Multiple Object Detection for Intelligent Robot Vision by Using Growing Neural Gas

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Abstract:
Recently, various types of robots have been researched and developed for supporting our life. Also, the perceptual system for the robot is researched. Visual perception includes a lot of valuable information and it is useful for all intelligent robot system. In this paper, we discuss intelligent robot vision in order to detect multiple object and human. There are many visual sensors and we use the range-imaging camera to detect distance and image data. We propose a method for perceive moving target by using growing neural gas and Genetic algorithm. In the experimental results, we show the potency of our method.

1. Introduction

Visual information include a lot of important information for human and animals. Therefore vision system such as digital image processing have been researched. Also, various types of robots have been researched and developed such as human-friendly robots, pet robots, amusement robots, and partner robots. Such a robot requires many intelligent visual perceptions. Visual perception has been discussed from various points of view. The robot vision is based on the time-series of image processing, not the processing on a single image. Various technologies for image processing are required for realizing the robot vision, e.g., color processing, target detection, template matching, shape recognition, motion extraction, and optical flow. Furthermore, multiple objects tracking and people tracking should be done in the robot vision. We have applied spiking neural networks, cellular neural networks, self-organizing map, and others for human detection, motion extraction, and shape recognition.

In this paper, we focus on multiple object detection and multiple human detection. Kalman filter, particle filters, genetic algorithms, particle swarm optimization, and others have been applied in appearance-based methods. Furthermore, dynamic model of human movement is also applied to improve the accuracy of people tracking. These methods try to detect the features of human appearance, and to trace them over time, but there are problems on variability of appearance features and computational cost in the real-time people tracking.

As for the visual perception, we can divide by the sensor and the processing function. Because the variety of vision sensor is developed, the camera sensor becomes popular. Usually, the robot have some vision sensor for sensing ambient environmental information. Generally, in the vision information processing, static image processing is useful for robot vision, and we can process sequential image to processing videos nowadays. In the visual image, there are so many useful information to extract. And we have to select and fusing the visual information by the task.

In this paper we propose clustering method for a lot of information by growing neural gas. Here we aim multiple object detection and human detection, get the shape information, or labeling to the detected object.

2. Visual System For Mobile Robots

Recently, there are many robots such as moving around us. Such robots should collecting external world information. And the robot have to equip many kind of sensors. There are a lot of sensors to get environmental information, and it have been researching. In the field of intelligent robotics, we usually uses vision sensors. The vision sensor can get varieties of information from the environment, and it is useful for such kind of robot. Human and other animate beings using a big part of the brain for the visual processing. We can analogize that vision information is very important for our life.

Robot vision is composed of "Processing", "Classification", and "Perception". “Processing" include the image emphasis or image filtering. “Classification” include the character recognition or labeling etc... “Perception” include the image understanding or information extraction etc... In this paper we explain about “Processing" and “Classification”.

2.1. Environmental Sensing

The static image processing is useful for robot vision, such as edge detection by laplacian filter, noise reduction by gaussian filter, and so on. And we can process sequential image to processing videos, such as by moving object detection by using difference picture or optical flow. However the vision sensors are easily influenced of environment light condition. And it is difficult to understanding physical relationship between objects. It is able to get 3 dimensional information by using multiple vision sensors, but it is difficult to setting cameras with accurate positional relationship.

On the other hand, we can get the distance data by ultra sonic sensor or laser range finder, and so on. However, these sensors only can get a point information or linear information. So if we wont to get the 3 dimensional distance data, we have to move or rotate these sensors. In general, these kind of sensors are uses for mapping or localize ones position.

2.2. Range Imaging Camera

In the case of gathering image data and 3 dimensional surface data simultaneously, we generally uses cameras and range sensors. However it is difficult to synchronize or we have to compute differences of physical relationship between sensors. In this paper we use SR-3000 range imaging camera (Table.1, Fig.1). Range imaging camera can gather image data and 3 dimensional surface data simultaneously. The SR-3000 is an optical imaging system which offers real time 3D image data. It has infrared camera so the gathering data is almost free of the influence of environment light, but alternatively, it can't gather color image.

By using this sensor, we don't have to prepare the transform formula for sensor fusion of image and distance data. And we can clustering these data for detecting objects, reintegrate the 3 dimensional image by radiance value, or labeling to the objects.

3. OBJECT DETECTION AND CLASSIFICATION

3.1. Digital Image processing

Here, we explanation about time difference filter for radiance value input(Fig.1(a)). Fig.2(e) shows the difference of value input between time "*t-1*" and "*t*". Here, we can see the moving objects. But if the target objects aren't moving, it is difficult to extract the target. Therefor, we divide the target by using difference between background and current input value. Here, the background data is made by formula bellow, as a long tarm memory.

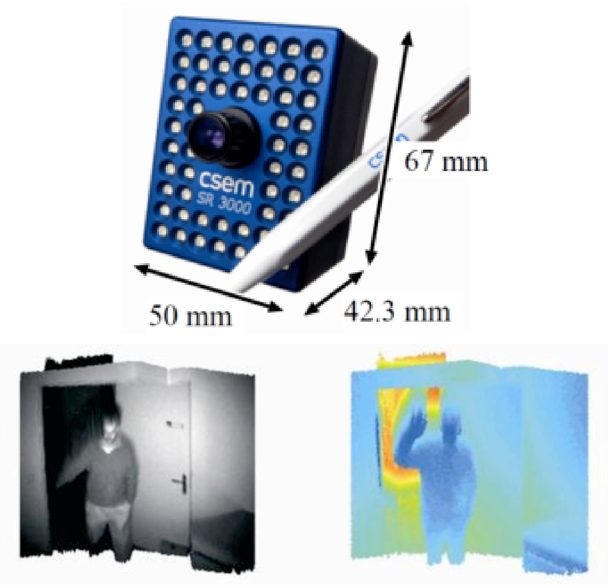
$$b(x,y,t+1)=(1-\alpha)\cdot b(x,y,t)+\alpha\cdot v(x,y,t) \tag{1}$$

Where, $v(x,y,t)$ indicate carrent value of time *t*, $b(x,y,t)$ indicate background value of time *t* as long tarm memory, α indicate the learning rate. Here, if the α is large, background value update fast by input value. Fig.2(f) shows the background value of $\alpha = 0.1$, Fig.2(g) shows the difference between background and current input value. In general, the difference area increases by the learning rate decreases. However, if the object motion is first, object passed area also detected as target, so trade-off analysis is necessary. Next, the rectangular space in fig.2(g) shows the barycenter of extracted difference between background and current input value. This indicate that the moving objects (=targets) are included in this area, and the system should pay attention to this area. And, filtering the distance data by using the target area distance information(Fig.2h). Here, we can see the 4 people in fig.2(d), and in fig.2(h), the shadow of four people is shown by the different digitized radiance value.

Here, the camera image include a copious information, so the digitization method has some availableness. However, averagely digitization is sometimes un-useful in case of many objects are observable. Because important information is not uniformly distributed in the space but biased. Therefore, we can say that better information can be collected by focused digitalization.

Table. 1 Specifications of the SR3000 (MESA Imaging AG)

Pixel Array Size	176 x 144 (QCIF)
Field of View	47.5 x 39.6 degrees
Non-ambiguous range	7.5 meters
Distance Resolution	1% of range, typical
Frame Rate	25 fps, typical



(a) Value input (a) Distance input

Fig. 1 SR3000 (MESA Imaging AG)

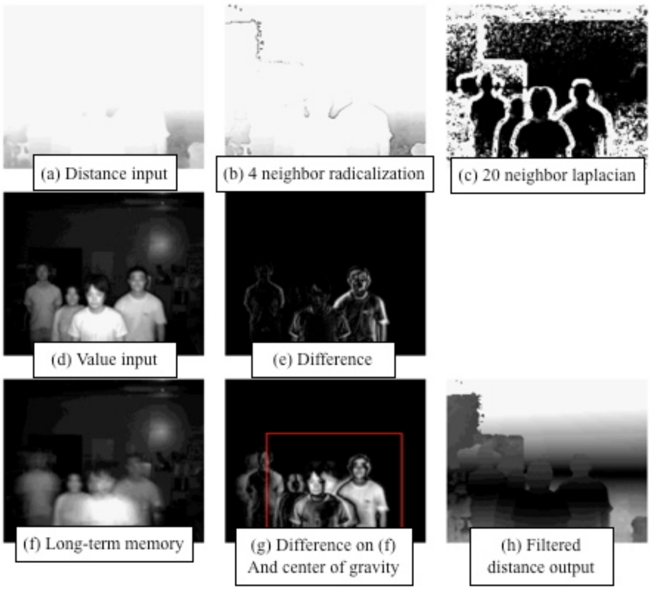

(a) Distance input
(b) 4 neighbor radicalization
(c) 20 neighbor laplacian
(d) Value input
(e) Difference
(f) Long-term memory
(g) Difference on (f) And center of gravity
(h) Filtered distance output

Fig. 2 Digital Image processing for multiple human detection

In fig.3(a), we digitization the distance data with many objects in the room into 25 stages. Here, we cannot discover useful information from the digitization image. Therefor, pre image processing, such as granularity digitization is found to be useful(Fig.4). For example, to extract the object area by laplacian filter(Fig.3(b): 4 neighbor, Fig.3(c): 20 neighbor). Here we can see the objects area clearly.

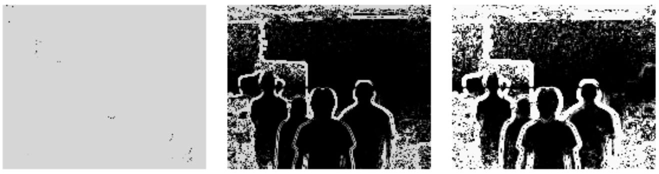

(a) (b) (c)

Fig. 3 Image digitization by distance and Laplacian filter

3.2. Growing Neural Gas

Various types of pattern matching methods such as template matching, cellular neural network, recognition, and dynamic programming (DP) matching, have been applied for human detection problems. In general, pattern matching is composed of two steps of target detection and target recognition. The aim of target detection is to extract a target candidate from an image, and the aim of the target recognition is to identify the target from classification candidates. In this paper, we focus on the target detection, because the main aim of this paper is to discuss on growing neural gas.

Unsupervised learning is performed by using only data without any teaching signals [12-20]. Self-organized map (SOM), neural gas (NG), growing cell structures (GCS), and growing neural gas (GNG) are well known as unsupervised learning methods. Basically, these methods use the competitive learning. The number of nodes and the topological structure of the network in SOM are designed beforehand [12,13]. In NG, the number of nodes is fixed beforehand, but the topological structure is updated according to the distribution of sample data [14]. 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, GNG does not delete nodes and edges, while GNG can delete nodes and edges based on the concept of ages [15,16]. Furthermore, GCS must consist of k-dimensional simplices 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 [17,18]. 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. Fig.5 shows how to cluster the data by GNG. GNG cluster the data by nodes and edges. GNG is topological clustering method, and it cluster the data with the shape (Fig5.(4)).

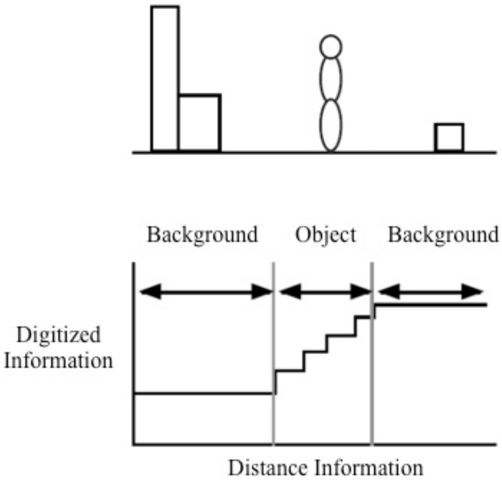
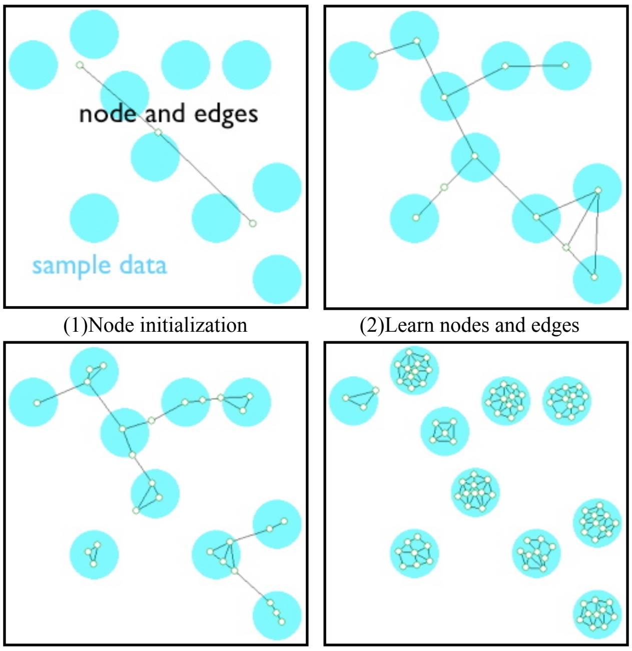


Fig. 4 Information extraction of intent area by the filter



(1)Node initialization (2)Learn nodes and edges

(3)Node and edge addition and deletion (4)Clustering

Fig. 5 Clustering by Growing Neural Gas

Table.2 shows preliminary simulation results of comparison among SOM, NG, GCS, GNG. In the preliminary simulation, the number of nodes in two-dimensional SOM is 100 (10x10), and the maximal number of NG node is 100. The parameters used in GCS simulations were: λ=200, η^{G}_{1}=0.04, η^{G}_{2}=0.001, α=1.0, β=0.0005, in GNG simulations were: λ=200, η^{G}_{1}=0.05, η^{G}_{2}=0.001, α=0.5, and β=0.0005. We used data distribution of three rings. We conducted comparison of these methods by using the sample data of three rings. Table.2 shows the comparison of evaluation values among SOM, NG, GCS, and GNG. The computational time of GCS is the shortest because the original GCS does not delete nodes and edges. NG needs much more computational time than others because the algorithm of sorting nodes is adopted every iteration. Furthermore, GCS successfully perform triangulation.

GNG can dynamically change the adjacent relation (edge) referring to the ignition frequency of the adjacent node. We apply GNG for unsupervised clustering of the distribution of radiance value and the distance data. The learning algorithm of GNG is shown as follows. The nth dimensional reference vector of the ith node is w_i; a set of nodes is A; a set of nodes connected to node i is N_i; a set of edges is C; and the age of the edge between the ith and jth node is $age_{(i,j)}$.

Step 1. *Select two units $c1$, $c2$ at random position w_{c1}, w_{c2} in $\boldsymbol{R}^n$. Initialize the connection set.*

Step 2. *Determine the nearest unit $s1$ and the second-nearest unit $s2$ according to input signal ξ by*

$$s_1 = \arg\min_{c \in A} \|\xi - w_c\| \quad \text{and} \quad s_2 = \arg\min_{c \in A \setminus \{s_1\}} \|\xi - w_c\| \qquad (2)$$

where ξ is composed of the position (x, y) and radiance value on the image (Fig.6(a)).

Step 3. *If a connection between $s1$ and $s2$ does not yet exist , create it. Set the age of the connection between $s1$ and $s2$ to zero.*

$$age_{(s1,s2)} = 0 \qquad (3)$$

Step 4. *Add the squared distance between the input signal and the winner to a local error variable E_{s1}.(Fig.6 (b))*

$$E_{s1} \leftarrow E_{s1} + \|\xi - w_{s1}\|^2 \qquad (4)$$

Step 5. *Adapt the reference vectors of the winner and its direct topological neighbors by the learning rate ε_b and ε_n, respectively.*

$$\nabla w_s = \varepsilon_b(\xi - w_s) \quad \nabla w_n = \varepsilon_n(\xi - w_n) \qquad (5)$$

Step 6. *Increment the age of all edges emanating from $s1$.*

$$age_{s1} \leftarrow age_{s1} + 1 \qquad (6)$$

Step 7. *Remove edges with the age larger than a_{max}. If units have no more emanating edges after this, remove those units.(Fig.6(c))*

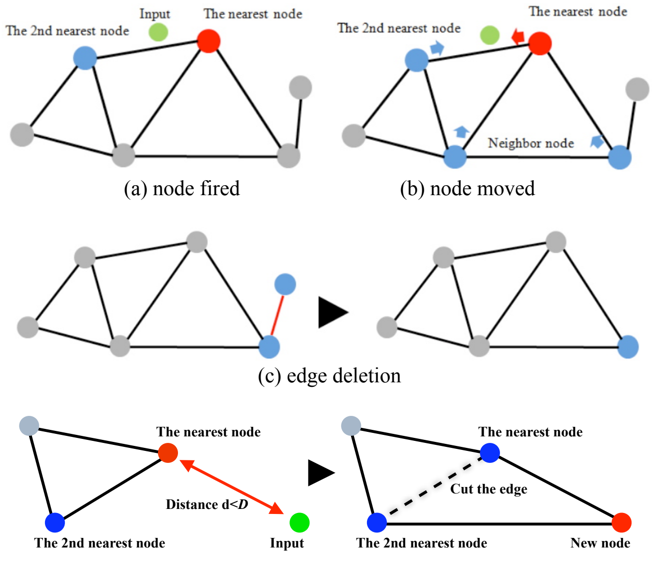
Step 8. *If the number of input signals generated so far is an integer multiple of a parameter λ, insert a new unit as follows.(Fig.6(d))*

In addition, the node is generated based on the distance of the intent objects. Paying attention to the object is useful for the reduction of nodes that indicate the useless obstacles. And also, we can separate off the adjacent object by paying attention to the object area. We set the node additional space threshold by the position of intent objects. In future we will be using normal distribution or gaussian membership function for node additional probability.

In this way, the radiance value distribution can be extracted from the image by using GNG.

Table. 2 Comparison of evaluation values

	Calculation Cost (ms)	Nodes	Edges	Deleted Edges
SOM	2100	100	180	0
NG	8600	100	193	280
GCS	1200	169	501	0
GNG	1900	168	369	392



(a) node fired

(b) node moved

(c) edge deletion

(d) node addition

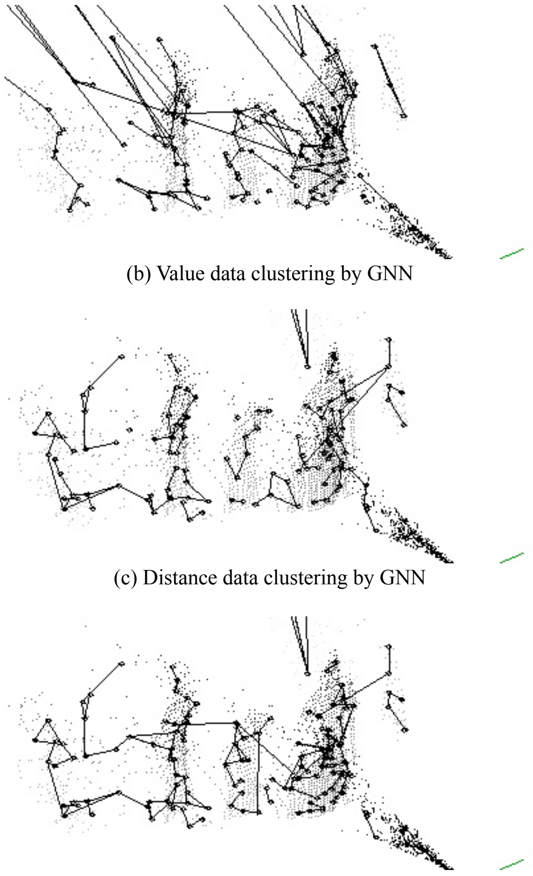
Fig. 6 How to learn GNG nodes and edge

4. Experimental Results

In the experimental results, we show the results of classification for detecting multiple human by using GNG for the range imaging camera data.

4.1. Sensor fusion of distance data and brightness value

Fig.7 shows the experimental results of sensor fusion with GNN, and it shows sensor data include 4 people. Because peoples aren't standing straight as a line but overlapping each other, it is difficult to classificate only using brightness value(Fig.7(b)). Fig.7(c) shows classificate results of distance data. Human who standing on left side, especially inside, are expressed by a number of node set. But some of the nodes are mutually connected. This cosed by similarity of distance and brightness value. So we have to refine the target domain and have to radicalization or accentuation of distance data. And also we have to use sensor fusion by using various sensor information. Though in fig.7(d), we can see the human


(b) Value data clustering by GNN

(c) Distance data clustering by GNN

(d) Distance and value data clustering by GNN

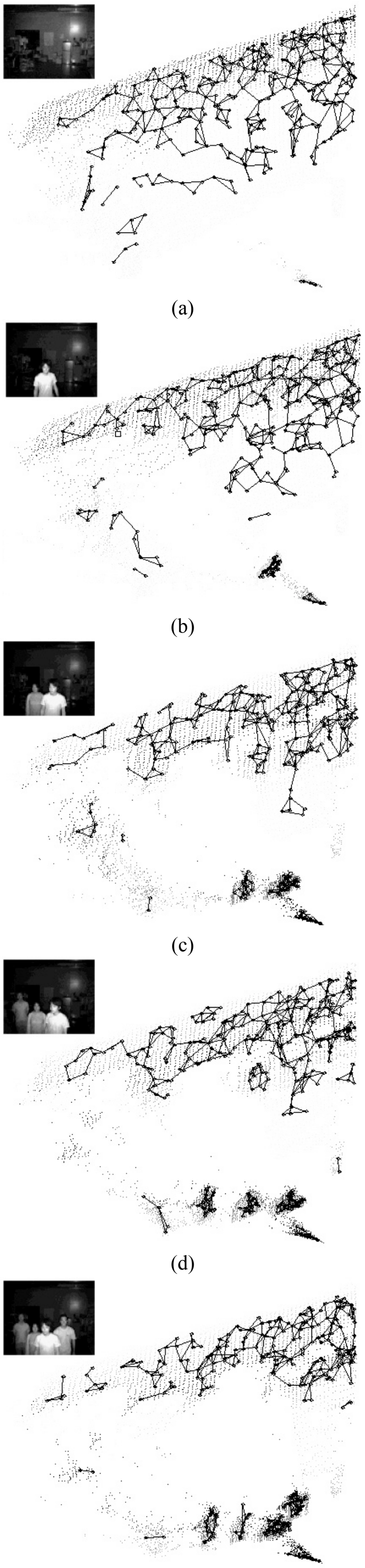
Fig. 7 Sensor fusion for multiple human detection (4 people)

classification is almost done, but it cannot divide to be exact. So we have to improve these algorithm.

4.2. Multiple human detection by GNG

In fig.8, we can see the experimental results of multiple human classification. Here, we use laplacian filter to brightness value for manage GNG edges. And, we improve the GNG metod for classificate the objects. We set density of nodes is high for near objects and low for far objects. It becomes easy for the objects to classify the human from background. Fig.8(a)-(e) shows the output of GNG when the human was 0, 1, 2, 3, 4. ere GNG can clearly made some clusters as human. Here, GNG can divide multiple human from background, but sometimes the classification is incomplete. And also, there are many irrelative set of nodes with human. So for the future works, we also use brightness value or upper layer of GNG.

In Fig9, the nodes were added around the distance where the object existed. Here, we can reduce the nodes in front of the camera error and the back ground nodes. We can show the human by enough number of nodes, and the separate division of each human was done.


(a)

(b)

(c)

(d)

(e)

Fig. 8 Multiple Human detection by Growing Neural Network

5. Summary

As mentioned before, range imaging camera and GNG is useful for multiple human detection. Range imaging camera can easily get a lot of information. However, proposal algorithm is unsatisfactory. So in the future tasks, we have to propose more effective algoritm such as difference filter, long-term memory filter, radicalization.

The research of the part of "Perception" in robot vision is still insufficient. The individual identification of the object, detection and identification of the movement, grouping of the objects are valuable for the intelligent robot vision. Here, we can assume that the labeling for the recognized object is useful for "Perception". And proposed method will be helpful for labeling the clusters, and utilize the information.

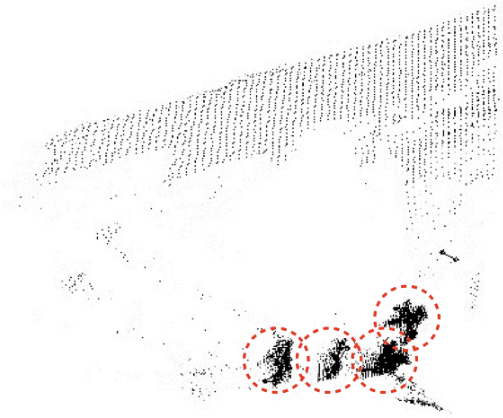


Fig. 9 Node reduction

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