THEORY AND EXPERIMENTAL RESULTS ON MAP BUILDING USING LASER SCANNERS AND AN AUTONOMOUS MOBILE ROBOT – SmartROB-2

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Abstract:

This article relates researches on Map-Building technique for mobile robots in unknown environments. Map-Building consists on: through sensors data, extract features from the environment and build a map that will be used by the robot to self-localize, plan paths and avoid obstacles in this environment. Our approach uses an algorithm for line and segment extraction and a simplified EKF (Extended Kalman Filter) for localization. We implemented this approach on a real platform, the mobile robot SmartROB-2, equipped with two SICK Laser Scanners and the real-time system XOberon. The results obtained were encouraging, nevertheless some problems were found due to the simplifications adopted. Solutions have been discussed with other researchers and a new approach is in progress.

Keywords: Map-Building, Stochastic Map, Laser Scanners, and Mobile Robots.

1. INTRODUCTION

Autonomous vehicles are programmable systems performing a multitude of tasks. Today, they are intended for material handling, transportation, decontamination, fire fighting, rescuing and many other hazardous activities. Therefore, the basic problem to produce an autonomous vehicle is a robot navigation problem that can be summarized by the following three questions: “Where is the vehicle?”, ”Where is it going?” and “How should it get there?” (Leonard & Durrant-Whyte, 1992). The first question is one of localization, the second and third ones are essentially those of specifying a goal and being able to plan a path that results in achieving this goal, avoiding any obstacle that is in its path (path planning and obstacle avoidance). As the answer of the first question is a precursor to obtain the path planing and obstacle avoidance behaviors in autonomous vehicles, our paper focus this problem.

A priori model maps are rarely available, costly to obtain, and when they are available, they usually introduce inaccuracies in the planning tasks (Castellanos *et al.*, 1999). An automatic construction of the map of the environment, in which the robot navigates, using the robot itself would be desirable. Previous work in navigation for mobile robots has tended to treat the problems of localization, obstacle avoidance, and map building in isolation. Nevertheless, since the beginning of 90’s years, one of the major motivations for the researchers in this area is the unified approach to navigation, i.e. simultaneous map building and localization. Such procedure is desirable because avoid rely on odometry or hand measuring of sensing locations, nevertheless has a high computational price, due to the necessity of maintain all environment previous observations during the exploration phase.

2. SIMULTANEOUS MAP-BUILDING AND SELF-LOCALIZATION

The aim of Map-Building is to produce and update autonomously maps of environments. This map will be used by the robot for self-localization in the environment without the need of modifying the environment (e.g. use of artificial beacon systems, code bars on the walls, etc.). To build autonomously a map of an environment consists basically on the following steps: Get data of the environment through some kind of sensor (e.g. optical sensors, ultrasonic, sonar, and laser); extract features from the sensory data; match observed features to the best fitting equivalent from the map; localize the robot with the matched features; match features with their re-prediction based on the robot new position; and, update the map features with their matched re-observation and store unmatched features as new ones (see Figure 1).

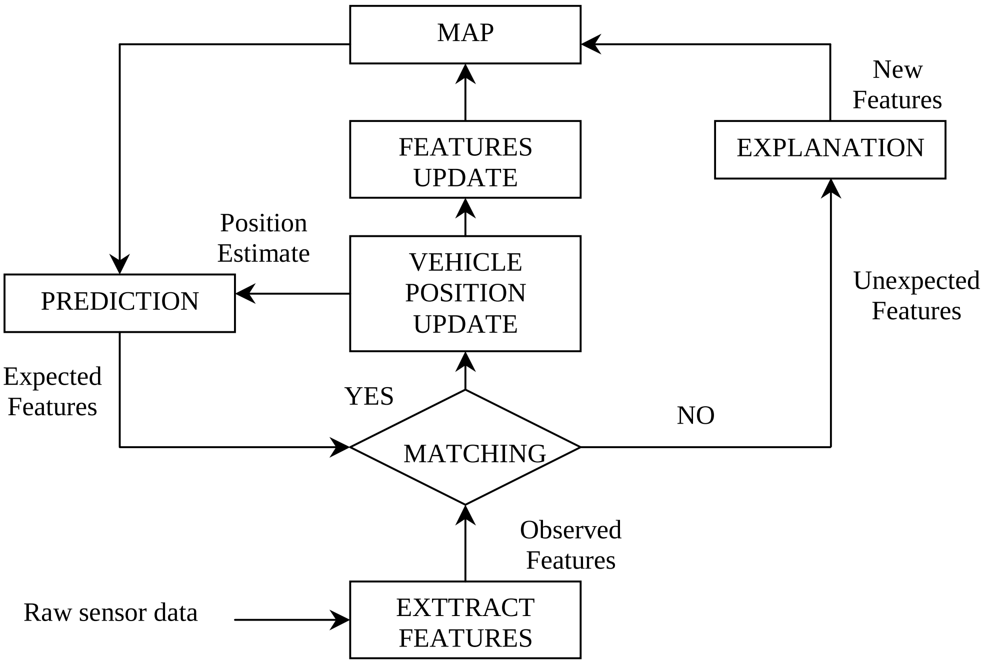


Figure 1 – Block diagram for simultaneous map building and localization.

There are many different approaches used to estimate the position of the robot during the map-building procedure. In this work, the basic tool that we used to localize the robot while it is building the map was the extended Kalman filter (EKF). Kalman filtering techniques have been used extensively to solve problems in localization, not only in robotic applications, but also, for other applications of navigation (for more details about EKF, see: Crowley, 1989, Leonard & Durrant-Whyte, 1992, and Grewal & Andrews, 1993).

The representation of the spatial information adopted was the called *stochastic map*. This representation is an exact mathematical approach to the simultaneous localization and map building problem, originally addressed by Smith *et al.* (1990), and contains the estimates of relationships among objects in the map, their uncertainties, and their inter-dependencies, given by all the available information provided by the sensors. In order to aid the comprehension of the EKF, the stochastic map, and the procedure and simplifications adopted in this work, the following terms are defined. A *spatial relationship* is represented by the vector of its *spatial variables*, x. Then, the position of the robot can be described by its coordinates, x and y, in a two dimensional Cartesian reference frame and by its orientation, ϕ, given as a rotation about the z axis:

$$\mathrm{x} = \begin{bmatrix} x \\ y \\ \phi \end{bmatrix} \tag{1}$$

An *uncertain* spatial relationship can be represented by a *probabilistic distribution*:

$$P(\mathrm{x}) = f(\mathrm{x})\, d\mathrm{x} \tag{2}$$

The uncertain spatial relationships are modeled by estimating the first two moments of its probability distribution, i.e. the mean, $\hat{\mathrm{x}}$, and the covariance, $C(\mathrm{x})$, defined as:

$$\begin{aligned} \hat{\mathrm{x}} &\stackrel{\Delta}{=} E(\mathrm{x}) \\ \tilde{\mathrm{x}} &\stackrel{\Delta}{=} \mathrm{x} - \hat{\mathrm{x}} \\ C(\mathrm{x}) &\stackrel{\Delta}{=} E(\tilde{\mathrm{x}}\,\tilde{\mathrm{x}}^T) \end{aligned} \tag{3}$$

Where E is the expectation operator, and $\tilde{\mathrm{x}}$ is the derivation from the mean. For the mobile robot, these terms are:

$$\hat{\mathrm{x}} = \begin{bmatrix} \hat{x} \\ \hat{y} \\ \hat{\phi} \end{bmatrix} \qquad C(\mathrm{x}) = \begin{bmatrix} \sigma_x^2 & \sigma_{xy} & \sigma_{x\phi} \\ \sigma_{xy} & \sigma_y^2 & \sigma_{y\phi} \\ \sigma_{x\phi} & \sigma_{y\phi} & \sigma_\phi^2 \end{bmatrix} \tag{4}$$

The diagonal elements of the covariance matrix are just the variances of the spatial variables, while the off-diagonal elements are the covariances between the spatial variables. To model a system of n uncertain spatial relationships, it is necessary to construct the vector of all spatial variables, which is called as the *system state vector*. As before, the mean of the mean of the state vector, $\hat{\mathrm{x}}$, and the *system covariance matrix*, $C(\mathrm{x})$, are estimated.

$$\mathrm{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \qquad \hat{\mathrm{x}} = \begin{bmatrix} \hat{x}_1 \\ \hat{x}_2 \\ \vdots \\ \hat{x}_n \end{bmatrix} \tag{5}$$

Defining:

$$\begin{aligned} C(\mathrm{x_i}, \mathrm{x_j}) &\stackrel{\Delta}{=} E(\tilde{\mathrm{x}}_\mathrm{i}\, \tilde{\mathrm{x}}_\mathrm{j}^{\,T}) \\ C(\mathrm{x_j}, \mathrm{x_i}) &= C(\mathrm{x_i}, \mathrm{x_j})^\mathrm{T} \end{aligned} \tag{6}$$

$$C(x) = \begin{bmatrix} C(\mathrm{x_1}) & C(\mathrm{x_1}, \mathrm{x_2}) & \cdots & C(\mathrm{x_1}, \mathrm{x_n}) \\ C(\mathrm{x_2}, \mathrm{x_1}) & C(\mathrm{x_2}) & \cdots & C(\mathrm{x_2}, \mathrm{x_n}) \\ \vdots & \vdots & \ddots & \vdots \\ C(\mathrm{x_n}, \mathrm{x_1}) & C(\mathrm{x_n}, \mathrm{x_2}) & \cdots & C(\mathrm{x_n}) \end{bmatrix} \tag{7}$$

Here, the x_i's are the vectors of the spatial variables of the individual uncertain spatial relationships, and the $C(x_i)$'s are the associated covariance matrices. The $C(x_i,x_j)$'s are the cross-variance matrices between the uncertain spatial relationships. These off-diagonal sub-matrices encode the dependencies between the estimates of the different spatial relationships.

To implement the map-building procedure, we adopted some simplifications, which reduced the computational requirements. The results rely on the so-called 2-D assumption, that is, the environment can be sufficiently described in 2-D since all observed structures keep their forms in the vertical dimension. Supposing that every horizontal slice of an obstacle has a closed contour, the goal of the exploration is to build a closed chain of extracted features around each contour in the environment. Open ends of a chain, i.e. the end of a feature, where the successive one is still missing, indicate a frontier where new information can be gathered. The final map is a collection of all chains of features observed during the exploration of the environment.

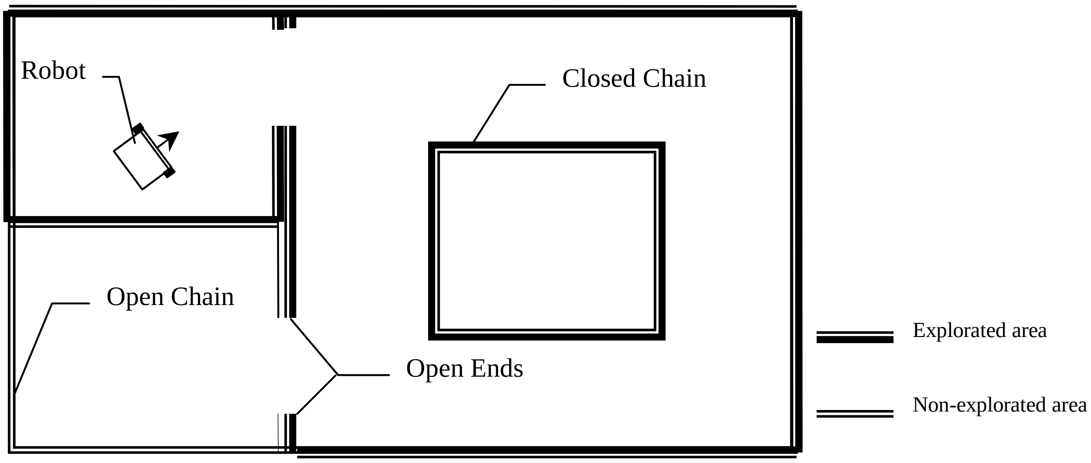


Figure 2 – Simple scene showing two chains (a closed and an open one) and the robot during the exploration phase. Observe that the Open Ends indicate the borders of the known environment.

The line extraction method (Arras, 1996, Wullschleger, 1999, and Wullschleger *et al.* 1999) is also used. This procedure delivers lines and segments together with their first order covariance estimate. The distinction of lines and segment is done as follow: A line is represented according to the Hessian model:

$$\rho \cdot \cos(\varphi - \alpha) - r = 0 \qquad (8)$$

Where (ρ, φ) is the raw measurement in polar coordinates and (α, r) the model parameters. They come along with their second moments, which hold the propagated uncertainty from the raw data level. Segments have a 4-D representation. Either by Cartesian coordinates of their endpoints or by a position, an inclination, and a length. In a hierarchical order, segments are below lines since they lie on a line (the supporting line) and thus have the same (α, r) pair. In all comparisons, matchings, and updates of map entities pairs of (α, r) with their covariance matrix are used. Although this representation provides consistent treatment of all feature model parameters and thus permits blind comparison and manipulation of features, reducing the computational requirements, this choice is a sub-optimal one. This occur because we are simplifying the EKF, i.e. all the cross-variance matrices were neglected (the cross-correlation's between robot to feature and feature to feature are not considered). If in a way it was possible to save computational time, in the other way, some problems during the matching and updating procedures happened.

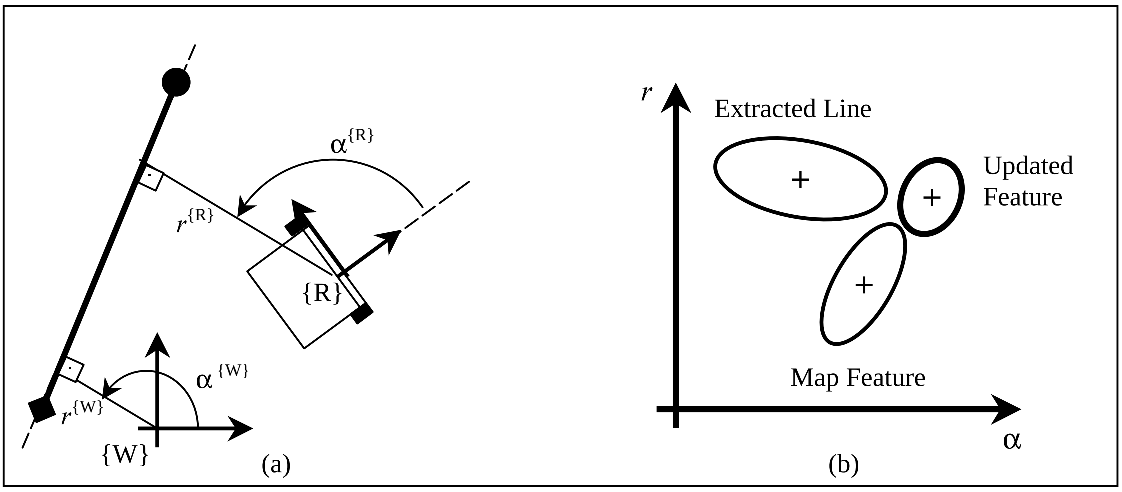
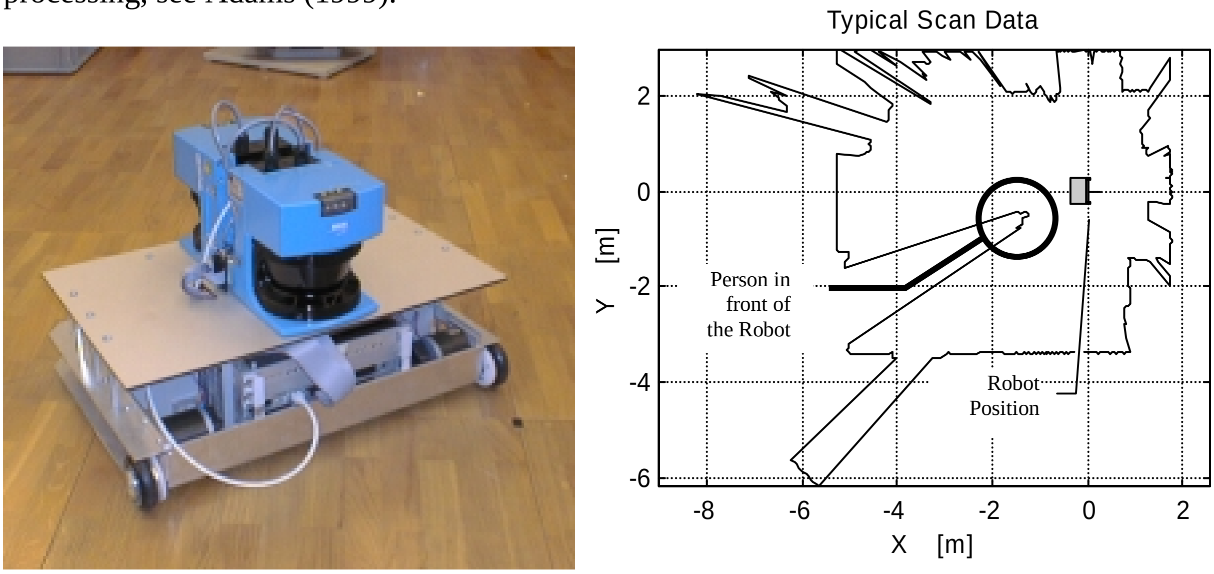


Figure 3 – A line (a) is represented by a Gaussian distribution in model space (b) with heading α and distance *r* as first moments.

As all operations (e.g. matching, fusing, update, etc) are done in the model space (Figure 3-b), the use of a simplified EKF causes an increment on the position uncertainties, deformation, rotation, and translation of the observed features, when compared with the real ones (Castellanos *et al*., 1999), and even creates "ghost features".

3. IMPLEMENTATION AND RESULTS

The implementation of the Map-Building procedure used a real platform, a differential drive mobile robot - SmartROB-2, whose dimensions were 0.60 m width x 0.35 m length x 0.40 m height (see Figure 4-a and Badreddin, 1992). The mobile robot was equipped with two SICK LMS200 Laser Scanners covering 360^o with a resolution of 2^o and radial error measurement less than ±20mm. The entire code was written in XOberon, a deadline-driven hard real-time operating system. For more informations about Laser Ssensors and data processing, see Adams (1999).



(a) (b)

Figure 4 – (a) Photo of the mobile robot SmartROB-2 equipped with two SICK LMS200 Laser Scanners and (b) plot of a typical laser scan data obtained by the robot during the experimental tests.

The sequence presented on Figure 5 shows the real exploration of the SmartROB-2 in an environment built in the laboratory. The lines “leaving” the SICKs laser scanners represent the matched laser scanner data and, the walls, the extracted features (remember the 2-D assumption). The robot assumed that its initial position is the position of the global reference frame {W} and started to move around to explore the environment, following the wall and trying to “close” all chains of the environment. The exploration ended on Step 18. It is possible to observe that on Step 15 there is a big area of non-matched data, i.e. signals of the rear laser scanner that the EKF could not match with previous observations.

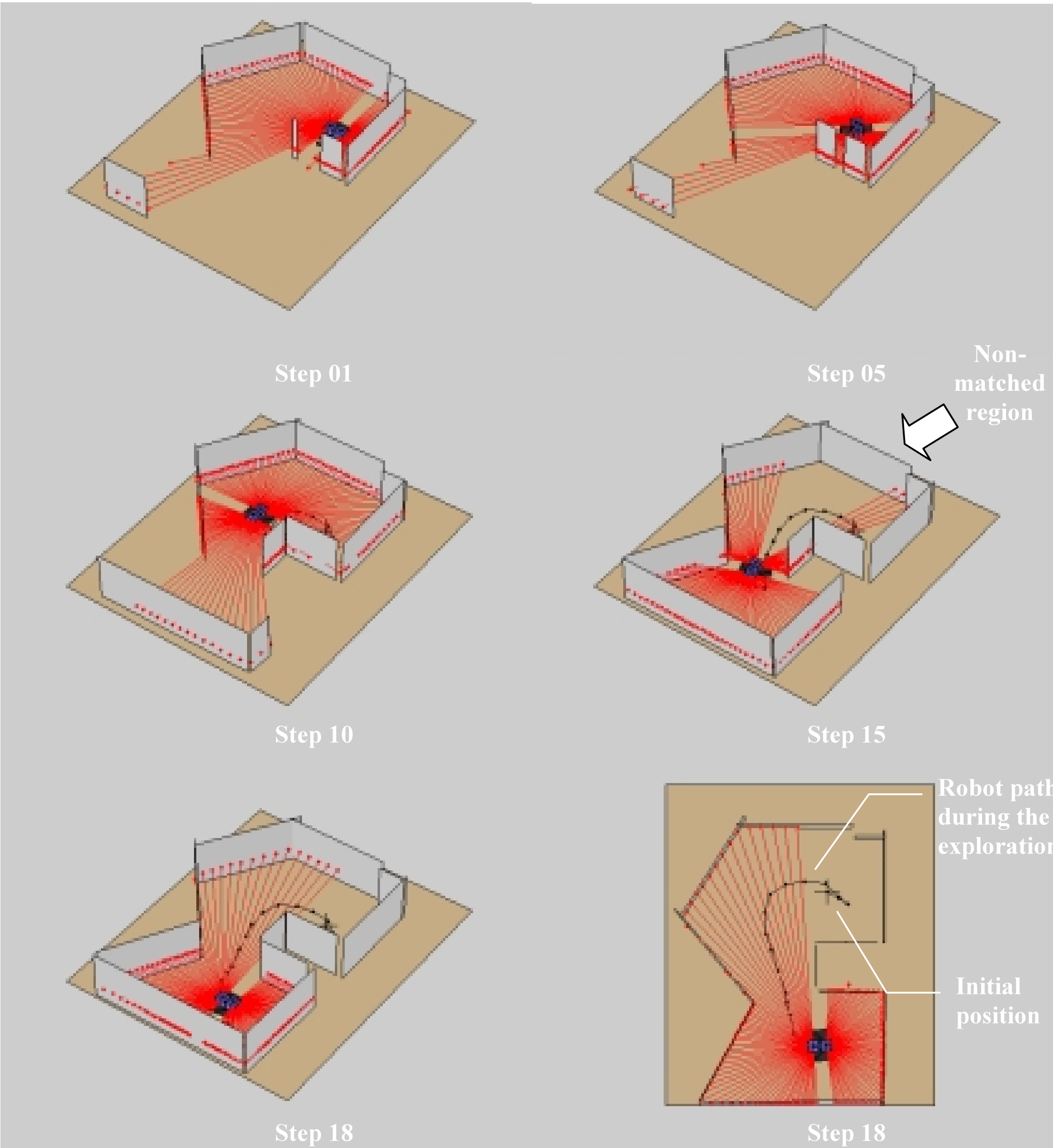
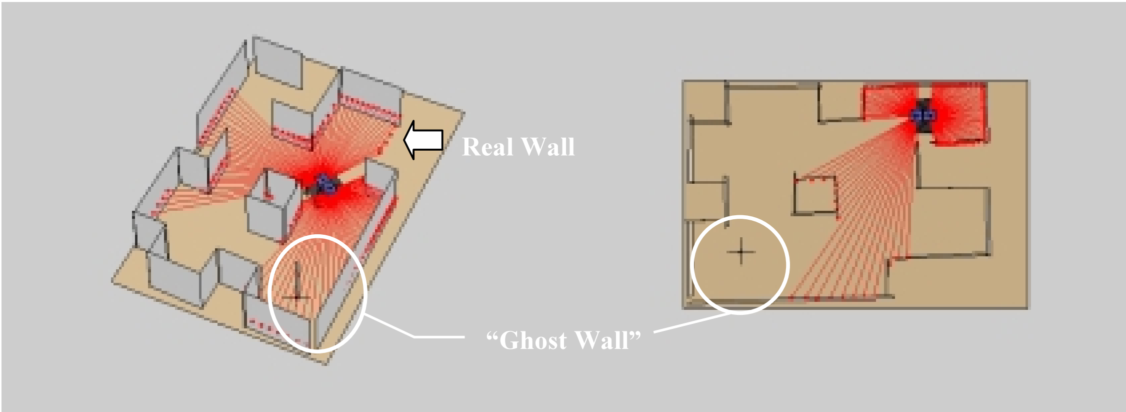


Figure 5 – Sequence of steps during a real exploration of an environment. See that in step 15, there is a big non-matched region behind the robot.

The Figure 6 shows an example of a more complex environment built in the laboratory, where the simplifications of the EKF produced “ghost features”. Figure 7 shows the matched walls and the position uncertainty of the robot during the exploration phase. Observe in Figure 7 that only 3 walls were matched (18, 40, and 43). The use of the complete EKF would solve these problems.



(a) (b)

Figure 6 – (a) Detail of the "ghost wall" during the exploration of the environment and (b) the final map of the environment, the "ghost wall" was not deleted from the map.

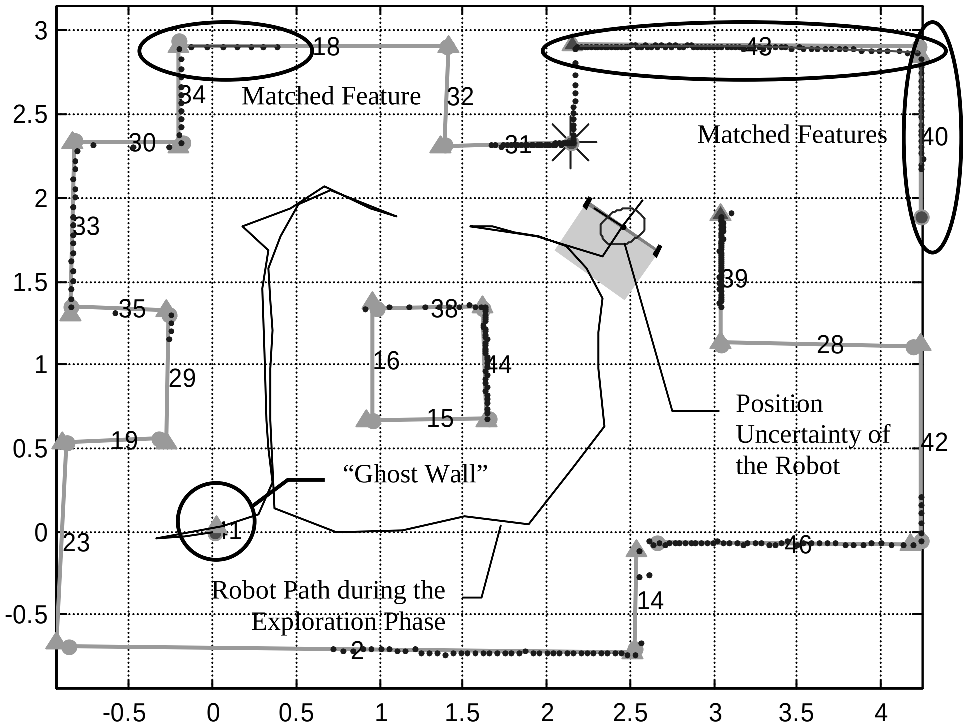


Figure 7 – Details of an exploration step using the simplifed EKF when the robot was driving to explore the non-closed area. The dots represent the raw data (scan data).

5. CONCLUSIONS AND OUTLOOK

Researches on Map-Building approach for mobile robots were developed. Our approach uses an algorithm for line and segment extraction and a simplified EKF (Extended Kalman Filter) for localization. We implemented this approach on a real platform, the mobile robot SmartROB-2, equipped with two SICK Laser Scanners and the real-time system XOberon. The entire framework was developed such that a fully autonomous system can execute the Map-Buildibg procedure without any off-board, off-line or post-processing procedures to get a pratical environment model.

The results obtained were encouraging, nevertheless some problems were found due to the simplifications adopted. To save computational time we used a simplified EKF and all the cross-variance matrices were neglected. This option caused an increment on the position uncertainties and thus, difficulties to match the sensor data. Solutions have been discussed with other researchers and we have some options to overcome the problems found: the implementation of the complete EKF, or the use of other kind of Filter for localization (e.g. the Condensation Algorithm, Meier & Ade, 1999).

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