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Generating Individual Maps from Universal Map for Heterogeneous Mobile Robots

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***Abstract*— In this research, a *Universal map*, which can be converted to individual maps for heterogeneous mobile robots, is proposed. A Universal map can be generated using our developed measurement robot, and it is composed of a textured 3D environment model. Therefore, every robot can use a Universal map as a common map, and it is utilized for various localization technologies such as view-based and LRF-based methods. In LRF-based localization, accurate localization is achieved using a specific map, which is generated from Universal map. In a view-based approach, localization and navigation are achieved using rendered images. The use of a Universal map enables generation of these maps automatically. The effectiveness of this approach is confirmed through experiments.**

I. Introduction

Maps are essential for localization and navigation, thus methods for generating maps have been studied. Recently, indoor and outdoor navigation have been achieved, so cooperative work of various robots is expected to work effectively in the near future. However, even if robots work at the same location, each robot has to create an individual map such as an LRF-based or a vision-based map. Furthermore, when the same sensor is installed in each robot, it is impossible to use a common map unless each sensor is set up at the same position. Therefore, "Map sharing" hasn't been achieved in heterogeneous robots.

Simultaneous localization and mapping (SLAM) have been studied actively for generating a map automatically[1][2]. Additionally, it has become possible recently to measure 3D environment maps by laser range sensors. For instance, abandoned mines were explored autonomously, and a 3D map was acquired[3]. Textured 3D maps were created using Laser Range Finders(LRFs) and a camera [4][5]. Furthermore, a 3D laser measurement system using multiple mobile robots was proposed[6]. Outcomes of these works show the feasibility of creating a 3D map automatically. Most of the researchers measured 3D environments for exploring and archiving, but they didn't consider reusing the 3D environment model. Therefore, we propose a "Universal map" for heterogeneous robots as reuse of the 3D environment model. The Universal map can be converted to some individual maps, thus it is possible to share the map as a common map in heterogeneous robots. The Universal map has 3D environment information including geometric and textural information, and we confirmed the feasibility of our proposed method to apply vision-based and LRF-based navigation.

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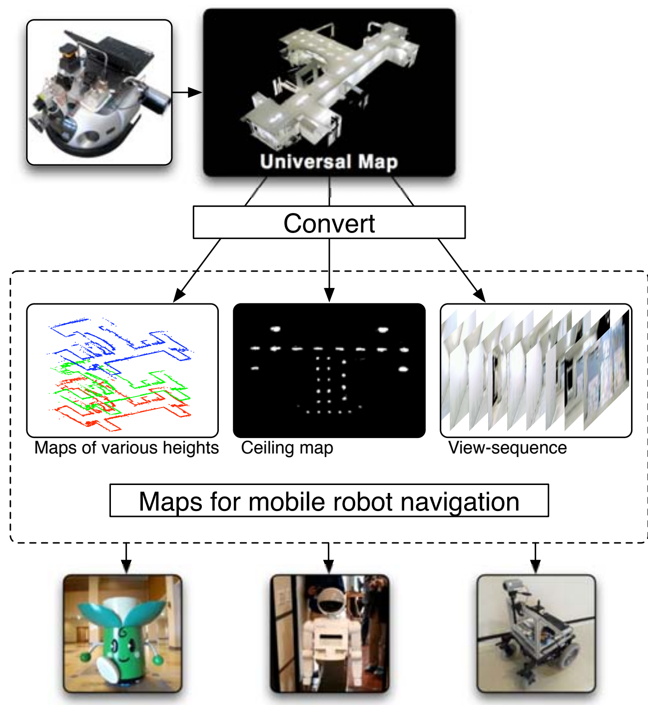

Fig. 1. Concept of the Universal Map

The rest of this paper is organized as follows: Section II describes an overview of the Universal map, and generation methods are described. Section III shows the results of localization and navigation based on the Universal map. Finally, we conclude the paper and describe future work in the last section.

II. Universal Map

Generating a map requires time and effort, so it is effective to share a common map for economy. However, robots cannot utilize a common map because system configurations are different in heterogeneous robots. In order to solve this problem, we propose using a 3D environment model ,which is called Universal map, as a technique for sharing a common map. In our concept, a Universal map that has rich information duplicating the real world can be converted to various individual and specialized maps. As shown in Fig.1, the Universal map has 3D geometric model and textures, so the Universal map can be converted to LRF-based and vision-based maps. We believe that "map sharing" is achieved by

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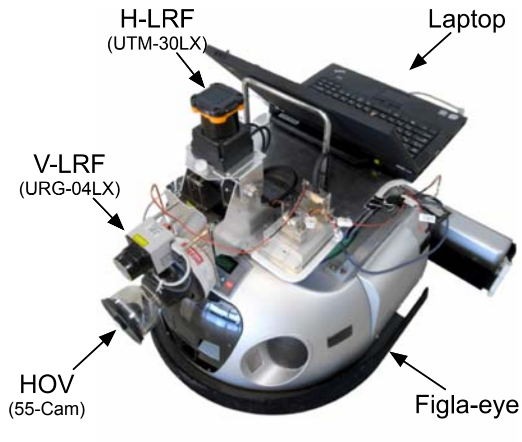

Fig. 2. measurement robot(Two laser range sensors and an omnidirectional camera are installed)

converting to an individual map that is suitable for each system. Additionally, the Universal map includes not only a 3D textured geometric model but also useful information such as trajectory of persons and illumination condition. If a 3D environment can be scanned completely, various types of maps can be generated, and robots can move more robustly and safety.

A. Measurement robot

Robots for measuring 3D environments have been developed. In general, there are no fast 3D sensors available, thus most researchers use a 2D laser range sensor working on an extra rotation device[7][8]. It is necessary to stop to measure at each scan in the case of using rotation devices; thus the use of an extra rotation device isn't suitable. Therefore, we built a mobile robot in order to measure details of a 3D environment easily as shown in Fig.2. An omnidirectional camera and two laser range sensors are installed in the robot. The laser range sensor (UTM-30LX), which can measure horizontal area, is utilized for SLAM, and the robot can acquire 3D points using the other laser range sensor(URG-04LX). In each step, 3D points are correlated with each estimated robot position by SLAM for generating a 3D map. Additionally, projected 3D points on the omnidirectional image are computed for coloring each 3D point.

B. Generation of Universal Map

The experiment for generating a Universal map was conducted in the corridor (about 25[m]) and elevator lobby (about 10[m]) at our university. An overview of generating the Universal map is illustrated in Fig.3 and the procedures are as follows:

1) Collect the environmental information including 3D geometric model and omnidirectional images
2) Estimate the robot position by FastSLAM[9][10]
3) Generate 3D map using vertical range data and the estimated robot positions
4) Color 3D points using omnidirectional images

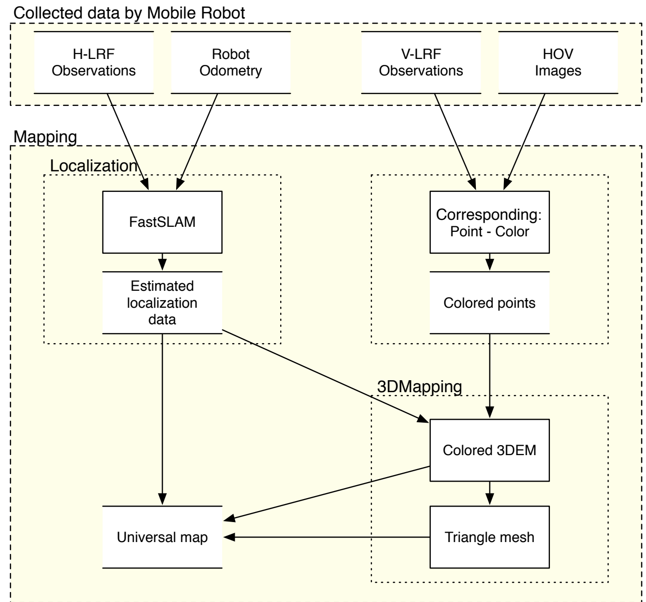

Fig. 3. Overview of the procedures to generate Universal map

Fig. 4. Result of map building by FastSLAM

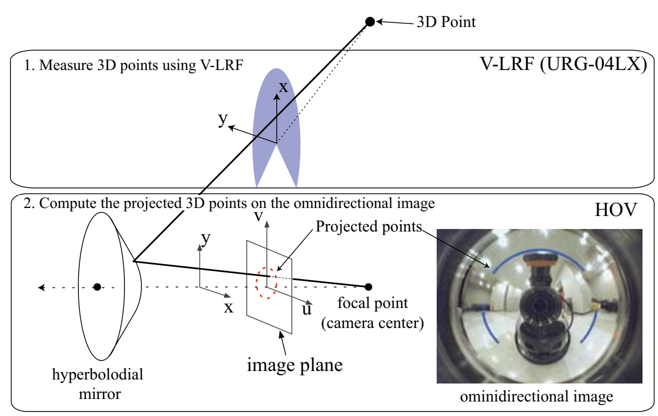

Fig. 5. Relationship between 3D point measured by LRF and its projection onto the omnidirectional image

5) Convert the colored 3D discrete points to polygon mesh for filling in blanks

Universal maps are generated offline after collecting the environmental data. First, the robot collects the environmental data. Next, FastSLAM is executed using a horizontal

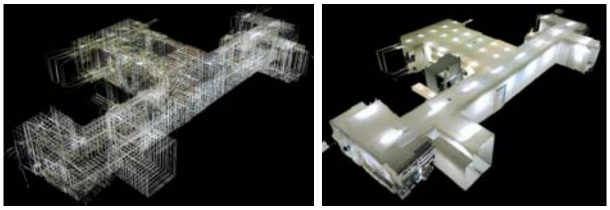

Fig. 6. Point-cloud(left) and rendering(right). The color of each point is estimated by projecting its 3D position onto the omnidirectional image

Fig. 7. Actual view of the environment (left) and Universal map (right)

laser range sensor and odometer for localization as shown in Fig.4. $\boldsymbol{z}_t = \{\boldsymbol{z}_t^1, \cdots, \boldsymbol{z}_t^m\}$ is defined as vertical range data that the robot can acquire at a time t, and $\boldsymbol{z}_t^k = [u_t^k, v_t^k, 0]^\top$ is coordinate of $k-th$ observation point. Then 3D map $\boldsymbol{M}_t^k = [X_t^k, Y_t^k, Z_t^k]^\top$ is computed by the following equation:

$$\begin{bmatrix} \boldsymbol{M}_t^k \\ 1 \end{bmatrix} = \begin{bmatrix} \boldsymbol{R}_{x_t} & \boldsymbol{T}_{x_t} \\ \boldsymbol{0}^\top & 1 \end{bmatrix} \begin{bmatrix} \boldsymbol{R}_{\mathrm{rt}} & \boldsymbol{T}_{\mathrm{rt}} \\ \boldsymbol{0}^\top & 1 \end{bmatrix} \begin{bmatrix} \boldsymbol{z}_t^k \\ 1 \end{bmatrix} \tag{1}$$

where $\boldsymbol{R}_{rt}$,$\boldsymbol{T}_{rt}$ are the rotation matrix and translation vector from LRF-coordinates to world-coordinates respectively. Additionally $\boldsymbol{R}_{x_t}$,$\boldsymbol{T}_{x_t}$ are the estimated pose of the robot in world-coordinates using FastSLAM. After that, the color of each 3D point is computed by omnidirectional image as shown in Fig.5. 3D points that correspond to vertical range data $\boldsymbol{z}_t^k$ are defined as $\mathbf{P}_t^k = [X, Y, Z]^T$.

$$\begin{bmatrix} \mathbf{P}_t^k \\ 1 \end{bmatrix} = \begin{bmatrix} \mathbf{R}_{hov} & \mathbf{T}_{hov} \\ \mathbf{0}^\top & 1 \end{bmatrix} \begin{bmatrix} \mathbf{z}_t^k \\ 1 \end{bmatrix} \tag{2}$$

where, $\mathbf{R_{hov}}$ and $\mathbf{T_{hov}}$ are the rotation matrix and translation vector from LRF-coordinates to HOV-coordinates. When the 3D points can be estimated on HOV-coordinates, it is easy to compute the color of 3D points[11], and the 3D environment model (point-cloud) can be generated as shown in Fig.6(left). Finally, in order to generate polygon meshes, the distance of the closest-point pairs are computed. When the distance is less than threshold (0.40[mm]), points are connected for composing polygon mesh. Furthermore, polygon mesh are colored by Grouaud shading as shown in Fig.6(right). Compared to the actual view, we confirmed that the real world could be re-created precisely in a Universal map as shown in Fig.7. It took about 15 minutes to collect the information of corridor and elevator lobby. Besides, the process of generating Universal map took about 10 minutes by Intel Core 2 Duo 2.20[GHz].

For evaluating the Universal map, we compared between the real environment and the Universal map. Reference points $S = [s_1, s_2, \cdots, s_N]$ are measured in the real world using total-station, and virtual reference points $Q = [q_1, q_2, \cdots, q_N]$, which correspond to reference points in the real world, are acquired from the Universal map. In this research, 25 ($= N$) points are measured as reference points, and Distances between reference points and virtual reference points $d_i = \|s_i - q_i\|$ are computed. Average and variance are $d_i = 0.067[m]$ and $\sigma^2 = 0,034[m]$ respectively, and we confirmed the accuracy of the Universal map.

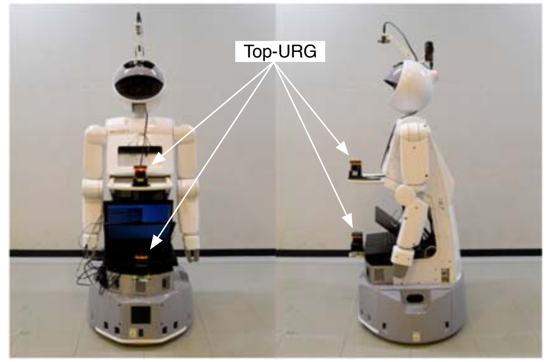

Fig. 8. System configuration of the service robot (enon) in which two laser range sensors are installed

III. Localization and Navigation Based on Universal Map

Localization and navigation are conducted for confirming feasibility of individual maps based on a Universal map. We applied three methods as follows:

1) LRF-based localization
2) Localization using the ceiling map as view-based approach
3) Navigation based on view sequence technique

First, the LRF-based method is selected, because LRF-based localization has been achieved robustly. Second and third, view-based localization and navigation methods are conducted for evaluating the textured 3D map.

A. LRF-based Navigation

It is possible to estimate the position robustly using a LRF; thus, a LRF is installed in a number of mobile robots. However, the system configuration such as type of LRF and setting position is different in each robot, and mobile robots have to create an individual map by themselves. It is inefficient for each robot to measure the environment to create maps individually; thus, we solve this problem by generating individual maps from a Universal map. Generally, a grid map is utilized for LRF-based localization and navigation, thus a grid map is generated form Universal map for LRF-based localization. The virtual robot can move in Universal map for creating the grid map. The virtual robot moves using path which is included as the path of measurement robot in Universal map.

For evaluating the LRF-based individual map, we built an experimental robot based on the Fujitsu service robot “enon”.

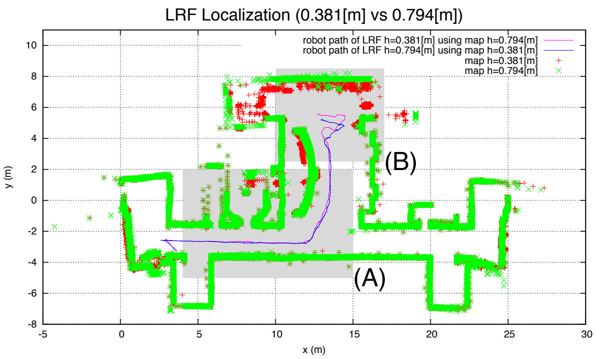

Fig. 9. Results of Monte Carlo Localization using map of wrong height

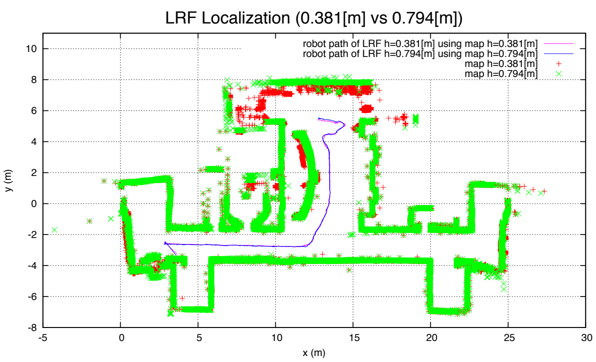

Fig. 10. Results of Monte Carlo Localization using map of correct height

Two types of robots can be simulated because the robot has two laser sensors (h_1=0.381[m] and h_2=0.794[m]) as shown in Fig. 8

Experiments of localization are performed as follows:

1) Localization is executed using occupied grid maps unmatched to position of the sensors
2) Localization is executed using occupied grid maps matched to the position of the sensors

The robot is controlled manually for evaluation, and Monte Carlo Localization is executed using a particle filter. In the case of experiment No. (1), the robot didn't utilize the appropriate map; thus, the results of estimated two path are different, as shown in Fig. 9. One path is estimated using an upper LRF and lower map, and the other is estimated using a lower LRF and upper map. Accurate localization is achieved in area (A) of Fig.9 because there is almost no variation in each height. However, observational results are different in area (B), so localization cannot be estimated accurately. On the other hand, occupied grid maps, which match sensor position, are selected in experiment No. (2). Figure 10 shows the results of estimated localization. The results show that robust localization is achieved because robot paths are matched completely; hence it is important to utilize an appropriate map for accurate localization, and the effectiveness of the individual map converted from the Universal map was confirmed.

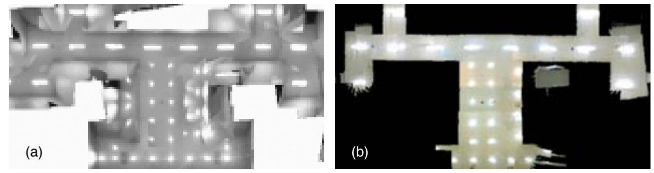

Fig. 11. Ceiling map created by image mosaic technique (a) and by threshold operation to Universal map (b)

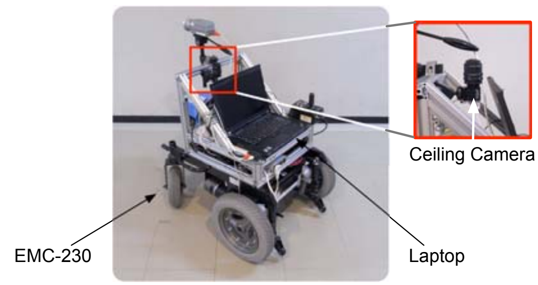

Fig. 12. System configuration of mobile robot with a wide conversion lens

B. Vision-based localization using ceiling map

Navigation and localization based on a ceiling map are achieved robustly in dynamic environments[12]. The ceiling map is also generated automatically using the Universal map by setting the height of ceiling. We assumed a flat ceiling for converting the ceiling mosaic, and 3D points, which are higher than threshold, are extracted as points of the ceiling. Figure 11(a) is created manually and (b) is generated automatically from the Universal map. Resolutions of (a) and (b) are about 16[pixel/m] and 25[pixel/m] respectively, thus we confirmed that Fig.11(b) isn't inferior as compared with (a). After generating the ceiling mosaic, it is converted to a binary image for the remaining light sources. The robot position is estimated robustly in a variable illumination condition using a binary image.

Figure 12 shows the developed experimental robot based on a wheelchair for the localization experiment using the ceiling map. A camera with a wide-conversion lens, is installed in the robot for capturing ceiling images. Intrinsic parameters are estimated for distortion correction by calibration in advance[13]. In general, particle filter is utilized for localization, but template matching is utilized for confirming the feasibility easily as shown in Fig.13. Figure 14 shows snapshots of running a path, while the robot is controlled manually, and the robot position can be estimated. It is possible to estimate the position during meandering and turning, so application to the ceiling map is effective.

C. Navigation based on View Sequence technique

The view-sequence navigation technique was proposed by Matsumoto[14]. This navigation method is composed of two steps. One is "recording run," and the other is "autonomous run". In the navigation using view-sequence, front of view images are utilized for memorizing a running route. In the case of using a Universal map, view-sequence images are

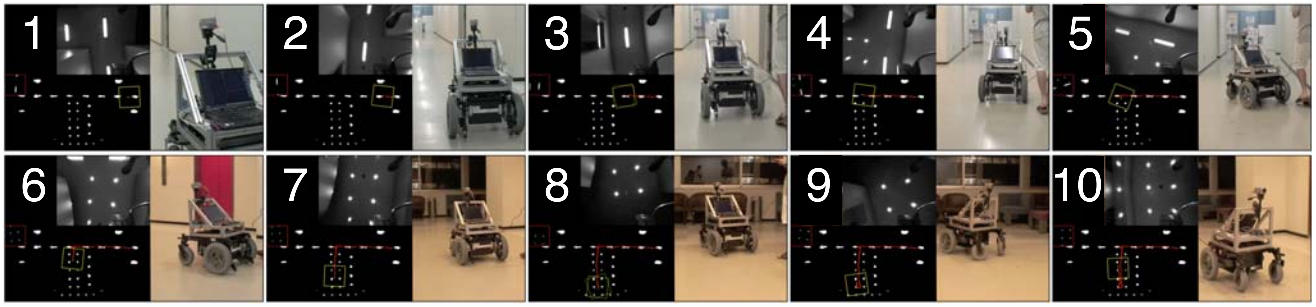

Fig. 14. Snapshots of localization based on ceiling map

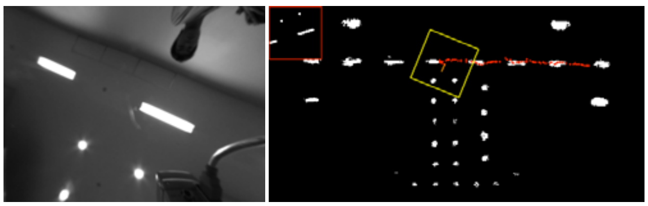

Fig. 13. The result of template matching for localization

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Fig. 16. Image of robot camera(left) and view simulation by Universal map(right)

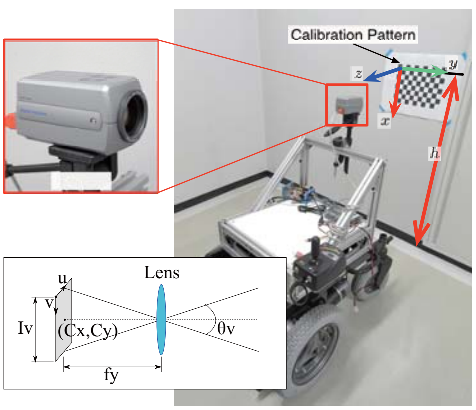

Fig. 15. Camera calibration using chess-pattern for view simulation and geometric camera model

generated automatically by setting a navigation route instead of the real "recording run."

For generating the view-sequence images from the Universal map, we have to estimate intrinsic and extrinsic parameters as shown in Fig.15. Intrinsic parameters (including scale factor) $\mathbf{A}$ are defined by the following equation:

$$\mathbf{A} = \begin{bmatrix} f_x & 0 & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 0 \end{bmatrix} \tag{3}$$

where c_x, c_y are center in image-coordinates, and f_x, f_y are focal length. I_v is defined as the number of image pickup devices in the vertical direction, and vertical angular field of view(Fig. 15) is computed by the following equation:

$$\theta_v = \tan^{-1}(\frac{c_y}{f_y}) + \tan^{-1}(\frac{I_v - c_y}{f_y}) \tag{4}$$

Figure 16 shows the result of view simulation using estimated parameters, and we can confirm the image, which is similar to the captured image by the normal front camera. The virtual camera moves to a destination at intervals of 0.1[m] in the Universal map. Captured images convert to gray scale images of 80×60[pixel], and 40×60[pixel] is defined as the area of template matching. The robot (Fig.15) is navigated using generated view-sequence images, which are different in brightness from camera images; thus normalized correlation is utilized for template matching.

The robot can run using view-sequence based on the Universal map as shown in Fig. 17, and Fig. 18 shows the result of template matching at No.(5) in Fig. 17. Left and right images are generated image as previous and next node respectively. The center image is the current captured image by the front camera. Figure 19 illustrates the result of variance of value of normalized correlation. The value of normalized correlation (red line) between a captured image and the generated image T_n decreases as frame number increases, and the value of normalized correlation (blue line) between a captured image and the generated image T_{n+1} increases. Although the average of normalized correlation is smaller than the value without the Universal map, the Universal map has sufficient quality for view-based navigation.

The benefit of using a Universal map for view-sequence navigation is to be able to move smoothly. The robot is controlled manually in the "recording run," so it is difficult to record a straight path. On the other hand, a straight path is defined easily in the Universal map. Additionally, dynamic route planning will be possible. If the robot finds an obstacle on the recording route, the robot will be able to create another path.

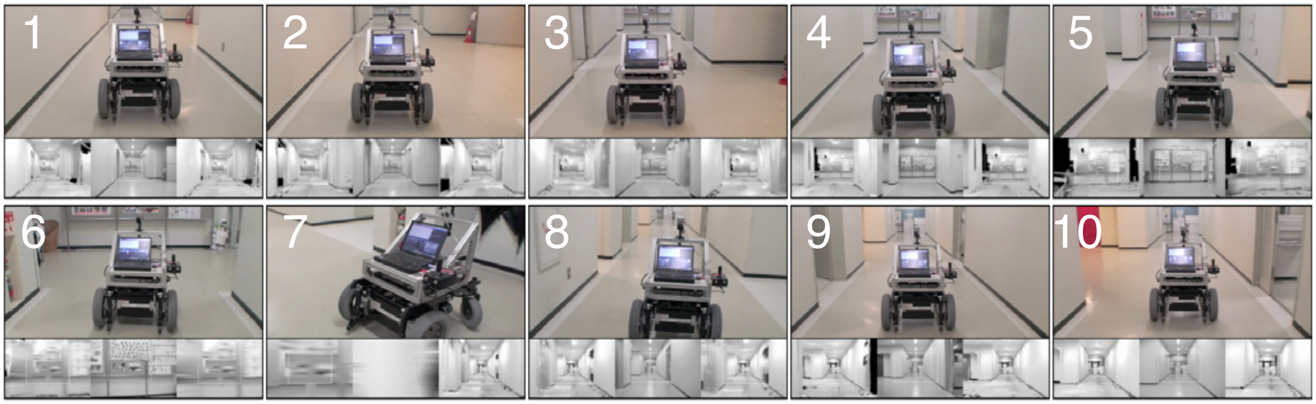

Fig. 17. Snapshots of navigation based on View-sequence

Fig. 18. The result of template matching to view simulation

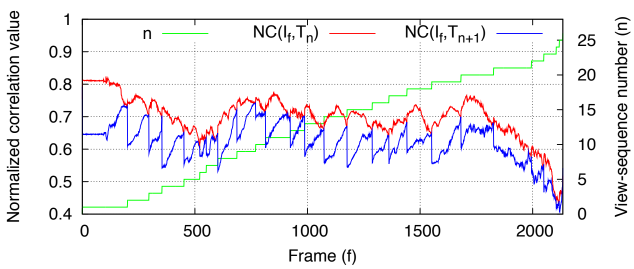

Fig. 19. Normalized correlation (NC) value

IV. Conclusion

In this paper, we proposed a Universal map, which can be converted to individual maps such as LRF-based and vision-based maps. First, a 3D colored map is generated as the Universal map by the developed robot in which two laser sensors and an omnidirectional camera are installed. Next, the feasibility of using each individual map is confirmed through experiments of localization and navigation. Universal maps have geometric information, thus a LRF-based map can be extracted. A LRF-based map of appropriate height is generated for each robot, and robust localization is achieved. Finally, localizations based on ceiling map and view-sequence navigation are also achieved as view-based navigation, and we confirmed the effectiveness of using the Universal map.

In this paper, we implemented a one-way conversion from universal map to specific maps. We believe that our concept can be applied to multiple heterogeneous robot, so we will try that a robot path will be represented in the universal map. Additionally, we will implement dynamic route planning in view-sequence navigation for avoiding obstacles, and we will try to convert to other maps as future work.

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