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A Novel 2D Laser Scan Matching Algorithm For Mobile Robots Based on Hybrid Features

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***Abstract*—This paper proposes a novel two-dimensional (2D) laser scan matching algorithm to estimate the motion of mobile robots, which is based on hybrid features consisting of point clouds and line segments. The algorithm is composed of three main procedures: associated line segments matching, heading angle calculation and coarse-to-fine translation search. Different from existing approaches, the proposed algorithm considers the rotational and translational components separately and adopts a two-stage strategy to complete the task. Comparative experimental results with respect to two classic scan matchers are presented to show superior performance of the proposed algorithm in terms of accuracy and efficiency in real environments.**

Keywords—scan matching, mobile robots, 2D laser, hybrid features

I. Introduction

Scan matching is one of the most critical technologies of 2D laser-based simultaneous localization and mapping (SLAM) system for mobile robots [1], [2], [3], [4]. The task of scan matching aims to register two consecutive laser scans and compute the relative pose transformation, which improves the accuracy of pose estimation compared with dead reckoning.

The essence of scan matching is to find a rigid-body transformation that maximizes the overlap between two laser scans. Iterative scan matching algorithms [5], [8], [9] typically construct a nonlinear cost function and adopt the gradient descent method to solve the problem. These approaches can obtain solutions quickly but not robust to initial errors. Since the cost function is usually non-convex, these approaches may fall into local optima when the initial estimation is far from global optimum. Pixel-accurate scan matching algorithms [1], [3], [11], [12] acquire global optimal pose estimation up to the searching resolution, which are based on brute-force search within a given range. However, the accuracy of these approaches are restricted by the searching resolution and they are time consuming. In summary, the primary challenge in designing a laser scan matcher is to simultaneously maximize the accuracy and efficiency.

Furthermore, most of the existing approaches which are based on point clouds registration do not use the geometric features such as line segments and corner points. These high-level features can intuitively describe the environmental information and be more reliable than point clouds especially in indoor environment.

In order to improve the accuracy and efficiency, this paper proposes a new hybrid feature-based scan matching algorithm, which adopts a two-stage strategy to solve the problem. Firstly, the increment of heading angle between two laser scans is calculated through line segments matching. Compared with pixel-accurate approaches, the accuracy of heading angles calculated by the geometric relationship of line segments is not restricted by angular resolution and thus it is more accurate. Associated line segments matching is the key step in this stage. The incorrect matching pairs are removed through the similarity measurement based on the length of overlap between two potential associated line segments. Secondly, the translational component is solved through brute-force searching within a given range so as to avoid falling into local optima. In addition, we maintain a sliding window of laser scans containing several previous scans with a certain data size and adopt coarse-to-fine matching scheme to speed up searching. Comparative experimental results show that our proposed approach presents superior performance over existing approaches in terms of accuracy and efficiency. The overall block diagram of the proposed algorithm can be seen in Figure 1.

We begin this paper with a brief review of related work in Section II. Our hybrid feature-based scan matching algorithm is described in Section III. Section IV describes the comparative experiments and analysis about scan matching. Finally, this paper is concluded in Section V.

II. Related Work

Scan matching is an approach of registering laser scans obtained at different poses and calculating the relative pose transformation. Since the precision of laser data is higher than wheel odometry [10], scan matching plays an important role in motion estimation of mobile robots. Besl and McKay propose the classic Iterative Closest Point (ICP) algorithm [5], which makes use of the nearest neighbor principle to search for corresponding matched points between two consecutive laser scans. According to these matched points, a cost function is constructed and solved through Horn's exact closed-form algorithm [6]. Censi proposes an improved approach based on the traditional ICP [8], which uses a point-to-line metric instead of the point-to-point original metric. The major disadvantage

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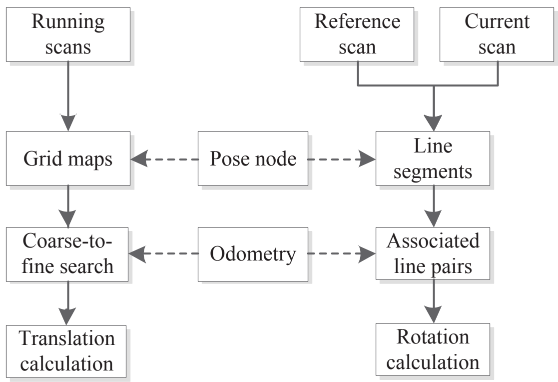

Fig. 1. Overall block diagram.

of ICP is the sensitivity to initial errors [11]. Poor initial pose estimation will cause these algorithms to converge to local optima or even diverge.

In order to obtain global optimal pose estimation, Olson proposes the correlative scan matching (CSM) algorithm [11], which is based on brute-force search over the entire space that contains the true robot pose. Laser scan points from reference scan are rendered into a probabilistic grid map called lookup table using a Gaussian kernel to approximate the uncertainty of laser data [12]. Two different implementations of this algorithm are presented to achieve real-time performance, including a multi-resolution approach for CPU and a parallel approach for GPU. On the basis of original CSM, an improved multi-resolution scan matching algorithm is proposed [12], which allows a set of aligned scans to be matched against another set of aligned scans. The CSM algorithm has been successfully applied to two open-source laser-based SLAM system: SRI Karto [1] and Google Cartographer [3].

In addition, a variety of other scan matching approaches have been reported, including histogram-based approach [14], the normal distributions transform-based algorithm (NDT) [9], polar scan matching (PSM) [7], [13], Hough transform-based algorithm [15] and range flow-based approach (RF2D) [16].

However, all the approaches mentioned above only use the single feature of point clouds. In this paper, we propose a new 2D laser scan matching algorithm, which is based on hybrid features consisting of point clouds and line segments. Through the design of associated line segments matching, heading angle calculation and coarse-to-fine translation search, the proposed algorithm achieves superior performance in terms of accuracy and efficiency.

III. Hybrid Feature-based Approach

A. Line Segment Extraction

In indoor environments, the original laser data may contain some unstable scan points, which are caused by the dynamic objects such as chair legs and human legs. In order to effectively filter out noise and suppress the influence of dynamic disturbances, a median filtering algorithm with a window size of 5 is used to smoothen the original laser data.

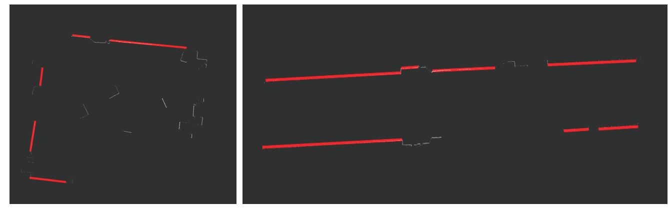

Fig. 2. The results of the seed region growing-based line extraction in two kinds of environment (left: laboratory; right: hallway). The white dots are laser scan points and the red line segments are what extracted by the line extraction algorithm.

There are many algorithms designed for extracting line segments from discrete and ordered laser scan points [17]. In this paper, we broadly follow the seeded region growing-based line segment extraction algorithm [18], which is composed of four modules: seed-segment detection, region growing, overlap region processing and endpoint generation. This approach has been verified by experiments to achieve better performance than Iterative End Point Fit (IEPF) [17] in terms of efficiency, correctness and precision. In addition, we only store line segments which are longer than 0.6 meters because longer line segments are more reliable than shorter ones. The orientation of line segment is defined as the direction vector of the start point to the end point and is normalized into the range of $(-\pi, \pi]$. The results of line segment extraction in the laboratory and the hallway are shown in Figure 2.

B. Associated Line Segments Matching

The associated line segment pairs between the current scan and the reference scan should be found to establish the correspondence between them. A two-stage screening method is adopted in order to guarantee correct matching. Firstly, the odometry data is used as the initial pose estimation of the robot at the current moment. Then the line segments in both current scan and reference scan are transformed into the global world coordinate system. For each current line segment, we follow the line correspondence criterions [19] and traverse in the reference line segment set to search for line segments that satisfy the following two conditions:

$$|\mathrm{normAngle}\,(\theta^c - \theta^r)| \leq \theta_0, \tag{1}$$

$$\frac{|a^r x^c + b^r y^c + c^r|}{\sqrt{(a^r)^2 + (b^r)^2}} \leq d_0, \tag{2}$$

where the superscripts r and c represent the reference scan and the current scan respectively. The parameters θ_0 and d_0 are two adaptive thresholds and in this paper we set them to $2°$ and $3cm$. Since the angles are not Euclidean, the function $\mathbf{normAngle}\,(\bullet)$ is used to re-normalize them after every subtraction. The meaning of these two criterions is that when the directions of two line segments are close to each other and the center point of the current line segment is close to the reference line segment, these two line segments are selected to constitute a potential associated line segment pair.

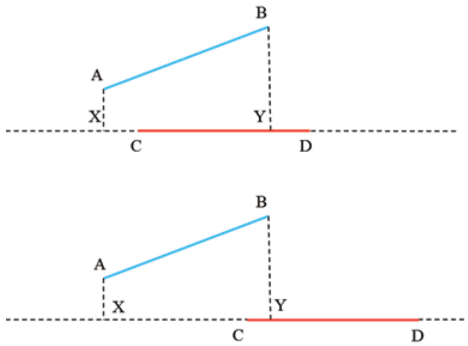

Fig. 3. The length of the overlap of line segment CD and XY is referred as the similarity measure, where AB and CD represent the current line segment and the reference line segment respectively and XY represents the projection of AB to CD.

However, the line correspondence criterions only ensure that two line segments which are collinear or nearly collinear can match up. In other words, two line segments that are collinear but not overlapping at all will be mistaken as an associated line segment pair. Moreover, a current line segment may match several reference line segments when the reference line segment set contains a number of collinear or near-collinear line segments with the current line segment, typically in the hallway environment. Therefore, wrong matching removing and multiple matching elimination are necessary.

In order to obtain a correctly matched pair of associated line segments, we project the current line segment onto the reference line segment and calculate the length of the overlap between the projection and the reference line segment. The ratio of the length of the overlap to the length of the reference line segment is regarded as the similarity measure. Through the first phase of screening, we have found a number of potential associated line segment pairs for each current line segment. From these potential associated line segment pairs, two line segments with the highest similarity are selected to constitute the final associated line segment pair. If the highest similarity is less than a given threshold (0.7 in this paper), we will remove the pair of line segments. Figure 3 illustrates two types of results of overlap calculated between line segments.

C. Heading Angle Calculation

Assume that several pairs of associated line segments are obtained, and the increment of heading angle can be calculated as follow:

$$\Delta\theta = \frac{\sum_i w_i(\theta_i^{Gr} - \theta_i^{Lc})}{\sum_i w_i}, \tag{3}$$

where θ^{Gr} is the orientation of the reference line segment in global coordinate system and θ^{Lc} is the orientation of the current line segment in local coordinate system. w is the similarity score between two associated line segments.

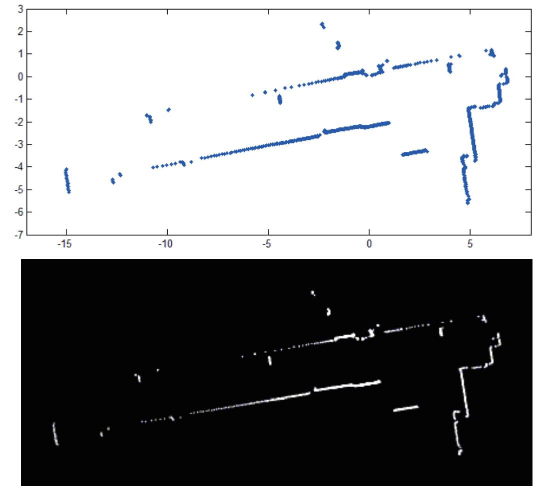

Fig. 4. Reference model rasterization. Top: the original scan points; bottom: schematic image of lookup table. Bright regions represent high probability of been occupied.

D. Coarse-to-fine Translation Search

In order to calculate the translation of the mobile robot, we make use of the CSM algorithm which is composed of three steps. The first step is to build a probabilistic grid map which is called lookup table or reference model by approximately using a Gaussian kernel with every laser point of the reference scan. The value of each cell of the grid map represents the probability of observing a point at that position. The example of lookup table can be visualized as an image, as seen in Figure 4. The second step is to iterate over each laser point in the current scan, project it and look up the score in the lookup table. And the last step is to repeat the second step for different position, calculate scores for each position and find out the highest score among these candidate positions. The best translation T^* is calculated as follows:

$$p' = R(\theta^*)\, p, \tag{4}$$

$$T^* = \arg\max_T \sum_i L(Tp'_i), \tag{5}$$

where p' represents the point acquired by rotating the original scan point p with the acquired heading angle θ^*. $L()$ is a function which takes a point and returns a probability of observing a point at that position. We take the initial position estimation of the current scan as the searching center and traverse in a certain square area. It should be emphasized that the step size of the translation search should not be less than the resolution of the lookup table. In the implementation of the proposed algorithm, we make the searching step size match the resolution of the lookup table.

Considering that the accuracy of brute-force search is limited by the searching step size and it is time consuming, we adopt a coarse-to-fine matching scheme to speed up searching. The two levels differ in resolution by a factor of 1 and the result of the coarse search will be the start position of the fine search. In addition, we set the offset of the fine search to half of the resolution of the coarse search, which can achieve best performance in our experiment.

Since the increment of heading angle has been calculated by associated line segments matching, the translation search is just consist of two nested loops and the running time of the proposed approach is significantly less than the naive implement of CSM. Furthermore, in the original implementation of CSM the author just simply use an earlier laser scan (the reference scan) to build the lookup table, which do not contain enough historical information and achieve good performance. In order to make full use of historical information, we maintain a sliding window of laser scans called running-scans, which is consist of several previous laser scans in a certain size. We rasterize the running-scans to build the lookup table. The experimental evaluation will illustrate the benefits of the proposed approach using scan-to-running scans matching compared with the the original implementation of CSM.

IV. Experiment

In this section we present the setup and results of the comparative experiments. The proposed approach has been implemented on the mobile robot shown in Figure 5, with the laser sensor being UTM-30LX produced by HOKUYO. The code is programmed in C/C++ and has been run on a laptop with a I5 processor and 4GB running memory.

Fig. 5. Experimental platform.

A. Hallway Environment

We select the hallway environment as a challenging experimental scene to compare our algorithm with several contemporary approaches. Firstly, we operate the robot to walk forward about 25 meters along the hallway in total. When the robot has walked about 12 meters, we make it turn round more than 90 degrees and then recover. The rough trajectory of robot motion is shown in the top picture in Figure 6.

We compare the proposed approach with Point-to-Line Iterative Closest Point (PL-ICP) [8]. As can be seen in Figure 7, PL-ICP has significant translation errors along the dominant direction of the hallway. This is because when the laser points exist on lines with a dominant direction, the registration could not converge to global optimum [20]. Compared with PL-ICP, the proposed approach which based on brute-force translation search does not fall into local optima and performs more accurate pose estimation in the hallway.

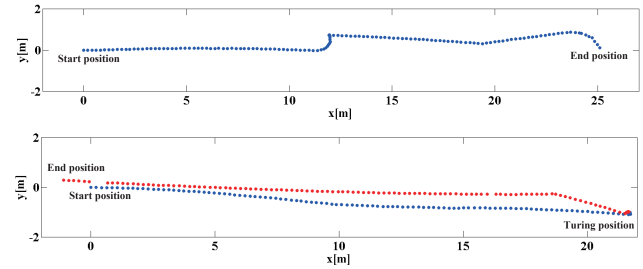

Fig. 6. Trajectory of robot motion in the hallway. Top: unidirection; bottom: forward (blue trajectory) and return (red trajectory).

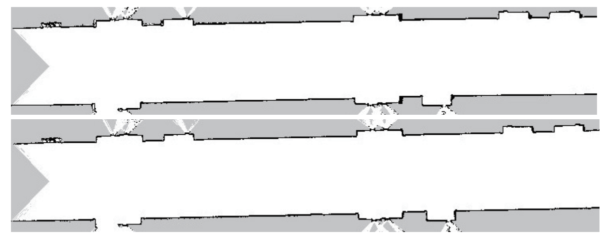

Fig. 7. Local comparative results of PL-ICP and the proposed approach in the hallway. Top: PL-ICP; bottom: the proposed approach.

Secondly, we operate the robot to walk forward about 22 meters and then control it to go back. The rough trajectory is presented in the bottom picture in Figure 6. In Figure 8, we compare the proposed algorithm against CSM. It is obvious that CSM has a significant deviation of heading angle calculation during the process of forward and return. While based on the direction information of line segments, the proposed approach achieves locally consistent performance. Note that neither two approaches use loop detection.

B. Laboratory Environment

We select a data set recorded in the laboratory where there are some clutters in the environment. The size of experimental area is about $5m \times 5m$ and the trajectory of robot motion is presented in Figure 9.

In this experiment, we compare the proposed approach against PL-ICP and CSM and the comparative results are shown in Figure 9. Among these three approaches, the proposed approach achieves the best performance in terms of accuracy. PL-ICP has obvious errors in both translation and rotation. Based on single scan-to-single scan matching, CSM can not get an accurate pose estimation when the overlap between two laser scans is too small. Compared with these two approaches, the proposed approach, which based on the geometric relationship of line segments to calculate heading angles and scan-to-running scans brute-force translation search to find global optimal position estimation, achieves high accurate performance in both translation and rotation.

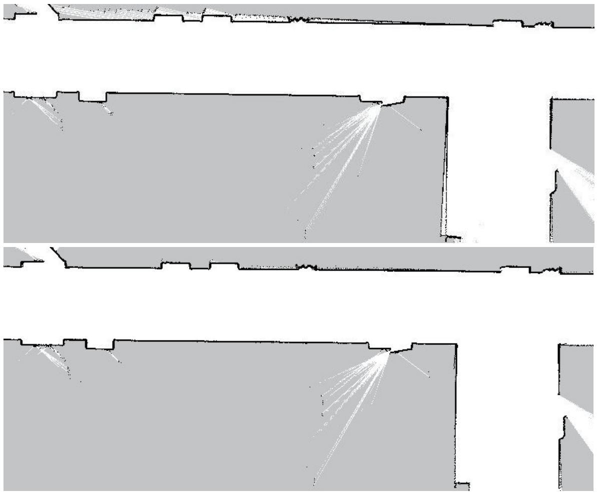

Fig. 8. Comparative results of CSM and the proposed approach in the hallway. Top: CSM; bottom: the proposed approach.

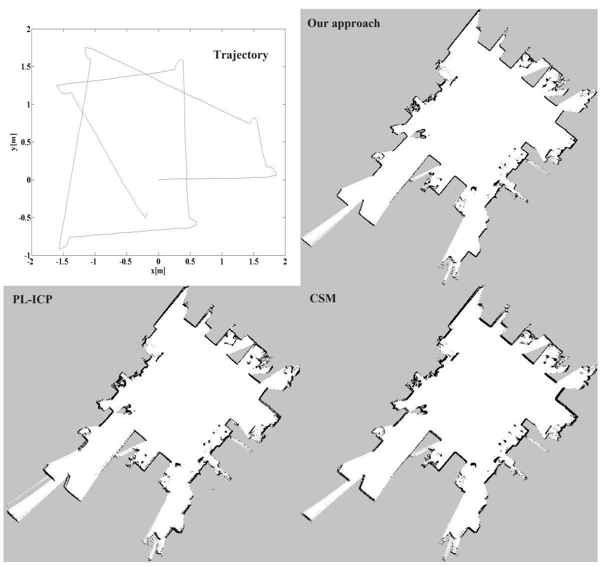

Fig. 9. Comparative results of PL-ICP, CSM and the proposed approach in the laboratory.

C. Loop-closed Hallway

Finally, we provide an experimental evaluation of the proposed approach with CSM in a long hallway contains a perfect loop. The size of the loop-closed hallway is approximatively $75m \times 50m$ and we operate the robot to walk at about $0.5m/s$. The results of trajectory are shown in Figure 10 and the start positions of all data are unified.

As time goes on, the error accumulation of wheel odometry is becoming more and more serious. At the beginning of first 30 meters, both CSM and the proposed approach achieve high accuracy closed to ground truth. After 1/4 circle, CSM has significant errors in the calculation of heading angles while the proposed approach still has an accurate result near the ground truth. At the end of this experiment, the error of termination points between CSM and ground truth is about

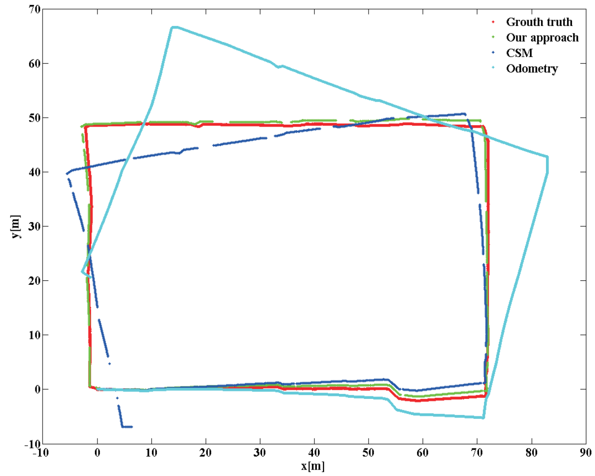

Fig. 10. Comparative results of CSM and the proposed approach in loop-closed hallway. a) red trajectory: ground truth; b) cyan trajectory: odometry; c) blue trajectory: CSM; d) green trajectory: the proposed approach.

9.15 meters while the error between the proposed approach and ground truth is about 2.56 meters. Considering that the robot has walked about 250 meters, the error rate of the proposed approach near 1% can be said quite small.

In addition, we make a comparison of efficiency and the running time results of matching two laser scans are presented in Table I. The running time of the proposed approach is approximately half of CSM. The result of the comparison is predictable since CSM contains three nested loops (for Δx, Δy and $\Delta\theta$) while the proposed approach just needs to calculate the translation and contains only two nested loops.

TABLE I
RUNNING TIME (IN MSEC) OF THE PROPOSED APPROACH AND CSM

	Mean	Std	Min	Max
Our approach	68.99	13.80	33.94	98.09
CSM algorithm	141.96	19.82	90.28	190.93

V. CONCLUSION

This paper has proposed a hybrid feature-based scan matching algorithm, which adopts a two-stage strategy to complete the task. The heading angles calculated by the geometric relationship of associated line segments is extremely robust for large rotation and the coarse-to-fine translation search can acquire global optimal position estimation within a given range. We compare the proposed algorithm with PL-ICP and CSM in various experimental scenes and demonstrate that the proposed algorithm can achieve superior performance in large-scale and challenging environments in terms of accuracy and efficiency. Future works will focus on hybrid map building and redundant line segments merging.

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