

Automatic Planning of Laser Measurements for a Large-scale Environment using CPS-SLAM System

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Abstract—In recent years, several low-cost 3D laser scanners are being brought to the market and 3D laser scanning is becoming widely used in many fields. For example, 3D modeling of architectural structures or digital preservation of cultural heritages are typical applications for 3D laser scanning. Despite of the development of light-weight and high-speed laser scanners, however, the complicated measurement procedure and long measurement time are still a heavy burden for the widespread use of laser scanning. We have proposed a robotic 3D scanning system using multiple robots named CPS-SLAM, which consists of parent robots with a 3D laser scanner and child robots with target markers. In this system, a large-scale 3D model can be acquired by an on-board 3D laser scanner on a parent robot from several positions determined precisely by the localization technique using multiple robots named Cooperative Positioning System, CPS. Therefore, this system enables to build a 3D model without complicated post-processing procedures such as ICP. In addition, this system is an open-loop SLAM system and a quite precise 3D model can be obtained without closed loops. This paper proposes an automatic planning technique of a laser measurement for CPS-SLAM. By planning a proper scanning strategy depending on a target structure, it is possible to perform laser scanning efficiently and accurately even for a large-scale and complex environment. Proposed technique plans an efficient scanning strategy automatically by taking account of several criteria, such as visibility between robots, error accumulation, and efficient traveling. We conducted computer simulations and outdoor experiments to verify the performance of the proposed technique.

Index Terms—Laser measurement, Multiple robots, 3D modeling, Automatic sensing planning

I. INTRODUCTION

Owing to the development of low-cost laser measurement systems such as FARO Focus 3D, Leica Scanstation, and TOPCON GLS-1500, laser measurement is becoming popular in recent years in civil engineering, construction, or digital preservation of historical cultural properties.

For acquiring a whole 3D model of a large-scale architecture, multiple laser scanning has to be performed repeatedly around the target architecture. Then the obtained partial range data are aligned precisely using predefined markers or data points themselves by ICP (Iterative Closest Point) or NDT (Normal Distribution Transform) algorithms. In these

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procedures, the Next Best View (NBV) problem, which plans best scanning positions to capture a whole 3D model efficiently, is quite important to reduce the measurement time and scanning cost. However, in actual fields, a scanning strategy is often determined by the operator's experiences and intuitions.

We have been developing a multiple robot system named CPS-SLAM, which consists of a parent robot and multiple child robots, for scanning a large-scale architecture. In this system, a parent robot is equipped with a laser measurement device such as a total station, and child robots are equipped with target markers. For localizing the parent robot, the child robots keep stand-still state and act as landmarks. Meanwhile, for localizing the child robots, the parent robot stops and acts as a landmark vice versa. By using the laser measurement device and the target markers, the robot positions are determined with the high accuracy of land surveying. Since the parent and child robots move coordinately to localize each other, we call this the cooperative positioning system or CPS [1]. Moreover, laser scanning is performed repeatedly by the laser scanner mounted on the parent robot at a number of locations whose positions are determined precisely by CPS. The obtained range data are aligned using their position information directly without applying ICP or NDT algorithms. We have performed a number of measurement experiments including the Dazaifu Tenmangu shrine in Japan or tunnel shape measurement experiments in construction sites [2], [3].

Although the NBV problem is quite important even in the CPS-SLAM system, the scan planning is usually determined manually based on the operator's experiences and intuitions. Therefore, the efficiency and optimality have not been considered qualitatively and explicitly, and thus, in some cases, measurement time tends to become longer since some regions are overlapped unexpectedly or unnecessary movements are planned.

This paper proposes a solution of the NBV problem for the laser measurement system using multiple robots, CPS-SLAM. We consider the visibility between robots, the suppression of error accumulation, and the efficient robot movements and develop an automatic planning technique of a large-scale architecture for CPS-SLAM.

II. RELATED WORKS

Optimum design of sensor positions which are utilized for, for instance, a security camera system has been studied for many years in the fields of computational geometry or computer vision [5], [6], [7].

In general, this problem can be categorized into two categories whether the geometry of an environment and/or a target object is known or not. In case that the geometrical information is available, the problem of optimum sensor positions which minimizes blind regions in a surveillance area or an efficient appearance inspection planning have been considered. Especially, an optimum layout problem of sensors (observers) in an indoor environment is called as “art gallery problem”, and has been studied in the field of computer science [8], [9]. Allen et al. [10] proposed an interactive layout planning system to reduce blind regions.

Topcuoglu et al. [11] shows a technique for a wide topological map which realizes an optimum sensor layout and the confidentiality of the sensors at a same time. Chen [12] and Scotto [13] proposed optimum observation planning techniques of an object with a known shape which achieves high efficiency and accuracy using a 3D range sensor. Prieto et al. [14] discussed an optimum inspection planning for an object with CAD data using a range sensor with high accuracy.

On the other hand, for an object with unknown geometrical information, observation planning techniques for a shape measurement [15], [16], [17], [18], [19] and active recognition systems utilizing sensor motions [20], [21] have been proposed. Okamoto et al. [22] proposed a fundamental scheme for the NBV problem which determines a proper observation location utilizing a stochastic observation model and probabilistic sensor fusion technique. Li et al. [19] utilized information entropy to describe an uncertainty of an observation model, and selected an optimum location at which the acquired information is expected to be maximized as a solution of the NBV problem.

The technique proposed in this paper belongs to the latter case. However, since CPS-SLAM utilizes the Cooperative Positioning System (CPS) for localization of multiple robots as described below, we have to consider some strong restrictions such that the robots must be seen each other. Therefore, the proposed approach is quite different from the conventional problems mentioned above in which the view position can be chosen freely.

III. LASER MEASUREMENT SYSTEM USING MULTIPLE ROBOTS FOR A LARGE-SCALE ARCHITECTURE, CPS-SLAM

This paper proposes an observation planning technique for a laser measurement system using multiple robots (CPS-SLAM) proposed so far [2], [3], [4]. In this system, the positions of parent and child robots are determined using the cooperative positioning system, CPS. Figure 1 shows a fundamental strategy of CPS consisting of a parent robot equipped with a laser measurement device (ex. total station) and two child robots.

Firstly, the parent is stopped at a known position. Then the following procedure is repeated.

- (1) Move the child robots 1 and 2 and stop them.
- (2) Measure the distance and the azimuth and elevation angles from the parent robot to the child robot 1

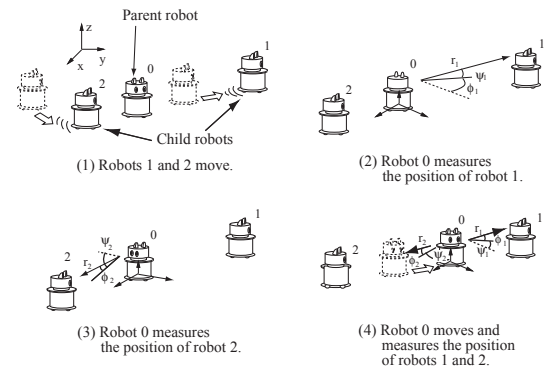


Fig. 1. Cooperative Positioning System, CPS

using the laser measurement device, and calculate the position of the child robot 1.

- (3) Determine the position of the child robot 2 with the same manner.
- (4) Move the parent robot while the child robot 1 and 2 keep stopping.
- (5) Measure the distance and direction to the child robots and determine the position of the parent robot.

In CPS-SLAM, the parent robot is equipped with a laser scanner in addition to the laser measurement device, and scans a target object from multiple locations which are localized precisely by CPS. Obtained partial range data are transformed to the world coordinate frame using the position information, and aligned precisely with simple algebra. No post processing procedures such as ICP or NDT are required to obtain a large-scale model. Figure 2 shows the 7th CPS-SLAM machine model (CPS-VII) equipped with a total station, a laser scanner, and corner cubes. We repeated measurement experiments in outdoor and indoor environments and confirmed that the accuracy of the CPS-VII is from 0.034 % (3D error is 116[mm] after the parent robot moved 343 [m]) to 0.054 % (98 [mm] for 181[m]) of total travel distance of the parent robot [4].

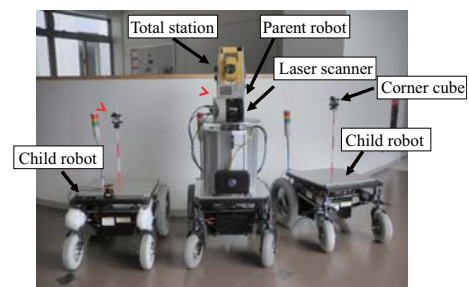


Fig. 2. CPS-SLAM machine model, CPS-VII

IV. AUTOMATIC PLANNING TECHNIQUE

To realize an automatic scan planning, we have to consider several conditions such as the efficiency of the laser measurement, the reliability to obtain the solution in any situations, the suppression of error accumulation and travel distance, collision avoidance between robots and environment, etc.

In the proposed technique, we assume that several scans have been performed and partial data of the environment has been obtained. The problem is how we choose the NBV in this situation. The strategy of the proposed technique is as follows: Firstly, we extract several candidate locations at which new geometric data will be acquired at most, and choose the best location among them considering the distance and error accumulation to reach each location.

Moreover, the visibility condition between parent and child robots must be satisfied in CPS-SLAM since the robots must be observed each other for the localization. However, this condition is quite hard to be satisfied in some cases, especially in a complex environment.

So in the case if the visibility condition cannot be satisfied, the proposed technique adopts the subgoal retrieval using the Visibility Graph [23], in which new subgoal positions are sequentially retrieved from the final goal position toward the start position by dividing total trajectory into several short paths. The overview of the proposed technique is shown in Fig.3.

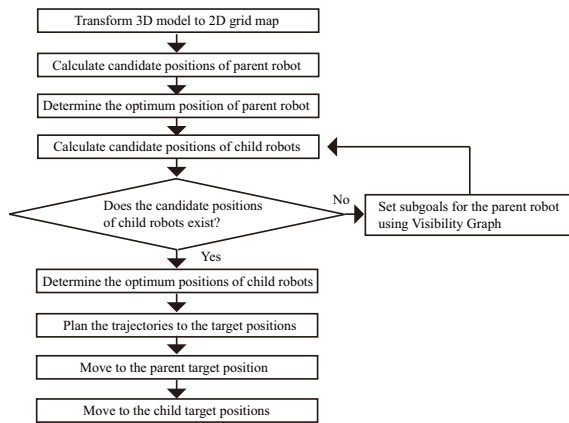


Fig. 3. Flowchart of automatic planning algorithm

In the following sections, we introduce the details of the proposed technique separately as follows.

- 1) Automatic planning of target position for the parent robot
- 2) Automatic planning of target position for the child robots

Note that we consider a planning problem in 2D space. To do so, the obtained 3D geometrical data is transformed to a 2D grid map at first.

A. Automatic planning of target positions for the parent robot

When we design the measurement locations for the parent robot, the following conditions should be considered.

- 1) New scanning position should be close to border areas between known regions which have been measured by the laser scanner so far and unknown regions which have not been measured.
- 2) New scanning position should be placed far enough from the environment to avoid collision.

- 3) New scanning position should be close to the current position.
- 4) Newly scanned region should be as large as possible.

However, if the environment is large and all the border areas are considered to be candidates, the planning cost will become quite large. Therefore, we adopt two-step strategy as described in the following section. Briefly speaking, we extract several candidate positions at first. Then optimum position which satisfies the conditions mentioned above is selected.

1) *Initial selection of candidate positions:* To extract several candidate positions in the border areas, K-means clustering technique is utilized. Figures 4 and 5 show the problem setting and the extraction procedure, respectively. Detailed procedure is as follows:

- (1) Find border lines between known (measured) and unknown (not measured) regions.
- (2) Scatter candidate points uniformly in the border area where the distance to the border line is less than a threshold value.
- (3) Apply clustering to the candidate points in Step 2.
- (4) Select centroids of each cluster as candidates of target points of the parent robot.

Note that the number of clusters are determined adaptively according to the size of border area.

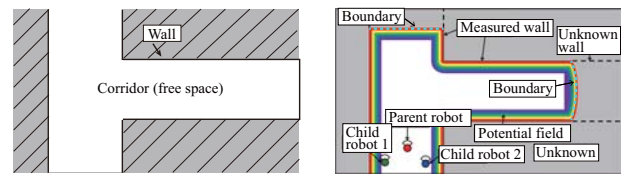


Fig. 4. Left: Problem definition. White and gray regions are free and occupying spaces. Right: White region is a measured free space. Detected walls and boundaries between the measured and unknown regions are shown in red and cyan lines.

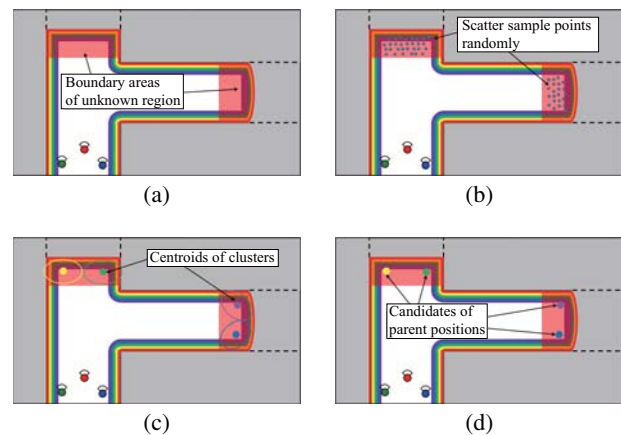


Fig. 5. Determined candidate positions for parent robot by K-means clustering

2) *Determination of target position from candidate positions:* Next, we determine the final target position from the candidate target positions based on the following conditions.

- (1) The candidate position must be located in the known

area and can be reached from the current parent position.

- (2) The candidate position must be distant from obstacles.
- (3) Travel distance from the current parent position is small.
- (4) Expected newly scanned area in unknown regions is large.

To choose an optimum target position which satisfies all the condition mentioned above, the following value is evaluated for each candidate target point.

$$G = R \cdot (P^{-1} + \alpha L^{-1} + \beta \cdot S) \quad (1)$$

where G is an evaluated value of each candidate target point, R is a constant value of 0 (unknown or inaccessible) or 1 (known and accessible) which shows the grid condition of the candidate target point, P is a potential value (inverse of distance from the closest obstacle), L is a travel distance from the current parent position, S is a size of an expected newly scanned area in unknown regions where no geometrical information has been obtained so far, and α and β are weights of terms, respectively. To calculate S , we assume that no objects other than the ones which have been measured until now exist in the environment. Then we count the number of grids which can be seen from the candidate target position directly without being blocked by obstacles and are located within the maximum range of the laser scanner except the areas scanned previously. We choose the position with the maximum evaluation value among the candidate target positions as the final target position of the parent robot.

B. Automatic planning of target position for the child robot

The target positions of the child robots have to be seen from both the final target position and the initial position of the parent robot, since the positioning with CPS is impossible if obstacles exist between the parent and the child robots and cannot be seen from each other. In this paper, we call a region from where both the initial and target parent positions are visible as “AND region”.

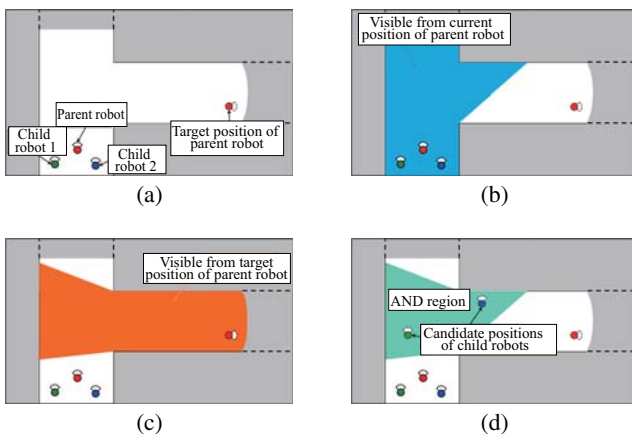


Fig. 6. AND region and candidate positions for child robots

The candidate target position of the child robot is determined in this AND region according to the following conditions.

- (1) The candidate position must be located in the AND region and can be reached from the current child position.
- (2) The candidate position must be distant from obstacle.
- (3) Distance from the parent robot is less than a threshold.
- (4) Relative angle between two child robots from the parent robot is close to 90 degrees.

where (3) is established due to the performance of the laser measurement device and (4) is set based on the fact that the error accumulation in CPS is suppressed at most if the relative angles of the child robots is close to 90 degrees [24].

To select the candidate positions of the child robots which satisfy the conditions mentioned above, the following value is calculated at every grids in AND regions to find optimum target positions of two child robots at the same time.

$$G_c = P^{-1} + \alpha_c \cdot |\theta - \theta_t|^{-1} + \beta_c \cdot |D - D_t|^{-1} \quad (2)$$

where G_c is an evaluated value of each candidate target point, P is a potential value (inverse of distance from the closest obstacle), θ is the relative angle between the two child robots, D is the distance from the target position of the parent robot, θ_t ($= 90$ degrees) and D_t are constant values, and α_c and β_c are weights of terms, respectively. If the current position of the child robot is located in the AND region, we do not determine the next position and keep the child robot staying at the current position.

C. Subgoal retrieval using Visibility Graph

In some cases in the procedure for determining the target position of the child robot mentioned above, proper candidate positions which satisfy the visibility condition cannot be obtained. For example, if the target position of the parent robot is quite far from the current position of the child robot and the child robot must pass through several corners to reach there, the AND region in which both the current and target positions of the parent robot can be seen directly does not exist. In these cases, we adopt the subgoal retrieval using the Visibility Graph [23], in which new subgoal positions of the parent robot are sequentially retrieved from the final goal position to the start position by dividing the total trajectory into several short paths.

The Visibility Graph is a graph representation of all the accessible paths connecting the vertices of the obstacles in the environment. Figure 7 shows an example of the Visibility Graph. By applying graph search algorithms, the shortest trajectory between the current and the target positions can be obtained. In this graph representation, each line connecting vertices indicates that both vertices can be seen from each other. Therefore, if all the robots travel along this line, each robot can be seen from each other and thus the CPS procedure is executable. Owing to this fact, we definitely obtain trajectories to move from the current parent position to the target parent position using CPS.

The detailed procedure for subgoal retrieval using the Visibility Graph is shown as follows:

- (1) Confirm whether the AND region exists between the current and target positions of the parent robot or not.

- (2) If no AND region exists, create the Visibility Graph and find the shortest trajectory.
- (3) Retrieve one subgoal for the parent robot along the shortest trajectory from the target position in Visibility Graph.
- (4) Calculate the AND region between the current robot position and the subgoal.
- (5) If the AND region exists, find the target positions of the child robot using Eq. (2).
- (6) If the AND region does not exist, retrieve a new subgoal along the shortest trajectory which is one-step closer to the current parent robot position.
- (7) Repeat Step 4 to 6 until the AND region exists.
- (8) Set the subgoal as the current parent position and repeat Step 4 to 7 until the parent robot reaches the target position.

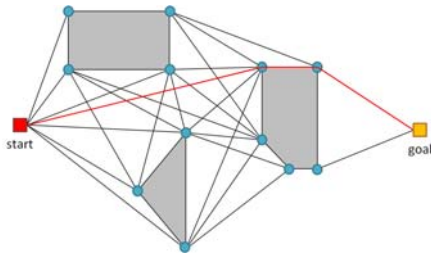


Fig. 7. An example of Visibility Graph. Red line is the shortest path connecting start and end positions.

D. Safety robot movement along Voronoi edge

As mentioned above, the robots can move from the initial position to the final target position along the edges connecting subgoals in Visibility Graph. However, since the subgoals are set on the vertexes of the obstacles, the obtained trajectories path close to the obstacles. To obtain safer trajectories, we calculate the Voronoi diagram [25] and set the Voronoi edges as actual trajectories. The robots move firstly to the nearest position on the Voronoi edges from the initial position, move along the Voronoi edges, and leave from the Voronoi edges to the final target position.

V. COMPUTER SIMULATIONS AND EXPERIMENTS

A. Computer simulations

Firstly, we evaluate the performance of the proposed technique by computer simulations. In this simulation, we prepare several 2D grid maps with the size of 800×600 grids (the grid size is $10\text{cm} \times 10\text{cm}$) as unknown environments, and start scans from several initial positions selected randomly. We set the maximum range of the omni-directional laser scanner on the parent robot to 20 [m]. Note that, although the structure of the environment is designed before starting the simulation, the robots do not have any knowledge about the environment at the beginning, and the measurement strategy is planed based on the map which is gradually expanded as the scans are repeated.

1) *Planning of target positions for the parent robot:* We verified the performance of the planning technique of the target positions for the parent robot proposed in Section IV-A by changing the parameters α and β in Eq.(1). We adopted following two simulation conditions.

- a) Select the paths which make the expected newly scanned areas S in unknown regions as large as possible ($\alpha = 0$).
- b) Select the paths which make the travel distance L of the parent robot as small as possible ($\beta = 0$).

As an example, we show the maps acquired sequentially for the case (a) in Fig.9. In this example, the initial position of the parent robot is indicated by asterisk in Fig.8.

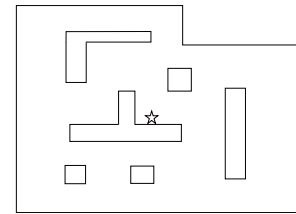


Fig. 8. An example of the environment

From Fig.9, we can see that, if we choose the parent target positions to maximize the expected newly scanned areas S , that is $\alpha = 0$, the subgoal retrievals are performed at 10th, 12th, 16th, and 18th measurements. This is because the distance to the target position is not considered in this condition, and thus invisible positions tend to be selected. Meanwhile, the number of the required scanning to obtain the map of whole regions becomes small and the planning is terminated at 18th scanning.

On the other hand, if we choose the parent target positions which is close to the current positions, that is $\beta = 0$, the subgoal retrieval is not performed since the selected target positions are all visible from the initial positions. However, the newly scanned areas at each scanning are small and thus the number of the scanning becomes large. Actually, we needed 23 scans to obtain a whole map shown in Fig.8.

2) *Planning of target positions for the child robots:* In order to evaluate the performance of the planning technique for the child robots proposed in Section IV-B, which suppressed the error accumulation, we carried out computer simulations by changing the parameters α_c and β_c in Eq.(2) and compared the accumulated errors. The simulation conditions to be compared are as follows:

- a) Select child robot positions randomly.
- b) $\alpha_c \neq \beta_c$
- c) $\alpha_c \gg \beta_c$
- d) $\alpha_c \ll \beta_c$

The condition (a) determines the positions of the child robots randomly without Eq.(2) so that the positioning is valid for CPS. The condition (c) determines the positions so that the relative angle between the child robots becomes 90 degrees as much as possible, and the condition d) determines the positions so that the relative distance between the parent and child robots becomes $D_t (= 3[m])$. The accumulated error

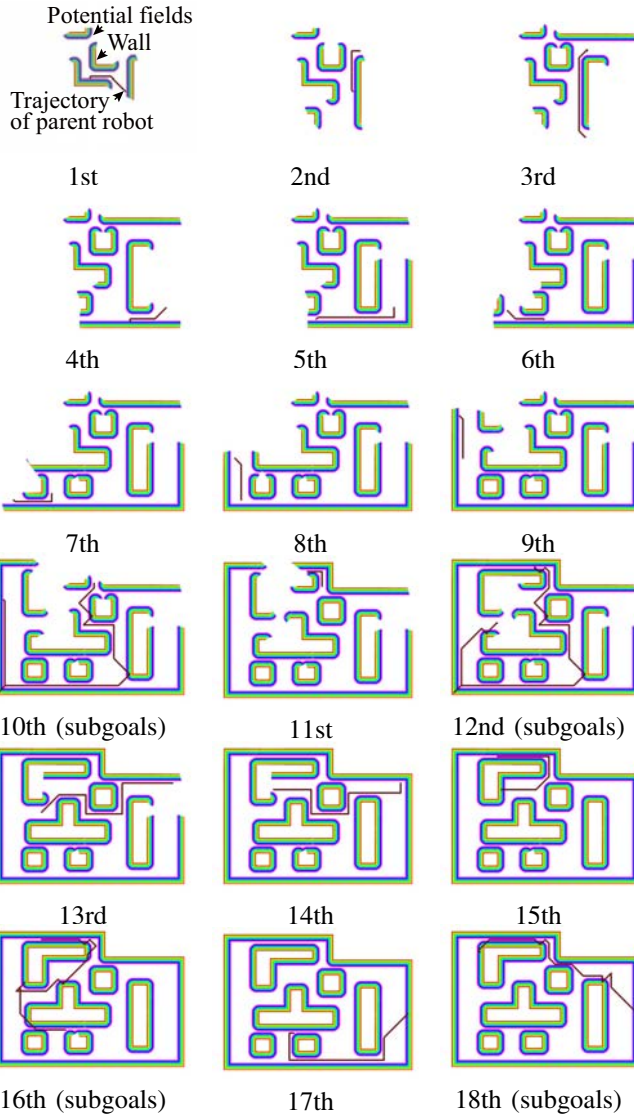


Fig. 9. Measured map and trajectories of parent robot in case that the target position where the measurable area is maximized is selected ($\alpha = 0$)

is calculated theoretically by the fundamental equation of the error propagation in [24]. In the simulation we adopted $\alpha = 0.01$ and $\beta = 0.001$ so that the expected measurement areas become large when the parent robot position is planned by Eq.(1).

An example of the accumulated error for each condition is shown in Fig.10. It is clearly shown that the errors are accumulated so much in the conditions (a) and (d) which did not consider the relative angles between child robots. On the other hand, the conditions (b) and (c) can suppress the error accumulations by selecting the positions where the relative angle becomes 90 degrees.

TABLE I
SPECIFICATION OF GPT-9005A (TOPCON)

Range	1.3 ~ 3,000m
Angular resolution	0.5"/1"
Accuracy (distance)	$\pm 2mm + 2ppm \times Distance$
Accuracy (angle)	1"

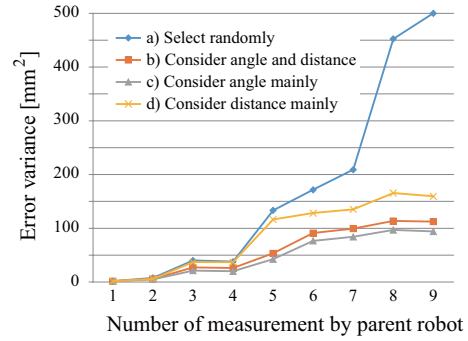


Fig. 10. Comparison of positioning errors



Fig. 11. Experimental environment

B. Outdoor experiment in real scene by CPS-VII

We conducted the actual experiment in an outdoor environment using CPS-VII in Fig.2 consisting of a parent robot and two child robots. The parent robot is equipped with a total station (TOPCON, GPT-9005A, Table I), auto-leveling system (Risumu, AS-21), 1-axis laser scanner (SICK, LMS-511), 1-axis rotation table (Chuo-Seiki, ARS-136-HP), and 2-axes inclinometer (Applied Geomechanics Inc., MD-900-TS). Figure 11 shows the measured environment.

The 3D model obtained after the robots moved around the building is shown in Fig.12(a) and (b), and the planned trajectories for all the robots are illustrated in Fig.12(c). The parent and child robots started to move from the initial position (top-left position in Fig.12(c)) and their trajectories are planned automatically as shown in dotted lines. In this experiment, the parent robot scanned 26 times around the building, and obtained 9.85 million points.

C. Outdoor experiment in real scene by CPS-VIII

We develop a new CPS-SLAM system named CPS-VIII shown in Fig.13. This system consists of a parent robot which is equipped with a laser scanner (Focus 3D, FARO) and several child robots including wheeled robots and quadcopters. The child robots hold light while balls as markers instead of corner cubes.

We applied the proposed automatic planning algorithm to the CPS-VIII consisting of the parent robot and four quadcopters, and scanned a large building. The obtained 3D model is shown in Fig.14. We can see that the quite precise 3D model is developed. The robots moved the trajectories determined by the proposed algorithm as shown in Fig.15. While the robots moved around the building, the parent robot scanned 14 times. The total travel distance of the parent robot

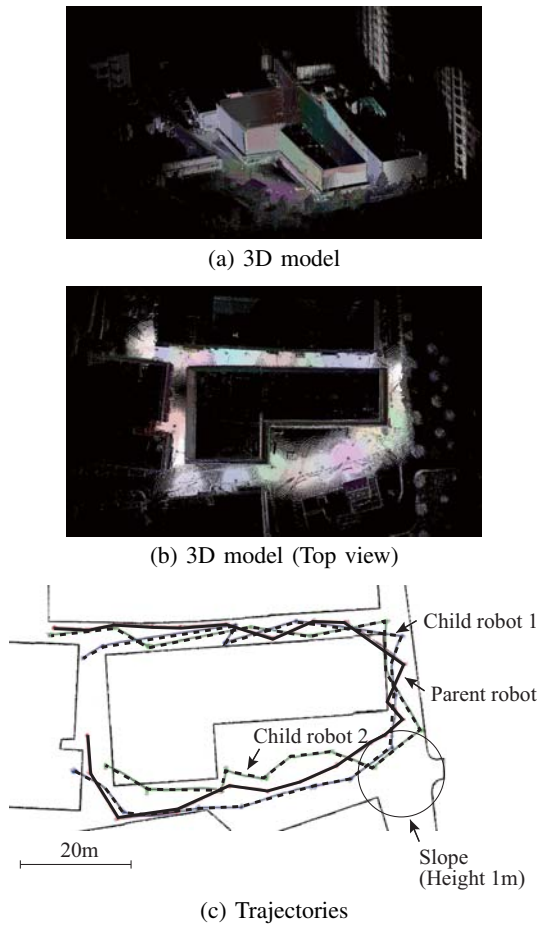


Fig. 12. 3D models and trajectories of parent and child robots (case 3)

is 270.1 [m]. The total number of points is 6.13 billions. We adopted $\alpha = 0.01$ and $\beta = 0.001$ for this experiment.

In addition, we evaluated the accuracy of the positioning and the 3D model by comparing positions of six corners of the 3D model which are in the circle shown in Fig.15 at 1st and 14th scanning. The average error of these six corners is 23.1[mm], which is 0.0085% of total travel distance (270.1[m]). This result shows clearly that the proposed CPS-SLAM performs a quite accurate 3D modeling comparing conventional SLAM systems. One of the reasons why the accuracy is improved comparing with CPS-VII is that the total station and the laser scanner in CPS-VII are integrated and replaced by the single laser scanner, and thus no calibration error between these sensors exist in CPS-VIII. Figure 16 shows the 3D model with some photos taken from the same positions.

Note that we can apply ICP to the measured point data as we did in [2]. However, we think that the absolute accuracy cannot be guaranteed for aligned data since each data is aligned so that the total relative error is minimized. In the worst case, the obtained 3D model differs from the real shape if the point correspondences are not determined appropriately. On the other hand, the proposed measurement system can guarantee the accuracy level in terms of the absolute accuracy, and thus it is quite useful for real applications

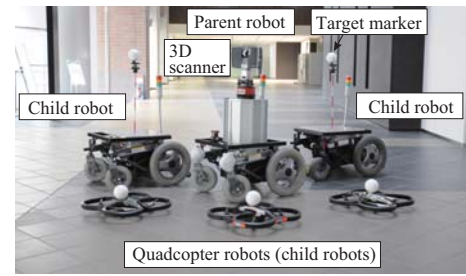


Fig. 13. The 8th CPS machine model, CPS-VIII



Fig. 14. 3D model created by CPS-VIII

such as field robot navigation or 3D shape measurements in construction sites.

VI. CONCLUSIONS

This paper proposes an automatic planning technique for an efficient laser measurement for the CPS-SLAM system, which realizes an accurate 3D modeling using multiple robots and a laser scanner. By planning a proper scanning strategy which satisfies several conditions to validate CPS motion, efficient and accurate laser scanning can be performed even for a large-scale environment. The proposed technique plans a reliable scanning trajectory using the subgoal retrieval by Visibility Graph, and the minimization of the error accumulation by considering the relative robot positions is also realized. The validity of the proposed technique is verified through computer simulations and actual



Fig. 15. Route planned by the proposed algorithm



Fig. 16. Comparison with photos and 3D models captured from points B, C, D, and E in Fig.15

experiments in the outdoor environment. Although this paper dealt with the planning in 2D space, the proposed algorithm can be applied to the planning in 3D space by considering mutual visibilities and expected newly scanned areas in 3D.

ACKNOWLEDGEMENT

The present study was supported in part by a Grant-in-Aid for Scientific Research (A) (26249029).

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