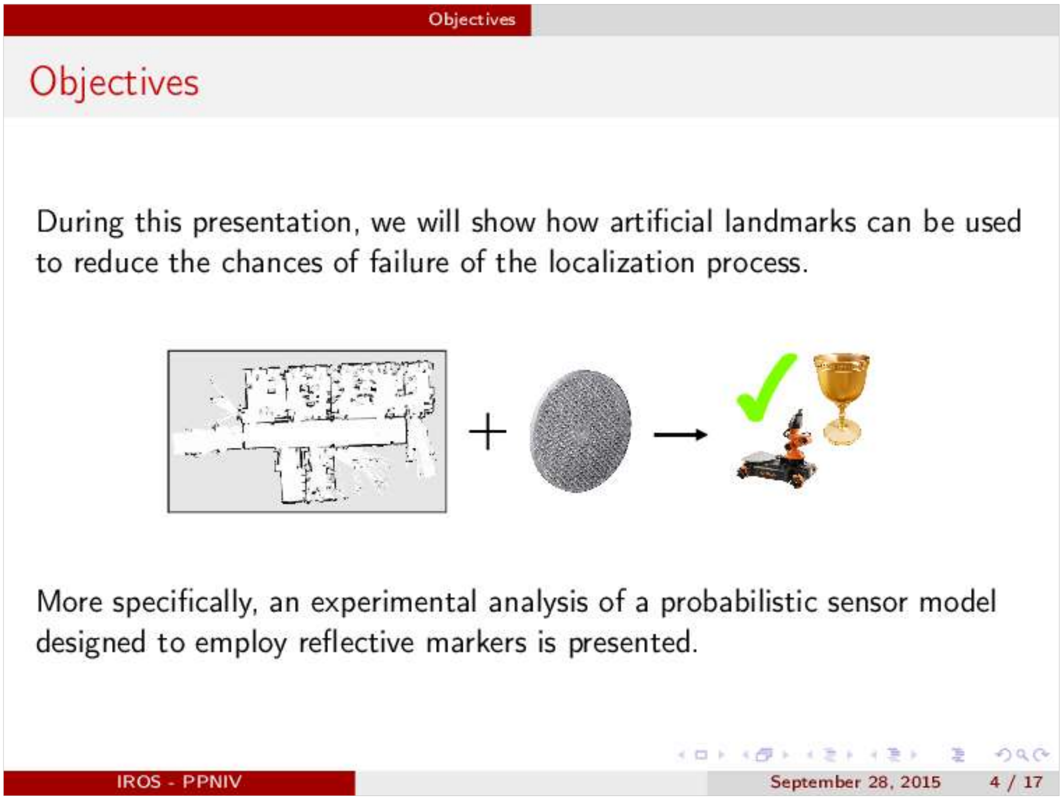


Here is the index of the presentation:

- First the context of the problem and motivations.
- Then the objectives of this work
- It will be followed by the localization using (AMCL) Augmented Monte Carlo Localization and the metodology to improve it by using a new sensor model.
- Then it comes the experimental set-up and results
- And finally the conclusions and future developments

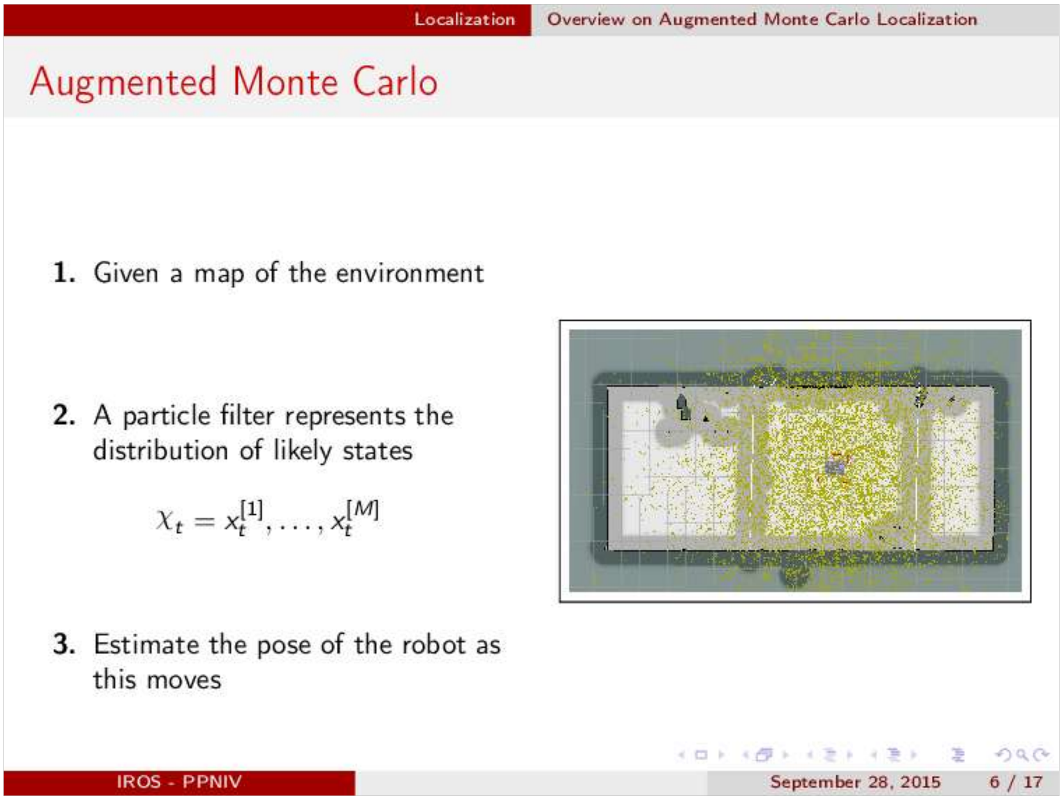


Robust localization is a fundamental requirement for many applications in mobile robotics. In particular we know that in order to be able to navigate autonomously, we must have precise information about our position in the environment. However, sometimes the environment does not help, as highly symmetrical and featureless environments (such as long corridors) may pose serious problems, which can eventually lead to a failure in the localization process.



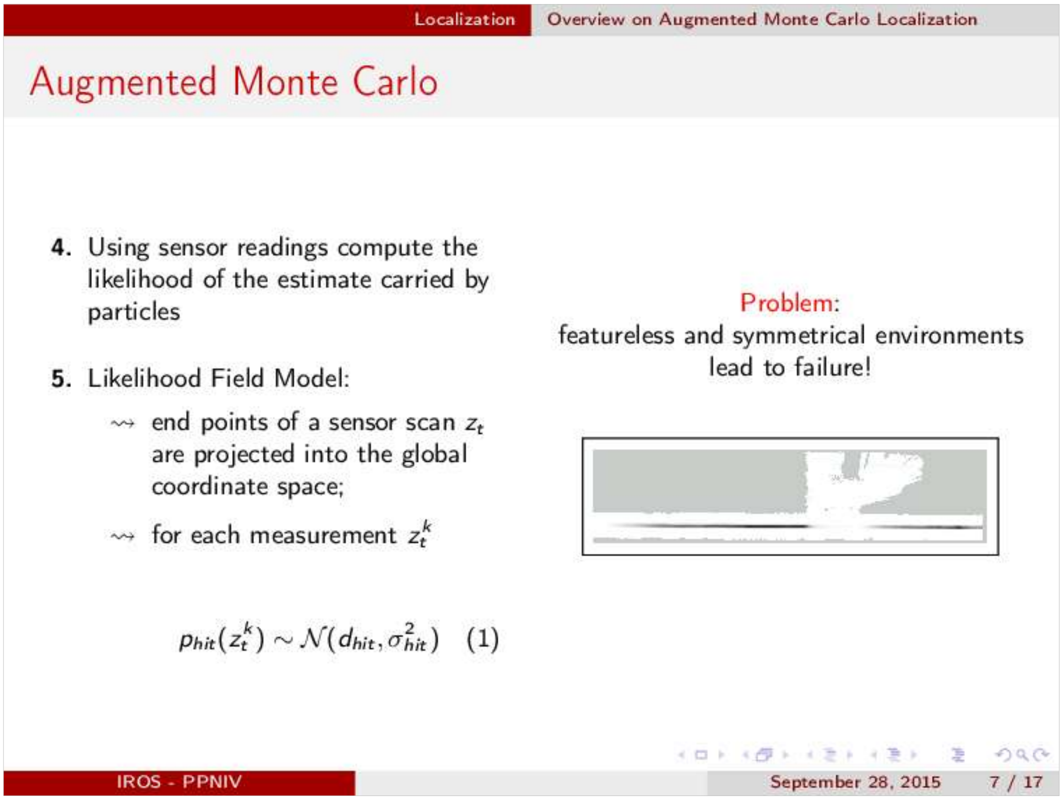
With this work we decided to investigate solutions which can be implemented in order to make localization more robust. In particular, we will show here how reflective markers placed at known locations in the environment can be used to reduce the overall ambiguity of the environment itself, leading to improved localization performances.

Localization



But in order to better understand the results let's go through the localization algorithm we decided to consider, that is the Augmented Monte Carlo Localization which is a technique based on the use of a particle filter and a map to keep track of the robot pose.

Whenever the robot moves, the set of particles, that represent the most likely pose estimates computed by the algorithm, are also updated according to a motion model.

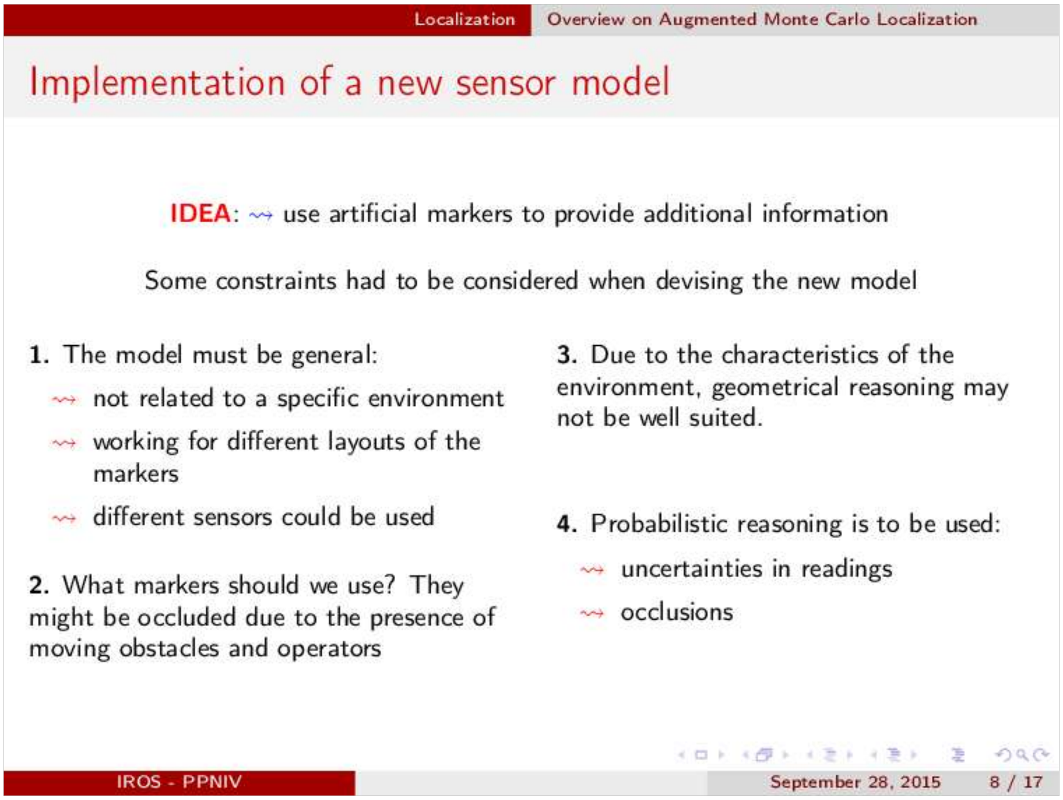


And when a new sensor reading is available, the algorithm updates for each particle the probability of the estimate according to that new information. To this end, different techniques can be used, here we decided to focus on the so called Likelihood Field Model, currently used in the ROS navigation packages.

The idea behind this model is as follows:

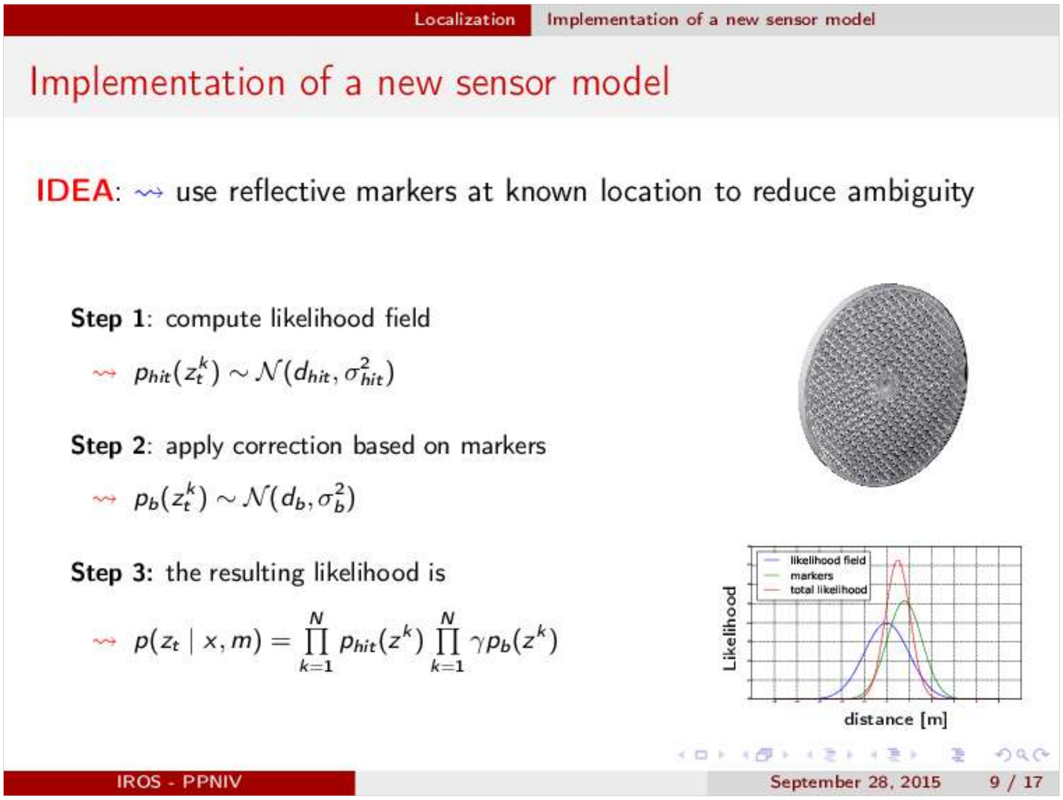
- given a sensor scan, we compute the projections of each laser beam into the global coordinate frame.
- at this point, we use the occupancy grid map to compute the distance between the sensor scan and the closest obstacle in the map. This distance is later fed to a Gaussian which can be used to compute the likelihood of the measurement.

Given this brief introduction, we can easily understand why featureless and symmetrical environments represent a problem: like for example in this corridor. All these positions project the measured scan on the walls of the corridor with the same probability in a longitudinal direction as no features are present, everything looks the same and therefore the algorithms will have difficulties in generating a most likely pose.



In an attempt to solve this problem, we decided to study what happens when artificial landmarks are added to the environment. Regarding the model used for these artificial landmarks, we keep into account different constraints:

- first of all, we wanted our model to be general. This means the model has to work for all possible environments, and all possible marker layouts. Moreover, we wanted to implement something that could be used for different sensors.
- another important point is: We need something which can work even if markers are not always visible
- due to the aforementioned points, we concluded that probabilistic reasoning was to be preferred over geometrical.

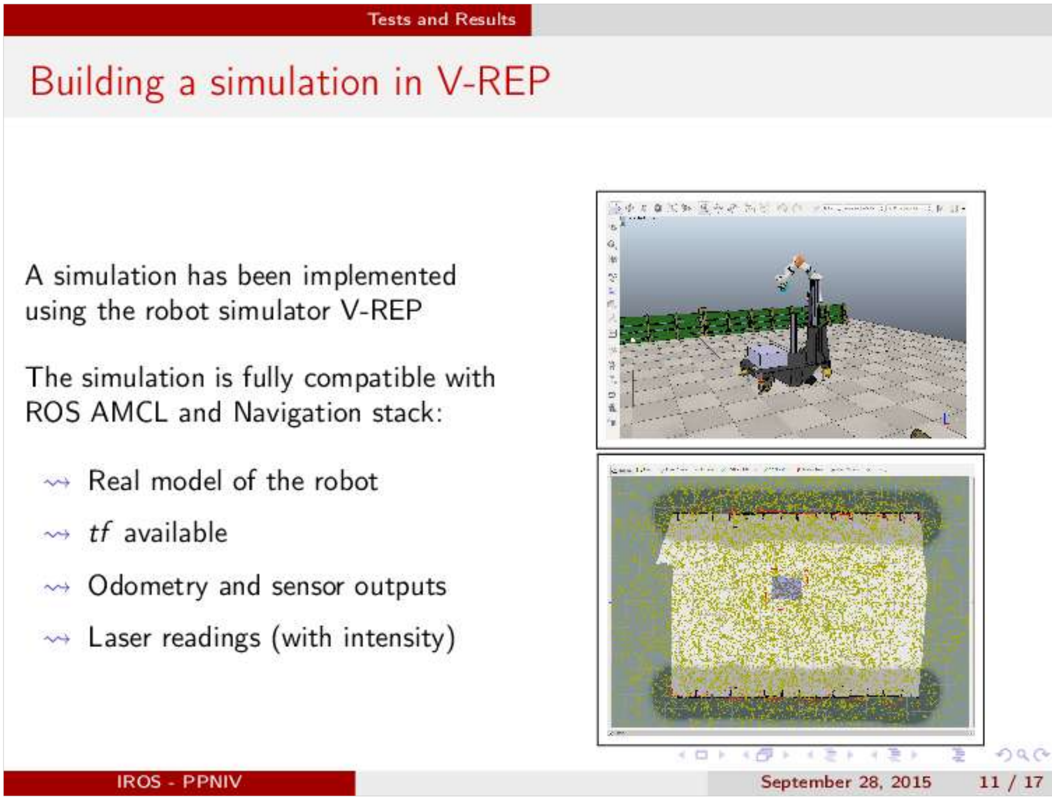


To satisfy all the needs mentioned before, we decided to use reflective markers placed at known locations in the environment.

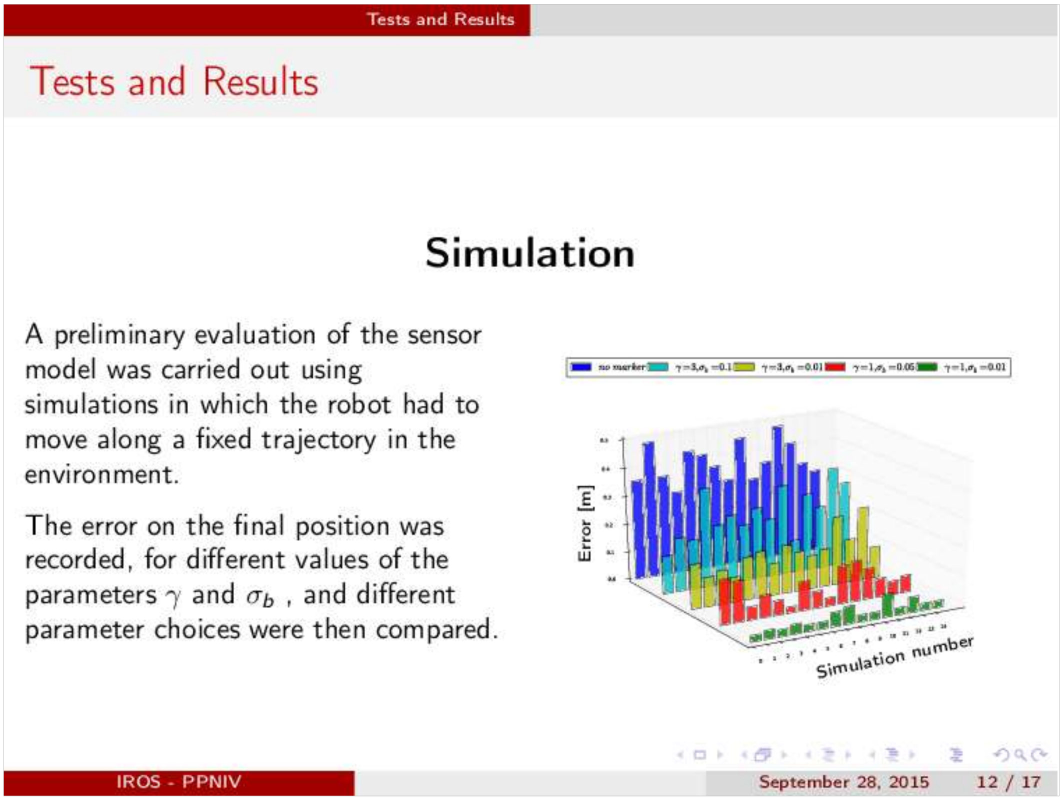
Since we did not want to modify the existing framework, we tried to integrate the new solution in the previously cited Likelihood field model.

- Step one computes the likelihood of a measurement as we already described previously
- Step two takes into account the reflectors and computes a coefficient based on the distance between the end projection of the laser scan and the closest reflector (similarly to what is normally done in step one with obstacles)
- Step three merges the two distributions in order to obtain a final distribution. It is important to notice here that two parameters (gamma and sigma b) can be modified to tune this merging process.

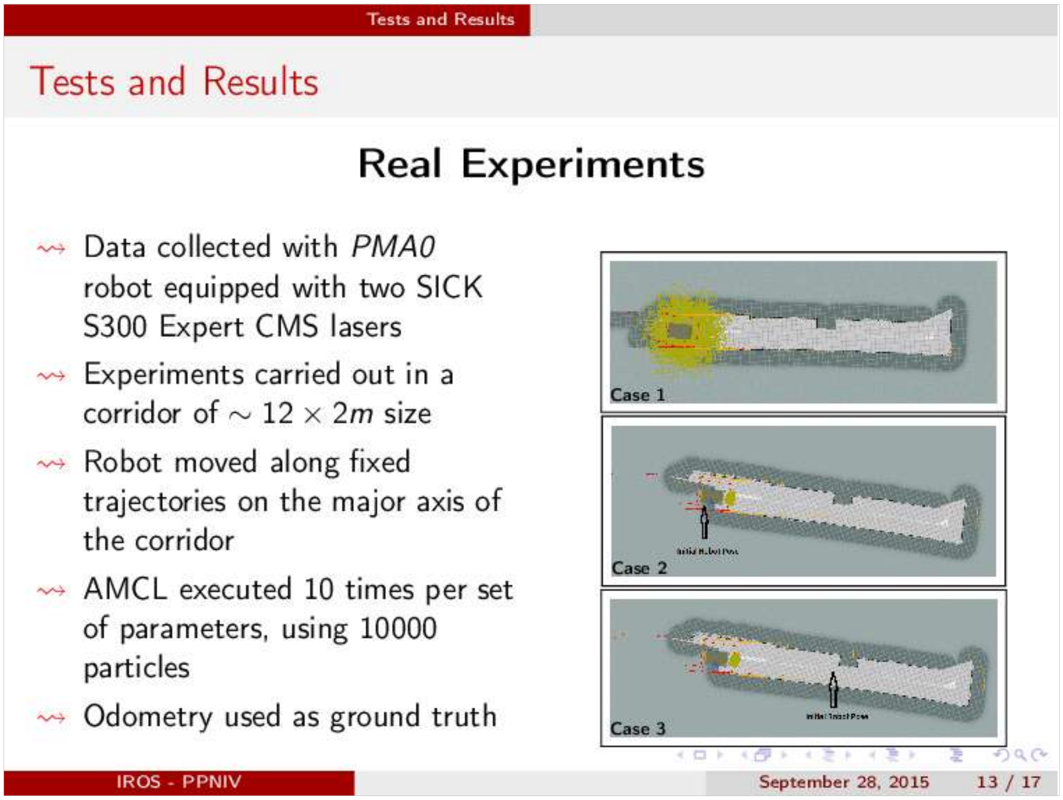
Tests and Results



Different tests have been carried out to test the proposed procedure. First of all, we implemented a complete simulation using the robot simulator v-rep. The software allows to build realistic simulations importing a model of the robot (urdf files), simulate laser readings (together with intensity of the reflected light) and odometry readings (with noise). All this made possible to run in simulation the same code we run on the real robot.



During the experiments, we moved the robot along fixed trajectories in the environment. For each simulation run, the error on the final position of the robot has been recorded. Different values for gamma and sigma b have been tested and compared. As it is possible to observe in the chart shown here, we see that the error obtained when no markers are used is more significant than the one we obtain when instead markers are placed in the environment (results here are obtained with 3 markers).



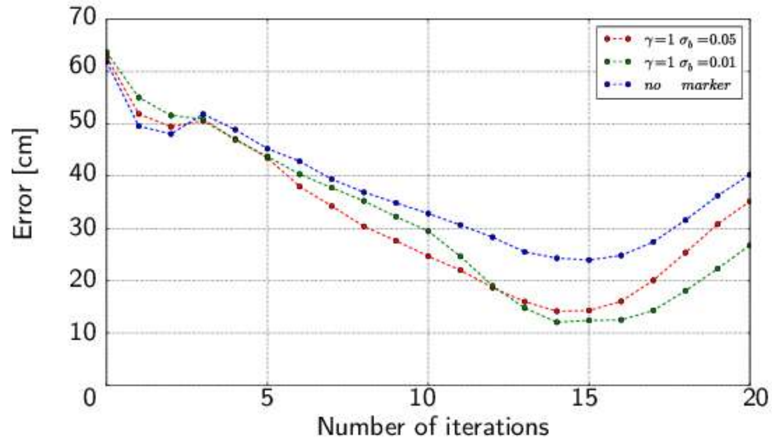
After testing in simulation, we did the tests in real environment.

In particular, we carried out tests using a mobile platform equipped with two sick lasers Sick S300. The robot was moving in a corridor as shown in the pictures, localization tasks were performed and odometry reading were used as ground truth for comparison (here it was possible because the set up was simple and controlled). At this stage, our aim was testing how the model behaves when different initializations are used for the particle filter.

- In case 1 we used a Gaussian initialization along x,y and theta as it is normally done. Here our objective is measuring precision compared with the normal AMCL.
- In case 2 we used instead a mixture Gaussian, with three clusters which only one is centered in the real robot pose. Here we try to measure how the robot discriminate the real position from another position in a symmetric environment.
- And finally in case 3 we tried the classical kidnapped robot problem by providing a completely wrong estimate to the system and studying to what extent the model helps recovering from a wrong estimate.

Tests and Results

Case 1 - Standard Gaussian



Average localization error with and without reflectors, and for different values of γ and σ_b. The marker is visible until iteration 15 approximatively.

Here we see that the basic AMCL already produces good results, but still the new model helps reducing the error o around 10 cm.

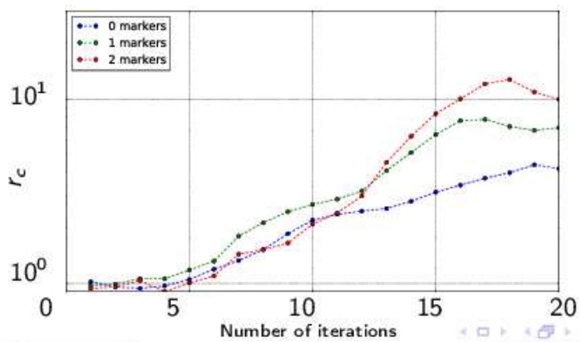
Tests and Results

Case 2 - Three Clusters

The evolution of the weights of the three particle clusters was monitored. A performance index r_c has been defined as:

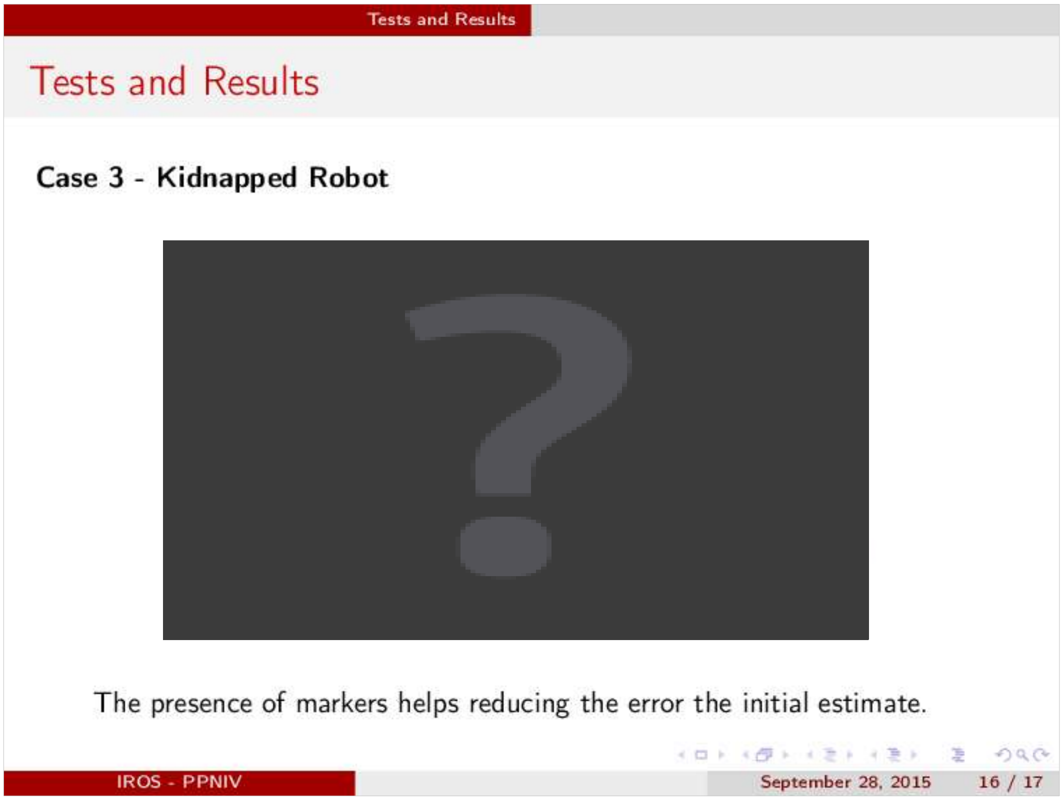
$$r_c = \frac{\omega_{first}}{\omega_{second}} \quad (2)$$

where ω_{first} is the weight of the cluster centred in the correct position, and ω_{second} is the second most weighted cluster.



In the second case, we defined a performance index rc which is defined as the ratio between the weight of the most likely cluster and the weight of the second one.

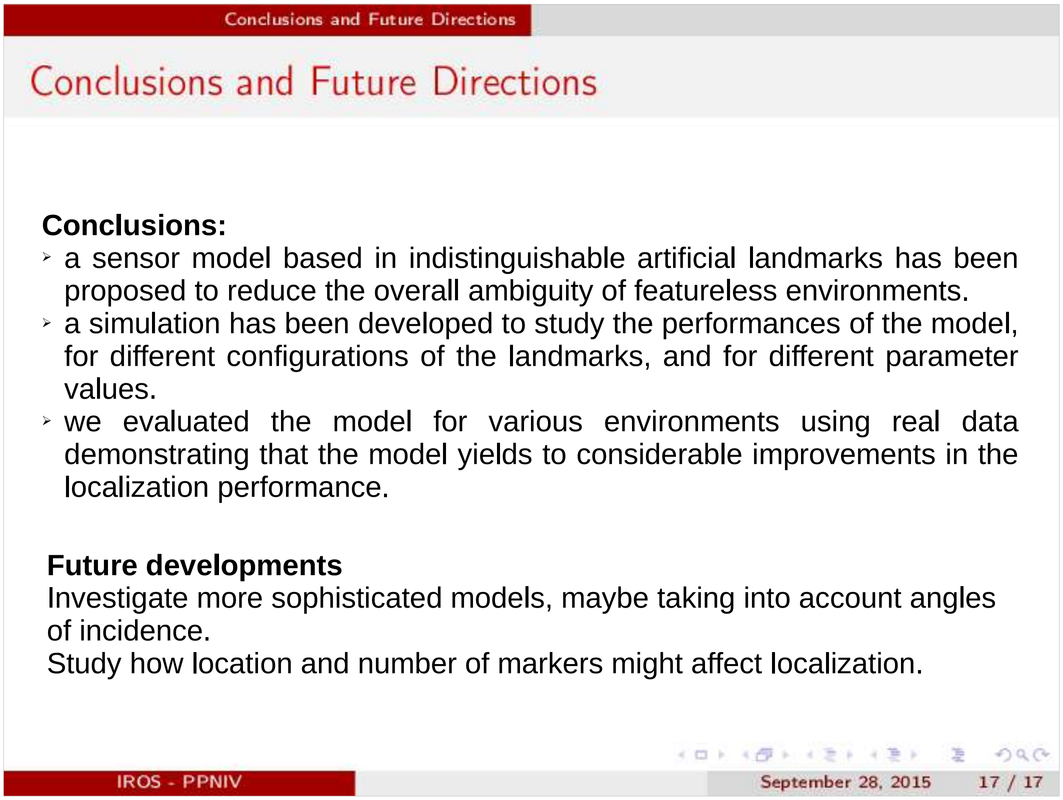
The graph here shows that as we increment the number of reflectors shown during the experiment we increase the confidence of the good estimate



Details about the Video (to be given before we play it):

- the map of the corridor is in the lower part of the video. The lines represents from right to left: the real robot position, the marker's position and the initialization position.
- the top plots is the experiment without a marker and the lower with 1 marker
- the blue clusters represent the particles (which are initially wrong positioned).
- the black thick bar represents the real robot
- the red triangles represent the marker's location

TO comment: at the beginning, when no markers are seen, both particle clusters are translating taking into account the robot movements. When the reflector is seen, we see that using the new model, particles start spreading converging finally to the right estimate, opposite to the case where there is no marker, where particles keep the wrong estimate and convergence is never attained.



Concerning the conclusions:

- we have proposed a sensor model based in artificial landmarks to reduce the overall ambiguity of featureless environments
- we have performed simulation experiments to study the performance of the model for different configurations of the landmarks and parameter values.
- we have evaluated the model using real data for different cases demonstrating that it yields to considerable improvements in the localization performance.

And regarding the future developments next steps could be

- investigating more sophisticated models considering for example the angle of incident of the laser with the marker
- studying how number and position of markers influence the localization performance.

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