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Collaborative Multi-Robot Monte Carlo Localization in Assistant Robots

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Abstract: This paper presents an algorithm for collaborative mobile robot localization based on probabilistic methods (Monte Carlo localization) used in assistant robots. When a root detects another in the same environment, a probabilistic method is used to synchronize each robot's belief. As a result, the robots localize themselves faster and maintain higher accuracy. The technique has been implemented and tested using a virtual environment capable to simulate several robots and using two real mobile robots equipped with cameras and laser range-finders for detecting other robots. The result obtained in simulation and with real robots show improvements in localization speed and accuracy when compared to conventional single-robot localization.

Keywords: mobile robots, collaborative multi-robot localization, Monte Carlo localization, assistant robots.

1. Introduction

Mobile robot localization is the problem of estimating a robot's pose (location, orientation) relative to its environment [19]. The localization problem is a key problem in mobile robotics and plays a pivotal role.

The mobile robot localization problem comes in many different flavors [3]. The most simple localization problem is position tracking. Here the initial robot pose is known, and the problem is to compensate incremental errors in a robot's odometry. More challenging is the global localization problem [4], where a robot is not told its initial pose but instead has to determine it from scratch. The global localization problem is more difficult, since the error in the robot's estimate cannot be assumed to be small. Consequently, a robot should be able to handle multiple, distinct hypotheses. More difficult is the kidnapped robot problem [8], in which a well-localized robot is tele-ported to some other place.

Probabilistic methods have been applied with remarkable success to single-robot localization [6,7,11,12], where they have been demonstrated to solve problems like global localization and localization in dense crowds. The global localization and kidnapped robot problem in a highly robust and efficient way can be overcome using Monte Carlo localization (MCL) algorithm [19]. Monte Carlo Localization is a family of algorithms for localization based on particle filters, which are approximate Bayes filters that use random samples for posterior estimation. Recently, they have been applied with great success for robot localization.

On the other hand, in the last years, the number of elderly or sick people in need of care is increasing dramatically. In the European Union it is estimated that 10-15% of the total population is over 60 years old. Besides, several reports also show that there is a strong relation between the age of the person and the handicaps suffered, the latter being commoner in persons of advanced age. Given the growth in life expectancy in the world (in the countries of the Organisation for Economic Cooperation and Development (OECD) it is expected that the proportion of older persons aged 60 years and above will have reached a ratio of 1 person in 3 by the year 2030), a large part of its population will experience functional problems. Aware of the dearth of applications for this sector of the population, governments and public institutions have been promoting research in this area in last years. Various research groups at a world level have begun to set up projects to aid communication and mobility of elderly with the aim of increasing their quality of life. These will allow a more autonomous and independent lifestyle and greater chances of social integration for them.

At the same time, the development countries are facing an explosion of costs in the health-care sector for elderly. Current nursing home costs range between $30,000 and $60,000 annually. Over the last decade along, costs have more than doubled. The dramatic increase of the elderly population along with the explosion of costs poses extreme challenges to society. The current practices of providing care for the elderly population are already insufficient. Undoubtedly, this problem will multiply over the next decade.

The society needs to find new technologies and alternative ways of providing care to the elderly, where the need for personal assistance is larger than in any other age group. Several factors suggest that now is the time to establish new applications in the home-care sector: Firstly, we actually have the technology (internet) to develop new applications in home health-care sector. Secondly, at the currently, the robots exhibit the necessary robustness, reliability, and level of capability. Thirly, the need for cost-effective solutions in the elderly care sector is larger than ever before. For this reason, assistant robots have received special attention from the research community in the last years. One of the main applications of these robots is to perform care tasks in indoor environments such as houses, nursing homes or hospitals, and therefore, they need to be able to navigate robustly for long periods of time. Nowadays exists several research groups working in this area, and some important projects such us "TelemediCare" [18], "Nursebot" [14] and "Morpha" [13].

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In order to offer a solution for described problem, a research group of Electronics Department at the University of Alcalá have been working in several projects called SIMCA [17] (spanish acronym for Assistant Collaborative Multi-robot System) and "ROBOCITY 2030" (spanish acronym for Service Robots Upgrading Urban Standards of Living) [15]. The main goals of these projects are the development of robots' fleet working together to make assistance tasks in a collaborative way. These personal robotic assistants must to provide several primary functions such us tele-presence, tele-medicine, intelligent reminding, safeguarding, mobility assistance and social interaction [16].

This paper is focused in a probabilistic algorithm for collaborative mobile robot localization based on Monte Carlo localization used in assistant tasks. The key idea of multi-robot localization is to integrate measurements taken at different platforms, so that each robot can benefit from data gathered by robots other than itself. Therefore, when one robot detects another, this information are used to synchronize the individual robots' beliefs, thereby reducing the uncertainty of both robots during localization [9].

The rest of the paper is organized as follows. In section 2 the Multi-robot Monte Carlo localization is commented. In section 3, the general architecture of the robots is presented as well as the navigation module. Sections 4 and 5 show the environment perception task and the detection model respectively. The experimentation results are explained in section 6. Section 7 presents a critical evaluation of the proposed approach in contrast to related works and finally, conclusions are given in section 7.

2. Multi-robot Monte Carlo localization

Monte Carlo Localization have been widely studied in [7,19]. MCL is a recursive Bayes filter that estimates the posterior distribution of robot poses conditioned on sensor data.

The key idea of Bayes filtering is to estimate a probability density over the state *x* space conditioned on the data. This posterior is typically called the *belief* and is denoted:

$$Bel(x_t) = p\left(x_t \middle| \; o_t, a_{t-1}, o_{t-1}, a_{t-2}, \ldots, o_0\right) \tag{1}$$

where x_t is the state at time *t*, *o* denotes *observations* (*perceptual data* such as laser range or vision measurements) and *a* represents *actions* (*odometry data* which carry information about robot motion).

Bayes filters estimate the belief recursively. The initial belief characterizes the initial knowledge about the system state. In the absence of such knowledge, it is typically initialized by a uniform distribution over the state space. In mobile robot localization, a uniform initial distribution corresponds to the global localization problem, where the initial robot pose is unknown.

To derive a recursive update equation, (1) can be transformed by Bayes rule to:

$$Bel(x_t) = \eta \cdot p(o_t | x_t, a_{t-1}, \ldots, o_0)\, p(x_t | x_{t-1}, a_{t-1}, \ldots, o_0) \tag{2}$$

$$\eta = p(o_t | a_{t-1}, \ldots, o_0)^{-1} \tag{3}$$

Bayes filters assume that the environment is Markov, that is, past and future data are (conditionally) independent if one knows the current state. The Markov assumption implies:

$$p(o_t | x_t, a_{t-1}, \ldots, o_0) = p(o_t | x_t) \tag{4}$$

$$p(x_t | x_{t-1}, a_{t-1}, \ldots, o_0) = p(x_t | x_{t-1}, a_{t-1}) \tag{5}$$

Therefore, the belief can be denoted by:

$$Bel(x_t) = \eta \cdot p(o_t | x_t) \cdot \int p(x_t | x_{t-1}, a_{t-1}) Bel(x_{t-1}) dx_{t-1} \tag{6}$$

where $p(o_t * x_t)$ is called *perceptual model* and $p(x_t * x_{t-1}, a_{t-1})$ represents the *motion model*.

The key idea of multi-robot localization is to integrate measurements taken at different platforms, so that each robot can benefit from data gathered by robots other than itself. Therefore, when a robot *n* is detected by robot *m* it is necessary to introduce the detection model according with data obtained r_m in (6). In the absence of detections, the Markov localization works independently for each robot. A summary of the multi-robot Markov localization algorithm is:

- Initialize the belief $Bel_n(x)$ according with initial data (typically uniform distribution).
- If the robot *n* receives an observation on (new sensory input) o_n, it is applies the perception model:

$$Bel_n(x) = \eta \cdot p(o_n \mid x) \cdot Bel_n(x) \tag{7}$$

- If the robot n do some action an (receives a new odometry reading), It is applies the motion model:

$$Bel_n(x') = \eta \cdot \int_x p(x' \mid x, a_n) \cdot Bel_n(x) \cdot dx \tag{8}$$

- And finally, if the robot n is detected by the m-th robot it is applies the detection model:

$$Bel_n(x') = \eta \cdot Bel_n(x) \int_x p(x_n = x' \mid x_m = x, r_m) \cdot Bel_m(x) \cdot dx \tag{9}$$

The idea of MCL is to represent the *belief* by a set of *m* weighted samples distributed according to *Bel(x)*:

$$Bel(x_t) \approx \{x^i, w^i\}_{i=1,\ldots,m} \tag{10}$$

where x^i is a *sample* of the random variable *x* (pose) and w^i is called *importance factor* and represents the importance of each sample. The set of samples, thus, define a discrete probability function that approximates the continuous belief *Bel(x)*.

The initial set of samples represents the initial knowledge $Bel(x_o)$ about the state of the dynamical system. For instance, in global mobile robot localization, the initial belief is a set of poses drawn according to a uniform distribution over the robot's universe, annotated by the uniform importance factor 1/m. If the initial pose is known up to some small margin of error, $Bel(x_o)$ may be initialized by samples drawn from a narrow Gaussian centered on the correct pose.

The recursive update is realized in three steps:

- Sample x^i_{t-1}– $Bel(x_{t-1})$. Each such particle x^i_{t-1} is distributed according to the belief distribution $Bel(x_{t-1})$.
- Sample x^i_{t-1}– $p(x_t * x^i_{t-1}, a_{t-1})$. In this case, x^i_t is distributed according to the product distribution $p(x_t * x_{t-1}, a_{t-1}) \cdot Bel(x_{t-1})$.
- The importance factor is assigned to the i-th sample:

$$w^i = 0 \cdot p(o_t * x^i_t) \tag{11}$$

3. General Architecture

The general objective of this work is to develop a robots' fleet working together to make assistance tasks in a collaborative way (Fig.1).

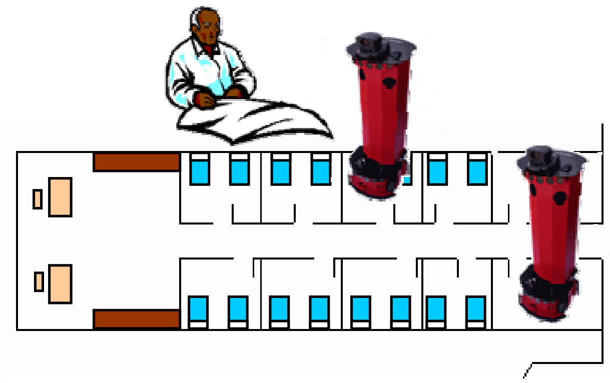


Fig. 1. robot's fleet working.

Therefore, a goal is to develop a workbench for testing collaborative mobile robot localization based on Monte Carlo localization. For this, we have implemented a testing platform that permit simulate and work with real robots in an indoor environment (Fig 2).

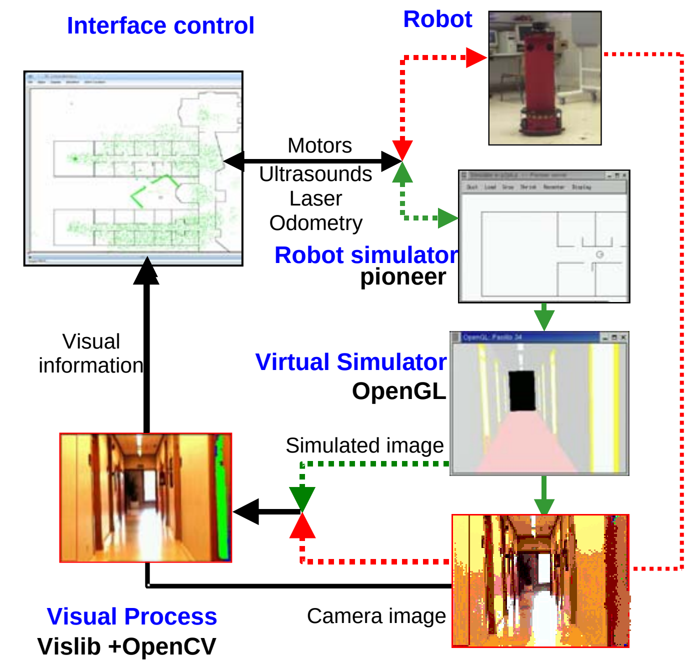


Fig. 2. General architecture.

3.1 Robots

Two robotic platform have been developed (based on PeopleBot and pioneer AT robots of ActivMedia Robotics [1]). Its architecture is composed of four large modules: environment perception, navigation, human-machine interface and high-level services as we show in Fig. 3. The perception module is endowed with encoders, bumpers, sonar ring, laser sensor and a vision system based on a PTZ (pan-tilt-zoom) color camera connected to a frame grabber. The human-machine interface is composed of loudspeakers, microphone, a tactile screen, the same PTZ camera used in the perception module, and wireless Ethernet link. The system architecture includes two human-machine interaction systems, such as voice (synthesis and recognition speech) and touch screen for simple command selection (for example, a destination room to which the robot must go to carry out a service task). The high-level services block controls the rest of the modules and includes several tasks of tele-assistance, tele-monitoring, providing reminding and social interaction [2].

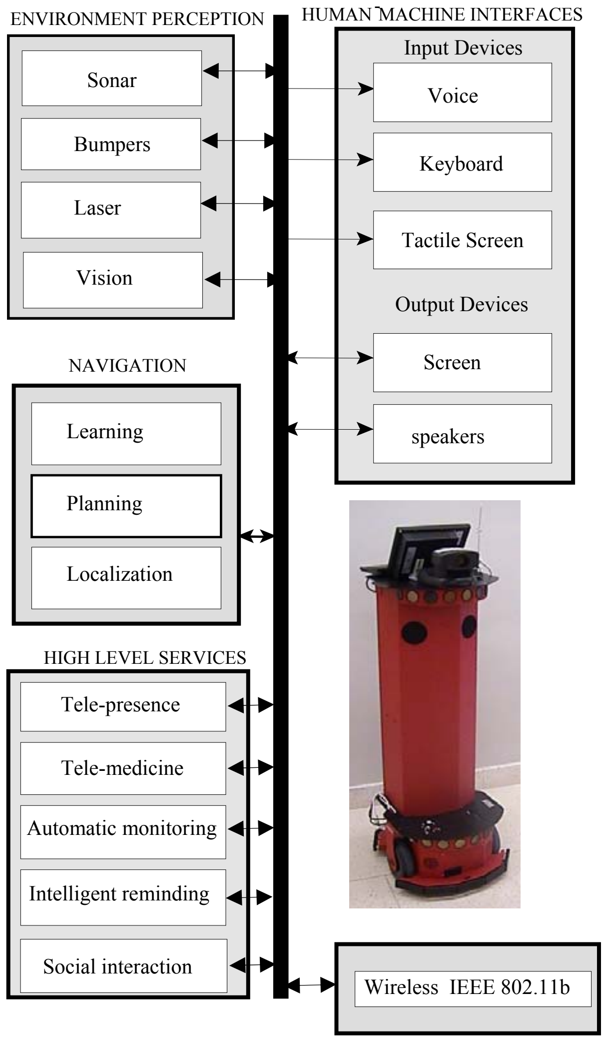


Fig. 3. General architecture of the robots.

3.2 Navigation Module

The navigation module combines information from perception module for carrying out different tasks.

The core of this module is CARMEN (Carnegie Mellon Robot Navigation Toolkit) [5] which is an open-source collection of software for mobile robot control. CARMEN is modular software designed to provide basic navigation primitives including: base and sensor control, obstacle avoidance, localization, path planning, people-tracking, and mapping.

This source has been modified to implement the multi-robot localization, because CARMEN only permits works with a single robot, and different initial distribution for studying the robot localization. This source implements the motion, perception and detection models. Besides, a virtual simulator has been developed for testing the detection model using visual information and the localization process.

4. Environment Perception Task

To be able to carry out assistance tasks in a collaborative way it is necessary that the robots are able to perceive the environment. Therefore, it is necessary to implement the tasks of estimate of the robot's position and of robots' detection in the environment.

4.1 Estimation of the Robot's Pose

The objective is to estimate the robot's pose (x,y,θ). For this, laser data is used. The process consists on comparing the real measure obtained by the laser with those that would be obtained if the robot is in the position of each particle. This is the perception model $w^{i} = \theta \cdot p(o_t * x^{i}_t)$.

Fig. 4 represents the measures obtained by the laser sensor when the robot will enter in the corridor. Figs 5 and 6 shown the robot's belief (initial uniform distribution modified in function of the laser data), this is, the pose and weight of each particle.

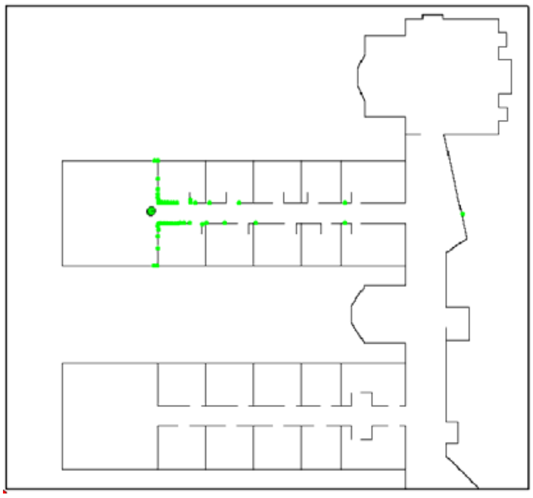


Fig. 4. Laser data in corridor.

Fig. 5. Initial robot's belief (pose).

4.2. Robots Detection

Robots must possess the ability to sense each other. To determine the relative location of other robots, visual information obtained from an on-board camera with proximity information coming from a laser range-finder are combined. The robots are marked by a unique and coloured marker (Fig. 7) to facilitate its recognition (green cylinder). This way, the marker can be detected regardless of the robot's orientation.

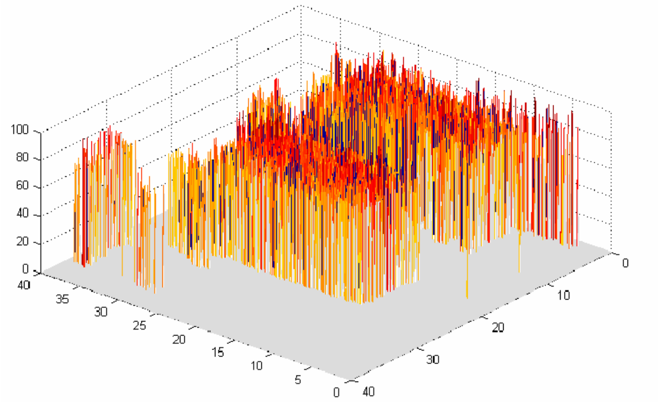


Fig. 6. Initial robot's belief (weight).

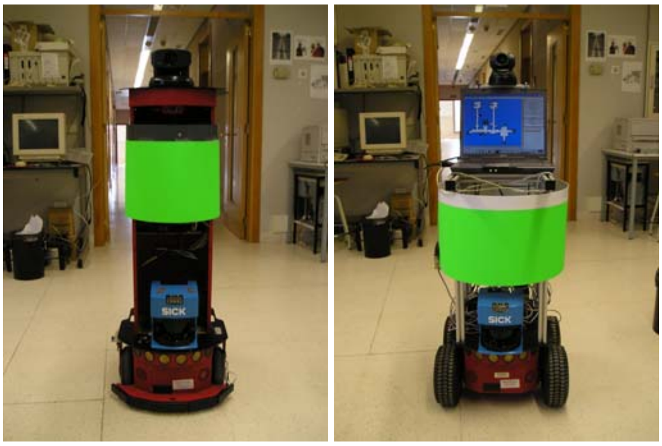


Fig. 7. Robots with colored marker.

Fig. 8. Robot wandering in a laboratory.

Camera images are used to detect other robots and together with laser range-finder scans are used to determine the relative position of the detected robot and its distance. The process consists on:

- Filtering the image by employing local colour histograms (HIS space colour).
- Thresholding to search for the marker's characteristic colour transition.

- If an object is found, this implies that a robot is present in the image.
- Once a robot has been detected, we process de object detected (size and position in the image) and the laser scan for calculating the relative location of the robot.

Fig. 8 shows the real image obtained by the robot camera. Fig. 9 is the colour pattern used to detect robots and Fig. 10 represents the filtering process using the colour pattern. Starting from figure 10 is obtained that a robot is located at 113º. Then, the laser sensor data (Fig. 11) is used to determine the robot's distance accurately (2.2 m). Knowing the angle and the distance is calculated the detected robot's relative position, this is, robot's location (x,y) = (-0.85m, 2.02m).

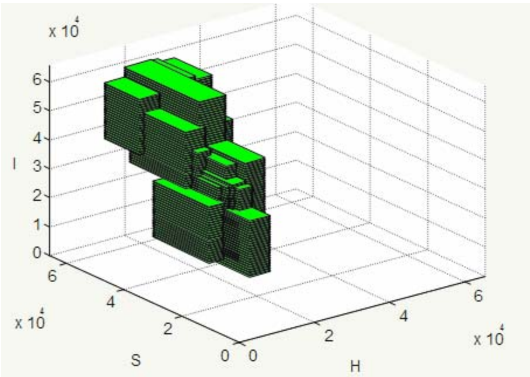


Fig. 9. Colour pattern used.

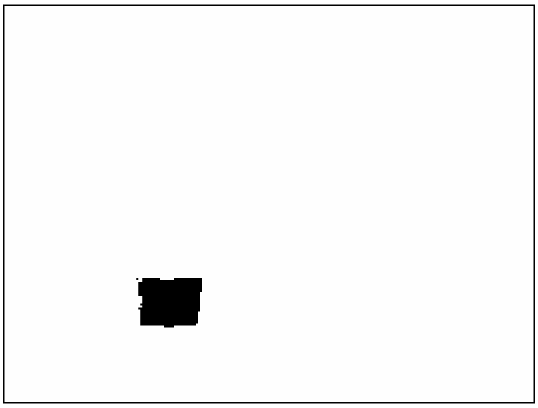


Fig. 10. Robot detected using the colour pattern.

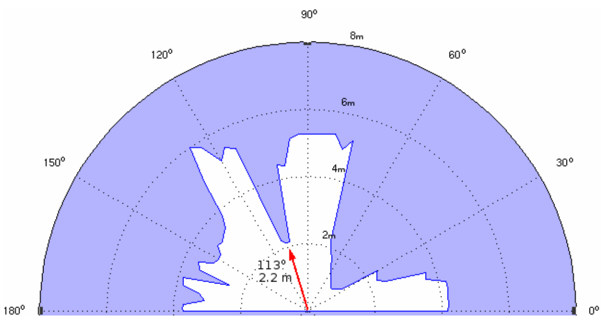


Fig. 11. Laser data.

5. Detection Model

The detection model describes the probability that robot n is at location x, given that robot m is at location x' and perceives robot n with measurement r_m. The key idea of the detection model consists on projecting the robot's particles (robot that detects) to the detected robot's space.

The detection model can be implemented in different ways: by means of euclidean distance, using grids,…etc. However, in practical test, the results obtained using grids are successfully and the algorithm is the simplest.

When a robot detects to the other one a detection model is generated, this model represents the probability that the detected robot is in this point. This detection model is introduced in the equation 9 to carry out the adjustment of the particles by means of Collaborative Monte Carlo localization. Fig. 12 shows the detection model pseudo-code.

Suppose you that the robot m detects the robot n:

1. *The robot m detects the robot n in r_m=(dis, ang).*
2. *To spread the robot's particles m toward where it has been detected the robot n.*

$$x_m' = x_m + dis \cdot \cos(ang) + \eta \cdot \cos(ang)$$

$$y_m' = y_m + dis \cdot sen(ang) + \eta \cdot sen(ang)$$

3. *To upgrade the robot's particles m*

$$w_n' = w_n \cdot f(x'_m, y'_m, w'_m)$$

Fig. 12. Detection model pseudo-code.

Next, an example of two robots' collaborative localization is commented. Fig. 13 represents the electronics department map (whose dimensions are 40x40m). Robot 1 is located in the position [x, y] = [6, 21] with a gaussian distribution of particles shown in Fig. 14. On the other hand, robot 2 is really in the position [16, 21] and it has an uniform distribution of particles in the whole environment (see Fig. 15). If it is considered the robot's position like the mean value of the position of the particles, we obtain that the robot 1 is in position [6.0481, 21.0060] and robot 2 in [24.1551, 13.2715]. It can be observed that robot 1 are practically well located while robot 2 are very bad located.

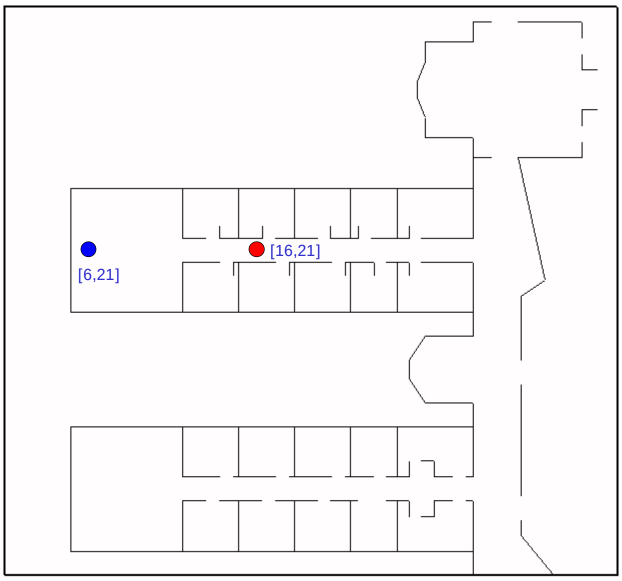


Fig. 13. Electronics department map.

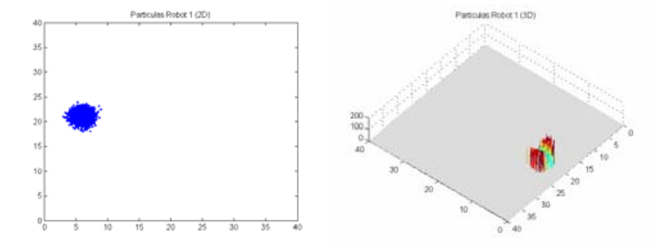


Fig. 14. Robot 1 initial distribution of particles.

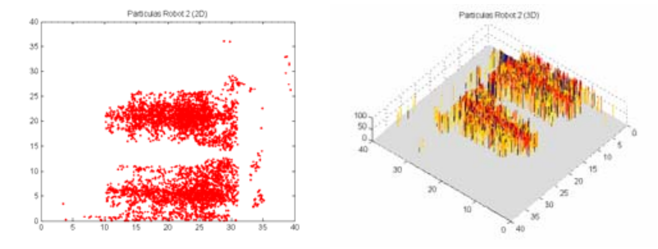


Fig. 15. Robot 2 initial distribution of particles.

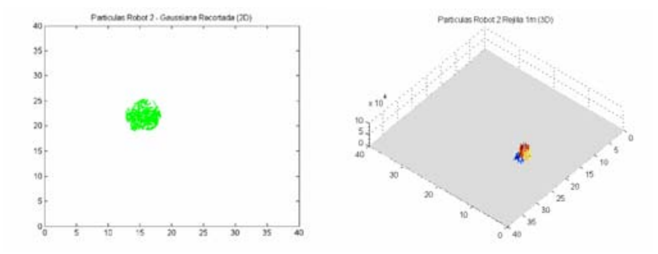


Fig. 16. Robot 2 particles after detection model.

When robot 1 detects robot 2, a detection model is generated and is sent to robot 2 and the particles weights are adjusted in function of this model giving place to a new localization of the particles (Fig. 16). It can be observed that detection model allows to reduce the uncertainty vastly on the localization of robot 2. Now the robot 1's position is [x,y] = [6.0481, 21.0060] and for robot 2 is [x,y] = [16.3800, 21.1525]. Now, the new position of robot 2 practically it coincides with the real one.

6. Results

This section shows results obtained with real and simulated robots. The objective is to show how cooperative multi-robot localization improves the individual localization process.

6.1 Simulation Results

In the following experiments it is used a simulation tool (based on navigation tool from CARMEN) which simulates robots on the sensor level, providing raw odometry and proximity measurements. Besides, a visual simulator using OpenGL have been developed for simulating the camera image.

Robot detections have been simulated by using the positions of the robots extracted from the map and the camera image simulated extracted from visual simulator.

In the simulation experiments we use two robots, which are all equipped with laser and camera sensors. The task of the robots is to perform global localization in the environment of the Department of Electronics composed by laboratories, offices, corridors and halls. Firstly, we are going to study the conventional single-robot Monte-Carlo localization and after that, the collaborative multi-robot Monte-Carlo localization.

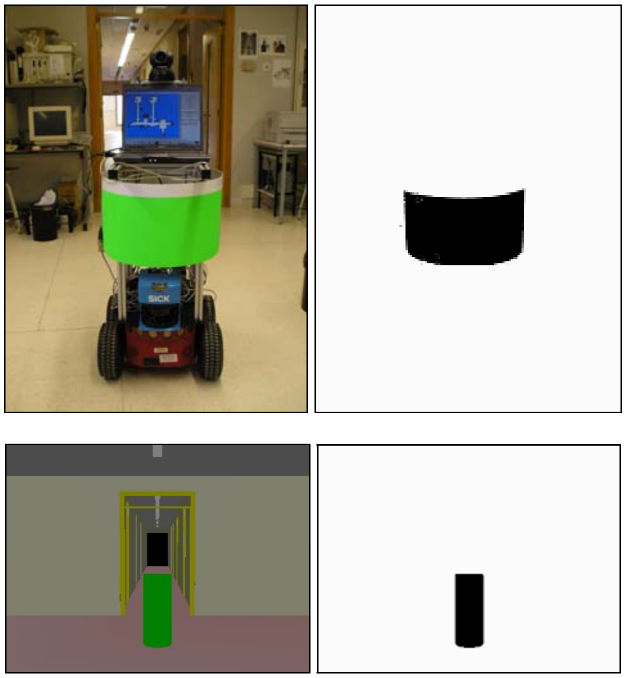


Fig. 17. Robots detection in real environment and simulation.

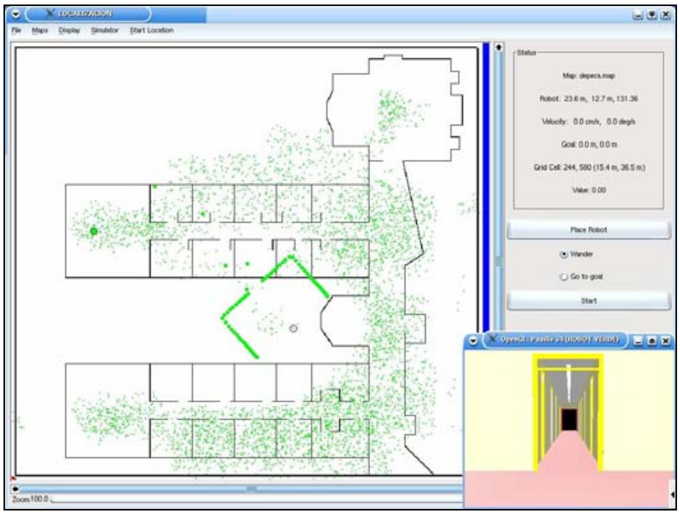


Fig. 18. Initial uniform belief's robot.

6.1.1 Conventional single-robot Monte-Carlo Localization

In this experiment, we place one robot in a laboratory and it wanders off in the direction of the longest point detected by laser sensor. The initial belief's robot is setup to uniform distribution modified in function of the laser sensor data as can be see in Fig. 18. The robot starts to walk around the laboratory and reaches the corridor (Fig. 19). At this moment, the belief is focussed in both corridors, this is, the localization module knows the robot is in a corridor, but unknows where is. When the robot walk across the corridor, it is localize inside the corridor but unknows in which corridor is (Fig. 20). When the robot reaches the vertical corridor it is localized (Fig. 21). Therefore, the conventional single-robot localization needs to walk across the whole corridor and reaches a certainty point (another corridor where symmetry is broken) to locate with accuracy.

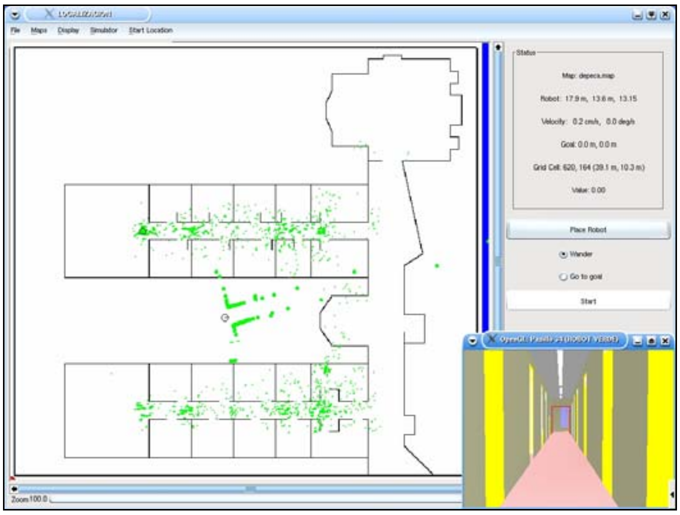


Fig.19. Belief's robot when starts the corridor.

Fig. 20. Belief's robot in the corridor.

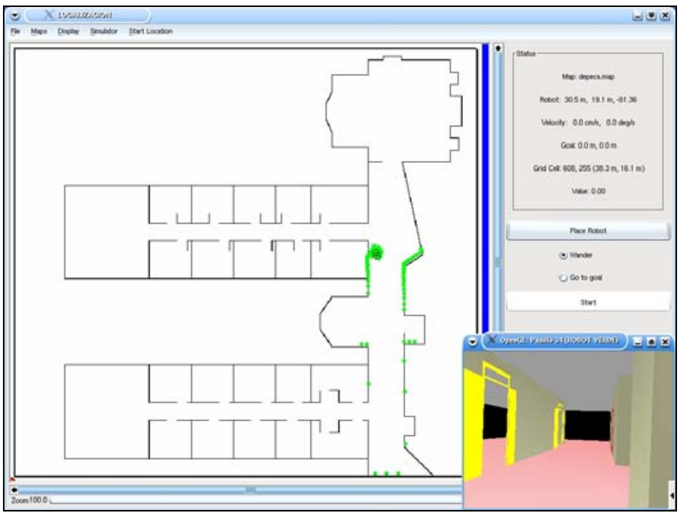


Fig. 21. Belief's robot when reaches the vertical corridor.

6.1.2 Collaborative Multi-Robot Monte Carlo Localization

For studying the multi-robot localization we work with two robots fixed in the laboratory (robot 1) and in an office 2 (robot 2). The objective is to test the global localization of the robot 1 (with initial uniform belief) with different initial belief of robot 2.

Uniform distribution. Firstly, we study the global localization of the robot 1 with uniform belief of robot 2 (Fig. 22).

In this case, results are similar to conventional single-robot Monte-Carlo localization because robot 2 unknows its position. Robot 1 starts in laboratory with uniform belief and wanders across top horizontal corridor, when robot 2 detect robot 1, the robot 1 upgrades its belief but it keep particle in two horizontal corridors, and therefore, until it does not reach the vertical corridor, it does not localize himself (see process in Fig. 23).

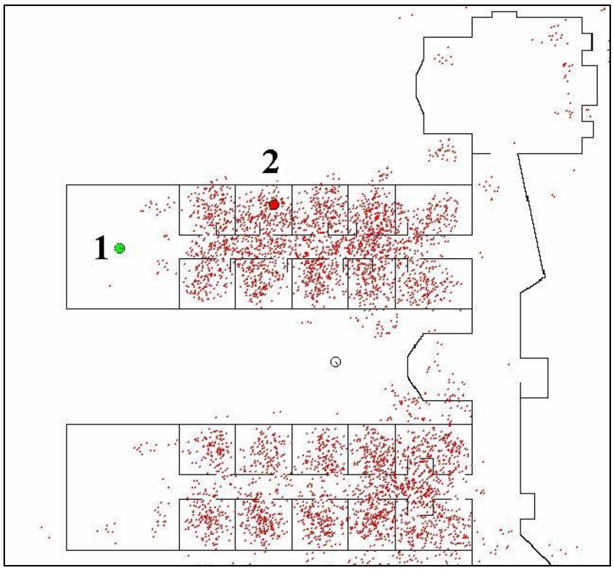


Fig. 22. Initial uniform belief for robot 2.

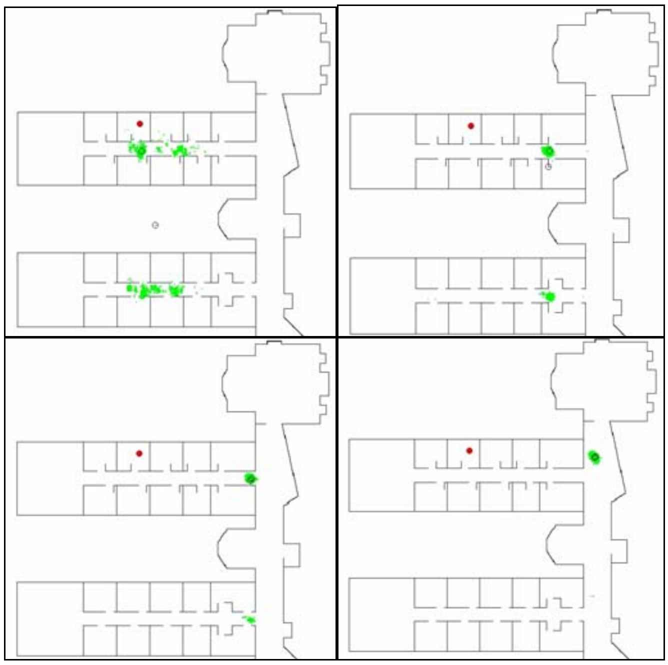


Fig. 23. Belief's robot 1 (Robot 2 with uniform belief).

Gaussian distribution. Firstly, we suppose robot 2 is located but it has a great uncertainty. This can be modelled using a gaussian belief with a high standard deviation σ = 0.8 (Fig. 24). Now, when robot 2 detects robot 1, the robot 1 upgrades its belief, it can be see that only exists particle in the top horizontal corridor. Therefore, the robot knows in which corridor is but it unknows where is with accuracy, but before reaches the end of the corridor, it is localized himself correctly (Fig. 25).

Fig. 24. Initial gaussian belief for robot 2 (σ = 0.8).

Fig. 25. Belief's robot 1 (Robot 2 gaussian belief σ = 0.8).

On the other hand, if we suppose robot 2 is located with accuracy, we can model its belief using a gaussian with narrow standard deviation σ = 0.2 (Fig. 26). In this case, when robot 2 detects robot 1 in the corridor, the belief's robot 1 is upgraded with precision and it know where is in the corridor with accuracy. When robot 1 is located in the map we can send navigation task, such as, to reach a goal (Fig. 27).

Fig. 28 shows the position error among the robot's estimate position (mean value of the particles) and the robot's real position for the different localization strategies commented in the previous examples. It can be appreciated that working with single-robot localization, the position error goes diminishing progressively until the robot is located. When one works with collaborative localization it is observed how when the robots are detected (iteration 80) a gap takes place in the position error. It is observed that if the robot 1 possess an uniform distribution the detection model hardly improves the robot 2 location, but when the robot 1 possess a Gaussian distribution (its position is almost knows) the detection model improves the knowledge of the position of the robot 2 because the position error decreases considerably.

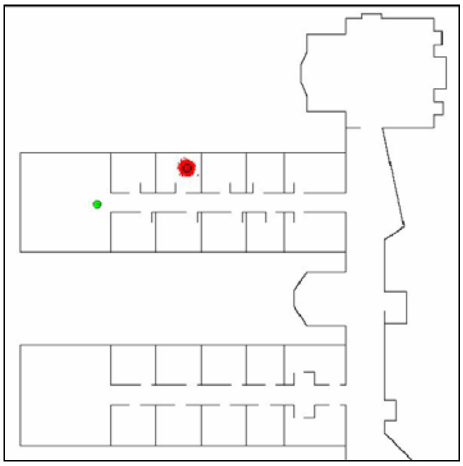


Fig. 26. Initial gaussian belief for robot 2 (σ = 0.2).

Fig. 27. Belief's robot 1 (Robot 2 gaussian belief σ = 0.2).

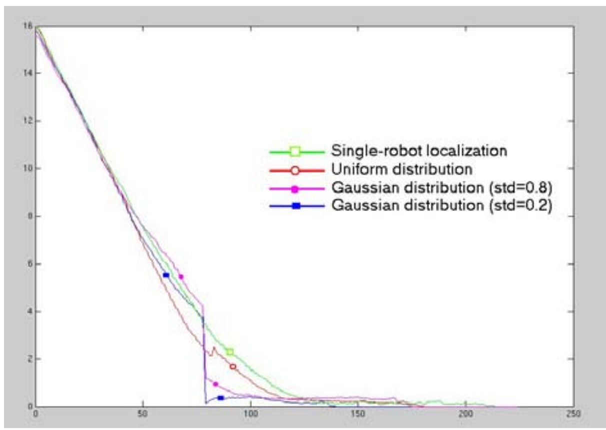
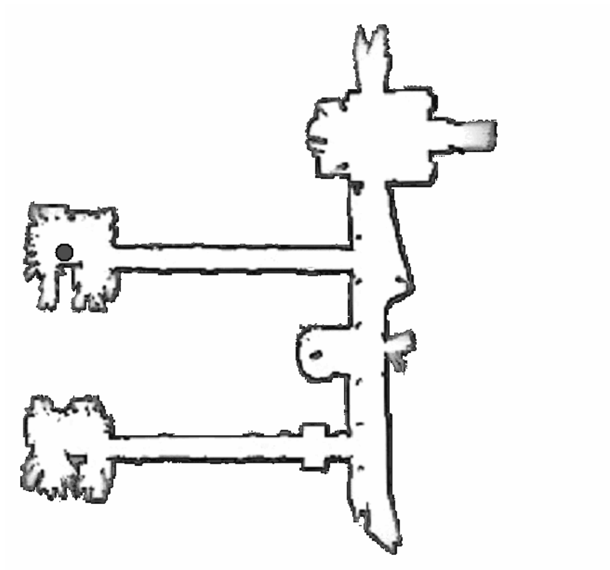


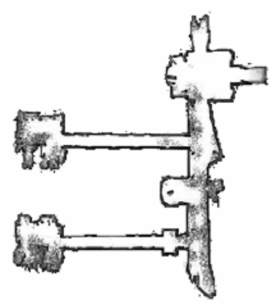
Fig. 28. Position error.

6.2 Results Using Real Robots

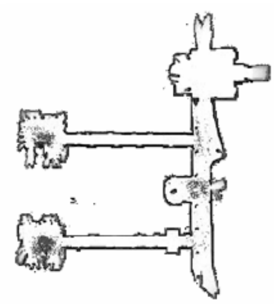
The obtained results working with real robot are similar to the obtained ones in simulation since in simulation we have worked with sensors with noise and the visual simulator has



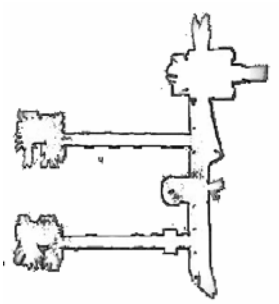
a)



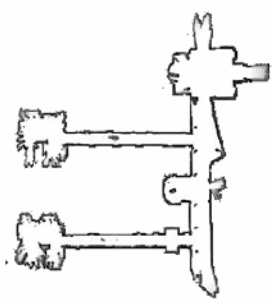
b)



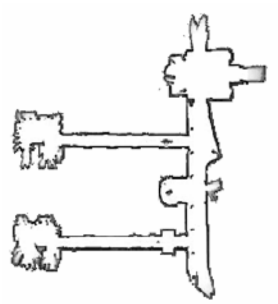
c)



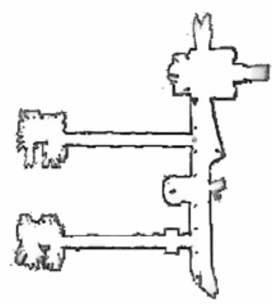
d)



e)



f)



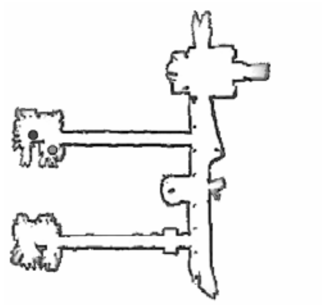
g)

Fig. 29. Single-robot Monte-Carlo localization process.

been implemented the most realistic possible. Therefore, the system implemented to study the results in simulation can be transferred to a real environment with minimum changes. The main appeared problems working with real robot are related with the odometric positioning system since slips take place (due to the floor surface) not wanted in the followed trajectories. This makes that the process localization obtains worse results that the simulation. Nevertheless, it is also observed that multi-robot collaboration in localization tasks improves the individual localization of each one of them.

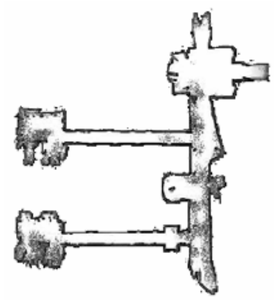
First of all, we have acquired a map of the working environment. For studying the conventional single-robot Monte Carlo localization Robot 1 is placed in laboratory with uniform belief and wanders across top horizontal corridor, and until it does not reach the vertical corridor, it does not localize himself (see process in Fig. 29).

Next, two robot are placed in the laboratory. The objective is to study the collaborative multi-robot Monte Carlo localization. Robot 1 is initialized with uniform belief and Robot 2 with gaussian belief. Figs. 30a.b show initial robots' position and Figs. 30c.d show the initial distributions of particles.

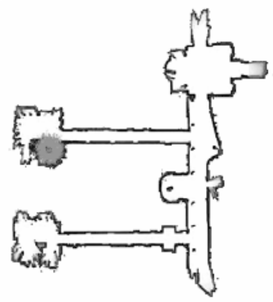


a)

b)



c)



d)

Fig. 30. Initial distributions.

If Robot 1 wanders across top horizontal corridor (Fig. 31a), when Robot 2 detects Robot 1 (Fig. 31b), the detection model is sent and Robot 1 updates its belief distribution. This way Robot 1 is well-located before reaches the corridor (Fig. 31c).

7. System Evaluation

As it has been commented, the final objective of this work is to develop a robots' fleet that allows to carry out assistance tasks inside the health-care sector in a collaborative way (in hospitals, geriatrics, homes, etc). Next, a brief evaluation of our proposal in contrast to related works is carried out:

- *Development of Assistance tasks* as tele-assistance, tele-monitoring, intelligent reminding, social interaction, etc. In this sense, the tasks that have been implemented are the typical ones in assistance systems (health-care sector) and they are similar to the developed in projects [13,14,18].

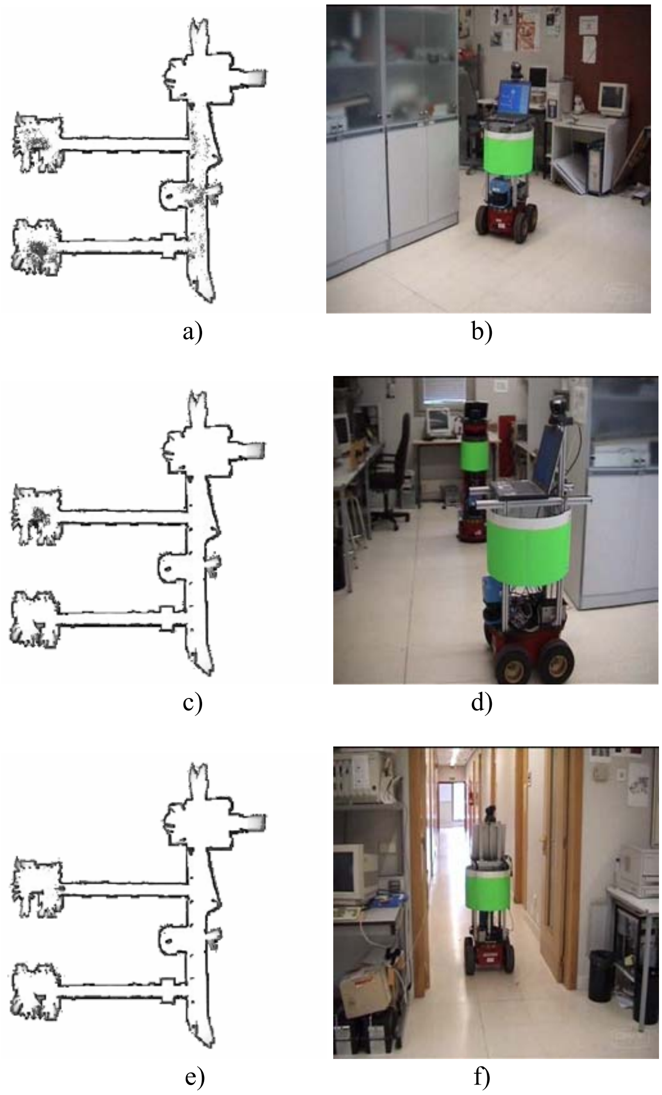


Fig .31. Collaborative multi-robot Monte Carlo localization.

- *Easy installation in new environments.* That it is fundamental not to have to introduce a initial map of the environment. The robots should be able to recognize the environment and to generate a map by itself. The systems [13,14,18] don't outline this objective and are based on an off-line well-known map of the environment. The portability to other working environments implies the introduction and codification of new maps. In our case, we have adapted the Carmen software to be able to carry out this task. The robots can navigate across the environment (with a wander behaviour) and generate the map. This task is based on the proposal developed in [10,20].
- *Robustness and reliability.* The robustness and reliability of the navigation system is more important than the precision of the movements. It is more valuable than the robot finally arrives to their destination that having a precise localization during their movement toward the same one. In fact, the sources of uncertainty that can be subjected the sensorial systems and the robot's actuators are multiple, especially in applications where a high grade of interaction exists with users whose reactions or behaviours can be unexpected. The navigation system should be robust and reliable in the face of these uncertainties. In conclusion, it doesn't care the robot to get lost during certain lapses of time and it should be able to recover for itself of this situation, avoiding the intervention of a user that supervises this operation. Having this present, the localization system is based on Monte Carlo localization [19] but it has been modified adding verisimilitude and distance parameters that improve the knowledge on the robot's state. A new module of vision has also been developed that allows to improve this localization process (the previous works used basically in this step data from laser and odometry sensors). The vision module also allows detect other robots in the environment and through the detection model (incorporated in the Multi-robot Monte Carlo Localization) improves the process of each robot localization. This allows us to discern more easily when a robot is in the localization or guidance step (it also allows to detect if a robot gets lost) and this way the robustness and reliability of the implemented system are improved.
- *Collaboration to carry out the assistance tasks.* A general planner has been developed in order to assign the task to carry out to the best located robot. This depends on the type on task and of the means that the robot prepares to carry out it. The communication between robots and the planner is carried out by means of sockets.

8. Conclusions

This paper studies the multi-robot Monte Carlo localization algorithm applied to assistant robots in a collaborative way. The results obtained shows improvements in localization speed and accuracy when compared to conventional single-robot localization. Therefore, if a robots' fleet is working in a hospital or geriatric, this system permits to upgrade the localization module of each robot when detecting another, and this way, each robot is located in a robust and effective way.

In this work we have focussed our effort in navigation task, but we are working in developing human-machine interfaces and high-level services (assistance, monitoring, providing reminding and social interaction) that are necessary in assistance tasks too. In near future we hope to implement this prototype in a geriatric centre.

Acknowledgments

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