Enhanced Robot Pose Estimation Method Using Selective Scan Data in Structured Environments

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***Abstract*—This paper suggests enhanced robot pose estimation method by using selective scan data in structured environments. Previous pose estimation approaches, which estimate the pose by scan matching method, use scan data of constant interval. However, these approaches do not consider the property that scans matching result is affected by the scan data distribution in the overlapping areas between two consecutive scans. Our proposed method varies scan interval in order to adjust overlapping areas between current and next scans. Through the experiments, we compared our method to the previous approaches which use constant interval scans and verified improved performance of our new approach.**

***Index Terms*—robot, pose estimation, scan matching, map building, selective data process**

I. Introduction

For mobile robots, recognizing their surrounding environments is the most fundamental problem before applying various robot applications. Among these recognition problems, the most typical techniques such as map building and pose estimation are studied by various researchers [1], [2]. Scan matching is one of the most important techniques for these map building and pose estimation problem. The most general algorithm is the Iterative Closest Point (ICP) algorithm which is suggested by P. J. Besl *et al.* [3]. This algorithm calculates the rotation and translation matrix between two scan data and performs iteration until the sum of distances between all the points in the scan becomes minimum. Another algorithm Normal Distributions Transform (NDT) method, which is developed by P. Bieber, divides the model scan data by the grid and makes Gaussian distribution for each grid in order to reduce the computational loads which cost high for point-to-point matching [4].E. Takeuchi et al. extended the NDT method to 3D case [5].Also, A. Diosi *et al.* proposed Polar coordinates Scan Matching (PSM) algorithm which uses polar coordinates system [6]. All these and other previous scan matching algorithms combined scan data of the same interval [7]. However, the scan matching result is influenced by the distributions of the points in the overlapping areas between two consecutive scan data. This is proved in our previous work [8]. In our previous research, we performed 3D object registration with the scan matching algorithm. We changed the overlapping areas between two consecutive scan data for the efficiency of the registration. This technique is Selective Data Process (SDP). This technique alters the overlapping areas according to the prior scan data distribution. In this paper, we will extend this SDP, which is used for the object registration, to the robot pose estimation problem.

The rest of this paper is organized as follows: Section II describes the problem of previous constant interval scan matching algorithms. Section III gives an overview of the SDP which is our previous work. Section IV describes detailed technique of our new approach. In section V, the experimental results are shown and the results of our new approach and previous approach are compared. Finally, we conclude the paper with an outlook on future work in section VI.

II. Problem Description

Commonly, scan matching algorithms use constant interval data when they are used in pose estimation. However, this brings about problems. For example, 2D points data, which are acquired by Laser Range Finder (LRF) sensor in structured environments such as only wall-exists corridor environment, look like a line in ideal case.

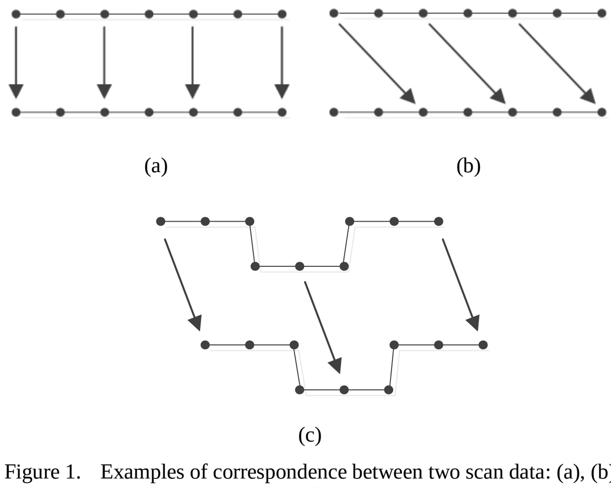

Figure 1. Examples of correspondence between two scan data: (a), (b) Feature non-existing case. Two figures show the same data with different correspondence. Many correspondences exist when there are no features. (c) Feature existing case. There is only one correspondence.

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In this case, we cannot know the exact correspondence between two scan data (see Fig. 1 (a) and (b)). However, if there exists a feature in the corridor like a door, we can verify the correspondence between two data (see Fig. 1 (c)).

Therefore, in case of complex and special data distributions in the overlapping areas, it is more likely to succeed in finding the correspondence between two scan data even if the overlapping areas are small. On the contrary, if there are no special but simple distributions of the points in the overlapping areas, it might be better to increase the overlapping areas for the higher possibility to succeed. With this key idea, we can improve the accuracy of the estimated robot pose and build the accurate map at the same time.

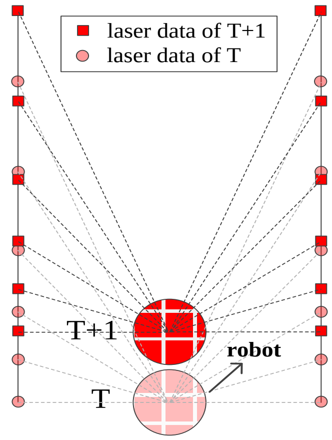


Figure 2. Discreteness of the scan data: Because of the discreteness of the LRF data, the scan matching cannot be perfect.

Also, Adjusting scan interval makes it possible to reduce the total number of scan data which are used in the scan matching process. This is important part because too many matching accumulates the error. This is because of the fact that scan data are discrete (see Fig. 2). The LRF acquires scan data with the same resolution. At time T, the robot acquires point data with the LRF and those points are depicted as red small circles in Fig. 2. At time T+1, the acquired points are depicted as red square in Fig. 2. There is no perfect matching because of this discreteness of the point data. As a result, reducing the total number of scan data decreases the number of matching. This process results in the reduction of the error.

Through the experiments, we certified our hypotheses which are stated above. This is stated in Section V.

III. Selective Data Process (SDP)

Selective Data Process (SDP) is a next data selection method before the scan matching process. Usually, scan matching shows high performance when many features exist in the overlapping areas of two consecutive scan data. In this chapter, we give an overview of our previous work which is applied to the 3D object registration.

TABLE I. Computing Depth Changing Rate

Algorithm	
Input	x_{min}, x_{max}, **dist**,**# of layers**
Output	$\mathbf{E}_{layer}[\sum|\mathbf{diff}|]$
1:	for i = 1 to (**# of layers**)
2:	for j = x_{min} to $(x_{max} - \mathbf{1})$
3:	diff[j] ← |dist[j+1] – dist[j]|
4:	diff_sum ← diff_sum+ diff[j]
5:	diff_sum_layer[i] ← diff_sum
6:	diff_sum_layer ← diff_sum_layer +diff_sum_layer[i]
7:	$\mathbf{E}_{layer}[\sum|\mathbf{diff}|]$ = (diff_sum_layer / # of layers)

A. Basic Idea and Analysis

We can formulate complexity of the structured environment with changing rate of the depth or distance of the scan data. For instance, we can express the roughness of the object surface by using the changing rate of depth value along the x-axis (see Fig. 3). We can calculate the summation of the absolute value of the depth changing rate, $\sum|\text{diff}|$, with the algorithm in Table I. In case of rough surface, this depth changing rate value is large (see Fig. 3 and Table II).

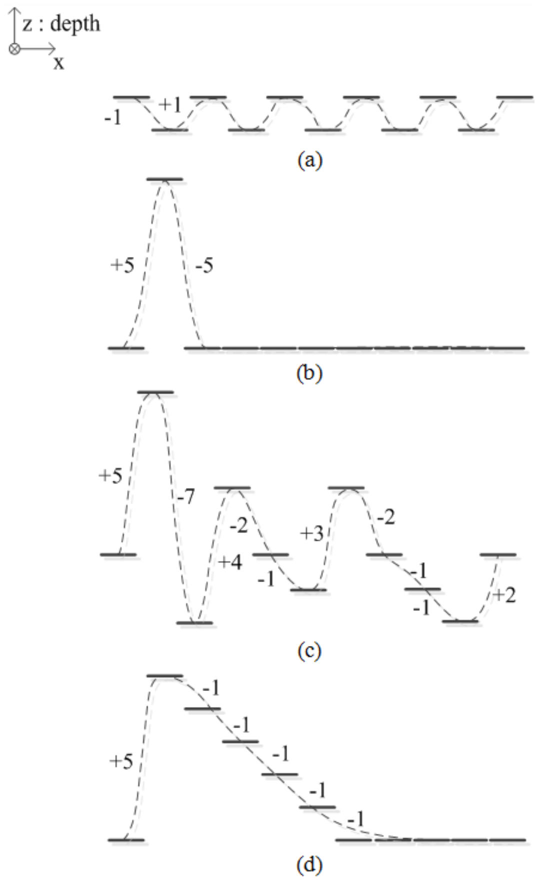


Figure 3. Four examples of different surfaces: The bold lines mean point data and dotted lines are real surface of the object or the environment.

TABLE II. Two Complexity Parameters about Fig. 3

	∑|diff|	∑|diff2|
(a)	10	0
(b)	10	15
(c)	10	7
(d)	28	43

TABLE III. COMPUTING SECOND DEPTH CHANGING RATE

Algorithm
Input x_{min}, x_{max}, **diff**,**# of layers**
Output $\mathbf{E}_{layer}[\sum|\mathbf{diff2}|]$
for i = 1 to (**# of layers**)
for j = $\boldsymbol{x_{min}}$ to $(\boldsymbol{x_{max}} - \mathbf{2})$
diff2[j] ← |diff[j+1] – diff[j]|
diff2_sum ← diff2_sum+ diff2[j]
diff2_sum_layer[i] ← diff2_sum
diff2_sum_layer ← diff2_sum_layer+ diff2_sum_layer[i]
$\mathbf{E}_{layer}[\sum|\mathbf{diff2}|]$ = (diff2_sum_layer / # of layers)

B. Normalization Regarding the Object Size

As the object size increases, the two complexity parameters, $\sum|\text{diff}|$ and $\sum|\text{diff2}|$, also increase. The two parameters need to be normalized so as not to be affected by the object size. The first parameter, $\sum|\text{diff}|$, is proportional to the object radius because it is similar to the length of the observed surface. Therefore, the parameters can be normalized by dividing with the object radius.

C. Determination of the Overlapping Areas

The overlapping areas between two scans can be determined by the following score function:

$$\mathrm{T} = \frac{c_1 * \mathrm{E}_{layer}(\sum|\text{diff}|) + c_2 * \mathrm{E}_{layer}(\sum|\text{diff2}|)}{r_o} \qquad (1)$$

The notation $\mathrm{E}_{layer}(\cdot)$ represents average value for all the layers. The two parameters, c_1 and c_2, are weighted constants which are determined heuristically and r_o is the radius of the object model.

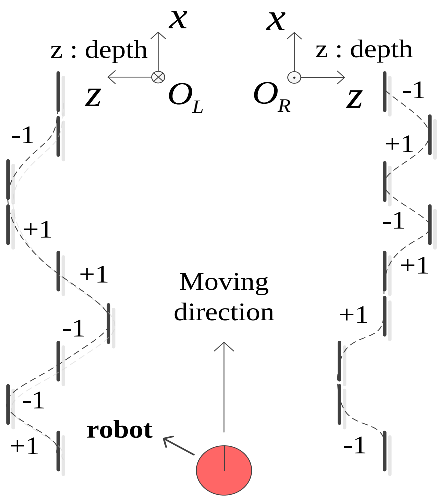


Figure 4. Concept of the selective data process for pose estimation: Red circle represents a mobile robot and two dotted lines are each left and right wall. Bold lines show reflected point data.

TABLE IV. COMPLEXITY PARAMETERS ABOUT FIG. 4

$\sum|\text{diff}_L|$	$|+1| + |-1| + |-1| + |+1| + |+1| + |0| + |-1| + |0| = 6$
$\sum|\text{diff2}_L|$	$|-2| + |0| + |+2| + |0| + |-1| + |-1| + |+1| = 7$
$\sum|\text{diff}_R|$	$|-1| + |0| + |+1| + |0| + |+1| + |-1| + |+1| + |-1| = 6$
$\sum|\text{diff2}_R|$	$|+1| + |+1| + |-1| + |+1| + |-2| + |+2| + |-2| = 10$

IV. SELECTIVE DATA PROCESS FOR POSE ESTIMATION

In our previous work, we used SDP for efficient 3D object registration. In this section, we extend our SDP to apply into the pose estimation problem and suggest a new method Selective Data Process for Pose Estimation (SDP-PE).

A. Key Idea

The SDP is a preprocessing method which determines the overlapping areas between current and next scan data. This technique changes the overlapping areas according to the distributions of the point data. The Selective Data Process for Pose Estimation (SDP-PE) method, which is proposed in this paper, is the extended version of the SDP for the purpose of applying into robot pose estimation. Our previous technique, SDP, analyzed the distributions of the object surface scan data. Similarly, our new method, SDP-PE, analyzes the distributions of the left and right wall scan data.

B. Scan Data Distribution Analysis

First of all, we denoted origin of coordinate of the left wall as O_L and the right wall as O_R respectively. The depth changes of each wall along the moving direction are depicted in Fig. 4. Two complexity parameters can be computed for each wall. The result is represented in Table IV.

C. Determination of the Scan Data Interval

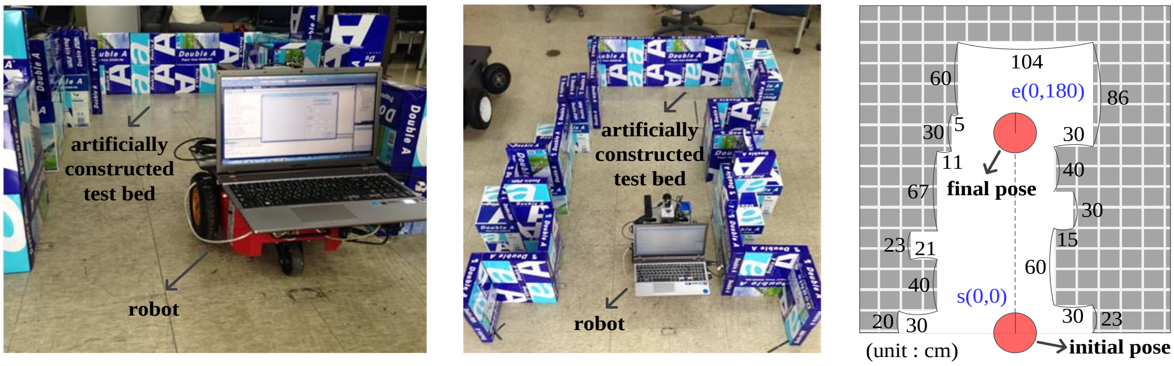
Interval of the scan data is determined by the following score function:

$$\mathrm{T}_{\mathrm{PE}} = \frac{w_1 * \sum|\text{diff}_L| + w_2 * \sum|\text{diff2}_L| + w_3 * \sum|\text{diff}_R| + w_4 * \sum|\text{diff2}_R|}{2} \qquad (2)$$

This is the average of the score function (1) about the left and right wall. The difference between (1) and (2) is the existence of normalization term, r_o . In pose estimation problem, we used 2D laser scan data which are composed of 181 points. This is why we do not need to consider normalization. The four parameters, w_1, w_2, w_3 and w_4, are weighted constants which are determined experimentally.

V. EXPERIMENTAL RESULTS

The experiment is conducted on artificially designed test bed. The environmentist depicted in Fig. 5. The real test bed is shown in Fig. 5 (a) and (b). In Fig. 5 (c), specification of the environment is represented. We compared several constant interval case and our SDP-PE method. We used ICP algorithm for merging the scan data. The scan data are acquired by using LRF sensor which is developed by the Hokuyo and the maximum sensing range is up to 30 meters which is enough to cover our experimental environment. Also we used pioneer 3-DX mobile robot which is developed by Mobile robots as a mobile platform. All the processes are carried out on PC (Intel(R) Core(TM) i7-3770 CPU @ 3.4GHz 3.90GHz).



(a) (b) (c)

Figure 5. Experimental environment: The experiment is performed in artificially constructed our own test bed. (a) Robot view of the test bed. (b) Top view of the test bed. (c) Specification of the test bed.

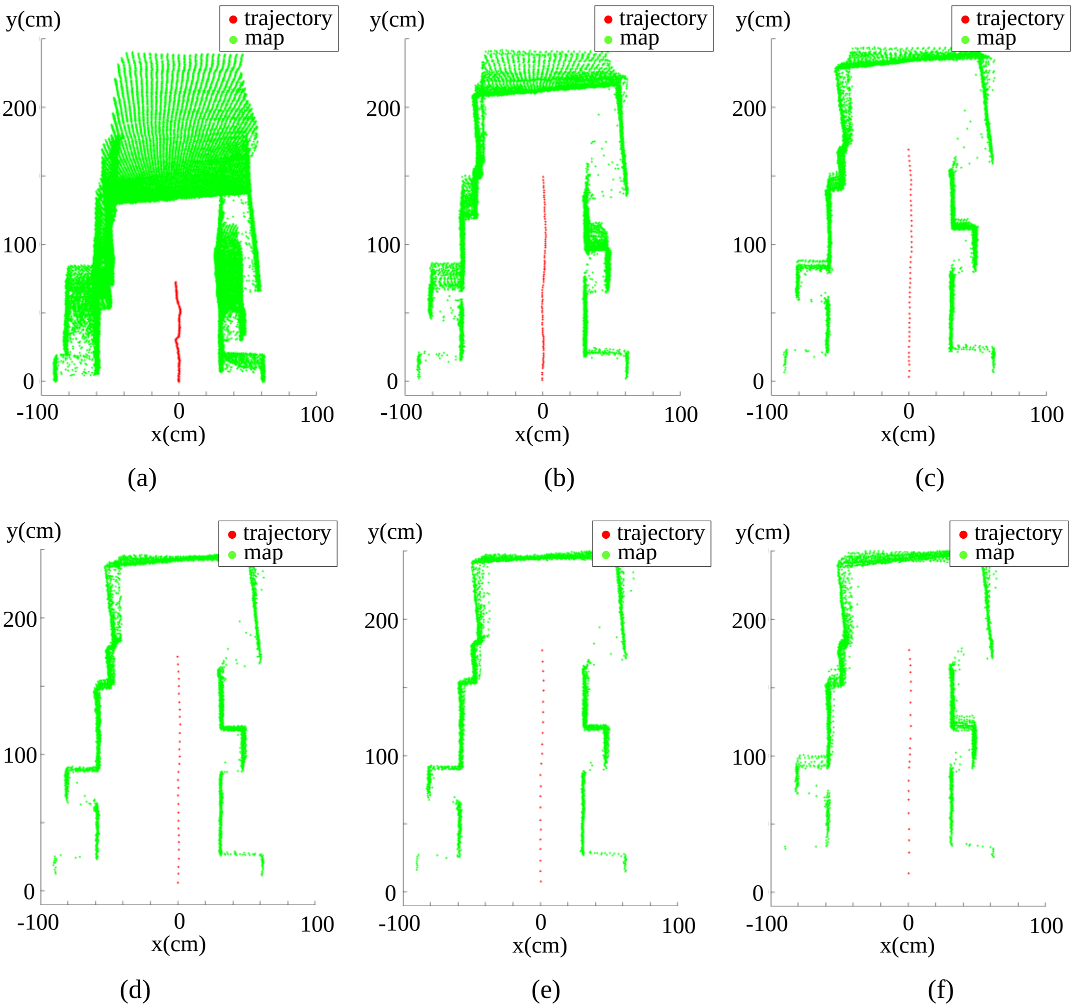


Figure 6. Pose estimation results: (a) Result of 1step interval data. (b) Result of 5 steps interval data. (c) Result of 10 steps interval data. (d) Result of 15 steps interval data. (e) Result of 20 steps interval data. (f) Result of our SDP-PE method.

The coordinate of starting point is (0, 0). The robot moves to the ending point (0, 180). The unit is centimeters. The robot moves 1.9cm/step. We compared six results. Five of them are results which used constant interval scan data and the rest one used selective data. All six results are shown in Fig. 6. The red dots mean the estimated robot pose at each step and the green dots show map of the test bed. From Fig. 6 (a) to (e) describe the results which used constant interval scan data and Fig. 6 (f) shows the result which is applied suggested method, SDP-PE.

As we can see in Fig. 6, all results show different map. We measured the distances between final estimated pose of the robot and final real pose of the robot. This distance means the error and represents the accuracy. We compared the error for all six cases. The comparison of performance is shown in Fig. 7. Fig. 7 (a) is the errors for each case. The errors are 107.6, 30.6, 10.8, 8.3 and 3 centimeters about each constant interval case from 1 to 20. In case of SDP-PE, the error is 2.4 centimeters. We verified a hypothesis that our proposed method, SDP-PE, decreases the error of the robot pose and enhances the accuracy of the robot pose. Also, as we can see in Fig. 7 (b) the computation times are decreased like 26, 3.7, 1.8, 1 and 0.8 seconds about each constant step interval from 1 to 20 and our proposed method, SDP-PE, took the shortest time, 0.7 seconds. The total number of scan data, we used in the experiments, are 462, 93, 47, 31 and 24 about the constant step interval from 1 to 20 respectively. In our proposed method case, the total number of scan data, which are used during the scan matching process, is 23.

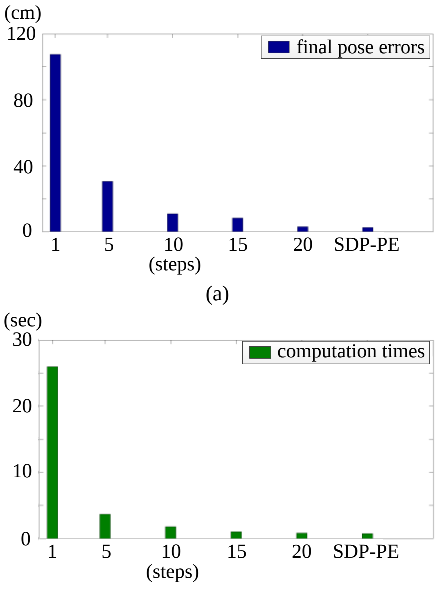


Figure 7. Performance comparison: (a) Final pose errors of the robot. (b) Computation times. Our proposed method SDP-PE showed the best result.

VI. Conclusion

In this paper, we suggested enhanced robot pose estimation method, SDP-PE, by using selective scan data in structured environments. This is the extended version of our previous work, SDP. General scan matching algorithms are using constant step interval scan data. However, this is not efficient because of the property of the general scan matching algorithm. It is more likely to succeed in scan matching when the distributions of the scan data in the overlapping areas between two consecutive scan data are complex. Thus, we regarded this property and varied the overlapping areas. Through the experiments, we certified our hypothesis that our proposed method, SDP-PE, shows enhanced performances compared to the general methods which use non-selective data.

In the experiments, we determined the weighted constants of the score function heuristically. We plan to develop numerical method which determines the overlapping areas automatically. Also, we restricted the environments to structured place. The final objective of our research is to extend our technique to the unstructured environments.

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