A Localization System Solely Based on Vision for Autonomous Lawnmowers

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Abstract

The navigation systems of commercially available autonomous lawnmowers rely on sensors measuring the magnetic field created by a perimeter wire. Some experimental systems rely on even more expensive sensing devices, like differential GPS or laser tracking systems that help locate the mowers exactly within a yard, but are considered too expensive for a domestic robot. Knowing a mower's exact position will allow for much advancement in lawn care and maintenance. For example, improved cutting quality and reduced cutting time. The navigation system that we propose requires only a standard web camera and the existence of some landmarks visually recognisable. The key idea is to induce the absolute positions of the landmarks from apparent angles derived from panoramic views taken from a few observation points. In this paper, the localization system is fully described and its accuracy is demonstrated in simulation.

1 Introduction

Navigation systems based on range sensors such as radar, GPS, laser or ultrasonic sensors [1-3] are significantly more expensive than navigation systems relying only on vision. However, obtaining accurate position estimations of a lawnmower from vision alone is still an open research problem. Navigation systems of commercially available autonomous lawnmowers [4, 5] rely on the sensing of the magnetic field created by a perimeter wire.

This paper presents a localization system for a lawn-mower which uses only a camera with a parabolic mirror to obtain a panoramic view. Because of our system does not require expensive sensors, it is low cost solution. Moreover, the method that we introduce for locating the mower is not sensitive to wheel slippage and motor vibrations.

The requirements that we set ourselves for the localization system were as follows; the system should rely only on the apparent angles of a small number of landmarks. The absolute positions of the landmarks are not available to the localization system. By absolute position of an object, we mean the coordinates of the object with respect to a Cartesian reference system with a fix origin. The only information that the lawnmower robot can access is the relative angles of the landmarks derived from the panoramic images taken by the on-board camera. We assumed also that the robot would be able to move around to collect a few observations (an observation is a panoramic view) before starting mowing.

In our system, the observations are used to induce the absolute positions of the landmarks. Given the absolute positions $(L_1, L_2, \ldots, L_n)$ of n landmarks and the absolute position R of the robot, we can compute using elementary geometry the relative angles $(a_1, a_2, \ldots, a_n)$ of the landmarks as seen from the robot (this will be sketched in Section 3). In other words, the mapping $(a_1, a_2, \ldots, a_n) = \varphi(R \mid L_1, L_2, \ldots, L_n)$ does not pose any problem. However, for practical purposes, we are interested in the inverse mapping $R = \varphi^{-1}(a_1, a_2, \ldots, a_n \mid L_1, L_2, \ldots, L_n)$. Again, this problem is easy when the exact positions

$(L_1, L_2, \ldots, L_n)$ of the landmarks are known. It is well known that when the landmarks are in general position, $n = 3$ angles are enough to determine the position R of the robot. But, for a successful and practical system, it is preferable not to assume that the exact positions of the landmarks will be known, as a user friendly solution should not require the user of the lawn-mower to perform such tedious measurements. Therefore our system will induce itself these absolute positions by first making a guess for the positions of the landmarks, and then refining this initial *hypothesis* by exploiting the observation data and minimizing a distortion error. This distortion error (that will be defined precisely in Section 2.2) is high when the landmark positions hypothesis is bad and equals zero when the landmark positions hypothesis corresponds to the real positions of the landmarks.

Section 2 reviews previous work on self-localization. Section 3 describes our proposed self-localization system based solely on apparent angles. Section 3 contains also experimental results that demonstrate the validity of our approach. Finally, Section 4 discusses future work.

2 Previous work

Typically, an omni-directional vision sensor is composed of a digital camera aiming at a catadioptric mirror [6-9]. The camera and the mirror are mounted on the top of the mobile robot's platform. The images grabbed from the sensor are orthographic projections of the ground plane. The images (obtained without rotating the robot) are 360 degree view of the environment and therefore are not sensitive to wheel slippage and small vibrations. This low cost sensing device provides enough information for our navigation system. Although it is not straightforward to obtain distance estimations from an omni-directional image due to shape of the mirror, the apparent angles of objects from the robot are relatively accurate and easy to derive from the image. Rizzi [6] proposed an omni-directional sensor with special conical reflecting surface that takes omni-directional images from artificial landmarks with different colours. Other omni-directional (catadioptric) vision systems have been used for robot navigation [6-10]. They are all inspired from the biology of insects and arthropods [11]. Delahoche [9] presented a system which merged odometry and omni-directional image data using an Extended Kalman Filter. Self-localization with such a system is efficient but the absolute positions of the landmarks in the environment must be given in advance. Moreover, odometry error due to wheel slippage affects the accuracy of the localization.

Given the absolute positions of some landmarks and readings from range sensors, a robot's position can be calculated by triangulation [12]. Unfortunately, triangulation methods require the knowledge of the absolute positions of the landmarks (or some range data).

Our system relies only on the apparent angles to estimate all objects' positions in the environment including the landmarks and the robot itself.

3 A localization system that induces the absolute positions of landmarks from a few panoramic views

3.1 The geometry of apparent angles

Three points in general position L_1, L_2 (two landmark positions) and R (a robot position) determine uniquely a circle; the locus of points from which the apparent angle between L_1 and

L_2 is equal to some constant α is the arc of a circle going through L_1 and L_2 (see Figure 1). Let R' be the point such that $R'M$ is orthogonal to the segment L_1L_2 (where M is the centre of the segment L_1L_2). If the distance d of the segment L_1L_2 is known, then the centre C of the circle and its radius r can be calculated by computing d_{90} using the fact that $\tan(\alpha)\, d_{90} = d/2$.

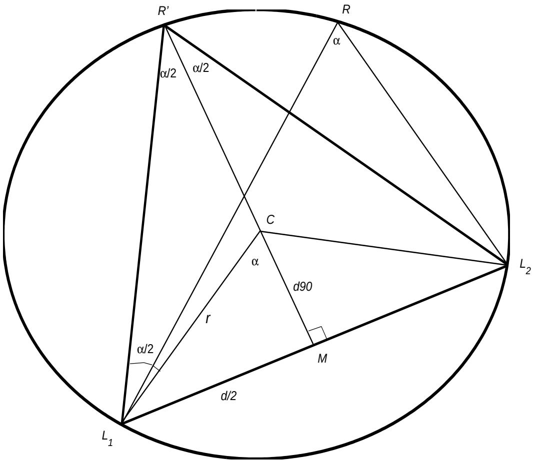

Figure 1, Locating the robot with 3 landmarks. The locus of points for which the relative angle between the two landmarks L_1 and L_2 is α is the arc of a circle passing through L_1 and L_2.

When the absolute positions and the apparent angles of three landmarks L_1, L_2 and L_3 are given, the robot's position can be estimated by considering the three circles associated with the three possible pairs of landmarks. In Figure 2, Circle 1 is associated with the pair $\{L_1, L_2\}$, Circle 2 is associated with the pair $\{L_2, L_3\}$, and Circle 3 is associated with the pair $\{L_3, L_1\}$. If the estimated landmarks' positions are correct, the three circles meet in one point and this point is the robot position. Otherwise, the three pair-wise intersections of the circles define three distinct points. The sum of squared distances between these pair-wise intersection points provides a measure of the goodness of our current hypothesis with respect to the absolute positions of the landmarks. We call this sum of squared distances the *distortion* of the hypothesis. When the hypothesis corresponds to the actual absolute positions of the landmarks, the distortion is zero.

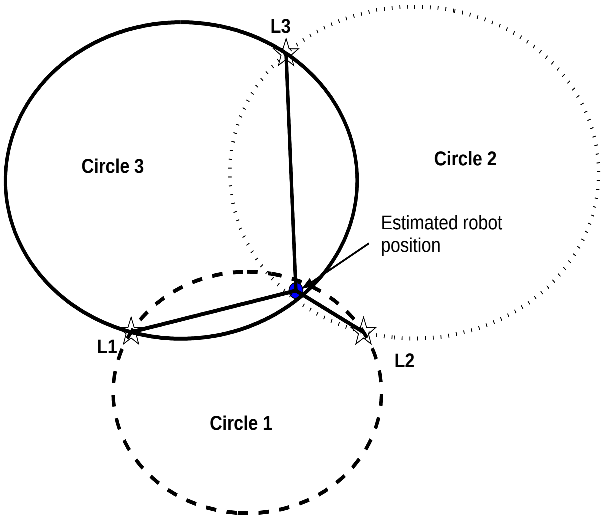

Figure 2, The estimated robot position is the mean of the pair-wise intersections of the circles.

3.2 Search for a good hypothesis

The distortion of a hypothesis $\left(L_1, L_2, \ldots, L_n\right)$ with respect to an observation $\left(a_1, a_2, \ldots, a_n\right)$ of n landmarks is the variance of $\varphi^{-1}\left(a_{i_1}, a_{i_2}, a_{i_3} \mid L_{i_1}, L_{i_2}, L_{i_3}\right)$ where $\{i_1, i_2, i_3\} \in \begin{pmatrix} \{1,2,\ldots,n\} \\ 3 \end{pmatrix}$. That is, we consider all combinations of three landmarks. For m observations of n landmarks, we consider the average distortion over the m observations.

In order to minimize the distortion, we have tried different variations of gradient descents and greedy stochastic searches. Experimental results show that a greedy stochastic search provides the best results. The parameter vector w that we optimize is the vector whose entries are the estimated absolute positions of the landmarks. Without loss of generality, we set the origin at landmark L_1, and give L_2 the position $(d,0)$. The role of the constant d is to set the scale of the robot coordinate system. The dimension of w is therefore $2(n-2)$. In the greedy stochastic search, we draw randomly a step direction h in $R^{2(n-2)}$. If the distortion at $w+h$ is lower than the distortion at w, then $w+h$ becomes our current hypothesis. We repeat this candidate hypothesis generation until the current hypothesis stops improving or the maximum number of iterations has been reached.

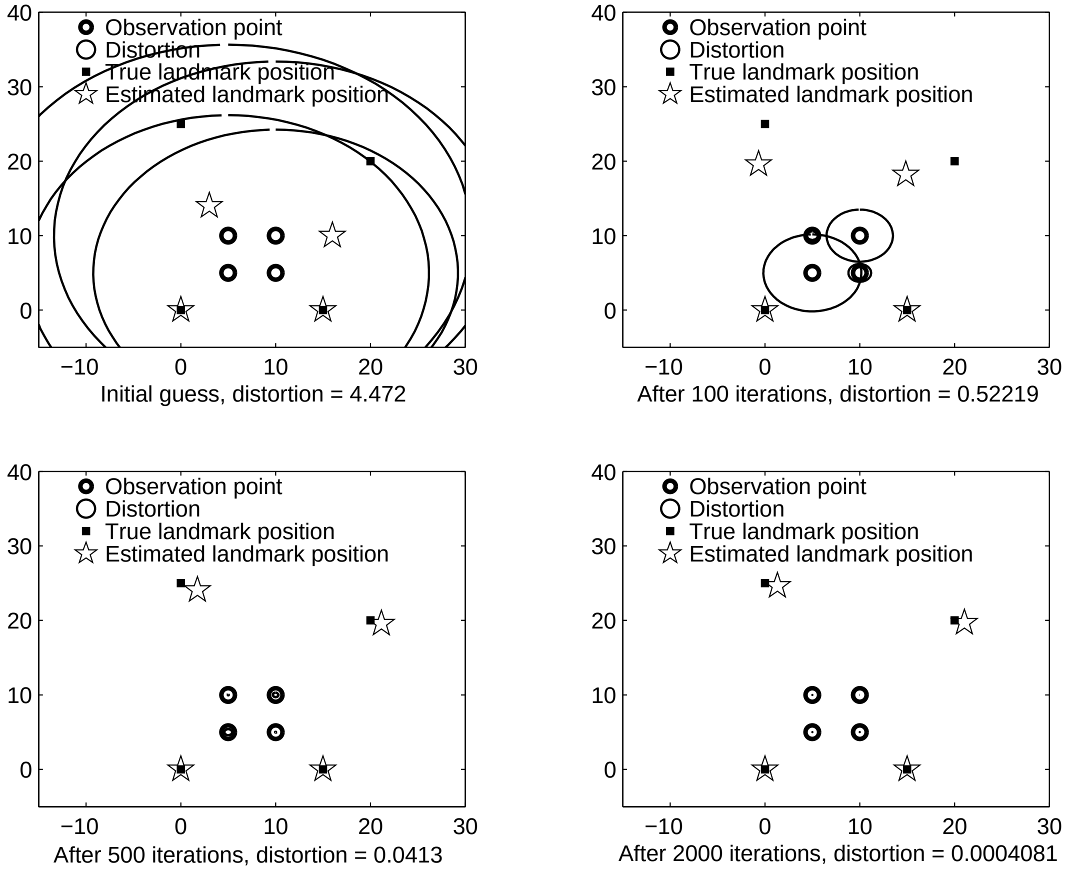

Figure 3, Stochastic greedy search of the landmarks' absolute positions.

Figure 3 represents a typical hypothesis search with 4 landmarks from 4 observations. The large circles on the first subplot are centred on the observation points and are proportional to the distortion of their respective observation. As the estimated landmarks' positions improve, the distortion becomes smaller and smaller. On the last subplot, the circles corresponding to the distortion are reduced to points. In Figure 4, the current hypothesis is used to estimate the robot positions from a test set. Again, the initial guess produces a very poor estimation of the robot positions, but as the search progresses, the estimated positions become closer to the actual positions of the robot.

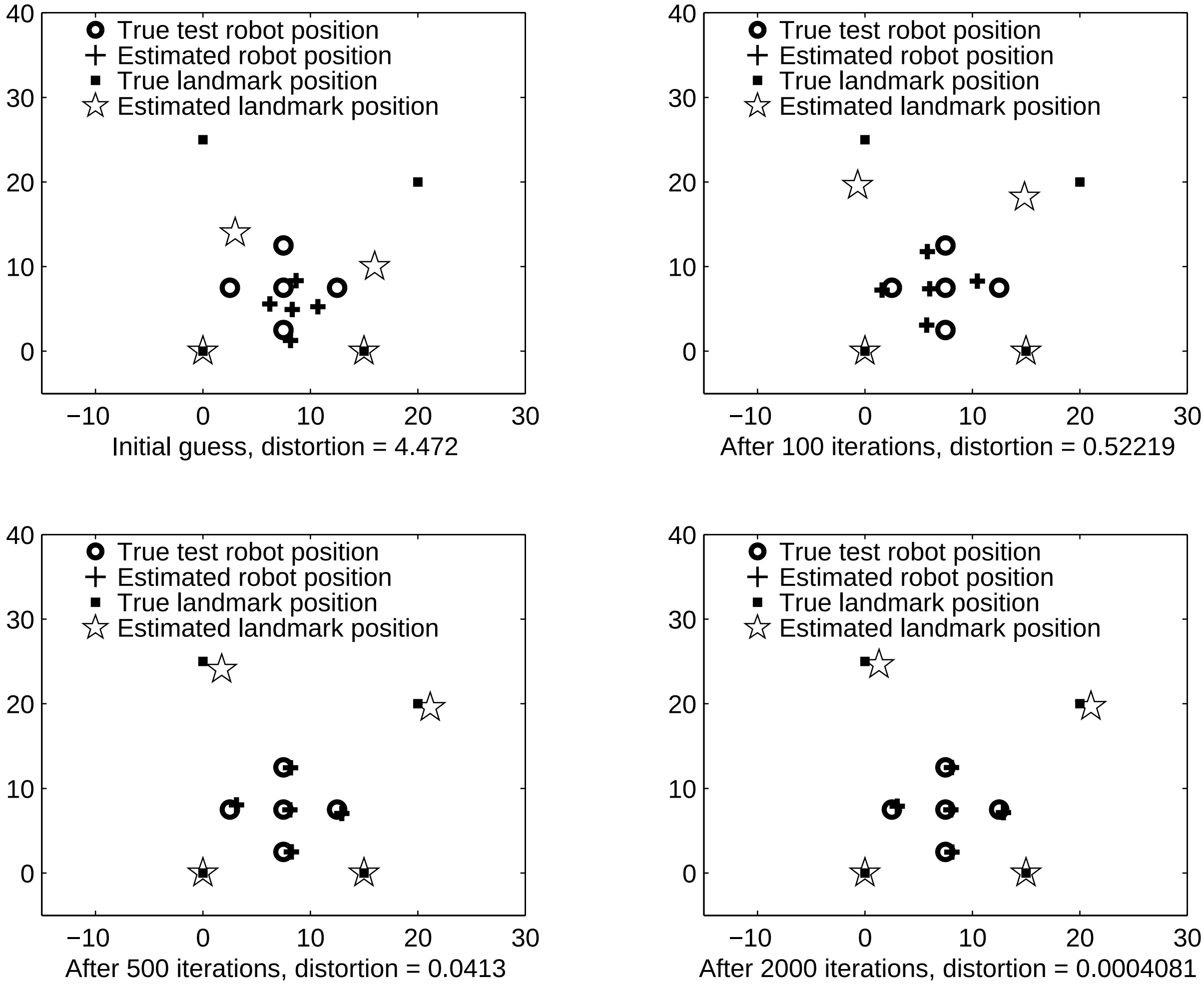

Figure 4 Evolution of the error on a test set.

For practical purposes, the distortion errors and the accuracy of the estimated positions are not significantly different if the number of observations is increased. As expected, Figure 5 indicates that annealing the step-size (that is, reducing its magnitude with time), will return better hypotheses more rapidly.

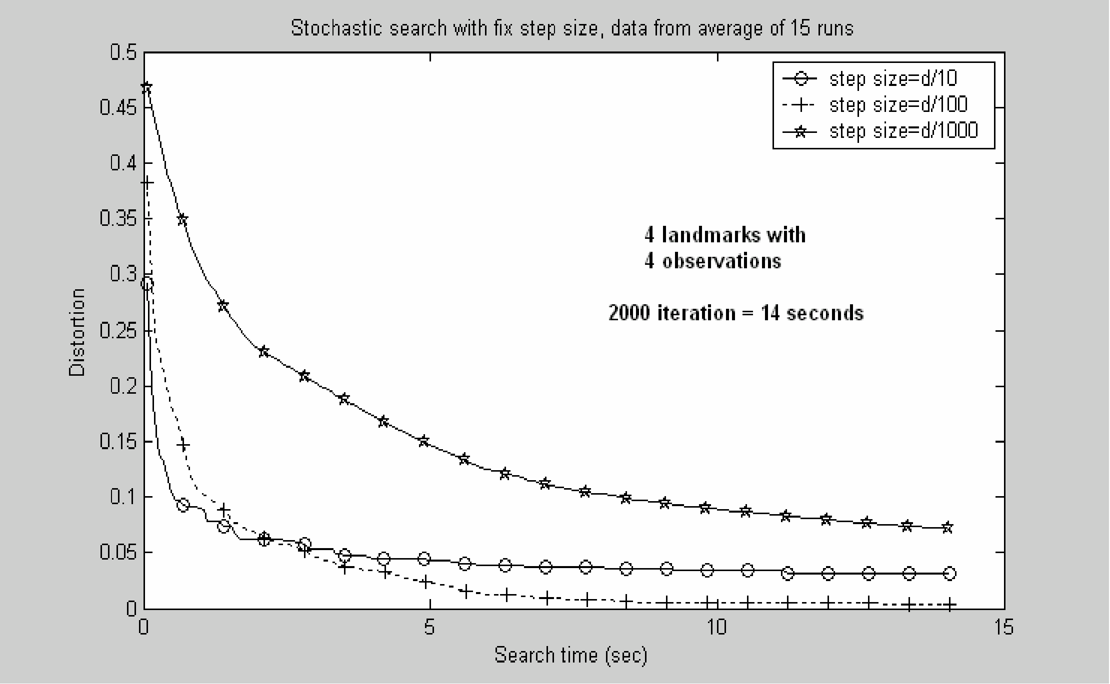

Figure 5, Distortion versus step-size.

4 Conclusion and future work

The induction of the absolute positions of landmarks gives enormous flexibility to our localization system. This learning capability spares the lawnmower's user a tedious calibration process. Most importantly, our localization system does not require a perimeter wire. The mowing strategy that iMow [5] uses can be adapted to our localization system. The user could define implicitly the zone to be mowed by moving the robot along a virtual (immaterial) perimeter. By trimming along the perimeter first, iMow edges the "mowing zone". When edging is done, the mower cuts the rest of the lawn in a triangular pattern.

We plan to test our system on a real robot and experiment with different cutting strategies. The technique introduced in this paper can also be adapted to vacuuming robots. However, the large number of occlusions in indoors environments will require the use of a network of local maps.

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