A Direct Localization Method Using only the Bearings Extracted from Two Panoramic Views Along a Linear Trajectory

Henry Huang, Frederic Maire, and Narongdech Keeratipranon

Faculty of Information Technology
Queensland University of Technology
Box 2434, Brisbane Q 4001
Australia
h5.huang@student.qut.edu.au, f.maire@qut.edu.au,
n.keeratipranon@student.qut.edu.au

Summary. To operate successfully in any environment, mobile robots must be able to localize themselves accurately. In this paper, we describe a direct method (in the sense it does not use an iterative search) based on vision for localizing a mobile robot in an environment with only two observations along a linear trajectory. We only assume that the robot can visually identify landmarks and measure their bearings. Contrary to other existing approaches to landmark based navigation, we do not require any other sensors (like range sensors or wheel encoders) or the prior knowledge of relative distances between the landmarks. Given its low cost, the range of potential applications of our localization system is very wide. In particular, this system is ideally suited for domestic robots such as autonomous lawn-mowers and vacuum cleaners.

1 Introduction and Related Research

Conventional SLAM (Simultaneous Localization and Mapping), involves fusing observations of landmarks with dead-reckoning information in order to track the location of the robot and build a map of the environment [3]. Robustness to noise in the sensors can be achieved with probabilistic methods such as Extended Kalman Filters [12, 5] or Particle Filters [9]. Navigation systems based on range sensors such as radar, GPS, laser or ultrasonic sensors are significantly more expensive than navigation systems relying only on vision [2, 6, 7]. Because of this high cost, navigation systems of commercially available autonomous lawnmowers rely on sensors measuring the magnetic field created by a perimeter wire [11, 13]. Some experimental systems work with more expensive sensing devices, like differential GPS or laser tracking systems that help locate the mowers exactly within a metre, but are considered too expensive for a domestic robot.

An omni-directional vision sensor is composed of a digital camera aiming at a catadioptric mirror. Although it is not straightforward to obtain distance estimations from omni-directional images due to the shape of the mirror, the bearings of landmarks relative to the robot are reasonably accurate and easy to derive from omni-directional images [10, 14, 4].

A localization system relying only on landmark bearings is highly desirable. A recent approach [8] uses an iterative search method to induce the absolute positions of the landmarks using only the bearings of three or more landmarks derived from panoramic views taken from a set of random observation points. The search is performed by minimizing a distortion error which measures the inconsistency of the hypothesized positions of the landmarks and the observation points. However, this iterative search does not guarantee to return the global minimum. The method that we propose in this paper does not require an iterative search, but directly computes the relative Cartesian coordinates of the landmarks and the observation points. The only extra requirement that we make is that the robot should be able to move in a straigth line and make two observations to extract the bearings of two landmarks L_1 and L_2. This requirement is satisfied by wheeled robots even if they do not have wheel encoders. Compared to [8], our system is more practical as it requires fewer landmarks (only two), and does not need a training set of observations.

To the best of our knowledge, the system we propose is the first robot navigation system capable of localizing itself with only the bearings of two landmarks. Such a system will be invaluable to an indoor robot as well, as the bearings of the sides of a door frame can play the roles of the landmarks L_1 and L_2 and tell the robot exactly where it stands relative to the door. The localization method we propose can be integrated into hybrid navigational systems [1] for outdoors urban environments. These systems rely on a vision system that use local landmarks to determine a vehicle's location, when external signals from beacons, radio signals or the satellite-based global-positioning system (GPS) are not available.

Section 2 describes the localization system. In Section 3, we present experimental results. Finally, in Section 4, we discuss future work.

2 Proposed Approach

In this section, we show how to compute from landmark bearings the Cartesian positions of two observation points O_1 and O_2 relatively to two landmarks L_1 and L_2. We consider two right-handed coordinate systems, B_L and B_R as shown in Figure 1. In B_L, the coordinates of L_1 and L_2 are respectively $[0\ 0]^T$ and $[1\ 0]^T$. Similarly, in B_R the coordinates of R_1 and R_2 are respectively $[0\ 0]^T$ and $[1\ 0]^T$. The distance $\|L_1 - L_2\|$ is taken as unit measure for the localization system. In order to describe our solution we need to introduce some notation. The line going through two points A and B will be denoted by $\mathcal{L}(A, B)$, and α_i^j will denote the bearing measured at O_i with respect to

L_j. See Figure 1(b). The position in B_R of L_j is computed as the intesection of the two lines $\mathcal{L}(O_1, L_j)$ and $\mathcal{L}(O_2, L_j)$. The line equations of $\mathcal{L}(O_1, L_j)$ and $\mathcal{L}(O_2, L_j)$ are obtained from the bearings α_1^j and α_2^j, using the fact that in B_R, we have $\|O_1 - O_2\| = 1$. Once we have the coordinates of L_1 and L_2 in B_R, we can determine the affine transformation that relates the coordinates X_{B_R} and X_{B_L} of a point X in the two coordinate systems B_L and B_R. That is, an expression of the form $X_{B_L} = A * X_{B_R} + b$. The coordinates of O_1 and O_2 in B_L are then easily derived.

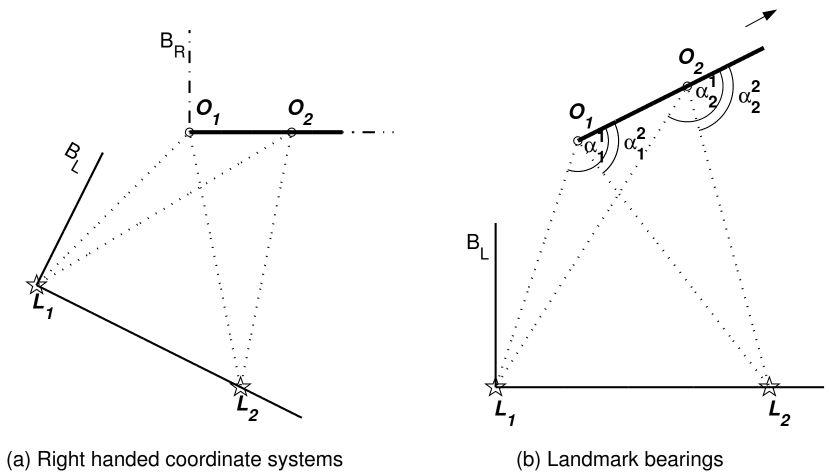

Fig. 1. From the bearings of two landmarks observed at points O_1 and O_2, the coordinates of L_1 and L_2 in B_R are computed. Then a simple change of coordinates gives the coordinates of O_1 and O_2 in B_L.

In order to determine the relative position of a landmark, this landmark should not be on the line $\mathcal{L}(O_1, O_2)$. For example, if L_1, O_1 and O_2 are on the same line, then $\mathcal{L}(O_1, L_1) \cap \mathcal{L}(O_2, L_1)$ is not a single point but a whole line.

Experiments in simulation and on a real robot (see Section 3) indicate that the accuracy of the localization system is sensitive to the relative the difference of bearings.

Figure 2 shows that $d_o = d * \sin(\alpha_2^2) = e * sin(\beta)$, where $\beta = \alpha_2^2 - \alpha_1^2$, d_o is the distance between L_2 and $\mathcal{L}(O_2', L_2')$, and $d = \|O_2 - O_2'\|$. We have $e = \frac{d*\sin(\alpha_2^2)}{\sin(\beta)}$. When the angles are small, the ratio $\frac{e}{d}$ will be approximately equal to $\frac{\alpha_2^2}{\alpha_2^2 - \alpha_1^2}$. That is, the position error ratio will be approximately equal to the inverse of the relative change of the bearings. This result confirms our intuition that a large relative change in bearings should give a more accurate position estimate.

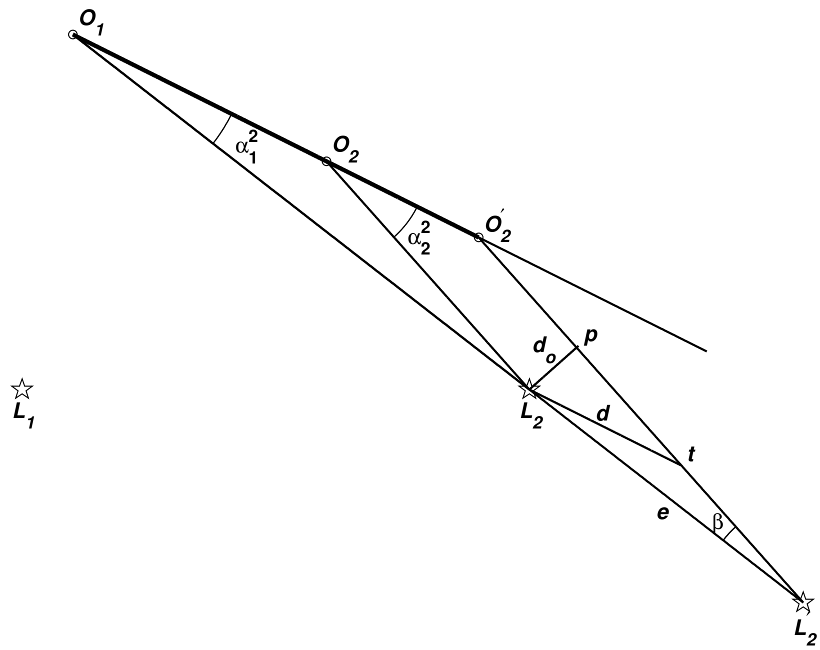

Fig. 2. The error e in the estimated position of L_2 depends on the relative difference in bearings.

3 Empirical Evaluation

Our localization technique was evaluated on a Khepera robot equipped with a color camera (176 x 255 resolution). The error between the measured and actual bearing is about $\pm$ 2 degrees. In the experiment, the second landmark was placed 20 centimetres away from the first landmark. Four different starting positions have been used, and 20 trials at each position have been conducted. The moving distance in all cases was 30 centimetres. The moving direction was Westwards parallel to the landmarks. The experiment results are shown in Figure 3. In this figure, landmarks are denoted by stars, trajectories are shown as arrows, and the estimated positions by our localization method are displayed as scatter points.

The localization error, average distances between the estimated positions and the actual positions, at position a, b, c, and d (in Figure 3) were respectively 0.6, 1.2, 2.2, and 2.8 centimetres. The errors are small compared to the diameter of the robot (6 centimetres). Other experimental results have confirmed that the error is inversely proportional to the relative difference in bearings.

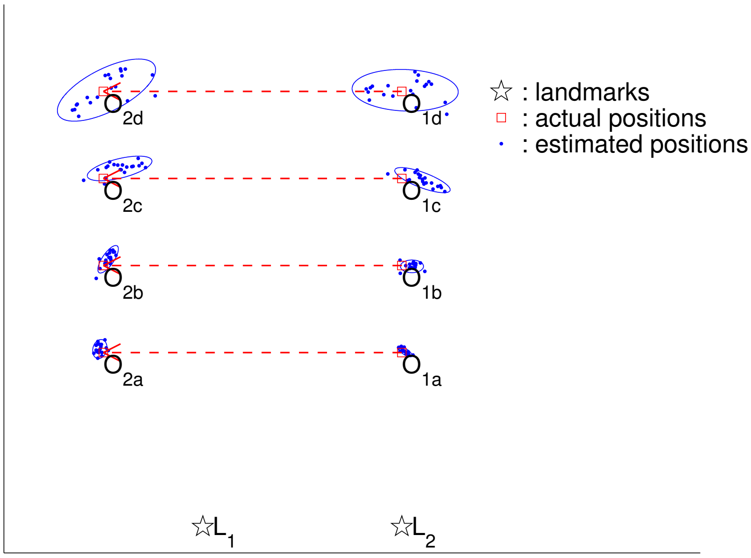

Fig. 3. Estimated positions of the robot determined by the proposed localization method.

When more than two landmarks are present, the localization accuracy can be further improved by fusing the estimated positions, giving more importance to the estimated position returned by the pair of landmarks that has a larger relative difference of landmark bearings.

4 Discussion and Future Work

In summary, we have introduced a novel effective approach for robot self-localization using only the bearings of two landmarks. This technique can be viewed as a form of stereo-vision. The method we propose is well suited for real-time system as the it requires very little computation. The promising initial results encourage several follow-up research directions. In particular, we would like to extend the approach to 3D environments (aircrafts and submarines).

When more than two landmarks are visible, the robot can determine the relative positions of the landmarks provided some weak visibility constraints are satisfied. Indeed, suppose there are two pairs of landmarks $\{L_1, L_2\}$ and $\{L_3, L_4\}$ visible from a segment O_1O_2 (notice that $\{L_1, L_2\}$ and $\{L_3, L_4\}$ do not have to be in direct line of sight). Then using three different bases, the first one $\mathcal{B}_O$ attached to O_1O_2, the second one $\mathcal{B}_{1,2}$ attached to L_1L_2, and the third one $\mathcal{B}_{3,4}$ attached to L_3L_4, we can determine the change of basis matrices $M_{\mathcal{B}_O,\mathcal{B}_{1,2}}$ and $M_{\mathcal{B}_O,\mathcal{B}_{3,4}}$. The matrix product $M^{-1}_{\mathcal{B}_O,\mathcal{B}_{1,2}} M_{\mathcal{B}_O,\mathcal{B}_{3,4}}$ allows us to compute the positions of the pairs of landmarks $\{L_1, L_2\}$ and $\{L_3, L_4\}$ relatively to each other. Occlusions occuring in indoors environments present interesting challenges for the automated integration of such local maps.

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