Review of SLAM Data Association Study

Wu Zhou[1, a *], Shiju E[1, b], Zhenxin Cao[1, c] and Ying Dong[1, d]

[1]Engineering College of Zhejiang Normal University, Jinhua 321004, China

[a]zhouwu@zjnu.cn, [b]esx_2001@zjnu.cn, [c]zxcao@zjnu.cn, [d]doingdone@zjnu.cn

* The corresponding author

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Abstract. Simultaneous localization and map building (SLAM) is a key problem for an intelligent robot to accomplish autonomous navigation. And the results of data association are of key importance to the success of the SLAM. In this study, two bottleneck issues constraining SLAM data association are discussed in detail. One issue is the filtering data association of SLAM, the other issue is the loop closure of SLAM. The research status of the two issues is explained in detail. On this basis, the inadequacies of existing research are pointed out. And some advices for future research are provided. The work of this paper is of a certain reference value for both comparison of existing data association studies in SLAM and future intensive SLAM research.

Introduction

SLAM is a core problem in the intelligent robot navigation community. The definition of SLAM is that an autonomous robot starts in an unknown location in an unknown environment and then incrementally builds a map of this environment while simultaneously using this map to compute the robot's location [1]. The SLAM issue has become a hot topic in the intelligent robot field over the past decade.

Data association is a basic part of SLAM. It refers to matching the observed information with the existing map information. In the SLAM process, the results of data association are of key importance to the success of SLAM. Data association is a basic prerequisite for successful implementation of SLAM. Small amounts of data association failures may cause the whole SLAM process to fail. SLAM data association includes two bottleneck issues: filtering data association and loop closure. Details of these two issues are described as follows.

Filtering Data Association

According to the type of SLAM sensors, the filtering data association of SLAM can be divided into two categories: feature based data association and scan matching.

Feature Based Data Association. A premise of feature based data association is that credible features can be extracted from the observation of sensors, which can be divided into two categories: distance measuring sensors and visual sensors. Laser range finder, as a typical distance measuring sensor, has high precision and large measuring range. Some features, such as points and lines, can be extracted from the scanning data of a laser range finder. As to the visual sensors, commonly used visual feature extraction algorithms include Harris corner detection [1], SIFT [2], etc. Ethan [3] proposed a method to extract lines from visual information. And it is applied to SLAM.

Feature based SLAM data association algorithm includes Nearest Neighbor (NN) [4], Multi-Hypothesis Tracker (MHT) [5], Joint Compatibility Branch and Bound (JCBB) [6], Multidimensional Assignment (MDA) [7], and Highest Order Hypothesis Compatibility Test (HOHCT) [8], etc. The NN uses mean square distance as the threshold criterion. When there are several features satisfy the threshold criterion, the feature with the shortest regular distance is selected as the associated feature of the observed feature. MHT maintains multiple association assumptions for each observed feature. It improves the success rate of data association by tracking multiple hypotheses. However, the number of hypotheses grows exponentially with time, resulting

in exponential growth of storage space and computational amount. Thus, MHT has a poor performance in real time. When JCBB is concerned, joint compatibility test criteria is used to test the compatibility between the observed features and existing map features. The advantage of JCBB is its high success rate, while the disadvantage is its high computational complexity. As for MDA, several adjacent frames of observed information are combined to make the association decision. And the data association problem is turned into an optimization problem, searching for association results with the minimum cost function value. MDA also owns the disadvantage of high computational complexity. Edmundo et al [8] presented a data association method called Highest Order Hypothesis Compatibility Test (HOHCT), which was applied to SLAM. They pointed out that conventional data association methods tended to adopt a single compatibility rule. And combined compatibility rules should be used to improve the reliability of data association.

Many improved solutions for feature based data association have been proposed in recent years. For instance, Rex et al [9] proposed the 3-scanning JPDA data association algorithm for dynamic environments. It could detect slow-moving object in dynamic environments. Booij et al [10] used connected dominating set (CDS) for data association according to the characteristics of visual sensors. Bacca et al [11, 12] proposed feature stability histogram (FSH) model according to the principle of the human memory model. And the FSH model is successfully applied to visual SLAM.

The aim of feature based data association is searching the matching results between observed features and existing map features. And the matching results are used to correct the SLAM estimation error. Present researches tend to improve the success rate of data association algorithm. However, it is impossible in real application to ensure that each association obtains the correct results, especially in the case of large observation error. A single data association failure may cause the entire SLAM process to fail. On the other hand, a basic premise of feature based data association is to obtain reliable features from the observation. How to extract reliable features from observed information of the laser range finder and visual sensor is a bottleneck, which is particularly difficult in unknown environments.

SLAM is for unknown environments, in which the feature based data association has severe uncertainty. Therefore, feature based data association methods are only applicable when reliable features can be obtained. In all, feature based data association is still a difficult research problem.

Scan Matching. Data association between two scans is called scan matching. When distance measuring sensors, such as a laser range finder, are used to create the grid map of an environment, a frame of observed information from the sensor is called a scan. The aim of scan matching is finding the common portion between two scans, and determining the relative movement of a robot between the two time instances of obtaining scan information.

Researchers have proposed a number of practical and reliable scan matching algorithms, such as ICP [13, 14, 15], Histogram Matching [16], Normal Distributions Transform [17], as well as Machine Learning Method based on Conditional Random Fields [18], and so on. Besl et al [13] proposed an efficient algorithm named Iterative Closest Point (ICP) in the early 1990s, aiming at registration of 3D point sets, curve and surface. The minimum distance of ICP is obtained through the iterative optimization of the mean-square distance metric. Lu et al [14, 15] firstly applied ICP to the robot orientation estimation based on matching between two adjacent scans. They laid the foundation for scan matching applications in robot navigation and also promoted the development of scan matching SLAM. Many researchers proposed improved algorithms of the original ICP. There are up to hundreds of improved ICP algorithms derived from ICP. François et al [19] proposed a framework for comparing the performance of various ICP variants and provided an open source database to evaluate the ICP-derived algorithms. Jihua Z et al [20] fulfilled SLAM by combining ICP with the Rao-Blackwellize particle filter. They constructed a grid map of the environment with observed data of the laser range finder and odometer. Xian-shan L et al [21] applied Normal Distribution Transform (NDT) to scan matching SLAM, using a home service robot to construct the map of indoor environments. Cihan et al [22] introduced a scan matching algorithm based on multi-layered normal distribution transform (ML-NDT). It performs well in both computational efficiency and robustness. Zuolei S et al [18] proposed a scan matching method

based on conditional random fields (CRF). They withdrew and managed various features from two adjacent laser scans. And machine learning method was used to realize the scan matching between two scans. It performs well in complex environments.

Scan matching is directly realized with the original observation of the laser range finder, while the feature based data association is applied with features extracted from observation of sensors, such as the visual sensor and laser range finder. From this perspective, the scan matching is much more reliable than the feature based data association, for the reason that the observation information of scan matching is original and without the intermediate feature extraction process, thus avoiding the uncertainty of feature extraction process.

Existing scan matching methods perform well in estimating the robot motion between two adjacent scanning time instances. However, only a grid map can be generated directly with the scanning information and scan matching method. In order to get a map with abundant information, typical features needs to be extracted from the scanning information, and other information, such as color and texture of the environment, are expected to be obtained from observation of visual sensors. On the other hand, the classic ICP based scan matching algorithms use spatial Euclidean distance between two point sets as the single scale for determining the relationship between two scans. They perform poorly in matching two adjacent scans of complex environments. Furthermore, SLAM is extremely strict for the filtering data association step. As long as the scan matching step fails once, the whole SLAM process is likely to diverge. Thus, in account of abundant map information and reliability, further improvements are needed for scan matching.

Loop Closure

Closed loop detection, which is referred to loop closure for short, is a basic problem of SLAM. The targets of loop closure are determining whether the current position of the robot has been visited and its accurate corresponding position. Loop closure is of key importance for reducing the uncertainty of the SLAM estimation. The effect of loop closure is shown in Fig. 1 [23].

(a) Experimental place (b) Map before loop closure (c) Map with loop closure

Figure 1. Effect of loop closure [23]

The robot explores the environment shown as Fig. 1(a). With the sensor information and SLAM solution, the environment can be mapped as Fig. 1(b). It can be seen in Fig. 1(b) that there is a gap at the lower right corner. But the gap doesn't exist in the physical environment, in which both ends of the line corresponds to the same position. When loop closure is incorporated into the SLAM process, the environmental map is shown as Fig. 1(c), in which the original gap disappears. Therefore, the estimation error of SLAM is greatly reduced.

Loop closure is a data association problem essentially. And it is usually independent of the robot pose estimation, which maintains large error. It is difficult to achieve accurate loop closure with the estimated robot pose. According to the type of commonly used sensors, loop closure methods can

be divided into the following two classes.

For the laser range finder sensor, we introduce herein the following two common loop closure methods. One is Local Registration and Global Correlation, proposed by Gutmann et al [24]. They calculated the correlation between the local map and the global map at each iteration cycle of SLAM. If the correlation value is very high, a closed loop is assumed to exist. And they corrected the map and robot path estimation with the loop closure results and the method put forward by Lu and Milios [25]. Tomatis et al [26] applied multi-hypothesis tracker to loop closure in the process of creating hybrid maps. The closed loop is detected in the topology map. Two robot location hypotheses are generated respectively in current map and previous map. When the probability of two hypotheses is similar, a closed loop is confirmed. And the robot path and map estimation is further revised. The other loop closure method is proposed by Karl et al [27], who use pairwise comparison of laser point clouds to detect closed loops. To start with, they extracted rotation invariant feature clouds, characterizing the geometry and statistic characteristics of the environment, from the observation information of a laser range finder. Then, the feature clouds are processed with the AdaBoost algorithm [28]. The closed loop is finally detected through the machine learning and pairwise comparison process. Considering the fact that the extracted features are rotation invariant, the pairwise comparison of feature clouds can be applied in any direction. Karl G et al tested the performance of the feature clouds matching for loop closure in robot navigation experiments of wide range environments. More than 60 percent of closed loops are detected, while no false loop closure occurs. Their loop closure algorithm has certain reference value in comparison with the existing loop closure algorithms with a view to its good performance. However, the loop closure method of feature clouds matching has two limitations. Firstly, the AdaBoost classifier needs to be trained with priori information of the environment. Besides, the displacement error between the real robot position and the estimated robot position should be less than 3 meters before reaching the closed-loop position, or else the closed loop can not be detected. But SLAM is for unknown environments, of which prior information is not obtainable before SLAM. On the other hand, it is impossible to guarantee that position estimation error is less than 3 meters, especially in large-scale environments. Therefore, the algorithm proposed by Karl G can only be applied to environments with priori information. It has considerable uncertainty for unknown environments.

For visual sensors, we introduce two classes of loop closure methods: loop closure methods based on probability [29] and loop closure methods based on image similarity [30]. In loop closure methods based on probability, loop closure is viewed as a Bayesian estimation problem. The posterior probability of newly obtained image corresponding to existing images is calculated to detect closed loops. In loop closure methods based on image similarity, the loop closure problem is turn into a visual similarity matching problem. The image of current position is matched with the previously acquired images in the feature space. When the similarity value is higher than the given threshold, it is considered that loop closure occurs at the position corresponding to the current image. For visual loop closure methods, a key image significantly different from the previous reference image should be extracted from image series before detecting the closed loop. A large number of similar objects and structures exist in real environments. Thus, different environmental areas are likely to exhibit high similarity in the perspective of visual sensors. This affects the accurate detection of closed loops. Therefore, visual loop closure is still an open problem.

Summary

All in all, SLAM data association includes two fundamental issues: filtering data association and loop closure. Filtering data association is run continuously in the process of filtering estimation, while loop closure occurs occasionally. Both of them are the premises of successful SLAM. According to above discussion, it is concluded that existing studies cannot fully solve the SLAM data association problem. Thus, it is necessary to study the SLAM data association solution further.

For filtering data association, many researchers tend to simplify the sensor system. However, filtering data association of SLAM is for unknown environments. Thus, the sensor system should be strong enough to get reliable filtering data association results. In addition, combined evaluating

principles and quantitative indicators should be used to test the performance of the filtering data association solutions.

For loop closure, existing researches are for specially chosen environments. There is severe uncertainty when existing loop closure methods are applied to unknown environments. The existing loop closure methods perform well in the environments chosen by researchers. However, future loop closure research should be conducted in truly unknown environments so that the new loop closure algorithm has low uncertainty and universal adaptability to various environments.

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