

An Autonomous Mobile Robotic System for Surveillance of Indoor Environments

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Abstract: *The development of intelligent surveillance systems is an active research area. In this context, mobile and multi-functional robots are generally adopted as means to reduce the environment structuring and the number of devices needed to cover a given area. Nevertheless, the number of different sensors mounted on the robot, and the number of complex tasks related to exploration, monitoring, and surveillance make the design of the overall system extremely challenging. In this paper, we present our autonomous mobile robot for surveillance of indoor environments. We propose a system able to handle autonomously general-purpose tasks and complex surveillance issues simultaneously. It is shown that the proposed robotic surveillance scheme successfully addresses a number of basic problems related to environment mapping, localization and autonomous navigation, as well as surveillance tasks, like scene processing to detect abandoned or removed objects and people detection and following. The feasibility of the approach is demonstrated through experimental tests using a multisensor platform equipped with a monocular camera, a laser scanner, and an RFID device. Real world applications of the proposed system include surveillance of wide areas (e.g. airports and museums) and buildings, and monitoring of safety equipment.*

Keywords: *surveillance; site security monitoring; intelligent control; robot sensing systems*

1. Introduction

The increasing need for automated surveillance of indoor environments, such as airports, warehouses, production plants, etc. has stimulated the development of intelligent systems based on mobile sensors. Differently from traditional non-mobile surveillance devices, those based on mobile robots are still in their initial stage of development, and many issues are currently open for investigation (Everett, H., 2003), (DehuaI, Z. et al. 2007).

The use of robots significantly expands the potential of surveillance systems, which can evolve from the traditional passive role, in which the system can only detect events and trigger alarms, to active surveillance, in which a robot can be used to interact with the environment, with humans or with other robots for more complex cooperative actions (Burgard, W. et al. 2000), (Vig, L. & Adams, J.A., 2007).

In the last years, several worldwide projects have attempted to develop mobile security platforms.

A notable example is the Mobile Detection Assessment and Response System (MDARS) (Everett, H. & Gage, D. W., 1999). The aim of this project was that of developing a multi-robot system able to inspect warehouses and storage sites, identifying anomalous situations, such as flooding and fire, detect intruders, and determine the status of inventoried objects using specialized RF transponders. In the RoboGuard project (Birk, A. & Kenn, H., 2001), a semi-autonomous mobile security device uses a behavior-oriented architecture for navigation, while

sending video streams to human watch-guards. The Airport Night Surveillance Expert Robot (ANSER) (Capezio, F. et al. 2005) consists of an Unmanned Ground Vehicle (UGV) using non-differential GPS unit for night patrols in civilian airports and similar wide areas, interacting with a fixed supervision station under control of a human operator. A Robotic Security Guard (Duckett, T. et al. 2004) for remote surveillance of indoor environments has been also the focus of a research project at the Learning Systems Laboratory of AASS. The objective of this project was that of developing a mobile robot platform able to patrol a given environment, acquire and update maps, keep watch over valuable objects, recognize people, discriminate intruders from known persons, and provide remote human operators with a detailed sensory analysis.

Another example of security robot is the one developed at the University of Waikato, Hamilton, New Zealand (Carnegie, D. A. et al. 2004). It is named MARVIN (Mobile Autonomous Robotic Vehicle for Indoor Navigation) and has been designed to act as a security agent in indoor environments. In order to interact with humans, the robot is provided with speech recognition and speech synthesis software as well as with the ability to convey emotional states, verbally and non-verbally.

Following this trend, we developed a number of algorithms including both specific surveillance tasks, e.g. people and object detection (Milella, A., et al. 2007), (Di Paola, D. et al. 2007), (Marotta, C. et al. 2007), and basic navigation tasks, e.g. mobile robot localization and

environment mapping (Milella, A. et al. 2008a), to be used by an autonomous mobile robot for site monitoring applications.

In this paper, we describe the implementation and integration of all these functionalities under a unique framework. The aim is that of developing a multisensor mobile platform able to autonomously navigate in the environment and perform surveillance activities. For the design of such a system, a major challenge is the integration of high-level decision-making issues with primitive simple behaviors for different operative scenarios. In our work, we tackle this problem by developing a modular and reconfigurable system capable of addressing simultaneously low-level reactive control, general purpose and surveillance tasks, and high level planning and sequencing algorithms.

The paper also presents a set of experiments performed in the ISSIA-CNR Mobile Robotics Laboratory to test the overall system. The results suggest that the developed surveillance robot could be effectively employed in real-world applications.

The remainder of the paper is organized as follows. After an overview of the system architecture in Section 2, the basic localization and mapping tasks are detailed in Section 3. Section 4 provides a description of the specific surveillance tasks. Discussion and conclusions are drawn in Section 5.

2. System Overview

This section describes the three-layer architecture developed for the surveillance system. The component layout, depicted in Fig. 1, reveals the modular nature of the system. We propose a reconfigurable component-based approach in which the three main components can be viewed as containers of dynamic libraries that can be configured for the particular scenario. More specifically we can select what primitive behaviors (e.g. avoid obstacles, wandering, go forward, etc.), complex tasks (e.g. robot localization with RFID and vision, detect

removed or abandoned objects, detect people, etc.) and control algorithms (e.g. event detection, task sequencing, human operator interaction, etc.) have to start.

To obtain this reconfigurable scheme a key role is played by the sensory data management sub-system. Each of the three main components, i.e. controller, executor, and supervisor, is connected with the sensory input. This information is used in different ways: at the highest level, sensory data are converted into events, which are used to control task executions; at the middle level, sensory data are used to monitor and control the execution of the task in progress; finally, at the lowest level, sensory inputs are used by active behaviors to perform the associated actions.

The **Controller** performs control functions at the behavior level. This component contains all the behaviors needed to accomplish all possible tasks. Multiple behaviors can be executed at the same time, in case different tasks are active. Each behavior computes an output and when multiple behaviors are active at the same time, a predefined behavior arbitration algorithm (e.g. subsumption (Brooks, R.A., 1991), cooperative methods (Payton, D.W. et al. 1992), fuzzy logic (Cupertino, F. et al. 2006)) is used to obtain the final control signal. In our implementation, we use an instance of a cooperative method, in which all behaviors are fused via vector summation. In particular, all active behaviors produce a motor output that contributes to the final control signal, using a gain parameter that represents the behavior priority. Moreover, the Controller interacts with the upper component in two ways: it receives the information about the activation and configuration of the behaviors to be performed (Behaviors To Activate, in Fig. 1); it sends the information about the behaviors that are currently being executed (Behaviors On Execution).

The **Executor** handles the execution of the tasks as commanded by the upper level. Similarly to the Controller, this component is considered as a continuous-state controller container. Each task can be viewed as a procedure to achieve a result. At the end of the task, the completion flag and the result is sent to the upper level. Two different classes of tasks are considered: Basic Tasks which are general purpose tasks (common for service robots) for environment mapping, safe navigation, global localization and path planning; and Surveillance Tasks which are specific algorithms for scene analysis, in particular for object and people detection. For each class of tasks, the Executor sends the corresponding commands to the Controller. Finally, the Executor sends, at each sample time, information about completed tasks (Tasks Completed, in Fig. 1).

The **Supervisor** implements the high-level functionalities, monitoring the mission execution and generating events through the evaluation of sensory data. More specifically this module controls the execution of missions in progress (e.g. guaranteeing the satisfaction of precedence constraints), sends the configuration information about the tasks that must be started (Tasks To Start, in Fig. 1) to the Executor module and receives the information about the completed tasks. The Supervisor performs its work

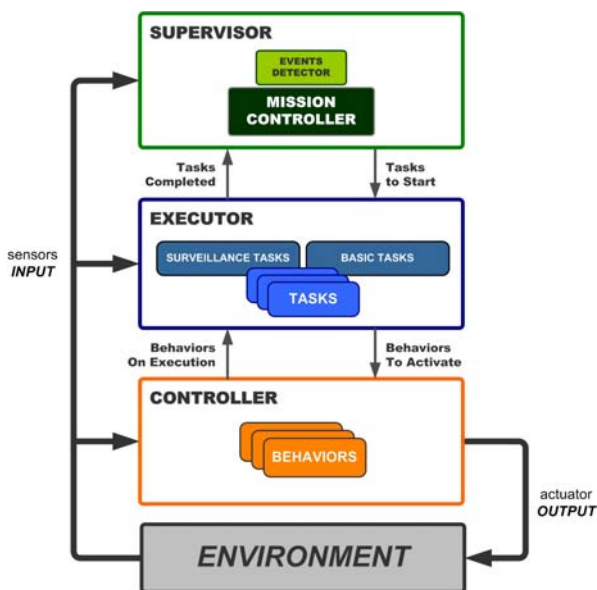


Fig. 1. Block diagram illustrating the system architecture.



Fig. 2. The robotic platform.

using a discrete-event model of the domain, a task execution controller, and a conflict resolution strategy, which are described in detail in (Di Paola, D. et al. 2009). The proposed architecture is implemented using MARIE (Côté, C. et al. 2006), an open source robotic development framework, under GNU/Linux OS.

The architecture was tested on commercial robotic platforms (PeopleBot and Pioneer P3-AT by MobileRobots Inc.). Fig. 2 shows the PeopleBot platform equipped with sonar and infrared sensors, a SICK LMS-200 laser range finder, an AVT Marlin IEEE 1394 FireWire monocular camera, and an RFID device. The latter consists of two circularly polarized antennas and a reader. The system has three processing units, the robot embedded PC and two additional laptops: a Pentium M @ 1.6 Ghz used for the vision processing on board the robot and a Pentium M @ 1.5 Ghz used for application control and user interface.

In the two following sections, basic and surveillance tasks are described. In particular, for each task, after a description of the developed algorithms, the results of experimental tests are shown.

3. Basic Tasks : Mapping and Localization

In this section, basic navigation tasks are described. These tasks are implemented using a set of algorithms that allow the robot to autonomously build a map of the environment, self-localize and navigate safely, using laser, RFID and vision data.

3.1. RFID augmented mapping

For a mobile robot to perform successfully surveillance tasks, it primarily needs a map of the environment. Environment mapping is a widely investigated topic in the mobile robotics field, and many methods are available in literature. Most of them use data acquired by an on board laser rangefinder. Here, we propose to augment a laser-based map, using an additional sensory input: i.e., passive RFID.

In the last few years, passive RFID has been receiving great attention in object identification and tracking applications. Compared to conventional identification

systems, such as barcodes, RFID tags offer several advantages, since they do not require direct line-of-sight and multiple tags can be detected simultaneously (Finkenzeller, K., 2003).

Recently, RFID has appeared on the scene of mobile robotics, promising to contribute efficient solutions to data association problems in common navigation tasks (Hähnel, D. et al. 2004), (Tsukiyama, T., 2005), (Kulyukin, V. et al. 2004). Nonetheless, problems, like how to deal with sensitivity of the signal to interference and reflections, and missing tag range and bearing information are still open (Schneegans, S. et al, 2007).

Our system tackles these issues based on a fuzzy logic approach. Specifically, we propose the use of fuzzy logic both to model the RFID device and to automatically localize passive tags wherever located in the environment, using a mobile robot equipped with a RF reader and two antennas.

In Fig. 3 the RFID-augmented mapping process is illustrated. During the procedure of Simultaneous Localization And Mapping (SLAM) based on laser and odometry data, the reader interrogates the tags. As soon as a tag is detected the SLAM procedure is interrupted and the tag localization algorithm is triggered. After this phase, the tag ID and position are added to the map and then the SLAM procedure can continue. Details of the tag localization approach can be found in (Milella, A. et al. 2008a).

Using this technique, we built a map of our laboratory augmented with RFID tags (as depicted in Fig. 4). Tags define a set of objects and zones to monitor, and can be used to support robot navigation and surveillance tasks, as will be described in the next sections.

3.2. Global localization: RFID and Vision

For a mobile robot, it is primary to know its global position, in the environment, at every time instant. To obtain this fundamental information, we propose a global localization method that combines RFID and visual input from an onboard monocular camera (Milella, A. et al. 2008b).

The proposed approach assumes that RFID tags are distributed throughout the environment, along with visual landmarks. As soon as a tag is sensed, the bearing of the tag relative to the robot is estimated. Bearing information is, then, used to trigger a rotational movement of an onboard camera, so that it is oriented toward the visual landmark associated to the tag. This reduces computational complexity than the case of using the vision system only to search for landmarks in the whole environment. Once the image of the landmark has been acquired, computer vision methods are used to accurately estimate the robot pose.

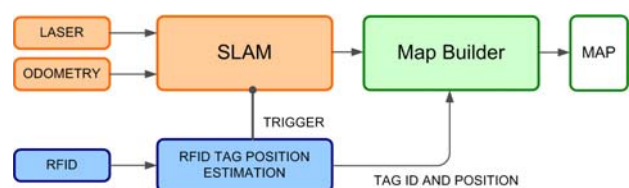


Fig. 3. RFID-augmented mapping process

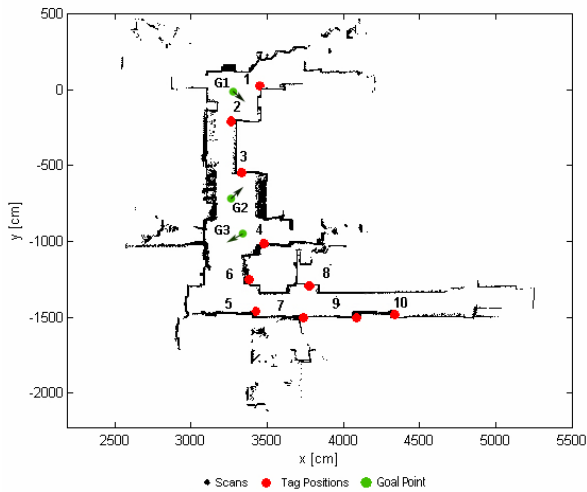


Fig. 4. Map of the environment with RFID tags (red) and goal points (green).

Fig. 5 illustrates the phases of the method for one of the tests. Specifically, Fig. 5(a) shows the robot at the first detection of the tag. A picture of the robot after rotation according to the result of tag bearing estimate is shown in Fig. 5(b). The result of landmark recognition and point feature extraction for localization is shown in Fig. 5(c).

It is worth to note that the success of the localization procedure is related to the accuracy of tag bearing information, since the correct estimation of the tag bearing relative to the robot is a necessary condition to properly rotate the camera toward the visual landmark. Furthermore, poor lighting conditions and shadows may affect image segmentation causing the failure of the vision-based localization algorithm. Nevertheless, at least approximate robot pose information is always available thanks to the RFID system.

4. Surveillance Tasks: Object and People Detection

In this section, specific surveillance tasks are described. The main purpose of these tasks is to obtain information about environment changes in a predetermined area. In particular, we have developed two different classes of tasks, using a multisensor approach. The first one monitors the position of predefined objects or the presence of new ones, whereas the second one detects the presence of intruders reacting with predefined actions (e.g. following the person).

4.1. Abandoned and removed object detection

As described in the previous section, we assume that the surveillance system operates in an indoor environment in which RFID tags have been placed as goal-point markers. RFID tags may provide information about the surrounding region or instructions for the robot to perform a certain task.

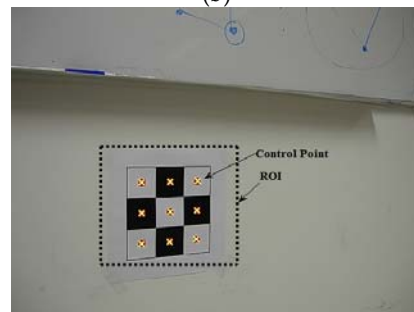
Once mapping is completed, the robot navigates throughout the environment to reach the goal-points. At each goal station, the robot stops and analyses the scene searching for abandoned or removed objects. The rationale behind this task is that of comparing the current scene with a stored one, regardless of small variations in



(a)



(b)



(c)

Fig. 5. Pictures of the robot at the first detection of the tag (a) and after rotation (b): in the final configuration (b), the robot is oriented so as the camera points toward the tag; (c) picture of the landmark acquired after rotation, with overlaid the result of landmark recognition and point feature extraction.

the viewpoint of the scene. Visual information obtained from a monocular camera (Di Paola, D. et al. 2007) and input from a laser rangefinder (Marotta, C. et al. 2007) are employed. Sensorial information is analyzed using various filtering, clustering and preprocessing algorithms run in parallel. The outputs of the various algorithms are then passed to a fuzzy logic component, which performs sensor fusion and decide if scene changes have occurred. The vision module of this task works as follow. The Principal Component Analysis-Scale Invariant Feature Transform (PCA-SIFT) (Ke, Y. & Sukthankar, R., 2004) detects points of interest, referred to as keypoints, which are invariant to image scale and rotation, changes in the viewpoint, and variations of the illumination conditions. The keypoints extracted from both the current image and the stored one are matched to look for differences between the scenes. In addition, color-based image segmentation is performed by a histogram difference method, which uses hue (H) and saturation (S) planes. First, the HS histograms are built for each image, separately. In these histograms,

each bin maps a small range of hue and saturation values. In the difference histogram, obtained by the difference of the reference and the current histogram, respectively, positive bins indicate HS values in the current image that were not present in the reference one; conversely, negative bins indicate HS values in the reference image that are no longer present in the current one. Afterwards, selected positive and negative bins are back-projected onto the current and the stored scene, respectively. Finally, a clustering algorithm is used to group these pixels according to their relative distances.

Similarly to the vision sensor, the laser sensor performs a matching between the local reference and the current range data to look for scene variations. This is achieved as follows. For each scene, several readings are taken and a median filter is applied. Due to localization errors, which cause the robot to stop at a slightly different point than the planned goal, at each goal point the scenes are always acquired from a slightly different viewpoint with respect to the reference scene. Hence, for the matching process to be properly performed, a registration technique has to be applied. At the end of the matching process, we get two kinds of information: the relative displacement between the two point clouds, due to the localization error of the robot; and the classification of the points belonging to the current scene into matched and unmatched points. The latter are also referred to as outliers and represent the variations occurred in the current scene with respect to the stored one.

A validation of the matching process is performed, based on the ratio of the number of outliers to the total number of points in the current scene.

Outliers are processed by a clustering technique. In this context a cluster is intended as a set of points close to each other and therefore probably belonging to one single object. Once clustering is completed, clusters with a small number of points are discarded.

Integration of sensorial data is obtained using a fuzzy logic system that compares each cluster of one sensor with all the clusters from the other. The fuzzy system must determine if the compared clusters lie in the same area of the scene (in case this circumstance is detected, the clusters are considered as corresponding to the same object), and if the observed area corresponds to a scene variation. The final output of this algorithm is an index of likelihood that a scene variation occurred for each cluster in the merged set.

In order to validate this particular surveillance task within the whole surveillance system we performed several experiments. We defined a set of zones to be monitored and corresponding goals within the geometrical map of the environment augmented with RFID tags. In the following, two goal positions are described.

At the first goal, a new object (a fire extinguisher) is introduced, as shown in Fig. 6 (stored scene) and Fig. 7 (current scene). The detection modules produce indexes corresponding to a new object, indicated on the figures. The values for vision and laser sensors are 0.672 and 0.722, respectively. The fuzzy data fusion leads to a final likelihood index equal to 0.713, which is a clear indication of a change in the monitored environment.

The proposed algorithm can also be used for people detection. As an example, Fig. 8 and 9 show the successful detection of a person entering the scene. The indexes resulting from the visual and laser modules are of 0.790 and 0.810, respectively. It can be noticed that, in this test, the vision-based part of the method was not able to detect the lower part of the person, mainly due to the absence of a significant number of features in the corresponding portion of the picture. Nevertheless, the data fusion module estimates a scene variation with a 0.80 likelihood level. Note that this module does not include any recognition function. A module to recognize human legs using laser data is, instead, described in the following section.

4.2. Laser-based people detection and following

We employ laser data for detecting people, based on typical human leg shape and motion characteristics (Milella, A. et al. 2007). Due to safety reasons, laser range sensors have to be attached near the bottom of the mobile robot; hence, laser information is merely available in a horizontal plane at leg height. In this case, legs constitute the only part of the human body that can be used for laser-based people-tracking and following.

The method for people detection and following consists of two main modules:

- the Leg Detection and Tracking module: this module allows the robot to detect and track people using range data based on typical shape and motion characteristics of human legs;
- the People-Following module: this module enables the mobile platform to navigate safely in a real indoor environment while following a human user. During the tour the robot can also acquire data for environment mapping tasks.

The Leg Detection and Tracking method allows the robot to detect and track legs, based on typical human leg shape and motion characteristics. The algorithm starts by acquiring a raw scan covering a 180° field of view. Laser data are analyzed to look for scan intervals with significant differences in depth at their edges (Feyrer, S. & Zell, A., 2000). Once a set of scan intervals has been selected, a criterion to differentiate between human legs and other similar objects, such as legs of chairs and tables and protruding door frames, must be defined. To achieve this aim, first, the width of each pattern is calculated as the Euclidean distance between its end-points and is compared with the typical diameter of a human leg (from 0.1m to 0.25m). Then, a Region of Interest (ROI) is fixed in proximity of each candidate pattern. A leg-shaped region detected within each ROI at the next scan reading is classified as a human leg if the displacement of the pattern relative to its previous position has occurred with a velocity compatible to a typical human leg velocity (from 0.2 m/s to 1 m/s). Note that if the robot is moving and thus so is the scanner, the effect of ego-motion must first be accounted for. This can be done employing the information provided by the on-board odometers or by the laser scanner.

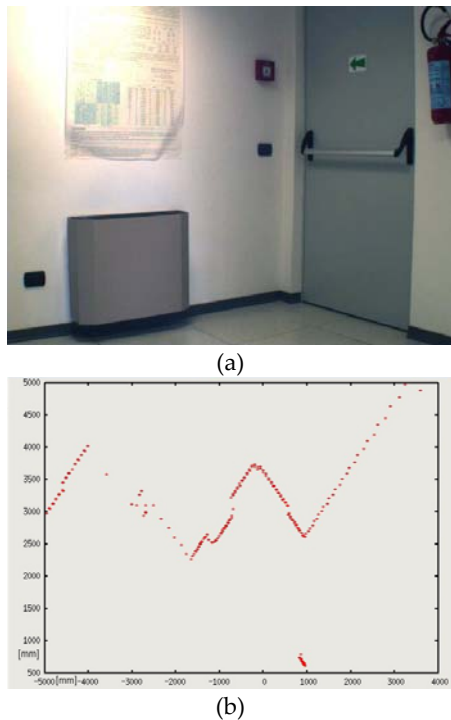


Fig. 6. Goal #1: image (a) and laser scanning (b) of the observed scene during the learning task.

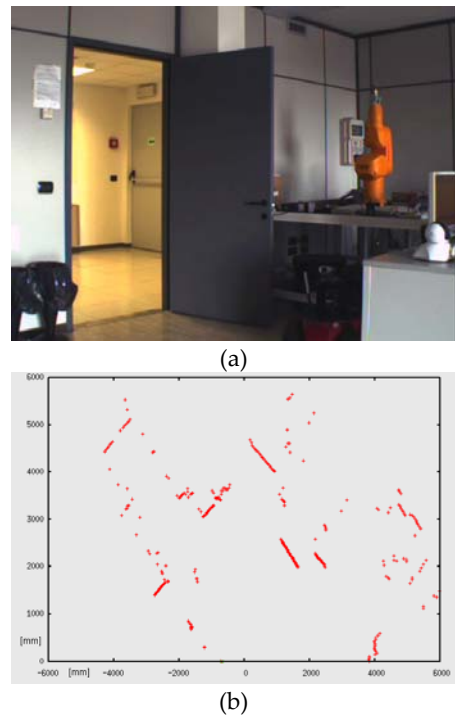


Fig. 8. People detection: image (a) and laser scanning (b) of the observed scene during the learning task.

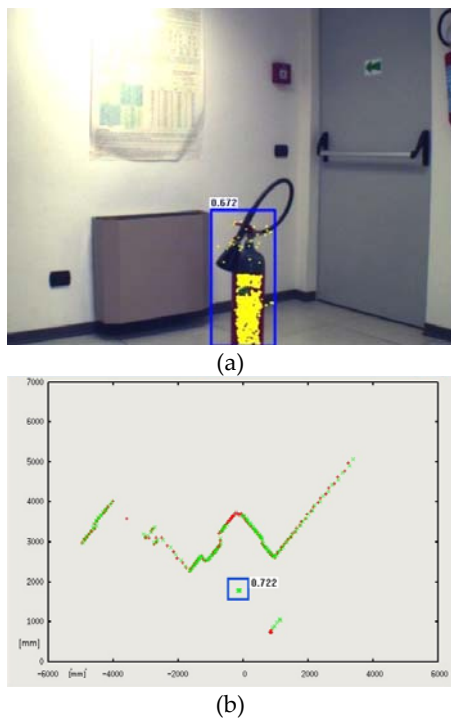


Fig. 7. Goal #1: image (a) and laser scanning (b) with related LSV index of the observed scene during the patrolling task

The people following algorithm consists of the following steps:

- detect human legs;
- choose the closest moving person within a certain distance and angular position relative to the robot;
- keep track and follow the target person until he/she stops or disappears from the scene.

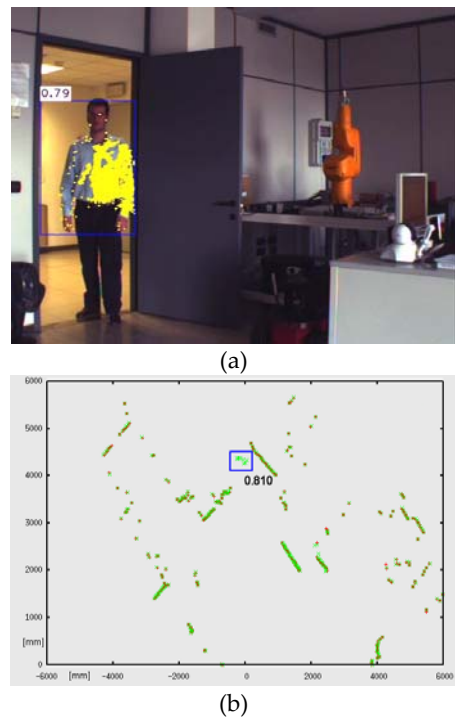


Fig. 9. People detection: image (a) and laser scanning with related LSV index (b) of the observed scene during the patrolling task.

The employed control loop sets speed and turn rate of the robot, based on the distance from the person and from other objects present in the environment.

In order to test both the performance of the people detection and tracking algorithm and the effectiveness of the people-following method, experimental tests were performed. Some results are shown in Fig. 10 and Fig. 11. Specifically, in Fig. 10 two people cross the scene

surveyed by the robot which is not moving. Assuming that the motion direction of each person does not vary significantly, the system is able to keep track of the two trajectories separately. In Fig. 11, the robot follows the intruder maintaining a safety distance from him.

5. Discussion and Conclusion

In this paper, we presented the implementation and integration of several autonomous navigation and surveillance functions on a multisensor mobile robot for robotic site monitoring tasks.

The major aim of the paper was that of providing a comprehensive overview of the system, as well as

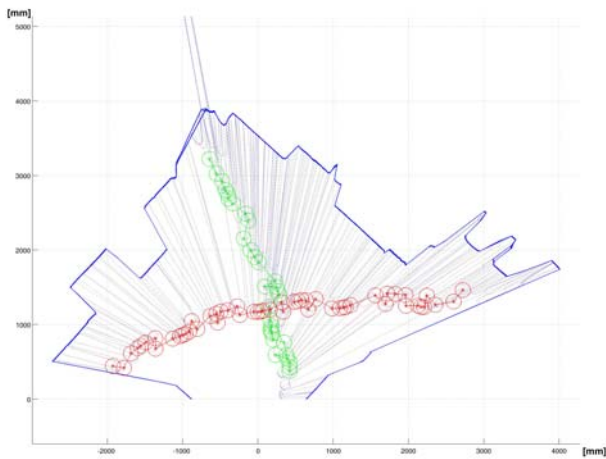
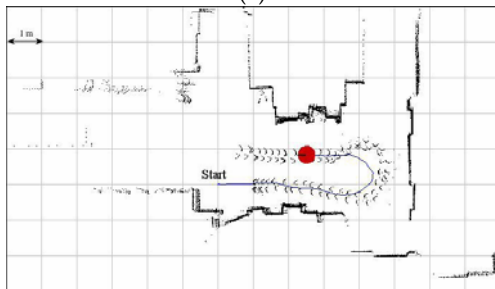


Fig. 10. The trajectories of two people crossing the area surveyed by the robot.



(a)



(b)

Fig. 11. People following: (a) image taken during the pursuit of a person, (b) robot trajectory and laser scanned legs plotted in the environment map.

experimental results in real contexts, in order to show the feasibility of the proposed methods in real-world situations.

First, we described the architecture of the system based on a three-layer scheme that allows for modularity and flexibility, and may supervise a number of basic navigation tasks and specific surveillance tasks. The control system makes the robot able to execute autonomously multiple heterogeneous task sequences in dynamic environments, since it models the sequential constraints of the tasks, defines the priority among tasks and dynamically selects the most appropriate behaviors in any given circumstance.

In this paper, we also presented the localization and mapping modules that use vision, laser and RFID data. Then, the implemented modules for abandoned/removed object detection and people detection and following were introduced. Preliminary experimental results are promising and show the effectiveness of the overall system.

The implemented tasks provide the first steps toward the development of a fully autonomous mobile surveillance robot. Nevertheless, there are several important issues that must be addressed. The primary aim is to provide the robot with the ability of automatic interpretation of scenes in order to understand and predict the actions and interactions of the observed objects based on the information acquired by its sensors. In particular, the implemented algorithms for object and people detection represent the first stage for the development of more complex behavior analysis and understanding tasks.

One limitation of the presented system is that object and people detection are accomplished at pre-defined goal positions where the robot stops and stays still in order to process data. Our current and future work aims on the one hand at improving the overall system by adding new tasks, such as people and object recognition, and on the other hand at studying and developing new modules for the detection of moving objects from a moving platform. The use of stereovision for motion estimation and segmentation is being especially investigated.

Improving the reactivity of the system to unforeseen environmental variations (e.g. light changes, dynamic obstacles, etc.) is another major issue that calls for the research of novel reactive decision policies, in which the weight of each sensor can be dynamically adjusted in response to the new perceptions.

Furthermore, following current trends in multi robot systems, our research activity is also focused on the distribution of the tasks among a set of independent robots to obtain a multi-agent surveillance system, which would guarantee greater efficiency and robustness.

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