Accurate Large-Scale Bearing-Only SLAM by Map Joining

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Abstract

This paper presents a bearing-only SLAM algorithm that generates accurate and consistent maps of large environments by joining a series of small local maps. The local maps are built by least squares optimization with a proper landmark initialization technique. The local maps are then combined to build global map using Iterated Sparse Local Submap Joining Filter (I-SLSJF). The accuracy and consistency of the proposed algorithm is evaluated using simulation data sets. The algorithm is also tested using the DLR-Spatial-Cognition data set and the preprocessed Victoria Park data where the range information is ignored. The global map results are very similar to the result of full least squares optimization starting with very accurate initial values. As I-SLSJF is able to join a given set of local maps and associated uncertainties efficiently without any information loss, these results demonstrate that focusing on generating accurate local maps is a promising direction for solving large-scale bearing-only SLAM problems.

1 Introduction

Simultaneous localization and mapping (SLAM) is the process by which a mobile robot can build a map of the environment and, at the same time, use this map to compute its location [Dissanayake *et al.*, 2001]. The main research work on SLAM has been focused on improving computational efficiency while ensuring consistent and accurate estimates for the map and robot poses [Durrant-Whyte and Bailey, 2006]. There has also been much research on issues such as data association, observation nonlinearity, and landmark parametrization and initialization, all of which are vital in achieving a practical and robust SLAM implementation.

SLAM using range-bearing measurement to landmarks has been well investigated by SLAM researchers. One of the popular solutions in SLAM is extended Kalman Filter (EKF) based approach, which has already been applied in indoor and outdoor, underwater, and airborne system [Durrant-Whyte and Bailey, 2006]. The sensors for getting range-bearing information such as laser scanners are more expensive compare to vision sensors. However monocular vision sensors provide bearing only measurement, where it is needed to overcome landmark initialization problem [Bailey, 2003], [Kwok *et al.*, 2005].

Most of the researchers have used EKF approach to solve the bearing-only SLAM problem. Unfortunately, the EKF is ill-suited for the problem of bearing-only SLAM because of the highly nonlinear measurement model [Deans, 2002]. Several approaches have been proposed to overcome this problem such as SPRT Based Gaussian Sum Filter [Kwok *et al.*, 2005], bundle adjustment [Deans, 2002],[Strasdat *et al.*, 2010], iterated Kalman filter [Trully *et al.*, 2008], and total least squares [Dogancay, 2005].

For range-bearing SLAM problems, map joining has been introduced to reduce the computational complexity of SLAM [Williams, 2001]. One of the map joining methods that have been developed recently is Sparse Local Submap Joining Filter (SLSJF) [Huang *et al.*, 2008a] which substantially reduces the computational cost of the global map construction by exploiting the sparseness of information matrix involved in the local map joining process. SLSJF is further improved as Iterative SLSJF (I-SLSJF) [Huang *et al.*, 2008b] such that the consistency of the global map is greatly improved.

This paper considers 2D bearing-only SLAM problem. We demonstrate that large-scale bearing-only SLAM can be achieved by first building small-scale bearing-only SLAM map and then join the small maps together using map joining algorithms originally developed for range-bearing SLAM (such as I-SLSJF). A simple landmark initialization technique together with the linearized least squares approach is proposed to solve the small-scale bearing-only SLAM problem for building small maps.

The use of map joining not only reduces the computational cost of the global map construction, but also improves the reliability of the landmark initialization.

The paper is organized as follows. Section 2 discusses some related work of this research. Section 3 presents the building of small local maps, where the method for landmarks initialization and linearized least squares approach is explained. The structure of I-SLSJF as a map joining strategy is described in Section 4. Section 5 provides simulation and experiment results. Finally, Section 6 concludes the paper.

2 Related Work

In this section, some recent work on large-scale bearing-only SLAM and their relation to the method proposed in this paper are discussed.

2.1 Landmark initialization in bearing-only SLAM

One of the challenges in bearing-only SLAM problem is landmark initialization. Constrained initialization has been introduced within EKF framework in [Bailey, 2003]. In this work, the observations for not-yet-initialized landmark are kept in the state vector together with the corresponding robot poses. A Gaussian sum filter is introduced within EKF framework [Kwok *et al.*, 2005] to represent the inaccurate range information of the landmarks. Recently, the inverse-depth feature parametrization is demonstrated to be more robust than the traditional Euclidean parametrization especially for distant landmarks [Civera *et al.*, 2008] but sometimes the inverse-depth can become negative [Parsley and Julier, 2008]. A unified framework is proposed to overcome an inability to deal with the landmarks that are effectively at infinite distance [Trawny and Roumeliotis, 2006]. They presented a unified formulation capable of incorporating information from nearby and distant landmarks as well as those lying in the direction in which the robot travels. Landmark initialization with unknown data association has also been discussed by some researcher [Deans, 2002] and [Costa *et al.*, 2004]. The strategy for landmark initialization is to ignore the landmarks if the angle of intersecting is small [Deans, 2002]. In most of the work listed above, EKF is used in the estimation process and the algorithms were tested using relatively small data sets.

In this paper, because we are using map joining approach, landmark initialization only needs to be performed in the local map building process where accumulated robot pose error is very small, this makes the landmark initialization a lot easier. To guarantee the accuracy of the landmark initialization, we check the angle between two bearing observations. If the angle of intersecting is not large enough or the intersection point is not in the positive direction of the bearings, we will wait for the next observation to perform the landmark initialization. From the simulation and experimental result it is shown that this simple delayed landmark initialization strategy together with linearized least squares approach can produce good quality local maps in bearing-only SLAM.

2.2 Linearized least squares for local map building

Many researchers used EKF as a tool for solving bearing-only SLAM problem. However, in bearing-only SLAM, the highly nonlinear measurement model can cause serious problem for EKF SLAM. The potential inconsistency of EKF SLAM with range-bearing information has been reported in the recent years [Huang and Dissanayake, 2007],[Bailey *et al.*, 2006]. It is clear that EKF SLAM with bearing-only information can have even severe inconsistency problems [Sola, 2010]. To overcome this nonlinearity problem iterated filter has been introduced by [Trully *et al.*, 2008]. In their paper, the iterated Kalman filters (IKF) are proposed and combined with inverse-depth parameterization. [Deans, 2002] and [Strasdat *et al.*, 2010] presented the comparison between EKF SLAM and bundle adjustment and suggested the use of bundle adjustment. It is claimed that the bundle adjustment is robust enough to overcome the lack of range information in the bearing-only SLAM problems. Dogancay [Dogancay, 2005] introduced total least squares (TLS) for bearing-only target localization. TLS estimation algorithm is developed based on the method of orthogonal vectors, and then constrained TLS algorithm also developed to improve estimation accuracy.

In this paper, because we are only building small local maps using the bearing-only SLAM, we can afford to use the more reliable least squares approach (bundle adjustment) to build the bearing-only local maps. Moreover, the sparseness of the information matrix further reduces the computational cost of the local map building process. For the least squares approach, a good initial value is needed for the algorithm to converge to the global minimum. A poor quality landmark initialization may cause the state estimate to diverge or being trapped into a local minimum, so it is important to keep the local maps relative small such that the initialization error is limited.

2.3 Map joining to solve large-scale SLAM problem

Recently, some researchers have proposed map joining to improve the efficiency of construction of large-scale maps, mostly for SLAM using range and bearing data. For example, EKF is applied in the map joining process in [Williams, 2001]. The Atlas framework in [Bosse *et* *al.*, 2004] performed a high level optimization to adjust the relative positions among the local maps. In [Huang *et al.*, 2008a], the extended information filter (EIF) is used for fusing submaps and the information matrix associated with SLSJF is exactly sparse. Iterated-SLSJF (I-SLSJF) is an improved version of SLSJF where the consistency of the global map is further improved by occasionally performing least squares optimization [Huang *et al.*, 2008b]. Another approach for map joining is to build submaps that can share information and thus conditionally independent. The map joining is carefully performed to avoid the information reuse [Pinies and Tardos, 2008].

This paper uses the I-SLSJF as map joining approach for solving large-scale bearing-only SLAM mainly because (i) there is neither information loss nor information reuse when I-SLSJF is applied to join local maps; and (ii) the potential inconsistency of filter based map joining algorithms is avoided in I-SLSJF. The simulation and experimental results clearly demonstrate that large-scale bearing-only SLAM can be solved by building small bearing-only maps and then joining the small maps using I-SLSJF.

3 Building Small Local Maps

This section presents the process of the landmark initialization and linearized least squares approach for small local map building.

3.1 Bearing-only SLAM problem

There are two kinds of information available in bearing-only SLAM. One is the bearing-only observations which is related to the landmark position and the robot pose, another is the odometry information which is related to the two consecutive robot poses.

Suppose the robot pose i is denoted as

$$X_{r_i} = (x_{r_i}, y_{r_i}, \phi_{r_i}) \tag{1}$$

and the position of landmark f is denoted as

$$X_f = (x_f, y_f) \tag{2}$$

The odometry from pose i to pose $i+1$, denoted as O_i^{i+1}, can be regarded as a measurement of the relative pose between pose i and pose $i+1$ and is given by

$$O_i^{i+1} = f_{odo}(X_{r_i}, X_{r_{i+1}}) + w_i^{i+1} \tag{3}$$

where w_i^{i+1} is the odometry noise which is assumed to be Gaussian with zero-mean and covariance matrix C_i^{i+1}. The function $f_{odo}(X_{r_i}, X_{r_{i+1}})$ is the relative pose between pose i and pose $i+1$ and is given by

$$\begin{aligned} & f_{odo}(X_{r_i}, X_{r_{i+1}}) \\ &= \begin{bmatrix} (x_{r_{i+1}} - x_{r_i})\cos\phi_{r_i} + (y_{r_{i+1}} - y_{r_i})\sin\phi_{r_i} \\ -(x_{r_{i+1}} - x_{r_i})\sin\phi_{r_i} + (y_{r_{i+1}} - y_{r_i})\cos\phi_{r_i} \\ \phi_{r_{i+1}} - \phi_{r_i} \end{bmatrix}. \end{aligned} \tag{4}$$

The bearing-only observation from pose i to landmark f, denoted as θ_i^f, is a measurement of the bearing angle from robot to the landmark and is given by

$$\theta_i^f = f_{obs}(X_{r_i}, X_f) + w_i^f. \tag{5}$$

where w_i^f is the observation noise which is assumed to be Gaussian with zero-mean and variance C_i^f. $f_{obs}(X_{r_i}, X_f)$ is the observation function given by

$$f_{obs}(X_{r_i}, X_f) = atan2(y_f - y_{r_i}, x_f - x_{r_i}) - \phi_{r_i}. \tag{6}$$

The bearing-only SLAM problem is to estimate the landmark positions and the robot poses using the odometry and bearing-only information given in (3) and (5).

3.2 Landmark initialization

In bearing-only landmark initialization, to determine the landmark location, a single measurement is insufficient to estimate the location of landmarks and at least two bearing measurements from two different robot poses are required [Bailey, 2003]. The intersection of two lines as shown in Figure 1 is a calculated location of landmark. The formula is given by [Bailey, 2003]

$$\begin{aligned} X_f &= g(X_{r_i}, X_{r_j}, \theta_i^f, \theta_j^f) \\ &= \begin{bmatrix} \frac{x_{r_i} s_i c_j - x_{r_j} s_j c_i + (y_{r_j} - y_{r_i}) c_i c_j}{s_i c_j - s_j c_i} \\ \frac{y_{r_j} s_i c_j - y_{r_i} s_j c_i + (x_{r_i} - x_{r_j}) s_i s_j}{s_i c_j - s_j c_i} \end{bmatrix} \end{aligned} \tag{7}$$

where

$$\begin{aligned} s_i = \sin(\phi_{r_i} + \theta_i^f),\ c_i = \cos(\phi_{r_i} + \theta_i^f), \\ s_j = \sin(\phi_{r_j} + \theta_j^f),\ c_j = \sin(\phi_{r_j} + \theta_j^f). \end{aligned} \tag{8}$$

One of the problems for intersection method is that the initialization is inaccurate when the angle of intersection is not large enough [Bailey, 2003]. If the intersecting angle is small, the obtained location of landmark may be very far away from the real location. Another problem is sometimes the intersection point is on the negative direction of the observation line meaning that a completely wrong landmark location is calculated.

In this paper the first two observations are first used to calculate the landmarks location. If the intersection point is in the negative side of one of the two observation lines or the angle of intersecting is smaller than a threshold, then the landmark will not be initialized until the next observation is available. The landmark is

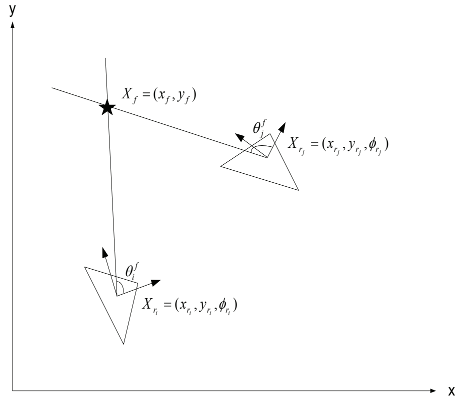

Figure 1: Landmark initialization via the intersection of two bearing measurements

calculated if the pair fulfills the criteria as desired. Basically, we are looking for an observation pair such that a reliable landmark initialization can be obtained. So this is a delayed initialization approach which is suitable for least squares based bearing-only SLAM algorithm.

3.3 Linearized least squares method

The bearing-only SLAM problem can be formulated as a nonlinear least squares problem. The variables X contains all the robot poses and all the observed landmark positions. The objective is to find X to minimize

$$(Z - F(X))^T C^{-1} (Z - F(X)) \tag{9}$$

where Z is the vector containing all the relative odometry information O_i^{i+1} in (3) and all the bearing observations θ_i^f in (5), $F(X)$ is a function of state vector X that relating X to Z expressed by f_{odo} in (4) and f_{obs} in (6), C is the covariance matrix of the measurement error in vector Z which can be obtained by matrices C_i^{i+1} in (3) and C_i^f in (5). Since C is a block diagonal matrix, C^{-1} is also a block diagonal matrix that can be constructed by $(C_i^{i+1})^{-1}$ and $(C_i^f)^{-1}$.

Once an initial value of X is obtained, the least squares problem can be solved by Gauss-Newton iteration or more robustly by Levenberg-Marquardt algorithm. Since the associated Jacobian and the matrix C^{-1} are both sparse, sparse linear equation solver can be used to keep both the memory requirement and the computational cost small.

For both Gauss-Newton iteration and Levenberg-Marquardt algorithm, a relatively accurate initial value of the state vector is needed to guarantee the algorithm converge to the global minimum. Since we only use least squares to build local maps, the initial value obtained from accumulating odometry (for robot poses) and the landmark initialization (for landmark positions) are accurate enough.

4 Map Joining

This section presents the structure of I-SLSJF [1] [Huang *et al.*, 2008b] and explains how to use it in large-scale bearing-only SLAM.

4.1 The input and output of I-SLSJF

The input to the I-SLSJF is a sequence of local maps constructed by some SLAM algorithm. A local map is denoted by

$$(\hat{X}^L, I^L) \tag{10}$$

where $\hat{X}^L$ (the superscript 'L' stands for the local map) is an estimate of the state vector

$$X^L = (X_r^L, X_1^L, \cdots, X_n^L) \tag{11}$$

and I^L is the associated information matrix (the inverse of the covariance matrix). The state vector X^L contains the robot final pose X_r^L (the subscript 'r' stands for the robot) and all the local landmark positions $X_1^L, \cdots, X_n^L$, as typically generated by conventional EKF SLAM. The coordinate system of a local map is defined by the robot pose when the building of the local map is started, i.e. the robot starts at the coordinate origin of the local map.

It is assumed that the robot starts to build local map $k+1$ as soon as it finishes local map k. Therefore the robot end pose of local map k (defined as the global position of the last robot pose when building local map k) is the same as the robot start pose of local map $k+1$ (Figure 2).

The output of I-SLSJF is a global map. The global map state vector contains all the landmark positions and all the robot end poses of the local maps (see Figure 2). The global map result is given in the form of a global state estimate X_G, an information vector i_G and an information matrix I_G.

There are two important features of I-SLSJF that worth mentioning. One is that the information matrix involved is exactly sparse which make the algorithm very efficient. Another is that an optimization step is performed whenever necessary such that the linearization error is reduced and the consistency is maintained.

4.2 Apply I-SLSJF to bearing-only SLAM

In order to apply I-SLSJF to large-scale bearing-only SLAM, the local maps built by the bearing-only SLAM algorithm need to be transferred into the correct form.

[1]The MATLAB code of I-SLSJF is available on OpenSLAM website: http://openslam.org/

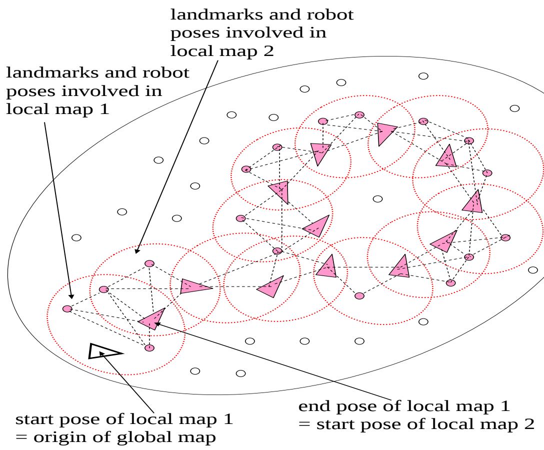

Figure 2: Structure of I-SLSJF: small ellipses indicate the landmarks and robot poses involved in the local maps. The final global map state vector contains the locations of all the shaded objects.

That is, a state vector and the corresponding information matrix that involve all the local landmarks and the final robot pose. Since our small bearing-only local maps are generated using least squares based algorithm, the state vector of each local map contains all the robot poses but only the last pose is needed. The required state vector can be easily obtained by simply removing the other poses. The required information matrix can be computed through Schur complement.

5 Simulation and Experiment Results

Simulation and experimental results are used to demonstrate the accuracy and consistency of the proposed bearing-only SLAM algorithm.

5.1 Simulation results

The simulation environment contains nearly uniformly distributed features. The robot starts from the bottom-left corner of the square and performs two loops and then finishes at the top-right corner (Figure 3). The range-bearing sensor is assumed to have a range limit of 6 meters with a field of view of 180 degrees and we ignore the range information when implementing the bearing-only SLAM algorithms. In this data set, there are 256 robot poses, 75 observed landmarks and 1283 bearing measurements.

Figure 3 shows the linearized least squares result when ground truth of the landmark positions and robot poses are used as the initial value. This can be argued as the best result one can get and will be used to evaluate our map joining result. In Figure 3, all the robot poses and all the landmarks in the map are shown. The red stars are the ground truth of landmark positions and the black circles represent the estimated landmark positions using the linearized least squares approach. The red crosses are the ground truth of the robot poses and the cyan squares are the estimated robot poses.

It is worth mentioning that when applying the landmark initialization strategy for the whole data and use the result as the initial value, neither the Gauss-Newton iteration nor the Levenberg-Marquardt algorithm can converge to the correct solution. This is probably because of the large accumulated odometry error in the long trajectory. On the other hand, when building small local maps where the trajectory is short, the linearized least square algorithm using the landmark initialization as initial value works fine for both Gauss-Newton iteration and Levenberg-Marquardt algorithm.

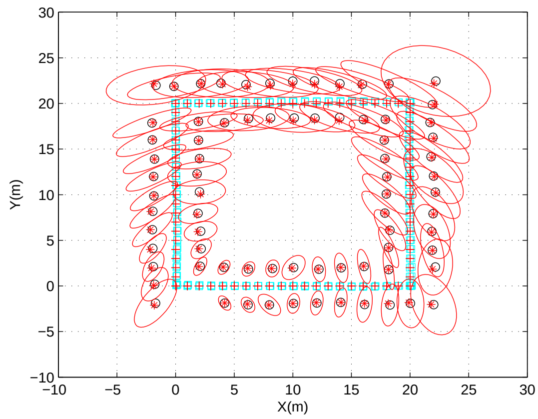

Figure 3: The best bearing-only map one can achieve using simulation data together with the 2σ uncertainty ellipses. The result is obtained by performing linearized least squares optimization with ground truth as initial value. Since the data contains noises, the global minimum is not exactly the same as ground truth.

We perform the local map building and map joining using I-SLSJF. Figure 4 shows the first local map we obtained and Figure 5 is the map joining result of joining all the 5 local maps. To evaluate the accuracy of the map joining approach, we overlap the map joining result with the “optimal” least squares result of the single map (with ground truth as initial value) in Figure 6. The blue crosses represent for landmark and green diamond represent for robot pose from the map joining using I-SLSJF. The black circle is representing the landmark and red star representing the corresponding robot poses from the single map result. From the result it is shown that I-

SLSJF can produce very similar result as that of the best possible solution using the bearing-only information.

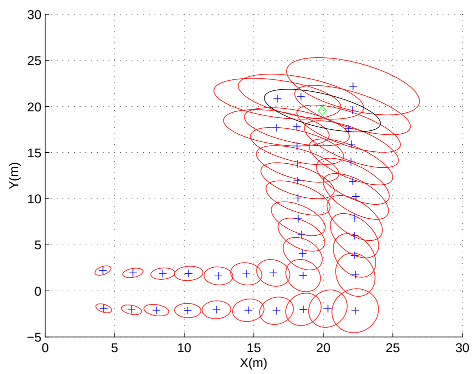

Figure 4: The result of local map 1 for simulation data set. The blue crosses are the estimate of landmark positions and the red ellipses show the corresponding 2σ uncertainty. The green diamond shows the estimated position of the final robot pose in the local map and the black ellipse shows the corresponding 2σ uncertainty.

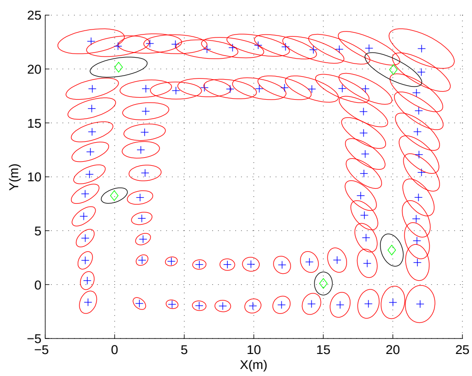

Figure 5: The result for the map joining of 5 local maps using simulation data set. The blue cross represent for landmark estimate and green diamonds represent the estimates of the robot end poses of the 5 local maps.

5.2 Consistency analysis

Figure 7 shows the robot pose estimation error and 2σ bounds for the map joining result. Since there are 5 local maps, the output of I-SLSJF only contains 5 poses that corresponding to the robot end poses in each local map. It is clear from Figure 7 that the estimate of the 5 robot poses is consistent.

To have a proper check on the consistency of the map joining results, we run the simulation experiments 5 times each with a different random seeds for the odometry and observation noises. Then we compute the Normalized Estimation Error Squared (NEES) using the resulting state estimate error and the information matrix as in

$$\text{NEES} = (X_G - X_G^{true})^T I_G (X_G - X_G^{true}) \qquad (12)$$

where X_G is the global state estimate and X_G^{true} is the corresponding ground truth. I_G is the sparse information matrix which is part of the output of I-SLSJF.

The NEES result is summarized in Table 1. The average NEES is 99.08 while the 95% confidence gate is 198.15. Thus the estimate of the proposed map joining algorithm is consistent.

5.3 DLR-Spatial-Cognition data set

The DLR-Spatial-Cognition data set is collected using a robot equipped with a camera. This

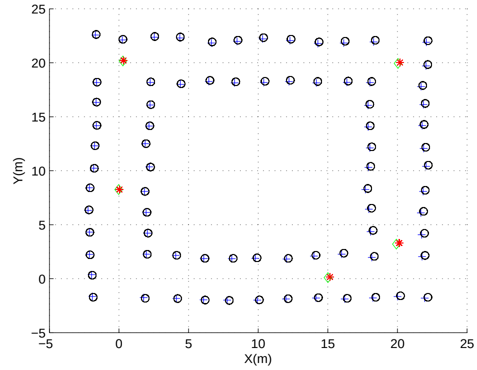

Figure 6: The overlap result between the map joining using I-SLSJF (Figure 5) and the "best" single map (Figure 3) using simulation data. The blue cross represents for landmark and green diamond represents for robot pose from the result of I-SLSJF. The black circle and red star represent the results from the single map result.

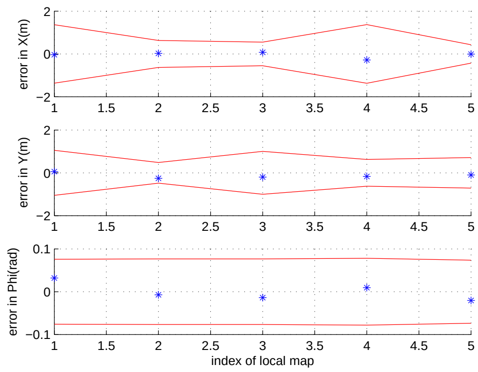

Figure 7: The robot pose estimation error and 2σ bound of the map joining result.

Table 1: NEES Test on Global Maps

Run	NEES	95% confidence gate (state dimension: 167)
1	102.71	198.15
2	100.94	198.15
3	104.24	198.15
4	89.07	198.15
5	98.45	198.15
average	99.08	198.15

data is available at http://www.sfbtr8.spatial-cognition.de/insidedataassociation/ data.html. The robot moved around in the building with artificial landmarks (white/black circles) placed on the ground. The image data has been preprocessed and the relative positions of the observed landmarks with respect to the observation point are provided. In this data set, there are 3297 robot poses, 539 landmarks and 14163 measurements. To test our bearing-only SLAM algorithm, the bearing information is calculated from the relative position data provided in the data set. All the range information is ignored.

To get the best possible map that we can compare with, we use all the odometry and range-bearing information to perform a full least squares and obtain the robot poses and landmark positions. This is then used as the initial value for the full least squares using the bearing-only information and odometry information to build a single bearing-only SLAM map. We believe this is the best bearing-only SLAM result one can get. Figure 8 shows this best possible bearing-only SLAM result one can achieve using DLR data set.

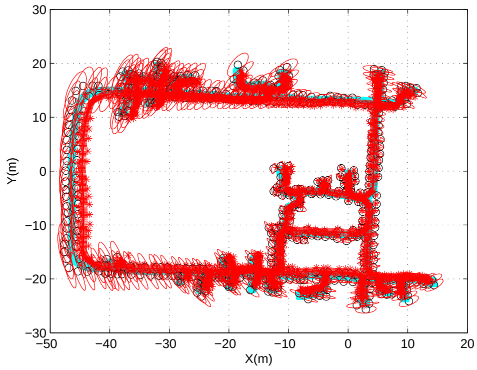

Figure 8: The best bearing-only SLAM result one can achieve using DLR data set (full least squares with range-bearing SLAM result as initial value).

The data is then divided into nine groups and used to build nine local maps. Figure 9 shows the result for local map 1 and Figure 10 is the map joining for the nine local maps. In Figure 9 and Figure 10 the blue dot represents landmarks and the green diamond represents the robot poses. Figure 11 shows the overlap of the map joining result and the best single map result for DLR data set. From Figure 11, it can be seen that the proposed approach can produce almost the same result as the best achievable result.

The data is then divided into 18 groups and used to build 18 local maps and joined together using I-SLSJF. Figure 12 and Figure 13 show the map joining result and the overlapping with the best single map. From Figure 12, it can be seen that using larger number of local maps may produce low quality global map due to the information loss in the local map building process. In fact, when the size of local maps is small, the observation information of some landmarks has been lost because it is impossible to get good initialization of the landmarks.

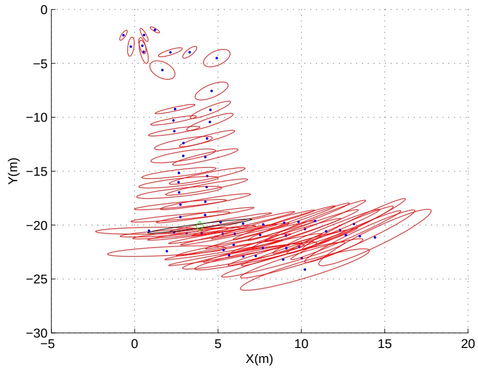

Figure 9: The first bearing-only local map using DLR data set. The blue dot represent for landmark and green diamond represent for robot pose.

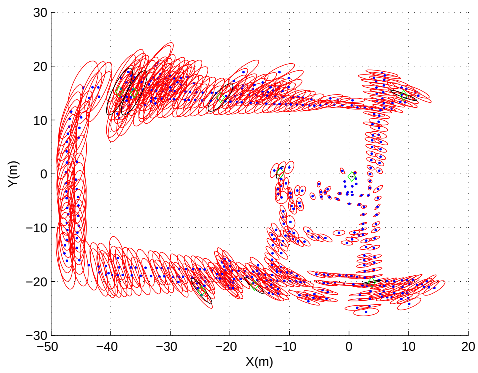

Figure 10: The result of map joining of 9 bearing-only local maps using DLR data set. The blue dot represent for landmark and green diamond represent for robot poses.

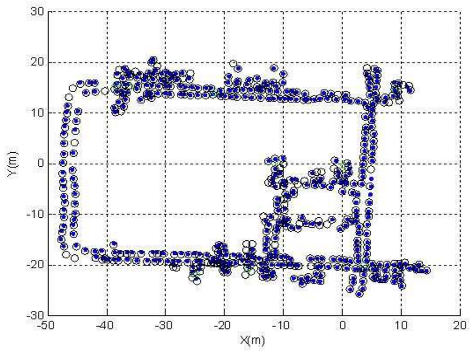

Figure 11: The overlap result between the map joining of 9 local map using I-SLSJF (Figure 10) and the best single map (Figure 8) for DLR data set. The blue dot represent for landmark and green diamond represent for robot pose for map joining using I-SLSJF. The black circle is representing the landmark in single map result.

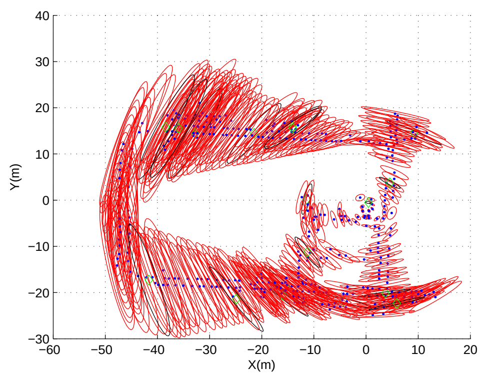

Figure 12: The map joining result of joining 18 small bearing-only local maps using DLR data set. The blue dot represent for landmark and green diamond represent for robot poses.

5.4 Victoria Park data set

The proposed bearing only I-SLSJF was also applied to the popular Victoria Park data set [Guivant and Nebot, 2001] where again all the range information is removed. The preprocessed data available at OpenSLAM (within the project 2D I-SLSJF) is used where the data association is given. Although the original data is not collected through camera, we want to demonstrate that the algorithm we proposed can be applied to this popular data set. In this data set, there are 6898 robot poses, 257 landmarks and 45379 measurement. Figure 14 shows the best result one can achieve. Namely, a full

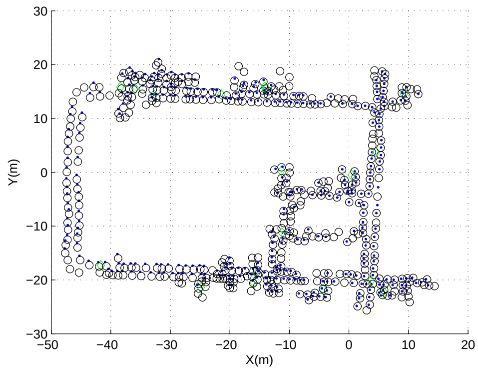

Figure 13: The overlap result between the map joining of 18 local maps using I-SLSJF and the best single map. The blue dot represent for landmark and green diamond represent for robot pose for map joining using I-SLSJF. The black circle is representing the landmark in single map result.

least squares using bearing-only information with range-bearing SLAM result as initial value. All the robot poses and all the landmarks are shown in the map. Figure 15 shows the map joining result by joining 18 bearing-only local maps using our approach. Figure 16 shows the overlap between the map joining result (Figure 15) and the best single map (Figure 14). The blue dot represent for landmark and green diamond represent for robot pose for map joining result. The black circle is representing the landmark in single map result. From Figure 16, it can be seen that the proposed approach can produce good quality result.

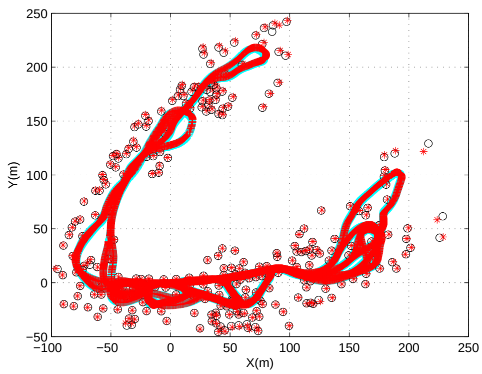

Figure 14: The best bearing-only result one can achieve using Victoria Park data set (full least squares using bearing only information with result from range and bearing SLAM as initial value).

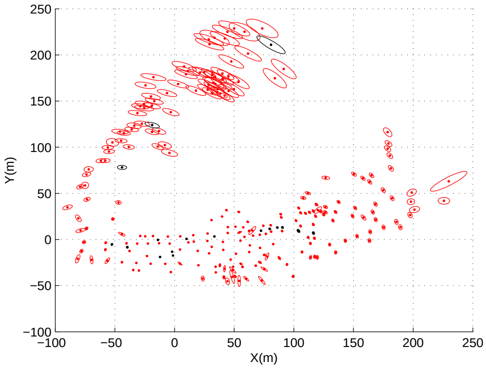

Figure 15: The result of joining 18 bearing-only local maps for Victoria Park data set. The blue dot represent for the landmark and green diamond represent for the robot poses.

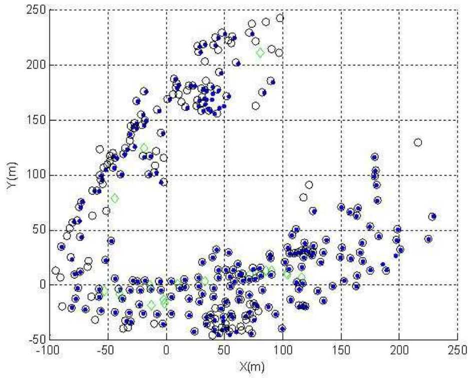

Figure 16: The overlap result between the map joining using I-SLSJF (Figure 15) and single map (Figure 14) for Victoria data set. The blue dot represent for landmark and green diamond represent for robot pose for map joining using I-SLSJF. The black circle is representing the landmark in the single map result.

6 Conclusion

In this paper, we demonstrate that I-SLSJF can be successfully applied to large-scale bearing-only SLAM problems. Basically, we separate the large-scale bearing-only SLAM problem into two parts: (i) building small local maps using linearized least squares based bearing-only SLAM algorithms, and (ii) applying I-SLSJF to join the small local maps together to form the global map. Extensive testing using simulation data, the Victoria Park data set, and the DLR-Spatial-Cognition data set show that the proposed approach can generate almost the same result as that obtained by full least squares with very accurate initial values for robot poses and landmark positions.

Thanks to the map joining approach, the landmark initialization only needs to be performed in local map building process where robot pose accumulated error is limited. The proposed simple landmark initialization approach combining with least squares optimization can reliably generate good quality local maps. Unlike many other bearing-only SLAM techniques where EKF is used as a tool to solve SLAM problem, we proposed least squares for local map building and I-SLSJF for map joining. Both least squares and I-SLSJF are optimization based approach which can avoid the potential consistency issue involved in most of the filter based SLAM techniques.

In this work, there is some information loss especially when the size of the local maps is too small. The reason is that some landmarks cannot be properly initialized due to the lack of enough bearing observations from different angles. Also, our focus is on the accuracy and consistency of the bearing-only SLAM where data association is assumed. Although data association is still a major topic in SLAM problems, we assume that data association can be solved through another method (such as using feature descriptors like SIFT [Lowe, 2004]).

We believe that building reliable bearing-only local maps and using map joining to construct global map is a promising direction for completely solving large-scale bearing-only SLAM problems. We are currently extending the proposed approach to monocular SLAM in real 3D scenarios [Zhao *et al.*, 2010]. In the future, we are planning to develop the robot trajectory planning strategies such that it can perform the bearing-only SLAM more reliably and more efficiently.

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