Obstacle Modeling for Environment Recognition of Mobile Robots Using Growing Neural Gas Network

Min Young Kim, Hyungsuck Cho, and Jae-hoon Kim

Abstract: A major research issue associated with service robots is the creation of an environment recognition system for mobile robot navigation that is robust and efficient on various environment situations. In recent years, intelligent autonomous mobile robots have received much attention as the types of service robots for serving people and industrial robots for replacing human. To help people, robots must be able to sense and recognize three dimensional space where they live or work. In this paper, we propose a three dimensional environmental modeling method based on an edge enhancement technique using a planar fitting method and a neural network technique called "Growing Neural Gas Network." Input data pre-processing provides probabilistic density to the input data of the neural network, and the neural network generates a graphical structure that reflects the topology of the input space. Using these methods, robot's surroundings are autonomously clustered into isolated objects and modeled as polygon patches with the user-selected resolution. Through a series of simulations and experiments, the proposed method is tested to recognize the environments surrounding the robot. From the experimental results, the usefulness and robustness of the proposed method are investigated and discussed in detail.

Keywords: Three dimensional environment recognition, polygon modeling, mobile robot, growing neural gas network.

1. INTRODUCTION

Intelligent autonomous mobile robots used as service robots or industrial robots have been the subject of great interest in recent years. This type of robotic systems is often used so that it can execute routine tasks autonomously in partially known environments. To complete the task successfully, the robots need to recognize the navigation environment without human intervention; hence, this environment must be modeled. Many researchers have tackled and studied the modeling of navigation environment from several different aspects of the applications [1-4]. Previous approaches to tackle this problemcan be divided into three categories: the geometric primitive based method, the polygon modeling based method, and the grid modeling based method. As an application using the first method, Feddema and Little [1] constructed the world model via range data fitting by using geometric primitives. In this research, they dealt with the object modeling problem with the assumption that the range data can be pre-segmented by operator. As another example, the world modeling technique introduced in [2] is based on the autonomous segmentation of the range image and the manual surface fitting using geometric primitives. The acquired range image is segmented to group a set of range points into surfaces, and then the segmented surface patch is fit to a user selected quadric or plane. As one of the second method applications, Barry and Jones [3] utilized the conventional polygon modeling technique of the computer graphics for building an accurate world model of robot workspace. Even with noisy data filtering, manual data editing, and less important polygon elimination, around 100,000 polygons are required for displaying the recognized environment. Moravec [4] proposed the 3D evidence grid method, which is classified into the third category for robot spatial perception. The 6× 6× 2*m* space is modeled as a grid 256 cells wide by 256 cells deep by 64 cells high. Certainly, this is a simple environment representation method for robot navigation, but is not good for environment recognition in view of information compression. As mentioned above, the previous approaches are not adequate and efficient for the applications related to autonomous environment recognition.

In this paper, we propose a method for modeling

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the 3D shape of the indoor environments and recognizing the cluttered obstacles, using neural network called the growing neural gas and edge enhancement technique of the voxel image. The purpose of the growing neural gas model is to generate a graph structure that reflects the topology of the input data (topology learning). This graph has a dimension that varies with the dimension of the input data. The resulting structure can be used to identify and model clusters in the input data. The nodes in the structure can be used as a codebook for vector quantization of the input data. Through these methods, the 3D environments around the robot can be autonomously segmented into the isolated objects and modeled as polygons with the user-selected resolution.

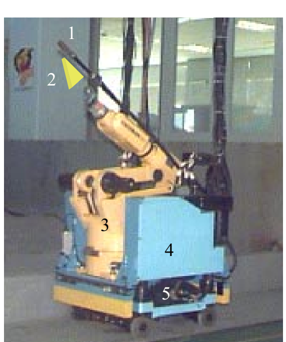
The organization of the paper is structured as follows: In Section 2, we address the environmental recognition problem of the mobile robot, and propose a recognition strategy for the intelligent mobile robot system. In Section 3, a neural network structure for the obstacle classification and modeling is proposed, the structure which is known as the growing neural gas network. The principle and characteristics of this network are described, and an edge enhancement technique is applied to modify this network. Finally, in Section 4, a series of experimental tests are performed to verify the efficiency and the effectiveness of the proposed environmental recognition method. The experimental results are discussed in some detail.

2. MOBILE ROBOT AND ENVIRONMENTAL RECOGNITION

For autonomous mobile robot navigation, mobile robots must have intelligence that can sense and recognize its navigation environment.

2.1. Mobile robot for industrial applications

As an example of the autonomous mobile robot for industrial application. Fig. 1 shows an intelligent mobile welding robot used for ship construction. For autonomous mobile robot navigation, the functions of the environmental sensing and recognition are essential to it. This robot can sense the welding task environment and track the weld seam by robot hand mounted laser visual sensor [5]. By using the laser scanning technique, this robot can measure the object distances of its surrounding three-dimensionally. In this work, it is assumed that the navigation space is one of the partially known environments with some CAD information that is given prior to its navigation. In this space, the robot must navigate autonomously and safely through the careful sensing and recognition on the environment.



1. welding torch
2. visual sensor system
3. welding robot
4. mobile platform
5. mechanism for welding robot lifting

Fig. 1. The mobile welding robot.

2.2. Environment sensing and representation

To fulfill the environment recognition task and the welding task, the mobile welding robot is equipped with a sensor system to be able to track the welding seam and to recognize the partially structured environments. In this case of the seam tracking, the optical triangulation method using the structured light has been widely used [6-8]. A variety of machine vision techniques, such as controlled illumination, stereoscopy, photometric stereo, and shape-from-shading have been developed for the determination of 3D scene geometric information from 2D images. However, because of the nature of the manufacturing or welding environment and the type of features of interest, structured lighting is most appropriate and has been widely applied in the sensing tasks mentioned above. In this work, the structured lighting was utilized for environmental sensing. The sensor system consists of two lipstick cameras and three laser diodes [5,9]. Using this sensor system and the scanning technique, the 3D range data on the environment surrounding the robot can be obtained. First of all, it must be represented in an efficient data structure that the robot can understand. Many different environment representations can be used according to the type of task to be performed, the kind of environment, and the type of sensor used. The most significant types of representations can be classified into cell decomposition models, geometrical models and topological models [10]. In this work, we select the cell decomposition modeling technique as an environment representation method. This technique is not able to exactly represent an object to be modeled. However, it has an advantage that any object can be represented in a simple way. Fig. 2 shows the cubic cells with 100x100x100 size for 3D environment models. The one cubic cell (voxel) has 10x10x10mm volumetric size. This volumetric size was determined on considering that the laser vision sensor mounted on the robot hand has the 10mm resolution at maximum range [9].

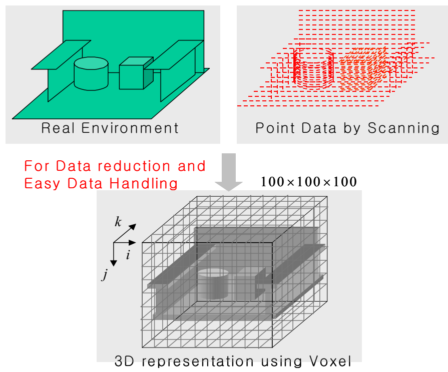


Fig. 2. Voxel representation of measured data.

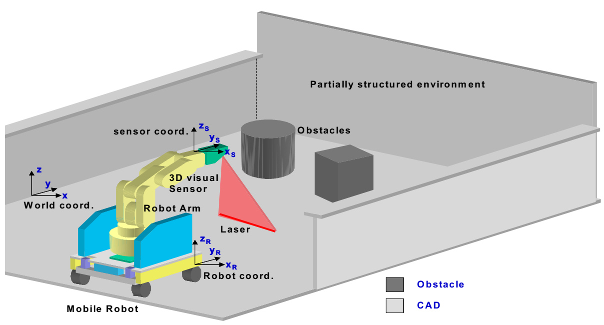
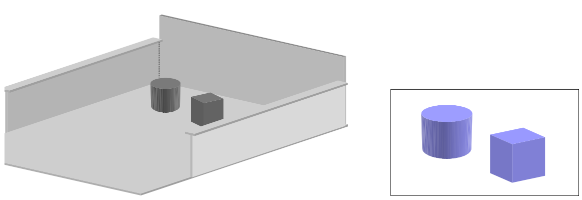


Fig. 3. Mobile robot navigation in 3D environment.



a) measurement data b) obstacle data

Fig. 4. Obstacle extraction from 3D measurement. data using CAD information

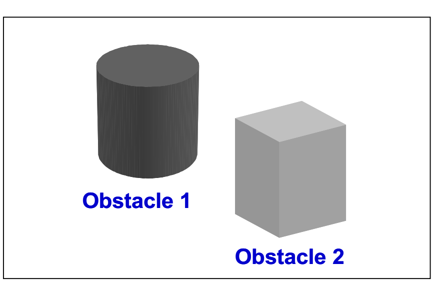


Fig. 5. Obstacle clustering from extracted obstacle data.

2.3. Environmental recognition

On the basis of the measured data, the intelligent robot must be able to model and recognize the environments. In this study, the proposed recognition strategy is as follows [9]: When the robot navigates the partially known space as shown in Fig. 2, it can extract the obstacle data from the acquired environment data. This task is accomplished by comparing the measured environment data with the known CAD data [11]. Fig. 3 shows the concept of extracting obstacle data from 3D measurement data including obstacle and CAD information simultaneously. First, through the self-localization, the robot is localized on the world coordinate frame. Using the robot localization data, the local sensing data on the robot coordinate frame is transformed into the global map represented on the world coordinate frame. Then, the CAD data and measurement data represented on the same coordinate frame are compared in view of the geometrical distance, and the obstacle data of not existing on the CAD data can be extracted from the measurement data. After the obstacle data extraction, the obtained data must be clustered into several groups as shown in Fig. 4. Each group, which represents a lump of an obstacle, is modeled by the geometric primitives, the triangular patch or the rectangular evidence grid. From the modeling of the clustered data group, the posture and shape information of each object can be obtained. In next section, we deal with problems of clustering and modeling by using the extracted obstacle data.

3. OBSTACLE CLASSIFICATION AND MODELING

In most conventional object recognition systems, the clustering procedure and the modeling procedure are divided into parts. In this section, we propose a new method that can efficiently integrate the two procedures. The proposed method consists of a neural network part and an edge enhancement part of the 3D image.

3.1. Growing neural gas network

The purpose of the growing neural gas model is to generate a graph structure that reflects the topology of the input data (topology learning). This graph has a dimension that varies with the dimension of the input data. The resulting structure can be used to identify and model clusters in the input data. The nodes in the structure can be used as a codebook for vector quantization of the input data. The detail description of this method is found in [12]. The networks consists of the followings: 1) a set $\boldsymbol{A}$ of nodes. Each node unit, $c \in \boldsymbol{A}$, has a reference vector, $w_c \in \Re^n$, and a local error variable, E_c. 2) a set $\boldsymbol{C}$ of connections among pairs of nodes. These connections are not weighted, and their purpose is the definition of topological structure of the input data space. Each connection has a variable, age, which denotes the freshness level of it. Fig. 6 shows the structure of the growing neural gas network. There is a number of n-dimensional input signal $\boldsymbol{\xi}= (x_1, x_2, \ldots , x_n)$ obeying the probability density function $P(\boldsymbol{\xi})$.

The algorithms for learning the input data space using this neural network are summarized as follows:

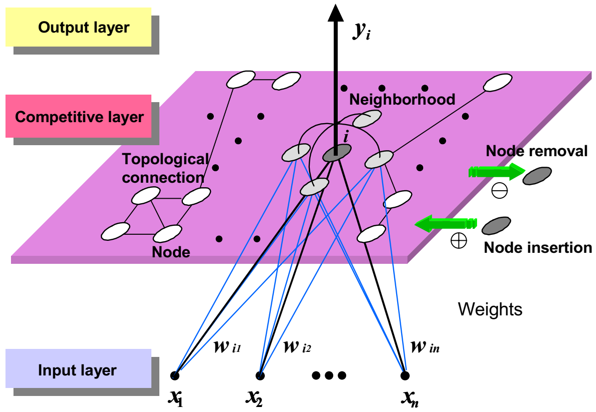


Fig. 6. Structure of the growing neural gas network.

i) Start with a set $\boldsymbol{A}$ of two units a and b at random positions $w_a = (w_{a1}, w_{a2}, \ldots, w_{an})$ and $w_b = (w_{b1}, w_{b2}, \ldots, w_{bn})$ in $\mathfrak{R}^n$:

$$A = \{a, b\}. \tag{1}$$

Initialize the connection set $\boldsymbol{C}$ to contain a connection between a and b, and set the age of this connection to zero:

$$\boldsymbol{C} = \{(a, b)\}, \quad age_{(a,b)} = 0. \tag{2}$$

ii) Generate an input signal $\boldsymbol{\xi}$ according to the probability density function, $P(\boldsymbol{\xi})$.

iii) Find the nearest node s_1 and the second-nearest node s2 for the input signal (s_1 and $s_2 \in A$). Here, the output variable yi of each node is utilized to find a node with maximum similarity to the input data:

$$y_i = \boldsymbol{w}_i \cdot \boldsymbol{\xi} = [w_{i1}\ w_{i2}\ \cdots\ w_{in}] \cdot [x_1\ x_2\ \cdots\ x_n]^T. \tag{3}$$

iv) If any connection between them does not already exist in $\boldsymbol{C}$, insert the connection to $\boldsymbol{C}$:

$$\boldsymbol{C} = \boldsymbol{C} \cup \{(s_1, s_2)\}. \tag{4}$$

In any case, set the age of the connection to zero:

$$age_{(s_1,s_2)} = 0. \tag{5}$$

v) Add the squared distance between the input signal and the nearest node in input space to the local error variable:

$$\Delta E_{s_1} = \left\|\boldsymbol{w}_{s_1} - \boldsymbol{\xi}\right\|^2. \tag{6}$$

vi) Move s_1 and its direct topological neighbors towards $\boldsymbol{\xi}$ by fractions ε_b and ε_n, respectively, of the total distance:

$$\Delta \boldsymbol{w}_{s_1} = \varepsilon_b(\boldsymbol{\xi} - \boldsymbol{w}_{s1}). \tag{7}$$

$$\Delta \boldsymbol{w}_i = \varepsilon_n(\boldsymbol{\xi} - \boldsymbol{w}_i) \qquad \forall i \in N_{s_1}. \tag{8}$$

where N_c denotes the set of direct topological neighbor of c.

vii) Increment the age of all connections emanating from s_1 :

$$age_{(s_1,i)} = age_{(s_1,i)} + 1 \qquad \forall i \in N_{s_1}. \tag{9}$$

viii) Remove connections with an age larger than the predefined value, age_{max}. If this procedure generates nodes having no emanating connections, remove them as well.

ix) If the number of input signals generated so far is an integer multiple of a parameter λ, insert a new node as follows:

Determine the node q, with the maximum accumulated error among the whole nodes.

$$E_q \geq E_c \qquad \forall c \in \boldsymbol{A}. \tag{10}$$

Insert a new unit r between q and its neighbor node f with the largest error variable, and interpolate the reference vector, $\boldsymbol{w}_r$, to locate between $\boldsymbol{w}_q$ and $\boldsymbol{w}_f$:

$$\boldsymbol{A} = \boldsymbol{A} \cup \{r\}. \tag{11}$$

$$\boldsymbol{w}_r = 0.5 \cdot (\boldsymbol{w}_q - \boldsymbol{w}_f). \tag{12}$$

Insert connections connecting the new node r with nodes q and f, and remove the original connection between q and f :

$$\boldsymbol{C} = \boldsymbol{C} \cup \{(r,q),(r,f)\}. \tag{13}$$

$$\boldsymbol{C} = \boldsymbol{C} - \{(q,f)\}. \tag{14}$$

Decrease the error variables of q and f :

$$\Delta E_q = -\alpha \cdot E_q, \qquad \Delta E_f = -\alpha \cdot E_f. \tag{15}$$

Initialize the error variable of r from q and f :

$$E_r = 0.5(E_q + E_f). \tag{16}$$

x) Decrease the error variables of all nodes:

$$\Delta E_c = -\beta \cdot E_c \qquad \forall c \in \boldsymbol{A}. \tag{17}$$

xi) If a stopping criterion to end is not satisfied, go to step ii.

Fig. 7 shows an example of topological learning using this method. The simulation result shows that the topology of the input data is well preserved in output represented by the network configuration. Especially, as shown in Fig. 7 c), the network characteristic that the distribution of nodes follows the input data distribution is applied to the modeling technique in the next section.

3.2. Application to the environmental recognition

Through this method, the 3D environments around the robot can be autonomously segmented into the isolated objects and modeled as the polygons represented as nodes and node connections with the user-selected resolution simultaneously. The extracted obstacle voxel data with the probabilistic density are used as the network input, and the network output consists of the nodes and the connection between nodes. A method of endowing input data with a probabilistic density is described in the next section, which is a 3D image processing technique in voxel space. The role of the probabilistic density is to give more chances that the input data is sampled during learning process of the neural network to the data at the region near to object edge. As mentioned in the previous section, input data with the high probabilistic density tends to attract the nodes intensively. The well-positioned nodes near the edge can represent the object better because more nodes are necessary for decreasing the modeling error at curved region or edge region to compare with planar region. The proposed obstacle recognition procedure is shown in Fig. 8.

3.3. Endowment of the probabilistic density to input data using 3D image processing technique

Every input data that represents obstacle may have a constant probabilistic density value. The network characteristic shown in Section 3.1 gives an idea for a detailed object modeling. Similar to the pattern recognition problem in 2D image, edge information in 3D space can be an important cue for the efficient object modeling. We utilize the network tendency in which nodes get together at the high probabilistic density region. The detailed procedure for the probabilistic density determination are summarized as follows:

i) Select the input signal ξ in $\mathfrak{R}^n$.

ii) Select a set of the neighbor points, $\boldsymbol{N}(\xi)$, among the input signal space:

$$\boldsymbol{N}(\boldsymbol{\xi}) = \{N_1(\boldsymbol{\xi}), N_2(\boldsymbol{\xi}), \cdots, N_m(\boldsymbol{\xi})\}. \qquad (18)$$

where m denotes the number of neighbor points.

iii) Using the input data, $\boldsymbol{N}(\xi)$, and the least square error method, find a plane equation fitting the input data with surface normal vector, $\boldsymbol{u}$, and minimum distance, v, from the origin to the plane of the world coordinate frame:

$$\boldsymbol{u}^T \boldsymbol{x} + v = 0. \qquad (19)$$

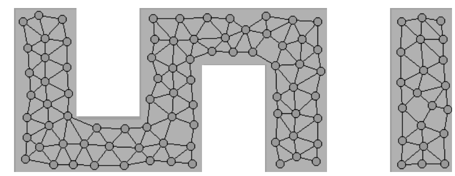
where $\boldsymbol{x}$ is a 3D vector.

Calculate the planar fitting error Eplane($\boldsymbol{\xi}$) and set it as the probabilistic density of the input signal $\boldsymbol{\xi}$, $P(\boldsymbol{\xi})$:

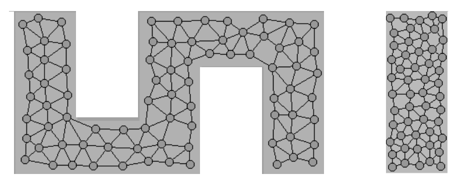
$$E_{plane}(\boldsymbol{\xi}) = \frac{1}{m}\sum_{i=1}^{m}(\boldsymbol{u}^T \boldsymbol{N}_i(\xi) + v)^2 = P(\xi) \ . \qquad (20)$$

Fig. 9 shows the probabilistic density endowing procedure on an example. As shown in this figure, the algorithms give the planar region the low probabilistic density, the curved region the middle probabilistic density, and the edge region the high probabilistic density,

a) simulation example of input data distribution : P(ξ).



b) nodes and connections representing the distribution(Pleft(ξ) of left side part = Pright(ξ) of right side part).



c) nodes and connections representing the distribution(Pleft(ξ) of left side part < Pright(ξ) of right side part).

Fig. 7. Topological learning by growing neural gas network.

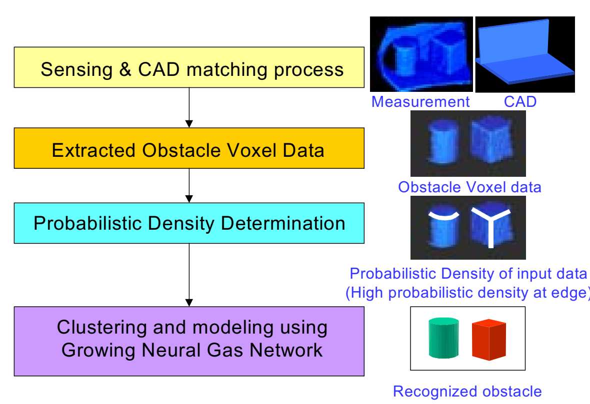


Fig. 8. Obstacle recognition procedure.

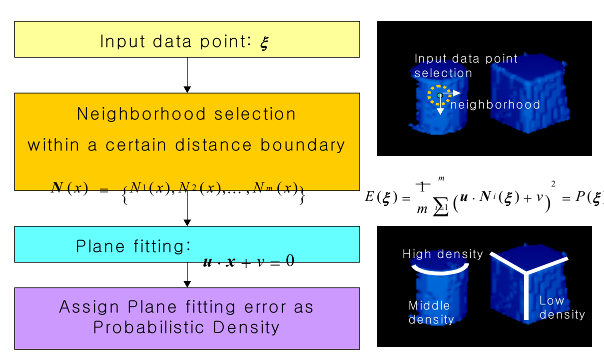


Fig. 9. Probabilistic density endowing procedure.

respectively. According to the probabilistic density value, the probabilistic chance that the signal is sampled can be varied during the neural network learning procedure.

4. EXPERIMENTS: ENVIRONMENT MODELING

In this section, the proposed environment modeling technique is verified through a series of experiments. Fig. 10 shows an environment composed of a cylinder, a cubic, and several flat plates for the recognition experiments. The information on the structure of flat plates is previously given as the CAD information, and the others are obstacles. Using the laser vision sensor described in Section 2.2, the sensing on this environment was performed. A voxel representation of the acquired 3D measurements on the scene is shown in Fig. 11 a), and a priori given CAD information is in Fig. 11 b). Fig. 12 shows the obstacle extraction result by comparing CAD data and measurement data on the world coordinate frame. The detail description on this procedure is in [11], which is a 3D image processing technique. Finally, the proposed modeling method is applied to the extracted obstacle data shown in Fig. 12. The algorithmic parameters of the neural network for these experiments were selected as follows: $\lambda=600$, $\varepsilon_b=0.05$, $\varepsilon_n=0.0006$, $age_{max}=88$, and $\beta=0.0005$. The obstacle clustering and modeling results by GNG network are represented with variations of maximum node number in Fig. 13. The variation of the number of nodes is limited to 50, 100, 150, 200, and 250, respectively. As expected, a large number of nodes lead to more accurate object modeling. The results show that two clusters well reflect the input data distribution with the nodes and connections adapted on the input data space. Using the connection information, we can extract each obstacle from the modeling result. Table 1 represents the modeling error of the results with variations of the number of nodes. Input data represented in Fig. 12 was about 3200 voxel point data. By using the proposed modeling technique, the input data space can be compressed into 250 nodes and their connections with 3.2*mm* average modeling error and 2.6*mm* standard deviation. The modeling error is defined as the normal distance between the input data and the related polygon patch.

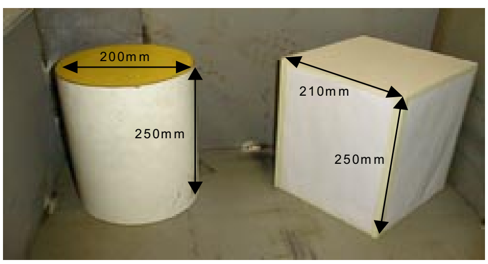
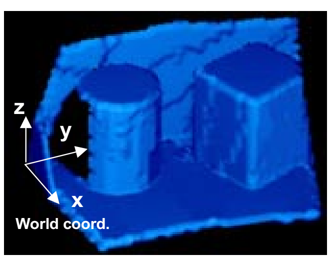
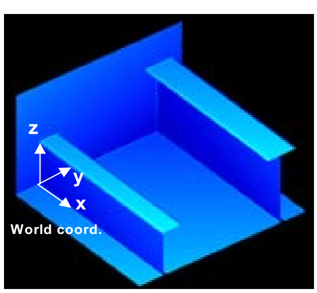


Fig. 10. Environment for the modeling experiment.



a) voxel representation of the measured data.



b) the priori given CAD data.

Fig. 11. 3D measurements on the scene shown in Fig. 10 and the priori given CAD data.

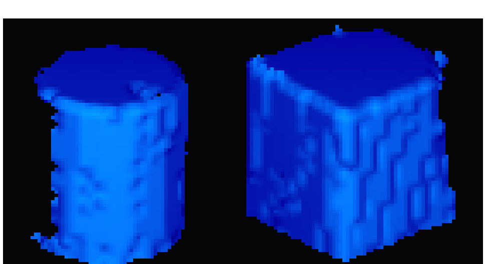
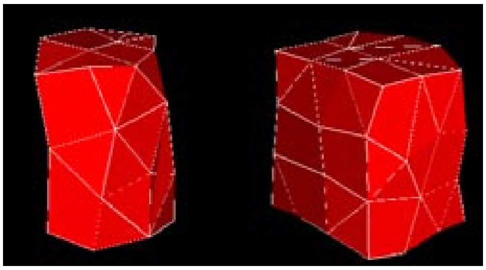


Fig. 12. Obstacle extraction by comparing CAD data and measurement data (about 3200 voxel points).

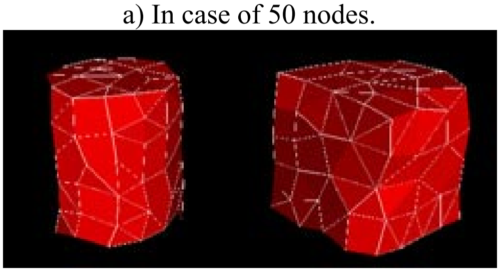
5. CONCLUSIONS

For autonomous mobile robot navigation, mobile robots must be equipped with functions that allow them to sense and recognize their environment with intelligence. In this paper, we proposed a three dimensional environment modeling technique using Growing Neural Gas Network and edge enhancement technique. Comparing with the conventional environmental modeling methods, the proposed method efficiently integrates the segmentation of the 3D obstacle data and the modeling of each obstacle. The role of this neural network is to generate a graphical structure that reflects the topology of the input space and to cluster the obstacle data into isolated objects. Through this method, the 3D surroundings around the robot were autonomously segmented into isolated objects and modeled as polygon patches with the user-selected resolution. Though the performed experiments are not much general, the experimental results show the possibility of the proposed method for the environment modeling application of mobile robots. Presently, we are studying the recognition tasks for the objects with more complex shapes. The development of endowing this robotic system with intelligence is still under way. Future studies should investigate the following issues:

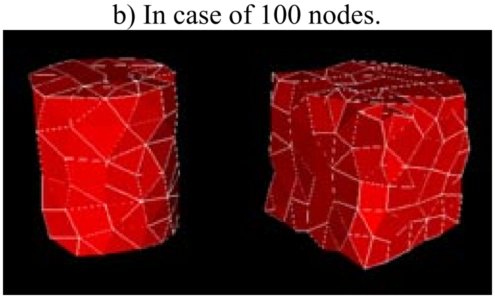
Robust and efficient environment recognition method using the neural network and the geometric primitives. Autonomous navigation and task execution of the mobile robot using recognized results.



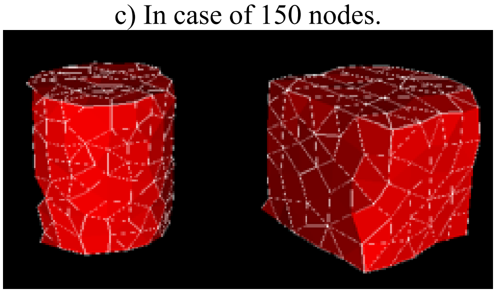
a) In case of 50 nodes.



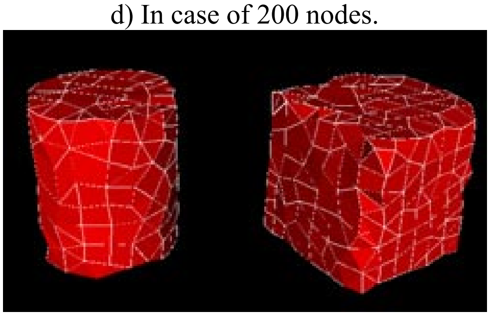
b) In case of 100 nodes.



c) In case of 150 nodes.



d) In case of 200 nodes.



e) In case of 250 nodes.

Fig. 13. Obstacle clustering and modeling with variations of the number of nodes.

Table 1. Modeling error analysis with variations of the number of nodes.

Node number	Modeling error (*mm*)	Standard deviation (*mm*)
50	6.8	±6.30
100	4.6	±3.84
150	3.9	±2.98
200	3.8	±2.73
250	3.7	±2.65

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