

Hough Transform based Localization for Mobile Robots

LUCA IOCCHI and DANIELE NARDI
Dipartimento di Informatica e Sistemistica
Università di Roma “La Sapienza”
Via Salaria 113, 00198, Roma, Italy
{iocchi,nardi}@dis.uniroma1.it

Abstract: - Knowing the position and orientation of a mobile robot situated in an environment is a critical element for effectively accomplishing complex tasks requiring autonomous navigation. Techniques for robot self-localization have been extensively studied in the past, but an effective general solution does not exist, and it is often necessary to integrate different methods in order to improve the overall result.

In this paper we present a self-localization method that is based on matching a geometric reference map with a representation of range information acquired by the robot’s sensors. The technique is adequate for indoor office-like environments, and specifically for those environments that can be represented by a set of segments. We exploit the robustness properties of the Hough Transform for recognizing lines from a sets of points in order to define an effective and robust self-localization method for dynamic environments.

We have implemented and successfully tested this method in the RoboCup environment and we believe that it has been a good benchmark for its use in office-like environments populated with unknown and moving obstacles (e.g. persons moving around).

Key-words: - Self-localization for Mobile Robots, Geomtric map matching, Hough Transform.

1 Introduction

A general problem in mobile robot navigation is knowing the robot’s pose (position and orientation) in the environment. This is a crucial feature for autonomous robots performing complex tasks over long periods of time.

Techniques for robot self-localization (see [2] for a survey) can be distinguished in the use of *relative* or *absolute* positioning methods. Each of these techniques provides good results as long as some assumption are verified. For example, dead reckoning approaches are accurate only over short runs of the robot, since error in positioning constantly increases over time. Moreover, global positioning systems and artificial landmark recognition are effective as long as the environment can be appropriately structured. Since none of these techniques provides for a global solution to the self-localization problem, it is often necessary to integrate different localization methods in order

to improve the overall result. A typical solution is to rely on dead reckoning methods (such as odometry) for a short period of time, and then to apply an absolute positioning method.

One of the most common class of methods for absolute positioning is model matching, that is the process of determining the pose of the robot by a matching between a given model of the environment (a map) and the information acquired by the robot’s sensors. Observe that these methods require an a priori knowledge of the environment (a map), but they do not require ad hoc modifications in the environment.

In this paper we present a self-localization method that is based on matching a geometric reference map with a representation of range information acquired by the robot’s sensors. The technique is quite adequate for indoor office-like environments, and specifically for those environments that can be represented by a set of segments. We exploit the properties of the Hough Transform for

recognizing lines from a sets of points, as well as for calculating the displacement between the estimated and the actual pose of the robot. We tested the approach in the RoboCup environment [1] with good results.

2 The Hough Transform

The Hough Transform is a robust and effective method for finding lines fitting a set of 2D points [5]. It is based on a transformation from the (x, y) plan (a Cartesian plan) to the (θ, ρ) plan (the Hough domain).

The transformation from (x, y) to (θ, ρ) is achieved by associating every point $P(x, y)$ in the Cartesian plan with the following curve in the Hough domain $\rho = x \cos\theta + y \sin\theta$. At the same time, a point in the Hough domain corresponds to a line in (x, y) . Notice that this is a *unique and complete* representation for lines in (x, y) as long as $0 \leq \theta < \pi$.

A graphical representation of the Hough Transform can be obtained by generating a discrete grid of the (θ, ρ) plan (let $\delta\theta$ and $\delta\rho$ be the step units), and by defining $HT(\theta, \rho)$ as the number of points in (x, y) plan whose curve lies within the interval $(\theta \pm \delta\theta, \rho \pm \delta\rho)$.

Observe that it is possible to consider a Hough grid as a voting space for points in (x, y) . In other words, every point in (x, y) “votes” for a set of lines (represented as points in (θ, ρ)), that are all the lines passing through that point. Notice that, in the case of a set of aligned points in (x, y) , the point in the Hough domain that “receives” the highest number of votes is the one corresponding to the line passing through these points.

The Hough Transform has a number of interesting properties:

1. Given a set of input points, a local maximum of $HT(\theta, \rho)$ corresponds to the best fitting line of these points. Given a set of input points originally belonging to several lines, local maxima of $HT(\theta, \rho)$ correspond to the best fitting lines for each subset of points relative to a single line.
2. With respect to other techniques for extracting segments from a set of points, the Hough Transform is very robust to noise produced by isolated points (since their votes do not

affect the local maxima) and to occlusions of the lines (since point distances are not relevant).

3. Measuring displacement of lines in the Cartesian plan corresponds to measuring distance of points in the Hough domain. Indeed, the distance between parallel lines and the angular difference between lines is given respectively by a $\Delta\rho$ and a $\Delta\theta$ between the corresponding points in the Hough domain.

3 Hough Transform based Self-Localization

The self-localization method we are going to describe applies to any robot equipped with sensors that are able to give range information about the environment. For example, ultrasonic sonars, laser range finders, stereo vision systems are different ways to measure distances of objects around the robot.

We thus consider any sensor which returns a set of points, in the local coordinates of the robot, corresponding to a surface of an object. Observe that, in general, these sensors do not allow for simple implementation of object recognition techniques and thus they often retrieve range data from objects in the map (e.g. walls in the environment) as well as from unpredicted obstacles (such as persons moving in the world).

Given this set of points acquired by the robot’s sensors and a model of the environment, we want to calculate the displacement between the estimated and the actual pose of the robot.

Under the assumption that the environment can be represented by a set of segments, and in order to exploit the properties of the Hough Transform, we address the localization problem in the Hough domain. In this way the model of the environment is represented by a set of points in the Hough domain and the range data points acquired through the sensors are transformed in the Hough plan. The map matching process is performed over points in the Hough domain and the displacement needed for a correct re-positioning of the robot is easily calculated in the Hough plan.

Summarizing, the Hough Transform based localization method consists in the following steps:

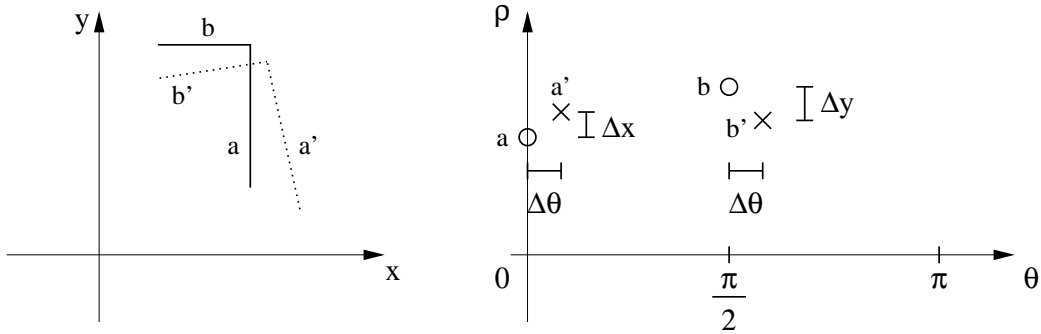


Figure 1: Map matching in the Hough domain

1. extracting range information from the environment in the form of a set of point in the (x, y) plan,
2. applying the Hough Transform to the set of points generating a discrete Hough grid $HT(\theta, \rho)$,
3. determining the local maxima by a threshold,
4. finding correspondences between local maxima and reference points,
5. measuring the displacement between local maxima and the corresponding reference points in the Hough domain.

Observe that the second step requires a discretization of the Hough plan. This parameter must be accurately tuned since when the discretization is too fine, several local maxima can be found in the same “region” of the Hough plan and this involves ambiguities in the matching process. On the other hand, the grid intervals represents a bound in the precision of positioning (larger intervals involve lower precision). Therefore, a trade-off between precision and matching ambiguities must be considered when setting the discretization of the Hough plan.

Moreover, it is important to notice that the choice of the threshold for identifying the local maxima (third step) is not a critical factor, since $HT(\theta, \rho)$ presents very high peaks in presence of aligned points and thus a percentage over the overall number of input points is appropriate for identifying the best fitting lines of a set of points.

Instead the fourth step is more critical, since in some cases it can be difficult to decide which is the correct correspondence between points. We adopt

two different strategies: (i) assuming that odometry provides for an almost correct position over a short time, the matching is performed between a local maximum and the nearest reference point; (ii) in case of ambiguities, we apply a more general procedure that acquires a greater amount of data about the environment (by integrating different sensory data) and performs an overall match between the set of local maxima and the set of reference points.

Consider the example shown in Fig. 1, where the robot faces a corner. The solid segments a , b represent the map model and the set of points a' , b' represent data coming from sensor devices. The four segments are also displayed in the Hough domain: a , b (indicated by a circle) are the reference points, while a' , b' (indicated by a cross) represent the local maxima of the Hough Transform applied to the set of input points. In the Hough domain it is easy to calculate the displacement between the estimated and the actual pose of the robot $(\Delta x, \Delta y, \Delta \theta)$.

In the example, $\Delta \theta$ is the difference $a'_\theta - a_\theta$ or $b'_\theta - b_\theta$. In ideal conditions these differences should be the same; if not, an average between these values allows for a good approximation. After the correction $\Delta \theta$ is applied to the robot's representation of the map, it is possible to calculate the other two factors $\Delta x = a'_\rho - a_\rho$ and $\Delta y = b'_\rho - b_\rho$.

In the next section we discuss an application of this localization technique in the RoboCup environment.

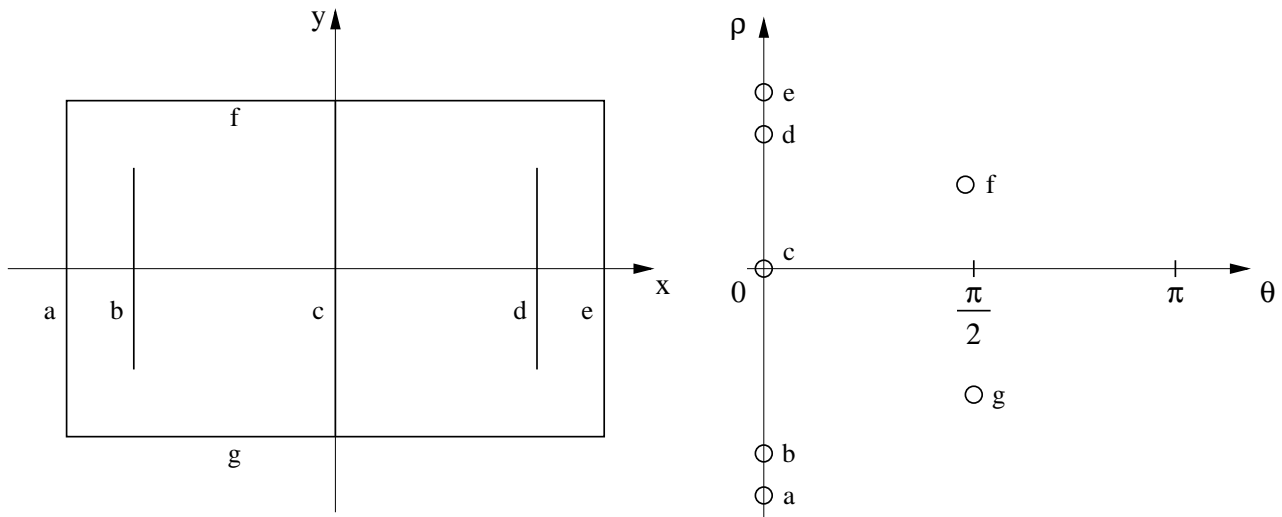


Figure 2: The RoboCup world model

4 Self-Localization in the RoboCup environment

The RoboCup competition consists of soccer matches between robotic teams [1]. Each soccer player is equipped with on-board acting and sensing devices, while global positioning systems are not allowed.

The RoboCup environment assumes the following characteristics that must be considered for the choice of localization methods: (i) the geometry of the walls delimiting the field and of the lines drawn on the field is known, (ii) the environment is highly dynamic (there are many robots and the ball moving in the field); (iii) the task must be performed continuously for a “long” time (the length of each period is 10 minutes); (iv) the environment cannot be modified; (v) crashes among robots are possible. All these factors determine a difficult scenario for localization methods. Indeed, dead reckoning methods are not effective for localization, since they accumulate errors over time and they cannot deal with crashes among players. Absolute positioning methods based on map matching must consider the high noise in acquiring range information from the environment due to other robots moving in it.

It is worth noticing that the above characteristics are very similar to those of an office-like environment delimited by walls and populated with unknown and moving obstacles (e.g. persons moving around).

In order to provide our robot soccer players with an effective and robust localization method for the RoboCup environment, we apply the Hough Transform based localization method. Because of the peculiar definition of objects properties in the RoboCup environment (the ground field is green and the walls and the lines are white), we decided to extract range information from walls and lines by using a simple color camera, a line extraction procedure, and a triangulation technique for computing the distances of points in the 2D plan around the robot.

The model of the RoboCup environment is shown in Fig. 2. We consider seven segments corresponding to the four walls a, e, f, g and the three lines b, c, d . Observe that the walls are real obstacles for the robot, while lines are drawn in the field and do not correspond to obstacles.

A self-localization task is displayed in Fig. 3. In the upper part there are the image acquired by the camera and the extracted points, while in the lower part there are local views of the robot before and after the re-positioning process. Observe that isolated noisy points (that are due to the high luminosity in the center of the image) do not affect the displacement measures. We have also verified that the method is very robust to occlusion of lines, thanks to the properties of the Hough Transform.

The performance of the system are adequate for real-time execution with a low-cost color camera and a conventional Pentium based PC, that is

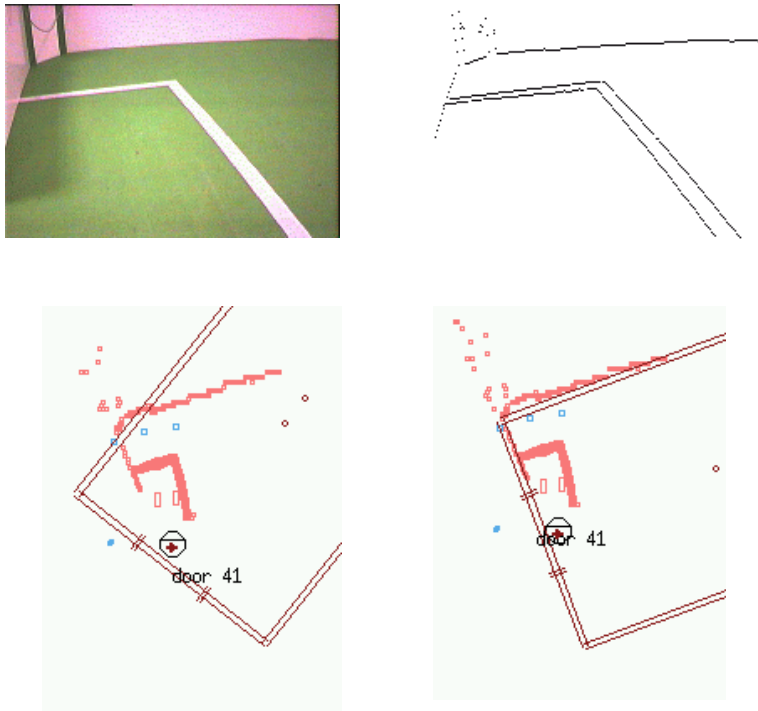


Figure 3: A Self-Localization Example

on board of the robot. In fact, in our case, most of computation time (a few tenths of second) is taken by the image processing procedure for line extraction. As for accuracy, we obtain good results with a discretization of the Hough grid (and hence an average precision) of 3 degrees for θ and of 10 cm for ρ .

5 Conclusion

Knowing the position of a mobile robot in an environment is a critical element for effectively accomplishing complex tasks requiring autonomous navigation. The localization problem has been thus addressed in the past from many different perspectives. In particular, absolute positioning methods based on map matching have been extensively studied (see [4, 10] for occupancy grid matching strategies, [8] for the angle histogram method, [3] for a probabilistic approach, [7] for scan matching techniques, and [6] for experimental comparisons).

They present different solutions that are generally robust to sensor noise, ambiguous situations, partial model description. However, in a moderately crowded and dynamic environment, map

matching based localization methods must also be robust to noise given by unknown objects sensed by range sensors. The difficulty in dealing with this kind of noise, that is typical in real environments, is that it cannot be appropriately modelled.

We have presented a self-localization technique for mobile robots in office-like environments, that is suitable with any kind of sensors able to provide range information about objects in the world. We exploit the robustness properties of the Hough Transform for defining an effective and robust self-localization method for dynamic environments. We have successfully tested this method in the RoboCup environment and we believe that it has been a good benchmark for its use in office-like environments delimited by rectilinear walls and populated with unknown and moving obstacles (e.g. persons moving around). We are working on testing the method in an actual office environment by making use of accurate range data extracted by a stereo vision system [9].

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