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SPATIAL HABITUATING SELF ORGANIZING MAP

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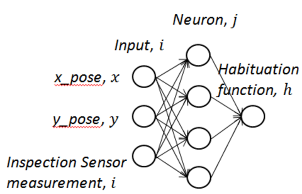
Graphical abstract



Abstract

This paper presents the development of Spatial Habituating Self Organizing Map (SHSOM) network. This project is inspired by the challenges in underwater wall/pipe or cable inspection application using inspection robot. When exposed to the underwater natural elements, robot's sensor readings are varied over space and time. Hence, the AUV need to be able to continuously adapt to its environment while performing inspection. For this reason, a new inspection system based on spatial Habituating Self Organizing Map (SHSOM) network is proposed. SHSOM allows the robot to continuously learn and adapt to new changes in its environment by using habituation principle which considers spatial information. WEBOT simulator is used to simulate an inspection scenario involving a mobile robot a changing environment. Simulation results show that the robot successfully learn and detect novel events during inspection.

Keywords: Underwater inspection, neural network, habituating self-organizing map

Abstrak

Kertas kerja ini membentangkan pembangunan rangkaian Spatial Habituating Self Organizing Map (SHSOM). Projek ini diilhamkan oleh cabaran aplikasi pemeriksaan struktur paip/dinsing di bawah laut oleh sistem robot pemeriksa bawah laut. Bacaan pengesan berubah terhadap ruang dan masa kerana terdedah dengan unsur semulajadi bawah laut. Robot perlu sentiasa menyesuaikan diri terhadap persekitarannya. Justeru, sistem pemeriksaan baru berasaskan SHSOM dicadangkan. Dengannya, robot dapat berterusan belajar persekitaran baru menggunakan prinsip habituasi yang mengambil kira prubahan ruang. Simulator WEBOT digunakan untuk mensimulasi senario pemeriksaan robot dalam persekitaran yang berubah. Keputusan simulasi menunjukan robot berjaya belajar dan mengesan keadaan baru ketika pemeriksaan.

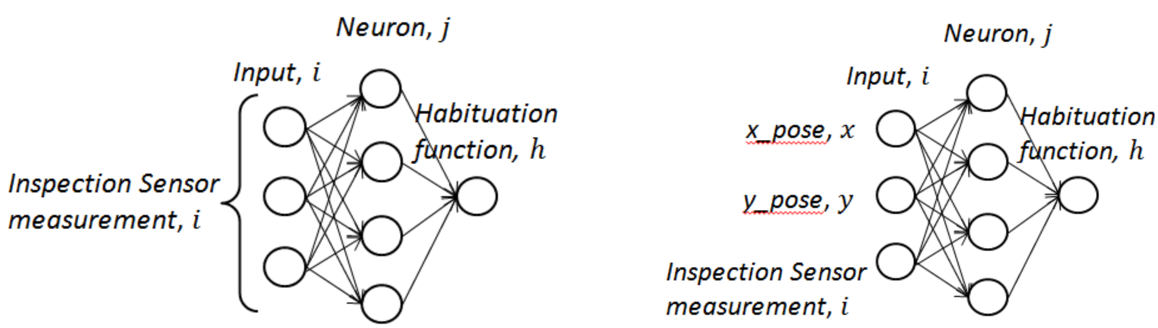
Kata kunci: Pemeriksaan di bawah air, rangkaian neural, peta tabiat aturan sendiri

1.0 INTRODUCTION

Study on underwater inspection starts to grow based on the requirements of industries in maintaining concrete structures, pipelines, and cables that being installed under the water. The reason were to cater any deteriorate factors such as opening or cracking concrete, diminish wall thickness, checking marine growth at the surrounding area and detecting any metal corrosion [1]. Even though there are human divers for underwater inspection, the deep and cold water, poor visibility and high water stream make it difficult and hazardous for human to perform inspection task [2]. Thus it is more applicable if we able to robotize underwater inspection task.

Two main problems with regard to underwater inspection are inspection and navigation problems. Calvo *et al*. [3] use sonar images and image processing attached into their Automatic Underwater Vehicle (UAV) to sense underwater pipelines. Based on the data, they interpreted the next movement by using neural network. Loisy *et al.* [4] inspect water tunnel pressure by using attachable imaging instrument to remotely maneuverings underwater vehicle (ROV) to detect and locate the main leaks at the tunnel. Shin *et al*. [5] prototyped a UAV to inspect underwater harbor facilities and use image processing for inspection, while using Extended Kalman Filter (EKF) with kinematics to estimate the maneuverings position. Kim *et al.* [6] cover both maneuverings and inspection problems by using visual simultaneous localization and mapping algorithm (SLAM) along with their autonomous AUV. This technique improves the image processing performance in underwater system inspection. Jacobi [7] *et al.* maps data from various sensors in estimating the defect along the pipe lines. Instrumentation system consist of scan sonar to detect any anomalies in certain distance from the pipelines, a sub bottom profiler and a magnetometer detect the subsided pipelines and color camera that provide image which easy to be interpreted by humans. With this a map for path and colored image pipelines for inspection can be predicted.

Based on the literature, most researchers use AUV as the main maneuverings mechanism in underwater inspection since ROV limits the distance travel from the surface and the period of monitoring. Most researchers also presented sensory system to the AUV as tools in path planning along the pipelines or underwater structure and as well as for anomalies detection. However, from the best of our knowledge, no system presents intelligent technique in adapting to and detecting the inspection information. Thus in this project we would like to propose a new intelligence technique that could adapt to normal measurement and detect novelty in the inspection environment.



(a) (b)

Figure 1 (a) usual HSOM network with all input associated to inspection sensor measurement. (b) HSOM network with spatial information as its input.

2.0 ADAPTATION TO SPATIAL NORMALCY

Habituating Self Organizing Map (HSOM) has been introduced by Marsland for robotic inspection application in [8] but the network does not consider spatial information. Miskon *et al*. then included spatial information into the network by using regional mapping [9, 10] hence the network able to learn spatial normalcy. Sha'abani *et al*. then attempted to include the spatial information as part of the network itself but in the form of hierarchical representation [10]. This means that the spatial information is associated but not clustered together with inspection sensory readings.

In this paper, HSOM is applied in underwater inspection application to make inspection robot able to adapt to its environment. In order to do that, the author has modified HSOM to suits underwater application requirement where the position of the AUV is taken into account as one of the input vector (see Figure 1). By doing this, the network could also learn spatial normalcy and hence detect spatial novelty. The same principle could also be use in learning temporal normalcy and detecting temporal novelty. Spatial and temporal normalcy are phenomena that need to be considered when working in real environment since normalcy varies within space and time due to environmental condition along the cable/pipelines.

In order to learn or adapt to the environment, first the robot moves in its environment. While moving, the robot takes measurement of the environmental states as well as its position. For each set of measurement (input vector), the robot compares the input vector to all neuron that it have.

Each neuron, j is a vector that consist of its number of input vector, i (see the neuron weight matrix in Equation 1). Each neuron also is associated to a habituation counter, o.

$$w = \begin{array}{c} \\ i=1 \\ i=2 \\ i=n \\ o_{w(j)} \end{array} \!\!\begin{array}{c} \begin{array}{ccc} j=1 & j=2 & j=n \end{array} \\ \begin{bmatrix} w_{11} & w_{12} \dots & w_n \\ \dots & \dots & \dots \\ w_{n1} & w_{n2} & w_{nn} \\ o_1 & o_2 & o_n \end{bmatrix} \end{array} \qquad (1)$$

A neuron wins when input vector, s is highly similar to the neuron weight, w_{ij}. In this project Euclidean distance, d as shown in Equation 2 is used as the measure of similarity. Since the input comes from different type of input such as GPS and IR, weightage, k_i is multiplied on the each type. The purpose of k_i is to determine how much each type contribute to the total Euclidean distance.

$$d_{ij} = \sqrt{\sum_{i=1}^{n}(k_i * (w_{ij} - s_i)^2)} \qquad (2)$$

Two values will be updated whenever a neuron wins i.e. the weight, w_ij and the habituation counter, o. Habituation counter of a winning neuron simply adds up discreetly. Whereas the weight of a winning neuron is updated by using Equation 3;

$$w_{ij}(t+1) = w_{ij}(t) + \theta \times \alpha \times (s_i(t) - w_{ij}(t)) \qquad (3)$$

where θ is the SOM neighborhood function that governs how neighboring neurons are updated and α is the learning rate that governs how fast a weight becomes similar to a given input.

Neighborhood function, θ takes the form of a Gaussian function as shown in Equation (4);

$$\theta(d,r) = e^{-\frac{d}{2r^2}}. \qquad (4)$$

where d is the distance between the neighboring neuron to the winning neuron by using Euclidean distance and r is the neighborhood size decreases over time according to an exponential function as shown in Equation 5. The value of γ in the equation controls the rate of the decay.

$$r = e^{\frac{-t}{\gamma}} \qquad (5)$$

Habituation h_w(j) is modeled by using an exponential formula as shown in Equation 6;

$$h_{w(j)} = Ae^{-\frac{o}{\tau}}. \qquad (6)$$

where A is the novelty initial value, o is the number of times a neuron matches the input vector and τ is the parameter to increase or decrease the habituation speed. As the habituation counter, o increases, h_w(j) will decrease exponentially. When h_w(j) is below a set novelty threshold, nt, the AUV artificial intelligence will consider the neuron, w(j) to be habituated. If the weight of habituated neuron, w_ij matches an input vector, s below a set Euclidean distance, the input vector is considered as normal measurement of the environment. On the other hand, if either a neuron that is best match is not habituated or if no neuron matches the input vector, then the input vector is considered a novelty.

In the actual operation, the robot first learns and habituates with/without human supervision. The robot continuously learns and habituates while monitoring. During monitoring, robot highlights novelty event when the input vector (sensor reading) does not match any neuron or if the habituated value of the working neuron is below a set threshold. When this happen, the robot could report the novelty event to a supervisory control system for further action. Figure 2 illustrates the Spatial HSOM overall process.

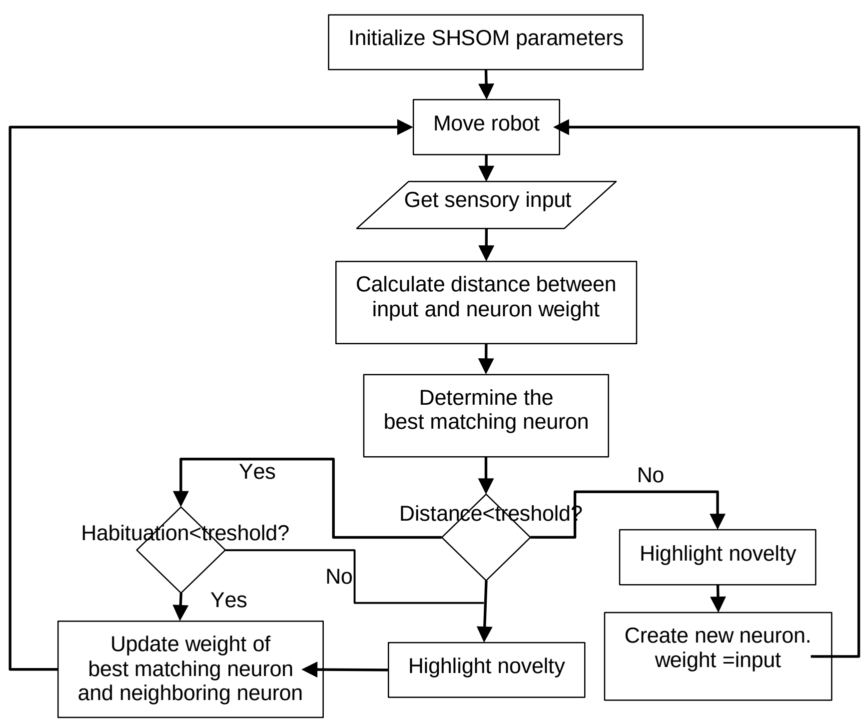


Figure 2 Illustration of spatial habituating self-organizing map process

3.0 RESULTS AND DISCUSSION

In order to test the feasibility of the spatial HSOM, a simulation using E-puck mobile robot in WEBOT 8 was conducted. WEBOT 8 [12] is commercial mobile robot simulation software developed by Cyberbotics Ltd. E-puck mobile robot is 7.4 cm in diameter and 4.5 cm high. It has 8 infra-red sensors (ps0-ps7 shown in Figure 3) measuring ambient light and proximity of obstacles in a 4 cm range.

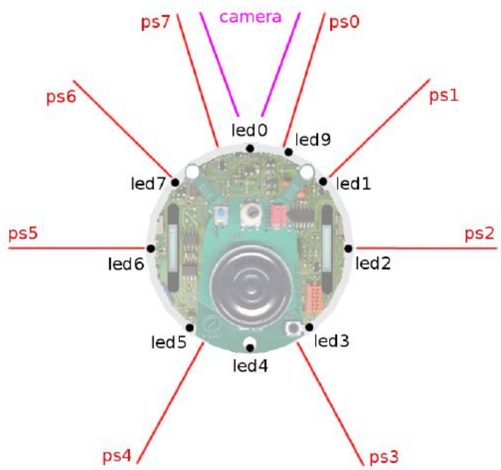


Figure 3 E-puck mobile robot

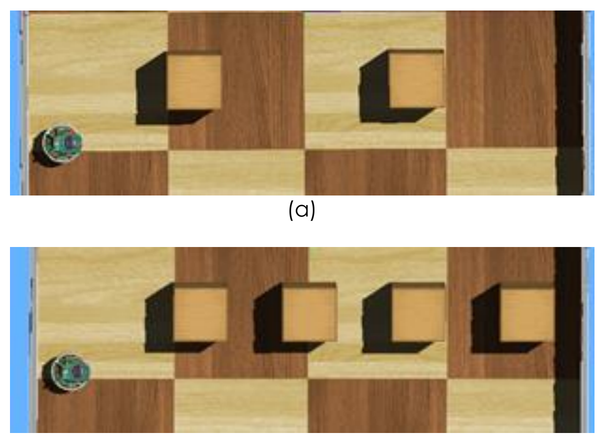
In the simulation, an E-puck robot was moved in forward and reverse motion between -0.5 m and 0.5 m along y axis in a 1 m x 1 m rectangle arena. Rectangular boxes with size of 0.1 m x 0.1 m x0.1 m were placed alongside the y axis within the detectable range of the E-puck infrared sensors.

Figure 4(a) shows the environment first setting which represents normal scenario. The first setting is done to validate that the robot could learn spatial normalcy. To create variation of normal measurement in different position, there are at least two variations of infrared sensor readings along the robot route i.e. measurement near and away from the boxes. The position of the boxes center along x-axis is -0.2 m and 0.2 m each. Figure 4(b) shows the second environment setting which represents novel scenario. In the second setting, 2 additional boxes are added. The position of the boxes center along x-axis is 0m and 0.4 m each. All boxes are aligned at -0.12 m along y-axis. The robot maintained its position at y-axis at -0.233 m when it travel forward and reverse direction along x-axis.

During the simulation, the E-puck continuously performs learning and inspection by using spatial habituation principles. The inputs provided to the robot are its x and y position information as well as the infrared distance measurement (ps0-ps7). The robot is made to travel at least 5 times back and forth in the first setting before the environment is change to the second setting. Table 1 summarized the parameter settings for the simulation.

Figure 5 shows the resulting neurons and their habituation values when the learning parameters; learning rate, α as well as the number of training runs were changed. From the results, we can see that when the learning rate is higher, neuron weights are easily influenced by the input vectors. Since the neurons are influenced by the positional input, the neuron weight accommodated to the neighboring positional input as the robot moves to the next position. This explains the vacuum space that occurs in Figure 5(b) between position -0.4 m and -0.3 m on x-axis.

Figure 5(c) and Figure 5(d) show as the learning rate is decrease, neurons weight is less influenced by input. The neuron is more evenly distributed. We can see that more neurons are created when the surroundings changes state near the box and the wall areas. As a consequence, as we can see in Figure 5(f) even after the run was increased to 18 times, neurons near the walls is not habituated since they are competing with other similar neurons created in the areas.



(a)

(b)

Figure 4 Environment settings in WEBOT simulator

Table 1 Simulation parameter settings

Variables	Settings
Learning rate, α	0.1, 0.01, 0.001
Neighborhood size decay rate, γ	1
Habituation speed constant, τ	10
Novelty threshold, nt	0.7
Euclidian Distance threshold, edt	40
Length of structure learned and inspected , m	1 m
Robot step size, m	0.02 m
Initial number of neurons	1
Number of training runs	2, 8, 18 times
IR distance weightage, k_{ir}	0.1
GPS position weightage, k_{GPS}	1

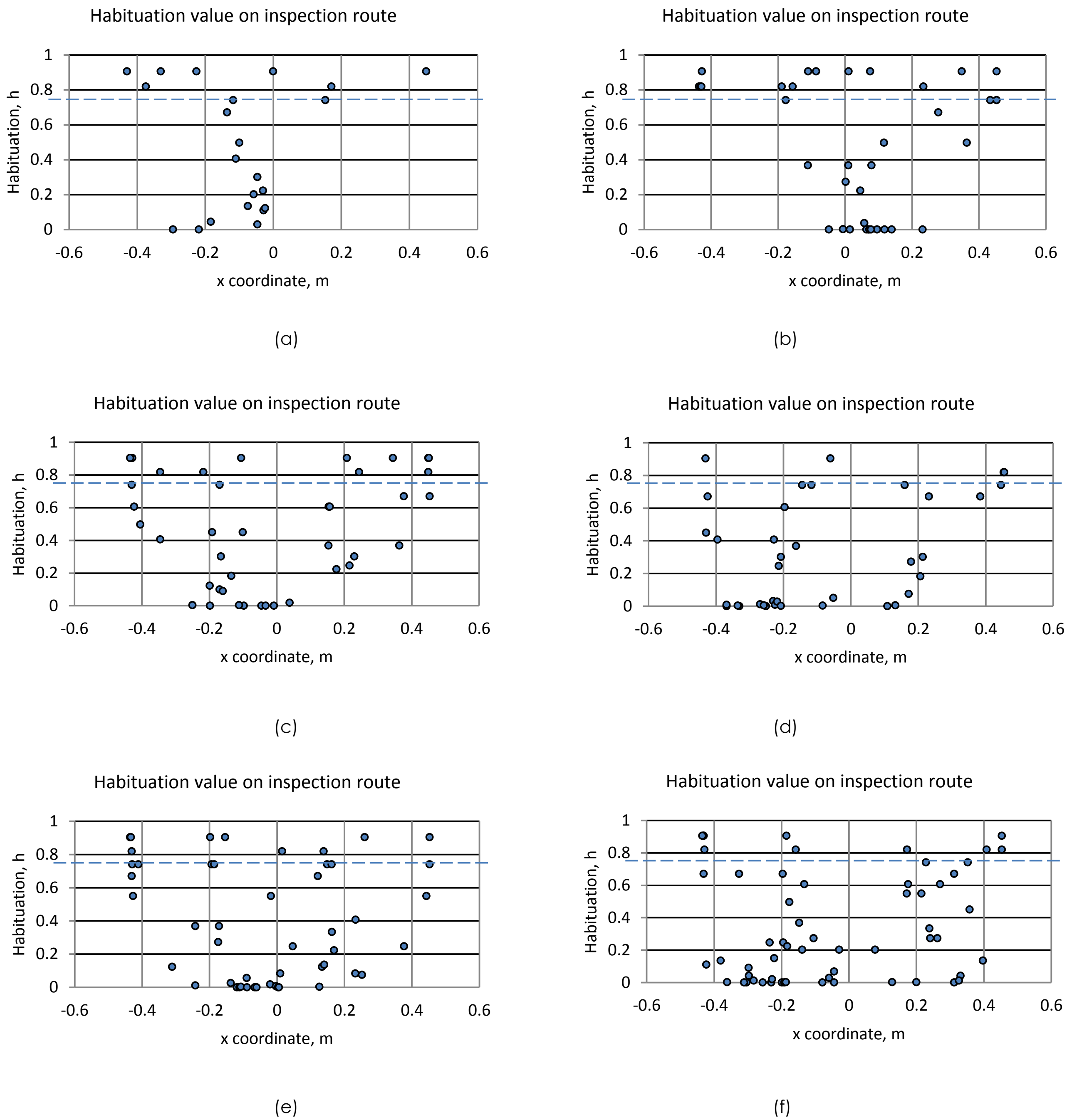
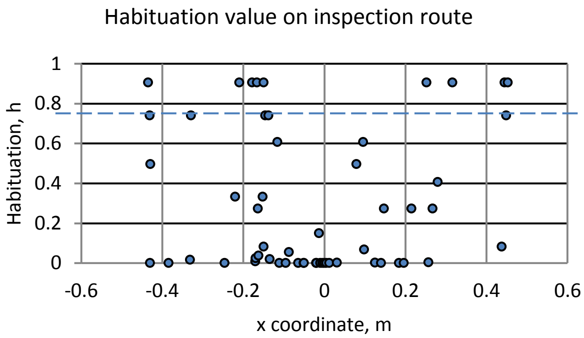
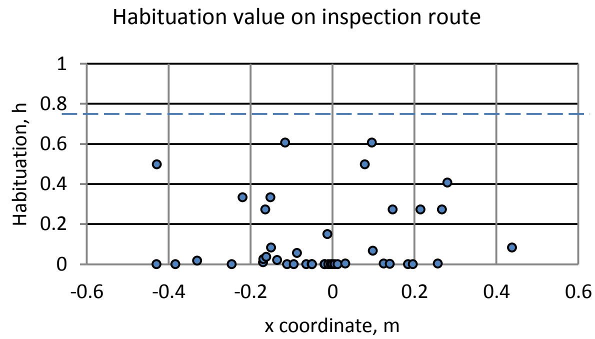


Figure 5 (a) A look at habituation value of all neurons after the first run where 22 neurons are created. The dotted blue line indicates the novelty threshold. (b) After 8 runs at learning rate = 0.1, neurons become more habituated where their habituation values continuously decreasing after several training runs. The number of neurons also increases to 38 neurons and their position changed. (c) After 8 runs at learning rate = 0.01, the number of neurons created is 43. Notice that all area are represented by neurons. Not all neurons are habituated. (d) After 8 runs at learning rate = 0.001, the number of neurons created is 37. Notice that all area are represented by neurons. More neurons are habituated when compared to the others. (e) After 18 runs at learning rate = 0.01, the number of neurons created is 50. Notice that all area are represented by neurons. More neurons are habituated when compared to the others. (f) After 18 runs at learning rate = 0.001, the number of neurons created is 59. Notice that all areas are represented by neurons. More neurons are habituated when compared to the others



(a)



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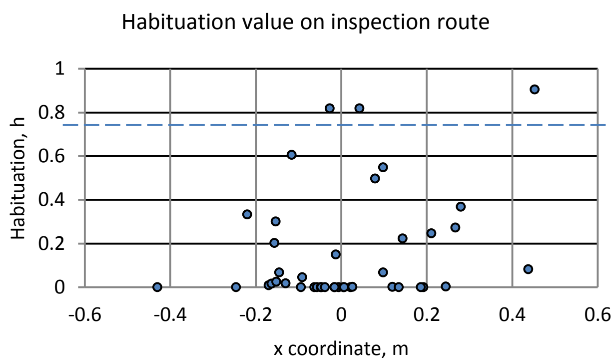

(c)

Figure 6 (a) After 18 runs at learning rate = 0.01, with neighboring habituation function turned on (b) The forgetting function unhabituated and remove anomalous neuron (c) Inspection using learned neuron from Figure 6 (b). New boxes are positioned on 0m and 0.4m of the x-axis. New neurons are created near 0m and 0.4m indicating detection of unknown object

To reduce the unhabituated neuron problem, neighboring neurons that are similar to the best matching neuron is habituated. The selection of neighboring neuron is done by finding the Euclidean distance between the best matching neuron and all the other neurons. If the distance between them is less than neighborhood threshold, *n,* the neuron is categorized as neighboring neurons. All neighboring neurons are habituated like the best matching neuron. Figure 6(a) is the result of network with learning rate of 0.01 and 18 runs with the neighborhood habituating function. The percentage of unhabituated neuron has lowered from 34% to 25%.

Upon further investigation on the reading of the unhabituated neuron, noisy sensor reading also play a major role in creating anomalous neuron. This problem can be overcome by using a more reliable sensor. On top of that, the network should also have the capacity to remove anomalous neuron by forgetting anomalous event as proposed by Marsland *et al*. [8]. By using this approach, all anomalous neuron is removed as shown in Figure 6(b).

Finally, the trained network is tested on the second environment. As expected the network was able to highlight the newly introduce boxes it their respected position as shown in Figure 6(c).

4.0 CONCLUSION

From the results, we can conclude that spatial HSOM network is a feasible method to learn spatial normalcy for novelty detection purposes. The limitation of the method is that since spatial information becomes part of the input vector of the HSOM network, the position information can be changed and the mapping is not exact. This is evident when the learning rate is high where the neuron position changed by an unacceptable distance. This can be solved with proper tuning of the network parameters. In the future, more simulations and experiments will be conducted to test the robustness of the method and to understand the influential factors that affect the performance of the method. On top of that, a new approach to associate temporal information with a neuron will be further investigated.

Acknowledgement

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