Goal Directed Reactive Robot Navigation with Relocation Using Laser and Vision *

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Abstract

This paper presents a method to perform a goal directed reactive navigation in unknown indoor environments. Two sensors cooperate to accomplish this task: trinocular vision and 3D laser rangefinder. Trinocular vision selects the initial goal location for the navigation task. Laser is used to accomplish a reactive navigation to avoid the obstacles. Laser is also used to periodically relocate the goal with respect to the robot, so the dead-reckoning drift is compensated. An Extended Kalman Filter is used to solve the data association problem and to perform the goal relocation while the robot navigates. Experimental results involving a real mobile robot are presented, validating the proposed method.

Keywords: *Mobile Robot Navigation, Robot Relocation, Vision and Laser Cooperation, Extended Kalman Filter.*

1 Introduction

Potential field based techniques are often used for mobile robot navigation purposes. In [2] some limitations of potential based methods are described, in particular the difficulty to go through narrow spaces between obstacles (e.g., door frames). Recent works [4] improve and adapt the classical reactive navigation potential field techniques. Moreover, several recent works solve the problem of accurately locating a mobile robot in indoor environments, by continuously fusing the information of several kinds of sensors to build geometric maps [3]. In [9] a technique based on evidence grids is proposed for continuous robot location, correcting the odometry information, but using an a priori map of the environment. There have been efforts to perform safe autonomous navigation using only trinocular stereo vision systems [7], but using specialized processors (DSP, transputers). In [10] a neural networks based robot location from landmarks –such as doors– is described, but a time consuming learning step is highlighted as its inconvenient.

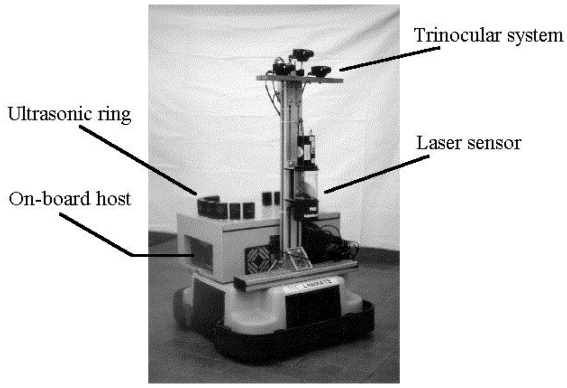

Figure 1: Location of laser and trinocular vision systems on our Labmate robot.

In this work a cooperation between complementary sensors to achieve a real time navigation is presented. No a priori information about the environment is used, and no dense maps are built while the robot moves (only relevant landmark locations are included in the map). A stereo vision system obtains a 3D geometric reconstruction of the scene, useful to locate several significant features, which allow the robot to plan a navigation task. The features considered in this paper are the doors present in the scene. Additionally, a laser rangefinder sensor provides simple and precise information that is processed in real time. We use the laser information for: a) performing a reactive navigation using a potential field technique [5]; and b) periodically reestimating the goal location using data association, while the robot moves. The problem of

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passing through a narrow passage has been solved by estimating its center to accurately place an intermediate goal. The goal is reestimated with respect to a reference associated to the robot, which is enough to perform the navigation. Moreover, these periodic reestimations allow to reduce the accumulated location errors due to the odometry drift. Hereinafter, the process to reestimate the goal with respect to a reference associated to the robot will be simply referred as *the relocation process.*

In section 2 we present the robot platform and its sensorial system. The technique to detect and locate a high-level feature from the vision system is briefly presented in section 3. The proposed technique to obtain the relocation of the feature while avoiding obstacles is explained in section 4. In section 5 experimental results are presented, which show how the cooperation between the two sensors improves the navigation task. Some conclusions and future works are related in section 6.

2 The robot and its sensorial system

The Labmate robot is a differentially driven mobile robot (developed by Helpmate Robotics, Inc). It has two active and four passive wheels. Its maximum speed is 1 m/sec. A control software has been developed to have a controller from an on-board host computer.

The stereo trinocular system is composed of 3 CCD monochrome cameras connected to each of the RGB inputs of a color frame grabber, so the three images are simultaneously taken. The 3D *lidar* laser rangefinder (Helpmate), radially scans the environment around the robot. The maximum range is 6.5 meters, and the accuracy of the distance measurement is 2.5 cm irrespective of the distance to the target. The location of the trinocular vision system and the 3D laser sensor on the robot structure can be viewed in Fig. 1.

3 High-level feature location

Due to the limited range of the laser sensor, the only way to locate some features placed far from the robot is using the vision system. Using the trinocular system on board the robot, a straight segment based 3D reconstruction of the scene is achieved. The reconstruction technique uses a probabilistic model to represent the location of the segments. Each segment is represented by a reference system attached to it, and by a covariance matrix representing its location uncertainty. To find a high level feature, such a door as presented in this paper, the system looks for a door pattern in the 3D reconstruction. The uncertainty information associated to each segment is used to find the pattern, also defined up to an uncertainty level. In the matching process to find the door, several unary and binary geometric constraints are verified, using tests based on the Mahalanobis distance to accept or reject hypotheses, following the formalism proposed in [8]. The whole process is summarized in the following steps:

1. Segments in the three gray-level images are detected.

2. Matching and 3D reconstruction are computed using the trinocular algorithm proposed in [6].

3. Small or non-vertical 3D segments are removed.

4. Pairs of 3D vertical segments whose distance belongs to an interval compatible with the width of a typical door are selected; thus, each selected pair is a possible door.

5. Possible doors which have a horizontal 3D segment over it are definitely considered as a door in the scene.

6. To test if the door is open or closed, the existence of a horizontal 3D segment at the door bottom is considered. Since this step is no so reliable as previous ones, the laser sensor is used to verify the door status when the robot is close to it.

This algorithm has been tested in indoor environments including corridors and rooms. As a result, the system locates 50% of the visible doors. The rest of the doors have not been detected due to bad illumination conditions, or have been imprecisely located and are considered as *bad* doors. Precision in the door location is about 10 cm in depth and 4 cm in its perpendicular direction. The precision decreases with the distance from the robot to the feature.

Finally, the system obtains one open door in the room, whose location $\mathbf{x}_0$ and location uncertainty covariance matrix $\mathbf{P}_0$ are used as initial values in the following navigation and relocation processes, explained below. It must be noted that other high-level features, such as corridors, intersection between corridors, etc., could be located from the 3D reconstruction, and then used for path planning purposes.

4 Continuous feature relocation

The task the robot must accomplish can be defined as follows: from any initial location in a room, it must pass through an open door, while avoiding obstacles

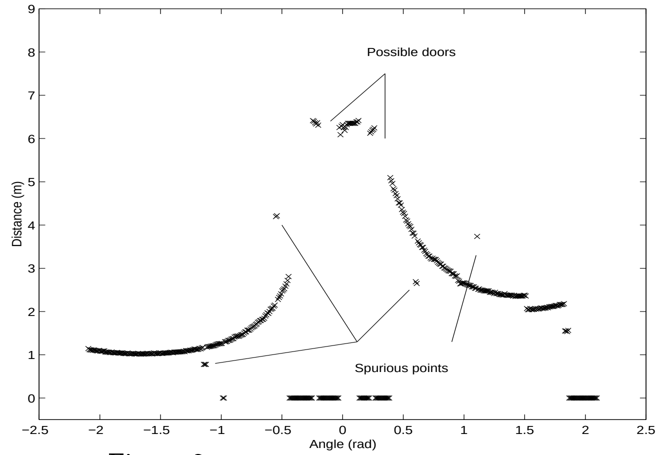

Figure 2: Laser scan information ρ vs. θ

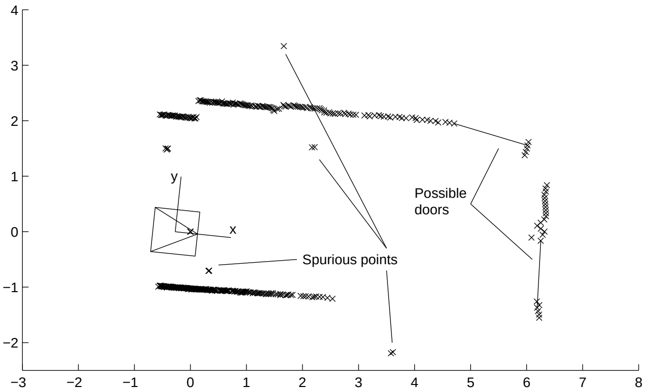

Figure 3: Scan obtained from an experimental location.

and relocating the door. There is no *a priori* information of the environment. The first step is to use the trinocular vision system to detect and obtain a first estimation for the door location, as described in the previous section.

Once the door location has been estimated, a goal beyond the door is computed, and a reactive navigation based on the laser information is performed, driving the robot towards the goal. The reactive navigation is based on artificial potential fields techniques: an attractive force is exerted by the goal, while repulsive ones are exerted by obstacles (and since there is no *a priori* information, walls are also considered as obstacles). The information provided by the laser is used both to perform the reactive navigation and to periodically relocate the feature with respect to the robot. To speed up the information processing required for navigation, only some points around the robot are used to compute the repulsive forces: the environment is scanned every 0.1 sec., this scan is sectored, and one representative point for each sector is selected. Since the scans are taken while the robot moves, the location of the selected points are updated using: a) the robot internal state information (location, and both linear and angular velocities) estimated from the odometry; and b) the time at which the scan has been taken (t_{scan}). This updating process is made in two steps: 1) selected points are referred to the laser location at t_{scan}; and 2), an integration of the selected points of the last 10 scans is performed, transforming the relative location of the sensed points to the current sensor location. See [5] for details about this technique. A wall-following technique is used to exit from potential field minima.

For relocation purposes, a set of possible features –doors, in this case– are detected from the laser information, and the nearest to the previous location estimation is selected by means of a probabilistic data association method. Thus, there are two main steps in the process to relocate the feature. First, a set of *holes* are detected in a planar scan (section 4.1). Then, a data association method is applied to perform the matching process (section 4.2).

4.1 The hole detector

The first step is to obtain a set of holes from the available environmental information. The aim in this phase is to make the simplest laser information processing that could serve to obtain a set of holes, from which a new door location could be obtained in the second phase. The low computation load of this phase allows to implement this method in real time on the mobile robot. This process is carried out as follows:

Scan acquisition. The laser sensor scans the environment at different elevation angles. In spite of this, the laser controller gives the data projected on a horizontal plane. One out of ten scans has an elevation angle between 0 and 7 degrees, which makes it useful to obtain the set of holes; this kind of scans will be called *quasi-planar* scans. The laser provides a quasi-planar scan every second, and all its points are corrected for the feature relocation task, in a similar way to the correction made for navigation purposes –in this case only selected points are corrected (see above).

Scan filtering. Fig. 2 shows a typical quasi-planar scan. Each scan consists of a set of points in polar coordinates (ρ, θ) with respect to the laser sensor reference; when the laser beam does not return, it sets $\rho = 0$; these points can be considered to be more distant than the maximum laser range. First a distance filter is applied: this avoids to take into account the environment beyond the door, because this can confuse the *hole detector*. The distance used as reference

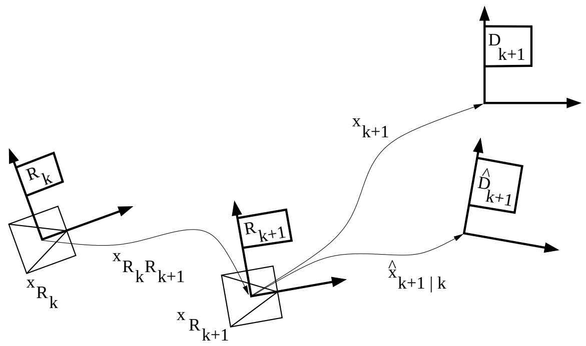

Figure 4: References used in the relocation process. R $\Rightarrow$ robot, D $\Rightarrow$ door

Figure 5: One image from the trinocular system.

is the distance between the robot and the door edges, which is estimated from the previous door location relative to the robot, and from the odometry system (though the odometry system has a drift, the travelled distance between two consecutive relocations is short, and the precision obtained is enough to accomplish the task). Since one of the scan component available is the distance ρ, this algorithm is extremely fast.

Due to reflections and other problems, isolated points can appear in the scan (see Fig. 3). These isolated points are considered spurious and are removed using a median filter applied to the distance component ρ of the scan, in a similar way as the one used in computer vision to filter the *salt-and-pepper* noise.

Hole detection. A hole is defined as a set of consecutive measurements with $\rho = 0$. Obviously, not all the holes are valid candidates to be a door, and distance between the extreme points that delimit each hole is computed to reject all the holes that are not within a width interval. It must be noted that with this simple method there is not needed to apply any kind of segmentation process to the sensorial information.

4.2 The relocation process

Once the set of possible doors has been detected, there is a data association problem that must be solved: only one hole must match the previous estimation for the door –it is even possible that none of the holes match the door. The data association problem is solved using an Extended Kalman Filter (EKF), with its three typical phases: prediction, matching and updating [1]. The variable estimated by the EKF is the location of the door relative to the robot, $\mathbf{x} = \mathbf{x}_{RD} = (x, y, \phi)^T$. In Fig. 4 the relative locations involved in the algorithm are shown. The state equation is:

$$\mathbf{x}_{k+1} = \ominus \mathbf{x}_{R_k R_{k+1}} \oplus \mathbf{x}_k \tag{1}$$

being $\oplus$ and $\ominus$ the location vector composition and its inverse, and where $\mathbf{x}_{R_k R_{k+1}}$ is taken from the odometry (see Fig. 4). And the measurement equation is:

$$\mathbf{x}_{R_k D_k} = \mathbf{x}_k \tag{2}$$

where the measurement $\mathbf{x}_{R_k D_k} = \mathbf{x}_{R_k L_k} \oplus \mathbf{x}_{L_k D_k}$, $\mathbf{x}_{R_k L_k}$ is the location of the laser sensor relative to the robot reference –that is constant and known–, and $\mathbf{x}_{L_k D_k}$ is the measured location for the door, relative to the laser reference.

EKF initialization. The vision system provides both an initial estimated location for the door $\mathbf{x}_0$, and an estimation for the geometric uncertainty with which the door has been detected –that is represented through a covariance matrix, $\mathbf{P}_0$ (see section 3).

Prediction. The prediction stage follows the next equations:

$$\hat{\mathbf{x}}_{k+1|k} = \ominus \mathbf{x}_{R_k R_{k+1}} \oplus \hat{\mathbf{x}}_{k|k} \tag{3}$$

$$\mathbf{P}_{k+1|k} = \mathbf{P}_{k|k} + \mathbf{F}_k \mathbf{Q}_k \mathbf{F}_k^T \tag{4}$$

where $\mathbf{P}_k$ is the covariance matrix that represents the uncertainty of $\mathbf{x}$, $\mathbf{Q}_k$ is the covariance matrix that represents the uncertainty of $\mathbf{x}_{R_k R_{k+1}}$, and $\mathbf{F}_k$ is the matrix that translates this uncertainty to the robot reference at $k+1$,

$$\mathbf{F}_k = \mathbf{J}^{-1}\left(\hat{\mathbf{x}}_{k+1|k}\right) \mathbf{J}^{-1}\left(\mathbf{x}_{R_k R_{k+1}}\right) \tag{5}$$

where $\mathbf{J}$ is the jacobian matrix to deal with the change in the base reference:

$$\mathbf{J}\{\mathbf{x}\} = \begin{pmatrix} \cos\phi & -\sin\phi & y \\ \sin\phi & \cos\phi & -x \\ 0 & 0 & 1 \end{pmatrix} \tag{6}$$

Matching and updating. A nearest neighbor matching process is performed in order to select the *hole* –if one exists– that corresponds to the door which location must be estimated. The matching process uses a probabilistic test: the hole with smallest Mahalanobis distance is matched with the predicted door location (only if this distance is less than a threshold).

From the measurement equation 2, the innovation is computed as follows:

$$\boldsymbol{\nu} = \mathbf{x}_{R_{k+1}D_{k+1}} - \hat{\mathbf{x}}_{k+1|k} \tag{7}$$

where the operator − has been used in place of the operator ⊖ since the equation has been linearized. From the innovation, the Mahalanobis distance is computed as follows:

$$\mathcal{D}^2 = \boldsymbol{\nu}^T \mathbf{S}_{k+1}^{-1} \boldsymbol{\nu} \tag{8}$$

where $\mathbf{S}_{k+1}$ is the covariance matrix associated to the measurement prediction, computed as:

$$\mathbf{S}_{k+1} = \mathbf{P}_{k+1|k} + \mathbf{G}_{k+1}\mathbf{R}_{k+1}\mathbf{G}_{k+1}^T \tag{9}$$

In this equation, $\mathbf{R}_{k+1}$ is the covariance matrix associated to the measurement –that is obtained from the sensor measurement characteristics–, and

$$\mathbf{G}_{k+1} = \begin{pmatrix} \cos\phi & -\sin\phi & 0 \\ \sin\phi & \cos\phi & 0 \\ 0 & 0 & 1 \end{pmatrix} \tag{10}$$

is used to translate the measurement uncertainty from the associated to the door location (D in the Fig. 4) to the robot location.

Since –under linear-Gaussian assumptions– the Mahalanobis distance follows a chi-square probability density with 3 d.o.f., the statistical test for accepting the data association is that $\mathcal{D}^2 \leq a$, where a can be found in the chi-square tables ($a = \mathcal{D}^2_{n=3,\alpha}$).

Only if a hole matches the door location estimation $\hat{\mathbf{x}}_{k+1|k}$, the rest of computations needed for the door relocation are done. This avoids to do these computations for *bad* holes, reducing the overall computation load. The new door location estimation $\hat{\mathbf{x}}_{k+1|k+1}$ after an observation $\mathbf{x}_{R_{k+1}D_{k+1}}$ has been matched is:

$$\hat{\mathbf{x}}_{k+1|k+1} = \hat{\mathbf{x}}_{k+1|k} + \mathbf{W}\boldsymbol{\nu} \tag{11}$$

and its associated covariance matrix is:

$$\begin{aligned} \mathbf{P}_{k+1|k+1} &= (\mathbf{I} - \mathbf{W})\,\mathbf{P}_{k+1|k}\,(\mathbf{I} - \mathbf{W})^T + \\ &\quad \mathbf{W}\mathbf{G}_{k+1}\mathbf{R}_{k+1}\mathbf{G}_{k+1}^T\mathbf{W}^T \end{aligned} \tag{12}$$

where $\mathbf{W} = \mathbf{P}_{k+1|k}\mathbf{S}_{k+1}^{-1}$.

If there is no valid measurement to relocate the door, the best possible estimation is

$$\hat{\mathbf{x}}_{k+1|k+1} = \hat{\mathbf{x}}_{k+1|k} \tag{13}$$

$$\mathbf{P}_{k+1|k+1} = \mathbf{P}_{k+1|k} \tag{14}$$

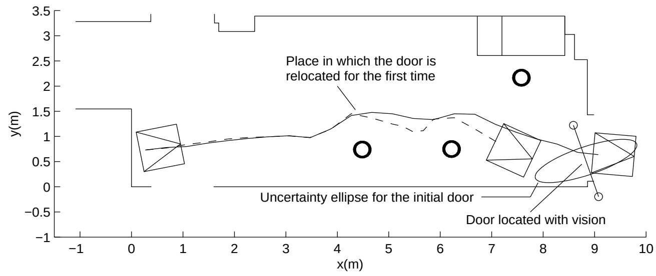

Figure 6: Experimental trajectories: — with feature relocation, and − − without it.

This implies a bigger uncertainty, because the robot has moved.

5 Experimental results

To validate the proposed method, the following experiment has been done. The robot is placed in a room (9×3.5 meters), close to one of its corners, and it must exit through the door located at the other end (see Fig. 6). At the initial robot location, the trinocular vision system takes three images (one of them is shown in Fig. 5), and from these images a segment based 3D reconstruction of the environment is computed. Thus, the door location shown in Fig. 6 is obtained, with the error that can be seen in the same figure, in which its uncertainty ellipse for the x and y components is represented.

Then, the robot performs a reactive navigation in order to cross the initial door provided by the vision system. The reactive nature of the navigation allows to avoid the obstacles that appear in the trajectory –like the cylinders that can be shown in the image and in Fig. 6. When the robot is close enough to *see* the door with the laser sensor (Fig. 7), the implemented algorithm is able to relocate it. For this purpose, one planar scan is obtained each second, and used to relocate the door as the robot moves at an average speed of 0.25 m/s. The location door is relocated in 16 of the 41 planar scans made in this experiment run.

Being all the relocation steps similar, let us analyze the first for which a new location door is obtained from laser readings. This is represented in Fig. 7, where the accumulated odometry drift causes the differences between the environment and the plotted laser readings. This is the most critical step on the trajectory, due to the big uncertainty associated to the door prediction, since the robot has moved ≈ 4.5 meters from the only door estimation available until this moment: the one obtained from the vision system. At this step the covariance matrix $\mathbf{P}_{k+1|k}$ associated to the prediction has grown due to the odometry drift. In spite of this,

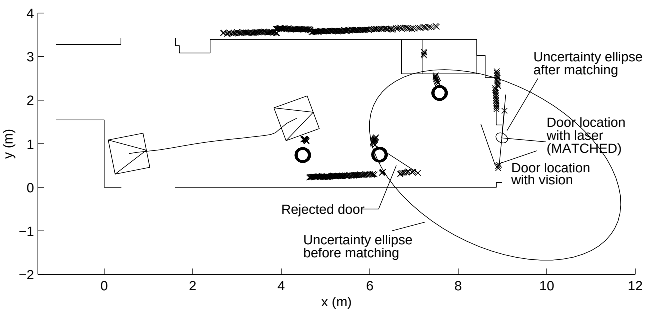

Figure 7: First door relocation.

the *bad* door is rejected, and the *good* door is matched with the previous door estimation. The Mahalanobis distance for the rejected door represented in Fig. 7 is high because of the door orientation. In this sense, a well tuned covariance model is essential to reject the measured holes that are slightly misoriented. These kind of holes, if matched, can cause the robot to cross the door from a non perpendicular direction. The robot can even bump against the door frame or can fall in a potential field minimum.

When the match between the previous door estimation and the correct hole has been done, the door location uncertainty is highly reduced –it is represented through the little ellipse in Fig. 7. Then, a goal beyond the relocated door is computed and passed to the reactive navigation task executor.

In Fig. 6 the door estimation obtained by the vision system is shown, with two experimental trajectories: one without periodic door relocation, and the other with the relocation process active. In the first the robot cannot reach the next room because it has become confused by the growing odometry drift (it has fallen into a potential field minimum) and stops.

6 Conclusions

Navigation of a mobile robot without a priori information in partially cluttered indoor environments is presented in this work. The cooperation between a fast and precise sensor (laser, with a limited scan range) with a sensor that provides geometric and semantic information (trinocular vision system, with a higher visibility range) is carried out. The vision system provides the goal location from a high level feature –a door– that is recognized and located from the 3D segment based reconstruction of the scene. The laser information is used both to perform a safe reactive navigation to the goal, and to periodically relocate the feature. The data association problem is solved using a probabilistic method (Extended Kalman Filter) that takes into account the geometric uncertainties. In this way, relocation notoriously improves the navigation task allowing the robot to pass through narrow ways, where a navigation based only on dead-reckoning fails due to the monotonically growing drift.

The proposed technique will be generalized to other typical indoor features used as landmarks, such as corridors or intersections in corridors. Thus, located features will be used as absolute references to the robot location when robot moves in the next room. In this way, a special high-level feature locations map of the environment will be built and used to reference the robot location in each step of the navigation process.

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