

Map Building in Planar and Non-Planar Environments

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Abstract

Mapping environments is a fundamental task for a rescue robot. In this paper we present techniques that we have developed for mapping rescue environments within the SPQR-Rescue team participating in the RoboCup 2004 Real Rescue competition. After an analysis of existing techniques for simultaneous localization and mapping (SLAM) we have devised a method suitable for planar environment (i.e. yellow-like arenas) able to deal also with different materials (glasses and mirrors). Moreover, the problem of mapping rescue scenario is in general non-planar and to this end we have performed a preliminary analysis towards the definition of a SLAM technique that will be suitable in such a situations.

1 Introduction

One of the main challenges for robots involved in rescue missions is to identify victims and report their location in the explored environment. Due to the characteristics of rescue environments, maps of the rescue site are usually not available or not usable for robots, therefore a critical task for rescue robots is the generation of a map of the explored environment in order both to localize itself and find its way back or recognize places that have already been explored and to determine exact position of identified victims.

Therefore, a main task for rescue robots is to reliably and efficiently build a map during their mission, that must be accurate enough for planning subsequent retrieval operations. Moreover, for a correct control of the robot exploration it is desirable that the mapping process works on line, showing an up to date map of the explored environment. This turns the problem of building a map in a problem of on line simultaneous localization and mapping (SLAM), since the robot has to concurrently estimate its position (in order to provide consistent maps) and build a map of the environment.

SLAM problem has been deeply investigated by the robotic community, and several techniques efficiently

solving it have been proposed. However, the rescue environments present some additional difficulties that are not considered in most of the SLAM approaches. First of all the rescue environments are supposed to be less structured than the traditional ones, and this imposes additional difficulties, since the a priori knowledge of the environment cannot be exploited by the SLAM process. Second, most of the SLAM approaches have been conceived for operating in planar environments, while the third dimension cannot be ignored in a rescue environment. Third, for building a map of a rescue environment, it is required to integrate the output of different sensors that can be used in the mapping process, since it is not possible to use a single sensor for detecting all of the materials in a rescue arena, and accurate enough for on line building of maps. As an instance the laser range finder, that has been successfully used for building metric maps of office like environments, fails in detecting glass, and mirrors, while the sonar, even if significantly less accurate, can detect these materials.

In this paper we address the main issues and present our developments in realizing mapping techniques in rescue arenas both for planar and non-planar environments. We will first review the most common on line SLAM techniques, treated as a filtering problem, and then present solutions and on going experimental evaluation of SLAM techniques applied to a four wheeled robot equipped with both a laser range finder and a stereo camera. We will use this method within the SPQR-Rescue team participating in the RoboCup 2004 Real Rescue competition.

2 Simultaneous Localization and Mapping

The problem of simultaneously evaluate the location of the robot and the map of the environment can be effectively expressed as evaluating at time t the joint probability distribution of the robot location s_t and the map of the environment m , given the exteroceptive sensor readings $z_{0:t}$ (i.e. readings coming

from sensors able to measure quantities relative to the environment, like laser range finders, sonars and cameras) and the proprioceptive sensor readings $u_{0:t}$ (produced by sensors that are able to measure quantities relative to the robot like odometry and gyroscopes) up to time t , analytically:

$$p(s_t, m_t | u_{0:t}, z_{0:t}) \quad (1)$$

If both the robot location and the maps are considered as the estimated system state, under the Markov assumption, it is possible to decompose Equation 1 according to the Bayes rule:

$$p(s_t, m_t | u_{0:t}, z_{0:t}) = \eta p(z_t | s_t, m_{t-1}) \times \int p(s_t | s_{t-1}, u_t) p(s_{t-1}, m_{t-1} | u_{0:t-1}, z_{0:t-1}) dx_{t-1} dm_{t-1} \quad (2)$$

Unfortunately a trivial solution to the mapping problem directly based on (2) is not tractable, being the probability distribution over maps and poses high dimensional. One of the most popular solutions to the SLAM problem [2] consists in assuming the noise to be zero mean and normally distributed, the map represented by a set of unique landmarks, and the system to be locally linearizable. Under this strong assumptions, the estimate of Equation (2) can be effectively performed by an Extended Kalman Filter (EKF). However, it has been shown in [3] that in most of the cases, the system noise and the observation noise are far to be Gaussian, and that the linearization of the system introduces systematic errors in the estimate.

In order to address the above problems it has been proposed in FastSLAM [8] the use of a rao-blackwellized particle filter that exploits the independence of the sensor readings, if the data association is known (unique landmarks). The approach consists in tracking the robot pose through a particle filter, and each particle carries its own map. Then the particles are evolved according to the motion command, and the landmark map is updated once per particle through the Kalman Filter Equations (the landmark error is assumed normally distributed). The strength of FastSLAM with respect to the standard EKF is that the data association hypotheses can be relaxed, since the particles are evaluated independently on each other, and the system is more likely to recover from failures, provided that at least one particle is in the right location; moreover the update process can be carried on by FastSLAM in time $O(n \log n)$ where n is the number of landmarks, while the EKF update takes $O(n^3)$.

However both the EKF and FastSLAM presents a drawback in the rescue context: they are landmark

based, and landmark maps are more difficult to handle for the rescue operators than metric maps. Techniques have been proposed for building on line metric maps, that are commonly based on the use of a laser range finder and work in planar environments. Most of these approaches falls out from the SLAM definition since they does not explicitly threat posteriors over maps and are usually unable to recover from wrong associations. In the work proposed by Lu and Miles in [6], for example, the readings of the laser are pairwise aligned in order to correct the robot pose. This approach provides maps that are locally accurate (since the scan matching process effectively reduces the odometry error), but globally inconsistent, since the error tends to be accumulated. This is particularly evident when the robot revisits a known area after mapping a large unknown one (formally the *loop problem*), in which the scan matching process has accumulated a large error that it is impossible to recover. In order to solve the loop problem in [7] a procedure for globally optimizing a set of scans as been proposed. Given that the topological relations among them are consistent, but it requires to operate on all of the readings at the same time, by performing a gradient optimization which takes $O(n^3)$ with n being the length of the path. Based on the Lu and Miles approach, Gutmann et al. in [4] proposed to create a map in real time by locally executing the scan matching, and detecting the loop closures. Each time a loop closure is detected, the feasible robot position in the old map is searched, and the global optimization is performed on all of the data related to the loop. This approach exhibits an almost real time behavior, but suffers of the main drawback that if the optimization phase fails once, then it is not possible to recover the correct map.

In the context of laser based SLAM GridFastSLAM [5], a dense sensor FastSLAM approach, has been recently proposed: the particles are evolved according to a laser corrected transition model (the data input stream is scan matched), and each particle carries its own map. The particles are resampled according to the likelihood computed by the scan matching process each time a new frame is added. This seems to give better performance than other proposed approaches, since it is suitable for real time operation. However, this method requires a high number of particles for working, since it is not able to correct the pose of past visited locations, and when closing a loop it requires to have at least one particle in the correct position.

While all the previous approaches make use of a laser range finder, in environments in which this sensor cannot be used, other sensors have been experimented. For example, Durrant White et al in [10] ad-



Figure 1: Rescue robot and arena used for experiments

dressed the problem of building undersea maps with a Kalman Filter approach, by using sonar reflective beams as artificial landmarks.

Even if most of the works on SLAM deals with the loop closure problem (that in fact represents a fundamental issue, since only when revisiting known locations the error accumulated when mapping new areas can be reduced), the typical rescue arena settings does not require to deal with such a problem (specially in planar environments), due to the reduced size of the environment, and to the fact that exploiting the precision of accurate sensors like the laser range finder, the error can be bounded so that no significant inconsistencies arises. Moreover, when interpreted by human operators, small errors in loop closures typically do not cause any misinterpretation of the map.

From the analysis of the common techniques for SLAM, we have devised and implemented a mapping method that is suitable in rescue environments. The method is an incremental scan matching technique that aligns each scan with the previously accumulated ones, by performing a local search around the odometry estimated position, trying to maximize the past and current scan overlapping. As a difference from the Lu and Miles approach our scanmatcher does not rely on the correspondence among the single readings. The evaluation of the function to optimize is made by considering the sum of the values $v_i = m(z_i \cos(\theta_i + \theta) + x, z_i \sin(\theta_i + \theta) + y)$ where (x, y, θ) is the robot location, z_i and θ_i are respectively the i^{th} , beam reading, and the angle of the i^{th} beam with respect to the center of the robot, and $m : \mathcal{R}^2 \rightarrow \mathcal{R}$ is the function resulting by convolving the past accumulated scans with a Gaussian kernel. It is very similar to the approach used by the carmen scanmatcher (vasco) [1], but presents some dif-

ferences in the map representation: in our implementation the map is fixed, while in vasco it is computed at each frame time step, based on the readings history. This results in an increased speed since the cost for building the reference map is constant instead that linear in the number of accumulated readings as in vasco.

3 Robot Settings and Techniques for building maps in Rescue environments

In this section we discuss the robotic configuration and SLAM techniques suitable for the exploration of different kind of environments, that requires different sensor equipments.

First we will present a setting for planar environments (suitable for example in the yellow Rescue Arena), in which we consider the problem of detecting different kinds of surfaces, requiring to use different sensors (we will focus on laser range finder and ultrasonic sensors), and we maintain the assumption that the robot moves on a planar environment and thus it creates a 2D map.

Then we will propose a setting for the SLAM algorithm that can be used when the environment is not planar (e.g. the orange Rescue Arena), in which the environment is not structured at all and the robot actually moves on a surface that is not planar. In this second scenario we will consider a wheeled robot equipped with a stereo camera and other sensors able to detect orientation and inertial properties of the mobile platform.

The experiments have been performed with a Pioneer AT robot (see Figure 1) in a Rescue arena built at the ISA laboratory in Rome and the implemented system will be used during the RoboCup 2004 Real Rescue competition. This robot has four driving wheels and

it is able to move over small obstacles. Moreover it is equipped with both a laser range finders and a stereo camera and it is thus suitable for experimenting SLAM techniques in both planar and non-planar environments.

3.1 Planar environments

As many works on SLAM have shown [4, 5, 9, 7, 6], the best setting for building maps in indoor environments is to use a wheeled robot equipped with a laser range finder. Even if such a sensor is not able to detect some kind of surfaces (like mirrors and glasses), its high accuracy allows to build accurate planar maps.

However, laser range finder cannot deal with any material; for example glasses and mirrors (that are typically present in a rescue environment) introduce large errors in the mapping process when only a LRF is used.

In order to deal with this aspect we have used also ultrasonic sensors, that, although less reliable and accurate of LRF, allow for dealing with these materials. The strategy we have adopted has been to discard all of the laser readings falling in the sensor cone, whose values are greater than the corresponding sonar reading. In this way we are able to recover several situations in which the LRF cannot detect a glass or mirror element in the environment.

The experiment have been performed by comparing our method based on scan matching and GridFastSLAM [5]. The results show that GridFastSLAM is more accurate when closing loops, while our scan matching method is more efficient. Moreover, the quality of the map provided by our scan matching method is good enough for a rescue robot.

Figure 2 provides an example of the maps generated by the implemented methods. The first image shows the odometry error of the robot in the environment; Figure 2b shows the results of our scan matching method; and Figure 2c shows the results of GridFastSLAM. The range data are acquired through the combination of values coming from a LRF and a set of ultrasonic sensors. The figure also shows both that the GridFastSLAM is more accurate than scan matching and that this difference is acceptable for the task of returning a map of an environment by a rescue robot.

On the other hand, computational time for the scan matching method is significantly reduced. Typical cycle time for processing data on our robot is 10 ms for the scan matching method against 100 ms for GridFastSLAM.

3.2 Non-Planar environments

When the robot that maps the area does not move on a plane, the problem of SLAM becomes more difficult, for the following reasons:

- The robot pose space passes from $\mathcal{R}^2 \times \mathcal{SO}(2)$ to $\mathcal{R}^3 \times \mathcal{SO}(3)$, that means that it goes from three to six dimensions. If we want to track the robot pose with a rao-blackwellized particle filter, we need a cubic number of samples, for having the same coverage of the pose space.
- If we are using a wheeled robot, the odometry sensors provides a worst estimate when moving on a non regular surface.
- The laser range finder, that can be safely used in planar environments loses its effectiveness, since it is able only to detect obstacles lying on the scanning plane, therefore we must switch to more inaccurate sensing device like stereo cameras. Moreover, as far as the laser can not be used all of the effective scan-match based approaches cannot be used.

For the above reasons the most proper sensor equipment for a 3D mapping robot includes an accelerometer, for dead reckoning, a compass, and a stereo camera as eteroceptive device. Moreover, since the stereo camera provides sparse and noisy informations it is extremely difficult to apply some dense sensor matching technique (like scan match), and it is needed to consider feature based SLAM techniques. In order to provide the operator with a feasible environmental representation for operation, a reconstruction technique can be used on the path estimated by the SLAM algorithm. The state transition is governed by the odometry, the accelerometer, and the compass. At each time a local view of the landmarks is built from the estimated pose and the map, and the data association is solved using the nearest neighbor principle as in many SLAM approaches. To increase the robustness of the approach with respect to association failures FastSLAM can be effectively used, provided that the sample space dimension has been reduced, by the use of the compass and the accelerometer.

We are currently performing a deeper analysis and more experiments in order to devise a suitable configuration and the appropriate technique that can be effectively used in non-planar environments.

4 Conclusions

Building the map of the explored environment is a fundamental activity for a rescue robot, and in order

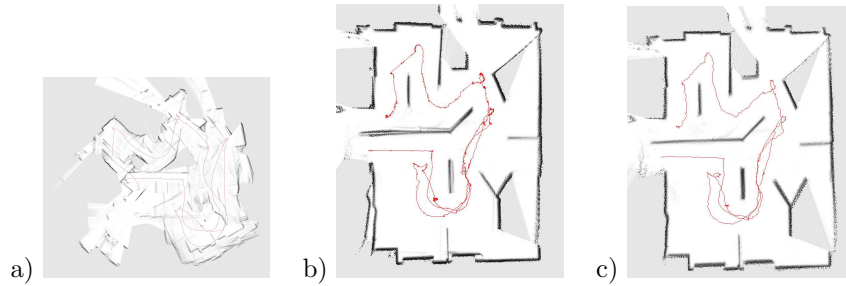


Figure 2: a) Occupancy grid generated by odometry data taken in the yellow rescue arena. The odometry is extremely bad. b) ScanMatch result b) the GridFastSLAM results. In this case the GridFastSLAM map is more consistent.

to generate consistent maps it is necessary to deal with this issue as a SLAM problem.

SLAM in indoor planar environments is a solved problem and this is suitable for simple and structured rescue environments, like a yellow arena. Acceptable maps of those environments can be built also by using a standard scan matcher. However, real rescue scenarios can be very different from an indoor structured planar environment and therefore it is necessary to devise SLAM techniques that are suitable also in non-planar unstructured contexts.

In this paper we have reported the development of a standard mapping approach in a structured planar environment as well as a preliminary analysis on the development of a SLAM method that is suitable for non-planar environments.

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