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SONAR-BASED SELF-ORIENTATION OF INDOOR MOBILE ROBOTS

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Abstract. In most applications, a mobile robot must be able to determine its position and orientation in the environment using only own sensors. Orientation estimation accuracy greatly influences the position estimation accuracy and is therefore crucial for a reliable mobile robot pose tracking. Our approach to orientation estimation is based on angle histograms matching. Angle histograms are obtained indirectly via Hough transformation combined with a non-iterative algorithm for determination of the end points and length of straight-line parts contained in obtained histograms. Sensors used for local occupancy grid generation are sonars. Test results with mobile robot Pioneer 2DX simulator show the capacity of this method.

Keywords. Robotics, Electric vehicles.

1. INTRODUCTION

Ability of a mobile robot to find or track its pose (position and orientation) in an unknown environment is a crucial feature needed for performing complex tasks over a long period of time [1]. The robot has to cope with two types of sensor uncertainties in order to map an environment: perception uncertainty and odometry uncertainty. The most common solution for this problem is to rely on dead reckoning methods (odometry) for a short period of time and then to apply additional sensors to update/correct the mobile robot pose [2, 3]. Dead reckoning approaches provide good results only for a short period of time due to significant error influence from wheel slippage, floor roughness, etc. Especially the orientation estimation is prone to significant error influence.

A lot of research has been done to improve the orientation estimation. For example, better odometry models have been developed in [4], and additional sensors have been used in [3, 5]. Additional sensors can be used to compute a correction to the actual mobile robot pose or as additional measurement information in an extended odometry model.

Mostly used sensors for additional measurement information in an extended odometry model are compass and gyro. Electronic compass is sensitive to magnetic interference that comes from ferromagnetic objects in the robot environment. Such objects are often present in man made environments including the mobile robot body and the noise produced by its drive system. Compass was used in [5] with the purpose to ensure that the robot environment is scanned with the same robot orientation angle at each place. In this way the complexity of the mobile robot pose tracking problem was greatly reduced because collected environment scans differ only in the x and y position. The problem is that this approach can't be used in environments with significant magnetic interference and with mobile robots that can't turn in spot.

To overcome the above-mentioned problem another characteristic of man-made environments can be used. Many objects in such environments lie in straight lines. Good examples are walls and doorways. In such environments it is possible to use line segments for the correction of the estimated mobile robot pose [6]. The Hough transform is widely used in computer vision for edge detection. An efficient algorithm [7] is used to determine the coordinate of the extracted line end points, line length and the normal parameters of a straight line using the Hough transform. Angles between the line segments and positive x-axis, weighted with line segment length, form an angle histogram. Comparison of angle histograms and their use for mobile robot orientation correction is the topic of our research. The angle histogram of current mobile robot pose is convolved with the angle histogram from the previous mobile robot pose. But all hypothetic robot orientations with equal minimal matching score obtained by angle histograms convolution (orientation hypothesis) are used to determine the best orientation with minimal distance in comparison to predicted orientation.

2. HOUGH TRANSFORM

The Hough transform is a robust method for detecting discontinuous patterns in noisy images. The basic idea of this technique is to find curves that can be parameterized like straight lines, circles, ellipses, etc., in a suitable parameter space. Our application considers the detection of straight-line segments in sonar data. Several variants of standard Hough Transform have been proposed in the literature to reduce the time and space complexity. When it is applied to detection of a straight line, represented by normal parameters, the transform provides only the length of the normal and the angle it makes with the x-axis. The transform gives no information about the length or the end points of the line. Because of that an efficient non-iterative algorithm is used to determine the coordinate of the end points and the length and the normal parameters of a straight line. These line segments form an angle histogram [7].

A straight line, represented by the normal parameterization, is expressed as (Fig. 1):

$$\rho = x\cos\theta + y\sin\theta\,, \tag{1}$$

where ρ is the length of the normal to the line from the origin and θ is the angle of normal with the positive x-direction. We assume that the origin of the x-y coordinate system is in the center of the input space. In the θ-ρ parameter plane (HT space), the line is mapped to a single point. Collinear points (x_i, y_i) in the input space, with $i = 1, \ldots N$, constitute a sinusoidal curve in the (θ, ρ) space, which intersect in the point (θ, ρ) (Fig. 2), given by:

$$\rho = x_i\cos\theta + y_i\sin\theta\,. \tag{2}$$

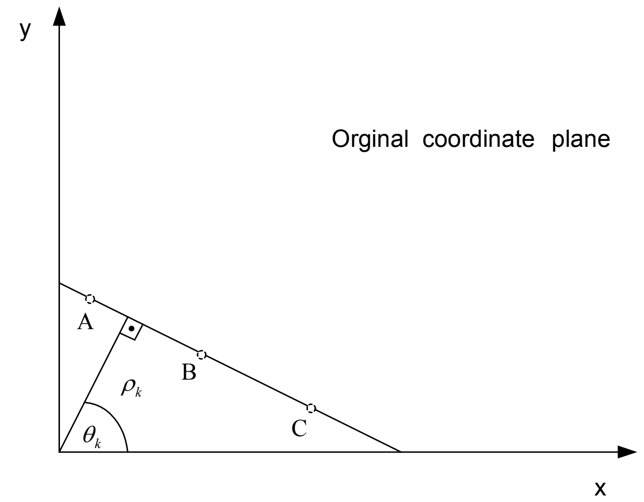

Fig. 1. (x,y) points in Cartesian space before applying the Hough transformation.

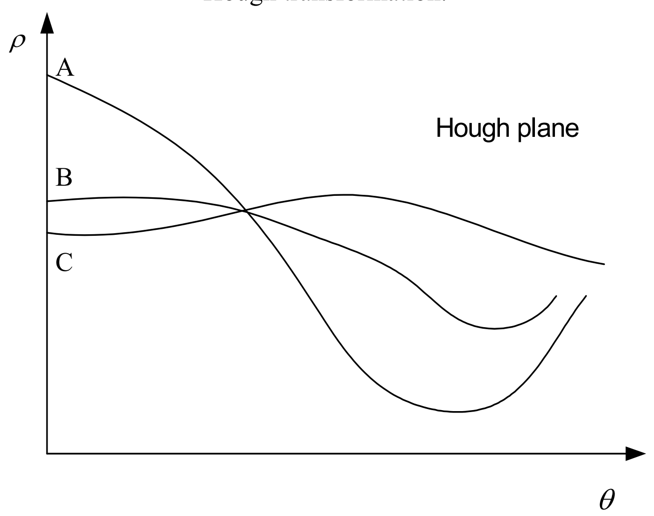

Fig. 2. (x,y) points in Cartesian space become sinusoidal curves in Hough space.

A sharp and distinct peak in the accumulator array is necessary for accurate parameterization of the line to be detected. The quantization resolutions $\Delta\theta$ and $\Delta\rho$ determine the mapping of input points to accumulator cells. In this way, the accuracy of detected features depends very much on the quantization parameters $\Delta\theta$ and $\Delta\rho$. Smaller values of $\Delta\rho$ and $\Delta\theta$ result in higher accuracy with which the line parameters can be detected. However, if the $\Delta\rho$ and $\Delta\theta$ are made too small, the detection of the peak becomes difficult due to the spread of the votes in the peak. The size of the cells in Hough domain in our approach is chosen to be $\Delta\rho = 5$ [cm], $\Delta\theta = 10$ [°].

Input space is formed by the two-dimensional distance readings stored in the sonar buffers. The distribution of the input points depends not only on the position of the sensors but also on the movements of the robots [8]. Fig. 3 shows an example of the current position of mobile robot in Hough domain. Points belonging to the same line reproduce intercepting unitary curves, which accumulate their values in the accumulator interception points.

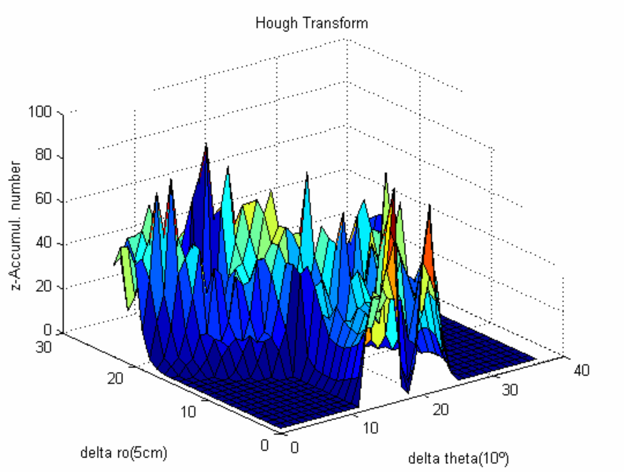

Fig. 3. Example of Hough transformation of current mobile robot scans, where the peaks (θ_p) are used to determine two columns C_q and C_r (end points of line segments).

Line segment description

The parameters of a line along with its length and coordinates of the end points are sometimes referred to as a complete line segment description [9]. Used algorithm for detection of those characteristics [7] is independent on the accuracy with which the peak in accumulator arrays for co-linearity detection is determined. This is a good characteristic because an accurate detection of the peak in the accumulator array is a non-trivial task. This is also the reason that θ value of the peak (θ_p) is only used to determine two columns C_q and C_r.

Two columns C_q and C_r whose cells correspond to the two sets of parallel bars have their normals inclined at angles θ_q and θ_r respectively with the positive x-axis (Fig. 4). The lengths of the normals ρ^q_1, ρ^q_2, ρ^r_1, ρ^r_2 to the bars can be determined from an accumulator array. The lengths of the normals to the bars correspond to the first and last non-zero elements in columns C_q and C_r. These normals can be expressed as:

$$\rho_1^{\,q} = x_1 \cos\theta_q + y_1 \sin\theta_q\,, \tag{3}$$

$$\rho_1^{\,r} = x_1 \cos\theta_r + y_1 \sin\theta_r\,, \tag{4}$$

$$\rho_2^{\,q} = x_2 \cos\theta_q + y_2 \sin\theta_q\,, \tag{5}$$

$$\rho_2^{\,r} = x_2 \cos\theta_r + y_2 \sin\theta_r\,, \tag{6}$$

where C_q, C_r are q-th, r-th column in the accumulator array, respectively. $\rho_1^{\,q}$ and $\rho_1^{\,r}$ are the lengths of the normal to the bar (in the image plane) corresponding to the first non-zero cell in C_q and C_r respectively (which corresponds to the bar $b_{i,k}$ in the image plane containing the end point (x_1, y_1). $\rho_2^{\,q}$ and $\rho_2^{\,r}$ are the lengths of the normals to the bar (in the image plane) corresponding to the last non-zero cell in C_q and C_r respectively (which corresponds to the bar $b_{i,k}$ in the image plane containing the end point (x_2, y_2).

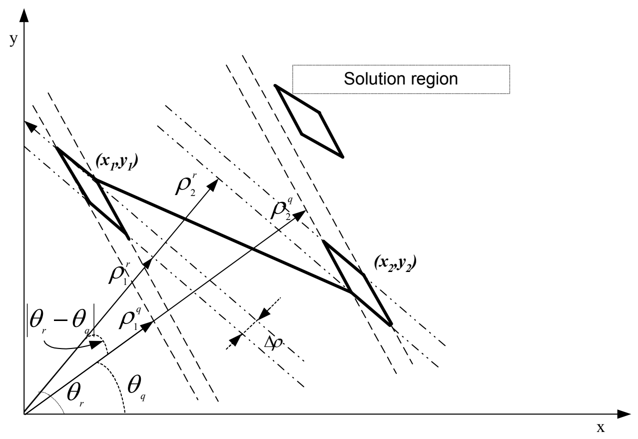

Fig. 4. Computation of the end points independent on θp.

We can express the coordinates of end points (x_1, y_1) and (x_2, y_2):

$$x_1 = \frac{\rho_1^q \sin\theta_r - \rho_1^r \sin\theta_q}{\sin(\theta_r - \theta_q)}\,, \tag{7}$$

$$y_1 = \frac{\rho_1^r \cos\theta_q - \rho_1^q \cos\theta_r}{\sin(\theta_r - \theta_q)}\,, \tag{8}$$

$$x_2 = \frac{\rho_2^q \sin\theta_r - \rho_2^r \sin\theta_q}{\sin(\theta_r - \theta_q)}\,, \tag{9}$$

$$y_2 = \frac{\rho_2^r \cos\theta_q - \rho_2^q \cos\theta_r}{\sin(\theta_r - \theta_q)}\,. \tag{10}$$

The line length (l_c) is obtained from the end points by

$$l_c = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}\,, \tag{11}$$

and parameters of the normal (ρ_c, θ_c – line parameters calculated from the end points of the line by using the method proposed in [9]) are obtained as

$$\rho_c = \frac{x_2 y_1 - x_1 y_2}{\sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}}\,, \tag{12}$$

$$\theta_c = \arctan\left(\frac{y_2 - y_1}{x_2 - x_1}\right) - 90° = a\tan 2\left(\frac{y_2 - y_1}{x_2 - x_1}\right). \tag{13}$$

Angle Histograms comparison

Line segments obtained by the Hough transformation with equal angle, are used to calculate the angle histogram. This histogram represents directly sums of the lengths of all edges with equal orientations. An example of angle-histograms for the actual and previous mobile robot environment scan is presented in Fig. 5. To remove small line segments from an angle histogram, each length is compared to a threshold. Threshold value is calculated for every sensor scan separately. Any line segment in an angle histogram, whose length is less than threshold for a certain scan, is removed. In this way, comparing of angle histograms give better matching results.

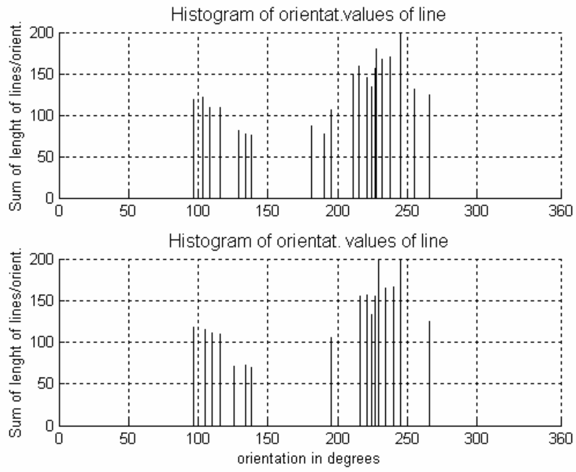

Fig. 5. An example of two successive angle histograms.

The analysis of measurements for comparing angle histograms is important, since the "intersection-measurement'' gives different results for matching histograms. Angle histogram intersection-measurement has been introduced for the comparison of color histograms [10]. In our approach, the calculation χ_{TH}^2 is used, because it gives the best results in mobile robot orientation tracking:

$$\chi_{TH}^2(H_i, H_{i-1}) = \sum_j \frac{(H_i(j) - H_{i-1}(j))^2}{H_i(j) + H_{i-1}(j)}\,, \tag{14}$$

where $H_i(j)$ and $H_{i-1}(j)$ are current and previous angle histograms, respectively.

The angle histogram of the current place is convolved with the histogram of the previous place, but all hypothetic orientation θ_j with equal minimum matching score from angle histogram (orientation hypotheses) are used to determine the best orientation. The comparison of orientation θ_j, which satisfies above criterion, with heading orientation gives the matching orientation value Θ_{Mi}.

Mobile robot orientation is predicted using updated value of orientation from previous step and orientation changes due to navigation:

$$\theta_{P_i} = \theta_{UPD}(i-1) + \Delta\theta , \qquad (15)$$

Updates of the θ coordinate are as follows:

$$\theta_{UPD}(j) = \theta_{Mj} + D \cdot (\theta_{pj} - \theta_{Mj}), \qquad (16)$$

where $0 < D < 1$ is a coefficient.

3. TEST RESULTS

Described global localization algorithm is tested using a Pioneer 2DX mobile robot simulator. The size of the environment is an 18x55m^2. The experimental scenario includes several orientation changes due to gradient navigation method. Fig. 6 presents obtained results regarding orientation tracking with calibrated odometry and with proposed localization algorithm. The actual robot orientations are also depicted in the figure.

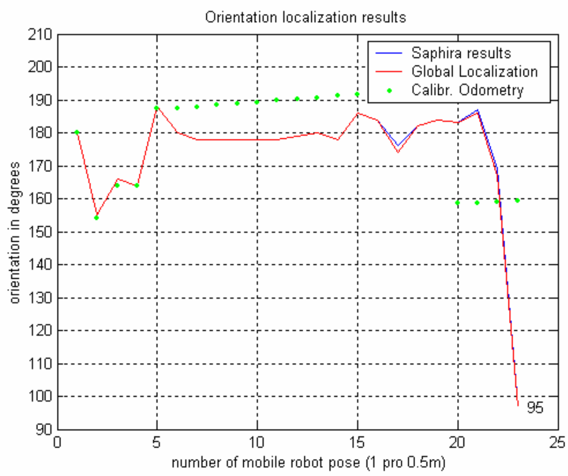

Fig. 6. Obtained orientation estimation results.

4. CONCLUSION

Mobile robot orientation correction technique using histograms and Hough transform has been implemented and compared to calibrated odometry using a mobile robot simulator. It is shown that Hough transform in combination with histograms, which was used for orientation correction, gives better results then orientation tracking based on calibrated odometry.

Our method of mobile robot orientation correction relies on the detection of straight-line features in the sonar sensor readings. The Hough Transform is widely used in computer vision for edge detection, so it is a good solution for object detections in man-made environment, which tend to lie in straight lines. The Hough Transform has a number of properties that are useful for self-localization, for example it is very robust to noisy sonar data and to occlusions of the lines. We used the correlation technique for orientation correction rather than the product of likelihoods. In this way, misleading sensor readings caused by multiple reflections are filtered out.

The proposed method for mobile robot orientation correction is a worth alternative to the use of magnetic compass, particularly in environments with high magnetic interference.

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