1
Introduction and Problem Definition

1.1.
Introduction

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Robotics

"Robotics is the science of perceiving and manipulation the physical world through computer-controlled mechanical devices" [1].

The word *robo*t was first introduced in 1921 by the Czech novelist Karel Čapek in his satirical drama entitled: *Rossum´s Universal Robots*. It is derived from the Czech word *robota*, which literally means "forced laborer" or "slave laborer" [2]. From there this word was popularized by science fiction, assigning it to machines with anthropomorphic characteristics, fitted with action and decision capabilities, similar or higher than humans [3]. Examples of successful robotics system include mobile platforms for planetary exploration, robotics arms in assembly lines, cars traveling autonomously on highways, actuated arms that assist surgeons and so on.

Mobile robot systems operate in increasingly unstructured environments, inherently unpredictable. "As a result, robotics is moving into areas where sensor input becomes increasingly important, and where robot software has to be robust enough to cope with a range of situations – often too many to anticipate them all" [1]. Robotics is becoming a software science, where the target is to develop sturdy software that enables robots to overcome the numerous challenges in unstructured and dynamic environments.

1.1.2. Uncertainty in Robotics

Uncertainty in robotics arises from five different factors [1]:

1. **Environment**. Environments such as private homes and highways are highly dynamic and unpredictable

2. **Sensors**. Limitation in sensors arises from their range and resolution. In addition, sensors are subject to noise.

3. **Robots**. "Robot actuation involves motors that are, at least to some extent, unpredictable, due to effects such as control noise and wear-and-tear" [1].

4. **Models**. Models are idealization of the real world. They only partially model the physical processes of the robot and its environment.

5. **Computation**. "Robots are real-time systems, which limits the amount of computation that can be carried out" [1]. Many algorithms are approximate, reaching timely response through slaughtering accuracy.

"Traditionally such uncertainty has mostly been ignored in Robotics" [1]. However, as robots are moving away into increasingly unstructured environments, the ability to deal with uncertainty is crucial for building successful systems.

1.2. Problem Definition

The scope of this work is related to the SLAM problem. SLAM (Simultaneous Localization and Mapping) is one of the most widely researched subfields of robotics, in special in mobile robotic systems.

Let's consider a mobile robot which is using wheels connected to a motor, actuators and a camera. Consider that the robot is manipulated by an operator mapping inaccessible places. The actuators allow the robot to move around, and the camera provides visual information for the operator to know where objects are and how the robot is oriented in reference to them. What the human operator is doing is an example of SLAM.

“Thus, the SLAM subfield of Robotics attempts to provide a way for robots to perform SLAM autonomously. A solution to the SLAM problem would allow a robot to make maps without any human assistance whatsoever” [4].

In the following, the SLAM idea is graphically presented (example taken from [4]).

1.2.1. Localization overview

Let’s consider a mobile robot in an environment which contains beacons or landmarks (points in the environment with a known exact location) from which the robot can calculate its distance and direction. Assume that the robot starts in some true known location R_0 (e.g. the red filled circle in Figure 1.1), and it has knowledge of a set L containing several landmark locations. When the robot moves a given distance in a certain direction (the movement vector u_1) to location R_1, it actually moves along some other vector to some location R'_1 which is nearby R_1, due to uncertainties in the actuators. Landmarks need to be relocated to determine the new robot position. Because the actuators are imprecise, the landmarks could not be reacquired by assuming they have moved inversely to u_1. Thus, the robot must search for the landmarks, starting near the expected location of the landmark and expanding outwards. Figure 1.1 presents this situation.

Note that R'_1 and vector u'_1 correspond to estimates rather than the actual values. Once the landmarks are reacquired, a new robot location estimate, R_1, can be made as shown in Figure 1.2.

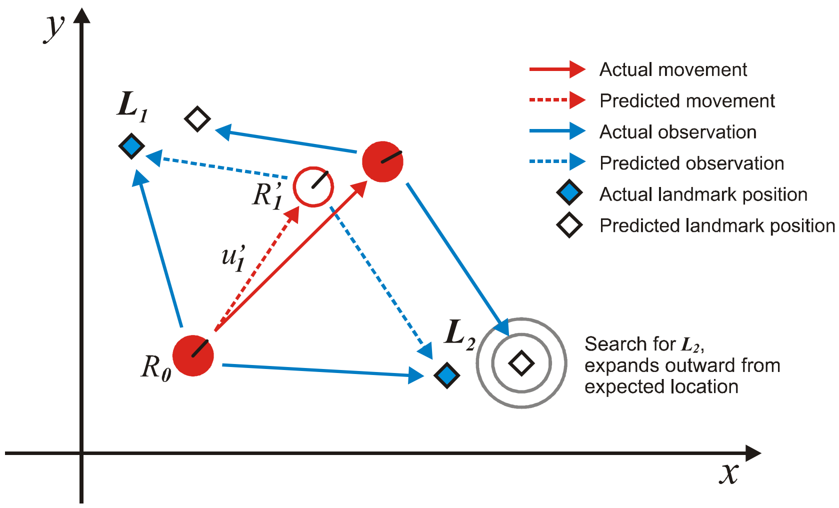

Figure 1.1: Localization Overview (search for landmarks)

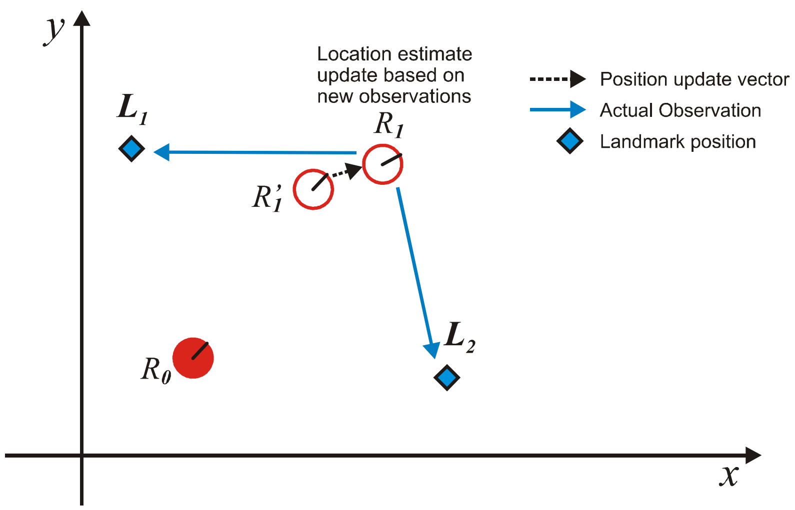

Figure 1.2: Localization Overview (location updated)

It is important to stress that R_1 is the location updated based on new observations, and therefore it is an estimated (white filled circle) robot position rather than the true position (red filled circle), which is impossible to perfectly measure.

1.2.2. Mapping overview

Mapping is, in a way, the opposite of localization. In mapping, it is assumed that the robot exactly knows where it is at all times. What the robot does not know, in the mapping context, is the locations of landmarks. Thus, the robot must locate landmarks to build a map $Z_t=\{L_{t1}\ L_{t2}\ \ldots\ L_{tn}\}$, where L_{tn} is the n^{th} landmark estimate at time step t. Of course Z_t only contains approximations of the actual landmark locations. As the robot moves, the map is usually more accurate.

Let's follow the same example from the previous section, beginning at R_0 and moving along u_1 to R_1. The robot will acquire the set of landmarks, but in this situation the perceived landmarks locations will have shifted from their expected location due to sensor inaccuracies instead of odometry inaccuracies. The landmarks can be relocated by searching nearby where the robot expects to find them. Thus, the robot will have built a new map Z_1, consisting of new locations of the landmarks in Z_0. Figure 1.3 demonstrates the process. For simplicity, in this example preservation of landmarks is assumed; in reality some landmarks are lost and new landmarks are acquired.

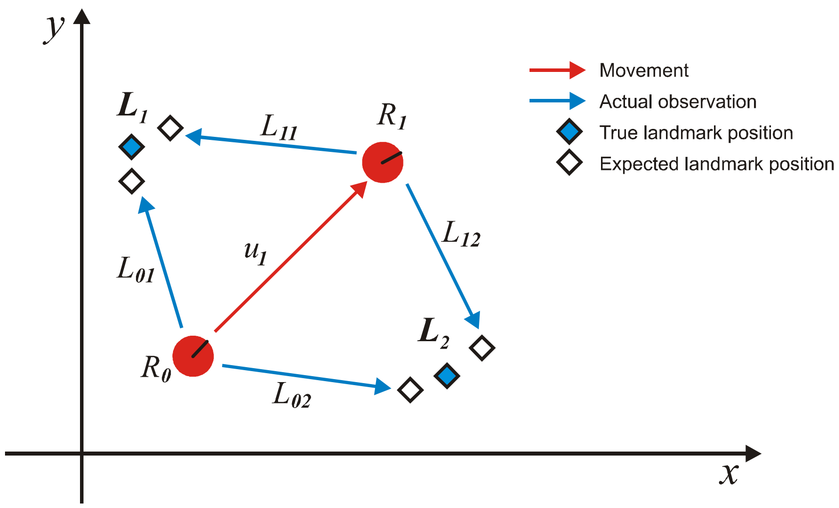

Figure 1.3: Mapping Overview

To generate a new map, Z_2, combining information of Z_0 and Z_1 but containing only one instance of each landmark, the robot can choose one of many options. For example, it can choose any point on the line connecting L_{0n} and L_{1n} (note that L_{0n} and L_{1n} are two conflicting perceived locations of landmark n).

Whichever the method selected for incorporating new sensor readings, it seems safe to assume that Z_t will improve as time t increases.

1.2.3. Simultaneous Localization and Mapping

The Localization Overview and the Mapping Overview presented before require something as an input that is unavailable in practice. Localization requires accurate landmark locations as input and conversely Mapping requires exact robot localization. This suggests that the two processes are related and could be combined into a single solution.

Suppose a robot starts moving from some known origin. It uses the Mapping process to construct a preliminary map. It then moves to a new location and updates its expected location as in Localization step. Finally, the new calculated pose is used to once again generate a new map, which is combined with the original map as described in Section 1.2.2. By repeating this process, one can provide a map for input into the Localization, and a location for input into the Mapping. Figure 1.4 demonstrates the basic Simultaneous Localization and Mapping idea.

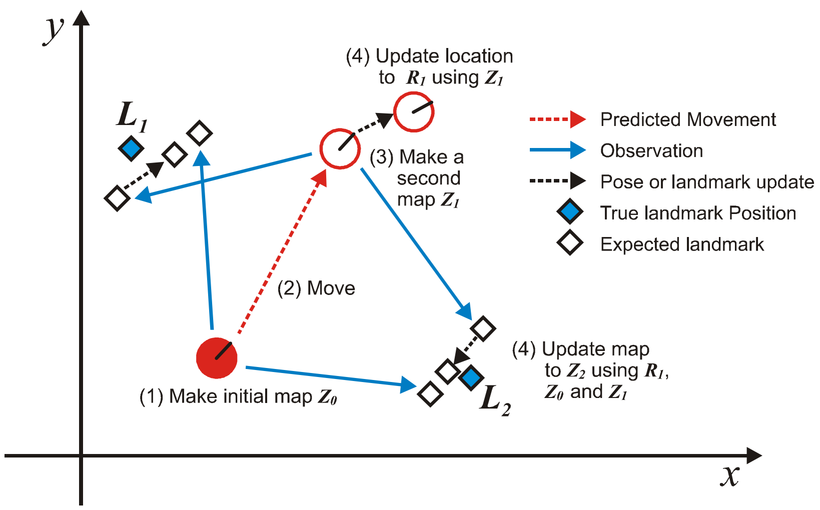

Figure 1.4: Simultaneous Localization and Mapping

One thing to notice with this combined localization and mapping algorithm is that one does not provide completely accurate input to either the mapping or the localization components.

1.3. Motivation

Petrobras operates in oil and gas exploitation at Amazon, in the province of Urucu (AM), at the Solimões River, about 650 km from Manaus City. To drain this production, it has been built two gas pipelines: Coari-Manaus and Urucu Porto Velho, with 420 Km of extension from Manaus as well.

In order to monitor these almost one thousand kilometers of pipeline in a hard access region and to avoid environment disasters, it was built a robotic amphibian vehicle, named Hybrid Environmental Robot (HER).

HER is able to move in many different grounds of Amazon: water, ground and aquatic microfiber, and it is also able to monitor different scenarios using many sensors, as shown in Figure 1.5. Moving into such an extended and remote areas and collecting data samples has become an important issue; thus, a precise position perception is needed, allowing the possibility for navigation and demarcation in areas of interest.

Figure 1.5: The Hybrid Environment Robot (HER)

HER acquires its position using a GPS system. However, it is prone to failure because of obstructions in satellite signal, caused by local vegetation. In this case, HER needs to acquire its position in a different way, in order to continue its mission or to search places with better satellite reception. The use of odometers is not a good choice due to frequent slipping on the ground; beyond, it does not have any utility over water. Localization by cameras also does not presents good results due to high similarity between vegetation images, making hard a reliable keypoints establishment. Inertial platforms would help in the localization of the robot, but would not have any utility to detect obstacles.

So, the use of a Laser Range Finder (LFR) represents great advantages, cause it is able, not only to locate the robot or mapping the environment, but also to detect obstacles on the robot´s path.

1.4. Objective

The objective of this work is to perform SLAM with limited sensor capabilities. More specifically, it is shown that localization and mapping can be performed without odometry measurements, just by using a single Laser Range Finder (LRF).

To accomplish that, first a detailed explanation of SLAM algorithms implementations is given, focusing on the: EKF-SLAM, FastSLAM, and DP-SLAM methods. Then, a Genetic Algorithm is implemented for Normal Distribution Transform (NDT) optimization, in order to obtain robot displacement without odometry information. An implementation for 3D mapping is shown, using DP-SLAM, which does not use predetermined landmarks (not dealing either with data association problems). Finally a virtual 3D environment is simulated including virtual Laser Range Finder (LRF) readings, to validate the presented methodology. Experimental data from actual LRF readings are also used to evaluate the performance of the algorithms.

1.5. Organization of the Thesis

This thesis is divided into six chapters, described as follows:

Chapter 2 comprises the theory necessary for Probabilistic Robotic. The basic concepts of representing uncertainties in a planar robot environment are shown. Also the main algorithms for scan matching are given, emphasizing on the Normal Distribution Transform(NDT). Concluding with Genetic Algorithms and Differential Evolution (DE).

Chapter 3 describes the principal algorithms for the SLAM solutions, including EKF-SLAM, FastSLAM and DP-SLAM. Besides, is presented a review for 3D SLAM solutions and 3D mapping.

Chapter 4 gives a detailed implementation of the principal SLAM solutions: EKF-SLAM, FastSLAM and DP-SLAM. Is explained also, the simulated Laser Range Finder (RLF) in a structured environment, developed for testing the proposed methods. In addition, is explained the NDT optimization using Differential Evolution, in order to get robot displacements without odometry information.

Chapter 5 presents the results obtained in simulated and real data acquired from the literature.

Chapter 6 presents comments and conclusions to the performed work.