Region of Interest Growing Neural Gas for Real-time Point Cloud Processing

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Abstract. This paper proposes a real-time topological structure learning method based on concentrated/distributed sensing for a 2D/3D point cloud. First of all, we explain a modified Growing Neural Gas with Utility (GNG-U2) that can learn the topological structure of 3D space environment and color information simultaneously by using a weight vector. Next, we propose a Region Of Interest Growing Neural Gas (ROI-GNG) for realizing concentrated/distributed sensing in real-time. In ROI-GNG, the discount rates of the accumulated error and utility value are variable according to the situation. We show experimental results of the proposed method and discuss the effectiveness of the proposed method.

Keywords: Growing Neural Gas, Point cloud processing, Topological structure learning.

1 Introduction

Recently, various types of robots have emerged in many fields as a progress of robot technologies. Especially, the expectation of disaster robots, which can be robustly utilized in a disaster area, is increasing for preventing the second disaster in the area [1]. It is important to extract the environmental information related to a movable area of the robot and a dangerous area such as rubble with the high possibility of collapse in order to act safely and quickly in the disaster area. In this paper, we focus on an environmental sensing technology using a 2D/3D point cloud for extracting the efficient and effective information in the disaster area. To realize the environmental sensing in the disaster area, an attention allocation for the target object is the one of the most important technologies because the robot should efficiently extract the detail object information for the target object and roughly monitor the other object for avoiding the collision of moving obstacles. Therefore, this paper proposes a Growing Neural Gas based real-time point processing method with the attention allocation function.

In our previous work, we proposed a framework for 3D point cloud processing [2]. Our proposed framework is based on Growing Neural Gas with Utility (GNG-U) because GNG-U can learn a topological structure of the 3D space environment and be applied to non-stationary data distribution. GNG-U proposed by Fritzke [3] is one of the competitive learning methods, and can dynamically change the topological structure based on the edge referring to the ignition frequency of the adjacent node according to the accumulated error. However, the standard GNG-U does not learn the topological structure of the 3D space environment and color information simultaneously. Therefore, we proposed the modified GNG-U (GNG-U2) [2], which uses the weight vector called as a relative importance for selecting the first and second winner nodes and the rule of node deletion is modified for adjusting the time series 3D point cloud quickly. However, GNG-U2 cannot realize the attention allocation function because the GNG based method learns the topological structure according to the data distribution appropriately. In this paper, we propose Region of Interest Growing Neural Gas (ROI-GNG) based on GNG-U2. ROI-GNG learns the dense topological structure for the target property and the sparse topological structure for the other properties by controlling the discount rate of the accumulated error. In addition, ROI-GNG adjusts the density of the total topological structure by controlling the discount rate of the utility value. By integrating these two updating rules of the discount rate, ROI-GNG can realize the attention allocation function for the topological learning method. Finally, we show an experimental result for verifying the effectiveness of our proposed method.

2 Modified Growing Neural Gas with utility value

We use a Growing Neural Gas(GNG) based algorithm for learning a topological structure of the point clouds. GNG proposed by Fritzke is one of the unsupervised learning methods [3]. Unsupervised learning is performed by using only data without any teaching signals. Self-organized map (SOM), neural gas (NG), growing cell structures (GCS), and GNG are well known as unsupervised learning methods [4-7]. Basically, these methods use the competitive learning. The number of nodes and the topological structure of the network in SOM are designed beforehand. In NG, the number of nodes is fixed beforehand, but the topological structure is updated according to the distribution of sample data. On the other hand, GCS and GNG can dynamically change the topological structure based on the adjacent relation (edge) referring to the ignition frequency of the adjacent node according to the error index. However, GCS does not delete nodes and edges, while GNG can delete nodes and edges based on the concept of ages. Furthermore, GCS must consist of k-dimensional simplexes whereby k is a positive integer chosen in advance. The initial configuration of each network is a k-dimensional simplex, e.g., a line is used for k=1, a triangle for k=2, and a tetrahedron for k=3. GCS has applied to construct 3D surface models by triangulation based on 2-dimensional simplex. However, because the GCS does not delete nodes and edges, the number of nodes and edges is over increasing. Furthermore, GCS cannot divide the sample data into several segments. In addition, GNG cannot apply the non-stationary data distribution because GNG can only remove the nodes that are the nearest node of the first winner node in GNG. Therefore, we use modified GNG with

Utility (GNG-U2) for learning the topological structure from 2D/3D space environment.

At first, we explain a modified GNG-U2 algorithm. The procedure and notation used in GNG-U are shown

h_i : the nth dimensional vector of a node

w: The nth dimensional weight vector

A : A set of nodes

c_{ij} : A set of edges between the ith and jth nodes

g_{ij}: Age of the edge between the ith and jth nodes

Step 0. Generate two units at random positions, w_1, w_2 in R^n where n is the dimension of input data. Initialize the connection set.

Step 1. Generate at random an input data v.

Step 2. Select the nearest unit (winner) s_1 and the second-nearest unit s_2 from the set of nodes by

$$\begin{aligned} s_1 &= \arg\min_{i\in A} \left\| w*\left(v-h_i\right)\right\| \\ s_2 &= \arg\min_{i\in A\backslash s_1} \left\| w*\left(v-h_i\right)\right\|, \end{aligned} \tag{1}$$

where * indicates elemental-wise product.

Step 3. If a connection between s_1 and s_2 does not yet exist, create the connection ($c_{s1,s2}$=1). Set the age of the connection between s_1 and s_2 at zero;

Step 4. Add the squared distance between the input data and the winner to a local error variable;

$$\begin{aligned} E_{s_1} &\leftarrow E_{s_1} + \left\| w*\left(v-h_{s_1}\right)\right\|^2 \\ U_{s_1} &\leftarrow U_{s_1} + \left\| w*\left(v-h_{s_2}\right)\right\|^2 - \left\| w*\left(v-h_{s_1}\right)\right\|^2 \end{aligned} \tag{2}$$

Step 5. Update the reference vectors of the winner and its direct topological neighbors by the learning rate η_1 and η_2 respectively, of the total distance to the input data.

$$\begin{aligned} h_{s_1} &\leftarrow h_{s_1} + \eta_1 \cdot \left(v-h_{s_1}\right) \\ h_j &\leftarrow h_j + \eta_2 \cdot \left(v-h_j\right) \quad if \quad \mathrm{c}_{i,j}=1 \end{aligned} \tag{3}$$

Step 6. Increment the age of all edges emanating from s_1.

$$g_{s_1,j} \leftarrow g_{s_1,j} + 1 \;\; if \;\; c_{s_1,j} = 1 \tag{4}$$

Step 7. Remove edges with an age larger than amax. If this results in units having no more connecting edges, remove those units as well.

Step 8. If the number of input data generated so far is an integer multiple of a parameter κ, remove the node as follows.

i. Select the unit u with the maximal accumulated error and the uint l with the minimum utility value.

$$\begin{aligned} u &= \arg\max_{i \in A} E_i \\ l &= \arg\min_{i \in A} U_i \end{aligned} \tag{5}$$

ii. Remove the unit from the topological structure if the following condition is satisfied.

$$E_u / U_l > k \tag{6}$$

Step 9. If the number of input data generated so far is an integer multiple of a parameter λ, insert a new unit as follows.

i. Select the unit u with the maximal accumulated error.

$$u = \arg\max_{i \in A} E_i \tag{7}$$

ii. Select the unit f with the maximal accumulated error among the neighbors of q.

iii. Add a new unit r to the network and interpolate its reference vector form q and f.

$$h_r = 0.5 \cdot \left(h_u + h_f \right) \tag{8}$$

iv. Insert edges connecting the new unit r with units q and f, and remove the original edge between q and f.

v. Decrease the error variables of q and f by a temporal discounting rate α.

$$\begin{aligned} E_u &\leftarrow E_u - \alpha E_u \\ E_f &\leftarrow E_f - \alpha E_f \end{aligned} \tag{9}$$

vi. Interpolate the local error variable of r from q and f.

$$E_r = 0.5 \cdot \left(E_u + E_f \right) \tag{10}$$

Step 10. Decrease the local error variables of all units by a temporal discounting rate $\beta$and χ.

$$\begin{aligned} E_i &\leftarrow E_i - \beta E_i \quad (\forall i \in A) \\ U_i &\leftarrow U_i - \chi U_i \quad (\forall i \in A) \end{aligned} \tag{11}$$

Step 11. Continue with step 2 if a stopping criterion (e.g., the number of nodes or some performance measure) is not yet fulfilled.

GNG based algorithm select the nearest unit (winner) s_1 and the second-nearest unit s_2 from the set of nodes and create the connection ($c_{s1,s2}$=1) if a connection between s_1 and s_2 does not yet exist. In GNG-U, each node has the utility value U_i. The node with the minimum utility value is removed from the topological structure if the following condition is satisfied;

$$E_u / U_l > k \tag{12}$$

Generally, the standard GNG-U2 removes the node in the node insertion. In addition, our method removes the node if the number of input data generated so far is an integer multiple of a parameter k for controlling the number of nodes. Furthermore, our method uses the weight vector w called as a relative importance to learn the topological structure of the 2D/3D space environment. By using GNG-U2, the point cloud data distribution can be learned appropriately.

3 Region of Interest Growing Neural Gas

In this section, we propose Region of Interest Growing Neural Gas (ROI-GNG). ROI-GNG learns the dense topological structure for the target property and the sparse topological structure for the other properties. In addition, ROI-GNG adjusts the density of the total topological structure.

3.1 Node density adjustment method for the total topological structure

The ROI-GNG uses the discount rate χ of the utility value as a variable for adjusting the density of the total topological structure. The discount rate χ^t_i of the ith node at time step t is defined by the following equation,

$$\chi_i^t \leftarrow r^t \cdot \beta_i^t \tag{14}$$

where r^t is the scale parameter of the discount rate of the utility value for the discount rate of the accumulated error of the ith node at time step t. The node density of the total topological structure is adjusted by defining a criterion according to the task or situation. Specifically, r^t is reduced if the node density is increased, and r^t is increased if the node density is reduced. In this paper, the objective of the 2D/3D point processing is to realize the real-time processing. Therefore, the updating rule of scale rate r^t is calculated as follows,

$$\begin{aligned} r^t &\leftarrow r^t - \delta \quad \text{if } t^p \le T^p \\ r^t &\leftarrow r^t + \delta \quad \text{otherwise} \end{aligned} \tag{13}$$

where T^p indicates the threshold value of the setting processing time and δ is the update width of the scale rate r^t. In this paper, δ is defined as the fixed value. In this way, ROI-GNG adjusts the node density of the total topological structure by controlling the discount rate of the utility value.

3.2 Node density adjustment method for target objects

In this subsection, we explain the node density adjustment method for different properties. ROI-GNG learns the dense topological structure for the data distribution with the target properties and the sparse topological structure for the other data distribution simultaneously. As mentioned before, the node density of the total topological structure is adjusted by controlling the discount rate of the utility value. On the other hand, the discount rate of the accumulated error is used for realizing the node density adjustment for different properties. Specifically, we define the discount rate of the accumulated error as the variable β^t_i of the ith node at time step t. In addition, the discount rate β^t_i is updated as the follows,

$$\beta_i^t = \begin{cases} b_{high} & \text{if the } i\text{th node has objective feature} \\ b_{low} & \text{otherwise} \end{cases} \quad (14)$$

where b_{low} and b_{high} ($\geq b_{low}$) are the fixed values, and the values are determined empirically in this paper. By using this approach, ROI-GNG can learn the dense topological structure of the data distribution with the target properties and the sparse topological structure of the other data distribution.

4 Experimental result

This section shows an experimental result for verifying the effectiveness of the proposed method in a 2D simulation environment. Fig. 1 shows the 2D point cloud that is composed of red, green and blue rings. The total number of the point cloud is 10000, and the numbers of the red, green and blue rings are 4000, 4000 and 2000, respectively. In addition, the input vector of ROI-GNG is 2D position and color information composed of RGB value ($\mathbf{v} = (v_x , v_y ,v_\mathrm{R}, v_\mathrm{G}, v_\mathrm{B})$), and the weight vector w of relative importance is w=(1,1,0,0,0) for learning the topological structure of only 2D space.

In this experiment, a target property is changed every 500 steps. The target property of the first 500 steps is the red ring in the point cloud, and the target property of the next 500 steps is the blue ring. The target property of the final 500 steps is red ring again. Table 1 shows the parameters of ROI-GNG in this experiment.

Fig. 2 shows a transition of the scale value r^t and the sampling time at each step for verifying the effectiveness of the node density adjustment of the total topological structure. In Fig. 2, the sampling time is increased and decreased around the setting time T^p (= 0.03 [sec]) by controlling the scale value r^t. Specifically, the scale value r^t is increased if the sampling time is less than the threshold value T^p for increasing the number of nodes. On the other hand, the scale value r^t is increased if the sampling time is more than the value T^p for decreasing the number of nodes. Here, the sampling is largely decreased around 550 and 1150 steps, due to the transition of the target property. In addition, the time delay of the node density adjustment is occurred because the update rule of the scale value r^t is changed after the sampling time is more/less than the threshold value T^p. Due to the time delay, the sampling time between 1100 and 1500 steps is more than 0.04 [sec]. However, the scale value r^t is headed for decreasing and the sampling time is near 0.03 [sec] at 1500 step. In this way, ROI-GNG can adjust the node density of the total topological structure by controlling the discount rate of the utility value.

Next, Fig. 3 and 4 show the experimental result of the node density adjustment for the target property. Fig. 3 (a) and (b) show the result of our proposed method and GNG-U2, and Table 1 (b) shows the parameters of GNG-U2. In our proposed method, the number of the target nodes is the most of any nodes without the target property in each 500 step. In addition, Fig. 4 shows examples of the learning result of the topological structure. In Fig. 4, the result of (a)-(f) is the same time step of (a)-(f) in Fig. 3 (a). From these results, our proposed method can learn the dense topological structure for the target property and the sparse topological structure for the other properties by controlling the discount rate of the accumulated error. On the other hand, GNG-U2 can learn the topological structure according to the data distribution of the 2D point cloud. This result indicates that GNG-U2 appropriately performs from the viewpoint of the unsupervised learning method. However, GNG-U2 cannot learn the dense topological structure for the data distribution with the target property. In this way, our proposed method realizes the real-time point cloud processing method with attention allocation.

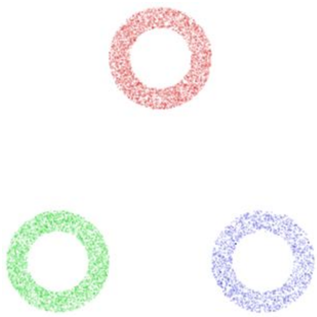


Fig.1 Experimental dataset

Table1 Setting parameters

(a) ROI-GNG

Learning rate η_1, η_2	0.05, 0.0006
Timing of node insertion λ	200
Maximum age $g_{\max}$	88
Discount rate of accumulated error α	0.5
Threshold k	3
Desired sampling time T^p	0.03 [sec]
Update range δ	0.01
Initial update rate r^0	1.00
Fixed discount rate b_{low}, b_{high}	0.00001, 0.005

(b) GNG-U2

Learning rate η_1, η_2	0.05, 0.0006
Timing of node insertion λ	200
Maximum age $g_{\max}$	88
Discount rate of accumulated error α, β	0.5, 0.005
Threshold k	3

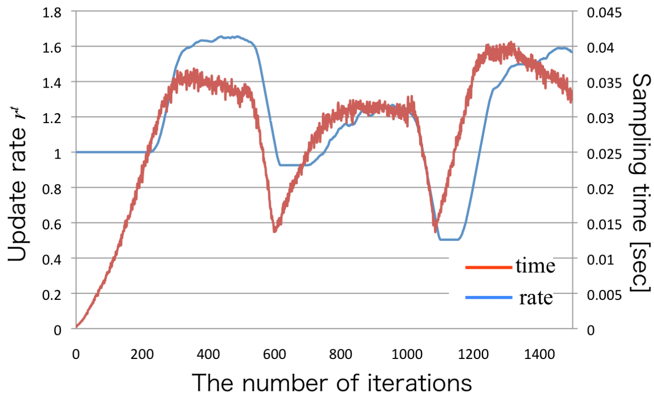
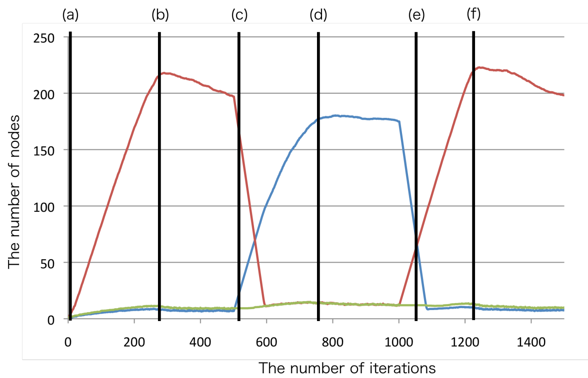
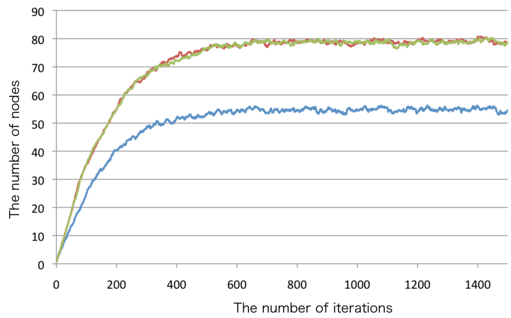


Fig.2 Transitions of update rate and sampling time



(a) Transition of the number of nodes (Proposed method)



(b) Transition of the number of nodes (GNG-U2)

Fig. 3 Experimental results (Red, green and blue lines represents the number of red, green and blue nodes, respectively)

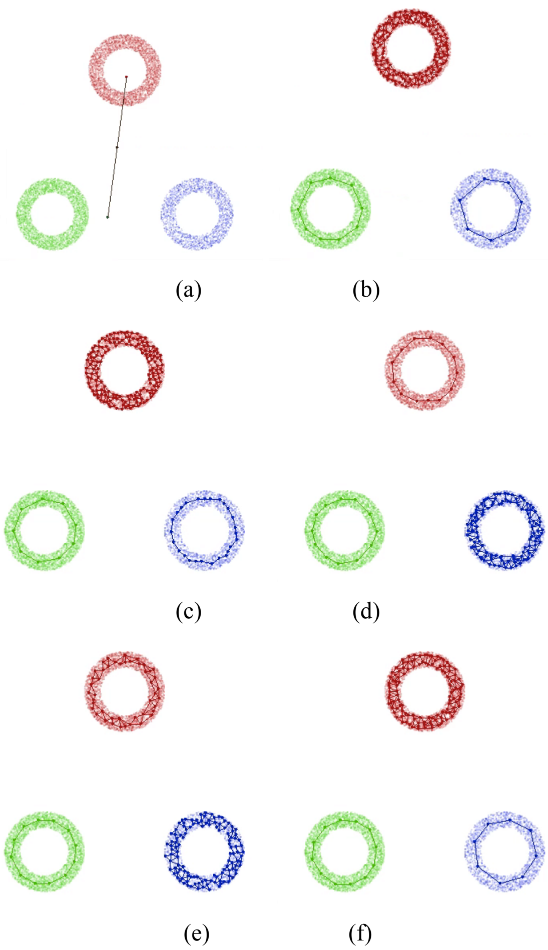


Fig.4 An example of topological structure

5 Conclusion

In this paper, we propose the Region of Interest Growing Neural Gas (ROI-GNG) for learning the dense topological structure of the target property and the sparse topological structure of the other properties in real-time. In ROI-GNG, the discount rates of the utility value and accumulated error are updated for adjusting the node density according to the target property and sampling time. Next, we conducted an experiment in 2D simulation environment, and showed the effectiveness of our proposed method. However, we did not apply our proposed method to a real sensing data such RGB-D camera. Therefore, we will apply our proposed method to 3D point cloud data, and verify the effectiveness of our proposed method.

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