THE USE OF NEGATIVE DETECTION IN COOPERATIVE LOCALIZATION IN A TEAM OF FOUR-LEGGED ROBOTS

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Abstract— In multirobot localization, the pose beliefs of two robots are updated whenever one robot detects another one and measures their relative distance. This paper proposes the use of a recently proposed localization algorithm that uses negative detection information to localize a group of four-legged Aibo robots in the domain of the RoboCup Standard Platform Four-Legged Competition. Our aim is to test the performance of this algorithm in a real world environment, where robots must use vision capabilities to detect the presence of other robots. Experiments were made with two robots and with three robots, using a cascade of detections to update the position of more than one of the robots. Experimental results show that negative detection localization allows us to localize the robots in situations where other algorithms would fail, leading to an improvement of the localization of real robots, working in a real world domain.

Keywords— Cooperative Robot Localization, Markov Localization, SIFT Algorithm.

1 Introduction

In order to perform their tasks, mobile robots need to know their poses within the environment. To do this, robots use their sensor measurements which provide information about robot's movement and about the environment. In the multirobot localization problem, each robot can use measurements taken by all robots, in order to better estimate its own pose. In this way, the main difference between single robot and cooperative multiple robots localization is that multirobot can achieve more information than a single robot.

A recently proposed cooperative multirobot localization (Odakura and Costa, 2006) makes use of negative detection information, which consists in the absence of detection information, which can be incorporated into the localization of a group of cooperative robots, in the form of the Multirobot Markov Negative Detection Information Localization algorithm.

The aim of this paper is to study this new detection algorithm in a more complex domain, that of the RoboCup Standard Platform Four-Legged League (RoboCup Technical Committee, 2006), where teams consisting of four Sony AIBO robots operating fully autonomously and communicating through a wireless network compete in a 6 x 4 m field. This domain is one of many RoboCup challenges, which has been proven to be an important domain for research, and where robot localization techniques have been widely used.

This paper is organized as follows. In Section 2, the cooperative robot localization problem is presented and the Markov localization technique is introduced. The negative detection multirobot localization is described in Section 3. The proposed experiment and its results are presented in Section 4. Finally, in Section 5, our conclusions are derived and future works are presented.

2 Cooperative Robot Localization

The cooperative multirobot localization problem consists in localizing each robot in a group within the same environment, when robots share information in order to improve localization accuracy. Markov Localization (ML) was initially designed for a single robot (Fox et al., 1999). An extension of ML that aims at solving the multirobot problem (MML) is presented by Fox et al. (Fox et al., 2000).

In MML, $p(\mathbf{x}_t = x)$ denotes the robot's belief that it is at pose x at time t, where $\mathbf{x}_t$ is a random variable representing the robot's pose at time t, and $x = (\mathsf{x}, \mathsf{y}, \theta)$ is the pose of the robot. This belief represents a probability distribution over all the space of $\mathbf{x}_t$.

MML uses two models to localize a robot: a motion model and an observation model. The motion model is specified as a probability distribution $p(\mathbf{x}_t = x|\mathbf{x}_{t-1} = x', \mathbf{a}_{t-1})$, where $\mathbf{x}_t$ is a random variable representing the robot's pose at time t, $\mathbf{a}_t$ is the action or movement executed by the robot at time t. In ML the update equation is described as:

$$p(\bar{\mathbf{x}}_t = x) = \sum_{x'} p(\mathbf{x}_t = x|\mathbf{x}_{t-1} = x', \mathbf{a}_{t-1}) \\ p(\mathbf{x}_{t-1} = x'), \quad (1)$$

where $p(\bar{\mathbf{x}}_t = x)$ is the probability density function before incorporating the observation of the environment at time t.

The observation model is used to incorporate information from exteroceptive sensors, such as proximity sensors and camera, and it is expressed as $p(\mathbf{x}_t = x|\mathbf{o}_t)$, where $\mathbf{o}_t$ is an observation sensed at time t. The update equation is described as:

$$p(\mathbf{x}_t = x) = \frac{p(\mathbf{o}_t|\mathbf{x}_t = x)p(\bar{\mathbf{x}}_t = x)}{\sum_{x'} p(\mathbf{o}_t|\mathbf{x}_t = x')p(\bar{\mathbf{x}}_t = x')}, \quad (2)$$

where $p(\mathbf{x}_t = x)$ is the probability density function after incorporating the observation of the environment at time t.

In order to accommodate multirobot cooperation in ML it is necessary to add a detection model to the previous models. The detection model (Fox et al., 2000) is based on the assumption that each robot is able to detect and identify other robots and furthermore, the robots can communicate their probabilities distributions to other robots. Let's suppose that robot n detects robot m and measures the relative distance between them, so:

$$p(\mathbf{x}_t^n = x) = p(\mathbf{x}_{t-1}^n = x) \\ \sum_{x'} p(\mathbf{x}_{t-1}^n = x|\mathbf{x}_{t-1}^m = x', \mathbf{r}_n)p(\mathbf{x}_{t-1}^m = x'), (3)$$

where $\mathbf{x}_t^n$ represents the pose of robot n, $\mathbf{x}_t^m$ represents the pose of robot m and $\mathbf{r}_n$ denotes the measured distance between robots. The calculation $\sum_{x'} p(\mathbf{x}_{t-1}^n = x|\mathbf{x}_{t-1}^m = x', \mathbf{r}_n)p(\mathbf{x}_{t-1}^m = x')$ describes the belief of robot m about the pose of robot n. Similarly, the same detection is used to update the pose of robot m.

To summarize, in the multirobot localization algorithm each robot updates its pose belief whenever a new information is available in the following Equation sequence: (1) is used when a motion information is available; (2) is used when an environment observation occurs; and when a detection happens, both robots involved use (3) to update their beliefs of poses.

Once a detection is made according to the detection model, the two robots involved in the process share their probabilities distributions and relative distance. This communication significantly improves the localization accuracy, if compared to a less communicative localization approach.

One disadvantage of this approach is that detection information is shared only by the two meeting robots and it is not used by the other robots in the group. Odakura and Costa (2005) have presented a detection model where all robots of the group can benefit from a meeting of two robots through the propagation of the meeting information. Other well known algorithms in cooperative multirobot localization are from Roumeliotis and Bekey (Roumeliotis and Bekey, 2002) and Fox et al. (Fox et al., 2000), that use Kalman filter and Particle filter as localization algorithms, respectively.

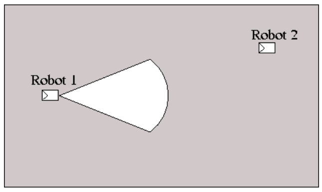


Figure 1: Negative detection information.

3 Negative Detection Localization

All sensor information provided to a single or multirobot in the Markov localization approach are positive information in the sense that it represents a sensor measurement of important features of the environment. Negative information measurement means that at a given time, the sensor is expected to report a measurement but it did not.

Human beings often use negative information. For example, if you are looking for someone in a house, and you do not see the person in a room, you can use this negative information as an evidence that the person is not in that room, so you should look for him/her in another place.

In the cooperative multirobot localization problem, negative information can also mean the absence of detections (in the case that a robot does not detect another one). In this case, the negative detection measurement can provide the useful information that a robot is not located in the visibility area of another robot.

Odakura and Costa (2006) proposed a negative detection model and its incorporation into multirobot ML approach. Consider two robots within a known environment and their field of view. If robot 1 does not detect robot 2 at a given point in time, a negative detection information is reported, which states that robot 2 is not in the visibility area of robot 1, as depicted in Figure 1.

The information gathered from Figure 1 is true if we consider that there are no occlusions. In order to account for occlusions it is necessary to sense the environment to identify free areas or occupied areas. If there is a free space on the visibility area of a detection sensor, than there is not an occlusion. Otherwise, if it is identified as an occupied area it means that the other robot could be occluded by another robot or an obstacle. In this case it is possible to use geometric inference

Figure 2: Test environment: The IIIA–CSIC field used during tests.

to determine which part of the visibility area can be used as negative detection information.

Let's suppose that robot m makes a negative detection. The negative detection model, considering the visibility area of the robot and the occlusion area, becomes:

$$p(\mathbf{x}_t^{m-} = x) = \frac{p(\mathbf{d}_t^- | \mathbf{x}_t^m = x, \mathbf{v}, \mathbf{obs}) p(\mathbf{x}_t^m = x)}{\sum_{x'} p(\mathbf{d}_t^- | \mathbf{x}_t^m = x', \mathbf{v}, \mathbf{obs}) p(\mathbf{x}_t^m = x')}, \quad (4)$$

where $\mathbf{d}_t^-$ is the event of not detecting any robot and $\mathbf{x}_m$ corresponds to the state of robot m, the robot that reports the negative detection information. The variables $\mathbf{v}$ and $\mathbf{obs}$ represent the visibility area and the identified obstacles, respectively.

Whenever a robot m does not detect another robot k, we can update the probability distribution function of each k, with $k \neq m$, in the following way:

$$p(\mathbf{x}_t^k = x) = \frac{p(\bar{\mathbf{x}}_t^k = x) p(\mathbf{x}_t^{m-} = x)}{\sum_{x'} p(\bar{\mathbf{x}}_t^k = x') p(\mathbf{x}_t^{m-} = x')}, \quad (5)$$

where $\mathbf{x}_k$, for $k = 0, \cdots, n$, represents all robots which were not detected.

In the case that a positive detection is reported, the robots involved in the detection update their beliefs according to (3).

The negative information has been applied to target tracking using the event of not detecting a target as evidence to update the probability density function (Koch, 2004). In that work a negative information means that the target is not located in the visibility area of the sensor and since the target is known to exist it is certainly outside this area. In robot localization domain, the work of Hoffmann et al. (Hoffmann et al., 2005) on negative information in ML considers as negative information the absence of landmark sensor measurements. Occlusions are identified using a visual sensor that scans colors of the ground to determine if there is free area or obstacle. The environment is a soccer field in green with white lines. So, if a different color is identified, it means that an obstacle could be occluding the visibility of a landmark.

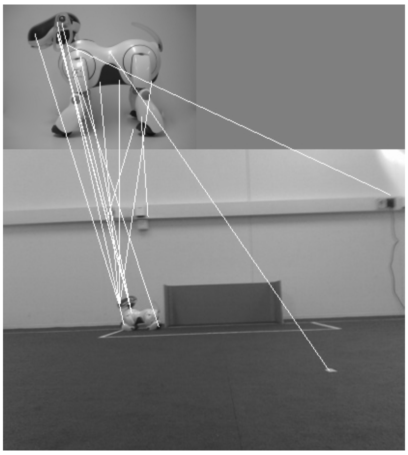


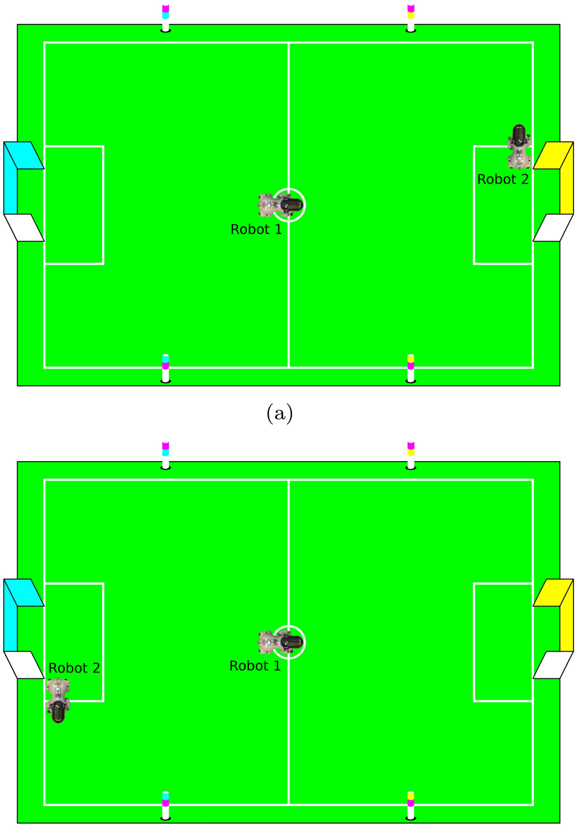
Figure 3: Robot detection: SIFT matching between the model (above) and the test image (below).

Negative detection model allows solving certain localization problems that are unsolvable for a group of robots that only relies on positive detection information. A typical situation is the case of robots in different rooms, in a way that one robot cannot detect the other.

4 Experiments in the RoboCup Standard Platform League Domain

Soccer competitions, such as RoboCup, has been proven to be an important challenge domain for research, where localization techniques have been widely used. The experiments in this work were conducted in the domain of the RoboCup Standard Platform Four-Legged League, using the 2006 rules (RoboCup Technical Committee, 2006). In this domain, two teams consisting of four Sony AIBO robots compete in a color-coded field: the carpet is green, the lines are white, the goals are yellow and blue. Cylindrical beacons are placed on the edge of the field at 1/4 and 3/4 of the length of the field. Considering only the white lines on the floor, that are symmetric, the field, shown in Figure 2, has dimensions 6×4 meters. The robot environment model is based on a grid, where each cell has dimensions of 0.3×0.3 meters, and angular resolution of 90 degrees. It results in a state space of dimension $18 \times 12 \times 4 = 864$ states.

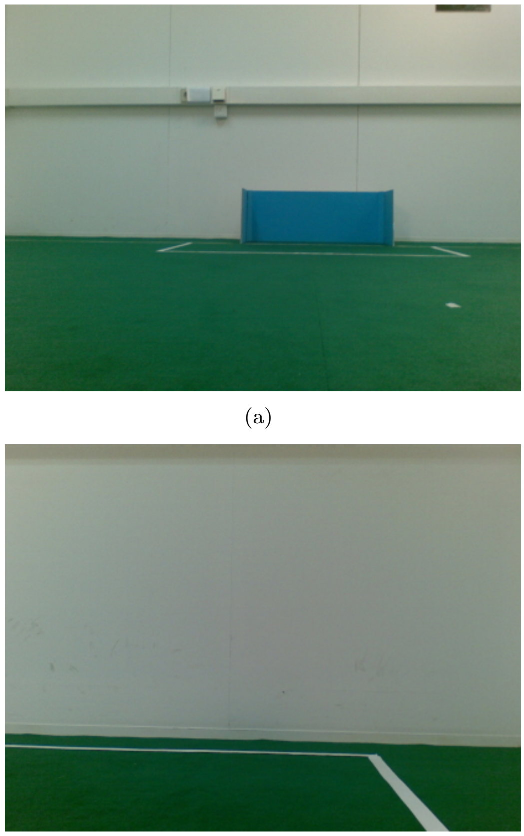
The robots used in this experiment were the Sony Aibo ERS-7M3, a 576MHz MIPS R7000 based robot with 64 Mb of RAM, 802.11b wireless ethernet and dimensions of $180 \times 278 \times 319$ mm. Each robot is equipped with a CMOS color camera, X, Y, and Z accelerometers and 3 IR distance sensors that can be used to measure the distance



(a)

(b)

Figure 4: First experiment: robot 1 at the center of the field and two possible positions of robot 2.



(a)

(b)

Figure 5: Images from the robot cameras: (a) Image seen by robot 1. (b) Image seen by robot 2.

to the walls in the environment.

The 416x320 pixel nose-mounted camera, which has a field of vision 56.9^o wide and 45.2^o high, is used as a detection sensor. In order to verify if there are any robots in the image and to measure their relative distance, we used the constellation method proposed by Lowe, together with its interest point detector and descriptor SIFT (Lowe, 2004).

This approach is a single view object detection and recognition system which has some interesting characteristics for mobile robots, most significant of which are the ability to detect and recognize objects at the same time in an unsegmented image and the use of an algorithm for approximate fast matching. In this approach, individual descriptors of the features detected in a test image are initially matched to the ones stored in the object database using the Euclidean distance. False matches are rejected if the distance of the first nearest neighbor is not distinctive enough when compared with that of the second. In Figure 3, the matching features between model and test images can be seen. The presence of some outliers can also be observed.

In this domain, there are situations in which the robots are not able to detect the color markers, such as the beacons or the goals (corner situations, for example). In these moments, only the lines are visible, and the robots must cooperate to overcome the difficulties found by the symmetry of the field.

We first conducted an experiment with two robots. Robot 1 is located at the center of the field facing the yellow goal. At a given moment, robot 1 knows accurately its pose, and robot 2 is in doubt about being at the yellow goal area or at blue goal area of the field. Figure 4 depicts this situation and Figure 5(a) shows the image from robot 1 camera. Due to the environment symmetry it is impossible to robot 2 to find out that its real pose is in the blue goal area of the field, considering that the colored marks, goals or beacons, are not in its field of view, as can be seen in Figure 5(b). However, robot 2 would be able to localize itself if negative detection information, provided by robot 1, could be used to update its pose belief.

Figures 6(a) and 6(b) show the probability density function of robot 1 and robot 2, respectively. In Figure 7(a) is shown the negative detection information derived from the belief of robot 1 and its visibility area. When robot 2 updates its pose using the negative detection information reported by robot 1, it becomes certain about its pose, as shown in Figure 7(b).

The second experiment was conducted with

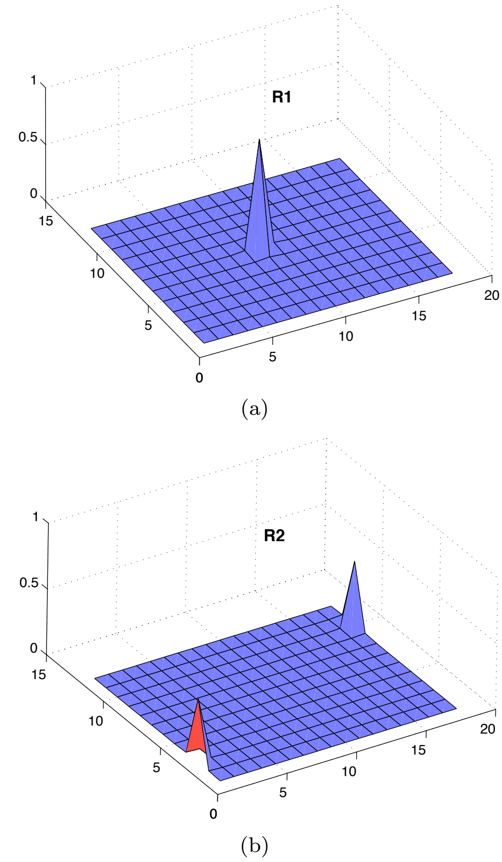


Figure 6: (a) Probability density function of robot 1. (b) Probability density function of robot 2.

three robots. Robot 1 and robot 2 have the same configuration as described in the previous experiment and robot 3 is in doubt about being at the top right corner or at the bottom left corner of the field. Figure 8 depicts this situation. Due to the environment symmetry it is impossible to robot 2 to find out that its real pose is in the blue goal area and it is impossible to robot 3 to find out that its real pose is at the top right corner of the field, considering that the colored marks, goals or beacons, are not in their fields of view. However, robot 2 would be able to localize itself if negative detection information, provided by robot 1, could be used to update its pose belief. Further than, once robot 2 is certain about its pose, robot 3 would be able to localize itself with negative detection.

Figure 7(b) show the probability density function of robot 2 after update its position with negative detection and Figure 9 show the probability density function of robot 3. In Figure 10(a) is shown the negative detection information derived from the belief of robot 2 and its visibility area. When robot 3 updates its pose using the negative detection information reported by robot 2, it becomes certain about its pose, as shown in Figure 10(b).

The experiments described above show the use of negative detection can improve localization

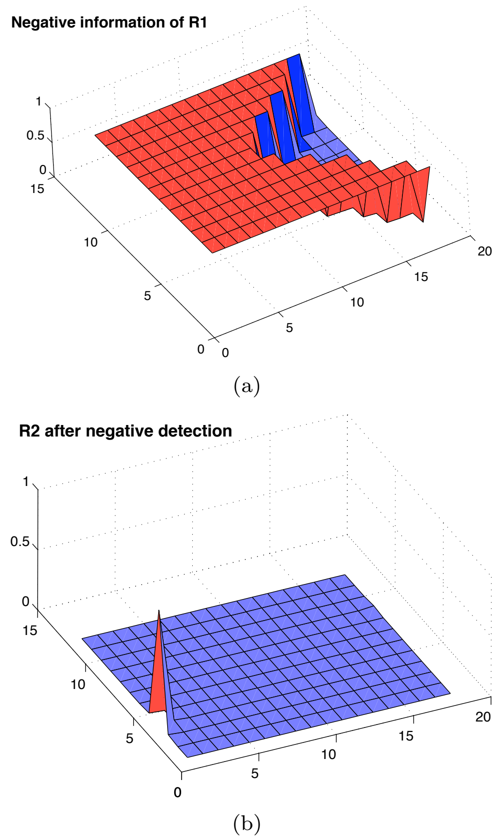


Figure 7: (a) Negative detection information reported by robot 1. (b) Probability density function of robot 2 after the incorporation of negative detection information.

accuracy if compared with a less communicative localization approach, as MML. In both experiments all robots became certain about their poses after the negative information exchange. If the negative detection was not available, the uncertainty robots would have to walk around until they could see useful landmarks in field, before being able to localize themselves.

5 Conclusions

Negative detection can be very useful to improve localization in ambiguous situations, as shown by the experiments. In both experiments, the robots configurations illustrated that cooperative localization, performed by negative detection, is the only way to improve robot's pose belief at that moment. In other way, robots should move, and wait until they can find useful marks to be able to localize themselves. Moreover, we give a contribution in the direction of a precise localization, that is one of the main requirements for mobile robot autonomy.

The experiments described in this paper are very initial ones, using the robots cameras to capture the images, and then a computer to analyze the image and compute the robots poses, in a

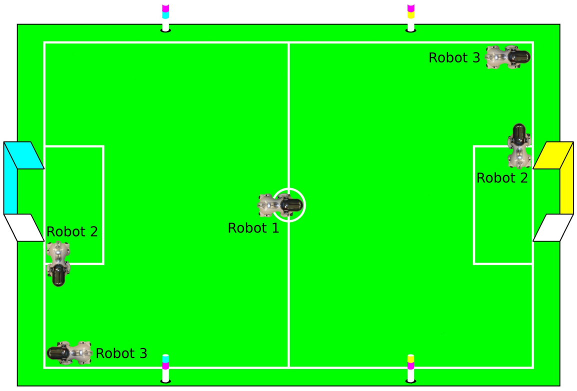


Figure 8: Second experiment: possible positions of robots 2 and 3.

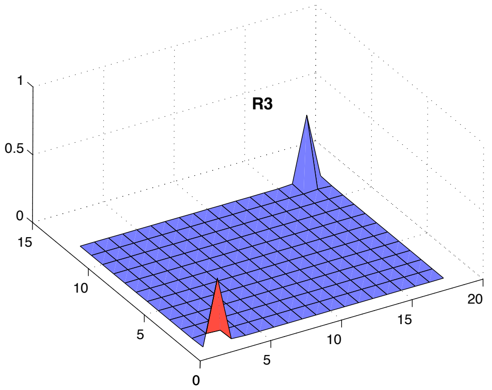


Figure 9: Probability density function of robot 3.

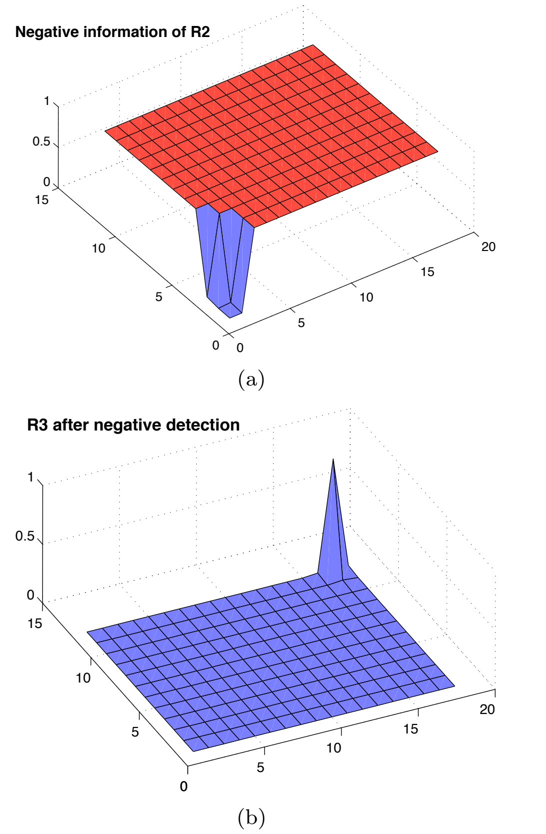


Figure 10: (a) Negative detection information reported by robot 2. (b) Probability density function of robot 3 after the incorporation of negative detection information.

static manner. The first extension of this work is to implement the negative detection localization in a way to allow its use during a real game. Finally, as part of our future work, we also plan to investigate other forms of information to update robot's pose belief.

Acknowledgements

This research has been conducted under the FAPESP Project LogProb (Grant No. 2008/03995-5) and the CNPq Project Ob-SLAM (Grant No. 475690/2008-7). Anna H. R. Costa is grateful to CNPq (Grant No. 305512/2008-0). Reinaldo Bianchi also acknowledge the support of the CNPq (Grant No. 201591/2007-3) and FAPESP (Grant No. 2009/11256-0).

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