

Paper:

Development of Intelligent Mobile Cart in a Crowded Environment – Robust Localization Technique with Unknown Objects –

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This paper describes a localization method for mobile robots. The proposed method is based on a three dimensional space observation model that provides stochastic information for robot location assumption. We previously developed a localization method based on the two dimensional space observation model to be used in an environment with many unknown obstacles such as pedestrians. The previous method used a two-dimensional laser scanner and particle filtering to realize robust effective localization of the mobile robot in such environments. It sometimes failed to estimate the robots' location due to a lack of information about its environment, so we extended the previous method based on a three-dimensional space observation model that is expected to use richer information about its environment. Experimental results showed that our proposed method localizes robots successfully in environments where the previous method could not localize robots accurately.

Keywords: mobile robot, localization

1. Introduction

Localization is an important element in realizing navigation by robots supporting human activities. Robot localization is mainly either GPS-based [1] or based on the comparison of environment maps and observation data (Map-based) [2]. Many studies are based on the Map-based method because it can be localized even in indoor environments that do not conduct GPS signals well [3–5]. Due to the effect of occlusion, e.g., by unknown moving obstacles, this method cannot ensure the constant observation of environment data for localization. This is a one of cause of localization failure in real environments containing many unknown objects. Thus, in real environments, ensuring robustness against unknown objects such as pedestrians is important. “Robustness” as used in this

article refers to accurate localization ability despite the presence of unknown objects.

Localization methods which ensure robustness were proposed – free-space observation [6], area observation [7] and space observation [8, 9] –. These methods achieved good result. However, those methods only use two-dimensional (2D) information on the scan plane of laser scanner and may fail to accurately localize in an environment where many objects exist at a height level other than that of the scan plane. Real environments include stairs, uneven steps, and many other space information that are useful for localization. So, localization stability improvement is expected by extending the observation range to the entire space.

There are many studies on a method for improving localization stability by observing the entire space, such as a method for voxel-based 3D environment [10] and a modeling method using 3D dots [11]. Other proposals include, though there are not many of them, methods created by applying the localization methods robust to unknown objects [6, 7] to 3D. Takeuchi et al. have proposed a method in which a 3D model of environment is created by approximating objects in the environment using cylinders or cubes so that the free space observation model [6] is applied to 3D [12]. Similar to [6], this method also evaluates the likelihood of estimated position by judging whether a beam of the laser scanner has penetrated a fixed object in the environment map. Rainer et al. have proposed a 3D extension method based on elevation map called MLS-MAP [13]. This method creates a 3D model of an environment by dividing the environment into multi height levels, creating a 2D map for each level, and overlaying those maps. The likelihood of an estimated position is evaluated by judging for each level whether a beam of the laser scanner has penetrated a fixed object. Similar to [6], since those methods only use observed free-space information, proper localization may not be carried out if the robot is placed over a long period of time in an environment where fixed objects exist only in one direction with respect to the robot.



On the other hand, localization methods robust to unknown objects [8,9] have solved the problem of [6,7] by counting not only observed free-space information but also occupied-space information. Those methods are used as a localization method in public spaces where pedestrians exist [14–17]. However, similar to [6] and [7], this method only uses 2D information of the scan plane of laser scanner. So, good localization may not be possible in some environments due to failure in obtaining significant information.

This research solves the problem by extending the observation target to the entire space so that the existing methods [8,9] are applied to 3D. The proposed method has the following advantages: the sensor model of [18] is approximated similarly to the existing method, and likelihood evaluation of self-position based on observed 3D data is efficiently carried out by matching voxels. We also propose a method to handle 3D voxels as a 2D grid map, so that we realize localization robust to unknown objects based on simple 3D information. The unknown objects in the environment used in this article refer to objects that did not exist at the time of creating environment data for localization. Such unknown objects include dynamic objects such as pedestrians, bicycles, and vehicles and temporarily placed signs.

2. Localization Based on 3D Extended Space Observation Model

Real environments have many characteristic objects such as road gullies and tree branches. So, observing and utilizing the entire space is expected to improve the stability of localization in environments where significant information is not obtained by 2D observation such as the previous method.

The proposed method uses voxels to express observed space information. This allows the previous methods [8,9] to be applied to 3D, thereby improving the stability of localization. The proposed method evaluates the likelihood by comparing voxels of observed space information with voxels of space information of map in each particle that expresses possible position attitudes assumed by the robot. This method has the following advantages: voxel-based expression of environment allowing the sensor model [18] of a laser scanner to be approximated, and simplification allowing voxel matching, which is a simple method, to perform likelihood evaluation. This method realizes likelihood evaluation as simple as that realized by the existing methods for all of three-dimensionally projected numerous beams of the laser scanner without requiring cumbersome geometric calculations.

Figure 1 presents a conceptual diagram of 3D expression. Firstly, the environment is divided into voxels in an arbitrary size. Based on observed laser scanner information, voxels through which beams of the laser scanner have passed are defined as a “free space,” and voxels through which beams have not passed due to the effect of objects are defined as an “occupied space.” In accor-

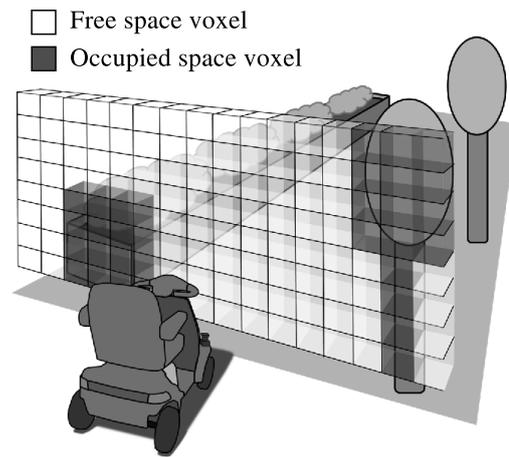


Fig. 1. Definition of space information by voxel.

dance with each particle position attitude, voxels of observed space information are matched to voxels of space information in the map. If a particle expresses a true position, the voxels of observed space information and the voxels of space information in the map are consistent. On the other hand, a particle expresses a false position attitude, the both are not consistent. Voxels are inconsistency in the following two cases:

- Observed free space and mapped occupied space are inconsistent.
- Observed occupied space and mapped free space are inconsistent.

Those events occur in different conditions. So, individually designing likelihood evaluation models for carrying out particle likelihood evaluation will realize stable localization even in environments where many unknown objects exist.

2.1. Matching Between Observed Free Space Voxels and Mapped Occupied Space Voxels

We will now discuss likelihood evaluation based on observed free space voxels. **Figs. 2(a)–(c)** present a typical inconsistency in space information of possible position attitude (particle) assumed by the robot. As presented in **Fig. 2(b)**, a particle that expresses true position attitude does not have inconsistency in space information between observed free space and mapped occupied space. As presented in **Fig. 2(c)**, the same is true in a particle that expresses false position attitude, away from a fixed object. However, as presented in **Fig. 2(a)**, a particle that expresses false position attitude close to a fixed object has inconsistency in space information where the observed free space is involved in the mapped occupied space.

Figure 2(d) presents transition of the number of inconsistent observed free space voxels in a position from the fixed object. In **Fig. 2(d)**, the solid line represents transition without any unknown object, and the chain line

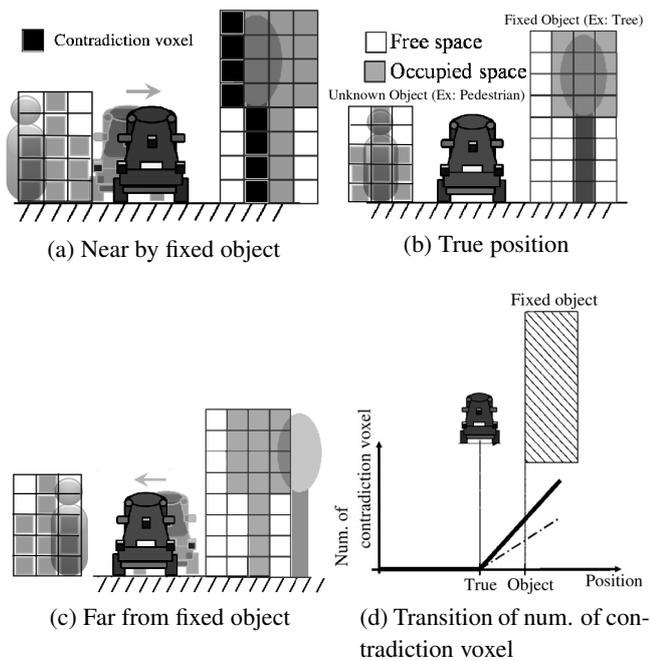


Fig. 2. Likelihood evaluation by free space voxel.

represents transition with an unknown object. The figure indicates that inconsistency of the observed free space increases as getting close to the fixed object. This particle is considered to be a false predicted position because this inconsistency is against an event that “beams of the laser scanner do not penetrate the object,” which is an assumption of this method. Accordingly, localization is possible similarly to the existing methods by giving penalty to the particle in accordance with the inconsistency amount in the space information.

Now we will discuss a likelihood evaluation method based on the inconsistency amount in a free space.

Let observed space information at a given time t be S_t , and let the total number of voxels in a free space at S_t be N_f . Where the total number of voxels that are inconsistent between observed free space and mapped occupied space when S_t is matched to the map in accordance with position attitude of a particle is denoted by N_l , the inconsistency amount F in free space is defined by the following expression:

$$F = \frac{N_l}{N_f} \dots \dots \dots (1)$$

Now, because only simple counting of the inconsistency amount is greatly affected by free space voxels in the environment, the parameter obtained by dividing N_l by the total number of observed free space voxels N_f is the inconsistency amount for likelihood evaluation.

This inconsistency in space information of the free space can be regarded as synonymous with that beams of the laser scanner penetrate a fixed object. Thrun has formulated the likelihood model by approximating a sensor model of a laser scanner in normal distribution about the true value of ranging [18]. Since space information in the

proposed method is observed by the laser scanner, likelihood model on inconsistency of voxels in free space can be approximated with a normal distribution model similarly to the sensor model by Thrun. Accordingly, the proposed method evaluates the likelihood using likelihood evaluation function P_p expressed by normal distribution as follows in accordance with the above-mentioned free-space inconsistency amount:

$$P_p = \frac{1}{\sqrt{2\pi}\sigma_p} \exp\left(-\frac{F^2}{2\sigma_p^2}\right) \dots \dots \dots (2)$$

In the Eq. (2), σ_p has the same value as that in the existing method [8].

In Fig. 2(d), if the predicted position of the robot is further transitioned towards the fixed object and stays sufficiently away from the fixed object, space information in the position and space information of environment data do not overlap and thus the inconsistency amount is reduced. At the same time, since great penalty is given to evaluation of predicted self-position by inconsistency in free space, the self-position candidate (particle) converges near the true position before the predicted position transitions to such a position.

2.2. Matching Between Observed Occupied Space Voxels and Free Space Voxels in Environment Map

The method by Takeuchi et al. [12] and the method by Rainer et al. [13] only use free-space inconsistency amount to evaluate the likelihood of a particle. Those methods may not properly estimate self-position depending on the environment because a particle away from the fixed object as presented in Fig. 2(c), which is false prediction, is regarded as an accurate prediction. Similar to the previous methods [8, 9], the proposed method realizes proper localization regardless of environment by adding likelihood evaluation based on information of observed occupied space.

Figures 3(a)–(c) present inconsistency in space information between observed occupied space and map in a typical robot position attitude predicted as in Section 2.1. As presented in Fig. 3(b), there is no inconsistency between space information in a particle that expresses a true position attitude. However, there is an inconsistency in space information between observed occupied space and mapped free space in position attitudes other than the true position attitude as seen in Figs. 3(a) and (c).

Figure 3(d) presents transition of the number of inconsistencies of observed occupied space voxels in a position from the fixed object. In Fig. 3(d), the solid line represents transition without any unknown object, and the chain line represents transition with an unknown object. It is notable that there are many inconsistencies in observed occupied space even in a particle away from the fixed object for which a proper likelihood evaluation was not possible only with free-space information. A proper evaluation of likelihood of particles is possible by focusing on a point that there are more inconsistencies between

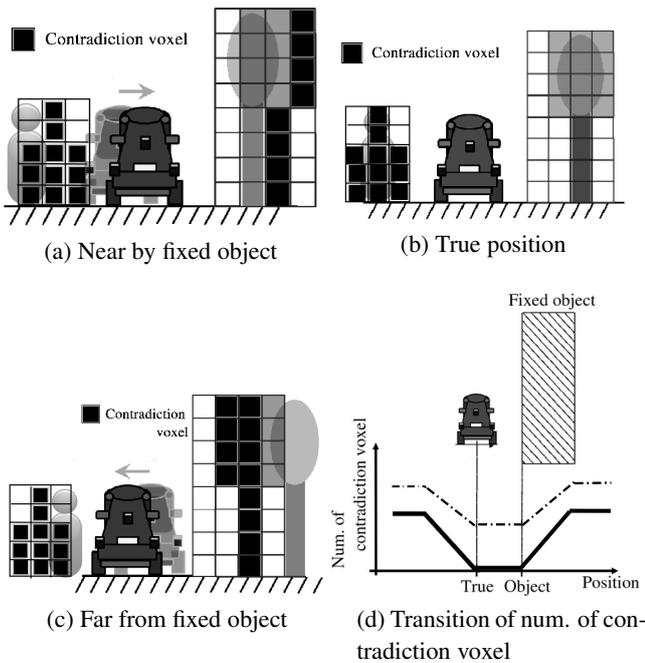


Fig. 3. Likelihood evaluation by occupied space voxel.

the observed occupied space and the mapped free space in this particle in false position attitude than that in true position.

Such inconsistency in space information indicates that an object came into an area that is originally a free space. Such inconsistency occurs in any of the following cases:

- Predicted position attitude is away from the fixed object more than its true value.
- An unknown object has come or occlusion has occurred.

In the former case alone, as in Section 2.1, penalty of normal distribution can be given in accordance with the inconsistency amount of observed occupied space. In the latter case, on the other hand, it is impossible to accurately predict its model. However, once this affects, a similar inconsistency may be observed in all particles including true position, and thus the likelihood will be uniform. The both phenomena happen simultaneously. So, similar to the existing method, the likelihood of particle is evaluated with a likelihood model approximated by a shallow normal distribution that includes the normal distribution of the former and the uniform distribution of the latter.

We will now discuss a likelihood evaluation method based on the inconsistency amount of space information of the observed occupied space. Let observed space information at a time t be S_t , and the total number of voxels in the occupied space at S_t be N_o . Where N_l denotes the total number of matches of observed occupied space voxels and mapped free space voxels when S_t is matched with a map in line with the position attitude of a particle, the inconsistency amount O of the occupied space is defined by the following expression:

$$O = \frac{N_l}{N_o} \dots \dots \dots (3)$$

Similar to the free space, simply counting the inconsistency amount may be greatly affected by occupied space voxels in the environment. So, the parameter obtained by dividing the total number of matches N_l by the total number of observed occupied spaces N_o is the inconsistency amount in the occupied space for likelihood evaluation. In the proposed method, the likelihood of particles is evaluated as in the following expression using a likelihood evaluation function P_l expressed in normal distribution in accordance with the inconsistency amount of occupied space:

$$P_l = \frac{1}{\sqrt{2\pi}\sigma_l} \exp\left(-\frac{O^2}{2\sigma_l^2}\right) \dots \dots \dots (4)$$

where σ_l has the same value as that in the existing method [8].

As presented in Fig. 3(d), if the predicted position of robot is transitioned towards the fixed object, the inconsistency amount of the occupied space is not generated. In other words, this evaluation method innumerably evaluates ‘true positions’ until the position involved in the fixed object from the true value. So, in this research, we simultaneously evaluates the predicted position by the free-space inconsistency and employs the product of both evaluation values of free space and occupied space as the likelihood of the predicted position, as described later.

2.3. Update of Estimated Position

In the proposed method, we regard the above-described two types of inconsistencies of space information as events independent of each other, calculate P_p and P_l for each predicted position (particle), predict as particles multiple position attitudes that can be assumed by the robot in accordance with the pre-calculated odometry error model where the likelihood is the product of them, and calculate the likelihood of all particles for each observation of the laser scanner. The true position attitude of the robot is estimated through resampling in accordance with the calculated likelihood distribution.

Figure 4(a) presents a likelihood distribution obtained by the proposed method. Fig. 4(a) is an expression in a configuration space of a likelihood distribution obtained based on the distance from true position and the difference in relative angles in an environment with an open side, which is common in the real environment as presented in Fig. 5 (the environment that is not well handled by the methods [6, 7], which only consider free space). (However, Fig. 4(a) is a result of calculation in a virtual environment that has similar properties to that of Fig. 5, presented in Fig. 7(a) described later.) The true value is the origin (0, 0) in Fig. 4(a), which indicated that the peak of the likelihood exists around the origin. Accordingly, even in an environment presented in Fig. 5, the proposed method is expected to provide convergence to the true position attitude by repeating particle update.

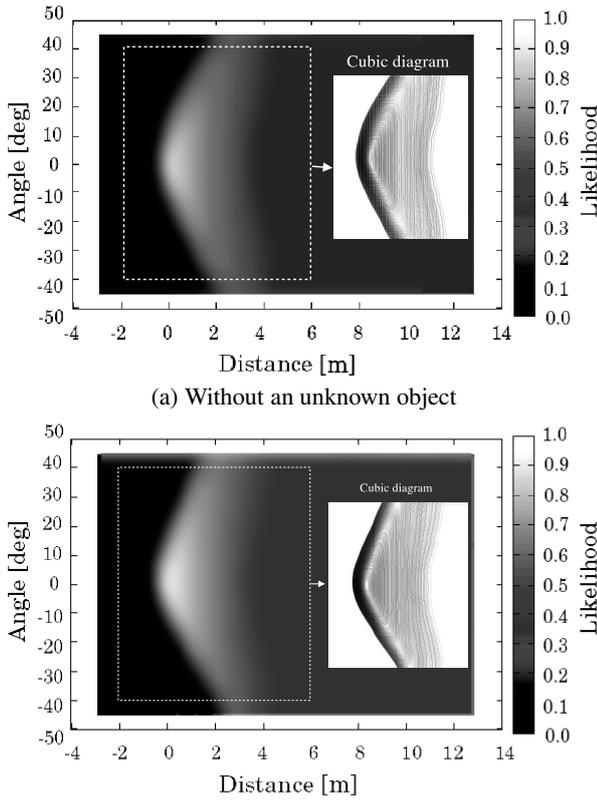


Fig. 4. Likelihood distribution of proposed method.

2.4. Implementation of the Proposed Method by a Grid Map Expression

If 3D space information of a real environment is handled directly as voxels, the amount of memory increases, which is not proper for actual operations. In this paper, we propose a method to handle 3D data through expression on a 2D grid map based on voxel information.

As presented in Fig. 6, in this research, a free-space voxel is denoted by “1” and an occupied-space voxel is denoted by “0.” Focusing on the voxels in the height direction, with each voxel value being a bit value, the entire space information in the height direction is regarded as binary information and expressed as a 2D grid map.

Since 3D voxel information is handled as a grid map, detection of inconsistent voxels is realized by a geometric calculation of rotation and translation of grid map in accordance with the position attitude of particles and a simple calculation of logical operation (AND) of grid values. Due to this, with the same calculation method as that by the existing methods [8, 9], which are the base of the proposed method, the proposed method achieves a more stable localization through likelihood evaluation of particles than that by the existing methods. For the purpose of illustration, voxels in the height direction are now expressed 8-bit. However, the actual number of bits is defined depending on the resolution with which the user expresses the environment.

The laptop PC (Lenovo ThinkPad T500, OS: ubuntu10.04, CPU: Core2Duo 2.5 GHz, memory:



Fig. 5. Example of environment.

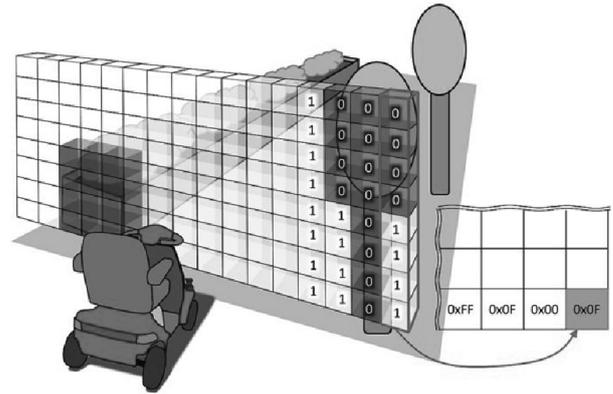


Fig. 6. Binary expression by the information of the voxels.

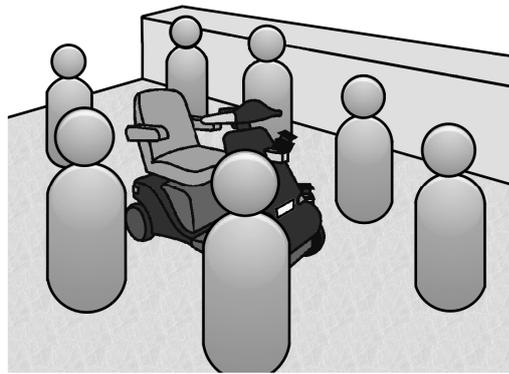
2.0 GB) mounted in the robot we developed is capable of carrying out a series of the following operations at a speed of about 80 ms: obtaining surrounding distance data through the laser scanner, calculation of space information, likelihood calculation of 100 particles, and resampling. As for the environment map data, a map around Tsukuba Station with a range of 650 m × 550 m can be created and retained in as small data capacity as 508 KB (the height direction of 16 bits and voxel size of 0.2 m square).

3. Evaluation Experiment

We conducted evaluation experiments to verify the effectiveness of the proposed method. One is a likelihood distribution simulation in the virtual environment to confirm whether the proposed method is robust to many unknown objects. The other is a comparison of results of localization of the robot running in the real environment between the proposed method and the previous methods. There are many unknown objects such as pedestrians and bicycles in the experiment environment.

3.1. Robustness Evaluation on Unknown Objects

In a virtual environment as presented in Fig. 7(a), where a wall exists on one side as a fixed object, we added virtual pedestrians as unknown objects and verified robustness of the proposed method to the unknown objects.



(a) Illustration of the experimental environment

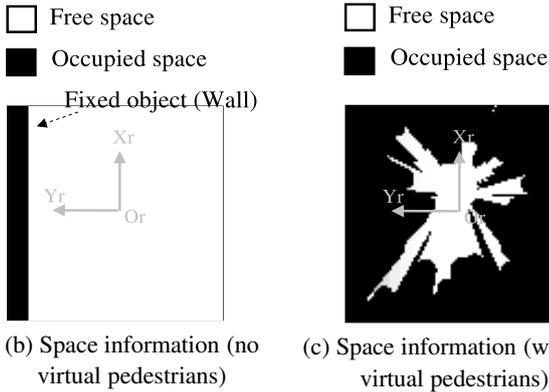


Fig. 7. Overview of the experiments.

We consider the virtual pedestrians approximated by circles as the unknown objects and placed them at random positions with random sizes. The circles of the virtual pedestrians are each given with a random diameter of 0.4 to 0.6 m including arms, which is the same as human width. The positions are randomly determined so that they do not overlap in about 5 m square around the robot and they do not overlap with the robot. The robot is placed at the coordinate origin presented in Figs. 7(b) and (c), with the size of 1.0 m high and 0.5 m wide. Through an experience at Tsukuba Challenge [a] we conclude that the number of unknown objects that surround the robot at once in a real environment is about 20 at maximum. We calculated the likelihood distribution with 30 virtual pedestrians, which exceeds the assumed maximum number of people, being added as noise to the space information.

Figures 7(b) and (c) present the space information actually acquired in the virtual environment of this experiment. Fig. 7(b) presents the space information including no unknown object, and Fig. 7(c) presents the space information including the 30 virtual pedestrians.

Acquired likelihood distribution is presented in Figs. 4(a) and (b). This figure expresses in the configuration space a likelihood distribution obtained from differences in distance and angle from the true value. This figure indicated that the peak of likelihood exists around the origin, which is the true value, even when many unknown objects are added. Accordingly, even in a situation



Fig. 8. Experimental environment and run route.



Fig. 9. Illustration of mobile robot.

where many unknown objects exist, the proposed method is capable of accurate likelihood evaluation without being greatly affected by the unknown objects, and is expected to provide convergence to the true position attitude by repeating particle update.

3.2. Performance Evaluation of Localization Method

To verify effectiveness of the proposed method, we carried out localization by the previous method and the proposed method in the real environment presented in Fig. 8. The real environment used for the experiment is a course of about 400 m on the campus of the University of Electro-Communications where pedestrians, bicycles, and vehicles come and go. There are not many characteristic irregularities at the height level of the horizontal laser scanner in Fig. 9.

3.2.1. System Configuration

As presented in Fig. 9, this study uses a modified electric seniorcar of Suzuki Motor Corporation as a mobile robot. For the proposed method, the robot is provided

with one laser scanner that swings right and left for three-dimensionally measuring the environment as an external sensor. The fluctuation sensor for 3D measurement has fluctuation cycle of 0.5 Hz. 3D information of the environment is obtained by the laser scanner swinging right and left. The robot is also provided with two horizontally mounted laser scanners for the previous method [8], which is a comparison target, and for avoiding obstacles. In addition, the robot is provided with an encoder and an optical fiber gyro as internal sensors. The optical fiber gyro is used for odometry calculation when creating an environment map, enabling an accurate environment map to be created because of its high accuracy with an error about 10 m for 1 km travel. The robot system is explained in detail in reference [9].

3.2.2. Environment Map Creation

The robot system of this study can create a whole environment map online once given a single manual training travel along the route with the following procedure.

1. Initialize the environment map (populate all the voxels with occupied space voxels = 0).
2. Manually run the robot along the route while obtaining information through the laser scanner and the gyro odometry.
3. Calculate space information voxels based on information from the laser scanner.
4. Overlap observed space information voxels on the position attitude of gyro odometry on the environment map.
5. Calculate the logical disjunction of the environment map and free space voxels of the observed space information voxels.
6. Repeat 2 to 5 until the robot travels through the entire route.

As a precondition for environment data used for this method, the environment data have to be free from unknown objects such as pedestrians and unobserved areas. Environment map data used for this study have to include accurately described occupied spaces by fixed objects existing in the environment. However, since unknown objects are handled as unknown objects at the time of localization, it is not required to thoroughly observe all the fixed objects. In this research, we fixed the laser scanner obliquely downward to obtain 3D information of the environment without any omission by ‘seining’ the environment shape and to measure the environment with no unobserved area left behind. The operations listed above are equivalent to sequential repainting of areas through which the beams of the laser scanner pass to free space voxels. Even if a moving obstacle exists during the training travel, after the moving obstacle has gone, the area is observed as free space voxels in the next observation and logical disjunction is calculated. So, the moving obstacle

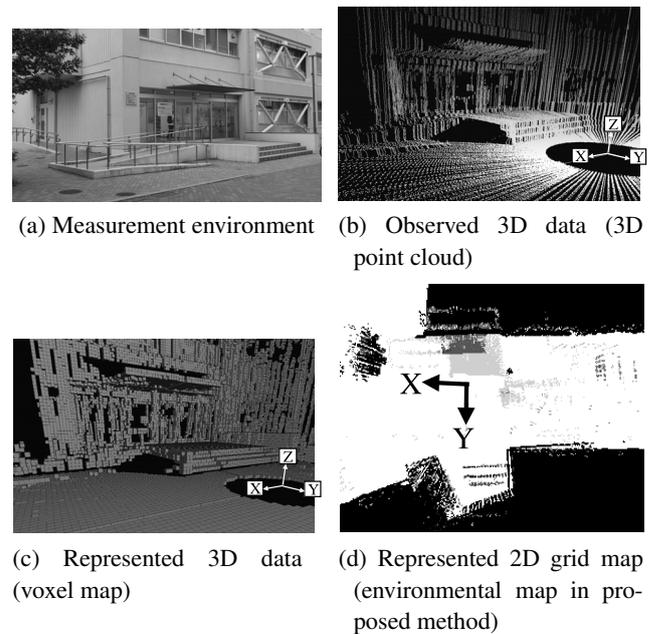


Fig. 10. Appearance of 3D measurement.

rarely remains the same as an occupied space on the map. If the moving obstacle remains, environment information is extracted and imaged for each 1 bit (layer) in the height direction and the moving obstacle is manually removed using the paint tool. For this reason, the proposed method is convenient as a map creation method in busy environments. In addition, the proposed method has an advantage of capability of creating an environment map online due to simplicity that what is required is calculation of logical disjunction of free space voxels in accordance with the gyro odometry.

Figure 10 presents an example of a map created with this method. **Fig. 10(c)** is an expression using voxels of the environment presented in **Fig. 10(a)** based on 3D information (**Fig. 10(b)**). **Fig. 10(d)** is an expression of the environment as a grid map based on voxel information. **Fig. 10(c)** is a high resolution expression of the environment expressed using voxels with the height resolution of the environment of 128 bits and the voxel size of $0.1 \times 0.1 \times 0.1$ m. **Fig. 10(d)** is a gray scale image with the height resolution of 8 bits and the voxel size of $0.1 \times 0.1 \times 0.2$ m and a width of 2.5 m is provided between voxels in the height direction.

3.2.3. Localization Experiment

Using both the existing method and the proposed method on the same course, we verified the effectiveness of the proposed method by carrying out localization in a real environment where pedestrians and other unknown objects come and go and comparing the estimation results. For the localization, we gave the robot a single advance training travel and used environment maps that were separately created at the same time as environment maps for each of the methods. In this method, the voxel size was defined in line with the most focused object existing in the

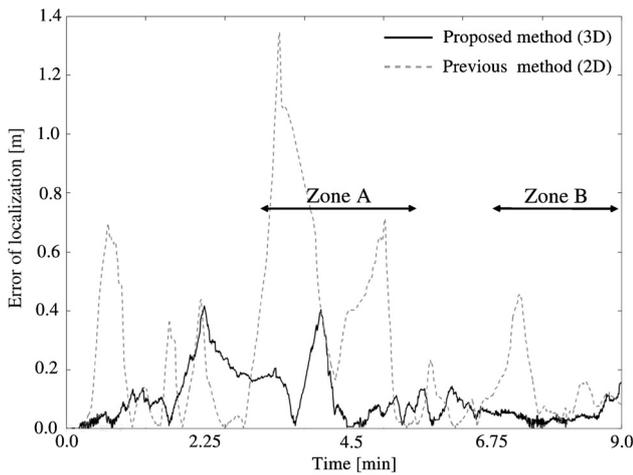


Fig. 11. Result of localization experiment (error of localization).

environment. In other words, setting a slightly smaller voxel size than the focused object enables beams of the laser scanner to be properly described in the space information without the beams running off the focused object in voxels. In this experiment, the voxel size was determined to be $W \times D \times H = 0.1 \text{ m} \times 0.1 \text{ m} \times 0.3 \text{ m}$ in line with a bollard, which is the smallest object to be described in the space information among the objects existing in the experiment environment, and the resolution in the height direction was 8 bit. The grid size of the space information in the previous method was $W \times D = 0.1 \text{ m} \times 0.1 \text{ m}$ in line with the voxel size.

In localization using the proposed method, space information is created based on 3D information measured using the sensor that swings right and left in a cycle of 0.5 Hz, so that the self-position is estimated. At this time, there is an unobserved area that was not observed by the swinging sensor. However, the proposed method is capable of observing such unobserved area by handling it equally to an unknown object as an occupied space. We used 100 particles for localization. The travel speed of the robot was about 3 km/h.

The result is shown in Fig. 11. The horizontal axis represents time, the vertical axis represents errors (deviation from the true value), the solid line represents the results of the proposed method, and the dashed line represents the results of the existing method. There is a particularly remarkable difference between the zones A and B. While the proposed method estimates the self-position with an error of 0.2 m, the existing method estimates the self-position with an error of 1.4 m at maximum. As presented in Fig. 12, this is because the proposed method successfully observed the bollard, which was not observed in the previous method, described it into the environment map, and gave a proper penalty to particles of the false position attitude. In the previous method, a significant fixed object that can be observed in this zone did not exist in the observation range of the laser scanner and a proper penalty was not given to particles of the false position attitude. These may have caused the disruption of position estimation.

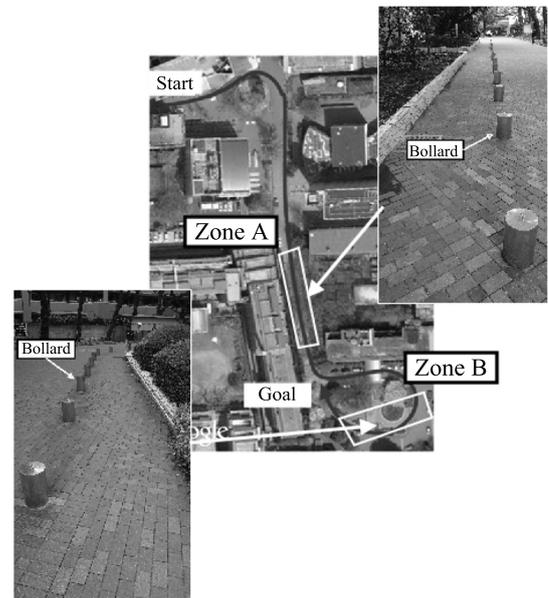


Fig. 12. Appearance of Zone A and Zone B.

On the other hand, the proposed method exhibits a worse estimation result than the existing method around 2.25 min. This is because objects not scanned well by the laser scanner such as glass walls and tiles that diffusely reflect environment light existed in the observation range of the laser scanner for 3D measurement. This resulted in failure of accurate measurement of the space information, thereby causing inaccurate likelihood evaluation of the self-position. However, such object did not exist afterwards, so the self-position was successfully estimated by accurately observing the space information without disrupting the self-position. In this way, the proposed method is very effective because it is capable of robust localization to unknown objects and capable of stable position estimation even in an environment where localization is disrupted using the existing methods.

4. Conclusion

In this paper, we described robust localization technique with unknown objects for mobile robot. We extended the previous localization technique to 3D based on the voxel expression. In the proposed method, we solved the problem of the previous method that localization fails if robot cannot acquire significant environmental data by 2D measurement. The proposed method evaluates the likelihood of a laser scanner sensor model by voxel matching. By treating voxel information as a bit value and expressing it as binary information, the proposed method handles 3D voxel data as a 2D grid map as similar the previous method. The proposed method has realized localization using a simple method in which 3D voxel information is handled as a grid map so that a map and voxels of observed space information are matched by simple geometric calculation (rotation and translation) and log-

ical operations. In evaluation simulation of robustness against unknown objects and localization experiments in a real environment, we have confirmed that the proposed method is effective. In future works, in order to reduce effort and time in map making, we aim to realize localization technique based on the existing map information such as Google Maps.

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