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Landmark Pair based Localization for Intelligent Vehicles using Laser Radar

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Abstract— **Localization, namely pose estimation is of great importance in the research of intelligent vehicles. In this paper, after a simple overview of existing methods, a method of Laser Radar Localization based on Landmark Pairs (L^3P) is presented, which is an improved algorithm of localization based on landmarks to overcome problems of traditional methods, such as low reliability and low robustness of landmark detection, etc. This algorithm has been verified on both synthetic data and real range data in the outdoor environment. Experimental results demonstrate its high accuracy, high robustness to noises and low computation.**

I. INTRODUCTION

POSE estimation is a key issue in intelligent vehicles, as well as a fundamental problem for mobile robots. Many methods in [1, 2, 3, 4] have been proposed to solve this problem in the past 20 years. The cheapest and simplest approach is DR (Dead Reckoning) which uses odometers or wheel encoders to obtain relative pose. Yet, DR method has its inherent difficulties, which are vulnerable to bad calibration, upsetting occurrences, imperfect wheel contact, etc. The second method, INS (Inertial Navigation Systems), uses gyros or accelerometers to provide relative pose estimation. Though having higher accuracy than DR, INS method is more expensive and has gyro drift, calibration problems, and sensitivity limitations. In addition, both DR and INS methods are not suitable for global pose estimation owing to its large cumulative errors over time.

Still another method, beacon or landmark based method, places some beacons or landmarks in the environment beforehand so as to be detected by sensors on board the vehicles. This method won't suffer from the problems mentioned above. Instead, the key technique is to detect landmarks reliably and accurately. In the past, various methods have been proposed to realize the detection, such as Monte Carlo Localization (MCL) in [5, 6], Fuzzy Landmark-based Localization in [7], and Color Landmark Based Self-Localization in [8], etc. The main drawbacks of these methods are poor reliability, complexity to realize and low robustness to noises.

This paper proposed an improved algorithm using laser radar, called Laser Radar Localization based on Landmark Pairs (L^3P). Landmark pairs are used as the feature to improve the reliability and robustness in landmarks detection. The proposed algorithm is compose of, three parts: landmark pair detection, localization based on landmark pairs and pose tracking. EKF (Extended Kalman Filter) is used in the pose tracking in order to improve the accuracy.

The remaining part of this paper is organized as follows. Section II describes the problem of pose estimation. Section III describes landmark pair detection, which is the key part of the proposed algorithm. Section IV describes the pose estimation using landmark pairs, and the pose tracking using EKF. Section V gives our experimental results with both real range data and synthetic data. Finally, Section VI concludes the paper with the discussion of future work.

II. PROBLEM DESCRIPTION

Pose estimation is to estimate the position of an intelligent vehicle in the global coordinates and its own state. In 2D environment, the pose of the vehicle is often expressed by (x, y, ϕ), in which (x, y) is the position of the vehicle in global coordinates, and ϕ is the orientation of the vehicle. The task of pose estimation is to estimate the pose (x, y, ϕ) at each instance t of motion.

Further, for pose estimation in certain environment, representation of environment map is very important. In history, there are three main representations, which are grid map, feature map and topology map respectively [9]. In the proposed method, before the vehicle works, the global map of the environment is already existed. On the other hand, artificial landmark is a very simple and powerful tool for self-localization with specific shape. At length, the landmark has some typical features, such as constant shape and size. Therefore, the feature map is utilized at this occasion. Thus far, the global map is composed of the poses of landmark pairs (see Fig. 1). The expression is like below,

$$\begin{aligned} M_{global} &= \{P_i\}, i = 1, 2, \cdots, m \\ P_i &= \{(x_{i1}, y_{i1}), (x_{i2}, y_{i2}), D_{i1}, D_{i2}, d_i, \theta_i\} \end{aligned} \tag{1}$$

where, (x_{i1}, y_{i1}), D_{i1} are the position and the diameter of landmark $i1$; (x_{i2}, y_{i2}), D_{i2} are the position and the diameter of landmark $i2$; d_i, θ_i are the distance and the orientation between the two landmarks, which constitute a landmark pair. The global map, is the expression of absolute poses of m landmark pairs ($m>0$).

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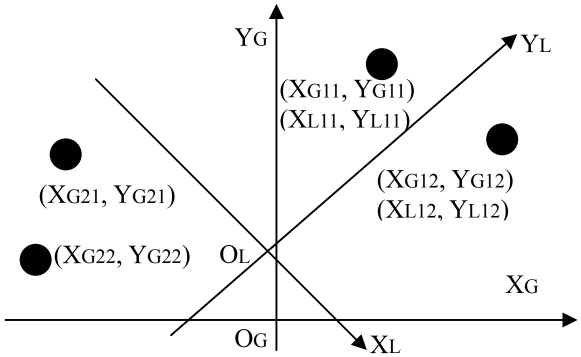

Fig. 1 The relationship between global and local maps

Set the pose of laser radar as the origin, and define the local map, which is the expression of relative poses of n ($0 \le n \le m$) landmark pairs to the pose of laser radar, as equation (2).

$$\begin{aligned} M_{local} &= \{Q_j\}, j = 1, 2, \cdots, n \\ Q_j &= \{(x_{j1}, y_{j1}), (x_{j2}, y_{j2}), D_{j1}, D_{j2}, d_j, \theta_j\} \end{aligned} \quad (2)$$

This expression is much the same with equation (1). If no landmark pairs is detected, $n=0$.

In the whole course, the global map is fixed. On the contrary, the local map changes from time to time. Therefore, each detected landmark pair in the local map should be identified to make a correspondence with a landmark pair in the global one.

III. Landmark Pair Detection

At the core of our algorithm, landmark pair detection is the premise. The sensor to the vehicle is just like the eyes to human beings. Here the laser radar as the sensor scans the environment periodically. The data of each scan is composed of a set of distance and angle values, which is shown in equation (3). In another word, they are a set of points in the local map.

$$Data = \{(r_i, \varphi_i), i = 1, 2, \cdots, l\} \quad (3)$$

where, r_i is the distance measured by the laser radar at the angle of φ_i. Parameter l stands for the number of scanning points and could be set to a fixed value in advance. By using these data, there are two steps to get the landmark pairs: one is data clustering and the other is feature extraction.

A. Data clustering

The aim of clustering, also known as data segment, is to divide the original points into several clusters according to the distances between adjoining measurement points in one scan. This process takes the proximity between each two adjoining points of one scan into account. In theory, a cluster is a set of points which are close enough to each other and considered to be on the same object. The segment criterion [10] is like this,

$$r_{k,k+1} \le C_0 + r_{\min} \frac{\tan\beta\sqrt{2(1-\cos\phi)}}{\cos(\phi/2) - \sin(\phi/2)} \quad (4)$$

where r_k, r_{k+1} are distance measurements of two adjoining points; $r_{min}=min\{r_k, r_{k+1}\}$, $r_{k,k+1}=|r_k-r_{k+1}|$; and ϕ is the angular resolution of the laser radar; β, which can be calculate according to schematic of clustering method in Fig.2, is introduced in order to reduce the dependency of the segment with respect to the distance between the laser radar and the object, and C_0 to handle the longitudinal error of the sensor.

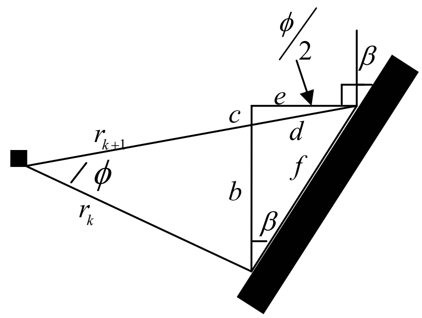

Fig. 2 Schematic of clustering method [10]

As a result of data clustering, several segments are obtained from equation (4). A segment is described by

$$seg_k = \{(x_k, y_k), D_k, \theta_k\} \quad (5)$$

where, (x_k, y_k) is the position of the segment; and D_k, θ_k are the diameter and orientation of this segment. The position equals to the mean of all points in the segment, the diameter equals to the distance between the two points on the two ends, and the orientation equals to the angle of the position in polar coordinates.

B. Feature extraction

Suppose that we have got n segments from data clustering, i.e.

$$\begin{aligned} E_{seg} &= \{seg_k\}, k = 1, 2, \cdots, n \\ seg_k &= \{(x_k, y_k), D_k, \theta_k\} \end{aligned} \quad (6)$$

Given the diameter of the landmarks D, first find the candidates of landmark which fulfill the criterion below,

$$|D_k - D| \le \varepsilon_1 \quad (7)$$

where ε_1 is an accepted error. After testing all the n segments, a set of landmark candidates is obtained.

$$\begin{aligned} E_{col} &= \{seg_{CLi}\}, i = 1, \cdots, k; k \le n\} \\ seg_{CLi} &= \{(x_{CLi}, y_{CLi}), D_{CLi}, \theta_{CLi}\} \end{aligned} \quad (8)$$

Next, match each pair of the landmark candidates to the real landmark pairs. The simplest way is to calculate distances of every candidate pair to match the database. However, this will introduce too much computing. A preferable way is to introduce a computing area of interest, namely the neighborhood of the landmark pairs in the local map. For a correct detection, the landmark pair detected should and must be adjacent to the real landmark pair. Therefore, only the candidate pairs close enough to the real landmark pair are in consideration. For instance, it is only necessary to consider landmark candidates pair (x_{c1}, y_{c1}) and (x_{c2}, y_{c2}) in Fig. 3.

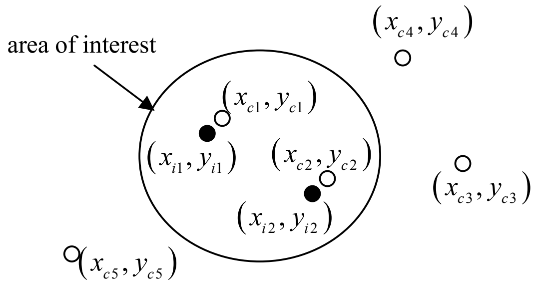

Fig. 3 Computational area of interest in the local map

To do this, given the pre pose estimation of the vehicle, transform the landmark pairs from the global coordinates to the local coordinates. Suppose (x_L, y_L, ϕ_L) is the pre pose estimation of the vehicle or the laser radar in the global map. Let (x_i, y_i) be the position of landmark i in the global map, and (x_{Li}, y_{Li}) be the corresponding landmark in the local map. Then there is an equation,

$$(x_{Li}, y_{Li}) = (x_i - x_L, y_i - y_L) \times \begin{bmatrix} \sin\phi_L & \cos\phi_L \\ -\cos\phi_L & \sin\phi_L \end{bmatrix} \quad (9)$$

Let the (x_{mLj}, y_{mLj}) be the middle of the jth landmark pair in the local map, where

$$(x_{mLj}, y_{mLj}) = ((x_{Lj1} + x_{Lj2})/2, (y_{Lj1} + y_{Lj2})/2) \quad (10)$$

By now, the area nearby the landmark pair is the area of interest. There are many ways to decide the range of the area of interest, such as a circle with (x_{mLj}, y_{mLj}) as its origin or a rectangular. The circle method is utilized in this algorithm. That is to say, if the distance between the midpoint of the landmark pair and the position of the candidate landmark $D_{L\text{-}C}$ is under a distance threshold, the very candidate is in the area of interest.

$$E_{aoi} = \{(x_{clj}, y_{clj}) \mid (x_{mi}, y_{mi}), 0 \le D_{Li-Cj} \le \varepsilon_2\} \quad (11)$$

where ε_2 is the distance threshold.

Finally, calculate the distance and orientation for each pair of candidates in the area of interest, and match this result with the corresponding landmark pair. If they match well, it is a detected landmark pair.

$$\begin{aligned} E_m &= \{P_i, Q_j, R_k\} \\ P_i &= \{(x_{i1}, y_{i1}), (x_{i2}, y_{i2}), D_{i1}, D_{i2}, d_i, \theta_i\} \\ Q_j &= \{(x_{j1}, y_{j1}), (x_{j2}, y_{j2}), D_{j1}, D_{j2}, d_j, \theta_j\} \\ R_k &= \{(x_{cli}, y_{cli}), (x_{clj}, y_{clj}), D_{cli}, D_{clj}, D_k, \theta_k\} \end{aligned} \quad (12)$$

To sum up, the result of landmark pair detection is one or several corresponding relationships between the real landmark pair and the detected landmark pair.

$$\begin{aligned} E_{r-d} &= \{P_r \leftrightarrow R_d\} \\ P_r \leftrightarrow R_d &= \begin{bmatrix} (x_{r1}, y_{r1}) \leftrightarrow (x_{d1}, y_{d1}) \\ (x_{r2}, y_{r2}) \leftrightarrow (x_{d2}, y_{d2}) \end{bmatrix} \end{aligned} \quad (13)$$

where P_r is the real landmark pair, and R_d is the detected landmark pair. By introducing computation area of interest, the computation lows, and the accuracy of detection grows.

IV. Localization Based On Landmark Pairs

A. Localization based on landmark pairs

Referred to equation (9), the relationship between the landmark pose in the global map and the corresponding one in the local map is known. In the equation, the pose of the laser radar is known. While at this occasion, localization is to decide the current pose of laser radar in the global map, where there are three variables, namely, x_L, y_L and ϕ_L. In consequence, at least three equations are needed to deduce them. Fortunately, from the result given by equation (13), four equations are obtained. So it is enough to deduce the variable (x_L, y_L, ϕ_L), and this means that localization based on landmark pair is feasible and correct. Along with the time goes on, the pose estimation at every instance can be obtained whenever one or more landmark pairs are detected.

B. Pose tracking using EKF

Localization based on landmark pairs has high accuracy and is reliable at most time. However, the scan areas of laser radar are often limited and no landmark pairs can be detected sometimes, when we can not do pose estimation. To overcome this problem, the EKF (Extended Kalman Filter) [11] is utilized to track pose of vehicle by combining the data of encoders and laser radar.

From the data of encoders and laser radar, the increments of distance and orientation, and the current pose of laser radar could be obtained respectively. Let the pose of the vehicle be the state vector $X=(x, y, \phi)^T$, the pose of the laser radar be the measurement vector $Z=(x_L, y_L, \phi_L)^T$, and the increments of distance and orientation be the control inputs $u=(\Delta S, \Delta\phi)^T$. The state function of the system is defined as equation (14).

$$\begin{bmatrix} x_{k+1} \\ y_{k+1} \\ \phi_{k+1} \end{bmatrix} = \begin{bmatrix} x_k \\ y_k \\ \phi_k \end{bmatrix} + \begin{bmatrix} (\Delta S + w_1)\cos(\phi_k + \Delta\phi/2) \\ (\Delta S + w_1)\sin(\phi_k + \Delta\phi/2) \\ \Delta\phi + w_2 \end{bmatrix} \quad (14)$$

where $w=(w_1, w_2)^T$ is the process noise. At the same time, the measurement functions can be defined as equation (15).

$$\begin{bmatrix} x_{L,k+1} \\ y_{L,k+1} \\ \phi_{L,k+1} \end{bmatrix} = \begin{bmatrix} x_{k+1} \\ y_{k+1} \\ \phi_{k+1} \end{bmatrix} + \begin{bmatrix} v_1 \\ v_2 \\ v_3 \end{bmatrix} \tag{15}$$

where $v=(v_1, v_2, v_3)^T$ is the measurement noise. At most time, the process noise and the measurement noise are assumed to be independent of each other, white, and with normal probability distributions.

$$\begin{aligned} p(w) &\sim N(0, Q) \\ p(v) &\sim N(0, R) \end{aligned} \tag{16}$$

In practice, the process noise covariance Q and measurement noise covariance R matrices are assumed to be constant. The experimental results proved that this assumption can simplify the system and provide good results.

At length, a control input is added into the system function to change the state vector at each instance. Whenever one or more landmark pairs are detected, a measurement vector is provided to update the pose estimation of vehicle using EKF. Of course, an initial state vector x_0 and its error covariance P_0 are given at the beginning. Generally speaking, the initial state vector x_0 is the starting pose of the vehicle. As for the initial error covariance P_0, it can be set as 0 (null matrix) in consequence of that the initial state is the absolute pose in the global map. In order to make the algorithm flexible, we start our filter with $P_0=I$ (unit matrix) instead.

V. Experiments

The proposed algorithm has been implemented and evaluated using both real range data and synthetic data. Firstly, we use synthetic data to analyze the performances of the algorithm, such as the accuracy and the robustness.

A. Simulations with synthetic data

A simulator has been developed in order to generate the synthetic data, in which a global map and a car model can be defined for different applications. The virtual car is controlled by the array keys. At the same time, by searching the distances between the pose of the car and the points in the map the data of laser radar can be acquired. There is a system error during the process of searching range data of laser radar in theory, which is just like the system error of the real pulsed Time-Of-Flight (TOF) laser radar.

In our case, a digital map, including some landmark pairs, is used. The laser data are a series of ranges in whole process, with a maximal range of 50m, range resolution of 1cm, angle field of view of 180°, angular resolution of 0.5°. Besides this data, the absolute poses of laser radar are recorded. Then, calculate the increments of distance and orientation of each time using the absolute poses to synthesize the data for DR (Dead Reckoning). Because there are always some noises in the real world, some Gauss Noises are added into during the calculating processes. They are the process noises w_1 and w_2 respectively. Owing to the characteristic of DR, set their distributions as

$$\begin{aligned} p(w_1) &\sim N(0, 0.1^2) \\ p(w_2) &\sim N(0, 0.01^2) \end{aligned} \tag{17}$$

The first step is to evaluate the key part of L^3P ---- Landmark Pair Detection. The detection algorithm is successful in all frames of laser data. Whether there is only one landmark pair or several landmark pairs, they can be extracted correctly and accurately. In a word, the algorithm can extract every landmark pair without any errors, as long as the laser radar should scan the landmark pair.

The second step is to evaluate the algorithm of pose estimation. In the simulation, the 'vehicle' runs a trajectory, and then use different algorithm to estimate the pose offline. With these synthetic data, three algorithms are tested, namely DR, L^3P without EKF and L^3P with EKF. The dashed line is the DR trace, the solid line is the L^3P trace and the dot-dashed line is the ground truth. Seen from the result figure (Fig. 4, 5 and 6), the DR trace is far from the ground truth and not so satisfying for its poor accuracy, special vulnerability to angular error, and cumulative errors along time. In contrast to the DR trace, the L^3P trace is too much closer to the ground truth, with higher accuracy than DR, and without cumulative errors. Unfortunately, owing to the system error, the L^3P trace without EKF which is obviously shown in Fig. 5 is a rough trajectory with some burrs and fluctuations like a spline. Needless to say, this is not suitable for realistic applications. At last, the L^3P trace with EKF is a smooth curve close to the ground truth, which has the highest accuracy, good smoothness, and no cumulative errors (See Fig. 6). Thus far, this result will be sufficient for realistic implementation.

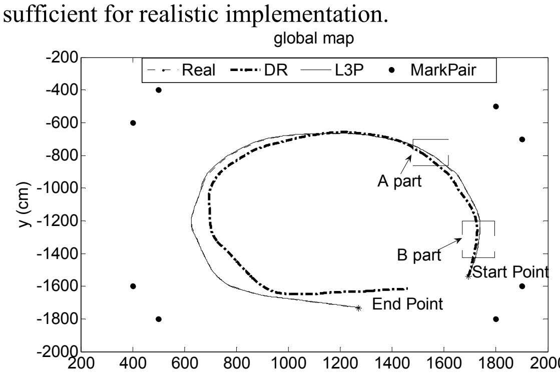

Fig. 4 Result figure of simulation

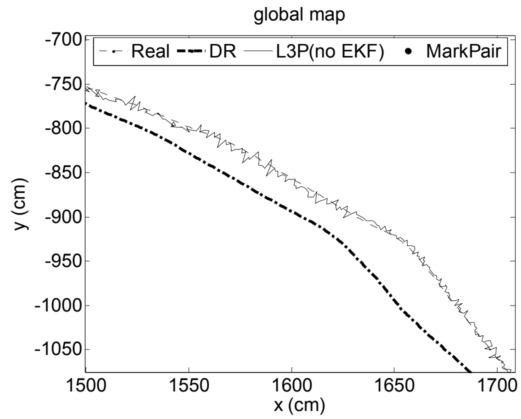

Fig. 5 Zoom in A part of Fig. 4 (no EKF)

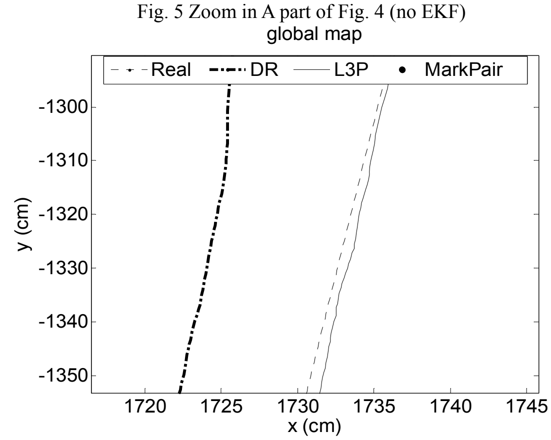

Fig. 6 Zoom in B part of Fig. 4 (with EKF)

To make the problem clearer, the errors between the ground truth and the three localization methods are analyzed statistically. Table 1 and Table 2 show the details of statistical results. As to distance error which includes the mean, the maximum and the standard covariance of the errors, from DR to L^3P without EKF and then to L^3P with EKF, it is decreasing in turn, which fulfills the very theory analyzed in the previous sections.

Table 1 Distance error comparison (Unit: cm)

Algorithm	Mean	Max.	Std.
DR	78.81	224.10	72.86
L^3P (no EKF)	3.81	18.59	2.56
L^3P (with EKF)	2.57	6.88	1.31

Table 2 Other error comparisons

	L^3P (no EKF)			L^3P (with EKF)		
	Max.	Mean	Std.	Max.	Mean	Std.
x (cm)	14.38	-0.49	3.43	4.78	-0.43	2.09
y (cm)	12.10	1.33	2.69	4.59	1.48	1.25
ϕ (deg)	0.020	-0.001	0.006	0.058	0.005	0.019

At last, simulations with different angular resolutions are done. The aim of this part is to see how to overcome the system error of laser radar. Fig. 7 shows the schematic of laser radar scanning in the simulator. Suppose there are two points a and b, which are on the edge of two angular areas. But the simulator considers them as a' and b' due to the angular resolution α. In this sense, the system error is introduced by the angular resolution.

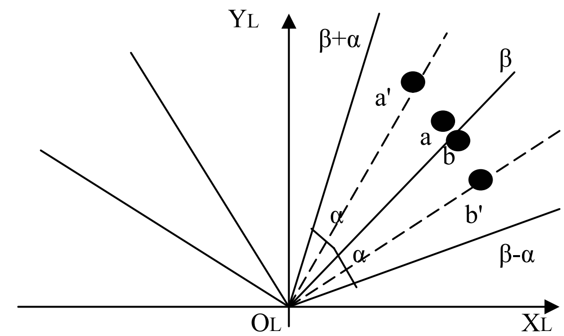

Fig. 7 Schematic of laser radar scanning in the simulation

The result of this part verifies that the algorithm will be better when the angular resolution is higher. (See Table 3)

Table 3 Error comparisons with different angle resolution

Angular resolution (degree)	L^3P Distance Error (cm)	
	Mean	Std.
1	5.17	3.59
0.5	3.81	2.56
0.25	3.05	1.71
0.1	2.13	1.70

B. Experiments with real data

We also do experiments with real range data from the CyberC3 vehicle, which is an intelligent vehicle developed at Shanghai Jiao Tong University. LMS291 laser radar made by Sick Ltd. is equipped on CyberC3 to provide range data. This is a pulsed TOF radar system with a maximal range of 80m, a range resolution of 1cm, an angular resolution of 0.5°, scan time of 26.6ms, and field-of-view of 180°. The outdoor environment is composed of four landmark pairs, walls, trees, and so on.

The CyberC3 can also provide the data of encoders. But the pose of landmark pairs can only be manually measured. What is worse, we cannot obtain the absolute pose of vehicle when it is running. In order to evaluate the algorithms, a pen which is tied on the vehicle is utilized and will draw a trace when the vehicle is running.

Several experiments have been done in different environments to test the algorithm, and the results are presented below.

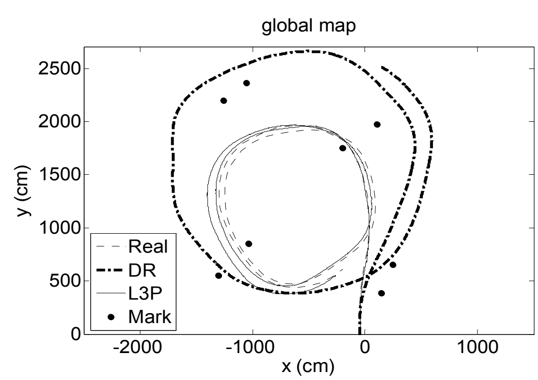

Fig. 8 An example of L^3P

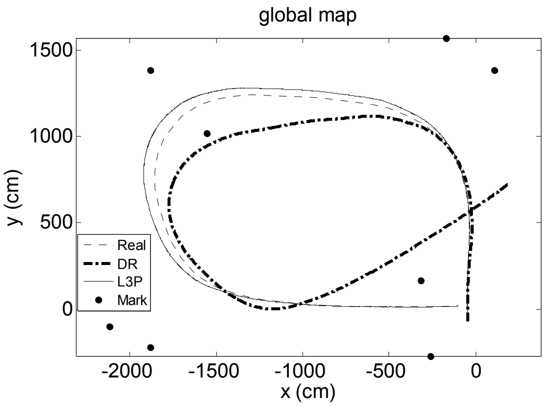

Fig. 9 Another example of L^3P

The results show two things. For one thing, the landmark pair detection algorithm is good enough, with high accuracy. For another, L^3P is much better than DR. At this time, we can only give the maximal distance error of L^3P, which is about 60cm. The factors, attributed to the error, are below: (1) the system error of laser radar; (2) the error of manual measurement of landmark pair poses, which may be the fatal cause to the algorithm failure; (3) other unexpected errors. As for the computing time, it costs about 5ms in one frame data processing. Since this is much less than the scan period of laser radar, the algorithm can afford real-time application.

VI. Conclusions And Future Work

In this paper, we proposed a novel algorithm of Laser Radar Localization based on Landmark Pairs (L^3P), with high accuracy of laser radar detection, low computation, and high robustness to noises, and without cumulative errors. By using landmark pairs, we can obtain a satisfying result of pose estimation, which is suitable for realistic application. Individual components of the system were evaluated in simulations and several demonstrations of the system as a whole were done in real experiments.

An extended effort of another self-localization method ICP (Iterative Closest Point) is expected in the upcoming studies. At the completion of artificial landmark based localization, natural landmark based localization will be carried out to experiment and observe the soundness and feasibility of the algorithm. More inspiring, the Simultaneous Localization and Mapping (SLAM) will be a central topic of future studies.

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