Robust mobile robot map building using sonar and vision

Evolving the navigation abilities of the ApriAlpha™ home robot

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We describe the development of a robust map acquisition method for mobile robots in indoor environments. A grid-based representation of the environment is derived from sonar sensor data, and, concurrently, corners and edges are detected and matched with visual landmarks in order to correct the robot pose estimation. We present experimental results of maps acquired using the ApriAlpha™ home robot.

Key Words: Map building, occupancy grids, Hough transform, robot localization, autonomous mobile robots.

1. Introduction

The ApriAlpha™ is a concept model of a home robot that has been developed by Toshiba Corporation as a robotic information home appliance. ApriAlpha™ is the acronym for Advanced Personal Robotic Interface Type Alpha, which integrates several communication technologies onto a robotic platform. The ApriAlpha™ has been developed as a user-friendly robotic interface between humans and home appliances. It is capable of controlling network connected equipment, and provides remote home surveillance. It is equipped with image recognition, voice communication, wireless communication, task planning, and motion control [1]. Currently, ApriAlpha™ utilizes predefined maps to perform path planning. The goal of our system is to exploit the robot's sensorial capabilities to learn a model of its surrounding environment.

In order to have a truly autonomous mobile robot it is desired that it possesses the ability to acquire a model of the environment by itself. Map building algorithms allow the acquisition of spatial models of physical environments using mobile robots. In the last two decades, robotic mapping has been an active research area in robotics [2]. At the moment, robust mapping methods exist for real time acquisition of indoor maps of static, structured, and of limited size environments. Despite all the achievements in this area, it still presents great challenges. Limitations and noise intrinsic to sensors characteristics hinder the map building process.

In this paper, we present a map building system that integrates geometric and stochastic mapping methods in a single framework. Grid maps are acquired by ApriAlpha™ home robot using odometry, sonars and stereo vision, and can be used for long-term navigation. The system incorporates mapping and localization. In the next section, we describe the theoretical background of the system. Then, we present experimental results of indoor maps acquired using the ApriAlpha™ home robot.

2. Methods

To build a map of the environment, the robot utilizes sensors to perceive and model the outside world. Sensors commonly utilized for this task are sonar, laser, infrared, camera, compasses, and GPS. The sensors are subject to measurement noise and present range limitation. The robot also needs to navigate through the environment while building the map.

We propose a map building system as shown in the scheme of Fig. 1. The robot starts with a simple exploration procedure. While the robot is moving, the sonar readings are interpreted to compose a grid-map of the environment. When an obstacle is found, the robot begins to follow its boundary. Features (corners or edges of the environment) are detected and matched directly with the grid-map. Some features may be selected to serve as landmarks for future robot localization correction using the stereo vision.

2.1 Grid Map Building

We implemented a variation of the well-studied occupancy grid mapping algorithm, proposed by Elfes and Moravec [3]. The method represents the environment by means of a two dimensional evenly-spaced grid. Each grid cell estimates the probability of the corresponding region being an occupied or free space area of the environment [4].

The traditional grid map algorithm uses the Bayes' rule to model the sensor measurement and combine the probabilities from multiple measurements. Notwithstanding,

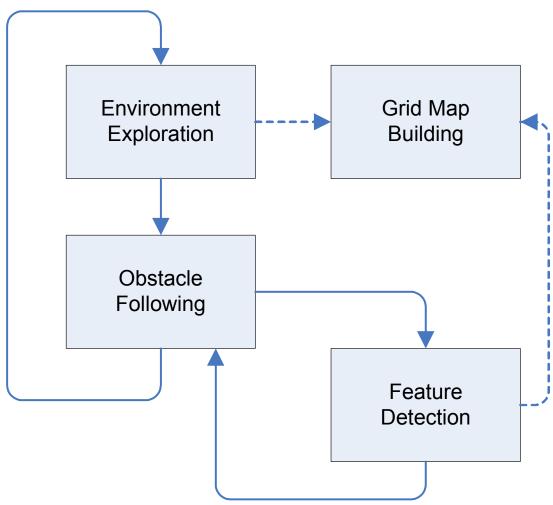

Fig. 1 Map building system scheme

experimental research have demonstrated that an alternative simple counting method may provide similar results with less computational burden, allowing safe real time operation [5].

In the simple counting method, the probability of occupancy for each Cell *(i, j)* may be calculated by the following equation:

$$C(i,j) = \frac{hits(i,j)}{hits(i,j) + misses(i,j)}, \quad (1)$$

where, *hits(i, j)* accumulates the number of cases in which the cell is located in the boundary region of the sonar beam, and *misses(i, j)* accumulates the number of cases in which the sonar beam passed through the cell. Fig. 2 shows the sonar sensor interpretation superimposed over the occupancy grid map.

2.2 Feature Detection

Sonar returns are characterized as specular or diffuse. Using a detailed sensor model, it is possible to group sonar returns and determine the type of the target in indoor environments [6]. Corners and edges can be modeled as point features. Walls could also be modeled as lines. However, point features are better suited for our purposes of improving the localization using visual information. The problem is to find groups of sonar beams intersecting on the same point. We implemented a robust technique using the Hough transform to deal with the large amount of spurious data due to sonar artifacts, specular reflections, and moving people.

The Hough transform accumulates in a voting table the evidence that sensor data present certain features compatible with the actual measurement. The possible feature location is represented in a discretized parametric space. The voting is performed in this Hough space, and the most voted cells correspond to the features present in the environment. We used a polar representation relative to the robot global reference position, since the precision obtained in point location from range sensors can be more accurately represented in this space.

The sonar *S* is modeled as a cone of aperture angle β, as shown in Fig. 3. The actual sonar reading from the location X_s is expressed by ρ^S . The superscript *B* refers to the global reference base. The angular quantization of the Hough space is determined by δ_θ. From the point feature modeling illustration, the equations for the Hough voting algorithm can be obtained. First the point features are translated to the sonar reading base to the global reference base using the following equations:

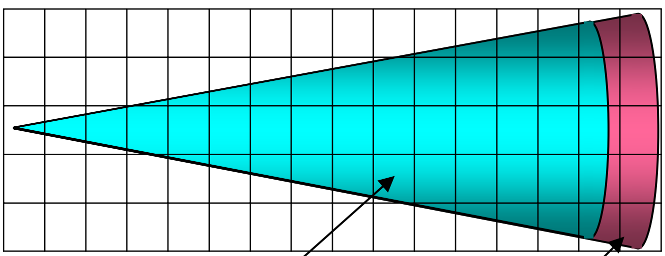

Fig. 2 Sonar sensor model in the occupancy grid framework

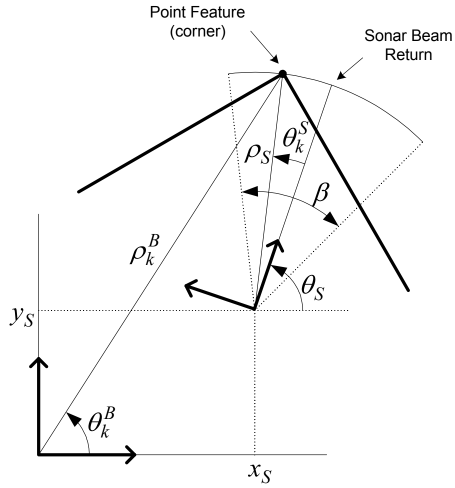

Fig. 3 Point feature corner modeling using the sonar sensor

$$x_k^B = x_s + \rho^S \cos(\theta_s + \theta_k), \quad (2)$$

$$y_k^B = y_s + \rho^S \sin(\theta_s + \theta_k). \quad (3)$$

The Hough voting table is updated for each point in the Hough space, defined by

$$\theta_k^B = \arctan \frac{x_k^B}{y_k^B}, \quad (4)$$

$$\rho_k^B = \sqrt{{x_k^B}^2 + {y_k^B}^2}. \quad (5)$$

The Hough voting table is then searched for local maxima. To accept a point feature, the number of votes must be above a defined threshold, and the sonar returns must have been taken from positions spread around the point.

Instead of storing the detected features in a stochastic map, we match the features' positions in the grid map, corresponding to corners or edges in the real world. When a new feature is found, it is possible to use the stereo vision to take a picture of the location, during the map building process. The corners and edges were chosen because they present more distinctive features that may be used in future versions of the method to identify natural landmarks, using algorithms such as [7].

The grid map building and the feature detection procedure can be realized incrementally, in real-time while the robot explores the environment, or off-line, using the log information of the robot positions and the sonar readings at each position. The grid mapping algorithm is the same in both cases, however, the robot position along the trajectories may be better corrected *a posteriori* using the landmark information. The Hough transformation may be recalculated off-line for the whole dataset and some features can be selected to correct the robot localization in later runs of the robot using the grid map. In the proximity of these selected features the robot may use the stereo vision to correct its position estimation.

2.3 Environment Exploration and Obstacle Following

Since the environment is initially unknown, the robot begins with an empty grid. While exploring the environment the robot processes the sonar readings sampled at fixed trajectory intervals. This procedure also avoids the problem of non-independent sensor readings, i.e., the ill-posed assumption that the sensor readings are conditionally independent of the state of the cell [8].

The exploration strategy and obstacle modeling scheme implemented followed the approach in [9]. The robot starts the exploration moving along a straight trajectory. As soon as an object is detected, it changes its motion control to an obstacle modeling mode, and the feature detection module is activated. The robot follows the obstacle boundary at a constant close distance and at a constant slow speed, to allow for the real time data processing.

The detected corners or edges could be used to automatically stop the obstacle modeling process. The obstacle is considered modeled if the first point feature found is reached again by the robot. This means that the robot moved through the entire extension of the obstacle boundary. In addition, a topological map may be derived from the point features and used to further plan the exploration of the least known region of the environment.

3. Results

The experiments were carried out using the ApriAlpha™ home robot to acquire maps of indoor environments. The robot is equipped with stereo cameras and five sonars in its frontal part, as shown in Fig. 4. The maximum range of ApriAlpha™'s sonars is approximately 2.1m. The width of the sonar beam is about 30 degrees.

The robot performs the exploration at 0.1m/s of speed. It samples the sonar data at each 5cm of displacement or 9 degrees of rotation, which happens first from the last reading. The following distance from the obstacle boundary is set to 50cm.

The grid map is composed by 80 x 80 cells with resolution of 20cm. To provide a visualization of the acquired map, the occupancy values are displayed as an inverse grey scale image normalized to fall in the interval [0, 1], where 0 (brighter regions) means probably empty cells and 1 (darker regions) means probably occupied cells.

In the simple counting method, the map was improved by considering closer sonar returns more reliable than distant ones. Thus, for sonar readings less than 600mm, cells in the *hit* region receive an increment of 10 and cells in the *miss* region receive an increment of 2. This produce walls more distinctively defined in the grid map.

The quantization of the Hough table was set to 100mm in position and 1 degree in orientation. The robot initial position with reference to the global grid was defined as the position (2.5m, 2.5m) in order to guarantee that all readings would fall in the first quadrant of the global reference Cartesian plane, the robot position and sonar readings are always positive during the trajectories. Thus, the Hough table does not need to cover all 360 degrees, only 90 degrees is sufficient. The Hough table threshold for point features was set to 70. The Hough transform is applied to the sonar readings acquired along short distances, 70cm of displacement or 70 degrees of rotation. These values were determined through experimentation in detecting corners and edges of a typical office environment.

a) b)

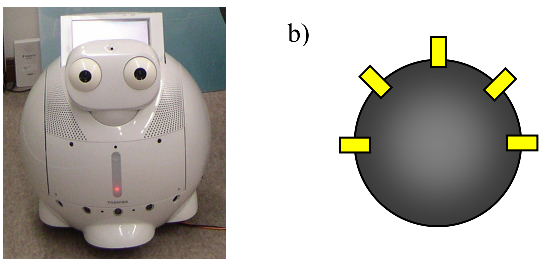

Fig. 4 a) Picture of the ApriAlpha home robot, stereo vision; b) The robot's sonar configuration

In the practical experiments, we utilized artificial landmarks placed beforehand at the corners to test the viability of the system. Using an already implemented image processing method of the ApriAlpha™, the exact location of the feature is calculated and the robot position estimation is corrected.

We present the results of two experiments in indoor environments. The first one was in an office composed of two rooms of approximately 3.5m x 7.5m, as shown in Fig. 5. The sketch of the office is displayed with the robot initial position and two visual landmarks positioned. The grid maps acquired in real-time and processed off-line are shown. The off line map was corrected using the visual landmarks.

The second experiment was the mapping of a larger environment, the Toshiba Science Museum's hall with approximately 16m x 8m. For this case, the grid was composed by 120 x 120 cells. The sonar data was taken at intervals of 10cm and 15 degrees. The following distance was 35cm from the obstacle boundary. The Hough transform threshold was 50, and five features were selected. We present the final corrected grid map with the selected features in Fig. 6.

4. Discussion

Even dealing with limited and noisy information, as those provided by sonar sensors, it is possible to acquire useful grid maps. By analyzing the results, we consider that the sonar interpretation using the simple counting method produced a reasonable representation of the environment. Besides the difficulty of how to assess the quality of the grid maps produced, its usefulness for the ApriAlpha™ navigation is undeniable. Spurious data is filtered by the stochastic nature of the counting methods utilized. Nevertheless, the odometry gives a rough estimation of the robot position which presents cumulative errors that greatly affect the resulting grid map.

The Hough transform method for corners detection during the mapping process in real time proved very robust and efficient. The proposed approach of using the detected corners of the environment allowed for a correction of the robot pose estimation. The grid maps could then be improved and the results were closer to the real world environment.

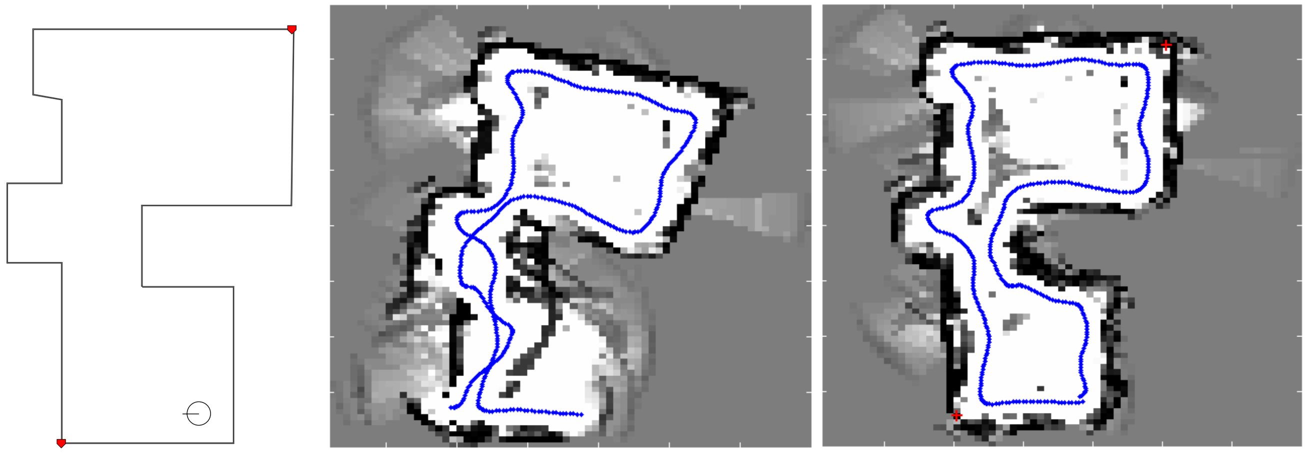

Fig. 5 a) Sketch of office room 3.5m x 7.5m, presenting the robot initial position and two visual artificial landmarks, in red at the corners;
b) Grid map acquired incrementally by the ApriAlpha, the robot's trajectory positions are displayed as blue dots;
c) Corrected grid map after robot pose adjustment using the landmarks information, the landmarks are displayed as red crosses

The proposed method did not treat the problem of dynamic environments. People moving around the room during the map building process may have caused the noise presented in the middle of the grid map's open areas. Also significant modifications in the environment, such as change in furniture locations, should lead to a re-acquisition of the grid map.

5. Conclusion

The main contribution of this project is to propose a map building system which integrates two robust robotic techniques, namely, occupancy grid maps and feature detection using the Hough transform. The grid maps have been used for the ApriAlpha™ navigation, and long-term usage can be achieved by using the landmarks for localization correction, when the robot is in the range of view of the selected landmarks. Being able to acquire a model of the environment is a great feature that adds up to the already extensive list of abilities of the ApriAlpha™, in the direction of becoming a truly autonomous home robot.

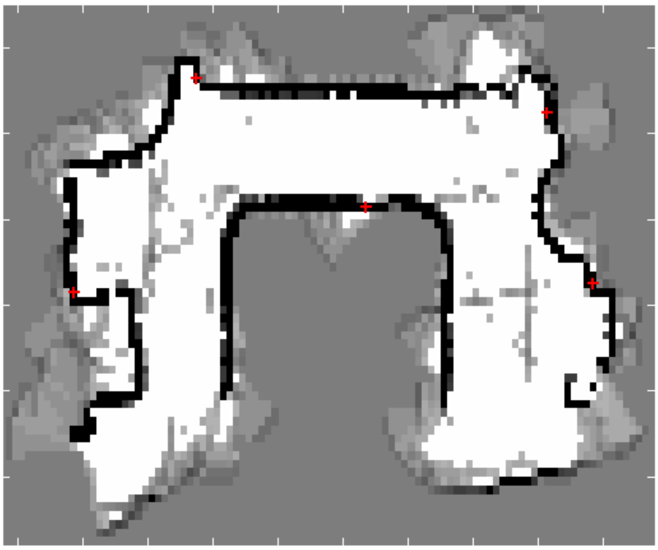

Fig. 6 Grid map of the Toshiba Science Museum's hall 16m x 8m, the selected features are displayed as red crosses

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