Object Detection and Localization Using Wireless Sensor Networks Based On Probabilistic Model

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الخلاصة

استخدمت شبكة الاستشعار اللاسلكية على نطاق واسع لرصد حيث يتم نشر أجهزة الاستشعار للعمل بشكل مستقل إلى الشعور الظواهر غير طبيعية. وقد صممت معظم أنظمة رصد الأجسام المقترحة استنادا إلى نطاق استشعار محدد سلفا لا يعكس موثوقية أجهزة الاستشعار وخصائص الكائن وظروف البيئة. قياس قدرة عقدة جهاز استشعار للكشف بدقة عن جسم متحرك داخل الاستشعار عن أهمية كبيرة لتطبيقات المراقبة. يقدم هذا البحث آلية فعالة للكشف عن الكائنات والموقع استنادا إلى نموذج الاستشعار الاحتمالي. وقد عرضت نماذج مختلفة نظريا في هذا البحث لدراسة قابليتها وتطبيقها على تطبيقات البيئة الحقيقية. وأظهرت النتائج العددية للتقييم التجريبي أن نموذج الاستشعار الاحتمالي يوفر مراقبة دقيقة وقابلية للتخلص من الكائنات، ويمكن استخدامه لسيناريوهات مختلفة للبيئة.

ABSTRACT

Wireless Sensor Network (WSN) has been widely used for monitoring where sensors are deployed to operate independently to sense abnormal phenomena. Most of the proposed objects monitoring systems are designed based on a predetermined sensing range which does not reflect the sensor reliability, object characteristics, and the environment conditions. Measuring of the capability of a sensor node to accurately detect a moving object within a sensing is of great important for surveillance applications. This paper presents an efficient mechanism for object detection and localization based on probabilistic sensing model. Different models have been presented theoretically in this paper to examine their adaptability and applicability to the real environment applications. The numerical results of the experimental evaluation have showed that the probabilistic sensing model provides accurate observation and delectability of objects, and it can be utilized for different environment scenarios.

Keywords: *Wireless Sensor Network (WSN), Surveillance and Monitoring, Object Detection and Localization*

1 INTRODUCTION

The advancing technologies of Micro-Electro-Mechanical Systems (MEMs) and communication protocols helped in the emerge of wide-scale Wireless Sensor Networks (WSNs) where a lot of sensor nodes connected for a specific monitoring purpose [١]. Sensor nodes are capable of operating autonomously, sensing the surroundings, processing the sensed data, reporting to and communicating with the interested unite [٢]. Therefore, WSNs have been utilized for several operations in military and civil domains, including surveillance, monitoring, and management [٣]. One of the effective functions of WSNs is the object detection and alerting. The application aims at detecting an exceptional behavior of an object and sending the sensed data to a specific stationary sink for processing, analysis, and management where detection is further verified [٤-5]. Applying certain recognition technique can help in determining the legitimacy of the moving object. In such application, a number of sensor nodes are set up within a particular area for monitoring the movement of an object of interest. The object can be human, animal, or vehicle, to name a few. According to the measurements of the monitoring and observations of group of sensor nodes close to the object, the localization of the object can be accurately. This paper focuses on detecting the emergence of individual mobile objects that are discretely appear in the sensing field based on a proper sensing accuracy function that represents different scenarios, and examines how well the object can be detected by a sensor. The concept is used in the proposed solution to accurately localize the presence of an object where the stationary sink collects all the sensed data from the sensor nodes observing the object. The rest of the paper is organized as follows: Section 2 reviews the most related works. The concepts of the proposed detection and localization mechanism are introduced in Section 3. Section 4 presents the experimental evaluation to validate the proposed mechanism. Finally, Section 5 concludes the paper and lays groundwork for potential future works.

2 Related Works

This section discusses some of the most related research works on monitoring and detection in WSN. There are many WSN monitoring and detection systems proposed in the literature concerning moving object detection and modeling. Objects detection is essential for other advanced applications including target tracking and classification and behavior learning [٦]. There are three main methodologies for moving object detection where most of the research works in this domain utilize; they are optical flow, frame difference and background subtraction [٧]. The major techniques for detection modeling are median filter linear prediction, single Gaussian background model, mixed Gaussian background model, kernel density estimation [٨-12]. These techniques have inherent limitations such as hollow space, streak phenomena, stretched moving objects; and offer low detection accuracy because of the changing light and noise parameters. In the same context, Sankari and Meena [١٣] proposed dynamic background subtraction method for detecting object in noisy environment. it combines statistical assumptions of moving objects depending on the previous frames in a noisy condition that dynamically varying. However, it has poor anti- interference ability and sensitive to the environment changes. S.Rakibe and D.Patil [١٤] proposed a background subtraction-based mechanism detect moving object from a static background scene to detect moving object based on. A reliable statistical background updating model was set up for that purpose. Morphological filtering and contour projection analysis were applied to remove the noise and the effect of shadow. Their mechanism had showed a strong adaptability; however, complete outline of moving object is difficult to be obtained, which results in inaccurate detection of the moving object. Huang et al. [١٥] proposed a motion detection technique based on radial basis function artificial neural networks that can precisely detect moving object in dynamic and static scenes. Nevertheless, it is not appropriate for real-time occasions as it suffers from high calculation overhead and sensitivity to noise.

3 Theoretical Modelling of the Proposed Probabilistic Object Detection and Localization Mechanism

This section presents the theoretical modelling of the proposed probabilistic object detection and localization mechanism.

Essentially, the current object detection models are designed based on a binary detection model where sensor placement plays a significant role [١٦-26] .In the binary model, where a fixed sensing radius is considered, sensor node *i* certainly detects an object *o* over the monitoring area, if its distance *d* to the object is less than its sensing radius *r*. However, this is considered as a rough approximation as the object detection typically depends on different variables and inference methods used to confirm on the accuracy of the detection. To have a better approximation, a probabilistic sensing accuracy model according to the Euclidean distance between the sensor node and the object at point *p* should be considered in every sensor node.

In most of object monitoring applications in WSNs, sensor nodes probabilistically activate themselves for sensing. The distance between sensor node and a specific point where the object appears is presented as a linear function which is inversely proportional to the sensing accuracy such that the probability of the sensing accuracy P(S_i) of sensor node *i* is:

$$P(S_i) = 1/(1+ \lambda * d(i,p)^K \quad \ldots\ldots\ldots\ldots\ldots\ldots(1)$$

where d(i,p) is the Euclidean distance between sensor *i* and an event (such as an object) at a specific point *p*, and λ and K are specific sensing technology parameters where λ is an adjustment parameter and that K varies from 1 to 4.

The sensing accuracy probability can also be inversely proportional to tan exponential function of the distance specified by:

$$P(S_i) = o^{-(\lambda * d(i,p))} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

Furthermore, the sensing accuracy probability can be an integrated model of linear and exponential functions with lower and upper limiting thresholds (thr_{low}, thr_{up}), such that:

$$P(S_i) = \begin{cases} 1, & d(i,p) < thr_{low} \\ 0, & d(i,p) > thr_{up} \\ \lambda\, o^{-(k*d(i,p))}, & thr_{low} < d(i,p) < thr_{up} \end{cases} \quad \ldots\ldots\ldots\ldots(3)$$

Although the sensing accuracy probability model presented in Equation (3) is more rational compared to the ones in (1) and (2), however, it has limited applicability. To have more boundless model, the sensing accuracy probability to detect an object should be as in Equation (4) below:

$$P(S_i) = \lambda\, \delta^{-(K*d(i,p))^a} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots(4)$$

where:

- λ is the detection accuracy parameter that indicates the maximum probability with which the object *o* is certainly detected by sensor node *i*, such that $0< \lambda \le 1$; that is, when d(i,p) =0 , then λ =1 .
- δ and *K* indicate the vertical and the horizontal location parameters respectively, where δ >1 and K>0 . A probability distribution can be formed based on reference point (a point that is used to define a location of another point) that is can be defined by (d_r (i, p_r) , P_r (S_i)) . It means that when an object *o* appears at d_r (i, p_r) distance away from a sensor node *i*, the probability with which the object is

detected is $P_r(S_i)$. Hence, making K $d_r(i, p_r) = 1$, would result in $P_r(S_i) = \lambda\, \delta^{-1}$, which help in selecting a reference point ($d_r(i, p_r)$, $P_r(S_i)$) .by determining the location parameters according to Equations (5) and (6) below:

$$\delta = \lambda * (P_r(S_i))^{-1} \quad \text{……………………(5)}$$

$$K = d_r(i, p_r)^{-1} \quad \text{…………………………(6)}$$

- α is a positive parameter ($\alpha > 0$) that indicates the sharp (or smooth) decrease of the sensing probability, from λ to 0, with respect to d(i,p) . If it is required to designate that at specified distance d' (i,p) , the accuracy sensing probability is $P'(S_i)$, the α should be set as follows:

$$\alpha = \log d_{K* d'(i,p)} \log_\delta (\lambda / P'(S_i)) \quad \text{……..(7)}$$

where d' (i,p) must be greater than $d_r(i, p_r)$, and $P'(S_i)$ must be less than $P_r(S_i)$, and vice versa.

As mention earlier, for a sensing accuracy model that is based on a fixed radius, a sensor node would definitely sense any object appears within its sensing radius, such that:

$$P(S_i) = \begin{cases} 1, & d(i,p) < r \\ 0, & \text{otherwise} \end{cases} \quad \text{……………….. (8)}$$

Sensing field (*SF*) is coverage of a WSN at any point *i* (p_i) is defined as the probability of a sensor detecting the object at that point.

$$SF(p_i) = 1 - \prod (1 - P(S_i)) \quad \text{………………(9)}$$

where SF(p_i) is the sensing coverage at specific location (p_i), and P(S_i) is the sensing probability of sensor node *i* at p_i of the sensing field.

Sensing Field Coverage C(SF, p_i) is that the sensing field SF is the efficient sensing measures at a at specific location (p_i) from all sensor nodes in the field. If there are *n* sensor nodes, the total contribution of detection functions of each node, which reflects the coverage of sensing field at point p_i , is:

$$C(SF, p_i) = \sum_1^n (S_i, p_i) \quad \text{…………….(10)}$$

4 Validation

The validation of the proposed probabilistic object detection and localization mechanism is done via thorough experimental evaluation using simulation. This section presents the scenario and settings used in the experimental evaluation followed by the discussion on the results gained from the simulation experiments.

4.1 Evaluation Scenario and Settings

A WSN of 800 sensor nodes were simulated using Network Simulator 2 (ns-2) on a computing machine running CentOS version of Linux. The sensor nodes are randomly deployed on a sensing field of on a 200 × 200 m 2. This means that the uniform density of the sensor nodes is 0.02 sensors per m 2. The sensing range for each sensor node is 20m while the transmission (communication) range is 100m that allows sensors to report their sensed data directly to a centralized base station that is located at the center of the sensing field. The corresponding parameters of the detection accuracy model were initially set as follows; $\lambda = 1$ (i.e.100% object detection), $\delta = 2$, K=0.1 (i.e. 50% detection of an object at 20m), and $\alpha = 4$.

The experimental evaluation considers the effect of each parameter (the detection accuracy parameter λ, the vertical location parameter δ, the horizontal location parameter K, and the sensitivity decreasing parameter α) with respect to node density which ranges from 0.1 to 0.6, and in comparison with the fixed radius-based sensing accuracy model where r=20m.

4.2 Results and Discussion

4.2.1 The effect of the detection accuracy parameter λ

This parameter indicates the sensor sensing accuracy. As there is no certainty in a real environment that a sensor node always detects a moving object due to some limitation of the sensor measurement and the object nature and behavior, this parameter is evaluated for various values where λ =1, λ =0.8, λ =0.6, respectively. This means that when d(i,p) =0 , the sensing accuracy probability $P(S_i)$ to detect a moving object is 1.0, 0.8, and 0.6, respectively. Figure 1 presents the results of the effect of the sensor sensing accuracy in terms of the average number of detection observations and the sensor node density at a point location where the object is sensed. The figure shows that when λ =1, the results of the average detection observations are almost statistically identical to that of the fixed radius-based sensing accuracy model. From the figure, it is noticeable that the proposed probabilistic sensing accuracy mechanism has higher detection accuracy confirming that greater inconsistency is captured by the proposed mechanism. Also, the figure shows, for different values of λ as the node density increases, the average number of detection observations increases, where at density value of 0.04, the detection observations for the cases when λ =1 and λ =0.8 are closed. (see appendix, figure 1)

4.2.2 The effect of the vertical location parameter δ

The vertical location parameter δ describes the probability P r (S i) of detecting an object at a reference point d r (i, p r) . This parameter is evaluated with different settings where δ =1/0.6 , δ =1/0.7 , and δ =1/0.8 , respectively. This implies that the probability with respect to the reference point at distance d_r (i, p_r) is 0.8, 0.7, and 0.6 respectively. It is clear that the probability is increasing as the parameter δ decreases. This means that the probability of the sensing accuracy is higher when the distance is d_r (i, p_r) . Such behavior is clearly confirmed by the results shown in Figure 2. (see appendix)

4.2.3 The effect of the horizontal location parameter *K*

The horizontal location parameter expresses the distance d r (i, p r) to the reference point from a sensor sensing an object. This parameter is evaluated for different values where K=25 , K=20 , and K=15 . This implies that the distance to the reference point is 25m, 20m, and 15m, respectively. From the results illustrated in Figure 3, if K value is decreased, then the distance d_r (i, p_r) is increased. This means that a distant sensor node has higher probability to detect the moving object. (see appendix, figure 3)

4.2.4 The effect of the sensitivity decreasing parameter α

This parameter reflects the decreeing tendency of the probability of the sensor sensing accuracy with respect to d(i,p) . This parameter is examined under various values where α =3 , α =5 , and α =8 , as shown in Figure 4. Increasing the value of α would result in a sharp decrease in the sensing accuracy probability. From the results in the figure, it is clear that the higher value of α drives the proposed probabilistic model to follow the fixed range one, where the results are almost identical for α =8 and d_r (i, p_r) =r=20m for different node densities. (see appendix, figure 4)

5 Conclusion and Future Work

This paper presented an efficient mechanism that is based on a probabilistic sensing accuracy model which is presented in the context of detection and localization of objects in a particular monitoring area using wireless sensor networks (WSN). To adapt to different environment scenarios, the proposed mechanism involves four parameters which are: detection accuracy parameter λ, vertical location parameter δ, horizontal location parameter K, and sensitivity decreasing parameter α. The capability of sensing accuracy model is evaluated under different settings for the aforementioned parameters and in comparison with the common predetermined radius-based model, considering the detection observation with respect to sensor node density. The results showed that the proposed mechanism can be used for wide range of monitoring applications and scenarios and it can help in controlling the sensing coverage and node density. In the future work, we are focusing on the prediction of the future direction and course of the targeted object. The concept of object detection presented in this paper will be utilized to build an efficient and reliable object tracking system.

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Appendix

Parameters Figures

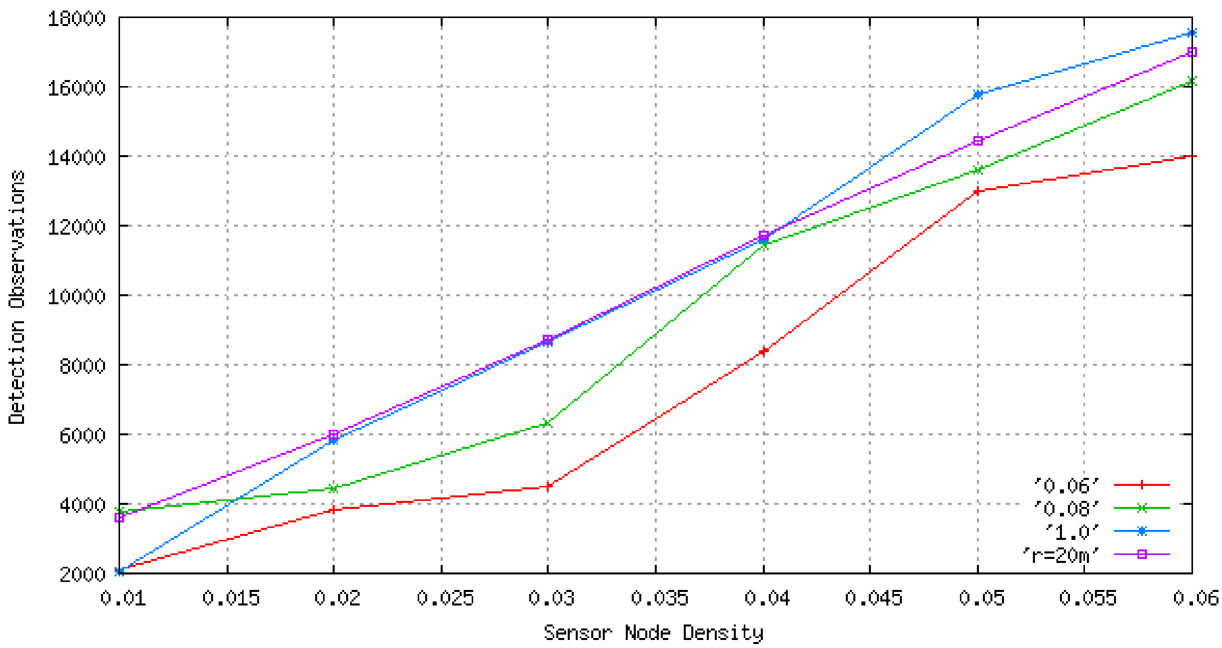

Figure 1: The effect of the detection accuracy parameter λ , for λ =1 , λ = 0.8 , λ =0.6

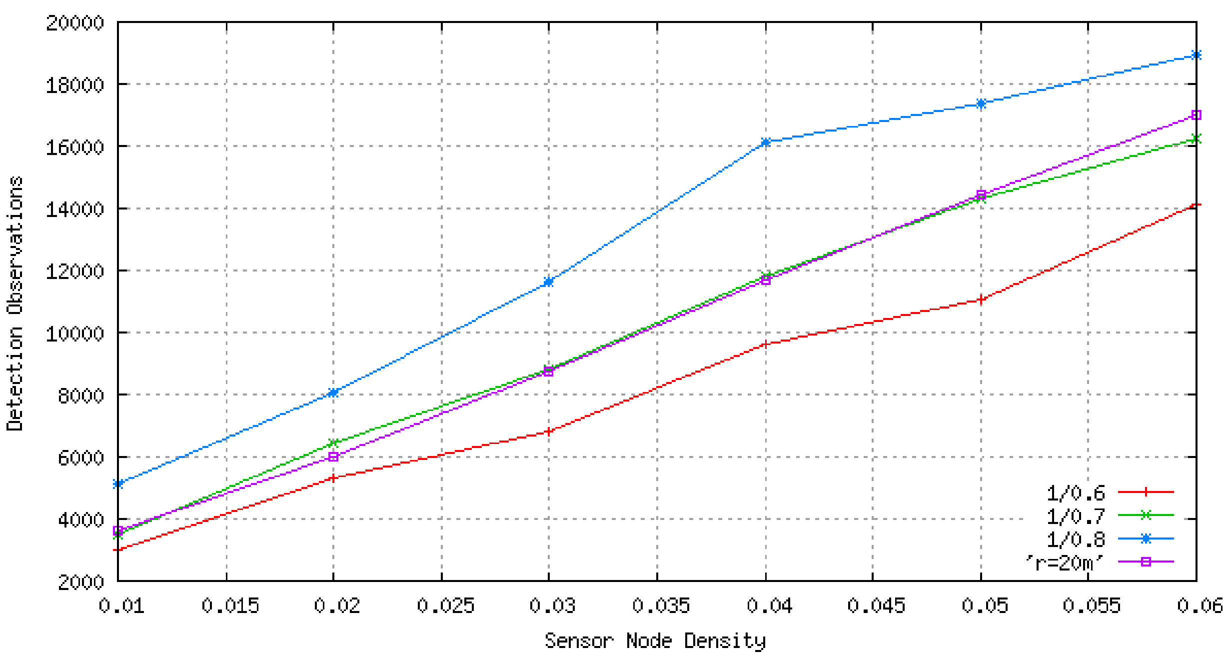

Figure 2: The effect of the vertical location parameter δ for δ =1/0.6 , δ =1/0.7 , δ =1/0.8

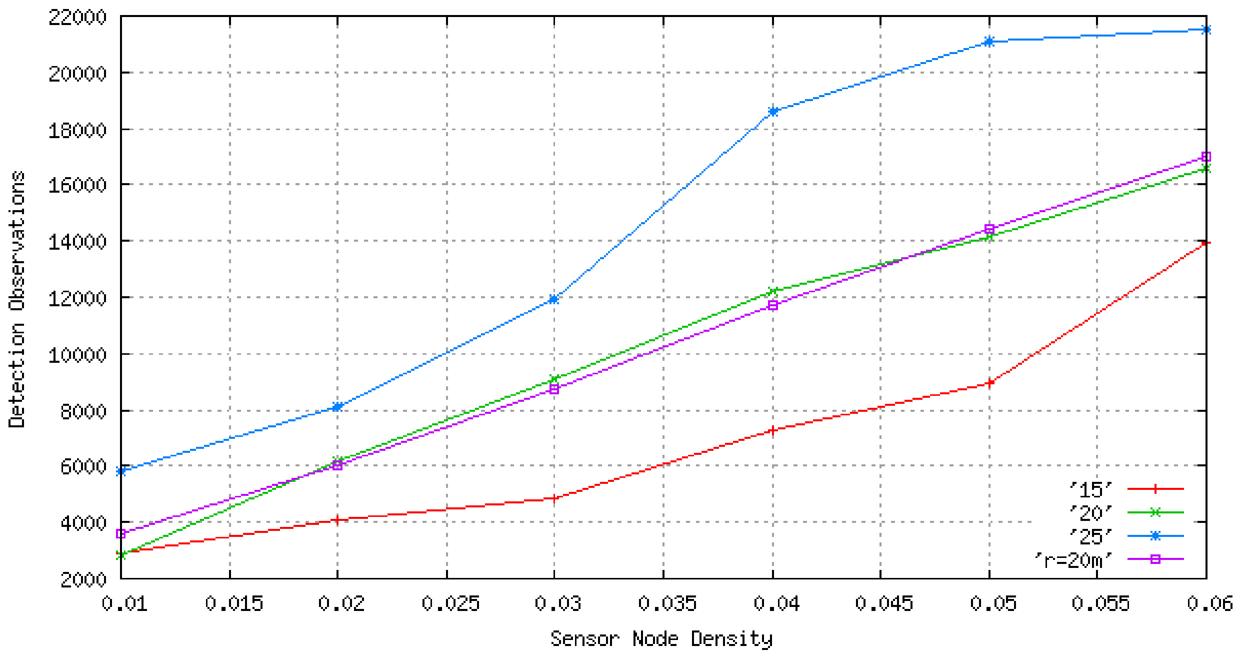

Figure 3: The effect of the horizontal location parameter *K*, for K=25, K=20, K=15.

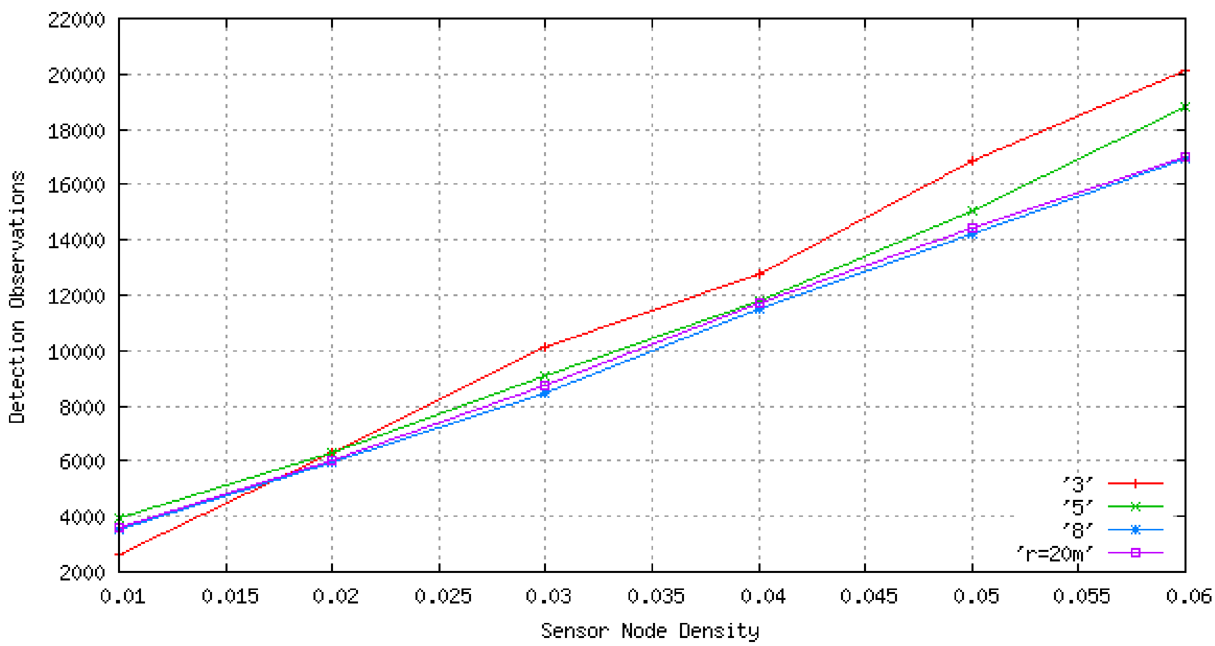

Figure 4: The effect of the sensitivity decreasing parameter α