A Probabilistic Method of Bearing-Only Localization by Using Omnidirectional Vision Signal Processing

Yingjie Duan, Runwei Ding
Key Laboratory of Machine Perception and Intelligence
Peking University, Shenzhen Graduate School
Shenzhen, China
Yingjieduan@gmail.com, dingrunwei@pkusz.edu.cn

Hong Liu
Key Laboratory of Machine Perception and Intelligence
Peking University, Shenzhen Graduate School
Shenzhen, China
hongliu@pku.edu.cn

***Abstract*—Self-localization is most necessary foundation for mobile robot's navigation system. Omnidirectional vision system is widely used in mobile robot. However, the accuracy of vision-based methods is not high enough for many applications. In this paper, a probabilistic method based on bearing-only localization is presented to accurately estimate mobile robot's position by using omnidirectional vision signal processing. Firstly, landmarks and bearings are detected from omnidirectional vision signals. Then, a probabilistic mapping that is composed of coordinates' weight is constructed. The weight of coordinate indicates the possibility that the robot's location is the coordinate of the point. Finally, Monte Carlo Localization is used to fuse probiotic method and odometer-based prediction model. Experiments in several scenarios show that the model using omnidirectional vision signal processing is robust and accurate for mobile robot localization.**

Keywords-Bearing-only localization; Monte Carlo; mobile robot; omnidirectional vision;

I. INTRODUCTION

Vision sensors have been widely used in mobile robot systems. Self-localization is one of the most necessary foundations for a navigation system of a mobile robot. However, conventional vision sensors have limited fields of view that make them restrictive in mobile robot's self-localization. The widely method to solve this problem is using Omni-cameras.

Vision-based Location method is widely used, especially using omnidirectional vision sensors. However, their accuracy is not high enough for many applications. Geometric localization based on the exploitation of landmarks or beacons have high accuracy. In general, geometric methods can be divided into two main categories, range-only method (trilateration localization) and bearing-only method (triangulation localization). Range-only localization [1] mainly makes use of the distance measurements pointing from robot to these landmarks, while bearing-only localization uses the angular separations between the lines connecting the robot and these landmarks [2][3][4].

In the general bearing-only localization system, at least three different recognizable landmarks are required or fixed in robot's workspace. Two lines, created by connecting a robot with any two of these landmarks, together with the angle they form, determine a circle that contains the position of the robot. Also, by the same way, another circle can be created. The robot locates right at the intersection of these two circles.

In bearing-only technology, three different recognizable landmarks are required or fixed at least in the workspace. A method proposed by Ilan Shimshoni provides a linear system at a low computational cost in the circumstances [5]. Another kind of bearing-only method approximates the resulting region of feasible states by a tight, complex-shaped, bounding set [6][7]. These methods performed in a standard circumstance, which means there are only three landmarks in the workspace. They do have not assumed the noise in the measurements obeying Gaussian distribution. Therefore, the resulting region only indicates an area that the robot may be within, but it has not indicated the likelihood of where the robot located.

In our system, the information used to self-localization acquired by omnidirectional signal processing, such as landmarks and bearings. With the original distribution of bearing measurements, the likelihood over all possible robot locations is estimated in order to derive a probabilistic mapping. With the probabilistic mapping, searching for the peak of maximum likelihood coordinate could provide a relative accurate location estimate of mobile robot. Many studies in probabilistic localization usually combined with other information fusion technique [8][9], i.e. Kalman Filter, Markov method or Monte Carlo localization [10][11].

The rest of this paper is organized as follows. Section II gives a brief review of omnidirectional signal processing for bearing-only system. In Section III, the theoretical derivation of the probabilistic mapping is provided. In Section IV, the probabilistic model combined with Monte Carlo technique is used to perform position estimate. The results of experiments are analyzed to demonstrate the applicability and accuracy of our method in section V. Section VI concludes the article.

II. OMNIDIRECTIONAL VISION SIGNAL PROCESSING FOR BEARING-ONLY LOCALIZATION

In global 2D Cartesian coordinate system, the robot's pose is described as $S_t = [x_t, y_t, \theta_t] \cdot [x_t, y_t]$ is the position coordinate and θ indicates the forward direction of the mobile robot. In the workspace, there are three known landmarks whose positions are described as $L_i = [x_i, y_i]$ where $i = 1, 2, 3$.

The bearings are measured by counterclockwise rotations from the robot's forward direction to the direction determined by the robot together with the landmark. These actual bearings are denoted as $\tilde{\alpha}_1$. Accordingly, the actual angular separations between the two directions pointing from the robot to the ith and jth landmarks is denoted as $\tilde{\alpha}_{ij} = |\tilde{\alpha}_i - \tilde{\alpha}_j|, i, j = 1,2,3\ i \neq j$.

In order to get the probabilistic mapping, a posterior probabilistic density function (PPDF) must be trained firstly. Via the PPDF, the distribution of actual angular separation in terms of a noisy input can be determined.

The random variable of actual angular separation is denoted as Z_{ij}. Meanwhile, the corresponding measurement is described as α_{ij}, which is a sample of random variable A_{ij}. In other words, α_{ij} is a once measurement of angular separation between the directions from the robot to the ith and the jth landmarks. As a result, the PPDF can be denoted as $p\ (Z_{ij}|\alpha_{ij})$. This function is trained out with the popular Bayesian statistic method that is illustrated in Fig.1 (b). In order to illustrate clearly, the test set are discretized and shown in the figure.

In our method, landmarks are detected by Omni-camera equipped in the robot. Thus, the observation of landmarks is presented canonically as two-dimensional Gaussian distribution [12], shown in Fig.1. Therefore, it is a reasonable assumption in this paper that the noises associated with the bearing measurement are considered as Gaussian distribution. Based on this assumption, an error model for bearing-only localization is represented by [13].

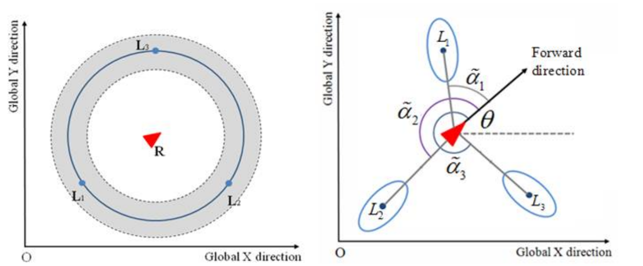


Figure 1. (a) The principle of bearing-only localization. The land- marks are detected as a 2-dimensional Gaussian distribution. (b) Training the PPDF by numerous angular measurements.

III. Probabilistic Mapping Construction

Given the PPDF of angular separation in the last section, we are ready to extend to the corresponding two-dimensional distribution. Two steps of theoretical derivation to form the probabilistic distribution are stated. They are: two crescent-shaped mappings are created and then these mappings are merged into the final desired probabilistic mapping.

A. Derivation of Crescent-Shaped Probabilistic Map

To achieve the crescent-shaped probabilistic mappings, three parameters are required: the coordinates of two land marks, L_i and L_j, known in advance and the random variable of angular separation Z_{ij}.

As is well known, Z_{ij}, Li and L_j produce a set of circles and due to the Z_{ij}'s randomness, each circle is dictated by a probability corresponding to Z_{ij} which indicates the likelihood that the robot stands on this circle. To formulate mathematically, the circle's probabilistic character can be described as a random vector, $C_{ij} = [X_{ij}, Y_{ij}, R_{ij}]$, where $[X_{ij}, Y_{ij}]$ prescribe the center and R_{ij} prescribe the radius.

Algorithm 1: Creation of Crescent-Shaped Map

Data: L_i, L_j, α_{ij} and *thr* that is the threshold for filtering the situations with very low probability.
Result: map (x, y), crescent-shaped probabilistic map.
begin
map ← ∅;
$p\ (Z_{ij}|\alpha_{ij})$ ← *GetPPDF* (α_{ij}); //get PPDF
foreach *coordinates* (x, y) ∈ Ω **do**
a ← *GetAngle(x, y, L_i, L_j)*;
//get angular separation $\angle L_i(x, y)L_j$
if $|a - \alpha_{ij}| \leq$ thr then
map(x, y) ← $p(a|\alpha_{ij})$;
else
map(x, y) ← *0;*
s ← $\iint_{\Omega} map(x, y)\, dxdy$;
foreach *coordinates* (x, y) ∈ Ω do
map(x, y) ← *map(x, y)/s;* //normalizaion
return *map;*

The distribution of C_{ij} can be replaced by the distribution of R_{ij} for simplicity. It's easy to verify that the radius can be expressed as:

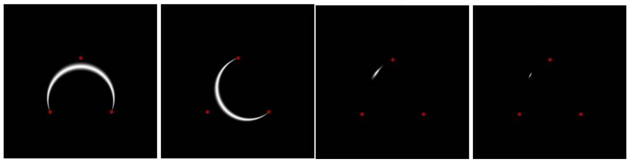
$$R_{ij} = \frac{d_{ij}}{2\sin(Z_{ij})} \tag{1}$$

where $d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$ means the distance between L_i and L_j. The posterior probabilistic density function could be solved by:

$$p(r_{ij}) = \frac{d_{ij}}{r_{ij}\sqrt{4r_{ij}^2 - d_{ij}^2}} p(\varphi|\alpha_{ij}) \tag{2}$$

where $\varphi = \arcsin\left(\frac{d_{ij}}{2r_{ij}}\right)$.

To traverse all the workspace and set the probability of every coordinate to circle, it could produce a 2D probabilistic mapping in which a higher crescent-shaped probabilistic region emerge (see Fig.2 (a)(b)). How to produce this 2D probabilistic mapping with applied program is depicted in Algorithm 1.



(a) (b) (c) (d)

Figure 2. (a)(b) Two Crescent-Shaped Probability Mappings. (c) The merged probabilistic distribution mapping. (d) The result from combination with Monte Carlo Localization.

B. *Fusing the Crescent-Shaped Probabilistic Mappings*

Suppose the two mappings are denoted as $M_1(x,y)$ and $M_2(x, y)$, where *(x, y)* indicates the coordinate. Notes that these two mappings are computed from two different frames from camera, so as to emphasize these mappings are unrelated. The final probabilistic distribution mapping can be obtained by combining two 2D probabilistic mappings with this method:

$$M_t(x, y) = \frac{M_1(x,y)\cdot M_2(x,y)}{\iint_{\Omega} M_1(x,y)\cdot M_2(x,y)dxdy} \tag{3}$$

where Ω means total space and t indicate the time step that prepare for the Monte Carlo filter in the next section. The example of $M_t(x, y)$ is shown in Fig.2(b).

IV. COMBINATION WITH MOTE CARLO LOCALIZATION

The Monte Carlo technology could provide a more rational probabilistic mapping through fusing the sensing model and the prediction model. The sensing model is usually constructed by a probabilistic mapping that is derived from the characters of the localization system itself. In our system, probabilistic mapping provided in the last section is the sensing model. On the other hand, the prediction model could be given by the translated sensing model of previous time, and the problem of how to translate is according to the log of odometer. It is obvious that the mapping processed by Monte Carlo technology is more convergent than that not processed (see Fig. 2(d)). The result of localization system can be the location corresponding to the peak of this mapping

$$\{[x, y, \theta(x, y, L_i)] \big| M(x, y) = max\{M(\mu, v); [\mu, v] \in \Omega\}\} \tag{4}$$

Making use of the coordinate [*x, y*], the function to compute the forward direction of the robot is:

$$\theta(x, y, L_i, \alpha_{ij}) = \arctan\left(\frac{y_i - y}{x_i - x}\right) - \alpha_i \tag{5}$$

The coordinate and the forward direction together indicate the pose $S = [x, y, \theta]$ of a robot.

V. EXPERIMENTS AND DISCUSSION

The measurements of angular separation used for training the parameter σ^2 are collected by an Omni-camera, PHILIPS SPC900NC, which is equipped by a HRI oriented robot called "Pengpeng II" (see Fig. 3). 2073 measurements of angular separation were collected from real circumstances (see Fig. 3(c)), and with these data σ^2 was trained out to be 0.011.

(a) (b) (c)

Figure 3. (a) The "Pengpeng II" robot equipped with an omni-camera. (b) Omni-camera. (c) experiments workspace.

There are 10 different scenarios are settled to estimate the 10m *10m real circumstances. Only three landmarks have been set randomly in each scenario. Totally, 33170 times of localizations were executed. A figure of position error is draw by these data of Table I (see Fig. 4). The green line with asterisks indicates position error using method of original bearing-only localization and the blue one with circlets denotes position error using combination method. The proposed method of combining our probabilistic mapping with Monte Carlo technique is more suitable for the area in which the original bearing-only localization is more unreliable.

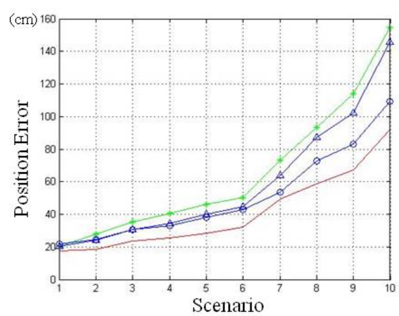
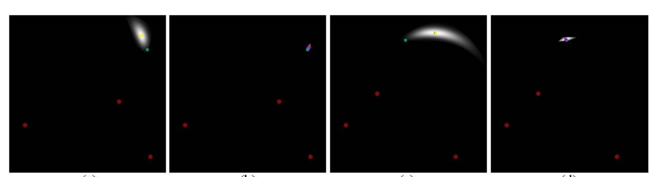


Figure 4. Position errors of three methods in 10 different scenarios



(a) (b) (c) (d)

Figure 5. The comparison of position estimate when the robot moves into the area far from triangle area

Figure 5(a) and (c) show the results of position estimates by original bearing-only localization when the robot is moving into the places far from the triangle area. The light blue point indicates the actual location of robot and the yellow point indicates the localization results by original bearing-only localization. The position errors of these two situations are 97.69cm and 195.49cm respectively. The corresponding position errors are 20.00cm and 8.49cm. We can see that the probabilistic mapping is so convergence to the actual location.

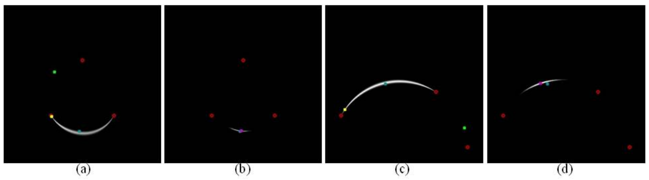


Figure 6. The comparition of position estimate when the robot moves into the Triangulation Difficult Region

When the robot and all landmarks lie on the same circle, even near to this circle (Triangulation Difficult Region), an extreme error of position estimate could come into being. Two instances are shown in Fig. 6 (a) and (c). The green point indicates the localization result by original bearing-only localization, light blue one is the actual position of robot and yellow point means the localization result by the method only with our probabilistic model. We can clearly intuit the extreme position error from these pictures. The original method seems to estimate the position in illogical way. Meanwhile, the localization results are also computed by the method of combining our probabilistic model and MCL in Fig. 6 (b) and (d). The values of position error of these two only are 16.00cm and 12.00cm. These tremendous results are so inspiring to users of bearing-only localization who are always faced with the headachy drawback of bearing- only localization system.

VI CONCLUSIONS

In this paper, a probabilistic method of brearing-only localization is proposed, which is based on omnidirectional vision signal processing in order to get informations include landmarks and bearings that are nessary for bearing-only localization. A probabilistic mapping which describe the probabilistic distribution of the possible locations of robot based on PPDF is trained by Numerous bearing measuring data. Then, a localization method with high performance of merging the probabilistic mapping and MCL together is represented. Experiments have shown that the method performs well even in some challenging situations, for example when the robot moves far from the triangle area or moves into the TDR.

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TABLE I. THE GENERAL PERFORMANCE OF POSITION ERROR AND COMPARISION USING THREE METHODS

Scenario No.	**I(cm)**	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**	**IX**	**X**	**Mean Value**
Original	20.2870	27.6124	35.5216	40.5737	46.0922	50.2814	73.0361	93.4556	113.8467	154.4803	65.5187
Using PM	20.2958	24.1909	30.8162	34.2364	40.2134	44.5676	63.8492	87.1620	102.2087	145.5092	59.30494
Combination	21.9149	24.6098	30.7995	33.0792	37.9967	42.6788	53.7679	72.6271	83.0358	109.3037	50.98134
PMC	17.5804	18.2761	23.6798	25.5369	28.5298	32.2746	49.5772	58.8614	67.0179	92.0546	-