SURVEILLANCE SYSTEM USING A MOBILE ROBOT EMBEDDED IN A WIRELESS SENSOR NETWORK

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Abstract: In this paper, we proposed a surveillance system for guard robots to perform indoor navigation using a wireless sensor network. The aim is to provide a generic surveillance solution for multiple indoor scenarios. The multi-sensor based localization method for the robot has been employed to overcome the shortcomings of the standard AMCL based localization technique. It is also helpful in dealing with sensor limitations. The proposed strategy has been implemented and tested within lab environments. The results show a fair reduction in processing time required by convergence of localization process.

1 INTRODUCTION

The motivation of this paper is to present a generic surveillance strategy for different indoor environments (offices or museums) by making use of a mobile robot and a static wireless sensor network (WSN). The proposed system consists of surveying an entire floor. The floor consists of different rooms and every room is equipped with at least one motion detector which is combined with a radio transmitter. A mobile robot carries a receiver node and a map of the environment and it resides in one of the rooms. In case of an intrusion the activated motion detector generates an alarm via the network and brings the robot into action. The robot being in an autonomous mode, navigates to the location of the detected intruder where it is switched to the teleoperated mode. A human safeguard (e. g. in another building) can make use of the robot's camera to identify the intruder who may be an employee or a burglar. In future such robots may be equipped to tackle the intrusion as well.

In the scenario the robot utilizes the principle of simultaneous localization and mapping (SLAM). The localization process is a prime issue in the field of autonomous mobile robots. Its accuracy depends on the preciseness of sensors and the exactness of the map. There exist different methods to estimate the position of a mobile robot for indoor and outdoor scenes. Global positioning system (GPS) is a standard method to localize a mobile robot in outdoor scenes but this turns out to be inefficient for indoor scenarios due to a poor reception of GPS signals. Therefore we have to look for an alternate technique for localization in our problem domain. In this regard, the term SLAM addresses a dependency of the mapping on the localization and vice versa. It has been comprehended in sufficient detail in various robotics literature (see (Durrant-Whyte and Bailey, 2004) and (Fresse, 2006)). The SLAM solutions based on particle filter effectively deal with non-linearities existing in environments (see (Arulampalam et al., 2002) and (Montemerlo et al., 2003)). Therefore, we have selected a particle filter based SLAM solution to implement our strategy. Normally, most of these techniques make use of sensor readings and then apply Bayesian classifier based calculations to perform localization. It is safe to presume here that SLAM methods based on particle filter yield the acceptable results in specific scenarios provided a precise *a priori* map of an environment is available. However, sensors are subjected to noise in the environment resulting in an imprecise perception. Therefore it is appropriate here to use a multi-sensor based localization solution as presented in (Castellanos and Tardos, 1999), (Wu and Johnson, 2008) and (Wold et al., 2002) instead of relying on a single sensor. This approach performs localization by fusing data received from different heterogeneous sensors. Navigation is another important aspect in the field of an autonomous mobile robots and it mainly aims at reaching a particular location while avoiding both dynamic and static obstacles.

The collaborative use of a mobile robot and WSN

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had been previously presented with different aspects. (Batalin et al., 2004) have discussed a mobile robot navigation using a sensor network. A mobile robot receive signals from different sensor nodes and decides which sensor node is nearest. It then performs localization. This method clearly obviates the use of a known map but the accuracy of estimation is poor. An interesting application scenario to perform the flying robot navigation using sensor network has been discussed in (Corke et al., 2005). The next section discusses the surveillance strategy.

2 SURVEILLANCE STRATEGY

The generic surveillance strategy is shown in the figure 1 which illustrates a multiple room scenarios. This work focuses mainly on building a robust and the reliable surveillance system for an indoor environments. Therefore, we have utilized standard techniques for path planning and navigation (local and global) whereas the process of localization is improved using a multi-sensor localization process.

As shown in figure 1 every room is deployed with radio transmitters R_n. The radio transmitters are connected to motion detectors and generate an alarm via the network upon the detection of any physical intrusion. The alarm message contains the transmitter node identification number and its position. The robot receives a wake-up call upon detection of intrusion and start to estimate its location using a multi-sensor localization process. The shortest path from the robot's current position to the target position of sensor node is generated using a wavefront based path planning technique. The robot then navigates toward the goal position while avoiding obstacles and performs visual sensing upon reaching its goal. The next sections provide a detailed discussion on different modules.

2.1 Establishing a Wireless Sensor Network

The first step involves the establishment of wireless sensor network. The *j=n-2* of total *n* radio nodes R_n are deployed in an area which the robot monitors. They are static and connected to motion detectors. The rest of the two nodes are attached to a mobile robot and a console PC. A mobile robot receiver picks up status messages generated by static transmitter nodes. The network is established among radio transmitters using a table based routing scheme. Each transmitter sends a beacon message to its neighboring nodes which acknowledges the beacon mes-

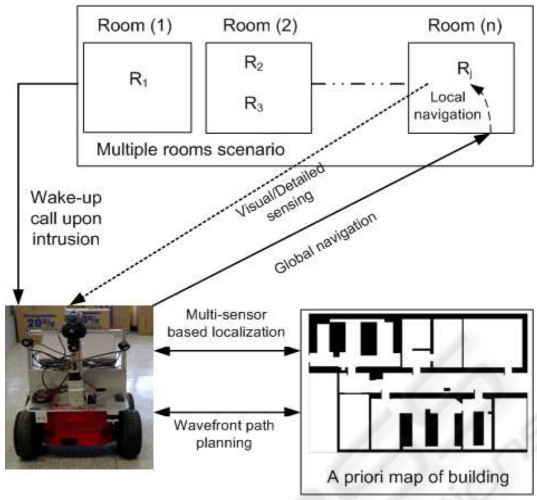

Figure 1: Generic surveillance strategy of a mobile robot.

sage with *routing table* messages. This is necessary to provide information about the next possible hop. After an exchange of acknowledgement messages, each node then broadcasts *node detected* messages to update the routing table. Each motion detector has its defined vicinity in which it can detect the movement of different physical objects. Whenever a movement is sensed by a transmitter node, it generates an alarm which is received both by a mobile robot and the console PC. The alarm contains an identification number of the transmitter node. The position of the transmitter node on *a priori* map is identified by its number. Figure 2 displays a graphical user interface (GUI) running on the console PC. The placement and status of each radio transmitter node in an established sensor network can be monitored through this designed GUI. It is dynamic in a sense that it is capable to load a map of a new operational environment and can adjust the placement of the sensor nodes in the new environment.

2.2 Localization: Pose Estimation of a Mobile Robot

Once an alarm is generated, the next step is to estimate the location of a mobile robot which is assumed to be unknown in the begining. In the current application, the presence of a noise in the sensor models and the imprecise actuator control of mobile robots makes it difficult to accurately estimate the robot position even for the known environments. A fast convergence of the estimated position is another challenge in the field of localization. In this regard, we propose a multi-sensor based localization scheme to deal with different issues faced during the position estimation

Figure 2: Graphical user interface on the console PC.

of a mobile robot in an indoor environments. A mobile robot performs the localization using an adaptive Monte Carlo localization (AMCL) technique (Pfaff et al., 2006). It is applicable to both local and global localization problems. It is simply a variant of particle filtering (Arulampalam et al., 2002). It makes use of the recursive Bayesian filtering scheme in order to estimate a mobile robot location in an environment. It also requires a decent sensor model and the motion model of a mobile robot. It is worth mentioning here that AMCL is very much capable to handle complex, multimodal (non-Gaussian) posterior distributions of a mobile robot locations. However, it has difficulties when the pose of a mobile robot is high dimensional because the number of particles increases exponentially with the dimensionality of state space and hence increases the computational complexity of the overall process. This is yet an open research issue in the field of SLAM and the human body tracking applications.

AMCL estimates the pose from an input data of an odometry sensor and a laser range finder. AMCL requires an accurate sensor model but it is difficult to design a perfect sensor for the varied environments. For example there are cases where a laser range finder fails to provide the reliable range data, especially in the presence of glass windows or doors. The presence of the bright light and the vibrations produced by a mobile robot also affect the performance of a laser range finder. In order to deal with these problems, we have implemented a multi-sensor based localization strategy as shown in figure 3. The scheme is inspired by the multi-sensor data fusion techniques presented in (Castellanos and Tardos, 1999) and (Wu and Johnson, 2008) with an aim to deal with drawbacks of a laser range finder with an added advantage of lowering the convergence time during pose estimation process. The main steps involve are:

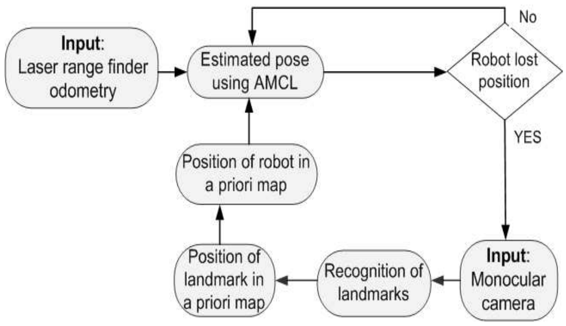

Figure 3: A Multi-sensor localization process.

1. **Exploration of the Environment.** A mobile robot explores an area using a monocular web camera mounted on a mobile robot.
2. **Recognition of Landmarks.** We have selected a segmentation method provided by (Aziz and Mertsching, 2006) in order to recognize the different landmarks. The segmentation is reliable for

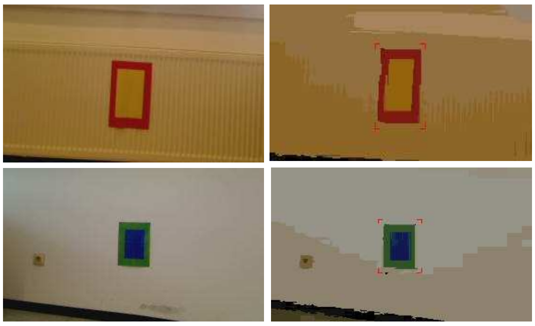

Figure 4: Left: original images and right: segmented output.

indoor scenarios. Figure 4 displays different landmarks and the segmented output. The landmarks are placed at known positions.

3. **Position of the Landmark in a Map.** The detected landmark is matched with known landmarks to determine its global position coordinates on the map.
4. **Position of a Mobile Robot in a Map.** The pose of the robot is calculated using the landmark's position and distance information obtained through a laser range finder. The procedure is explained in the subsequent section.
5. **AMCL.** The robot pose is provided to the AMCL localization module as an initial position of a mobile robot to estimate its actual pose in the map.
6. **Relocalization.** Steps 1-5 are repeated whenever the robot position is lost during navigation applications.

2.2.1 Orientation of Robot

Figure 5 illustrates the method to find out the orientation of the robot θ_r relative to a priori map in the world coordinates with following details:

1. The pose information of the wall (x_{wall}, y_{wall}, θ_{wall}) relative to the world coordinates is known.
2. The orientation of the camera θ_{cam} relative to the robot coordinates is also known.
3. The landmark is detected such that it should be in the middle of an acquired visual input. A laser range finder and a camera both are identically oriented with respect to robot coordinates.
4. The angles θ_{s1} and θ_{s1} are computed by adding and subtracting 10 degrees to θ_{cam}.
5. The distances d_1 and d_2 are then calculated using a laser range finder for θ_{s1} and θ_{s2} respectively.
6. The angle θ_{w-r} is calculated to find out the wall to a mobile robot orientation.

$$\theta_{w-r} = \arctan \frac{d_2 \cos\theta_{s2} - d_1 \cos\theta_{s1}}{d_2 \sin\theta_{s2} - d_1 \sin\theta_{s1}} \quad (1)$$

7. Finally, the orientation of a mobile robot relative to the wall θ_r is computed using:

$$\theta_r = \theta_{wall} - \theta_{w-r} \quad (2)$$

Finally a mobile robot location relative to a priori map is found out using θ_r and range information of landmark.

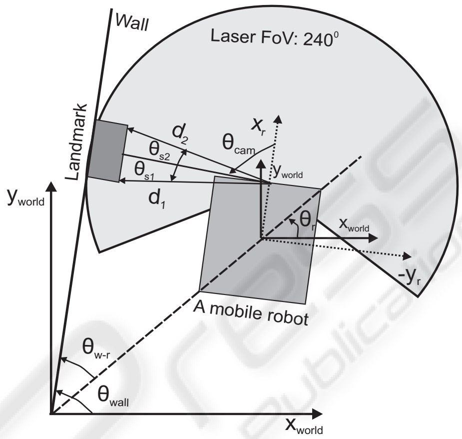

Figure 5: Pose estimation of a mobile robot in *a priori* map using multi-sensor localization.

2.3 Navigation

After estimating the global position of a mobile robot in a known map, the next step is to navigate a mobile robot to a goal location. The whole procedure of navigation is shown in figure 6. When any of the radio transmitters detects a motion in its vicinity, it generates an intruder alarm signal. It is then broadcasted to other wireless sensor nodes. This alarm signal provides the identification number (IN) of a particular transmitter node which generated an alarm. The *IN* is then found out using a table which contains a list of coordinate position of different transmitter nodes and this position is considered as a goal location for the navigator module. The goal location is needed to find a desired path from the actual position of the robot. The desired path is calculated using a path planning algorithm. Path planning is a well discussed topic in the field of a mobile robot navigation. We have selected the *wavefront* path planning algorithm (Behring et al., 2000) due to its suitability with grid based maps. The wavefront planning algorithm calculates a list of waypoints between a mobile robot position and a goal location. This list is necessary to generate the shortest possible path among them after taking into account the size of the robot and a safe distance from different obstacles. Once the successful path is discovered, the next step is to navigate a mobile robot between its present location and a goal

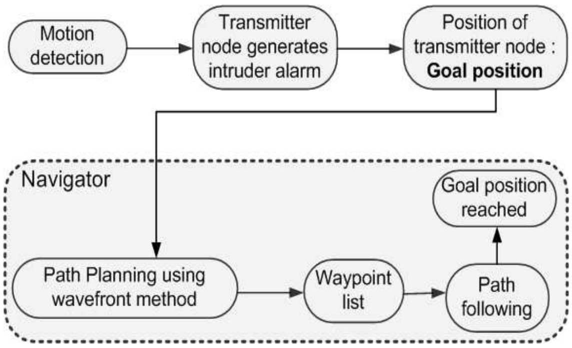

Figure 6: Navigation process.

by making use of the robust path following method. This also requires an integrated obstacle avoidance behavior for both the static and the dynamic obstacles. Normally, the list of static obstacles is known through an *a priori map* while a well defined local navigation strategy is required to deal with dynamic obstacles. There are different methods to perform this kind of navigation. We have utilized the *nearness diagram* (Minguez and Montano, 2004) approach. This approach provides a good methodology to avoid static as well as dynamic obstacles for indoor environments. The robot then follows a generated path and navigates safely toward its goal. Once it reaches the goal location, it generates a *goal reached* message. There is a provision to perform an exploration of the goal location surroundings with the help of an available visual sensor. This also enables a console PC to monitor a suspected area. The experiments and their outcomes are discussed in the next section.

3 EXPERIMENTS AND DISCUSSION

The experiments are conducted at GET lab, University of Paderborn. We used the customized Pioneer 3AT robot *GETbot* equipped with the two dimensional and a 240 degree field of view laser range finder (Hokuyo, 2009) and the pan-tilt based webcam for exploring an environment and avoiding the obstacles. Tmote sky sensor nodes (Tmote, 2009) are used as wireless nodes in a static WSN. They are attached to the motion detector. The map of the experimental setup and a pre-deployed static WSN of 6 nodes are shown in figure 2. It is a regular office environment with narrow door openings of about 90 cm. The nodes are deployed on the ceiling. Figure 1 shows the experimental mobile robot being employed. The surveillance strategy is implemented using a player-stage (Collet et al., 2005) robot control toolkit.

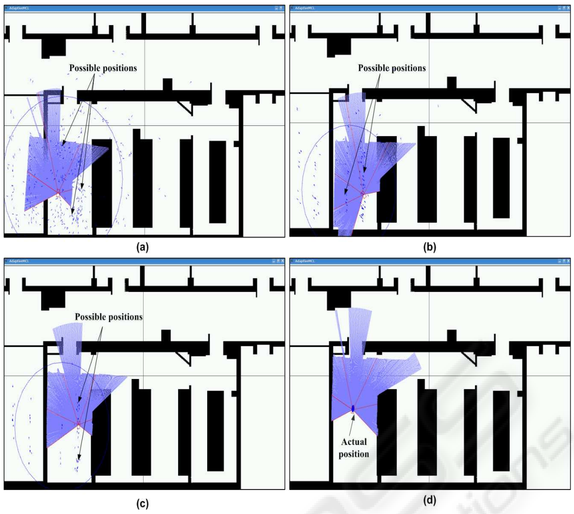

Figure 7: Robot localization using standard AMCL (a) T=0 s and particles=10,000. (b) T=10 s and particles=5000. (c) T=15 s and Particles=1000. (d) T=20 s and particles=100.

The experiments are performed on the basis of *event handling* and the generation of an alarm is considered as an event. The two different navigation behaviors are generated according to following conditions:

1. The first alarm received by a mobile robot is considered as the priority alarm which is then locked to reach the goal location. The alarms received afterwards are considered as the false alarms.
2. The last alarm received by a mobile robot is considered as a priority alarm.

A mobile robot reaches its goal location area with an accuracy of 0.25 meters. It is set as a parameter during the path computation step. The availability of an exact map of an environment increases the robust behavior. The results of localization performed using standard AMCL is shown in figure 7. The initial position of a mobile robot is unknown. Once a mobile robot starts its localization process, it begins matching the scans obtained through a laser range finder with a known map of an environment and awards high weightage to most probable matched places. In this way, a mobile robot tends to localize itself to most probable position over the time. The exact match sometimes takes up to several seconds to find an accurate estimation of a mobile robot pose as shown in figure 7. Symmetric environments are prone to false position estimations. In order to avoid these problems we have placed landmarks as shown in figure 4 at different places in the experimental scenario. It is important to highlight that the size and placement of landmarks is an important factor. The landmarks must be placed at the height of a laser range finder. This is advantageous in avoiding collisions with glass doors which are otherwise not detected by the employed laser range finder. The positions of landmarks on the map are known. The visual sensor is then utilized to perform a multi-sensor based localization process. This is quite useful in estimating a mobile robot pose on the map. It also speeds up the convergence process of the localization from around 20 seconds to 10 seconds. However, it depends on a good landmark detection scheme. It has been tested that this methodology works quite efficiently whenever the robot needs to perform self re-localization in wake of position loss. Overall this results into a more reliable and the efficient navigation behavior.

4 CONCLUSIONS AND FUTURE DIRECTIONS

We have presented a generic surveillance strategy for a guard robot using a wireless sensor network. The scheme has been implemented and worked out for different indoor scenarios. Our approach presents an improved localization process by employing a multi-sensor localization technique. It also allows the integration of different sensors to deal with different kinds of environment. The results show that a fast convergence of the localization process is achieved while effectively reducing the effects of a sensor noise. In the future work, we intend to see how the system performs reliably providing a relaxation in assumed conditions and parameters. The detailed comparison of a proposed localization strategy with other standard techniques is also an immediate step.

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