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Histogram Based Mobile Robot Localization

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Global localization refers to the problem of determining the pose of a mobile robot under global uncertainty. One solution to this problem is the usage of histograms as part of a topological map. The algorithm introduced here is based on the interacting multiple model and exploits a soft gating of the problem to reduce the computational requirements of presented approach. This localization algorithm consists of a position estimation and orientation estimation part. The position part is based on a xy histogram scan matching procedure, where xy histograms are extracted directly from local occupancy grid maps. The orientation part is based on the proposed obstacle vector transform combined with polar histograms. Introduced algorithm is tested using a Pioneer 2DX mobile robot simulator.

1. Introduction

In most applications, a mobile robot must be able to determine its pose (position and orientation) in the environment using its own sensors only. Pose awareness is very important to all mobile robot applications. Localization techniques can be divided into local and global localization techniques. Global localization is usually done by observing a multitude of different pose hypotheses, usually doesn't require initial pose information, and it's generally able to recover from arbitrary pose errors [1]. Keeping track of all the possible association hypotheses over time, as in the case for the multiple hypotheses tracker (MHT) [2] leads to hardness in real-time problem, since the number of associated hypotheses grows with the mobile robot environment dimension. So, methods are required to reduce the computational complexity.

The quality and precision of autonomous mobile robot systems is critically dependent on the appropriate choices of both: *data association* and *state estimation* algorithms.

The first problem refers to the selection of a good filter that copes with most of the situations in the application where it would be used. There are many data association techniques used in multiple target tracking (MTT) systems ranging from the simpler nearest-neighbor approaches to the very complex multiple hypothesis trackers [2]. The disadvantages of most of these methods are their computational requirements. One of the data association problem approach is also within the context of particle filtering. A method that combines the particle filtering technique with the philosophy behind the probabilistic data association filter (PDAF) [3] is presented in this approach. In order to minimize the computational burden of the particle filter algorithm we reduce the number of particles. This is done by rejection of particles with sufficiently small likelihood values, since they are not likely to be re-sampled using a soft-gating (SG) method [4]. The basic idea of SG is to; starting with a set of samples approximately distributed according to the best hypothesis from initialisation phase, generate new particles, which depend on the old state (clutter measurements) and new measurements. The update step is repeated until a feasible likelihood value is received.

Among the estimation algorithms, the *interacting multiple model* (IMM) estimator is the best-known single-scan positional algorithm and is most widely used for the purpose of tracking maneuvering targets [5]. The IMM approach computes the state estimate that accounts for each possible current model using a suitable mixing of the previous model-conditioned estimates depending on the current model [6]. Amongst the available multiple model techniques, the IMM is the best cost-effective implementation and for this reason chosen for this mobile robot localization approach.

The mobile robot has to cope with two types of sensor noise in order to map an environment: perception noise and odometry noise. The most common solution to minimize the influence of odometry noise is to rely on dead reckoning methods (odometry) only for a short period of time and then to apply additional sensors to update/correct the mobile robot pose. Often used sensors are the sonar, laser range finder, cameras, compass, gyro, etc. The compass as heading sensor is of particular importance to mobile robot localization because it can improve the orientation estimation accuracy of odometry. Orientation estimation accuracy greatly influences the position estimation accuracy and is crucial for reliable mobile robot localization. However, an electronic compass is sensitive to magnetic noise that comes from ferromagnetic objects or structures in the robot environment, from the mobile robot body and the noise produced by its drive system. So it is good to replace it with sonar sensors and extend the up to this point implemented histogram matching procedure [6], which can only correct the estimated mobile robot position, with a polar histogram that can correct the estimated mobile robot orientation. The compass is used to ensure that the xy histograms are always constructed with the same mobile robot orientation.

Histogram based matching procedures have many attractive features. For example, histograms provide a compact representation of a scan and thus require less memory space, which also makes the comparison of two histograms much faster than the comparison of two scans. Polar histograms are used in vision systems [8] and vector histograms for obstacle avoidance [9]. In our localization approach we extend their use for mobile robot orientation estimation using an *obstacle vector transform* (OVT). The idea is to first detect obstacles in the nearby mobile robot environment, present them using obstacle vectors and then to construct the polar histogram using only local sonar range readings.

2. Position tracking

In an occupancy grid map, a regular grid represents the mobile robot environment. Each cell's value is based on the likelihood of it being occupied. The certainty value is based only on sensor readings. Each occupancy grid cell represents an area of 10 [cm] x 10 [cm] and is considered as being in one of three possible states: occupied, empty and unknown. The state depends on the corresponding probability of occupancy for that cell.

To begin the global localization process, the robot takes a new sonar scan at its current pose and constructs a local occupancy grid. The scans are converted to three types of histograms before matching: x, y and angle histograms. Both x and y histograms are consisted of three one-dimensional arrays, which are obtained by adding up the total number of occupied, empty and unknown cells in each of the 60 rows or columns respectively (x or y histogram). An example of obtained x-histograms is presented in Fig. 1.

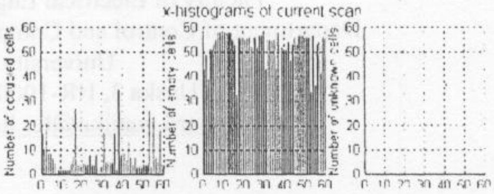

Figure 1. Example of obtained x-histograms.

Matching scores of stored histogram (nodes of hybrid map) and recognition-translated histogram of current place are calculated for x- and y-histograms as [7]:

$$M(H_{t-1}, H_t) = SCALE * \sum_j \left[\min(O_j^{t-1}, O_j^t) + \min(E_j^{t-1}, E_j^t) + \min(U_j^{t-1}, U_j^t) \right] \quad (1)$$

where O_j, E_j, U_j refer to the number of occupied, empty and unknown cells, contained in the j-th element of histogram H and SCALE scaling parameter.

For each of these hypotheses, the likelihood of sensor model $L(S|h_i)$ is calculated as the strength of the match between the current and stored histograms for each place hypothesis h_i:

$$L(S \mid h_i) \propto M_x^{i*} \times M_y^{i*}, \quad (2)$$

where are M_x-matching score of x-histogram, M_y-matching score of y-histogram, M_x^{i*} and M_y^{i*} are the best match scores, produced by the best matching alignment between histogram of chosen hypothesis h_i and translated histogram for the current place.

3. Polar Histograms

Polar histograms are constructed using straight line originating from a focus (Fig. 2.). In our case the focus is the mobile robot and straight lines are sonar range measurements. Angles between the vector obstacle segments and positive x-axis weighted with obstacle vector length form then the polar histogram (Fig. 3.).

3.1 Obstacle Vector Transform

A one-dimensional *polar histogram* is constructed around the robot's momentary location, using the OVT, which maps the local occupancy grid onto polar histogram. The histogram comprises n *angular sectors* of width $\alpha = 1°$. Each sector $0 \leq n \leq 360°$, holding a value of nearest obstacle distance, represents the polar obstacle vector in the direction that corresponds to sector k. The content of only active cells in the local occupancy grid, which are occupied, is now treated as an *obstacle vector*, the direction of which is determined by the direction β from the cell to the *Mobile Robot Centre Point (MRCP)*.

$$\beta_{ij} = arctan\left(\frac{y_j - y_0}{x_i - x_0}\right), \qquad (3)$$

The obstacle distance vector is as:

$$d_{ij} = \left((x_i - x_0)^2 + (y_j - y_0)^2\right)^{1/2}, \qquad (4)$$

where d_{ij} distance between occupied cell (i,j) and the MRCP in direction β, (x_i,y_j) and (x_0,y_0) are coordinates of obstacle cell (i,j) and MRCP respectively.

The minimization of the obstacle distance vector (MOD) in the direction, that corresponds to sector k follows:

$$d_k^{MOD}(D) = \arg\min_d \left[(d_{ij})_k\right], \qquad (5)$$

Fig. 2. shows a typical obstacle setup in our research environment (overlaying part of the local occupancy grid).

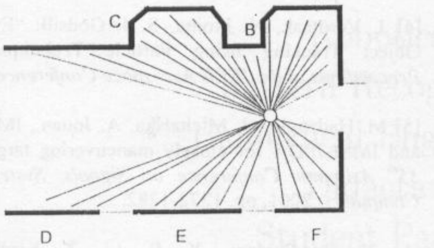

Figure 2. Part of our experiment environment.

The polar histogram corresponding to the momentary position of the autonomous mobile robot is shown in Fig. 3. The peaks A, B, C, D, E, and F in the polar histogram result from obstacle clusters A, B, C, D, E, and F.

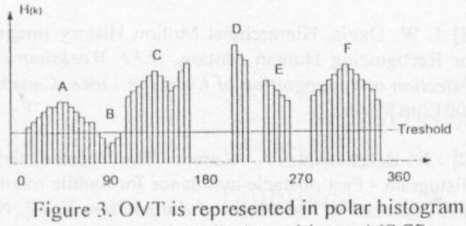

Figure 3. OVT is represented in polar histogram relative to the robot's position at MRCP.

3.2 Polar Histograms comparison

Obstacle vectors obtained by the OVT with sector direction β, are used to calculate the polar histogram. To remove small obstacle vector segments from polar histogram, each vector length is compared to a threshold. Threshold value is calculated for every sensor scan separately in the form of a mean value. Any obstacle vector segment in polar histogram, whose length is less than threshold for certain scan, is removed. In this way, comparing of polar histograms give better matching results.

The analysis of measurements for comparing polar histograms is important, since the "intersection-measurement" gives different results for matching histograms [10]. In our approach, the calculation χ_{TH}^2 is used.

$$\chi^2_{TH}(H(k),H(k-1)) = \sum_j \frac{(H_j(k)-H_j(k-1))^2}{H_j(k)+H_j(k-1)}, \qquad (6)$$

where $H(k)$ and $H(k-1)$ are current and previous polar histograms, respectively.

The polar histogram of current place is convolved with a histogram from previous place, but all hypothetic orientation θ_j with equal minimum matching score from polar 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_M.

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

$$\bar{\theta}(k) = \hat{\theta}(k-1) + \Delta\theta, \qquad (7)$$

Updates of the θ coordinate are as follows:

$$\hat{\theta}(k) = \theta_M(k) + K * \left(\bar{\theta}(k) - \theta_M(k)\right), \qquad (8)$$

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

4. Localization procedure

Due to highly uncertain nature of real-world sensors and signal processing, a probabilistic framework for mobile robot localization is used. The validation region or gate is, by definition, the region in which the true measurement will appear with a high probability. Measurements outside the validation region are too far from the expected location and thus are very unlikely to have originated from the target of interest [6].

The probability distribution over nodes in the map is updated whenever a new moving, in fact a new perception is made. Probability state is drawn from a mixture of the temporal prior and the initialization prior. The temporal prior combines information from the posterior probability distribution at the previous time instant with the temporal dynamics of the motion models. In this way, the posterior distribution is predicted and updated over time, integrating new information within the Bayesian framework. In order to keep the number of hypotheses low, the hypotheses for which $P(h_i) < \gamma$ can be eliminated. Threshold γ can be determined on basis average values of probabilities for each possible current model.

Whenever the global position of the robot is uniquely determined, the huge state space of the estimation problem can be reduced to a small cube P cantered around the robot's estimated position. The hypotheses containing the maximum probability within P is regarded as referring to the current position of the robot. Fig. 5. shows the mobile robot pose probability distribution change in the simulation environment.

Figure 5. Change of mobile robot position probability distribution during navigation.

A multi-modal distribution with several small local maxima is obtained after the first set of readings. The probabilities become more concentrated after a few set of readings, where the significant peak presents the real position of the robot and smaller peak indication for next possible hypothesis during moving.

5. Test results

Described global localization algorithm is tested using a Pioneer 2DX mobile robot simulator. The size of the environment is an $18 \times 55 m^2$. The simulation scenario included several orientation changes due to used gradient navigation method. Fig. 6. presents obtained results regarding orientation tracking with calibrated odometry and with proposed localization algorithm.

Figure 6. Global localization using the IMM + SG approach.

6. Conclusion

Mobile robot orientation correction technique using histograms has been implemented and compared to calibrated odometry using a mobile robot simulator. It is shown that OVT in combination with polar histograms, which were used for orientation correction, gives better results then orientation tracking based on calibrated odometry. The proposed method for mobile robot orientation correction is a worth alternative to the use of magnetic compass, particularly in environments with magnetic noise.

References

[1] J. Weber, K.-W. Joerg, E. Von Puttkamer, APR-Global Scan Matching Using Anchor Point Relationships, *the 6 the International Conference on Intelligent Systems*, Italy, 2000, p. 471-478.

[2] P. Konstantinova, K. Alexiev: A Comparison of Two Hypothesis Generation Algorithms in JPDAF Multiple Target Tracking, *Proceedings of the International Conference on Computer Systems and Technologies*, Bulgaria, 2001, pp. II 18-1-II 18-5

[3] R. Karlsson: Simulation Based Methods for Target Tracking, Ph.D. Dissertation, Department of Electrical Engineering, Linkoeping University, Sweden, 2002.

[4] J. Vermaak, N. Ikoma, S. J. Godsill: "Extended Object Tracking using Particle Techniques", in *Proceedings of the IEEE Aerospace Conference*, 2004.

[5] M. Hadzagić, H. Michalska, A. Jouan., IMM-JVC and IMM-JPDA for closely maneuvering targets, *the 35th Asilomar Conference on Signals, Systems and Computers*, 2001, pp. 1278-1282

[6] Y. Bar-Shalom, X. R. Li, T. Kirubarajan: Estimation with Applications to Tracking and Navigation, A Wiley –Interscience Publication John Wiley& Sons Inc., 2001.

[7] T. Duckett, Concurrent map building and self-localization for mobile robot navigation, PhD Dissertation, University of Manchester, 2000.

[8] J. W. Davis: Hierarchical Motion History Images for Recognizing Human Motion, *IEEE Workshop on Detection and recognition of Events in Video*, Canada, 2001, pp.39-46.

[9] J. Borenstein, Y. Koren: The Vector field Histogram - Fast obstacle avoidance for mobile robots, *IEEE Journal of Robotics and Automation*, Vol 7, No 3,1991, pp. 278-288.

[10] B. Schiele, J. L. Crowley, Comparison of Position Estimation Techniques Using Occupancy Grids, *in: Robotics and Autonomous Systems*, 12 (3-4), 1994, p. 163-172.