A Repetitive Observation Strategy for Recognizing a True Anomaly and Estimating its Position

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Abstract

For many surveillance situations, the use of mobile robots has several advantages over static sensors. One of the advantages is that immediate action or investigation can be undertaken when an anomaly is detected. This paper presents a surveillance mobile robot that uses novelty detection. In this project, a neural network is trained to remember the normal measurements of the robot sensors, and highlight any discrepancies from the normal encountered during the inspection period. The contribution of this paper is a new approach to estimating the possible location of the detected anomaly using sensors which provide directional information. The method reduces the number of false alarms by taking into account the location where sensor measurements are made and not just their value. This paper presents details of the method and experimental results demonstrating its application.

1 Introduction

Surveillance using mobile robots provides several advantages over static sensors alone. One important benefit is that it allows immediate action to be taken, such as performing further investigations regarding the anomaly. Due to robot mobility, sensors with a limited sensing range or sensors which are sensitive to detection angle can be taken closer to or oriented towards the vicinity of the suspected anomaly. This allows the robot to perform further inspection using close range sensor systems such as the mobile robotic electromagnetic sensor system in [Miskon and Russell 2007] and the mobile robotic gas sensor system described by Lilienthal, et al. [Lilienthal, et al. 2001].

For these reasons, we are currently developing a surveillance mobile robot that can position itself closer to a detected anomaly. In order to do this, the robot needs to first detect and then estimate the position of the anomaly. Then the robot can move to the estimated position of the anomaly and perform further investigations. However, the detection of anomalies is not a trivial task. A surveillance system that is not sufficiently sensitive will leads to a high rate of false negative detections (inability to detect true anomalies). On the other hand, if the system is too sensitive, many false positive detections (detecting an anomaly when the situation is actually normal) will occur. The usefulness of the system depends on producing a high percentage of detections that represent a true anomaly. In our application, false positive detection will cause the robot to waste its time and energy moving and reacting to it.

There are many methods that reduce the number of false positive detection. Usually, the problem is tackled at the machine learning level [Neto and Nehmzow 2005; Singh and Markou 2004; Crook and Hayes 2001; Dipanker and Forrest 1996]. Some also reduce false positive detection by using a rule based approach [Fumera, et al. 2000]. Others improve performance by combining machine learning and rule based approach sequentially to achieve better results such as the work by [Nagel, et al. 1998]. However, the most suitable approach for any system very much depends on the application of the method itself [Markou and Singh 2003a]. For example, the strategy proposed in this paper requires active observation from different point of view. Active observation requires the ability to move sensors to different positions. Mobile robots have this capability thus make the strategy suitable for mobile robot applications.

In the animal kingdom, when responding to unusual perception, a biological system always confirms its senses before taking further action. This is done either by gathering more information from other types of sensors or by simply performing repeated sensing using the same sensor. Usually, the repetition of sensing is done from a different angle and position [Dusenbery 1992]. In order to save energy, the animals will only react to repeated anomaly detection. Motivated by this effective behaviour, in this paper we propose a method to reduce false alarms by taking advantage of the mobility of a mobile surveillance robot. The method works by measuring the number of anomalies detected in a particular area, using data gathered from sensor measurements made at different robot positions.

This paper is organized as follows. Section II describes the proposed method in detail. Section III presents experimental results. Finally, discussion and conclusions are presented in Section IV.

2 Method

2.1 Hardware

The work presented in this paper is part of a surveillance mobile robot development project using novelty detection and a number of different types of sensors. For the mobile robotic platform, we use a Pioneer 3 mobile robot manufactured by ActivMedia Robotics (see Figure 1). It has built in odometry that is used for localization. The robot is also equipped with a Hokuyo URG 400 laser range finder with 0.35° bearing resolution and a scanning range of 270^{o}. The laser can measure objects up to a distance of 4000 mm.

The robot also carries a Young TS8000 series anemometer, which is used to measure the air velocity and airflow direction as well as ambient temperature. The robot is also equipped with a TGS2600 chemical sensor that measures the concentration of combustible gas molecules. Other sensors that are installed on the robot include an ambient light sensor, a tilt sensor, humidity sensor and an object surface temperature sensor.

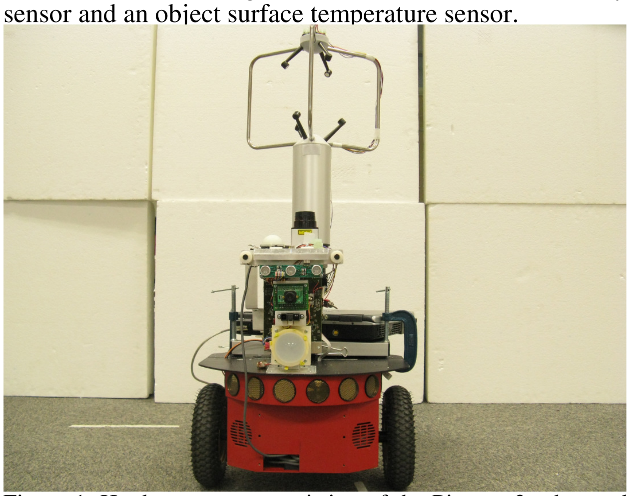


Figure 1. Hardware setup consisting of the Pioneer 3 robot and its sensors.

2.2 System Overview

The system can be viewed as having two parts i.e. novelty detection and the Repetitive Observation Strategy (see Figure 2). Novelty detection is performed by the Regional Habituatable Self Organizing Map or RHSOM which is described in Section 2.3. The contribution of this paper is in the second part and consists of the Repetitive Observation Strategy (ROS) method. This is composed of the anomaly observation and anomaly evaluation methods.

2.3 Mobile Robot Surveillance Using a Novelty Detection Approach

Novelty detection is the identification of unusual data that varies from the norm. With respect to our surveillance system, the robot is first trained to learn the normal state of its environment. Then during the actual inspection period, the robot compares its new sensor measurements with what it has learned, and highlights any unusual measurements. There are a lot of different approaches available for novelty detection [Markou and Singh 2003a; Markou and Singh 2003b]. However for this project, we employ a method from our previous work namely the Regional Habituatable Self Organizing Map or RHSOM. The RHSOM reduces false negative detection when implementing the method for the surveillance mobile robot application. At the same time, it can autonomously adjust the amount of storage required to map normal sensor measurements gathered in the robot's environment.

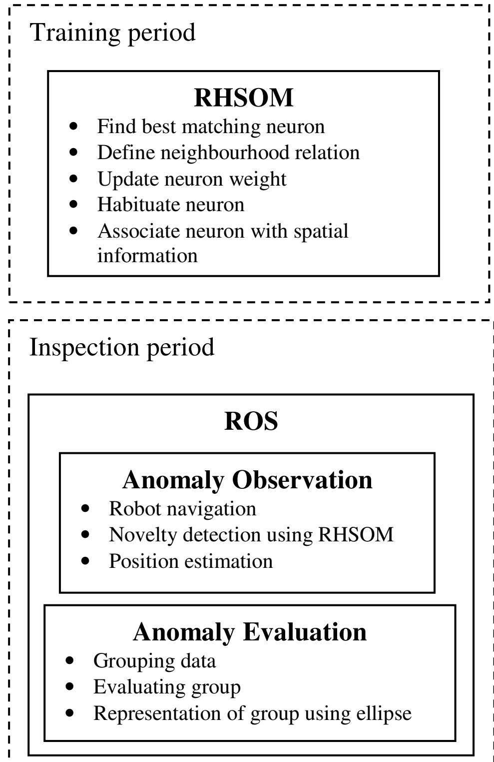


Figure 2. Overall system overview.

The RHSOM uses the Habituatable Self Organizing Map (HSOM) method to train the robot to autonomously learn normal sensor measurements gathered from the environment. The use of HSOM can be considered as having four phases. The first three phases are the phases required to train a Self Organizing Map (SOM) neural network. In the first phase of training the SOM network, an input measurement is compared with all neurons to find the best matching neuron (BMU). Then in the second phase, a neighbourhood relation between the BMU and other neurons is defined. In the third phase, all neuron weight vectors are updated using a predefined adaptive rule.

In the HSOM, each neuron is associated with a novelty measure, which shows how frequently the neuron fires. Following the normal training process for a SOM, the HSOM is realized by adding a fourth phase i.e. habituation, which is to update the novelty measure of each neuron using a predefined updating equation. The HSOM is described in detail in [Marsland, et al. 1999].

The HSOM method learns what is normal in terms of sensor measurements from the whole robot surveillance environment. However it does not take into consideration the position of the robot when taking each measurement. The disadvantage of not knowing the actual position of the robot is that the HSOM is unable to distinguish between similar measurements taken at different locations.

RHSOM overcomes this problem by further associating the fully trained HSOM neuron with spatial information. The neuron which represents the normal sensor measurement taken at a particular position is mapped onto the area/region where the measurement is taken. During inspection, the robot first determines which area it currently occupies. The robot then compares its current sensor measurement with the normal neurons of the area. The RHSOM is described in detail in [Miskon and Russell 2009].

2.4 Estimating Anomaly Position Using Sensors Giving Directional Information

A robot can estimate the vicinity of a detected anomaly by using the types of sensor that provide directional information. In this project, we use a laser range finder. As shown in Figure 3, the laser scan is divided into 8 regions. Each region consists of 85 laser scan points. The distance measurements within each region are averaged and become the input measurement vector which consists of 8 average distance values representing each scan region.

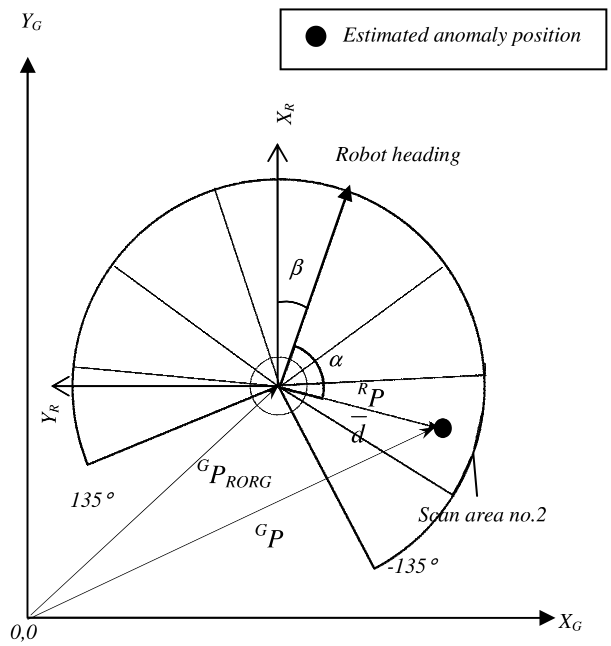


Figure 3. The laser scan is divided into 8 regions where scan area no. 2 is shown to have the highest dissimilarity (between the BMU and input measurement). The vector $\bar{d}$ carries the directional information and average distance value of the detected anomaly. The laser range finder is located closed to the centre of the robot and is indicated by the position of the robot, $^GP_{RORG}$.

During the inspection period, the robot performs its inspection task using RHSOM. When an anomaly is detected from its laser range finder measurements, the robot finds which of the scan areas gives the highest dissimilarity. The approximate direction of the anomaly, (α) with respect to the robot heading is determined from the angle of the centre of the scan area to the robot heading, (β).

The distance to the vicinity of the anomaly (d) depends on whether the anomaly highlighted is due to a missing object or the appearance of an unusual object. The actual distance measurement resulting from a missing object should be longer than the distance measurement of the related normal neuron. In contrast, the appearance of an unusual object makes the actual distance measurement less than the distance in the normal neuron. Using this assumption, the estimated distance (d) to the anomaly can be determined as shown in (1) where d_i is the distance measured during inspection and d_n is the distance of the normal neuron.

$$d = \begin{cases} d_i & , d_i < d_n \\ d_n & , d_i > d_n \end{cases} \tag{1}$$

By using the direction and distance to the anomaly, the estimated anomaly detection point in the global map, ^GP can be determined using (2).

$$\begin{aligned} {}^Gp_x &= p_{x\_RORG} - d\sin(\alpha+\beta) \\ {}^Gp_y &= p_{y\_RORG} + d\cos(\alpha+\beta) \end{aligned} \tag{2}$$

2.5 Clustering anomaly points

Clustering is the process of partitioning a dataset into subset or groups [Duda, et al. 2001]. In this project, clustering is used to group estimated anomaly detection points based on their distance from each other. Each anomaly detection point is detected during a different inspection cycle i.e. at a different time and robot position. Assuming that an anomalous object is static, the robot should observe it many times during successive inspection cycles; as long as the anomaly is within the detection range of the sensor (see Figure 4). Several characteristics that are used to recognize an anomaly from false positive detections are:

1. Repetitive observations of the anomaly should produce many anomaly detection points.
2. The points should be closely grouped together.

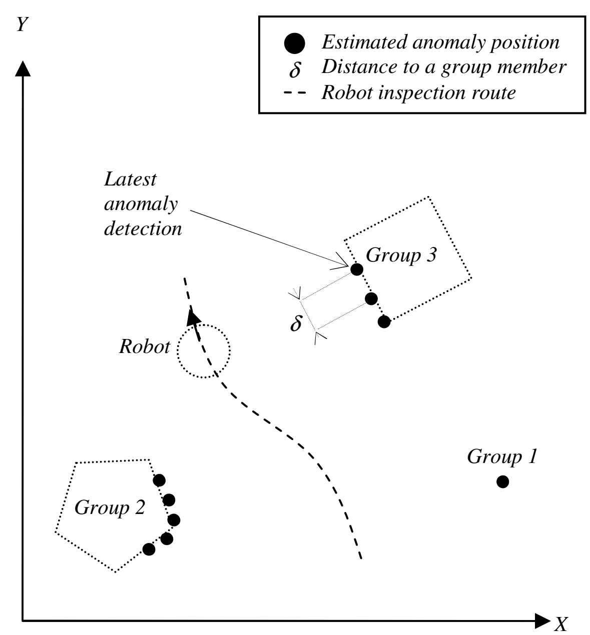


Figure 4. The robot observes anomalies from different positions on its route. The detection point that forms Group 1 is from a false positive detection.

For this reason, we have developed an on-line clustering technique to group anomaly points based on the distance from the latest input to any existing group member, δ. The minimum neighbour distance parameter, $\delta_{\max}$ determines the maximum allowable distance between group members. The algorithm of the clustering method is as follows:

```
Get_latest_detection_position( );
For_all_member_in_all_group{
  If ( δ < δmax ){
    Membership = Join_group (latest_detection_position);
    Break;
  }
}
If ( !Membership ) {
  Create_new_group (latest_detection_position);
}
```

2.6 Representing the Vicinity of the Anomaly using a Vicinity Ellipse

The spread of the estimated anomaly points is mainly due to measurements being taken from different points on the anomalous object. This happens because the laser measurements are taken from different positions along the inspection route (see Figure 5). By assuming that the mean of the distribution represents the centre of the anomaly, we can analyse the distribution statistically using a covariance matrix and vicinity ellipse.

The vicinity ellipse uses the concept of an error ellipse. An error ellipse is used for representing the standard deviation of multi dimensional data. However, for our application, rather than representing error, the ellipse is used to represent the vicinity of an anomaly. For that reason, we named it the vicinity ellipse. The properties of the ellipse serve a number of purposes for our method including:

1. The angle of the ellipse, θ: Provides information about the projection of the anomaly.
2. The major and minor axes of the ellipse, *a* and *b*: Provide information about the projection and the shape of the anomaly or the shape of part of the anomaly.
3. The perimeter of the ellipse: Provides navigation guidelines when the robot performs close range inspection.

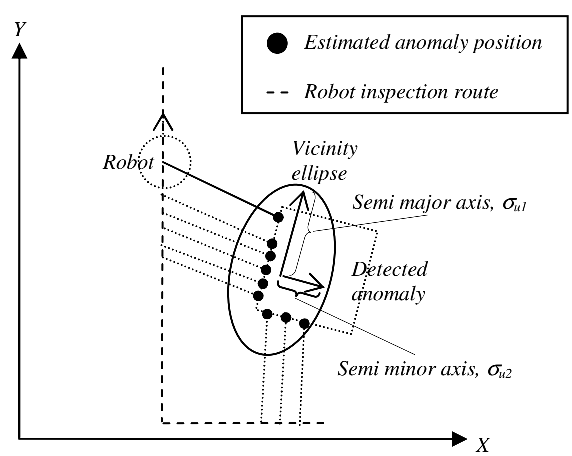


Figure 5. The vicinity ellipse created from collected data of anomaly positions in the global map.

The covariance matrix Σ as shown in (3) can be created using the estimated anomaly point data for each of the groups created by the clustering process. We can construct the vicinity ellipse (see (4) and (5)) from the covariance matrix. The angle of the ellipse θ is calculated using (4) to which there are 2 solutions, 90° apart. The semi major axis, σ_{u1} and semi minor axis, σ_{u2} of the ellipse can be calculated by substituting both solutions of θ into (5).

The equation of the ellipse in parametric form is shown in (6), where μ denotes the mean of *X*, υ denotes the mean of *Y*, θ is the direction angle of the ellipse (the major axis angle) and *t* is restricted to the interval of $-\pi \le t \le \pi$.

$$\Sigma_{xy} = \begin{vmatrix} \sigma^2{}_x & \sigma_{xy} \\ \sigma_{xy} & \sigma^2{}_y \end{vmatrix} \tag{3}$$

$$\theta = \frac{1}{2}\tan^{-1}\left(\frac{-2\sigma_{xy}}{\sigma^2{}_x - \sigma^2{}_y}\right) \tag{4}$$

$$\sigma^2{}_u = \sigma^2{}_x \sin^2(\theta) + 2\sigma_{xy}\sin(\theta)\cos(\theta) + \sigma^2{}_x \cos^2(\theta) \tag{5}$$

$$\begin{aligned} x &= \mu + \sigma_{u1}\cos(t)\cos(\theta) - \sigma_{u2}\sin(t)\sin(\theta) \\ y &= \upsilon + \sigma_{u2}\sin(t)\cos(\theta) + \sigma_{u1}\cos(t)\sin(\theta) \end{aligned} \tag{6}$$

2.7 Discriminating Factors to Determine a True Anomaly Detection

1. The number of points in a group/ellipse.

We believe that repeated detection of an anomaly over a compact area is the key for ensuring true detection. Thus an ellipse should contain more than a single anomaly detection point. In fact, the bigger the number of anomaly detection points forming an ellipse, the higher the probability of having detected a true anomaly. We assume that the estimated anomaly points that are derived from false alarms are distributed randomly over a wide area. Because of this, the wide spread of the false positive anomaly detection points should prevent them from forming a group.

2. Ellipses close to one another.

If the maximum neighbour distance parameter, $\delta_{\max}$ is set too small, it might be unusual to form a big group. Instead, many small groups will be formed. Nevertheless, these small groups will be in close proximity with each other for the case of detecting a true anomaly.

Based on these factors, the robot can have a measure of confidence that the ellipse truly presents an actual anomaly. Only if the robot is highly confident of detecting a true anomaly should it commit the effort required to move towards the vicinity of the detected anomaly and perform further investigations.

3 Experiments

The experiment was conducted in a corridor environment in Building 36, Monash University (Clayton campus). During the training and inspection period, the robot navigated using wall following and determine its position using odometry. To avoid accumulated odometry error, we manually corrected the robot position every 2 meters of travel. This is done by limiting the distance of travel using the autonomous wall following by a maximum of 2 meters for each continuous run. A real corridor environment was used to challenge the robot with real world data.

The objectives of the experiments are:

1. To observe the effect of changing RHSOM sensitivity and changing the maximum neighbour distance parameter to the number of anomaly detection points in a group.
2. To evaluate the performance of the RHSOM and the performance of RHSOM with ROS when they are tuned to various parameter settings.

3.1 Procedure

First of all, the robot was trained to learn normal sensor measurements in its environment. The sensor measurements are the 8 values of the average distance measurement from the laser range finder as describe in Section 2.4. As depicted in Figure 6, the robot navigated autonomously from point A to point B using the wall following algorithm. While travelling between the two points, it took distance measurement using its laser range finder and recorded its heading and current position at each 100 mm step. All of the measurements were logged. The process was repeated five times during the period that the environment was considered to be in its normal state. The process was also repeated several times while part of the environment was changed and therefore unusual. The environment settings during the normal and unusual situations are summarized in Table 1.

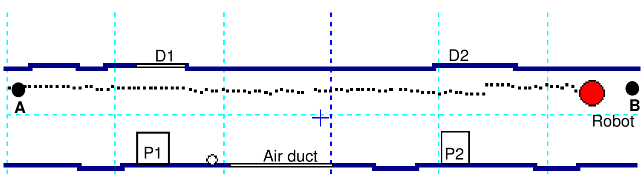


Figure 6. State of the robot's environment in its normal state. Door D1 was normally both closed and open while door D2 was always closed.

Table 1. Environmental settings during the experiments.

		Situation	
		Normal	Unusual
States	Door 1, D1	Closed or Open	Open
	Door 2, D2	Closed	Open
	Box	Missing	At P1
	Rubbish bin	Missing	At P2

Following the data logging process the logged data was used to train the HSOM network in an offline process. In order to train the network, first K mean clustering [Duda, et al. 2001] was applied to the logged data in order to initialize the weight vectors of the neuron so that they lie along the principal component of the data. Then the HSOM neurons were trained using data from the five runs. After training, the HSOM network was able to represent different patterns seen along the corridor and recognized which input patterns were normally seen.

In the next step, the position where the robot took the measurement was associated with the normal neurons that were trained previously. This step was done following the RHSOM method where normal neurons were mapped into regions. After the RHSOM network was trained, the robot was ready to perform the inspection task.

During the inspection period, the anomaly estimation algorithm was tested using the logged data which represented environment settings that were either normal or unusual. The number of ellipses that highlighted a true anomaly or a false anomaly was counted in the different situations listed in Table 1. Then by referring to the example in Table 2, the true positive rate, *TPR*, the false positive rate, *FPR* and the false negative rate, *FNR* were calculated using (7), (8) and (9).

Table 2. An example of how *FPR* and *FNR* are calculated.

Does the anomaly exist?		Actual state	
		Yes	No
Measured state	*Yes*	A	B
	No	C	D

$$TPR = \frac{A}{C + A} \tag{7}$$

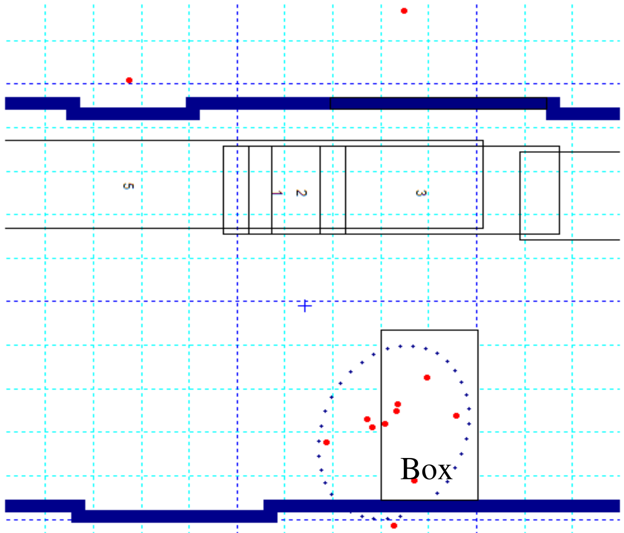
$$FPR = \frac{B}{B + D} \tag{8}$$

$$FNR = \frac{C}{C + A} \tag{9}$$

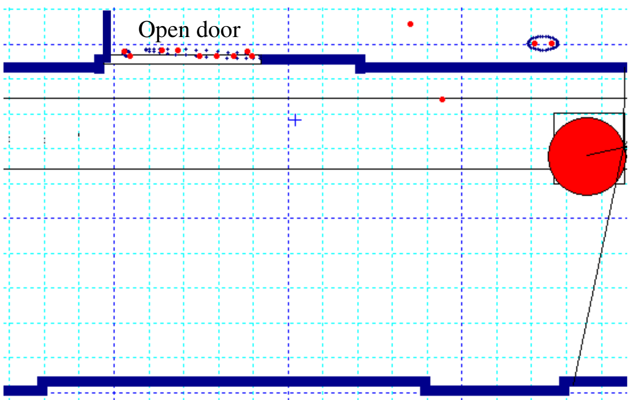
The experiments were repeated with different values of maximum neighbour distance parameter $\delta_{\max}$ (see Section 2.5) and the maximum SOM neighbourhood size parameter, d_{SOM}. The maximum distance parameter determines the size of a cluster. Changing the maximum SOM neighbourhood size parameter adjusts the sensitivity of the RHSOM network. We compare the performance of RHSOM coupled with ROS and the performance of RHSOM without ROS using the Receiver Operating Characteristic (ROC) analysis. An ROC graph depicts the trade off of having true positive and false positive when changing the sensitivity settings of the system [Fawcett, 2004].

3.2 Results

As we can see from Figure 7, the estimated anomaly points that are enclosed by an ellipse represent the detection of a true anomaly. Estimated anomaly positions which have no neighbours are categorized as false anomalies. In Figure 7 (a), we can see that some of the estimated anomaly points appear to be on the far side of the wall and others inside the box. This is mainly due to the fact that the laser measurements are taken as average readings over a certain scan region as mention in Section 2.4.



(a) A normally empty space is occupied by a box.



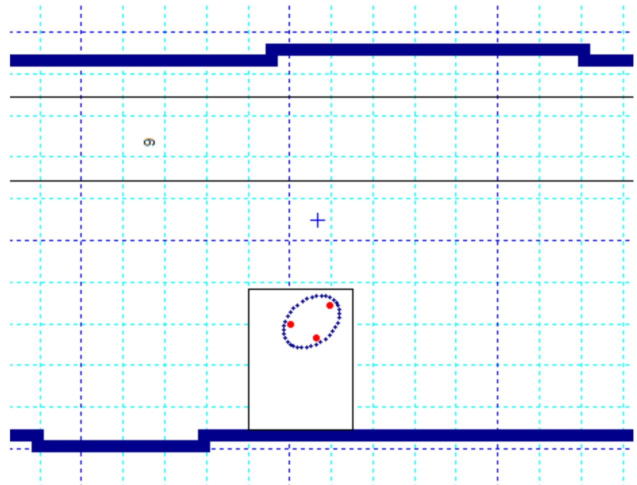
(b) A normally closed door is open during inspection.

Figure 7. Examples of detection results using the Repetitive Observation Method. The clustering process groups nearby estimated anomaly points (the red dots) and represents the groups using ellipses.

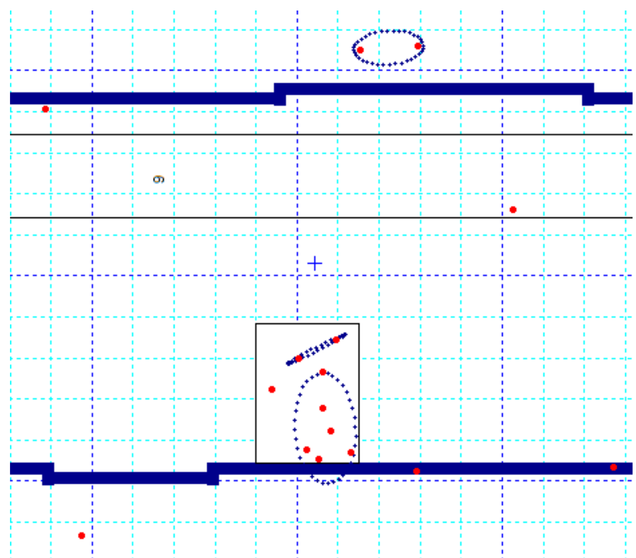
One of the objectives of the experiment is to observe the number of estimated anomaly points per group for true positive detection and for false positive detection. We want to see the effect of adjusting the RHSOM to different sensitivities on the number of points representing a group. This was done by adjusting the RHSOM's neighbourhood size parameter, d_{SOM}. RHSOM has a higher false positive detection rate when this parameter is tuned to a higher sensitivity.

As shown in Figure 8, by increasing the sensitivity of the novelty detection system, more ellipses are created that do not actually represent a true anomaly. However, the number of points in an ellipse that represents a true anomaly also increases. The number of ellipses within/near the vicinity of the anomaly increases and sometimes they overlapped each other. All of these factors can be used to further discriminate between a true anomaly and a false positive detection. In all cases, our assumption that a single anomaly point with no repeated observations means a false positive detection was proven to be correct.

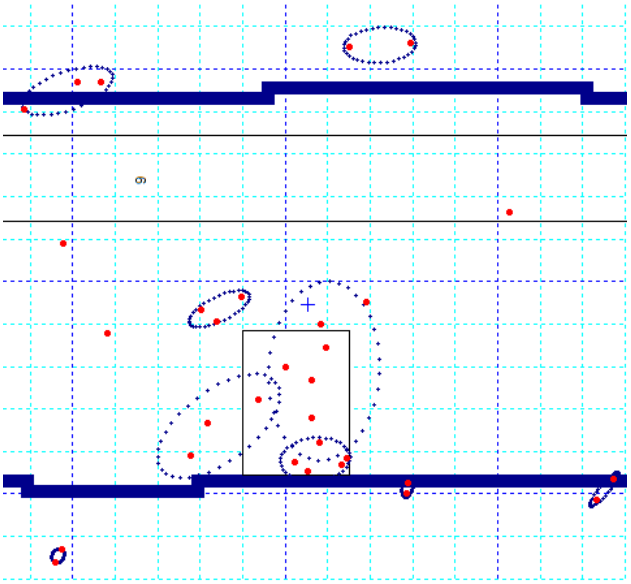
We performed a further investigation to see the effect of changing the maximum neighbour distance parameter δ_{max}. By using the same high sensitivity setting (d_{SOM} = 0.05), we change δ_{max} to 3 different settings (see Figure 9 and Figure 8 (c)). In Figure 8 (c), δ_{max} is set to 300 mm. From the result we can see that the higher the value of the maximum neighbour distance, the larger the groups become. However, the ellipses that do not represent a true anomaly do not change much due to a small number of neighbouring points. Based on our observations, the number of anomaly points within an ellipse rarely exceeds 3 points for a false positive detection. This is true even when RHSOM is set to its highest sensitivity and the δ_{max} for the clustering is set to a very large distance.



(a) Low sensitivity (d_{SOM} = 0.15).

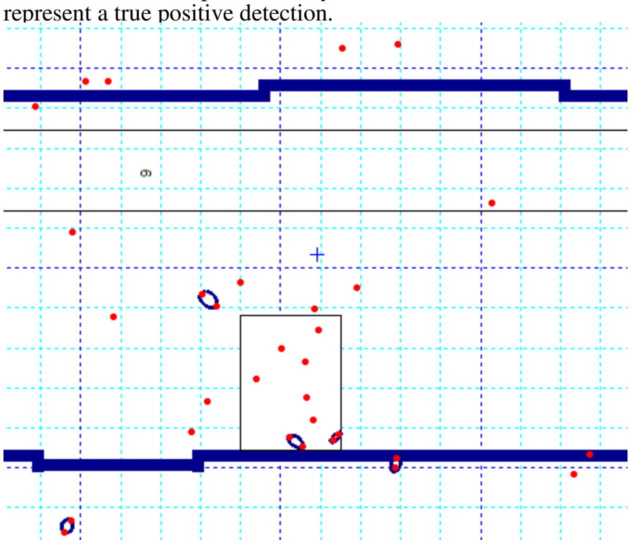


(b) Medium sensitivity (d_{SOM} = 0.10).

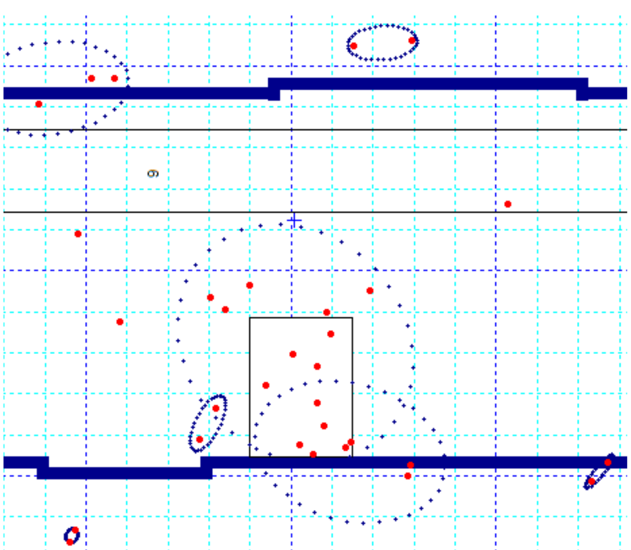


(c) High sensitivity ($d_{SOM} = 0.05$).

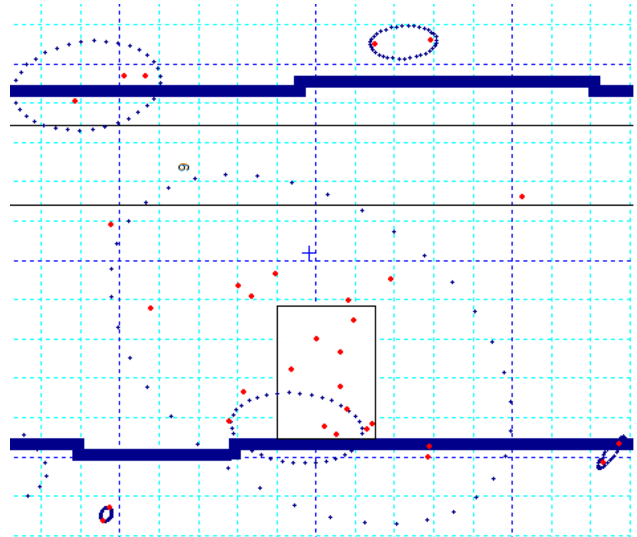
Figure 8. Different RHSOM sensitivity tuning. The anomaly points are represented by the red dots. The ellipses created near the rubbish bin represented by the box are considered to represent a true positive detection.



(a) Small group ($\delta_{max} = 100$mm).



(b) Medium group ($\delta_{max} = 400$mm).



(c) Large group ($\delta_{max} = 600$mm).

Figure 9. The maximum neighbour distance parameter δ_{max}, affects the size of the groups formed.

By considering that only groups with more than 3 units represent a true anomaly, the performance of the method is shown by using the receiver operating characteristic (ROC) analysis as shown in Figure 10. We can see from the figure that the Repetitive Observation Strategy (ROS) puts a limit on the RHSOM false positive rate.

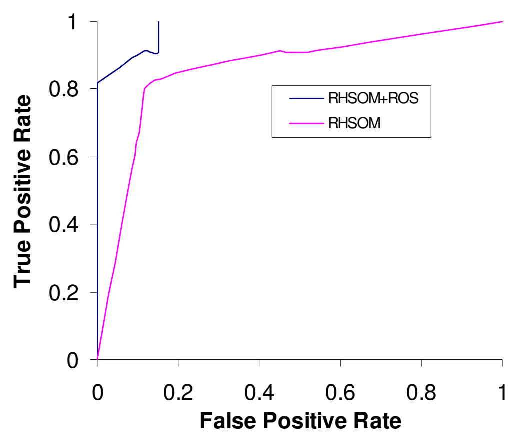
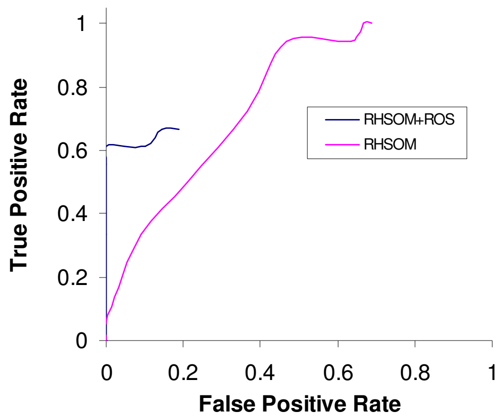
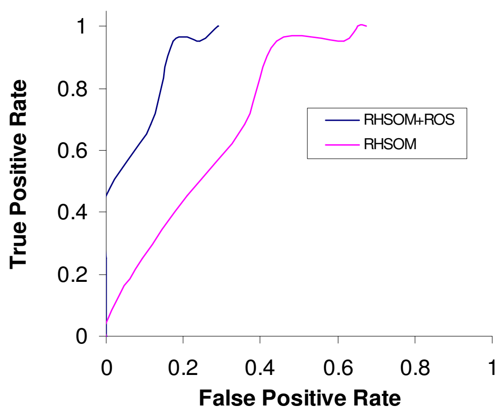


Figure 10. Comparison on a ROC curve of the RHSOM and RHSOM with ROS.

Tests using a different scenario shows the effect of selecting a bigger cluster size. As we can see in Figure 11 the performance of RHSOM with ROS is affected by the selection of small group size ($\delta_{max} = 300$mm). When the group size was increased (($\delta_{max} = 500$mm), an improvement in the true positive rate is achieved. Nevertheless, we should stress that the system was still able to recognize the anomaly object use in the experiment when using a small group size setting (see the two ellipses in Figure 12 (a)).

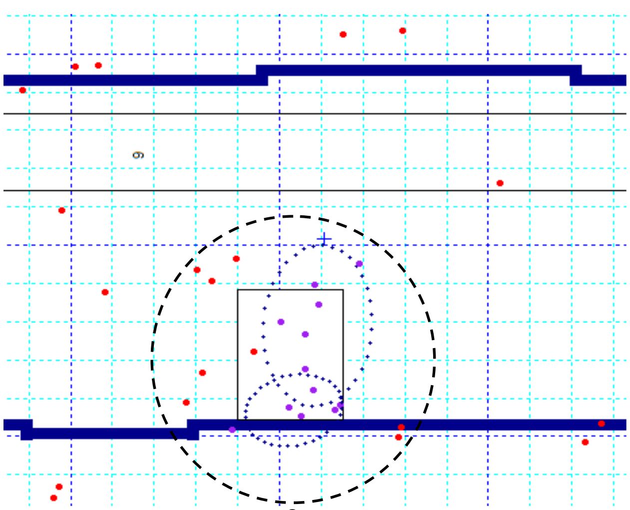


(a) Small/Medium group (δ_{max} = 300mm).

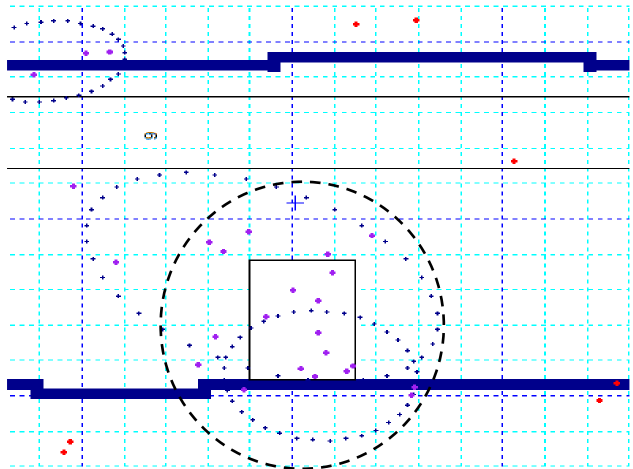


(b) Large group (δ_{max} = 500mm).

Figure 11. Comparison using a ROC curve for the RHSOM and RHSOM with ROS when using different group sizes.



(a) Small/Medium group (δ_{max} = 300mm). Many of the true positive detections near the anomaly object (represented by the red dots) are not near enough to be grouped together. Despite that, two ellipses were still formed to indicate the presence of the anomaly object.



(b) Large group (δ_{max} = 500mm).

Figure 12. Estimated anomaly position is considered as a true detection if its distance from the anomaly object is within the radius of 300 mm represented by the dashed circle.

4 Conclusion

We have presented the Repetitive Observation Strategy (ROS), which is a new method to reduce false alarm during surveillance using a mobile robot and a laser range finder. The method works by taking measurements repeatedly from different robot position to ensure the true presence of anomaly.

The experimental results show that ROS improve the performance of RHSOM. The advantage of implementing ROS is it allows a novelty detection system to be tuned to a higher sensitivity. This means that the novelty detection system is able to detect a true positive anomaly while maintaining a low false alarm rate. Since ROS is implemented during the inspection period, it can be coupled with any novelty detection approaches.

One drawbacks of using ROS is that it adds another parameter to the system that must be adjusted i.e. the maximum neighbour distance parameter δ_{max}. However, with a good observation data and correct tuning, ROS increases the overall performance of the RHSOM. Moreover, since anomaly points are now being analysed collectively, the robot will not be overwhelmed by all of the false positives detected by the RHSOM.

Currently the robot does not actively observe detected anomaly. Instead, it just takes measurements following its programmed navigation route. Nevertheless, the angle and position of the sensor are still changes with respect to the detected anomalous object position. In the future, ROS will be further developed to actively observe detected anomalous objects by performing action based on the robot current perception.

Other proposed future work includes developing the navigation strategy for inspection at close range making use of the ellipse parameters and also the application of the method to a wider range of sensors.

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