2023 32nd IEEE International Conference on Robot and
Human Interactive Communication (RO-MAN)
August 28-31, 2023. Paradise Hotel, Busan, Korea

2023 32nd IEEE International Conference on Robot and Human Interactive Communication (RO-MAN) | 979-8-3503-3670-2/23/$31.00 ©2023 IEEE | DOI: 10.1109/RO-MAN57019.2023.10309556

Add-if-Silent Rule-Based Growing Neural Gas for High-Density Topological Structure of Unknown Objects

Masaya Shoji, *Student Member, IEEE*, Takenori Obo, *Member*, *IEEE*, *and* Naoyuki Kubota, *Senior Member*, *IEEE*

***Abstract*— To realize a super-smart society (Society 5.0) where humans and robots coexist, there is a need for a perceptual system that can recognize unknown objects in various unknown environments quickly and flexibly. In unknown environments, the characteristics of objects cannot be known in advance, so prior learning-based recognition methods such as deep reinforcement learning cannot fully cover the problem. There have been many studies on environment recognition (clustering, etc.) using a combination of RGB images and distance images, but the recognition performance is unstable because it strongly depends on the lighting conditions of the environment. Therefore, in this study, we construct a 3D topological map of the environment in real-time using Growing Neural Gas (GNG), which can learn 3D topological structures even for unlearned objects, using only 3D point cloud data as input. In the real world, due to the characteristics of RGB-D cameras, sample density decreases for more far-away objects and only sparse depth information can be obtained, so conventional GNG cannot generate high-density topological structures of unknown objects. Therefore, if the object category labels of the winner nodes (nearest nodes) for the input vector (3D point cloud) match the unknown object and are within a predefined tolerance area, then it is judged to be useful input information for learning the topological structure of the unknown object, and the topological structure of the unknown object is learned. We propose Add-if-Silent rule-based GNG (AiS-GNG) which can generate high-density topological structures for far-away objects by directly adding input data as a reference vector. We verify the effectiveness of the proposed method through experiments using a 3D dynamics simulator.**

I. Introduction

In recent years, to realize a super-smart society (Society 5.0) in which humans and robots coexist, there is a need for a perceptual system that can recognize unknown objects in various unknown environments quickly and flexibly. In order for robots to recognize areas in which they can move and objects to avoid, it is necessary to quickly extract useful information from a huge volume of information about the environment.

Many kinds of research on 3D point cloud processing have been conducted, and many environment recognition methods [1], [2], [3] have been proposed, especially those using RGB-D cameras that can combine distance information with image information. However, these methods are dependent on the lighting conditions of the environment, which can cause unstable recognition results, and in many cases require manual parameter adjustment because the optimal parameters are different for each environment. Other researchers use deep convolutional neural networks mainly for 3D shape classification, 3D object detection and tracking, and 3D point cloud segmentation [4]. However, these systems require a lot of work, including pre-learning, and may not work properly in unknown environments where the training data is not fully covered. Therefore, many researchers have proposed recognition models using such algorithms as unsupervised learning algorithms based on competitive learning [5], [6].

The most common methodology used to learn spatial topological structures combined by nodes (units) and edges is the self-organizing map [7] proposed by Kohonen. However, SOM is difficult to apply to data with unknown distributions. Then, Fritzke proposed Growing Neural Gas (GNG) [8] as a methodology for learning unknown input data while adding and deleting nodes and edges depending on the data. But conventional unsupervised learning methods such as GNG [8] are not adaptive enough to learn appropriate topological structures when learning online in a real environment, and many improvements have been proposed. Specifically, the conventional GNG method, which removes nodes based on the age of edges, cannot quickly remove unnecessary nodes and cannot correctly learn the 3D topological structure of the real environment. To improve adaptability in online learning, modified GNG with Utility (GNG-U2) [9] has been proposed, in which each node has a Utility value to evaluate its usefulness, and redundant nodes with large accumulated errors and small Utility values are directly deleted. Although GNG-U2 cannot generate dense topological structures for objects of interest, some researchers have proposed the Region of Interest Growing Neural Gas (ROI-GNG) [10], which can generate dense topological structures for objects of interest by controlling the discount rate of the accumulated error and Utility value. However, this method adds nodes to separate the edges into two parts based on the accumulated error for each λ inputs, which may cause problems when there is a sudden change in the environment, such as not being able to keep up with the addition of nodes or adding nodes at the appropriate locations. In addition, since the system requires RGB information as well as 3D point cloud data as input, if the lighting conditions in the environment are poor, the learning process will be affected. Basically, in GNG-U2, when the distance between nodes is very close and densely generated, the distance between the first winner node and the second winner node becomes very close, resulting in a small Utility value, and the entire node is deleted. Therefore, Dynamic Density Growing Neural Gas (DD-GNG) [11] selectively samples from the neighborhood of the unknown object when detecting unknown objects, and increases the Strength values of nodes that are thought to exist inside or on the surface of the

Masaya Shoji is with Japan Branch, ROBOTIS Co., Ltd., Tokyo, Japan, Graduate School of Industrial Technology, Advanced Institute of Industrial Technology, Tokyo, Japan, and the Department of Mechanical Systems Engineering, Tokyo Metropolitan University, Tokyo, Japan (e-mail: toukairinn@robotis.com, toukairinn@tmu.ac.jp).

Takenori Obo and Naoyuki Kubota are with the Department of Mechanical Systems Engineering, Graduate School of Systems Design, Tokyo Metropolitan University, Tokyo, Japan (e-mail: t.obo@tmu.ac.jp, kubota@tmu.ac.jp).

unknown object. But, DD-GNG focuses on unknown objects after detection and performs the sampling process, but when used as a perceptual system for mobile robots, etc., it is necessary to first generate a high-density of nodes and identify the location and size of unknown objects as clusters in order to detect objects that are relatively far-away.

In this study, we propose an Add-if-Silent rule-based GNG (AiS-GNG) that can very quickly generate high-density topological structures for far-away unknown objects by applying a new self-growing process (node addition strategy) to GNG, one of unsupervised self-growing neural networks, using only 3D point cloud data, which is less sensitive to environmental lighting conditions. More specifically, if the object category label of the winner node (nearest node) with the nearest distance to the input vector (3D point cloud data) matches the unknown object and is within the pre-defined tolerance area, it is determined to be useful input data for learning the topological structure of the unknown object, and the input data is directly added as a new node (reference vector). This growing process (node addition strategy) can quickly generate the high-density topological structures of far-away unknown objects.

This paper is organized as follows. Section II provides an overview of the proposed method. Section III describes the details of the proposed Add-if-Silent rule-based GNG (AiS-GNG) and how it differs from the conventional method. In Section IV, the 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 future research directions.

II. System Overview

In this section, we describe an overview of the proposed method. Fig. 1 shows a flowchart of the proposed 3D topological map building system based on Add-if-Silent rule-based Growing Neural Gas (AiS-GNG), which uses only 3D point cloud data (point cloud). 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 local triangulated surfaces. The calculations of the normal vectors and labeling are described in detail in our previous work [11].

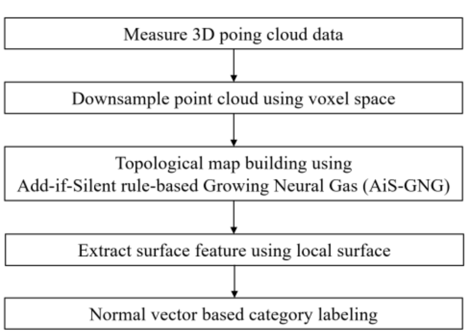


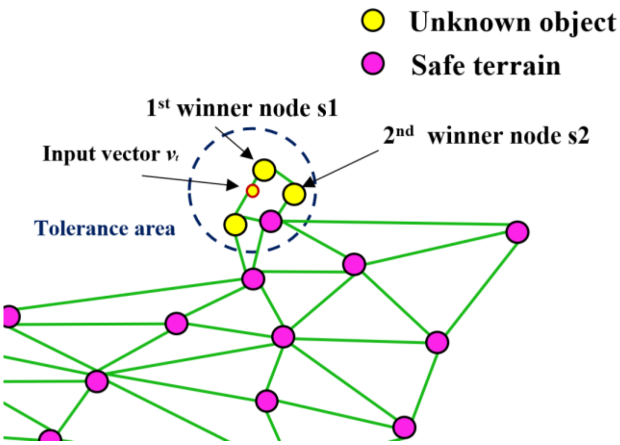
Figure 1. Total flowchart of our proposed method

III. Add-if-Silent Rule-Based Growing Neural Gas

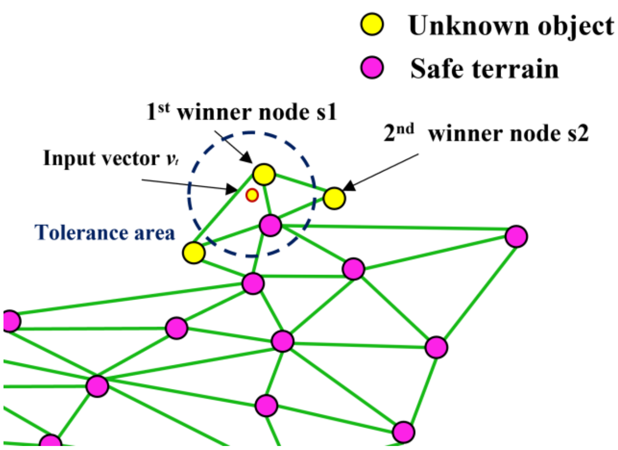
In conventional GNG [8], [9], a node is added every time λ input vectors are learned from all input vectors (3D point cloud data) based on the accumulated error. However, in real-world environments, point cloud data of object surfaces located far-away are rarely sampled, and even after repeated training, nodes are never generated densely enough to be detected as objects. This is due to the fact that the GNG's node addition process is structured in such a way that new nodes are added between reference vectors based on the accumulated error, meaning that nodes are only added in areas that are sampled frequently. In addition, DD-GNG [11] performs a focused sampling process after detecting unknown objects, but when used as a perceptual system for mobile robots, etc., in order 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. This is due to the nature of the camera that the closer an object is to the camera, the more densely the point cloud data is sampled, and the farther away the object is, the lower the sample density and the more sparse the information. In other words, it is difficult to perform high-density sampling after detecting a cluster (object), so it is necessary to consider how to generate nodes with high-density for the target object to which attention should be paid.

Therefore, instead of adding nodes between reference vectors based on the accumulated error, this study proposes an Add-if-Silent rule-based GNG (AiS-GNG). At the stage of selecting the input vector, it is not yet known whether the input data exists on the surface of the unknown object. Therefore, if the first winner node and second winner node for the input vector have category labels corresponding to the unknown object, and both nodes exist within a predefined tolerance area, the input vector is added as a reference node without modification. If there is no neuron (node) that responds to the input that is useful for learning the 3D topological structure of an unknown object, a new neuron (node) is added at that position, which is based on the Add-if -Silent rule [12]-[14], which is a learning rule used in the neo-cognition. The basic concept of AiS-GNG is shown in Fig. 2. As previously described if the 1st winner node and the 2nd winner node for an input vector exist within the tolerance area, and they each have a label indicating an unknown object category, then the input vector is considered useful for representing the unknown object surface and is added as a reference vector (Fig. 2(a)). If the winner nodes are outside the tolerance area (Fig. 2(b)) or if the labels indicate other than unknown objects (Fig. 2(c)), the reference vectors are not added.

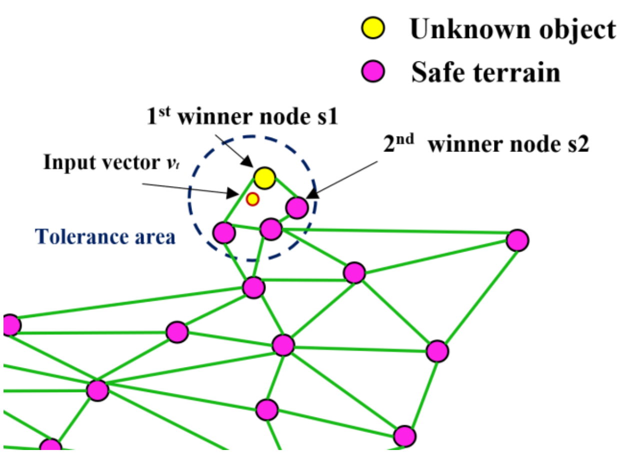
The pseudo-code for AiS-GNG is shown in Algorithm 1. Since many of the processes are common to GNG-U2 [9], detailed explanations are omitted, and only processes specific to AiS-GNG are described. In lines 9 to 15 of Algorithm 1, two conditions are checked: whether the label L_i of the first winner node s_1, and the second winner node s_2, for the input vector match the unknown object, and whether the Euclidean distance from the input vector to s_2 falls within the tolerance area. If both conditions are satisfied, the node is judged to be useful input data for learning the topological structure of the unknown object, and is directly added as a new node (reference vector). In this case, the reference vector h_r is the 3D position of input vector v_t, the accumulated error E_r of the newly created node r, the Utility value U_r is the average of s_1 and s_2, and the label L_r is the unknown object. The labeling of each node is done by the similarity of the normal vectors of each node based on the local surfaces included in the topological structure generated by the GNG.



(a) Case1



(b) Case2



(c) Case3

Figure 2. Add-if-Silent rule-based growing process

Algorithm 1 Add-if-Silent Rule-Based Growing Neural Gas

Generate two nodes at random position, $\boldsymbol{h}_1$, $\boldsymbol{h}_2$ in $\mathbf{R}^n$.
Initialize the connection set.
while $t < \lambda$ **do**
  Generate randomly an input data v_t
  Select the 1st winner node s_1 and 2nd winner node s_2

$$s_1 = \arg\min_{i \in A}\left(\left\| w \cdot (v_t - h_i) \right\|\right)$$

$$s_2 = \arg\min_{i \in A \setminus s_1}\left(\left\| w \cdot (v_t - h_i) \right\|\right)$$

  if $c_{s1,s2} = 0$ **then**
    $c_{s1,s2} = 1, \quad g_{s1,s2} = 0$
  end if
  Add-if-Silent rule-based growing process
  if $L_{s1}=L_{s2}=$ {Unknown Object} and $\|v_t - h_{s2}\| < \theta_{AiS}$ **then**
    $r \leftarrow r+1$
    $h_r = v_t$, $L_r = \{\text{Unknown Object}\}$,
    $E_r = 0.5 \cdot \left(E_{s1} + E_{s2}\right)$, $U_r = 0.5 \cdot \left(U_{s1} + U_{s2}\right)$
    $A \leftarrow A + \{r\}$
    $c_{r,s1} = 1, \quad c_{r,s2} = 1$
  end if
  Update error and utility variable:

$$E_{s1} \leftarrow E_{s1} + \left\| w \cdot (v_t - h_{s1}) \right\|$$

$$U_{s1} \leftarrow U_{s1} + \left\| w \cdot (v_t - h_{s2}) \right\| - \left\| w \cdot (v_t - h_{s1}) \right\|$$

  Update the reference vectors:

$$h_{s1} \leftarrow h_{s1} + \eta_1 \left(v_t - h_{s1}\right)$$

$$h_j \leftarrow h_j + \eta_2 \left(v_t - h_j\right), \; c_{s1,j} = 1$$

  Increment the age of all edges emanating from s_1:

$$a_{s_1,j} \leftarrow a_{s_1,j} + 1, \quad c_{s1,j} = 1$$

  if $g_{s1,j} > Age_{\text{Max}}$ **then**
    $c_{s1,j} = 0$
    if the j-th node does not have any connection **then**
      Remove the j-th node from the set $\boldsymbol{A}$
    end if
  end if
  if $(t \equiv \kappa)$ **then**
    $u = \arg\max_{i \in A}\left(E_i\right)$
    $l = \arg\max_{i \in A}\left(U_i\right)$
    if $E_u / U_l > k$ **then**
      $A \leftarrow A - \{l\}$
    end if
  end if
  $E_i \leftarrow E_i - \beta E_i (\forall i)$
  $U_i \leftarrow U_i - \chi U_i (\forall i)$
  $t \leftarrow t+1$
end while
Add a new node:
$r \leftarrow r+1$
$u = \arg\max_{i \in A}\left(E_i\right)$, $f = \arg\max_{i \in A, c_{i,u}=1}\left(E_i\right)$
$h_r = 0.5 \cdot \left(h_u + h_f\right)$
$E_u \leftarrow E_u - \alpha E_u$, $E_f \leftarrow E_f - \alpha E_f$
$E_r = 0.5 \cdot \left(E_u + E_f\right)$
$A \leftarrow A + \{r\}$

IV. EXPERIMENTS

A. Experimental Conditions

Gazebo [15], an open-source 3D dynamics simulator, was used as the physical simulation environment. The mobile robot used in the experiments is shown in Fig. TurtleBot3 is an official ROS platform [16] that can be easily customized for different purposes. In this study, we use TurtleBot3 Big Wheel 3RS [17] equipped with three RGB-D cameras (Intel RealSense D435i). This robot can handle point cloud data on the simulator as well as on the real robot.

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]. Since there are three RGB-D cameras mounted on the robot, the horizontal field of view is 212.5 [deg]. The robot does not move, since the objective of this experiment is to generate high-density topological structures for far-away objects.

Next, the experimental environment is shown in Fig.4 Case 1 is an environment with two objects, and the purpose is to analyze how nodes are generated for objects placed near and far-away from each other. The purpose of Case 2 is to analyze whether there is any difference in topological structure or processing time when the number of objects is increased.

In the last case, Case 3, 10 objects are placed in various directions and at various distances, and the objective is to analyze whether problems arise when the number of objects increases further.

The computer used in the experiment was an Intel NUC Core i7 with 8 GB RAM, and all GNG parameter settings were the same as in the previous study [9], as follows: $\lambda = 300$, $\kappa = 10$, $\eta_1 = 0.08$, $\eta_2 = 0.008$, $Age_{Max} = 88$, $\alpha = 0.5$, $\beta = 0.005$, $\chi = 0.005$, $\mu = 0.5$, $k = 1000$. In addition, the unique parameter of AiS-GNG, $\theta_{AiS} = 0.50$.

The conventional method GNG-U2 can also learn spatial (3D space) and color information at the same time, but in order to conduct a comparison experiment under the same conditions as AiS-GNG, only the spatial information (3D point cloud data) was used as input to generate topological structures.

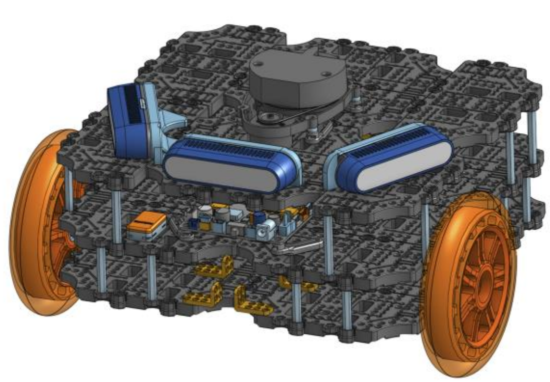
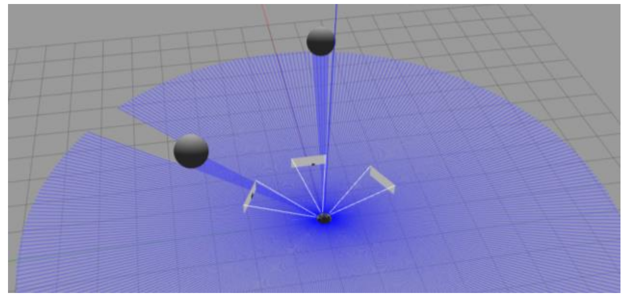
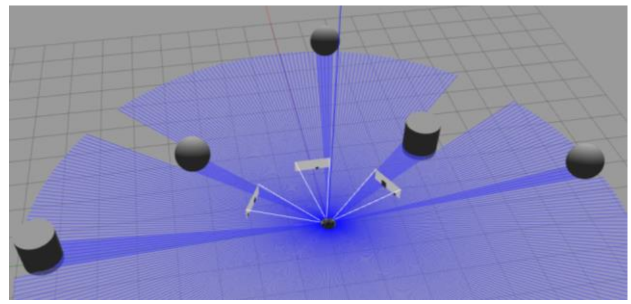


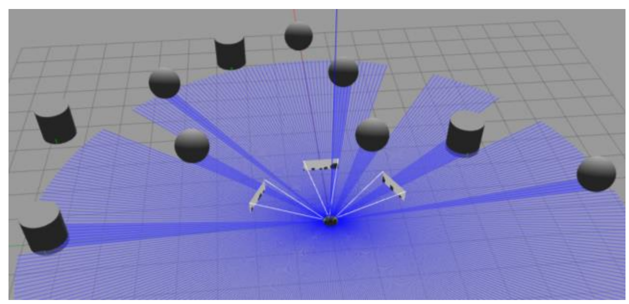
Figure 3. TurtleBot3 Big Wheel 3RS (ROBOTIS Japan Custom) [17]



(a) Case1



(b) Case2

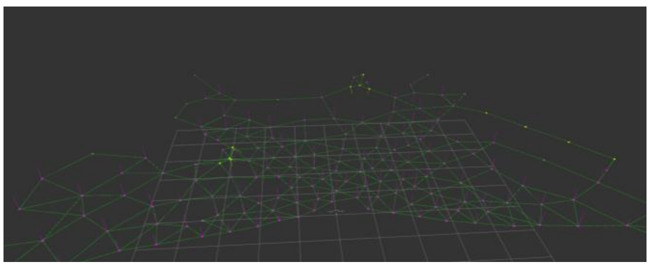


(c) Case3

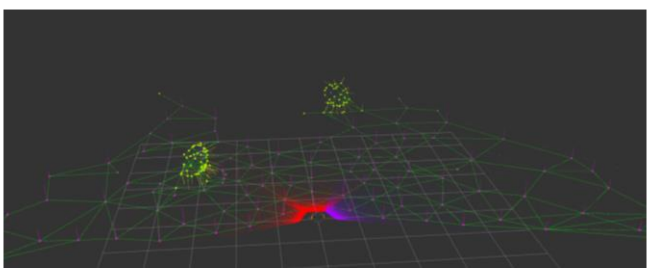
Figure 4. Experimental Environments

B. Experimental Results

Fig. 5, Fig. 6, and Fig. 7 show the results of comparison experiments in the same environment (Case1-Case3) between the case where the conventional method modified GNG-Utility (GNG-U2) [9] is applied and the comparison case where the AiS-GNG proposed in this paper is applied. The small yellow spheres indicate GNG reference nodes labeled as unknown objects, and the small pink spheres indicate GNG reference nodes labeled as safe areas (floor surfaces). The conventional method shown in Fig. 5(a) generates a few nodes for both nearby and far-away objects. The proposed method generates a very high-density of nodes for both nearby and far-away objects, indicating that it can appropriately learn the topological structure of unknown objects (Fig. 5(b)). Next, let us look at Case 2, where the number of objects is increased from 2 to 5. We can see that the conventional method generates a relatively higher number of nodes for nearby objects, but almost fewer nodes are generated for far-away objects, indicating that the shape of the unknown objects cannot be represented (Fig. 6(a)). The proposed method is able to generate a high-density of nodes for all unknown objects, as in Case 1, even when the number of objects increases, and it correctly learns the topological structure (Fig. 6(b)). Finally, looking at Case 3, which has 10 unknown objects, we can see that the conventional method hardly generates any nodes for all objects, and the shapes of the unknown objects are not known (Fig. 7(a)). On the other hand, the proposed method can generate a high-density of labeled nodes even when the number of unknown objects increases (Fig. 7(b)). However, as the number of unknown objects in the environment increases, the number of incorrectly generated nodes on the floor near the unknown objects also increases. This may be due to the fact that the current Add-if-Silent rule-based node addition is used, while the conditions for deletion, etc., have not been specifically considered. Further study is needed. Fig. 8 shows an expanded image of Case 1, in which the difference in topological structure generated for an unknown object can be easily seen. As expected, the conventional method generates only a few nodes for the unknown object, and its shape cannot be understood, but the proposed method generates high-density labeled nodes, which enables us to recognize the 3D shape of the unknown object.

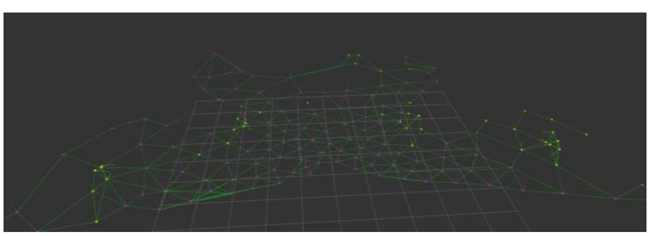


(a) Conventional method

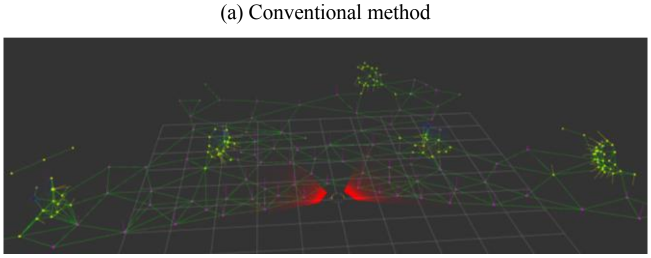


(b) Proposed method

Figure 5. Topological structure generation in Case1

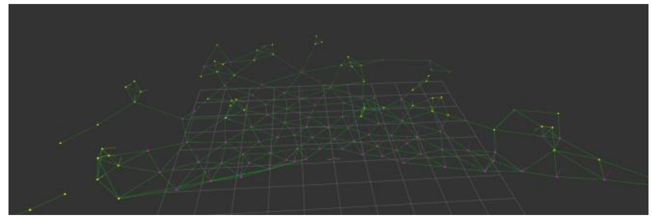


(a) Conventional method

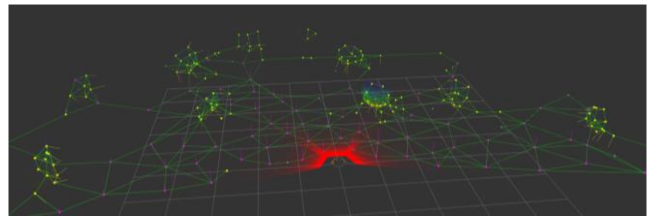


(b) Proposed method

Figure 6. Topological structure generation in Case2

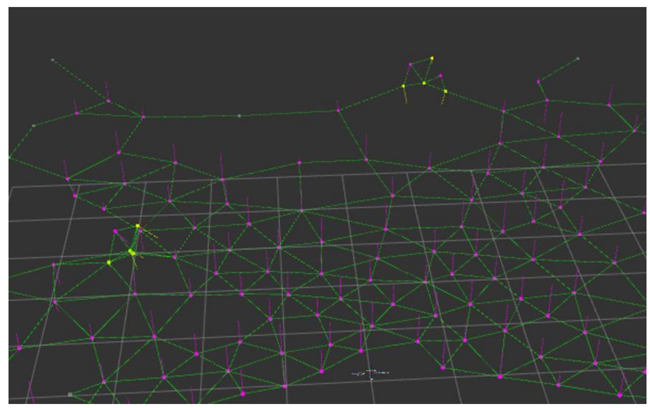


(a) Conventional method

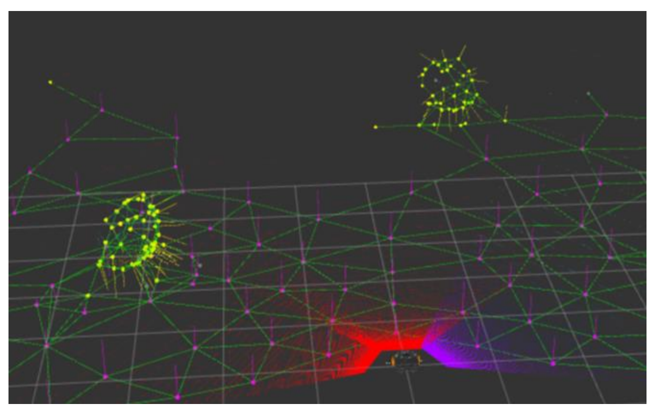


(b) Proposed method

Figure 7. Topological structure generation in Case3



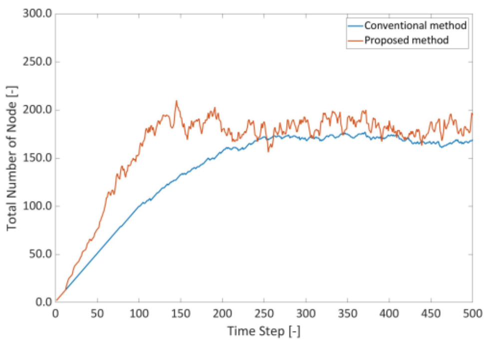
(b) Conventional method



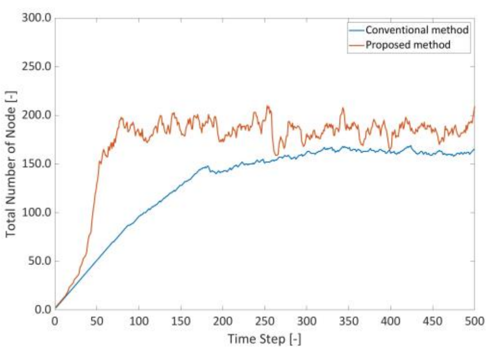
(b) Proposed method

Figure 8. Compared topological structure in Case1

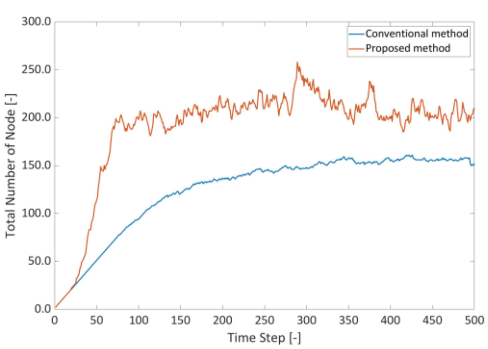
Next, Fig. 9 and Fig. 10 show the transition of the total number of nodes in the GNG for each environment and the transition of the number of nodes with unknown object labels. Looking at Fig. 9(a) and Fig. 10(a), it can be seen that in Case 1, the total number of nodes is stable at around 170-180 for both methods, while the number of nodes with unknown object labels is significantly different, ranging from around 10-15 for the conventional method to 75-100 for the proposed method. The number of nodes with unknown object labels is around 10-15 for the conventional method and 75-100 for the proposed method. Although the total number of nodes is similar for both methods, the conventional method enters a steady state around 250 [steps], while the proposed method enters a steady state around 100 [steps]. This means that the proposed method quickly learns the topological structure of the unknown object in the first 100 [steps] or so. In Case 2, where the number of unknown objects has increased, almost the same trend as in Case 1 is observed, but the final total number of nodes is slightly larger in the proposed method. This may be due to the fact that the number of nodes with labels of unknown objects increased in correspondence with the number of objects. Finally, looking at Case 3, the number of unknown objects itself is 10, which is much larger than in Case 1 and Case 2, and thus the total number of nodes also differs significantly. This means that the proposed method has more nodes added when the number of unknown objects increases than the conventional method.



(a) Case1

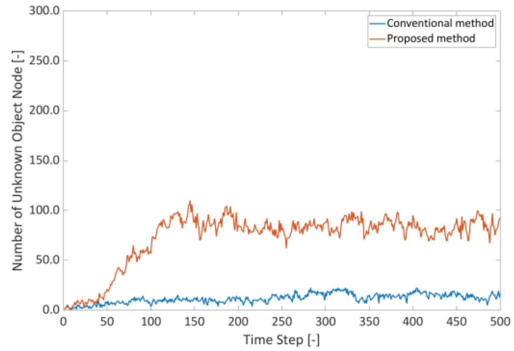


(b) Case2

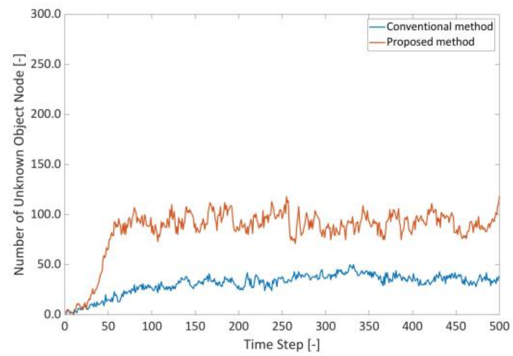


(c) Case3

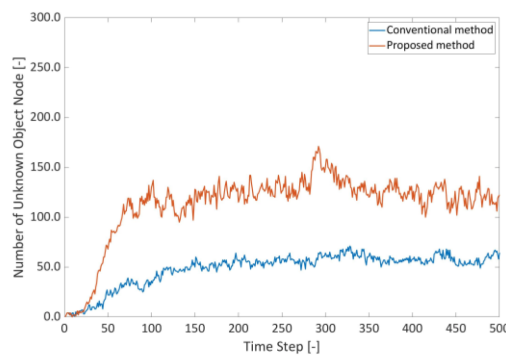
Figure 9. The transition of total number of nodes



(a) Case1



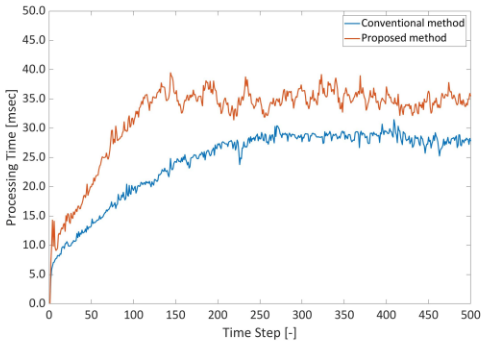
(b) Case2



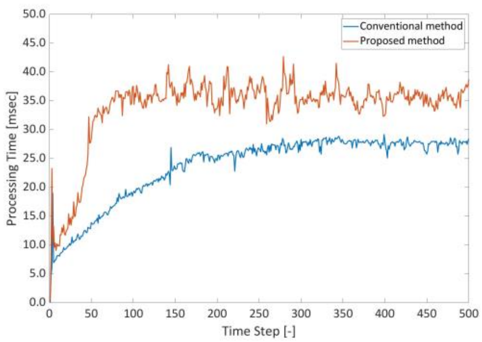
(c) Case3

Figure 10. The transition of the number of unknown object nodes

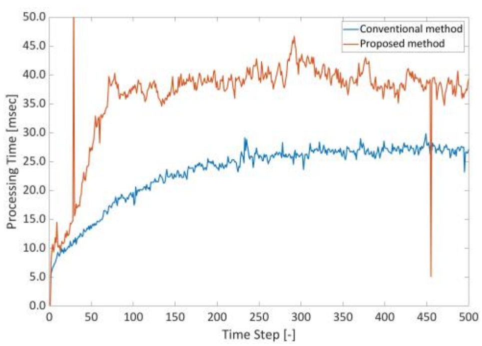
Finally, the processing time results are shown in Fig. 11. In Case 1, the difference between the conventional method and the proposed method is not so large, but in Case 2 and 3, the difference in processing time becomes larger as the number of unknown objects increases. This is because the difference in the total number of nodes increases as the number of unknown objects increases, and due to the characteristics of GNGs, the computational cost of the Euclidean distance between the input and reference vectors increases as the number of nodes increases. However, the proposed method, including Case 1 through Case 3, takes around 40 [msec], which is well within the practical range for operation on actual systems.



(a) Case1



(b) Case2



(c) Case3

Figure 11. The transition of the processing time

V. CONCLUSION

In this study, we solved the problem that conventional GNG cannot generate high-density topological structures of unknown objects in the 3D space environments because the sample density decreases for more distant objects and only sparse depth information can be obtained due to the characteristics of RGB-D cameras. If the object category labels of the winner nodes (nearest nodes) for the input vector (3D point cloud) match those of the unknown object and exist within a predefined tolerance area, it is judged to be useful input data for learning the topological structure of the unknown object, and the input data can be directly added as a reference vector. We proposed an Add-if-Silent rule-based GNG (AiS-GNG), which can generate high-dens topological structures even for distant objects by directly adding the input data as a reference vector. Through experiments using a 3D dynamics simulator, it was verified that the proposed method is able to generate a high-density of labeled nodes for multiple unknown objects located in far-away places and to learn 3D topological structures more appropriately than the conventional method. The number of labeled nodes increases as the number of objects increases to represent the shape of the unknown objects, and the processing time increases only by a reasonable amount of computational cost for each increase in the number of nodes, indicating that learning is fast.

Future work includes real-time learning of high-density 3D topological structures for moving objects such as pedestrians and cognitive map construction based on long-term memory of nodes.

ACKNOWLEDGMENT

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

REFERENCES

[1] Andrew Wing Keung, Gay Paul and Dikai Liu, "Surface-type classification using RGB-D", Automation Science and Engineering IEEE Transactions on 11.2, pp. 359-366, 2014.

[2] Julia Diebold et al., "Interactive multi-label segmentation of RGB-D images." in Scale Space and Variational Methods in Computer Vision, Springer International Publishing, pp. 294-306, 2015.

[3] J. Strom, A. Richardson and E. Olson, "Graph based segmentation of colored 3d laser point clouds", Proc. of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2010.

[4] Y. Guo, H. Wang, Q. Hu, H. Liu, L. Liu and M. Bennamoun, "Deep Learning for 3D Point Clouds: A Survey," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 43, no. 12, pp. 4338-4364, 1 Dec. 2021, doi: 10.1109/TPAMI.2020.3005434.

[5] J. Li, B. M. Chen and G. H. Lee, "SO-Net: Self-Organizing Network for Point Cloud Analysis," 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, Salt Lake City, UT, USA, 2018, pp. 9397-9406, doi: 10.1109/CVPR.2018.00979.

[6] N. Mirehi, M. Tahmasbi, and A. T. Targhi, "Hand gesture recognition using topological features," Multimedia Tools and Applications, vol. 78, no. 10, pp. 13361-13386.

[7] T. Kohonen, "The self-organizing map," Proceedings of the IEEE, vol. 78, no. 9, pp. 1464-1480, 1990.

[8] B. Fritzke, "A growing neural gas network learns topologies", Advances in Neural Information Processing Systems, vol. 7, pp. 625-632, 1995.

[9] Y. Toda, Zhaojie Ju, Hui Yu, N. Takesue, K. Wada and N. Kubota, "Real-time 3D point cloud segmentation using Growing Neural Gas with Utility," 2016 9th International Conference on Human System Interactions (HSI), Portsmouth, UK, 2016, pp. 418-422, doi: 10.1109/HSI.2016.7529667.

[10] Toda, Yuichiro, et al. "Region of interest growing neural gas for real-time point cloud processing." Intelligent Robotics and Applications: 12th International Conference, ICIRA 2019, Shenyang, China, August 8–11, 2019, Proceedings, Part III 12. Springer International Publishing, 2019.

[11] A. A. Saputra, W. H. Chin, Y. Toda, N. Takesue and N. Kubota, "Dynamic Density Topological Structure Generation for Real-Time Ladder Affordance Detection," 2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Macau, China, 2019, pp. 3439-3444, doi: 10.1109/IROS40897.2019.8968003.

[12] Fukushima, Kunihiko. "Add-if-Silent Rule for Training Multi-layered Convolutional Network Neocognitron." International Conference on Neural Information Processing (2014).

[13] Fukushima, K.: Artificial Vision by Multi-layered Neural Networks: Neocognitron and its Advances. Neural Networks 37, 103–119 (2013).

[14] Fukushima, K.: Training Multi-layered Neural Network Neocognitron. Neural Networks 40, 18–31 (2013).

[15] https://gazebosim.org/home

[16] ROBOTIS Co., Ltd., "e-Manual TurtleBot3", https://emanual.robotis.com/docs/en/platform/turtlebot3/overview/

[17] ROBOTIS Co., Ltd., "TurtleBot3 Friends: Big Wheel 3RS", https://github.com/ROBOTIS-JAPAN-GIT/turtlebot3_jp_custom/blob/master/README_en.md