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PROBABILISTIC LOCALIZATION AND MAPPING OF MOBILE ROBOTS IN INDOOR ENVIRONMENTS WITH A SINGLE LASER RANGE FINDER

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Abstract. *Undoubtedly, due to the recent advances in robotics, robots are increasingly autonomous. Therefore, for a robot, to have the ability to move within an environment without the assistance of a human being, it is required to have knowledge of the environment and its location within it at the same time. In many robotic applications, it is not possible to have an a priori map of the environment. In those situations, the robot needs to build a local map of its environment while executes its mission and, simultaneously, determine its location. A typical solution for the Simultaneous Localization and Mapping (SLAM) problem primarily uses two types of sensors: i) an odometer, which provides information of the robot's movement, and ii) a range measurement, which provides perception of the environment. In this work, a solution for the SLAM problem is presented using a DP-SLAM algorithm purely based on laser readings, focused on structured indoor environments. It considers that the mobile robot only uses a single 2D Laser Range Finder (LRF), and the odometry sensor is replaced by the information obtained from the overlapping of two consecutive laser scans. The Normal Distributions Transform (NDT) algorithm of the scan matching is used to approximate a function of the map overlapping. To improve the performance of this algorithm and deal with low-quality range data from a compact LRF, a scan point resampling is used to preserve a higher point density of high information features from the scan. A differential evolution algorithm is presented to optimize the overlapping process of two scans. During the development of this work, the mobile robot "iRobot Create", assembled with one LRF "Hokuyo URG-04LX", is used to collect real data in several indoors environment, generating 2D maps presented as results. The techniques, described in this work, enable a mobile robot, with a 2D laser scanner, to obtain precise maps of indoor environments, which can be useful in search and reconnaissance missions, e.g. in warehouses, production plants, and other industrial areas.*

Keywords: *SLAM, Scan Matching, Evolution Differential, Robot Mobile, Laser Range Finder*

1. INTRODUCTION

Recently, significant advances have been made in Mobile Robotics, allowing sophisticated robotics systems to be able to perform completely autonomous tasks. Basic tasks such as path planning, localization, and navigation are well understood and have been solved in a high degree. These components enable the robot to perform a variety of tasks with no human intervention or supervision. Several robotic systems need to have a fairly complete knowledge of the world, along with a reasonable map of the environment. This map, in addition to being accurate, should be fairly complete covering all the places that the robot can reach in its exploitation.

In the robotics community, the problem to build a local map of its environment while executing its mission and, simultaneously, determining its location, is known as Simultaneous Localization and Mapping (SLAM). SLAM has been a challenge to autonomous robots. The problems of localization and mapping appear as two distinct challenges but, in fact, problems are intricately intertwined. For a robot, to update the map correctly, it is necessary to know its location when the observations are made. However, in order to track the location of the robot, it is essential to have a good map to compare with the observations.

Thrun and Burgard (2006) reviewed the existing techniques to solve the SLAM problem, such as maximum likelihood estimation, expectation maximization, extended Kalman filter (EKF), or extended information filters (EIF). Besides these methods, the FastSLAM algorithm can be used to approximate the posterior probabilities of particles (Biber and Straber, 2003), while the DP-SLAM algorithm is purely based on laser readings, which plays an important role in 2D mapping (Eliazar, 2005).

Most algorithms that solve the SLAM problem have sensors to perceive the environment (such as a range measurement) and sensors for capturing the displacements of the mobile robot (such as an odometer). However, such sensors are subject to significant noise, and there are many objects that normally cannot be detected directly (Herrera 2011).

In this paper, a solution for the SLAM problem is presented using a DP-SLAM algorithm applied to the mobile robot iRobot Create, assembled with a single 2D Laser Range Finder (LRF) and without an odometer. This LRF, model Hokuyo URG-04LX, allows the robot to collect real data in several indoor environments, while the odometry sensor is replaced by the information obtained from the overlapping of two consecutive laser scans (Scan Matching) by the Normal Distributions Transform (NDT) algorithm.

Figure 1. Hokuyo URG-04LX Laser Range Finder.

This paper is organized as follows. Section 2 introduces the mathematical structure of the estimation-theoretic SLAM problem. Section 3 then provides an overview of the scan matching algorithm, and Section 4 describes the experiments and presents the results of the analysis using real data collected from the iRobot Create in indoor environments. Finally, Section 5 summarizes the work.

2. THE ESTIMATION-THEORETIC SLAM PROBLEM

The SLAM problem is best described as a probabilistic Markov chain. This section establishes the mathematical framework employed in the study of the SLAM problem. The Bayes' rule plays a prominent role in the area of probabilistic robotics (and probabilistic inference, in general). Suppose one wants to learn about a quantity m (map) or R_t (pose) based on measurement data. As in the SLAM process, there are two different types of data: sensor measurements z^t and control outputs u^t. Here, superscripts are used as an index of time t for the discrete data in the time period $[t-1, t]$. Then the Bayes' rule says that the problem can be solved by

$$(\quad) \qquad \int \qquad _{-} (_{-} \quad z^{-} \quad ^{-}) \quad _{-} \tag{1}$$

where and z refer to data leading up to time t, and is a normalizer of Bayes' Rule.

Note that Bayes' rule is recursive, that is, the posterior probability $(\qquad)$ is calculated from the same probability of an earlier time. The initial probability in time $t = 0$ is $(_0 \quad ^0 \quad ^0) = p(_0 \quad)$. In Equation (1), there are two important probability distributions: $_{-}$ and . Both are generative models of the mobile robot and its environment.

2.1 Motion model

The probability $_{-}$ is referred to as motion model, and specifies the control effect u_t on the state R_{t-1}. This model describes the probability that the control output u_t , if executed in the state R_{t-1}, can lead to state R_t. The main purpose of a motion model is to capture the relationship between the control effort of the mobile robot and changes in its position. Instead of using odometry sensors for displacement information of the robot, the proposed algorithm uses Scan Matching to extract this information.

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2.2 Measurement model

The probability p is referred to as the measurement model, which describes the process of formation through which the measurements of the sensors are generated in the physical world. In probabilistic terms, it describes how the sensor measurements are generated for different positions R_t in the environment.

The Measurement Model accounts for the uncertainty in the robot's sensors. In practice, it is often impossible to model a sensor with high accuracy. The recent development of Laser Range Finders (LRF) at reasonable prices quickly turned them into a dominant sensor to be used in the mapping problem.

3. SCAN MATCHING

Most mobile robots require some knowledge of their location in the environment. Scan matching approaches for localization are based on overlaying two scans, without making any assumption about their shape nor searching features. In other words, scan matching approaches rely on the raw data provided by range sensors, such as the LRF. Scan Matching is the problem of finding the roto-translations $(\Delta x, \Delta y, \Delta\theta)$ between a scan input S_{in} and a scan reference S_{ref} obtained from a device such as a LRF which maximizes the overlap between the parts of the environment represented by S_{in} and S_{ref}.

A definitive solution does not exist because scan matching is used in a vast range of operative conditions (Burguera and Gonzalez, 2008). Biber and Straber (2003) proposed a method called Normal Distributions Transform (NDT) that does not need correspondences of points. Thus, NDT makes an occupancy grid and subdivides the 2D plane into cells. To each cell, it assigns a normal distribution, which models the probability of measuring an obstacle in such cell. The result of the transform is a piecewise continuous and differentiable probability density, that can be used to match another scan using Differential Evolution (DE).

3.1 Scan matching algorithm

The Scan Matching algorithm for NDT can be outlined in the following steps:

i) build the NDT of the S_{ref} to determine the probability function associated with S_{ref};
ii) initialize the estimate for the roto-translations $(\Delta x, \Delta y, \Delta\theta)$;
iii) for each sample of the S_{in} and, for each point, determine the spatial transformation in the coordinate system of the S_{ref} according to the parameters $(\Delta x, \Delta y, \Delta\theta)$;
iv) evaluate each resulting point in the probability function associated with S_{ref}; and
v) optimize the parameters $(\Delta x, \Delta y, \Delta\theta)$ to obtain a maximum overlapping of the S_{in} and S_{ref}.

3.2 Differential evolution for scan matching

Differential Evolution (DE), like Genetic Algorithms, belongs to the family of Evolutionary Computation. It is an optimization technique that uses an exceptionally simple evolution strategy, which is significantly fast and robust, with a high likelihood to find a function's true global optimum (Pricel and Storn, 2005).

The use of DE is robust and useful to estimate the roto-translations $(\Delta x, \Delta y, \Delta\theta)$ between scans. These three displacement values are the variables to be codified; thus, one chromosome is composed as $(\Delta x, \Delta y, \Delta\theta)$, which are represented by real numbers. The fitness function is given by the probability function associated with the NDT algorithm.

The stopping criterion used in this paper for the optimization is given by two values. The first is the fitness value. Thus, the optimizations stop if the fitness value is less than a value acquired empirically. The second stopping criterion is based on a maximum number of generations.

3.3 Scan filtering

A crucial problem in Scan Matching is how to select points of scans that are useful for matching. Each scan contains hundreds of points, and many of them could be redundant, especially when the environment is so simple. Furthermore, redundant points of scans affect the efficiency and accuracy of the Scan Matching algorithm. The scan density strongly depends on parameters such as robot speed or the material of the obstacle (Tomono, 2005). To avoid this problem, it is necessary to resample the scan.

In this paper, scan filtering is performed with the goal of preserving important scan points and discarding redundant scan points, so points with low saliency information are eliminated. The Saliency-based Scan Point Resampling method calculates the saliency of each scan point according to the amount of information the scan point has, or the length of the line segment on which the scan point lies. This approach is able to resample a scan with a minimal loss of information, with very low computational requirements. Figure 2 exemplifies the effect of the resampling step.

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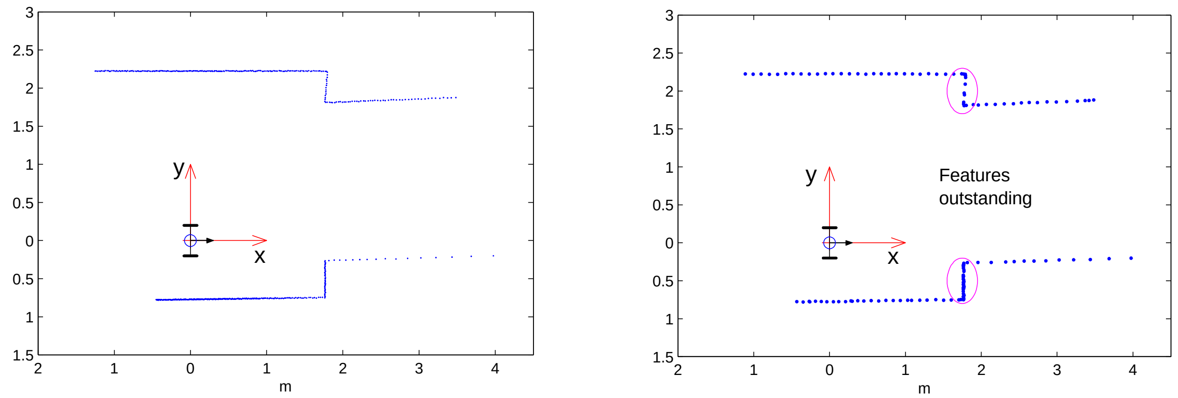

Figure 2. Set of laser readings before resampling (left) and after resampling (right).

Figure 2 shows results for a scan acquired in a corridor. The number of scan points is originally 682 per scan. But, after resampling, the number of points reduces to 134. As it can be seen in the figure, all the points around the corners are preserved as salient point and points on the walls are resampled almost uniformly, minimizing memory requirements without losing significant information about the map walls.

4. EXPERIMENTS

Indoor experiments are conducted in buildings from the Pontifical Catholic University of Rio de Janeiro. An iRobot Create mobile robot is employed, which is a two-wheeled mobile robot. A Hokuyo URG-04LX LRF is then mounted on it, with a scan range of 4m, angular resolution 0.35 degrees, and angular range between −240 and 240 degrees.

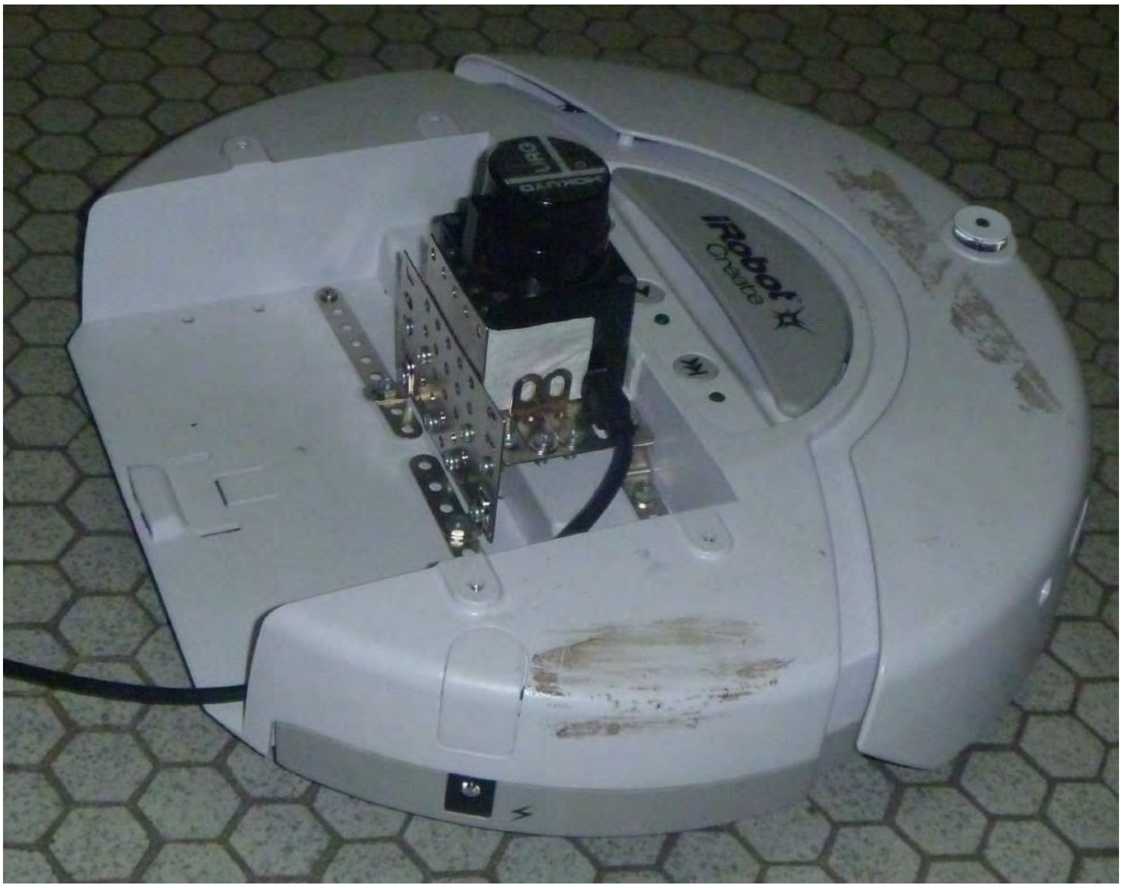

Figure 3. Mobile robot iRobot Create coupled with the Laser Range Finder.

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Data sets, gathered in seven different environments from the University, have been used. These environments consist of corridors and hallways with parallel walls, corners, doors and some features.

In order to obtain the solution for the SLAM problem, a single LRF sensor is used to get information on the location of the mobile robot and perform environment mapping along as the robot moves. First, the Scan Matching algorithm is used to replace the odometry information. Then, it is applied to solve the SLAM problem, while the DP-SLAM algorithm is used to improve the solution.

The NDT algorithm for Scan Matching was implemented and tested in experiments performed with the parameters shown in Table 1. This table presents the size of the grid (grid resolution) used in the NDT algorithm, and the population size, number of generations, scaling factor and crossover constant associated with the Differential Evolution algorithm to maximize the overlapping between two consecutive scans.

Table 1. Scan Matching parameters.

Algorithm	Parameters	Value
NDT	Grid resolution	0.5m
Differential Evolution	Number of Generations	50
	Population Size	100
	Crossover	0.95
	Scaling factor	1.00

Figure 4 shows two consecutive scans obtained from the LRF, followed by a figure with the matching and overlapping between them. By successfully overlapping both scans, it is possible to estimate the mobile robot displacement. In this example, the environment has distinctive features such as pillars, doors, corners and other characteristics, resulting in a low overlay error.

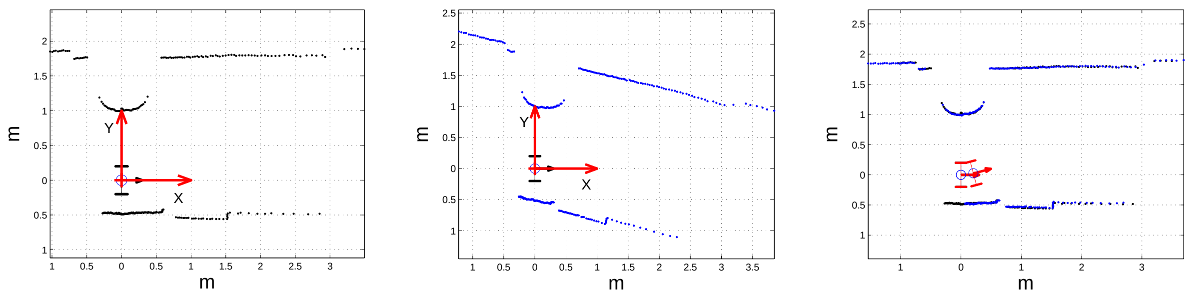

Figure 4. Scan matching in environments with special distinctive features, showing the first scan (left), second scan (middle) and the matching and overlapping between them, used to estimate the mobile robot displacement (right).

In a few of the experiments carried out, parts of the environment have few features, such as plain corridors with parallel walls. In this case, the scan matching algorithm presents a greater difficulty to find the overlay between two consecutive sensor readings, resulting in a poor estimate of the mobile robot displacement. Figure 5 shows this case, where two sensor readings are taken in an environment with parallel walls. Such overlay errors can be seen in the dashed region in the right image of Figure 5.

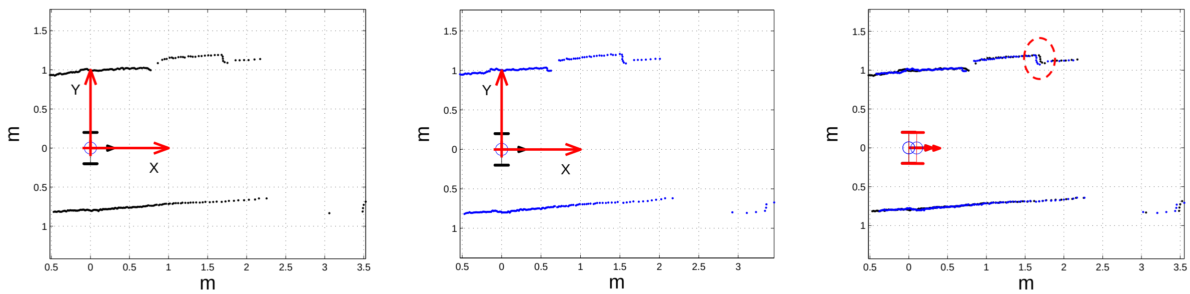

Figure 5. Scan matching in environments with special distinctive features, showing the first scan (left), second scan (middle) and the matching and overlapping between them, used to estimate the mobile robot displacement (right).

It is found that the SLAM problem can be solved with the Scan Matching algorithm, without the need for odometers. It is shown that it is possible to obtain the displacement $(\Delta x, \Delta y, \Delta\theta)$ between the positions of two

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consecutive sensor readings. Performing a coordinate transformation for all sensor readings in accordance with the displacement of two successive scans, one can obtain the trajectory of the mobile robot and the map where it moves.

Figure 6 shows the resulting maps from 2 experiments. The location of the mobile robot is represented in red dots and the detected environment in blue dots. Note that these environments basically present two parallel walls, with few distinctive features, which makes it more difficult to perform scan matching. Nevertheless, the generated map of the environments provides a reasonable outline of the real maps.

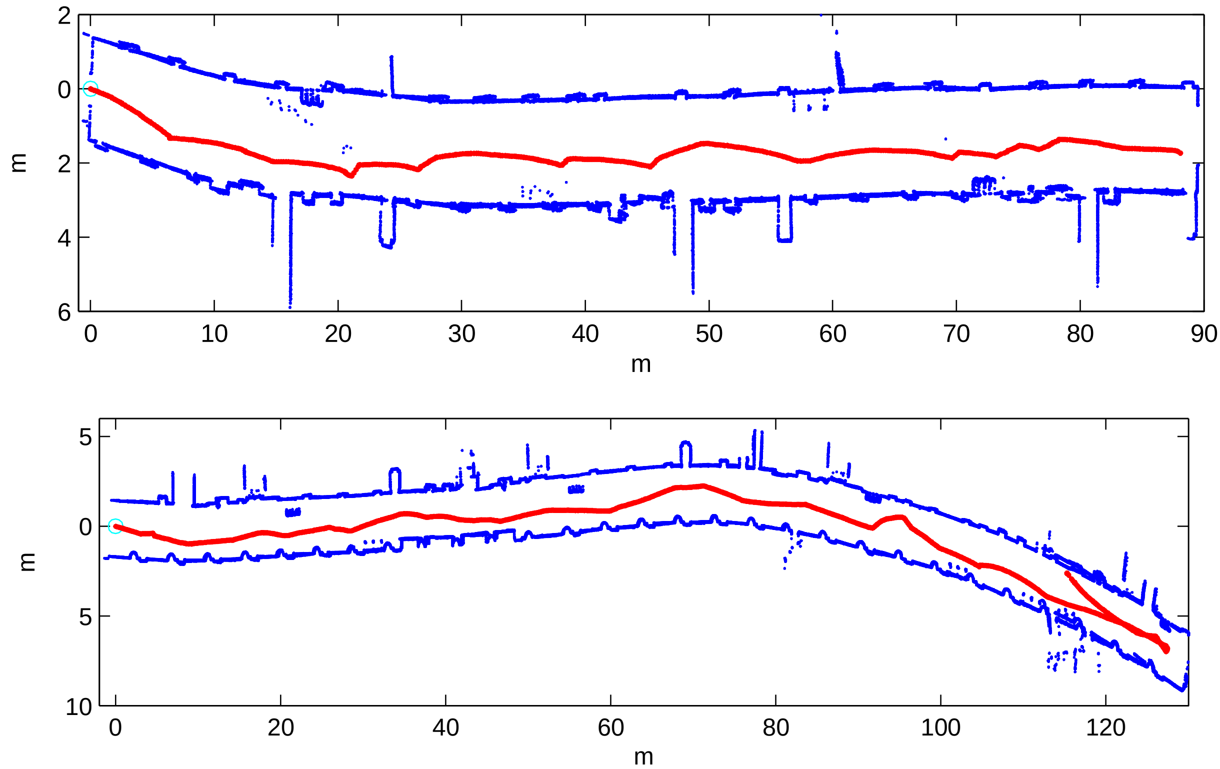

Figure 6. Maps generated by the mobile robot, showing the identified walls (in blue) and the estimated robot trajectory (in red) without the use of odometers.

Figure 7 shows another environment and the resulting map. This hallway presents several corners and perpendicular corridors, which results in a map with improved accuracy due to such distinctive features. Note that, during the movement of the mobile robot in this environment, the robot passes twice along the same part of the map, but it is able to distinguish both tours.

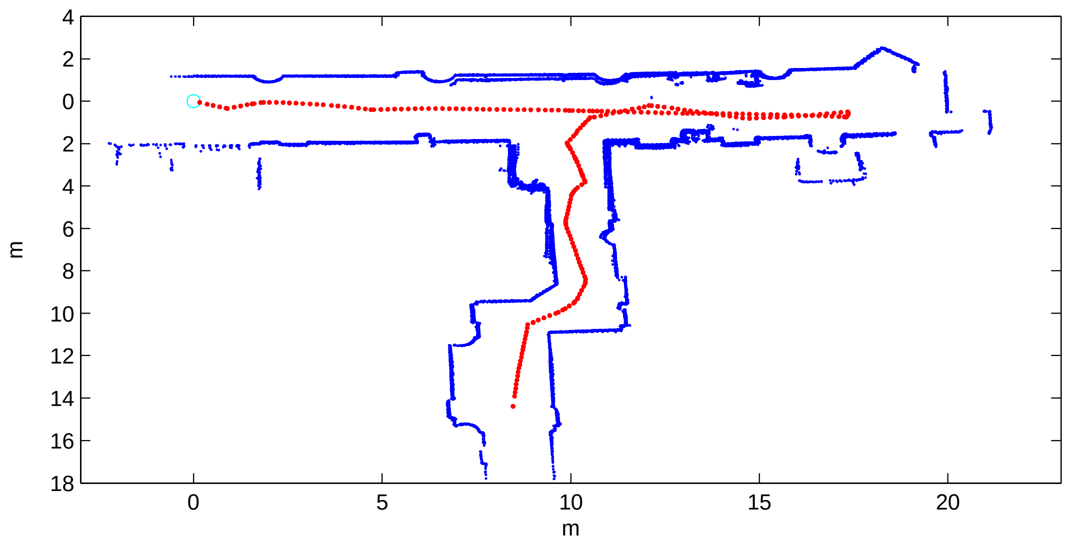

Figure 7. Map building and localization by scan matching.

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These maps are then improved by using a representation of the occupancy grid, provided by the DP-SLAM algorithm. Furthermore, DP-SLAM can be used to reduce the errors produced by the Scan Matching algorithm (Eliazar, 2004). Figure 8 shows the hallway for the same environment of the bottom map from Figure 6. In this map, one can observe more clearly the contours of columns, doors, elevators, trash cans, among other characteristics, resulting in a better map representation. Similarly, Figure 9 shows the representation using the DP-SLAM algorithm of the environment shown in Figure 7. Here, the perpendicular ways and other features of the environment are clearly observed.

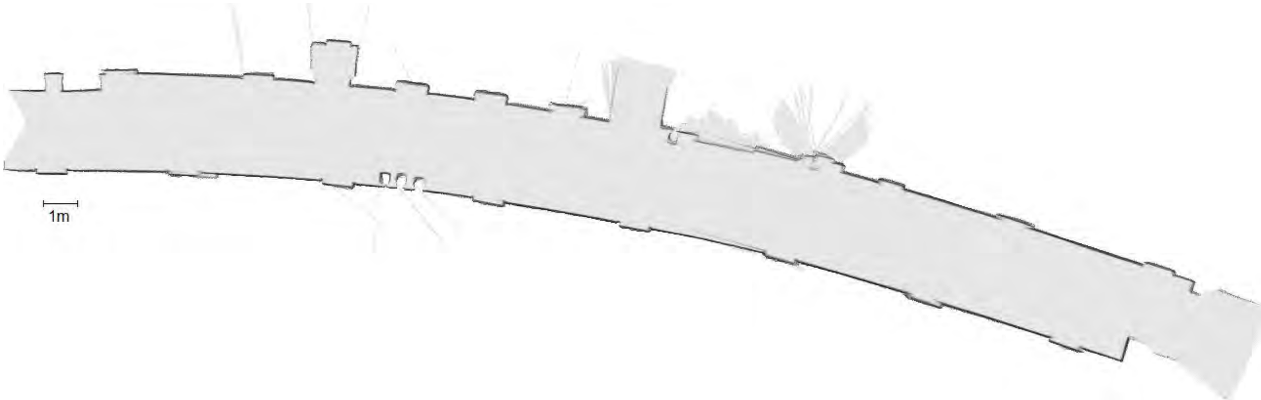

Figure 8. Resulting map after the application of DP-SLAM on the data from the bottom map from Figure 6.

Figure 9. Resulting map after the application of DP-SLAM on the data from Figure 7.

5. CONCLUSIONS

This paper proposed a method to improve the performance of the NDT Scan Matching using Differential Evolution for the maximization of the overlap between scans from a laser range finder (LRF), applied to the solution of the SLAM problem. The information obtained from the Scan Matching algorithm is useful to replace odometry sensors and create accurate maps using the DP-SLAM algorithm. The framework developed in this work allows a low cost mobile robot with a single 2D LRF to obtain accurate maps of indoor environments without the need for odometry sensors.

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