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To cite this article: M N A H Sha'abani et al 2013 IOP Conf. Ser.: Mater. Sci. Eng. 53 012018

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Hierarchical Self Organizing Map for Novelty Detection using Mobile Robot with Robust Sensor

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Abstract. This paper presents a novelty detection method based on Self Organizing Map neural network using a mobile robot. Based on hierarchical neural network, the network is divided into three networks; position, orientation and sensor measurement network. A simulation was done to demonstrate and validate the proposed method using MobileSim. Three cases of abnormal events; new, missing and shifted objects are employed for performance evaluation. The result of detection was then filtered for false positive detection. The result shows that the inspection produced less than 2% false positive detection at high sensitivity settings.

1. Introduction
Novelty detection is a process of identifying abnormalities in an environment. It has been widely used in several fields [1-3]. Recently, there are interests of novelty detection on mobile robot such in [4-6], which generally errands as surveillance and inspection application. The problems of training a robot for novelty detection are sensor error and the inconsistency localization of robot during training and inspection. This will affect the detection performance.

S. Marsland et. al [4] using habituation Self Organizing Map (SOM) to detect novel objects by measuring the novelty level of the same measurements. This work does not concern on locating the novel object. J. Fleischer and S. Marsland [6] then overcome the problem by using landmark categorization. Then, A. Gopalakrishnan et al. extracting salient features to detect landmark for novel position estimation [5]. However, these works are not locating novelty with respect to the robot location.

M.F. Miskon and A. Russel [7] using Flexible Region Map to compare the current and normal measurements based on habituating self organizing map. In this work, the consideration of robot heading for training and inspection is only for 0, 90, 180 and 270 degrees with a 10 degree of tolerance. The result shows that the robot was able to locate the novelty. However, by fixing the heading angle of robot for measuring data, it seems that the robot will lose information for any heading angle that is out of the angle range.

This paper presents a framework of the novelty detection mechanism that learns measurement data and associate the data to the robot pose. The work focuses on developing a mobile robot to act as an inspection agent in an indoor environment. The objective is to make the robot autonomously adapt to normal perception while considering sensor measurement error and localization error.

4 Corresponding Author.
This paper is organized as follows. First, the overview of the system is discussed. Then, the proposed novelty detection architecture is presented. This is followed by a detailed explanation of the research methodology. The simulation results are given in the next section and finally a conclusion is provided.

2. System Overview
The system is divided into two parts; mobile robot navigation system and novelty detection system. Six sonar sensors are used. The sensor array covers 180 degrees of scan area. The robot uses wall following algorithm to imitate a patrolling task and particle filter method for localization. A Repetitive Observation Strategy (ROS) [8] is used for observation where detection of anomaly is confirmed only if a repeated observation occurs. Data processing composed of novelty detection mechanism, clustering and false positive filter. Figure 1 shows the overview of the hierarchical novelty detector system.

![Figure 1. Overall system consisting of mobile robot and novelty detection system.](image)

3. Novelty Detection Mechanism
The novelty detection mechanism consists of hierarchical Self Organizing Map and statistical parameters; mean and variance. The architecture of novelty detection mechanism is shown in figure 2.

3.1. Self Organizing Map
SOM is an unsupervised neural network which has a capability in competitive learning. The importance of competitive learning in this network is to determine which neuron represents the robot pose at a certain place. The weight will keep updating and the network will keep growing if required until the training is stopped. Equation (1) shows how the neuron’s weight is updated,

$$w_y(t+1) = w_y(t) + \alpha(t)h_y(t)[v_y(t) - w_y(t)]$$

where $w$ is the weight vector for a neuron, $\alpha$ is the learning rate, $h$ is the neighbourhood function and $v$ is the input vector. The neuron’s weight vector is updated by three processes; competitive, cooperative and adaptive process [9]. In a competitive process, the neuron with the closest weight vector, $w$ to the current input $v$ will be chosen as a winner and updated. The cooperative process allowed the neighbouring neuron of the winning neuron also to be updated but with fewer amounts based on the neighbourhood function, $h$. The adaptability of the network to the input pattern is based on the value
of learning rate, \( \alpha \). The learning process is stopped when there are no significant changes in the network.

### 3.2. Statistical Parameters

The error of sensor measurement is depending on the distance measurement and angle of detection. To handle this problem, the statistical parameters of the measurement at a specific robot pose were calculated. The mean and variance is calculated using a single pass algorithm as shown in equation (2) and equation (3),

\[
\begin{align*}
    u_n &= u_{n-1} + \frac{x_n - u_{n-1}}{n} \\
    s_n^2 &= \frac{(n-2)s_{n-1}^2 + (x_n - u_n)(x_n - u_{n-1})}{n-1}, \quad n > 1
\end{align*}
\]

where \( x_n \) is the new input, \( u_n \) and \( s_n^2 \) is the new mean and variance of total number of samples, \( n \).

![Figure 2. The hierarchical novelty detection mechanism consists of three networks where each network has their own role in the determination of normalities.](image)

### 4. Methodology

The algorithm was tested using MobileSim simulator. MobileSim is a mobile robot simulator with ARIA platform. Figure 3 shows the environment setup and route plan for the robot to perform inspection. The robot was tested in three cases of novelty; presence of new objects, missing object and shifted object. Each of the case was trained by 10 times of complete rounds.

**4.1. Data collection**

By referring to figure 3, the robot was initially positioned at point ‘Start’ and run through the environment using wall following behaviour. As the implementation of ROS, data are collected for every 100 millimetres of robot movement until the robot reaches at point ‘End’. After each complete round, the robot was positioned again at the starting point.

**4.2. Training network**

The collected data was then fed into the network. A batch of data for each measurement \( V(i) = \{x_i, y_i, \theta_i, s_{i1}, \ldots, s_{iL} \} \), is separated into three parts; robot position, \( (x_i, y_i) \), orientation, \( \theta_i \),...
and sensor measurements, \((s_{i1}, \ldots, s_{ik})\) where \(k\) is the number of sensors used. The initial learning rate, \(\alpha\) was set to 0.2 for the first network and 0.01 for the second network. The initial radius of neighbourhood function, \(h\) for each network are 1000 mm and 1 degree. The network is trained within 10 times of complete round using offline learning.

4.3. Inspection
Initially, the robot was positioned at point ‘Start’. The inspection was done by moving the robot along the same path of training route. Along the inspection, the robot was trying to identify any changes of measurement based on the Euclidean distance method.

4.4. Anomaly detection
The identification of anomaly measurement is depending on the difference of mean and current measurement at specific pose. The first layer of network fined the best match of neuron with the current position of the robot. Then, the second layer is searching the best match of neuron for orientation. After the robot pose was confirmed to be matched from the previous training, the third layer was acting as the anomaly detector by comparing the current measurement for each sensor with its average measurement during training. If the difference is larger than the threshold value, it is classified as an anomaly. If the pose of the robot does not match to any neuron in the network, the current measurement is also classified as an anomaly.

4.5. Clustering
Clustering is a process of separating and grouping of unlabelled data set based on similar features. The similarity measure of anomaly is the distance between two anomaly points. By using equation (4), the distance can be expressed as

\[ r = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \]  

where \(r\) is the Euclidean distance between two anomaly points. The similarity measure can be set using a threshold value called maximum allowable distance, \(d_{max}\). This threshold was set by referring the resolution of measurement taken (100mm/input data). Any anomaly point that has distance lower than this threshold from its neighbour is grouped in the same group.

4.6. Filtering
Filtering is a process of rejecting untrusted detection. In this research, filtering process is done based on Singleton Filter method [8]. Any cluster containing only one anomaly point was simply rejected.

4.7. Environmental setup

By referring figure 3, it is mentioned that the object C is the subject of abnormalities. The summarization of environmental setup for the simulation is shown in table 1.

<table>
<thead>
<tr>
<th>Novelties</th>
<th>Condition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Missing</td>
<td>Normal: Present</td>
</tr>
<tr>
<td></td>
<td>Abnormal: Absent</td>
</tr>
<tr>
<td>Exist</td>
<td>Normal: Absent</td>
</tr>
<tr>
<td></td>
<td>Abnormal: Present</td>
</tr>
<tr>
<td>Shifted</td>
<td>Normal: Present</td>
</tr>
<tr>
<td></td>
<td>Abnormal: Shifted</td>
</tr>
</tbody>
</table>

*The novelty is referred to the object C.*

4.8. Parameters setup

The sensitivity setting of anomaly identification was varied from low to high by adjusting the different threshold of current and normal measurement. The purpose is to observe the relationship between true positive rate and false positive rate of the system, thus the performance of the system.

4.9. Performance parameters

Based on the Receiver Operating Characteristics (ROC) curve, there are four possibilities of detection outcomes; true positive, false positive, true negative and false negative detection. True positive detection occurs when the system was correctly identified an anomaly. If a normal measurement was detected by the system as an anomaly, it is a false positive detection. True negative is a classification for a normal detection, whereas false negative is a wrong classification of an abnormal as a normal. For false detection classification, a tolerance boundary of true positive region is created by considering the sensor and localization error. About 100mm of boundary around the surface of novel object was created as shown in figure 4.

5. Results

A sample of simulation results is shown in figure 4. The analysis of novelty detection performance is done after the robot finished a complete round of inspection.
Figure 4. Sample result of simulation for a present of new object at 0.75 sensitivity settings. The figure shows the result for before and after using Singleton Filter. As seen in figure, any single clustered member was rejected. Even some of the single cluster in the true positive region also rejected, the true positive rate is still significant to the performance of novelty detection.

By referring to figure 5, it can be seen that the performance for missing and exist cases are almost the same, so as the accuracy. For both cases, there are no significant changes on true positive rate at a false positive rate higher than 0.1 but the accuracy of the novelty detection performance reduces as the increment false positive rate. This means that, the higher the sensitivity settings, the occurrence of false positive detection also higher, thus producing high false alarm.

However, the result for shifted object case is unacceptable because the true positive rate and false positive rate are changing closely at the same rate. One of the reasons for this occurrence is because only small changes occurred in the environment. Only the best performance of this case may occur at the centre of the curve (0.5, 0.5). However, by considering the accuracy of detection, the result is unacceptable.
Table 2 shows the summarization result for all three cases of novelties. Note that the value of true positive rate and false positive rate for unfiltered and filtered are taken at the beginning of the higher true positive rate.

Table 2. Unfiltered and filtered results using the Singleton Filter of missing exists and shifted of novelties.

<table>
<thead>
<tr>
<th>Novelties</th>
<th>Unfiltered</th>
<th>Filtered</th>
<th>Percentage reduce (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>TP rate</td>
<td>FP rate</td>
<td>TP rate</td>
</tr>
<tr>
<td>Missing</td>
<td>0.97619</td>
<td>0.01033</td>
<td>0.92857</td>
</tr>
<tr>
<td>Exist</td>
<td>0.97619</td>
<td>0.01119</td>
<td>0.95238</td>
</tr>
<tr>
<td>Shifted</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The result of this case is unacceptable.

6. Summary and Conclusion
Novelty detection aims a performance of high true positive rate and low false positive rate of detection. However, it is a trivial task to implement it using a mobile robot. Thus, this paper proposed a method that handling both localization and perception error based on hierarchical Self Organizing Map and statistical approach. Based on the simulation results, it can be concluded that the mechanism is able to detect changes in its environment. For missing and exist cases, a high true positive detection was produced at more than 97% with a lower false positive detection (less than 2%). Furthermore, the implementation of Singleton Cluster reduces the false positive rate by 4% and true positive rate by 1%. Missing a few single clusters in true positive region does not affect the overall performance of detection. For future work, the algorithm will be implemented using an Amigobot mobile robot.

7. References