Improving Monte Carlo Localization using Reflective Markers: An Experimental Analysis

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Abstract— **Robust localization is a basic requirement for many applications in mobile robotics. Despite many techniques have been devised to find solutions to the localization problem, symmetrical or featureless environments represent a great challenge for most of the commonly used approaches. In this paper, we investigate 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. The analysis will focus on two central parameters of the model, several experiments are carried out to evaluate their effect on the overall localization process.**

I. INTRODUCTION

Mobile robot localization is the problem of determining the pose of a robot relative to a given map of the environment. Localization plays an important role in nearly all robotics tasks involving autonomous navigation, unfortunately the pose of a robot can usually not be sensed directly as most robots do not have noise-free sensors for measuring pose. Therefore pose-related information must be inferred from different sources of data (e.g. odometry, additional sensors etc.), sometimes making it difficult to achieve precise localization. Moreover, structurally symmetrical or featureless environments increase the chances of failure of these techniques: the ambiguity characterizing such environments may indeed result in different robot poses being indistinguishable based on sensor data. In this paper, we focus on the problem of employing artificial landmarks to counteract the effects of the aforementioned ambiguity on the overall localization process. In particular, we wish to propose an experimental analysis of a sensor model developed to take into consideration the additional information provided by reflective markers placed in the environment at known locations. Our main contribution is to provide experimental results related to the choice of central parameters of the model by considering a concrete instantiation of the localization problem in featureless environments. Furthermore, several experiments are performed, both in simulated and real environments, to show how the proposed model improves the overall localization performance.

The remainder of this paper is organized as follows. Section II gives a brief overview on several techniques used to improve localization using landmarks. The localization algorithm used is described in Section III, which is followed in Section IV by a formal description of the sensor model employed. Section V illustrates the results collected from simulated and real experiments. Finally, Section VI provides final conclusions and directions for future works.

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II. RELATED WORKS

A variety of techniques has been proposed to find solutions to the robot localization problem. Traditional approaches typically use natural landmarks present in the environment in which the robot navigates [1], [2]. These techniques, which have the advantage of not implying any change in the environment, are however prone to fail when the environment does not present suitable characteristics. This is when the use of artificial landmarks becomes beneficial. Some approaches consider landmarks which can be uniquely identified, such as RFID transponders [3], or 2D bar codes on the floor which can be detected with a camera [4] (see [5], [6] for other examples). These landmarks are used to guarantee accurate localization, greatly simplifying the localization problem. However, the mentioned solutions require specific landmark coding and the use of identification systems which are not always available on a robot. Using indistinguishable artificial landmarks like retro-reflective tape greatly alleviates this problem, as most robots are equipped with laser range finders. In [7], an approach is presented to compute a configuration of reflectors that decreases the overall ambiguity of the environment, thus increasing the robustness of the localization process. The authors addressed the landmark placement problem, formulated as the problem of selecting a subset of landmarks out of a finite set of possible configurations. This represents a fundamental problem, as there exist a relation between the localization error and the configuration of the selected landmarks as proven in [8]. The authors of [7] also developed a sensor model which allows to employ the reflectivity of the the measured objects, in addition to their range and bearing, to obtain robust localization. The sensor model, contrarily to other approaches [9], [10], does not rely on geometrical reasoning but instead operates in a probabilistic localization framework. This proves to be particularly beneficial in applications where occlusions and other uncontrollable events may make it impossible to use landmark information in a pure geometrical fashion. While the authors mostly focussed on the problem of finding an optimal placement for landmarks, our aim is to investigate the properties of the model. In this paper, we present the results of an experimental analysis of the sensor model, and study the effects it produces on the localization performance.

III. MONTE CARLO LOCALIZATION

Monte Carlo localization (MCL) [11] has been employed to estimate the pose of the robot. Given a map of the environment, the algorithm estimates the position and orientation of a robot as this moves and senses the environment. The algorithm uses a particle filter to represent the distribution of likely states, with each particle representing a possible state i.e. the belief $bel(x_t)$ is represented by a set of particles $\chi_t = x_t^{[1]}, \ldots, x_t^{[M]}$. The algorithm starts with a given distribution of particles over the configuration space. Whenever the robot moves, particles are shifted to predict the new state after the movement. Whenever a new sensor reading is available, particles are resampled based on recursive Bayesian estimation. Different sensor models have been implemented to compute the likelihood of measurements, likelihood field model [12], [13] has been used here. According to this model, in order to evaluate how well the actual sensed data correlate with the predicted state, the end points of a sensor scan z_t are first projected into the global coordinate space of the map. Then, for each measurement coordinate $(x_{z_t^k}, y_{z_t^k})^T$, the likelihood of measurement z_t^k is computed using the distribution

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

based on the distance d_{hit} between the end point of the measurement z_t^k and the closest obstacle on the map. The model assumes two additional sources of uncertainty i.e. failures, given by the point-mass distribution p_{max} and unexplained random measurements, modelled by the uniform distribution p_{rand}. The three distributions are finally combined together to compute the *importance factor* of each particle i.e. the likelihood of the estimate they carry.

MCL, in its basic implementation, solves the global localisation problem but cannot recover from robot kidnapping, or global localisation failures [12]. This is a consequence of the fact that as a position is acquired, particles at places other than the most likely pose gradually disappear. After some iterations, particles only survive near a single pose, and the algorithm is unable to recover if this pose happens to be incorrect.

This problem can be solved by injecting a number of random particles based on the estimate of localization performances. One possible way to implement this is to monitor the probability of sensor measurements $p(z_t \mid z_{1:t-1}, u_{1:t}, m)$ and relate it to the average sensor probability . This quantity can be approximated by the average of importance factor (by definition):

$$p(z_t \mid z_{1:t-1}, m) = \frac{1}{M} \sum_{m=1}^{M} w_t^{[m]} \tag{2}$$

The estimate is usually smoothed by averaging it over several time steps, since there exist multiple reasons why the measurement probability may be low, besides a localisation failure. For this reason, a short-term average of the measurement likelihood is maintained, and related to the long-term average when determining the number of random samples to add.

IV. THE SENSOR MODEL

The sensor model presents similarities to the one developed by the authors of [7], that is a variant of the likelihood field model introduced in Section III. However, contrarily to the model of [7],we decided to implement the sensor model in two steps to have more control on each phase of the localization process.

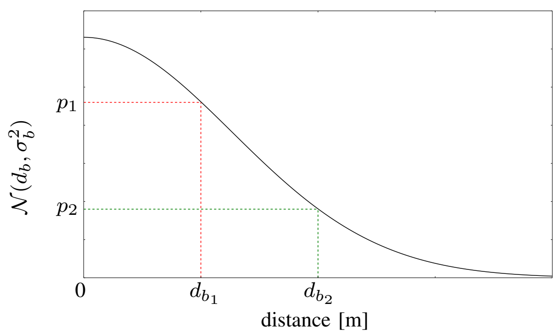


Fig. 1: In the second update step, a new coefficient is computed if markers are detected. The smaller the distance, the more likely the measurement is.

First, the likelihood of each range measurement is computed using the distribution

$$p_{hit}(z_t^k) \sim \mathcal{N}(d_{hit}, \sigma_{hit}^2) \tag{3}$$

where d_{hit} is again the distance between the end point of the measurement z^k and the closest obstacle on the map. This likelihood is used to perform a first update of the weights of the particle cloud. Next, a correction factor is applied to the weights of each particle according to the distribution

$$p_b(z_t^k) \sim \mathcal{N}(d_b, \sigma_b^2) \tag{4}$$

where d_b represents the distance to the marker which is the closest, as seen in figure 1. Here $\mathcal{N}$ represents a normal distribution with mean μ and standard deviation σ.

The resulting likelihood is therefore computed as follows:

$$p(z_t \mid x, m) = \prod_{k=1}^{N} p_{hit}(z^k) \prod_{k=1}^{N} \gamma p_b(z^k) \tag{5}$$

where γ denotes a coefficient used to weight the importance of the second update step.

V. EXPERIMENTAL EVALUATION

In order to evaluate the performances of the model considered, experiments were conducted in simulation and on a real robot. Different set-ups have been chosen, with a special focus on featureless and highly symmetrical environments. As already stated, our purpose was to carry out a thorough study of the sensor model introduced in Section IV. To this end, parameters γ and σ_b have been studied. Different combinations have been tested in order to assess how these parameters influence the localization process.

A. Simulation

A simulation has been implemented using the V-REP [14] simulation environment. The software allowed to build a fully operational simulation with which we could carry out different tests, each time focussing on a specific parameter.

The sensors used for the simulation were two Hokuyo URG 04LX laser range scanners, modified so as to return the reflectivity of the measured objects. The simulator implements laser models by means of proximity sensors or vision sensors, as physical simulations of light are not supported. In particular the model we used is based on proximity sensors, which can return the ID of the detected object. Given this, we simply decided what surface property to use depending on the object ID returned. As for the landmarks, we used round markers with a diameter of $100mm$.

The robot can be controlled using the ROS Navigation packages [15], localization was performed using the ROS implementation of MCL, called Augmented MCL (AMCL). The modifications of section IV have been applied to the general algorithm. The simulator provides built-in methods to output odometric data for the robot's pose and velocity, together with their covariance matrices.

Accurate occupancy maps of the simulated environments have been obtained using HECTOR SLAM techniques [16].

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.

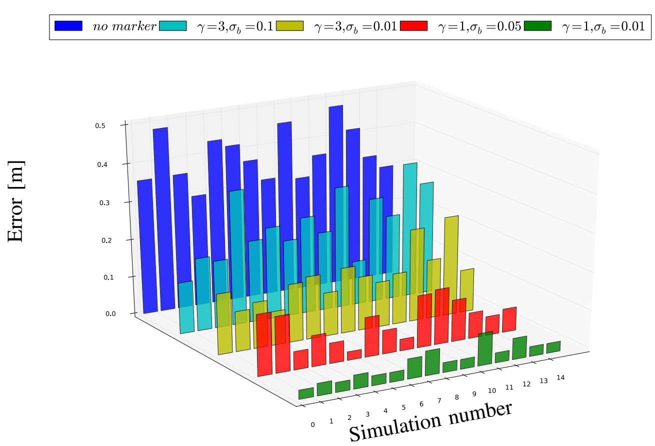


Fig. 2: Error on the final pose obtained in different simulation runs. Different values for γ and σ_b result in errors of different amplitudes. The model always produced better results when compared to traditional techniques.

As expected, the use of artificial landmarks improves the localization performance. Figure 2 shows that the average error obtained using one reflector is always lower than the one given by the traditional likelihood field model (i.e. without markers). Concerning the choice of the parameters, it is possible to notice that high precision is obtained when low values of σ_b are selected. This is normal as a sharper Gaussian in the sensor model removes more particle that are far from the real position. Such high degree of precision could be tested since experiments were run in a completely controlled environment, where uncertainties were kept to a minimum. Increasing values of the weighting coefficient γ led to a decrease in accuracy, which became more significant when higher σ_b values were chosen. This is normal as more particles survive when the Gaussian is wider, and their weight results increased by γ even if their estimate is not accurate.

B. Real Experiments

The sensor model has also been tested using real data gathered with an experimental mobile robot equipped with two SICK S300 Expert CMS laser range finders. An occupancy map of the environment was built, again using HECTOR SLAM. Experiments were carried out in a corridor of approximately $12 \times 2m$ size. In the following, the pose of the robot is defined in terms of (x, y, θ).

Three different scenarios have been considered:

a) The particle filter is initialized with a Gaussian distribution centred in $(6.10, -14.90, 0)$, the real pose of the robot. Here $\sigma_x = 0.5$, $\sigma_y = 0.5$ and $\sigma_\theta = \frac{\pi}{12}$.
b) The particle filter is initialized using a mixed distribution, with three Gaussian distributions centred respectively in $(6.10, -14.90, 0)$, $(6.70, -14.90, 0)$, $(7.40, -14.90, 0)$, all of them with $\sigma_x = 0.05$, $\sigma_y = 0.1$ and $\sigma_\theta = 0.1$. The first cluster (i.e. the one centred in $(6.10, -14.90, 0)$) represents the actual starting point of the robot.
c) The particle filter is initialized as above, but the actual starting position of the robot is actually $(12.60, -14.90, 0)$ i.e. we initialize with an initial error on x of $6m$.

Figure 5 shows the experimental setup described above.

When present, beacons have been placed at $(9.53, -13.51)$ and $(9.23, -15.57)$, as shown in figure 6.

To evaluate the model, we moved the robot along fixed trajectories on the major axis of the corridor (forward motion for cases 5a, 5b and backward motion in case 5c). The localization algorithm was executed 10 times per set of parameters, using 10000 particles initially distributed as described before. Odometry was used as ground truth to identify the correct pose of the robot at each iteration of the algorithm. When studying cases 5a and 5b, AMCL managed to provide good results both with and without reflective markers. However, we could still notice improvements in the localization performances obtained when reflectors were used, as particles are more quickly converging to the correct estimate. An analysis of the effects of different parameter sets on the the average localization error during position tracking has been carried out. Even in cases where the standard likelihood field model provided good results, the proposed approach led to improvements as shown in figure 3.

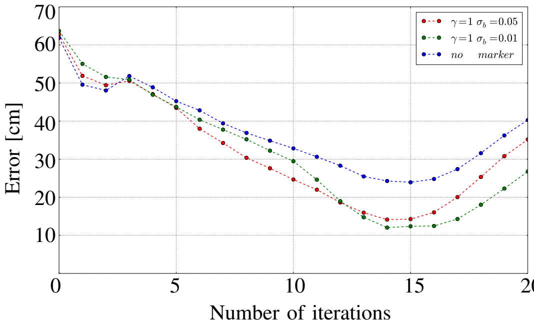


Fig. 3: Case 5a - Average localization error with and without reflective markers, and for different values of γ and σ_b. The marker is visible until iteration 15 approximatively.

Case 5b was used to gain a better understanding of the effects of the second update step introduced by the model (as explained in section IV). The evolution of the weights of the three particle clusters was monitored throughout several experiments. A performance index r_c has been defined as:

$$r_c = \frac{\omega_{first}}{\omega_{second}} \tag{6}$$

where ω_{first} is the weight of the cluster centred in the correct position, and ω_{second} is the second most weighted cluster. The presence of landmarks increased the confidence on the estimate as shown in figure 4.

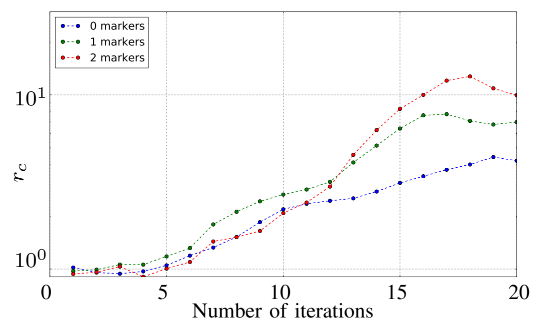


Fig. 4: Case 5b - Confidence in the estimate given by the filter.

It is possible to notice that a higher number of markers does not always result in better performances. Previous works suggest that parameters such as the number of markers and their location heavily influence the localization performance. If these parameters are not tuned properly (i.e. if the placement of landmarks is not optimal), the ambiguity of the environment may not be successfully reduced. This ultimately results in performances which are comparable to the ones obtained without markers.

When we considered a wrong initial estimate instead (case 5c), AMCL failed when no additional information was provided. Adding markers to the process helped improving the performances, allowing a significant decrease in the error. Tables I and II show the error on the final position, obtained using one marker.

Error on x (m)	Mean	Median	STD	Min. Value	Max. Value
No markers	5.17	4.59	3.50	0.29	9.92
One marker	1.96	0.81	2.41	0.06	13.17

TABLE I: Case 5c - Statistics on the x axis

Error on y (m)	Mean	Median	STD	Min. Value	Max. Value
No markers	0.57	0.18	0.82	0.01	2.66
One marker	0.25	0.25	0.15	0.03	0.50

TABLE II: Case 5c - Statistics on the y axis

Even though the robot was not able to recover completely, it is possible to see that the use of reflective markers helped reducing the localization error induced by a wrong initial estimate. In particular, table I shows that the average error on the x axis decreases from $5.17m$ when no beacons are used, to $1.96m$ when one beacon is introduced. This value would be even lower if few outliers were discarded: the median error is indeed $0.81m$, against $4.59m$ obtained without beacons. In both cases, localization provided good results on the y axis, as seen in table II.

VI. CONCLUSIONS

In this paper a study has been proposed on a sensor model which allows to use indistinguishable artificial landmarks to reduce the overall ambiguity of featureless environments. To this end, 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. The results demonstrate that the model yields to considerable improvements in the localization performance. We expect that a more sophisticated sensor model employing laser readings to their full potential could provide more robust result. For instance, this could be done by incorporating information related to the angle of incidence of the laser at the moment of hitting the marker.

REFERENCES

[1] Leonard, J.J.; Durrant-Whyte, H.F., "Mobile robot localization by tracking geometric beacons," Robotics and Automation, IEEE Transactions on , vol.7, no.3, pp.376,382, Jun 1991.

[2] Schmidt, T.; Hennig, D.; Fox, D.; Burgard, W., "Estimating the absolute position position of a mobile robot using position probability grids," Proceedings of the National Conference on Artificial Intelligence, 1996

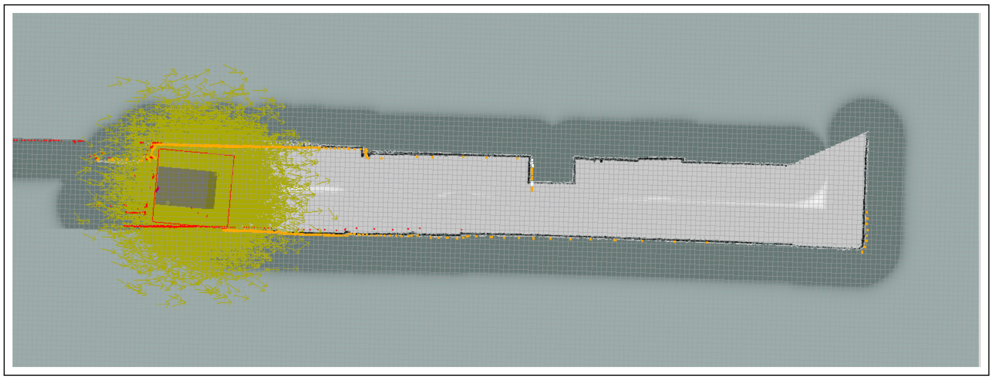
[3] Roehrig, C.; Heller, A.; Hess, D.; Kuenemund, F., "Global Localization and Position Tracking of Automatic Guided Vehicles using passive RFID Technology," ISR/Robotik 2014; 41st International Symposium on Robotics; Proceedings of , pp.1,8, 2-3 June 2014.

[4] Guizzo, E., "Three Engineers, Hundreds of Robots, One Warehouse," Spectrum, IEEE , vol.45, no.7, pp.26,34, July 2008.

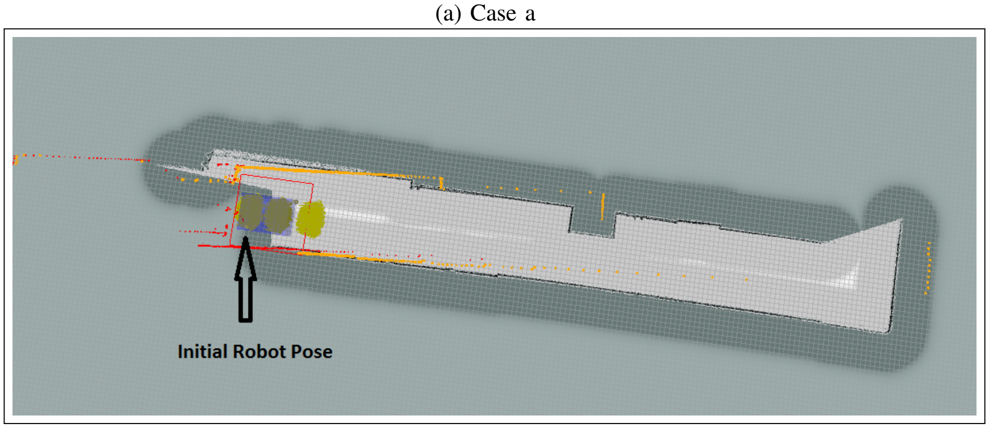
[5] Howard, A.; Mataric, M.J.; Sukhatme, G., "Relaxation on a mesh: a formalism for generalized localization," Intelligent Robots and Systems, 2001. Proceedings. 2001 IEEE/RSJ International Conference on , vol.2, no., pp.1055,1060 vol.2, 2001.

[6] Rafflin, C.; Fournier, A., "Learning with a friendly interactive robot for service tasks in hospital environments," Intelligent Robots and Systems 95. 'Human Robot Interaction and Cooperative Robots', Proceedings. 1995 IEEE/RSJ International Conference on , vol.3, pp.492,497, 1995.

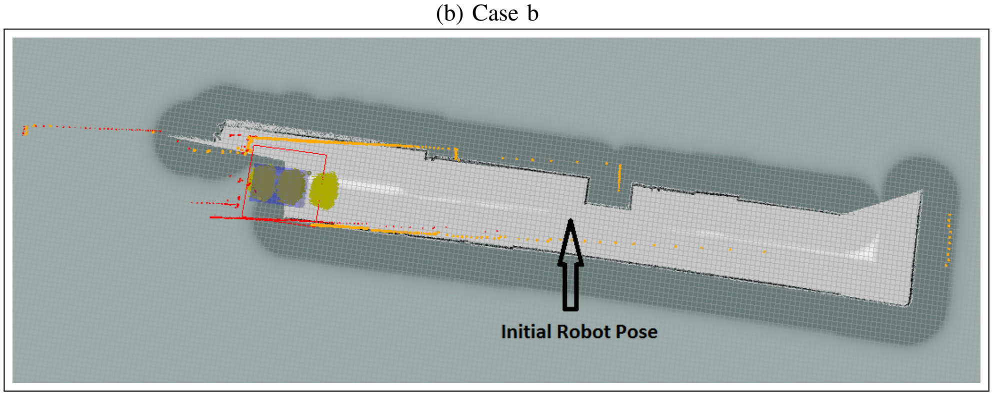
[7] Meyer-Delius, D.; Beinhofer, M.; Kleiner, A.; Burgard, W., "Using artificial landmarks to reduce the ambiguity in the environment of a mobile robot," Robotics and Automation (ICRA), 2011 IEEE International Conference on, pp.5173,5178, 9-13 May 2011.



(a) Case a



(b) Case b



(c) Case c

Fig. 5: Different initial conditions tested to evaluate the localization performance.

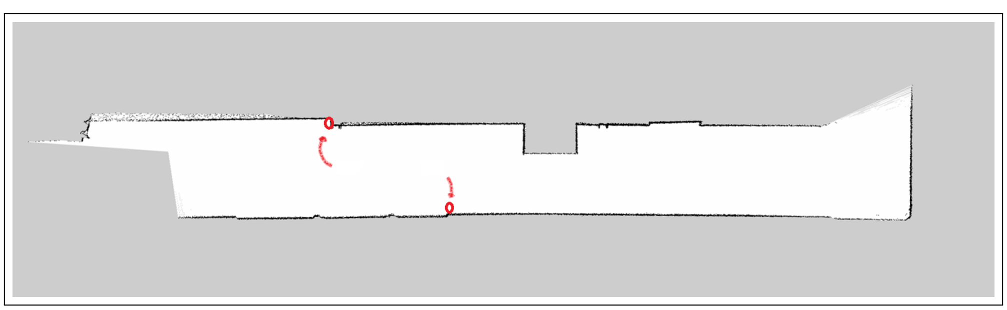


Fig. 6: Placement of the markers in the map

[8] Sutherland, K.T.; Thompson, W.B., "Inexact navigation," Robotics and Automation, 1993. Proceedings., 1993 IEEE International Conference on , pp.1,7 vol.1, 2-6 May 1993.
[9] Salas, J.; Gordillo, J.L., "Placing artificial visual landmarks in a mobile robot workspace," in Proc. of the Ibero-American Conf. on Artificial Intelligence (IBERAMIA), 1998.
[10] Sinriech, D.; Shoval, S., "Landmark configuration for absolute positioning of autonomous vehicles," IIE Transactions, vol. 32, pp 613-624, 2000.
[11] Dellaert, F.; Fox, D.; Burgard, W.; Thrun, S., "Monte Carlo localization for mobile robots," Robotics and Automation, 1999. Proceedings. 1999 IEEE International Conference on , vol.2, pp.1322,1328, 1999.
[12] Thrun, S.; Burgard, W.; Fox, D., "Probabilistic Robotics,", MIT Press, 2005.
[13] S. Thrun, "A probabilistic online mapping algorithm for teams of mobile robots," International Journal of Robotics Research, vol. 20, no. 5, pp. 335-363, 2001.
[14] Rohmer, E.; Signgh S.P.N.; Freese, M., "V-REP: a Versatile and Scalable Robot Simulation Framework," IEEE/RSJ International Conference on Intelligent Robots and Systems, 2013.
[15] ROS Navigation Stack, http://wiki.ros.org/navigation. Last accessed June, 18 2015.
[16] A Flexible and Scalable SLAM System with Full 3D Motion Estimation, S. Kohlbrecher and J. Meyer and O. von Stryk and U. Klingauf, Proc. IEEE International Symposium on Safety, Security and Rescue Robotics (SSRR) 2011.