RESEARCH ARTICLE | SEPTEMBER 06 2017

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AIP Conf. Proc. 1872, 020009 (2017)
https://doi.org/10.1063/1.4996666

Dynamic Sensing Model for Accurate Delectability of Environmental Phenomena using Event Wireless Sensor Network

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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 environmental monitoring systems are designed based on a predetermined sensing range which does not reflect the sensor reliability, event characteristics, and the environment conditions. Measuring of the capability of a sensor node to accurately detect an event within a sensing field is of great important for monitoring applications. This paper presents an efficient mechanism for even detection 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 an event, and it can be utilized for different environment scenarios.

I. 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 [4]. Sensor nodes are capable of operating autonomously, sensing the surroundings, processing the sensed data, reporting to and communicating with the interested unite [11]. Therefore, WSNs have been utilized for several operations in military and civil domains, including surveillance, monitoring, and management [14]. One of the effective functions of WSNs is the event detection and alerting. The application aims at detecting an exceptional environmental phenomenon and sending the sensed data to a specific stationary sink for processing, analysis, and management where detection is further verified [3] [2]. Applying certain recognition technique can help in determining the type of the event. In such application, a number of sensor nodes are set up within a particular area for monitoring the evolution of an event of interest. The event can be re, smoke, or gas leak, to name a few. According to the measurements of the monitoring and observations of group of sensor nodes close to the event, the localization of the even can be done accurately. This paper focuses on detecting the occurrence of an environmental events that are discretely appear in the sensing field based on a proper sensing accuracy function that represents different scenarios, and examines how well the event can be detected by a sensor. The concept used in the research is to accurately localize the presence of an event where the stationary sink collects all the sensed data from the sensor nodes observing the event. 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.

Mathematical Methods and Computational Techniques in Science and Engineering
AIP Conf. Proc. 1872, 020009-1–020009-8; doi: 10.1063/1.4996666
Published by AIP Publishing. 978-0-7354-1552-2/$30.00

II. 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 event detection and modeling. Event and target detection is essential for other advanced applications including event and target tracking and classification and behavior learning [15]. There are three main methodologies for event or target detection where most of the research works in this domain utilize; they are optical ow, frame difference and background subtraction [7]. The major techniques for detection modeling are median filter linear prediction, single Gaussian background model, mixed Gaussian background model, kernel density estimation [10] [22] [19] [9] [5]. These techniques have inherent limitations such as hollow space, streak phenomena, stretched targets; and offer low detection accuracy because of the changing light and noise parameters. In the same context, Sankari and Meena [13] proposed dynamic background subtraction method for detecting target in noisy environment. It combines statistical assumptions of the targets 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 [16] proposed a background subtraction-based mechanism detect a target from a static background scene. 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 the target is di-cult to be obtained, which results in inaccurate detection of the target.

III. THEORETICAL MODELLING OF THE PROPOSED DYNAMIC EVENT DETECTION AND LOCALIZATION MODEL

This section presents the theoretical modelling of the proposed dynamic event detection and localization model. Essentially, the current event or target detection models are designed based on a binary detection model where sensor placement plays a significant role [1] [12] [18] [23] [24] [20] [17] [25] [21] [8] [6]. In the binary model, where a fixed sensing radius is considered, sensor node i certainly detects an event over the monitoring area, if its distance d to the event is less than its sensing radius r. However, this is considered as a rough approximation as the event 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 event at location point l should be considered in every sensor node. In most of event monitoring applications in WSNs, sensor nodes probabilistically activate themselves for sensing. The distance between sensor node and a specific location point where the event appears is presented as a linear function which is inversely proportional to the sensing accuracy such that the probability of the sensing accuracy P_i of sensor node i is:

$$P_i = 1/(1+\gamma * d(s_i, l)^m \tag{1}$$

Where $d(s_i, l)$ is the Euclidean distance between sensor *i* and an event (such as an event) at a specific location l, and γ and m are specific sensing technology parameters where γ is an adjustment parameter and that m varies from 1 to 4. The sensing accuracy probability can also be inversely proportional to an exponential function of the distance specified by:

$$P_i = e^{-(\gamma * d(s_i, l))} \tag{2}$$

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:

$$P_i = \begin{cases} 1, & d(s_i, l) < thr_{low} \\ 0, & d(s_i, l) > thr_{up} \\ \gamma e^{-(m*d(s_i,l))}, & thr_{low} < d(s_i, l) < thr_{up} \end{cases} \quad (3)$$

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 event should be as in Equation (4) below:

$$P_i = \gamma v^{-(m*d(s_i,l))^{\beta}} \quad (4)$$

where:

- γ is the detection accuracy parameter that indicates the maximum probability with which the event is certainly detected by sensor node i, such that $0 < \gamma \leq 1$; that is, when $d(s_i,p) = 0$, then $\gamma = 1$.
- v and m indicate the vertical and the horizontal location parameters respectively, where $v > 1$ and $m > 0$. A probability distribution can be formed based on reference location point (a point that is used to define a location of another point) that is can be defined by $(d_r(s_i,l_r), P_r)$. It means that when an event appears at $d_r(s_i,l_r)$ distance away from a sensor node i, the probability with which the event is detected is P_r. Hence, making $md_r(s_i,l_r) = 1$, would result in $P_r = \gamma v^{-1}$, which help in selecting a reference point $(d_r(s_i,l_r), P_r)$. By determining the location parameters according to Equations (5) and (6) below:

$$v = \gamma * (P_r)^{-1} \quad (5)$$

$$m = d_r(s_i, l_r)^{-1} \quad (6)$$

- β is a positive parameter ($\beta > 0$) that indicates the sharp (or smooth) decrease of the sensing probability, from γ to 0, with respect to $d(s_i,l)$. If it is required to designate that at specified distance $d'(s_i,l)$, the accuracy sensing probability is P_i' , the β should be set as follows:

$$\beta = \log d_{m*d'(s_i,l)} \, log_v \left(\frac{\gamma}{P_i'} \right) \quad (7)$$

where $d'(s_i, l)$ must be greater than $d_r(s_i,l_r)$, and P_i' must be less than P_r, and vise versa. As mention earlier, for a sensing accuracy model that is based on a fixed radius, a sensor node would definitely sense any event appears within its sensing radius, such that:

$$P_i = \begin{cases} 1, & d(s_i, l) < r \\ 0, & otherwise \end{cases} \quad (8)$$

Sensing field (SF) is coverage of a WSN at any location point i (l_i) is defined as the probability of a sensor detecting the event at that point.

$$SF(l_i) = 1 - \prod (1 - P(S_i)) \tag{9}$$

where $SF(l_i)$ is the sensing coverage at specific location (l_i), and P_i is the sensing probability of sensor node i at l_i of the sensing field. Sensing Field Coverage C(SF, li) is that the sensing field *SF* is the efficient sensing measures at a at specific location (l_i) from all sensor nodes in the field. If there are k sensor nodes, the total contribution of detection functions of each node, which reflects the coverage of sensing field at a location point l_i, is:

$$C(SF, l_i) = \sum_{1}^{k} (s_i, l_i) \tag{10}$$

IV. VALIDATION

A. 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 ÃŮ 200m^2. This means that the uniform density of the sensor nodes is 0.02 sensors perm^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; γ = 1 (i.e.100% event detection), v = 2, m = 0.1 (i.e. 50% detection of an event at 20m), and β = 4. The experimental evaluation considers the effect of each parameter (the detection accuracy parameter γ, the vertical location parameter v, the horizontal location parameter m, and the sensitivity decreasing parameter β) 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 = 20m.

B. Results and Discussion

1. The effect of the detection accuracy parameter γ

This parameter indicates the sensor sensing accuracy. As there is no certainty in a real environment that a sensor node always detects the event due to some limitation of the sensor measurement and the event nature and behavior, this parameter is evaluated for various values where γ = 1, γ = 0.8, γ = 0.6, respectively. This means that when $d(s_i,l)$ = 0, the sensing accuracy probability P_i to detect the event 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 event is sensed. The figure shows that when γ = 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 γ 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 γ = 1 and γ = 0.8 are closed.

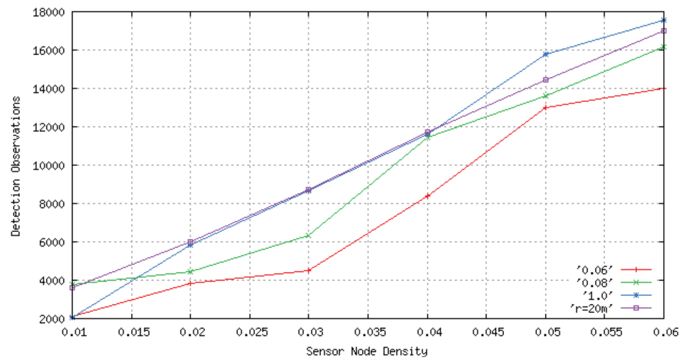

FIGURE 1. The effect of the detection accuracy parameter γ, for γ = 1, γ = 0.8, γ = 0.6

2. The effect of the vertical location parameter v

The vertical location parameter *v* describes the probability P_r of detecting an event at a reference point location $d_r(s_i,l_r)$. This parameter is evaluated with different settings where v = 1/0.6, v = 1/0.7, and v = 1/0.8, respectively. This implies that the probability with respect to the reference location point at distance $d_r(s_i,l_r)$ is 0.8, 0.7, and 0.6 respectively. It is clear that the probability is increasing as the parameter *v* decreases. This means that the probability of the sensing accuracy is higher when the distance is $d_r(s_i,l_r)$. Such behaviour is clearly confirmed by the results shown in Figure 2.

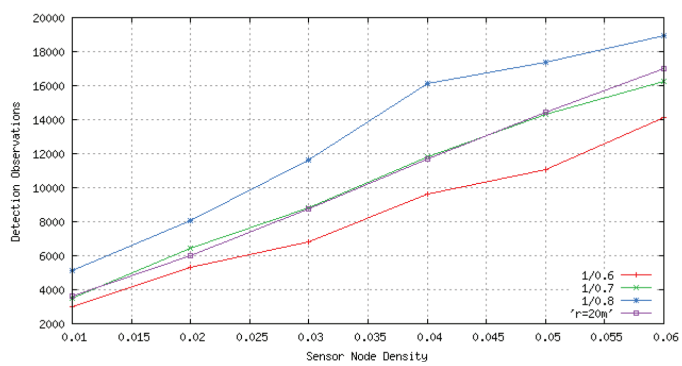

FIGURE 2. The effect of the vertical location parameter *v* for v = 1/0.6, v = 1/0.7, v = 1/0.8

3. The effect of the horizontal location parameter m

The horizontal location parameter expresses the distance $d_r(s_i,l_r)$ to the reference point from a sensor sensing an event. This parameter is evaluated for different values where m = 25, m = 20, and m = 15. This implies that the distance to the reference point is 25m, 20m, and 15m, respectively. Frome the results illustrated in Figure 3, if *m* value is decreased, then the distance $d_r(s_i,l_r)$ is increased. This means that a distant sensor node has higher probability to detect the event.

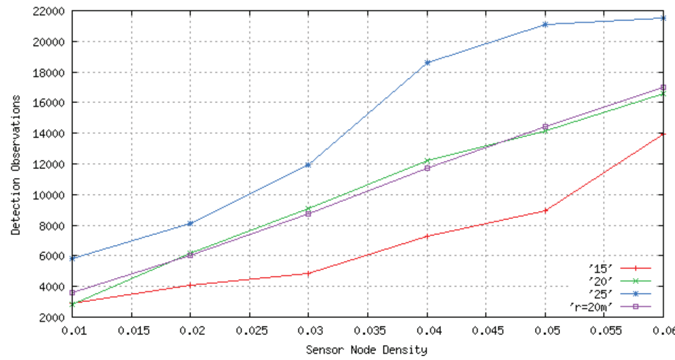

FIGURE 3. The effect of the horizontal location parameter m, for m = 25, m = 20, m = 15

4. The effect of the sensitivity decreasing parameter β

This parameter reflects the decreeing tendency of the probability of the sensor sensing accuracy with respect to $d(s_i,l)$. This parameter is examined under various values where $\beta = 3$, $\beta = 5$, and $\beta = 8$, as shown in Figure 4. Increasing the value of β 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 β drives the proposed probabilistic model to follow the fixed range one, where the results are almost identical for $\beta = 8$ and $d_r(s_i,l_r) = r = 20m$ for different node densities.

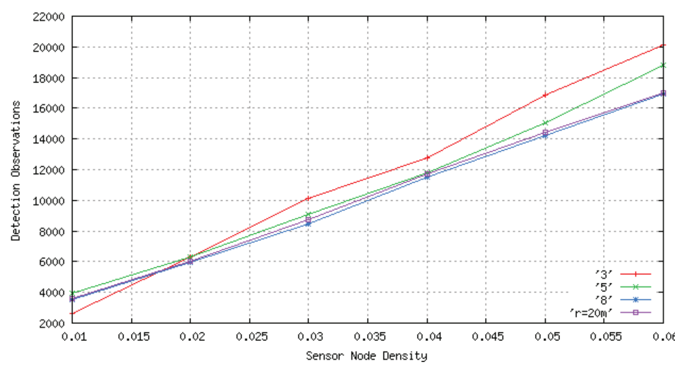

FIGURE 4. The effect of the sensitivity decreasing parameter β

V. 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 events 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 γ, vertical location parameter v, horizontal location parameter m,* and *sensitivity decreasing parameter β*. 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 event. The concept of event detection presented in this paper will be utilized to build an efficient and reliable event tracking system.

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