Role of the Observation Planning in Three-dimensional Environment for Autonomous Reconstruction

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Abstract: This paper presents an autonomous system for reconstruction of three-dimensional indoor environments using a mobile robot. The system is composed of a mobile robot, a three-dimensional scanning system, and a notebook computer for registration, observation planning and real-time three-dimensional data transferring. Three-dimensional scanning system obtains three-dimensional environmental data and performs filtering of dynamic objects. Then, it registers multiple three-dimensional scans into one coordinate system and performs observation planning which finds the next scanning position by using the layered hexahedral-map and topological-map. Then, the mobile robot moves to the next scanning position, and repeats all procedures until there is no scanning tree in topological-map. In concurrence with data scanning, three-dimensional data can be transferred through wireless-LAN in real-time. This system is experimented successfully by using a mobile robot named KARA.

Keywords: autonomous reconstruction, three-dimensional scanning system, observation planning, layered hexahedral-map

1. INTRODUCTION

Three-dimensional models are essential parts of Virtual Reality (VR) because VR is a simulated three-dimensional cyber space of a real or imagined environment. VR was mainly used for simulation but many researchers have taken growing interest recently for its wide applications such as real estates, architectures, educations, military affairs, medical treatments, games, and entertainments. VR can be classified into two categories: one to handle cyber objects and the other to navigate in a cyber space. Three-dimensional model for the former category has been studied in the field of computer-aided-design and computer-aided-manufacturing since early 1980s, and the exact three-dimensional model of an object can be reconstructed under the assumption that the size of the object is smaller than that of experimental systems [1,2]. Together with the improvement of three-dimensional object reconstruction technique and the development of better three-dimensional measurement system, many researchers have tried to reconstruct three-dimensional environmental models. Ioannis Stamos [3,4] reconstructed a three-dimensional model of a church by texture mapping using a video camera and a laser sensor. Lars S. Nyland [5,6] and Wagner T. Correa [7] reconstructed detailed three-dimensional office for computer graphics and tele-collaboration using a high quality three-dimensional laser scanner. Those approaches, however, require human intervention and efforts to make a whole three-dimensional model. It means that an operator has to obtain each scanned data manually and/or the operator should combine each scanned data into a global three-dimensional model to make the whole three-dimensional model.

So, in order to eliminate manual intervention and to make three-dimensional map for unknown environments, there have been proposed autonomous three-dimensional reconstruction systems using a vehicle – such as a mobile robot or an airplane - since the unknown environments could be dangerous to human beings. In [8,9], S. Thrun proposed an autonomous three-dimensional reconstruction system using a mobile robot and two laser scanners by applying Expectation and Maximization algorithm and Markov Localization.

In this paper, we make an algorithm that takes into consideration the three-dimensional space structure of common indoor environment. Our algorithm does not only cover unknown region but also covers partially covered region. We use layered hexahedral-map, which reflects three-dimensional space structure into two-dimensional grid-space, and topological map made of the result of registration. For three-dimensional data registration, we use modified ICP algorithm by odometer differences obtained from a mobile robot. This reduces the computational load of each process and also reduces the number of iterations drastically in comparison with the original ICP algorithm. Furthermore, the results of registration are the position and angle differences of three-dimensional laser scanner in three-dimensional space. Since we use the results of registration as the localized pose of the robot, we need neither a special map nor an additional process for localization.

The rest of the paper is organized as follows: In Section 2, we discuss the problems to be solved in this paper. Section 3 presents the modified ICP algorithm, and section 4 describes observation planning. In Section 5, real-time three-dimensional data transferring problems in wireless environments for using other VR applications such as skinning is presented. Section 6 shows experimental results of our system. Finally, we give the conclusion of this paper and discuss the future work.

2. PROBLEM DEFINITIONS

Autonomous reconstruction system of this paper is shown in Fig. 1. This system is composed of five independently executed modules such as data acquisition module, data registration module, observation planning module, mobility module, and multiple TCP client/server module. We set the problems to be solved in this paper as followings: data acquisition module acquires individual three-dimensional data set and eliminates unnecessary data from dynamic objects; data registration module registers multiple scans into one coordinate system; observation planning module finds the next scanning position according to three-dimensional space structure; mobility module moves the robot with obstacle avoidance to the next scanning position; multiple TCP client/server module transfers three-dimensional data through wireless-LAN for skinning in real-time. Autonomous reconstruction system has to be made with an organic combination of five modules.

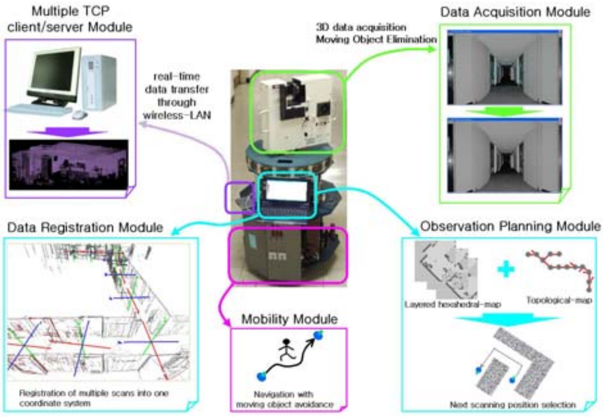

Fig. 1 An autonomous reconstruction system

3. DATA REGISTRATION WITH A MOBILE ROBOT LOCALIZATION

We register multiple three-dimensional scans into one coordinate system for a consistent three-dimensional environmental model. If the odometer data from a mobile robot in three-dimensional space are exact, registration is very easy. However, there must be errors even on the assumption that the robot moves on the two-dimensional plane. Iterative Closest Points (ICP) introduced in [10,11] is a widely used registration algorithm. This sets the first scan to be the model set and next scan to be the data set, then finds a closest point and calculates a three-dimensional transformation that minimizes the distance between two points. This calculation is formulated as follows:

$$\underset{\mathrm{R,T}}{\mathrm{nin}} \sum_i \left\| M_i - (\mathrm{R}\, D_i + \mathrm{T}) \right\|^2 \quad (1)$$

where R is 3×3 rotation matrix and T is 3×1 translation vector. After performing this calculation at all points of the data set, it calculates mean square error and iterates the above process until error is less than a given threshold. ICP algorithm is very powerful, but calculation time is proportional to the number of closest points ($O(n^r)$). Furthermore, ICP algorithm of two symmetrical scans could make a lot of iterations and/or may fall into the local minima if there is no position guidance. In this section, therefore, we show the methods for reducing the number of points and the number of iterations.

3.1 Points selection without performance reduction

Because our three-dimensional scanner system scans along $\phi + \Delta\phi$ lines at every $\Delta\theta$ degrees as shown in Fig.2, d Density of scanned data varies according to relative based on the scanner coordinate in our system. Each region has the same number of points, therefore, when the ϕ value, based on scanner coordinate, goes from 0° to 90°, the density of points in a uniform region becomes higher as the region becomes smaller. If we assume that $\Delta\phi$ and $\Delta\theta$ have very small values, the area of this region can be approximated as

$$a_{\phi_i} = \frac{\Delta\theta}{360} \times R^2 \times \Delta\phi \times \frac{\cos\phi_i + \cos\phi_{i+1}}{2}$$

and the region density at ϕ_i is

$$d_{\phi_i} = \frac{a_{\phi_0}}{a_{\phi_i}} = \frac{\cos\phi_0 + \cos\phi_1}{\cos\phi_i + \cos\phi_{i+1}}$$

We can reduce the number of points by using normal sampling according to the ϕ value without performance reduction.

$$\text{points reduction ratio} \approx \frac{0.64 \times N_{total}}{n_{sd}}$$

where N_{total} is total number of points and n_{sd} is sampling ratio of the real sample per degree.

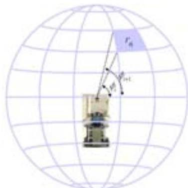

Fig. 2 Unit region r_{ϕ_i} with same number of points in scanning sphere of our three-dimensional scanner

3.2 Choice of the corresponding points using intensity data and odometer data

We have to apply other methods for data reduction since the above method cannot reduce the number of points to less than a half when we set to be 1. It is the most important process to select proper corresponding points for ICP algorithm because wrong corresponding points make it worse to calculate a three-dimensional transformation and increases the number of iterations. Our three-dimensional scanning system does not only obtain the position of each detected point, but also obtains intensity value of that point. Therefore, if we select the corresponding point among the point set whose intensity range is within intensity error , which is empirically obtained, the number of iteration should is reduced and corresponding points become more accurate. Although odometer data are inaccurate, we can calculate the boundaries of the possible pose. By applying the boundaries of odometer data, we do not only limit the region of comparative points, but also limit the size and direction of the error vector. We can exclude the following cases: the case when the intensity difference is bigger than intensity error ; the case when the position of the corresponding point is out of the error boundary calculated by odometer data; the case when the size of the error vector is bigger than the maximum size calculated by odometer data, or the direction of error vector differs from error direction calculated by odometer data. If a point in the data set has no corresponding point, we can remove this point.

The results of registration are the position and angle differences of three-dimensional laser scanner in three-dimensional space. Because the three-dimensional laser scanner is attached to the mobile robot, position and angle differences of three-dimensional laser scanner is same as those of the mobile robot. Since we use the results of registration as the localized pose of the robot, we need neither a special map nor an additional process for localization.

4. OBSERVATION PLANNING

While we obtain environmental data by using two-dimensional range sensor, e.g. two-dimensional map building by several ultra-sonic sensors, a mobile robot can obtain environmental data while it is moving because it is possible to obtain a whole environmental data fast and calculate the relative position of each detected point according to the motion of the mobile robot. In case of three-dimensional data obtainment, however, it is difficult to calculate the relative detective positions according to the motion of the mobile robot since there are too many points. Furthermore, there must be occluded region like in S. Thrun's method [8,9]. Therefore, the robot must stop at a position during scanning time. After scanning process ended, this robot decides the next scanning position and it scans the next data. The term "observation planning" is used in [12] to refer the process of finding the efficient observing points. H. Surmann [13] designs an algorithm with the best next viewing position using a horizontal plane of the scene. This algorithm can find the next viewing point minimizing occluded regions if target environment is a simple environment like a long corridor because it uses a two-dimensional horizontal plane of the scene. In a common complex environment such as an office, there are many complex objects and partially occluded region may occur. Surmann's algorithm cannot consider this region because there is no information about the partially occluded region in a horizontal plane of the scene. Therefore, the observation planning does not only cover the unknown region but also covers partially occluded region. For the observation planning, we use layered hexahedral-map that reflects three-dimensional space structure into two-dimensional grid-space and topological map that is made of the result of modified ICP algorithm.

4.1 Layered hexahedral-map

Let the original scanned data set to be

$$\{D_s(r,\phi,\theta), 0 < r < r_{\max}, 0 \le \phi \le \pi, \pi \le \phi \le \pi\}$$

in spherical coordinate, and

$$\{D_c(x,y,z), -r_{\max} < x < r_{\max}, -r_{\max} < y < r_{\max}, -r_{\max} < z < r_{\max}\}$$

in spherical coordinate. The rest of subsection 5.1 explains how to make layered hexahedral-map. First, we divide $D_c(x,y,z)$ into hexahedrons those have the same Δy according to its y-value.

$$D_c(x,y,z) = \bigcup_{[(i-1)\Delta y - r_{\max},\, i\Delta y - r_{\max})} H_i(x,z) \qquad i = 1,\cdots,\frac{r_{\max}}{\Delta y}$$

Each hexahedron has the same size of x and y. Then we tessellate each hexahedron into unit cubes

$$H_i(x,z) = \bigcup_{[(j-1)\Delta c - r_{\max},\, j\Delta c - r_{\max}),[(j-1)\Delta c - r_{\max},\, j\Delta c - r_{\max})} C_{j,k}(i)$$

$$\text{where } j = 1,\cdots,\frac{r_{\max}}{\Delta c} \text{ and } k = 1,\cdots,\frac{r_{\max}}{\Delta c}$$

Δc is the size x and z of unit cube and $C_{j,k}(i)$ is a set of data points (j,k) cube in ith hexahedron. Then we can calculate the detection probability of each (i,j,k) as

$$P(i,j,k) = T\left[r\left(C_{j,k}(i)\right), n\left(C_{j,k}(i)\right)\right]$$

where $r\left(C_{j,k}(i)\right)$ is the range from origin to $C_{j,k}(i)$ cube and $n\left(C_{j,k}(i)\right)$ is the number of points in $C_{j,k}(i)$ cube. If we regard the detection probability as the occupancy value, we can convert each hexahedron with detection probabilities into grid-map. We set a cell whose detection probability is bigger than a given threshold to be the occupied cell, and detection probability is set to be the occupied value. Empty cell and unknown cell are calculated based on the x-z position of the robot. In this grid-map, there can be occupied cells among unknown cells because radiating direction of three-dimensional laser scanner is not parallel to the x-z plane.

If the shape of environment is simple like a corridor, cells those have the same position among all layers have the same occupancy value. In this case, these can be projected into one two-dimensional grid-map and H Surmann's algorithm [13] is useful. However, there are many cells those have the different occupancy values in common environments, so we need another method. We refer these cells as conflicted cells and the meaning of these cells is the region where partially occluded.

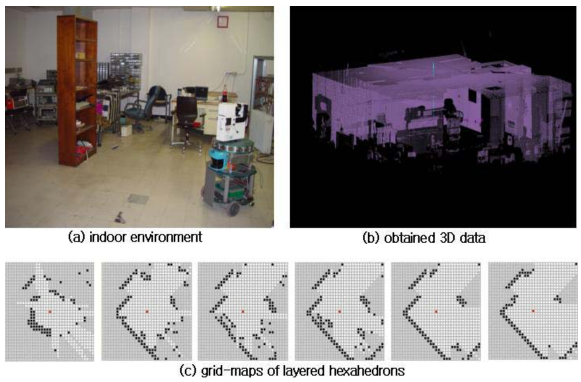

Fig. 3 Grid-maps made of layered hexahedrons of indoor environment

Layered hexahedral-map is a special version of grid-map reflecting three-dimensional space structure into two-dimensional grid and it is composed of three parameters. Motion parameter $m(x,z)$ is calculated by the following procedures. All cells are set to be immovable. Starting from the cell where the three-dimensional laser scanner exists, we spread and set motion parameter to be movable until it meet occupied cell. Motion parameter of a cell is set to be possibly movable when all grids of this cell are unknown or it is conflicted cell without occupied grid. hidden_area_coverage (HAC) parameter $hac(x,z)$ is the expected degree of hidden area coverage. We calculate it by radiating a virtual line from the cell where the three-dimensional laser scanner exists until it meets occupied cell and summarize total number of unknown grid-cells it goes through. conflict_area_coverage (CAC) parameter $cac(x,z)$ is the expected degree of conflicted area coverage, and it is calculated using a similar method to HAC. Scanning coverage $S(x,z)$ can be calculated as

$$S(x,z) = m(x,z) \times \left[hac(x,z) + \beta \times cac(x,z)\right] \qquad (2)$$

where β is weighted constant for CAC. We set small value of β if a user want to fast reconstruction, on the other hand, we set large value of β when we want to detailed reconstruction.

4.2 The next scanning position selection

In this sub-section, we define a term of reliable range as the maximum range where no laser reflection exists and an interval between two consecutive points is small enough to rely. A range reliability according to the laser range is shown in Fig. 4-(a). Overlapped region makes three-dimensional model more complete, but overlapped data detected from same direction work as noises. We make an overlap reliability as shown in Fig 5-(b). We summarize these two reliabilities into weight of reliable range $R(r(x,z))$ where is range from the cell where the three-dimensional laser scanner exists to (x,z) cell. Then we make an equation using and as

(3)

where is normalization constant. We select a position that makes maximum.

However, layered hexahedral-map uses only the instant scan data without memory. Therefore, we make a topological map composed of the connections where the mobile robot has to scan from the result of registration. Topological map gives the connection function of the direction where should be scanned, gives information of dead ally where the mobile robot should go back, and alarms the end of scanning. Finally, equation (3) is changed as

(4)

where is the angle. Observation planning finds relative (x,z) position where the robot should scan. In this result, there is no heading angle because our scanning system covers all directions. Therefore, it has no influence on the performance of making the entire model when a dynamic obstacle blocks the path to the next scanning position.

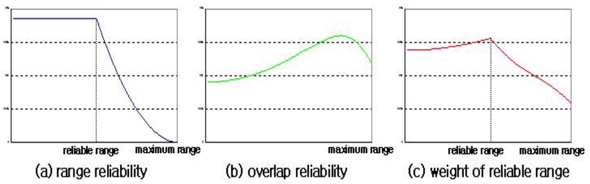

Fig.4 Weight of reliable range

5. REAL-TIME SOLUTION OF DATA TRANSFERRING THROUGH WIRELESS-LAN

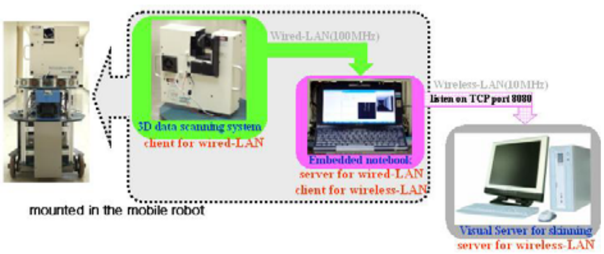

Fig. 5 Solution of the real-time data transfer through wireless-LAN

Because our scanning system use wired-LAN, we have to use multi-threading TCP client/server for transferring three-dimensional environmental data through wireless-LAN to another visual server for VR application such as skinning. The Fastest revolving speed of the mirror in our scanning system is 10Hz when we set the angle resolution to be 0.2 degrees, however, it makes many occlusions. The maximum revolving speed that makes stable scanned data is 6Hz with 0.2 degrees angle resolution. In this condition, the maximum number of points per 1 second is 8,100, and each point has (r,t,p,i) values. Our client can transfer 11,200 points with (r,t,p,i) values per 1 second.

6. EXPERIMENTAL RESULTS

6.1 Dynamic object elimination

The existence of dynamic objects, such as working people, is inevitable in an indoor environment. It is inconvenient for people to remain still in their own place until scanning process is over or to keep away from the scanning region. Therefore, we need to remove dynamic objects. There are several methods for removing dynamic objects. However, noise reduction method Szymon Rusinkiewicz [10] used is time-consuming, and rescanning method after detecting dynamic object [13] needs additional sensors and detecting method of dynamic objects. We remove dynamic objects by converting these unnecessary data into specific patterns using the characteristics of our three-dimensional scanning system without using any additional sensor or time-consuming process. We make three-dimensional scanning system to obtain vertical environmental data while it spins in a given angle resolution about the vertical axis of three-dimensional scanner. A dynamic object, which is not caught in a vertical scanning line, does not have influence on the environmental scanning, and a dynamic object caught in a vertical scanning line appears as few vertical lines with different intensity. Because these vertical lines have different positions and intensities from those of other environmental data, we can mask these data fast by applying simple horizontal masking. Horizontal masking eliminates both data of dynamic objects and salt-and-pepper-noise of laser sensor.

6.2 Experimental results

Three-dimensional laser scanner is mounted on top of the robot. The mobile robot navigates to the next scanning position and avoids dynamic obstacles by ultra-sonic sensors. Then it gains environmental data at the positions of numbered red circles planned by observation planning as shown in Fig. 6. As we mentioned before, it is better to know more than 3 planes in order to express a common three-dimensional object. It means that we commonly need more than two viewing points per one object. In this figure, we can see that most objects, except ones in dead allies, are scanned in more than 2 different directions.

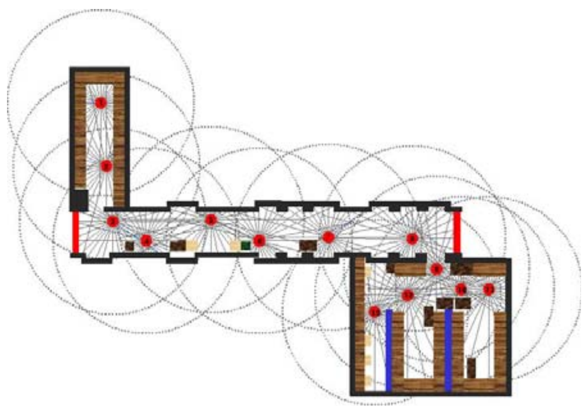

Fig. 6 Target environment and the next scanning positions planned by *observation planning*

The next scanning positions (no.2~no.13) are determined by *observation planning* algorithm as shown in Fig. 7. The left side of each picture in Fig. 7 illustrates instant three-dimensional data and their intensity image plotted in plane. The lower right of each picture shows determination procedure of the next scanning position and the upper right is topological map under construction. Each node denotes the scanning position and it has 8 directions. Each tree denotes the direction to be scanned, and is erased by registered data. Erased trees are denoted as red lines. Most of the next scanning position of *ith* picture in Fig. 7 is matched to the position in Fig. 6. However, we can see that there are some different results in 11^{th} and 13^{th} pictures. The next scanning position of 11^{th} is nearly the same as the 9^{th} scanning position. In this case it selects the second next scanning position because this makes overlapping of trees in topological map. If there is no second position, we ignore the result of 11^{th} and select other next scanning position of scan data connected to the closest extra trees. There is an extra tree in scan and it finds the 11^{th} scanning position. Similarly, next scanning position of 13^{th} position is also nearly same as the 9^{th} scanning position, but in this case we stop scanning because there is no extra tree in topological map. Fig. 8 shows entire registered model.

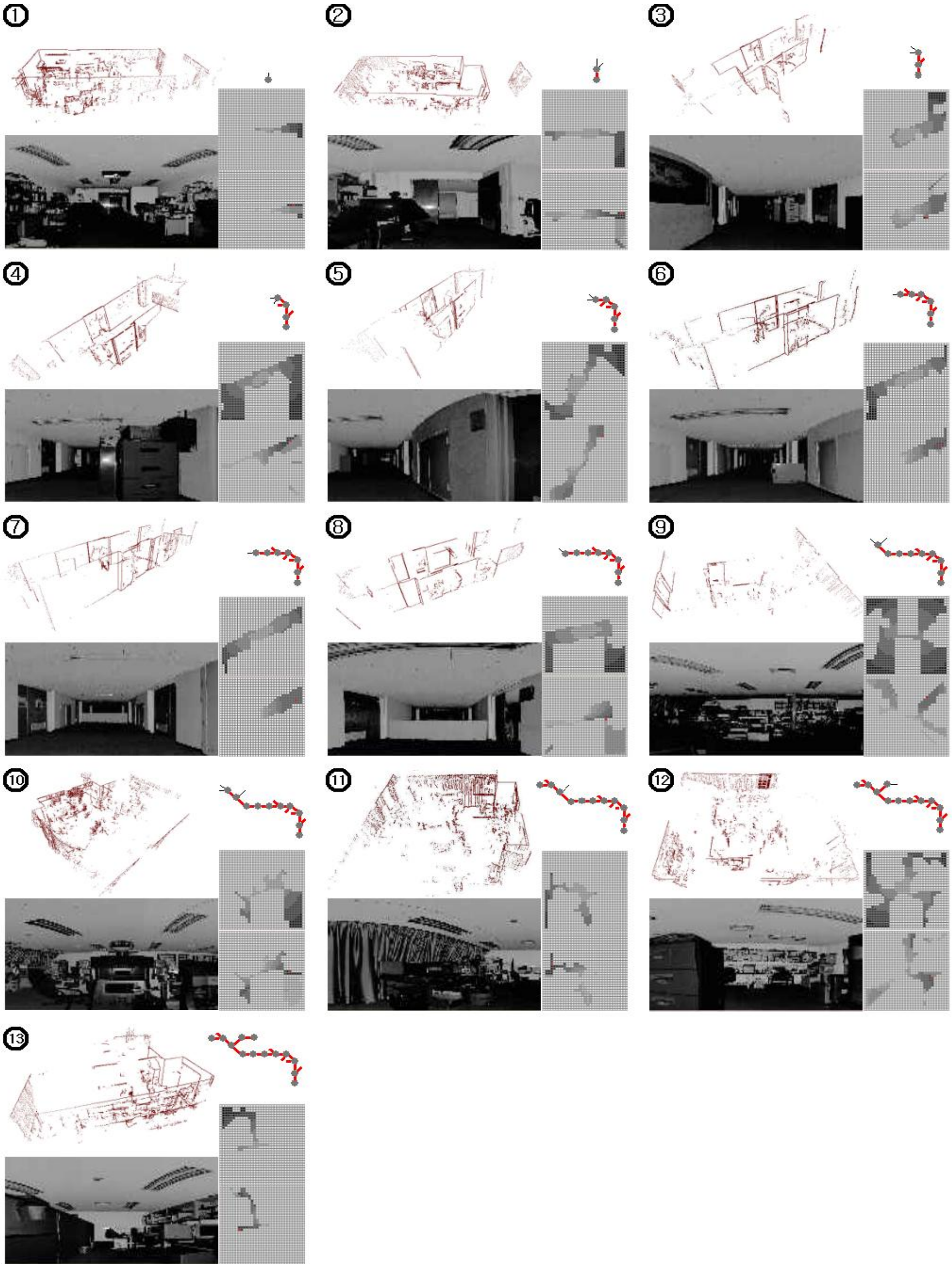

Fig. 7 Upper left of each picture: scanned three-dimensional data; Lower left: intensity images plotted in plane; Upper right: Topological map; Lower right: processes of *observation planning*

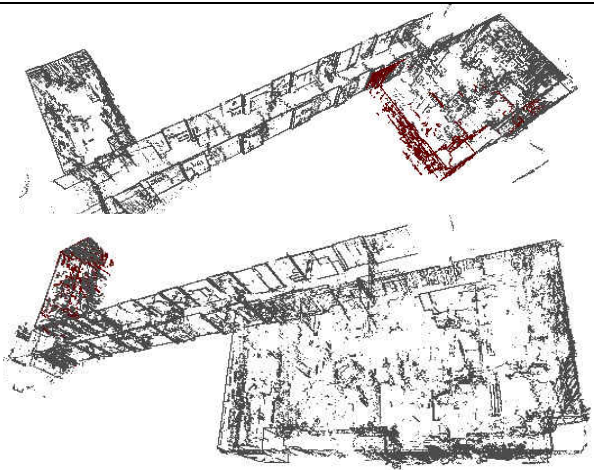

Fig. 8 Experimental results

7. CONCLUSIONS

We presented an autonomous reconstruction system of three-dimensional indoor environments. Our autonomous system was made with an organic combination of data acquisition module, data registration module, observation planning module, multiple TCP client/server module, and mobility module. Our dynamic object elimination method successfully eliminated dynamic obstacles fast, and the mobile robot navigated with dynamic obstacles avoidance by ultra-sonic sensors. Therefore, the existence of dynamic objects did not have an influence on both data acquisition and navigation. We applied the odometer data obtained from the mobile robot to the error vector calculation of ICP algorithm for reducing inaccurate corresponding points. We also used normally distributed points and their intensity values, and these make registration fast. Using a layered hexahedral-map that reflected three-dimensional space structure and a topological map, we determined the optimal next scanning position where did not only cover the unknown region but also covered partially occluded region. Real-time solution of data transferring through wireless-LAN can successfully transfer three-dimensional data to other visual server for future usage.

Future work is to make the registration algorithm faster by applying other speed enhancing methods or by making numerical transformation using reliable features. And we will apply colored image to three-dimensional model for making colored three-dimensional points model.

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