Topological Clustering for Spatial Perception Using Fuzzy Reliability-Based Growing Region Method

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2024 International Joint Conference on Neural Networks (IJCNN) | 979-8-3503-5931-2/24/$31.00 ©2024 IEEE | DOI: 10.1109/IJCNN60899.2024.10650182

***Abstract*—To support humans in various environments such as homes, nursing homes, and hospitals, robots need a spatial perception system that enables flexible and rapid recognition of unlearned objects. However, there is a problem that methods that require prior learning cannot fully deal with unlearned objects and that the input of RGB images is easily affected by the lighting conditions of the environment. In this study, a topological map is generated in real-time using Growing Neural Gas, a type of unsupervised self-growing neural network, with 3D point cloud data as the only input. However, in unknown environments, there is a problem that the size of clusters becomes unstable and cannot be detected stably if the region growing method, which checks only labels assigned based on normal vectors, is used to detect clusters such as unknown objects in the topological map. Therefore, we propose a methodology to stably detect clusters in a topological map by introducing the concept of age and a reliability based on fuzzy sets for each node and rejecting unstable nodes with low reliability even if the nodes to which they are connected have the same label. Also, the effectiveness of the proposed methodology is demonstrated by experiments through 3D dynamics simulations.**

***Index Terms*—Topological clustering, growing region method, spatial perception, growing neural gas, fuzzy sets theory**

I. Introduction

Perception systems that enable flexible and rapid recognition of unlearned objects are needed for robots to support people in various environments, such as homes, nursing homes, and hospitals. One widely used environment recognition method is the obstacle detector [1]. This technique's recognition performance, however, strongly depends on parameter settings, and in unknown environments where the environment cannot be assumed in advance, it may cause misrecognition, such as recognizing walls as small objects or failing to detect the obstacle itself. Therefore, these spatial perception systems require manual readjustment of parameters for each environment. Although many environment recognition methods [2]–[4] using RGB-D cameras that can combine distance and image information have been proposed, the performance of these methods strongly depends on the lighting conditions of the environment, resulting in unstable recognition results.

Thus, in this study, we use Growing Neural Gas [5], a type of unsupervised self-growing neural network, to construct a topological map in real time using only point cloud data as input. When detecting unknown objects, modified GNG with Utility (GNG-U2) reduces the risk of deletion even when nodes are densely generated and there are many redundant nodes by prioritizing sampling from regions close to unknown objects and adjusting Utility values according to node Strength values [6]. Dynamic Density GNG (DD-GNG) has been proposed for detecting moving ladders [7], real-time grasp affordance detection for robot manipulation [8], and sudden obstacle avoidance for multi-legged robots [9].

However, since DD-GNG assigns object category labels such as unknown objects to each node based on normal vectors and uses the standard region growing method for cluster detection, there are situations in which obstacles that are larger than the actual obstacles are mis-detected, as seen in the experiments. The video shows some cases where obstacles larger than the actual obstacle were detected incorrectly. In consideration of its application to robotics, it is very important to detect appropriate clusters and to recognize the appropriate size and shape of objects as a single mass when recognizing surrounding walls, obstacles, and graspable objects in an unknown environment. In the case of detecting clusters of unknown objects in a topological map using the general region growing method, only the labels assigned based on the normal vector are checked, so the cluster size becomes unstable in the boundary region between the floor and the unknown object, where the normal vector tends to be unstable, and the detection is not stable. Therefore, the cluster size becomes unstable and cannot be detected stably.

Then, we proposed a methodology to stably detect clusters in a topological map by introducing the concept of age and a confidence level based on fuzzy set [10]–[12] for each node, and rejecting unstable nodes with low confidence levels even if the nodes to which they are connected have the same labels. The methodology is proposed and its effectiveness is demonstrated by experiments through 3D dynamics simulations.

The paper is organized as follows. Section II provides an overview of the system of the proposed methodology. Section III describes the difference between the proposed Fuzzy Reliability-Based Growing Region Method for Topological Clustering and the general growing region method used in the past. In Section IV, experimental results of the conventional and proposed methods are compared and discussed. Finally, in Section V, we conclude and discuss the effectiveness of the proposed model and directions for future research.

II. System Overview

In this section, we describe an overview of the proposed method. Fig. 1 shows a total flowchart of the proposed spatial perception system using fuzzy reliability-based topological clustering, which uses only 3D point cloud data. In the proposed method, a depth camera (RealSense D435) is used to acquire only 3D point cloud data. After down dumping using a voxel grid, the acquired data is input to the AiS-GNG, which randomly samples predefined λ points (λ=300) instead of using all points for learning. Once the GNG has generated a topological structure represented by nodes and edges, the nodes are assigned labels such as wall surface, floor surface (safe terrain), or unknown object based on the normal vectors calculated from the positions of the topological neighborhood. The calculations of the normal vectors and labeling are described in detail in our previous work [7]–[9].

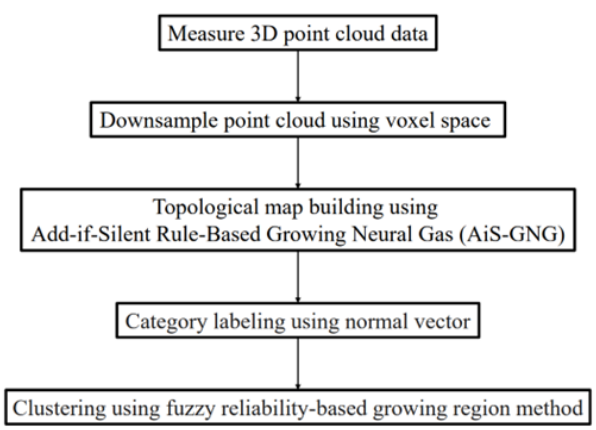


Fig. 1. Total flowchart of our proposed method

III. Topological Clustering Using Fuzzy Reliability-Based Growing Region Method

A. Topological Mapping using Add-if-Silent Rule-Based Growing Neural Gas

In conventional GNG [5], [6], a node is added every time λ input vectors are learned from all 3D point cloud data based on the accumulated error. However, in real-world environments, point clouds of object surfaces located far away are rarely sampled, and even after repeated training, nodes are never generated densely enough to be detected as objects. In addition, DD-GNG [7], [9] performs a focused sampling process after detecting unknown objects, but when used as a perceptual system for mobile robots, etc., to detect objects that are relatively far away, it is necessary for nodes to be generated in high-density first, and then detected as clusters. However, due to the characteristics of RGB-D cameras, it is difficult to generate a high density of nodes for objects that are far away from the camera.

The pseudo-code for the Add-if-Silent rule-based growing process is shown in Algorithm 1. Since much of the processing is common to GNG-U2 [6], a detailed description is omitted and only the processing specific to AiS-GNG [13] is described. In the first line of the algorithm, two conditions are checked: whether the labels L_i of the first and second winner nodes s_1 and s_2 are unknown objects or dynamic objects for the input vector, and whether the Euclidean distance from the input vector v_t to the winner nodes is within a tolerance area. If both conditions are satisfied, the node is considered to be useful input data and is added as a new node. In this case, the reference vector h_r is the 3D position of input vector v_t , the accumulated error E_r and Utility value U_r of the newly created node r are the average value of s_1 and s_2, and the label Lr is an unknown object. This Algorithm 1 is executed at the same time as the search for the winner node, and if the condition is not satisfied, it does not add any nodes.

Algorithm 1 Add-if-Silent Rule-Based Growing Process

1: **if** $L_{s1} = L_{s2} = \{\text{Unknown Object or Dynamic Object}\}$
and $\theta^{AiS}_{Min} < \|\boldsymbol{a}_t - \boldsymbol{h}_{s1}\| < \theta^{AiS}_{Max}$
and $\theta^{AiS}_{Min} < \|\boldsymbol{a}_t - \boldsymbol{h}_{s2}\| < \theta^{AiS}_{Max}$ **then**
2: $h_r = v_r, E_r = 0.5\left(E_{s1} + E_{s2}\right),$
$U_r = 0.5\left(U_{s1} + U_{s2}\right), L_r = \{\text{Unknown Object}\}$
3: $A \leftarrow A + \{r\}$
4: $c_{r,s1} = 1, c_{r,s2} = 1$
5: **end if**

B. Category Label-Based Growing Region Method

Each node in the topological map is assigned a category label based on its normal vector, which is efficiently obtained by using information from neighboring nodes (topological neighbors). Therefore, it is effective to examine the labels of neighboring nodes to determine where clusters (e.g., unknown objects) are located. If a node has the same label as the reference node, it is considered to be an element constituting the same cluster, and the cluster is detected by gradually growing the region.

C. Fuzzy Reliability-Based Growing Region Method

It is possible to detect the clusters themselves by using the growing region method based on the category labels possessed by each node as described above. However, in the boundary region between an unknown object and the floor surface, the normal vector itself changes rapidly due to the position update of the reference vector, and the category labels are frequently reassigned, making the method unstable. If the incorrect label is temporarily assigned to a node, the cluster size may change drastically or clusters of clearly wrong size may be detected (Fig. 2). This is a major problem when using the topological map generated by GNG for tasks such as obstacle avoidance.

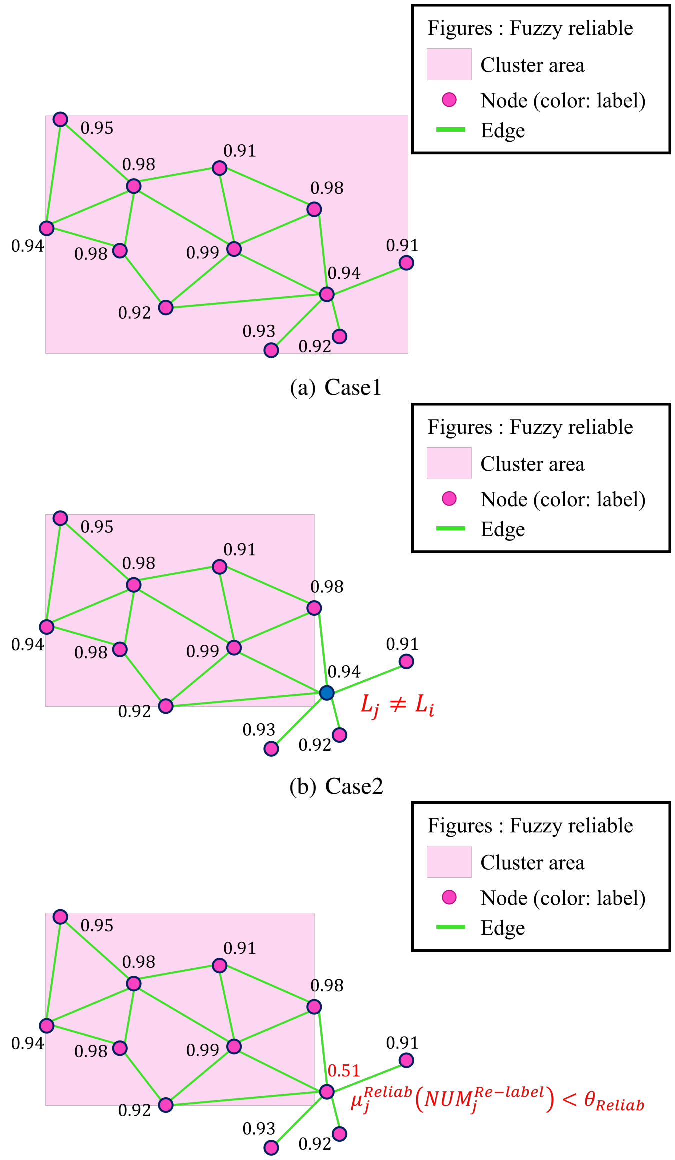
Then, we introduce the concept of age for a node. We increment the age of a node every λ training cycles since its creation and set the age of the newly created node $Age_i^{Node} = 0$. Therefore, if a node is useful in acquiring the topological structure of the environment, it will remain and not be deleted, and its age will increase.

Therefore, we can assume that the age of the node will increase. In order to determine how much a node has been replaced in relation to its age, the following fuzzy set of triangular type membership functions are input to the fuzzy set that indicates the reliability of each node.

$$\mu_i^{Reliab}\left(NUM_i^{Re\text{-}label}\right) = \frac{\left|Age_i^{Node} - NUM_i^{Re\text{-}label}\right|}{Age_i^{Node}} \quad (1)$$

where μ_i^{Reliab} is the reliability of the node and $NUM_i^{Re\text{-}label}$ is the number of times the label of the i-th node has been re-labeled. A node with low reliability is not stable because its label has been re-labeled many times between the creation of the node and the current time, and there is a high possibility that the label it holds is incorrect. Therefore, when performing cluster detection based on the region growing method, the following conditions are met, the cluster is rejected even if it has the same label.

$$\text{if}\mu_i^{Reliab}\left(NUM_i^{Re\text{-}label}\right) < \theta_{Reliab} \quad (2)$$



(a) Case1

(b) Case2

(c) Case3

Fig. 3. Topological clustering using growing region method

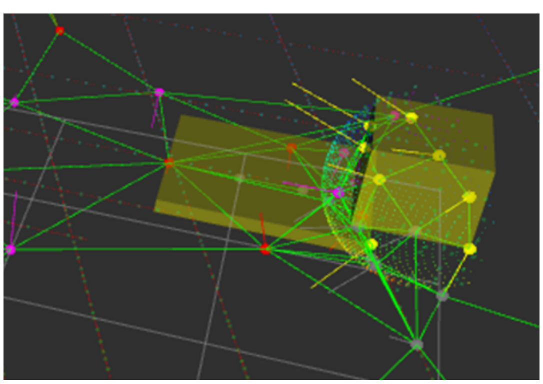


Fig. 2. The problem of occurring dead nodes

where θ_{Reliab} is a threshold value for reliability, and nodes below this threshold are not used for cluster detection. When a cluster of nodes is detected that exceeds θ_{Size}, it shall be recognized as a single cluster.

A specific example is shown in Fig. 3. In Fig. 3(a), all the labels are the same and all the reliability values are above the threshold, so they are detected as one cluster; in Fig. 3(b), the j-th node is not added to the cluster because the labels of the j-th node and the i-th node are different; in Fig. 3(c), the labels of the i-th node and the j-th node are the same, but they are not added to the cluster because the fuzzy reliability values are below the threshold.

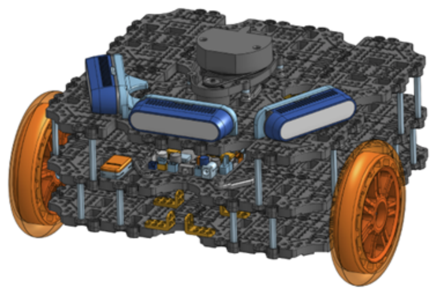
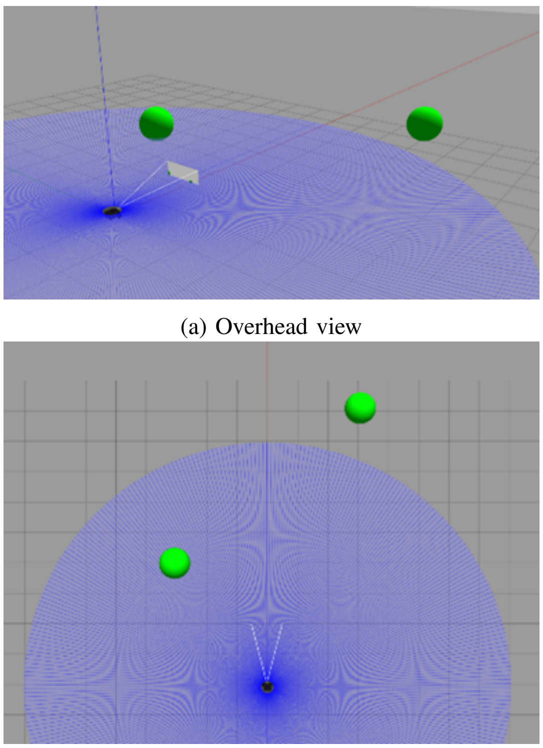


Fig. 4. TurtleBot3 Big Wheel 3RS (ROBOTIS Japan Custom) [14]



(a) Overhead view

(b) Top view

Fig. 5. Experimental environment

IV. EXPERIMENTAL RESULT

A. Experimental Conditions

In this study, experiments were conducted in a static unknown environment to estimate the volume of unlearned objects by clustering the topological map generated by the GNG using the region growing method and to compare the clustering performance based on the difference from the true value of the volume. Gazebo [15], an open source 3D dynamics simulator, was used as the physical simulation environment. In this study, we use TurtleBot3 Big Wheel 3RS [14] (Fig. 4) equipped with three RGB-D cameras (Intel RealSense D435i); TurtleBot3 is an official ROS platform [16] and can be easily customized for various purposes.

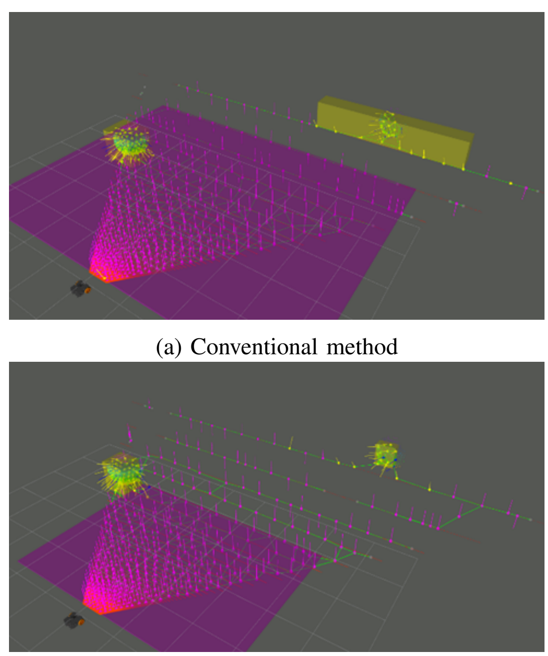
In this experiment, only depth information was used, and the measurement range was set to 0.2 [m]-10.0 [m], the same as the actual RealSense D435 specifications. The resolution can be the same as that of the actual device, and in this case, the coarsest resolution of 424×240 [pixels] was used to reduce the computation cost, and the sampling rate (frame rate) was set to 30 [fps].

The computer used in the experiment was an Intel NUC Core i7 with 8GB RAM, and all GNG common parameter settings are the same as in the previous study [6]. In addition, the unique parameter of AiS-GNG and fuzzy reliability-based growing region method, $\theta_{Min}^{AiS} = 0.25$, $\theta_{Max}^{AiS} = 0.50$, $\theta_{Reliab} = 0.9$, $\theta_{Size} = 6$.

B. Experimental Results

The results of performing topological clustering by the conventional region growing method on the topological maps generated by GNG-U2 and AiS-GNG and the results of performing topological clustering by the fuzzy reliability based region growing method, which is the proposed method, are shown in Fig. 6 and Fig. 7.

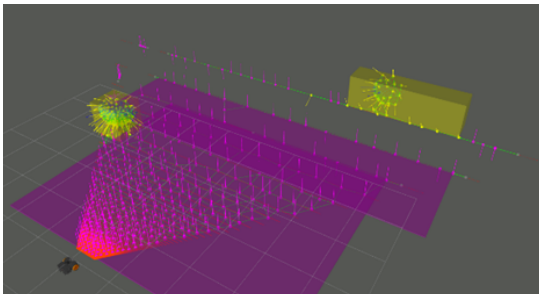
In common with both GNG-U2 and AiS-GNG, it can be seen that the conventional method mis-detects the cluster size significantly. In particular, the error is larger for objects that are farther away than for closer objects in the front. This is probably because the farther away the object is, the less sparse the sampled point cloud data becomes, making it difficult to generate nodes, and as a result, fewer nodes are connected to sufficient edges and the normal vector becomes unstable. When the normal vector is not stable, the labels change from hour to hour, and the conventional region growing method may consider nodes that are temporarily mislabeled as the same cluster, resulting in abnormally large cluster sizes.



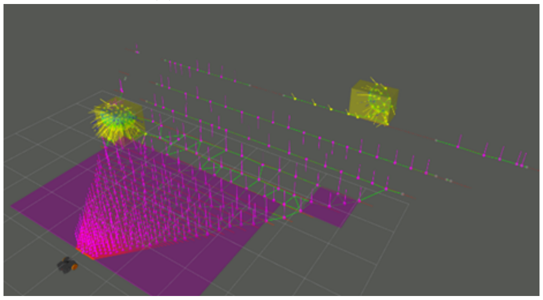
(a) Conventional method

(b) Proposed method

Fig. 6. Topological mapping and clustering (GNG-U2)



(a) Conventional method



(b) Proposed method

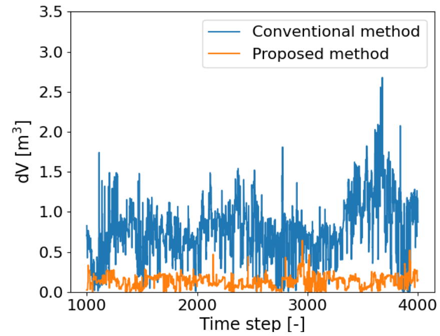
Fig. 7. Topological mapping and clustering (AiS-GNG)

On the other hand, the proposed method is able to stably detect clusters by rejecting unstable nodes that are temporarily mislabeled, even if they have the same label, instead of assigning them to the same cluster, because they are less reliable. The same trend is observed for both GNG-U2 and AiS-GNG, but the cluster size is slightly larger for AiS-GNG because AiS-GNG generates nodes with higher density even for distant objects, resulting in shorter edge lengths and making the deletion by edge length less effective (Fig. 8).

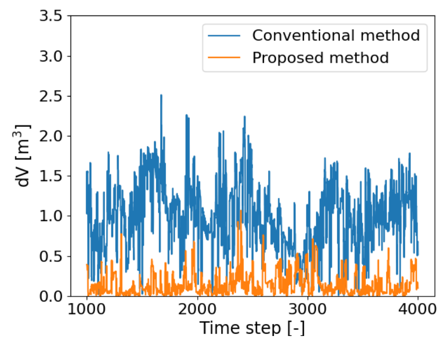
Finally, Fig. 9 shows that the total processing time for both GNG-U2 and AiS-GNG, including training, labeling, and clustering, is less than 10 ms, indicating that they are very fast. The AiS-GNG has a self-growing process based on the Add-id-Silent Rule, which sometimes results in rapid node additions, which may increase the processing time.

V. CONCLUSION

In this study, to solve the problem of unstable detection of clusters in a topological map generated by GNG in an unknown environment, we introduced the concept of age and reliability based on a fuzzy set for each node. For this reason, we proposed a methodology to stably detect clusters in a topological map by introducing reliability based on the concept of age and fuzzy set for each node, and rejecting unstable nodes with low reliability even if the nodes to which they are connected have the same label. The effectiveness of the proposed methodology was shown by experiments through 3D dynamics simulations. Specifically, we showed that forming clusters based on reliability stabilizes the cluster volume (smaller variance) by temporarily rejecting incorrectly labeled nodes to avoid including them in the cluster.

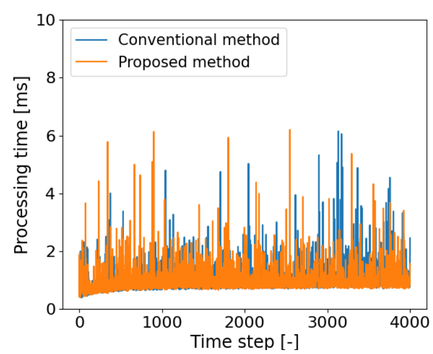


(a) GNG-U2

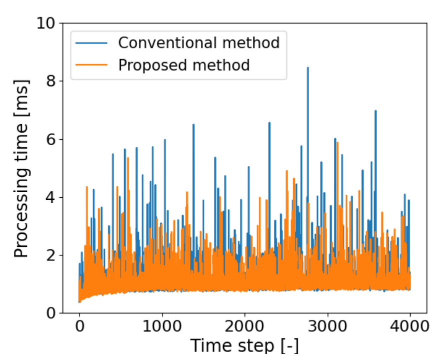


(b) AiS-GNG

Fig. 8. Absolute difference of volume between true and each GNG method



(a) GNG-U2



(b) AiS-GNG

Fig. 9. The transition of the processing time

In addition, the problem of mislabeling nodes that appear at the boundaries between the floor (Safe terrain) and unknown objects as clusters could be improved by forming clusters based on edge lengths. On the other hand, for methods such as AiS-GNG, which increase the number of nodes for unknown objects, the mean and variance of the volume error tended to be larger than for GNG-U2 because the edge length of the boundary became shorter.

In the future, we would like to work on the methodology for continuous identification of clusters at the next time step and its application to the building of cognitive maps with long-term memory.

ACKNOWLEDGMENT

This work was partially supported by JST [Moonshot R&D][Grant Number JPMJMS2034].

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