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Scan Matching for Graph SLAM in Indoor Dynamic Scenarios

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Abstract

SLAM (Simultaneous Localization And Mapping) plays an essential and important role for mobile robotic autonomous navigation. SLAM in dynamic environments with moving objects is a challenging problem. We focus on scan matching for Graph-SLAM in indoor dynamic scenarios. Scan matching algorithm is proposed and implemented, which consists of the following phases: *first*, conditioned Hough Transform based segmentation is performed to extract and group line features; *second*, occupancy-analysis based moving objects detection is done to detect and discard the segments corresponding to the moving objects; *third*, linear regression based line feature matching is executed to estimate the roto-translation parameters. Simulations to estimate roto-translation and the entire trajectory of the robot effectively verified the robustness of this algorithm in a dynamic scenario. The proposed algorithm is based on the line features of the indoor environment. It is robust to disturbances from moving objects in the dynamic scenario, and is especially suitable for the case when large rotational displacement is present.

Introduction

SLAM (Simultaneous Localization And Mapping) aims at estimating the travelled trajectory of a mobile robot. SLAM in dynamic scenarios with moving objects is a critical application for mobile robots to achieve robust autonomy in navigation and safe coexistence with humans in populated environments. In many cases, the mobile robot deploys *Laser Range-finders* to perceive the obstacles in the environment and *Wheel-Encoders* to obtain its own odometric information. Based on the sensor data, Graph-SLAM constructs and optimizes one topological graph to solve the SLAM problem. We do research on scan matching to construct the edges for graph SLAM in dynamic scenario. Scan matching targets at estimating the relative *roto-translation* displacement between two robot poses. This geometrical displacement relationship represents an *edge constraint* in the graph.

In the literature of scan matching, there are generally two categories of approaches: point-based matching and feature-based matching. Point-based matching uses the direct point information from the laser scan range data for matching, while feature-based matching first extracts the higher-level features from the original scan range data, and then matches these features for roto-translation. The review of the state-of-art scan matching algorithm is presented in the section of related work. Point-based approach works well when the initial guess of roto-translation does not deviates much from the true value, but the performance suffers when there is much rotational error and especially when the scenario is disturbed by moving objects. This is the motivation for the work here.

In this paper, a new scan matching algorithm is proposed. The work presents the following contributions: the main straight-line features of the indoor office-like environment is used, it is *robust* to the disturbances of the moving objects and suitable for dynamic scenario, and it also deals well with the moving objects of irregular shapes, since they will be discarded directly due to the absence of line features. Moreover, line features are matched based on a point-to-line metric, so it is especially suitable when there is a large rotational displacement.

Related Work

Iterative Closest Point *(ICP)* (Besl and McKay 1992) chooses the closest point couples as the corresponding point couples from the target point clouds and the reference point clouds in terms of one defined distance metric, and then minimizes the cost function of the square error between the couple pairs to estimate the transformation estimation. Iteratively the process is repeated until a satisfactory condition is achieved. There are also variants of ICP (Rusinkiewicz and Levoy 2001). Nearest Neighbour Search consumes too much time and converges quite slowly when the function approaches a local minimum(Lu 1995).

Iterative Dual Correspondence *(IDC)* (Lu and Milios 1997)(Lu 1995) uses point-to-point correspondence to construct a squared error function and proposes two sets of correspondences: one by Euclidean distance and the other by angular distance. There are also variants of IDC approach. *IDC (X)*(Bengtsson and Baerveldt 1999) only uses $X\%$ of the best corresponding points for alignment; *Sectored IDC*(Bengtsson and Baerveldt 1999) divides the scan data into sectors, detects and removes the sectors that have changed and matches only the unchanged sectors. The disadvantage of IDC and Sectored IDC approaches are the heuristic way to find the correspondence. In (Bengtsson and Baerveldt 2001) they estimate the uncertainty in the computed roto-translation, i.e., the covariance matrix.

Metric based ICP Scan Matching(J. Minguez and Montesano 2005)(Montesano 2006) first constructs the correspondence pair, then it minimizes the objective function of summed square error to estimate the roto-translation. It uses a distance metric which includes the angular displacement term as a contribution to the traditional ICP algorithms.

Probabilistic Scan-Matching approach (L. Montesano and Montano 2005) uses the Gaussian distribution and total probability integrating over all possible locations of the target point and all possible current transformations to compute the correspondence likelihood for the reference point set. Then the expectation value is calculated as the most probable reference point, and the distance between the computed reference points is minimized to find the optimal transformation. The contributions of this approach regard the uncertainty model of both the sensor measurement and the sensor displacement.

PL-ICP (Point-to-Line Iterative Closet Point) (Censi 2008) approach proposes a point-to-line metric to increase the convergence speed of the algorithm. It follows the traditional ICP iterative procedures, but proves to be much more efficient: it computes the assumed-to-be correspondence points in the reference frame for each point in the current scan, and chooses two actual points from the reference point set closest to the previously calculated correspondence point; then it uses trimming procedures to eliminate outliers and rewrite the error function based on the previously computed point-to-line distances and minimizes the error function.

Prediction-based geometrical feature extraction approach(Yilu Zhao 2011) is proposed to detect line and circle features: instead of traditional two-phased data segmentation/breakpoint detection and feature separation, it calls for only one phase to extract the features based on a prediction approach. For line detection, it computes the predicted crossing point of line features with the subsequent laser emitting radial line, and calculates the distance between the previously predicted point and the actual testing scan sample point. Then the distance is judged to distinguish whether this testing scan sample point is breakpoint/turning point or not according to a certain threshold value.

Nearby Line Tracking approach was proposed in (Lilian Zhang) (Zhang and Ghosh 2000) based on searching nearby lines in parameters space: the corresponding lines are assumed to have similar parameters such as line parameters in Hough Space, the length and the middle points of line segment. The distance between these line parameters with weighting coefficients is defined to the objective function to be minimized. For each line in the first image, its nearest line in the second image is selected according to the objective function if the function value is smaller than a global threshold.

In *DATMO (Detection and Tracking of Moving Object)*(Chieh-ChihWang and Thrun 2003), scans are grouped into segments using a distance criteria in the preprocessing phase, and the segments over different time frames are integrated into objects. *Direct method*, namely ICP (Iterative Closest Point), is used to register the scan segments over different time frames for localization. For two sets of scan range data, *Sampling-based Approach* is used to estimate the uncertainty in correspondences: it finds ambiguities by generating the initial guesses randomly and registering the scan data for the roto-translation. *Grid-based Approach* together with *Correlation-based Approach* is used to estimate the measurement noises, and the normalized correlation responses are also assigned as weights to the samples from the sampling approach. The weighted samples are used for non-Gaussian pose estimate.

Expectation Maximization (D. Hahnel and Burgard 2002) is also used for dynamic environments. In the *expectation process*, likelihoods is computed to estimate which measurements correspond to the static objects, and in the *maximization process* the estimate is used to calculate the position of the robot and the map. The advantage is that this approach does not require a previous knowledge of the map and use point features instead of any predefined features.

Problem Formulation

Given two sets of laser scan range data and the initial guess of their spatial geometrical relation, as illustrated in Fig. 1, the goal is to estimate the relative roto-translation through

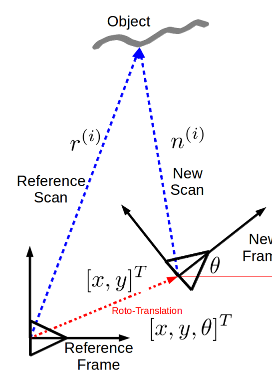


Figure 1: Reference Scan and New Scan

matching the correspondence parts of the two sets of laser scan range data: Then the estimated roto-translation value could be used to construct the motion constraints as the edges of the graph for Graph-SLAM.

The new range data $n^{(i)}$ could be transformed to the reference frame as follows:

$$h_q(n^{(i)}) = \begin{bmatrix} x \\ y \end{bmatrix} + \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} n_x^{(i)} \\ n_y^{(i)} \end{bmatrix} \tag{1}$$

The goal is to find the optimal solution to the minimum of the following equation which leads to the estimation of the roto-translation value.

$$J(q) = \|r_c^{(i)} - h_q(n_c^{(i)})\|^2 \tag{2}$$

Segmentation, Moving Object Detection and Roto-Translation Estimation

Method Overview

Scan matching algorithm is proposed to solve the relative roto-translation estimation problem in indoor dynamic environment. It consists of three phases, as is shown in Fig. 2: *first*, conditioned Hough Transform based segmentation is used to extract and group line-feature candidate samples into segments; *second*, occupancy-analysis based moving objects detection is performed to detect and discard the segments corresponding to the moving objects; *third*, linear regression based roto-translation estimation is applied to estimate roto-translation by matching the merged independent line features.

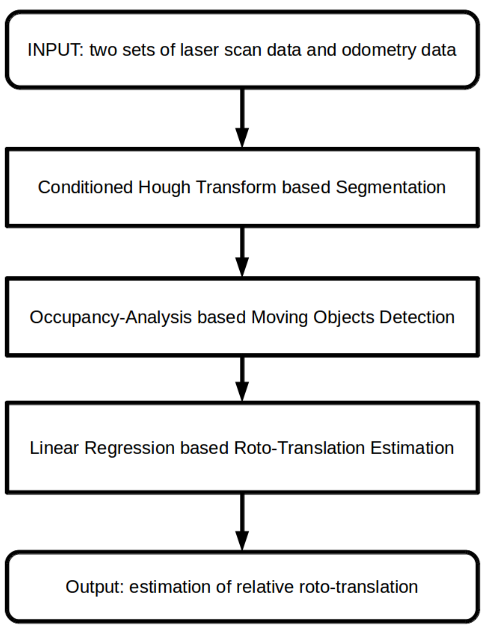


Figure 2: Overview of the Phases in Scan-matching Algorithm

Conditioned Hough Transform based Segmentation (CHTS)

Segmentation is performed for the set of laser scan range data based on line features, and the steps are illustrated in Fig. 3. Hough Transform line detection is applied to detect the sample points which represent the small-scale line segment. *Hough Transform*(Yilu Zhao 2011)(Richard O. Duda) is in nature a voting based approach dealing with robust statistics contaminated with input outliers, suitable for the case here with line features of different parameters; we add one *conditioning part* to the output of the previous algorithm for anomaly detection to ensure that the line features sample points extracted are close in scanning index (Bishop 2006).

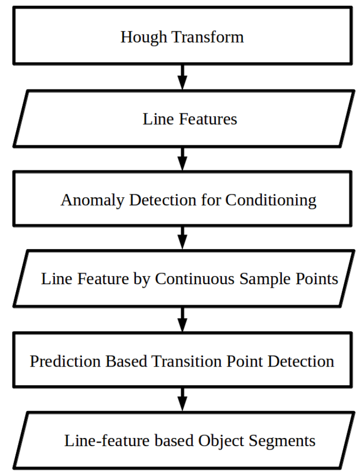


Figure 3: Conditioned-HT based Segmentation

Then, we use a prediction based judgment to find the breakpoints and perform segmentation. Inspired by (Yilu Zhao 2011), the detected small line segment information is used to predict the possible coordinates of the subsequent points in index if we assume they are on the same line. We compare these supposed-to-be coordinates with their actual coordinates to check whether they are the breakpoints or not.

Occupancy Analysis based Moving Object Detection (OAMOD)

Moving object analysis is performed to distinguish the common static parts of the environment from the segmentes detected in the previous phase for the reference scan and the new scan. For the case of moving objects as depicted in Fig. 4, we compare the two scan range data segment by seg-

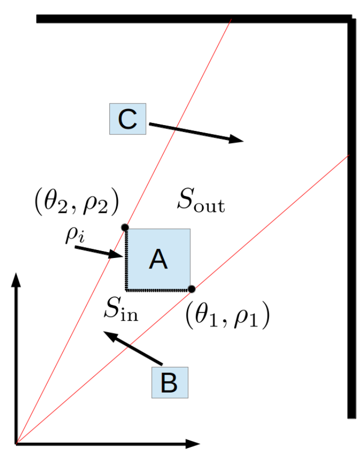


Figure 4: The Case of Moving Object

ment. We take the angular span $[\theta_1, \theta_2]$, and use the line feature segment from one scan range data within $[\theta_1, \theta_2]$ to divide the area into two parts: one part with the polar distance from the origin of scanning smaller than the polar distance ρ_i of the observed scan range data, and the other part with the polar distance greater than ρ_i, like S_{in} and S_{out} divided by the dotted boundary of object A in Fig. 4. S_{in} is marked as free space, and S_{out} is marked as unknown space. Then for the line features from the other scan range data and within $[\theta_1, \theta_2]$, if they appear inside area S_{in} like object B, then for sure they correspond to moving objects. But if they show up inside area S_{out}, then the judgment depends on the distance from A: if the distance is relatively small like object C in Fig. 4, then they correspond to moving object; if it is relatively large, then they correspond to static environment. The whole judgment flow chart is illustrated in Fig. 5.

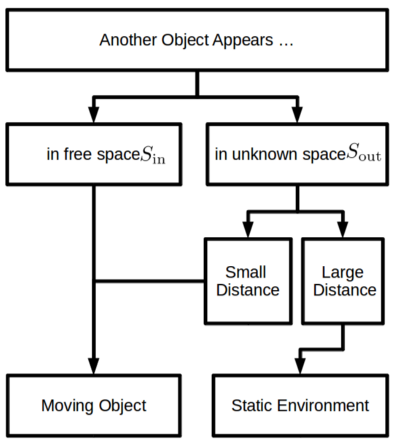


Figure 5: Moving Object Judgment Flow Chart

Linear Regression based Line Feature Matching (LRLM)

The relative roto-translation value is estimated by matching the static-environment line features, as is shown in Fig. 6: *initially*, pre-processing is done to figure out the larger-scale

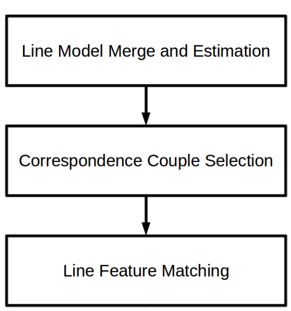


Figure 6: Flow Chart of Line Matching Algorithm

line features on each segment by analyzing their associated $\{\rho, \theta\}$ values from phase I: the ones with similar $\{\rho, \theta\}$ values are treated as probable larger-scale line feature sample points; *then*, we use linear regression technique (Bishop 2006) to merge all points from the pre-processing result for each segment to estimate the line parameters for each independent line feature; *thirdly*, we find the correspondent line features from the reference scan data for each of the line feature in the new scan data according to the angles between the direction vector of each line feature and the distance from the middle point of the line feature in the new scan to the line feature of the reference scan; *finally*, we find the roto-translation parameters that can map the new line-feature sample points to the correspondence reference line features.

For line matching, we consider the following two cases:

1). when the line model is not orthogonal to x axis as shown in Fig. 7, the perpendicular distance from the point to the line is as follows:

$$d^{(i)} = \sqrt{\frac{1}{1+(K^c_{\mathtt{r\_1}})^2}}|K^c_{\mathtt{r\_1}} x^{(i)} + b^c_{\mathtt{r\_1}} - y^{(i)}| \tag{3}$$

where $\{K^c_{\mathtt{r\_1}}, b^c_{\mathtt{r\_1}}\}$ stand for the slope and intersection parameter of the line feature model from the reference scan range data that is correspondent to the point $(x^{(i)}, y^{(i)})$. and

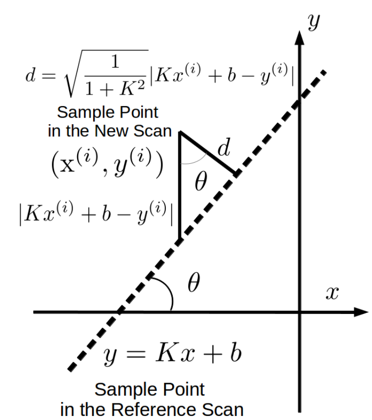


Figure 7: Perpendicular Distance for the Point away from the Line

the line matching objective function is constructed as follows:

$$J(x,y,\theta) = \frac{1}{\sum_{c=1}^{\mathrm{l_{n\_1}}} \mathrm{num}^c_{\mathrm{n\_1}}} \sum_{c=1}^{\mathrm{l_{n\_1}}} \sum_{k=1}^{\mathrm{num}^c_{\mathrm{n\_1}}} \frac{1}{2}[d^{(k)}_c]^2$$
$$\begin{bmatrix} x^{(k)}_c \\ y^{(k)}_c \end{bmatrix} = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x^{(k)}_{\mathrm{n\_1}} \\ y^{(k)}_{\mathrm{n\_1}} \end{bmatrix} + \begin{bmatrix} x \\ y \end{bmatrix} \tag{4}$$

where $\mathrm{num}^c_{\mathrm{n\_1}}$ is the number of sample points on the c segment for the scan to be matched, and $\mathrm{l_{n\_1}}$ is the number of segments for the scan to be matched.

2). when the line model is almost orthogonal to the x axis, we just substitute the parameter set $\{K, b\}$ of the non-vertical line model with the functional equivalent parameter set $\{\frac{1}{K}, \frac{-b}{K}\}$ of the vertical line model. For reason of simplicity, the details are not described here.

Threshold Parameters Tuning For The Combined Scan-Matching Algorithm

There are several parameters which determine the performances of the scan-matching results. To find a balanced solution for all the parameters mentioned above and find a suitable solution for roto-translation estimation, we use the Genetic Algorithm Optimization Toolbox in MATLAB.

Experimental Verification

To verify the effectiveness of the scan matching algorithm for the domestic indoor scenario, we have performed experiments using ROS (Robotic Operating System). For simulation, we use the map of Robotics Lab 10 at Politecnico Di Torino, together with one robot equipped with wheel encoders and laser scanner, and three objects able to move around. We use *stage* simulator to perform the experiment, as shown in Fig. 8. The proposed scan matching algorithm

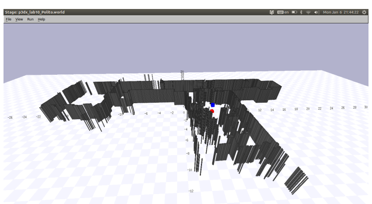
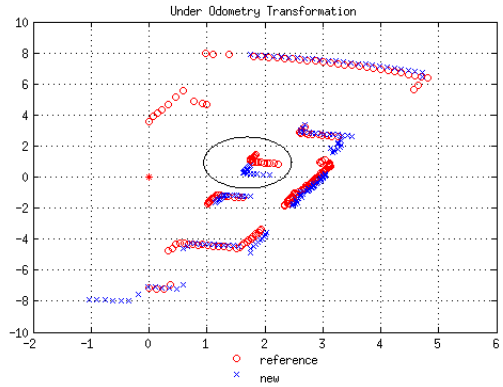


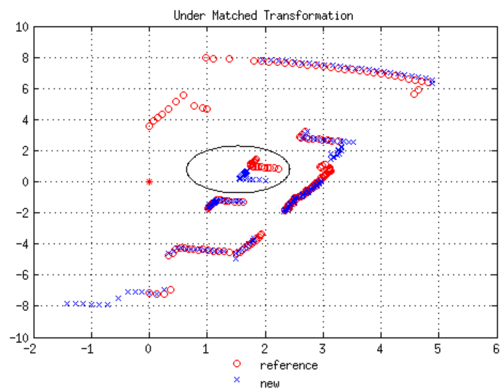
Figure 8: Simulation Environment for Robotic Lab

is implemented in MATLAB for fast prototyping. The accuracy of the estimated roto-translation value can be judged from the degree of coincidence between the two sets of laser scan range data where they are transformed and plotted in the same frame, as shown in Fig. 9. Here (a) refers to the case under the odometry roto-translation value, and (b) under the estimated roto-translation value. In (a), the parts of the two scan range data corresponding to the same physical object are not coincident. The deviation shows the error in rover's displacement. The parts shown by large ellipse which exist in the reference scan range data but disappear in the new scan range data refer to the moving objects. While in (b), the parts corresponding to the static environment are well matched after the procedure.

The results shown above only consider the local relative roto-translation estimation. The effectiveness of the scan matching algorithm can be further proved by feeding a set of relative roto-translations as motion constraints to graph construction and optimization. We present the robot's estimated trajectory from graph optimization using scan matching based Graph-SLAM in Fig. 10; for the details on the graph optimization approach, please refer to(Carlone et al. 2012). The ground truth retrieved from simulator is included



(a) Odometry Transformation



(b) Matched Transformation

Figure 9: The Two Scan Range Data In Reference Frame

as a comparison, and the robot's odometric trajectory is also shown in the figure. The euclidean distance between the poses on the estimated path and the correct ones on the the ground truth is plotted in Fig. 11 with the distance between the poses from the odometry and the ground truth as a comparison. We can see that the rover trajectory from scan matching based graph optimization is much closer to the ground truth, more accurate than the odometry data.

Conclusion

In this paper, we proposed and implemented a scan matching algorithm for domestic dynamic scenarios, and experimental results have verified the effectiveness of the proposed algorithm.

However, one weak point still exists: when the moving objects are close to the walls and especially when their contour includes many line feature sample points, they may be mistaken as walls within the tolerable deviation range. The selected common static part is the remaining ones inside the entire line feature union after the moving objects have

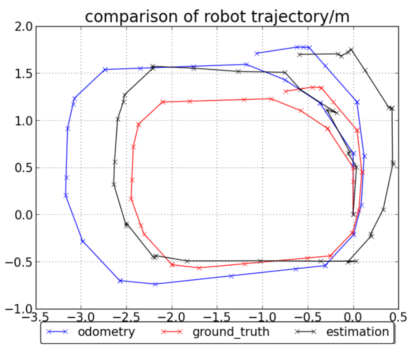


Figure 10: The Estimated Robot Trajectory from Scan-Matching based Graph-SLAM

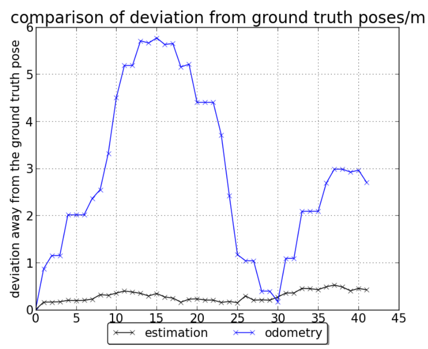


Figure 11: The Comparison of the Deviations from Ground Truth for Estimated Results and Odometry

been detected and discarded. Future work should be devoted to discriminating static parts directly from the line feature union, which can be more robust to dynamic environment and can be even adapted for place recognition.

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