Probabilistic Coverage for Object Tracking in Sensor Networks

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I. Introduction

Object-tracking quality and network lifetime are two critical and conflicting objectives to object-tracking applications in a sensor network. Full sensing coverage [3] is too restricted and expensive to support long-time monitoring applications, and provides little leverage to tune the object-tracking quality and the battery power consumption. Recently, a relaxed sensing coverage — probabilistic coverage where any point in a sensing field is sensed with a certain probability at any time — was proposed [1], [2], which is a more appropriate approach to balancing the object-tracking quality and the battery power consumption.

Under probabilistic coverage, we present an analytical model to investigate the object-tracking quality with respect to various network conditions and sensor scheduling schemes. The analytical model facilitates performance evaluation of a sensing schedule, network deployment, and sensing scheduling protocol design. The contributions of our analytical model are three-fold.

- First, together with simulation to evaluate performances of different scheduling protocols, this analytical model can give more solid and thorough understanding about various protocols and provide insights into the pros and cons of each protocol.
- Secondly, the analytical model helps to plan a sensor network with certain object-tracking quality requirements and battery power budget. The analytical model is flexible enough to capture the interaction among the system parameters, object-tracking quality requirements, and network energy limit.
- Thirdly, in sensing scheduling protocol design, aside from determining the parameters for sensing scheduling protocols, our analytical model can direct new protocol design.

We validate the correctness of our model through extensive simulation experiments, and use this model to design scheduling algorithms.

II. Object Tracking Under Probabilistic Coverage

In this poster, we analyze the tracking quality and lifetime with respect to the several network and scheduling parameters. We define *detection probability* (DP) as the expected probability that an object is detected in a certain observation time, and *stealth distance* (SD) as the average distance an object travels before it is detected for the first time. Taking the energy constraints into account, we define the *system lifetime* (LT) as the elapsed working time from system startup to the time when the object-tracking quality requirement cannot be met for the first time if nodes do not vary their sensing periods.

TABLE I
System Modeling Parameters

System Parameter	Definition
d	density of sensors
R	sensing radius of a sensor
v	constant velocity of a motion object
P	sensing period of sensors
f	active ratio of sensors in P
t_a	observation interval

We assume that sensors are randomly and independently deployed in a sensing field where a motion object passes through along a straight line with a constant speed, and the size of motion object can be neglected. These system parameters of a sensor network are summarized in Table I.

III. Object-Tracking Quality Analysis

We consider two scheduling schemes, random sensing schedule and synchronized sensing schedule. In a random sensing schedule, a node independently and randomly chooses the starting time of its active interval fP in P; while in a synchronized sensing schedule, all nodes start their active interval fP at the same time in P. We examine the random schedule to show how a sensing schedule in general affects the tracking quality and lifetime, and investigate the synchronized schedule to show how coordination among nodes affects the performance. Suppose all nodes have the same initial energy capacity such that they can continuously work for time T. It is easy to see that under the two sensing schedules the lifetime is $LT = \frac{T}{f}$.

A. Random Sensing Analysis

1) Detection Probability: Consider a motion object that travels the distance of $[\frac{-vt_a}{2}, \frac{vt_a}{2}]$ on x-axis during the obser-

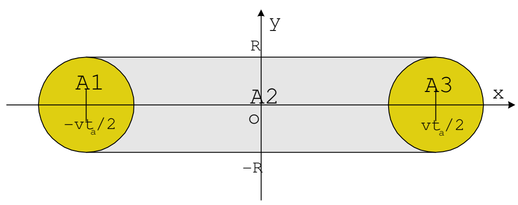

Fig. 1. The Active Area in Random Sensing Schedule.

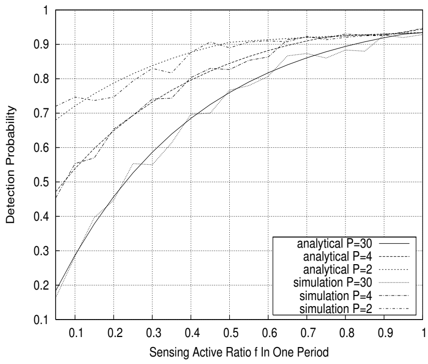

Fig. 2. DP under Random Schedule: Vary P and f. The parameters are: $d = 0.01$, $R = 8$, $v = 1$, and $t_a = 1$.

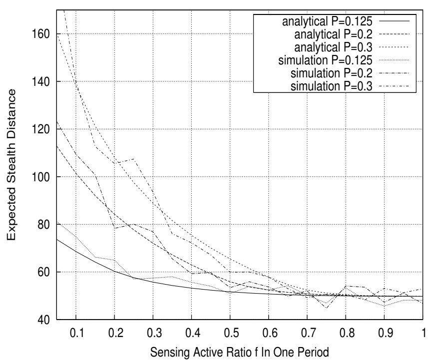

Fig. 3. SD under Random Schedule: Vary P and f. The parameters are: $d = 0.2$, $R = 0.05$, and $v = 1$.

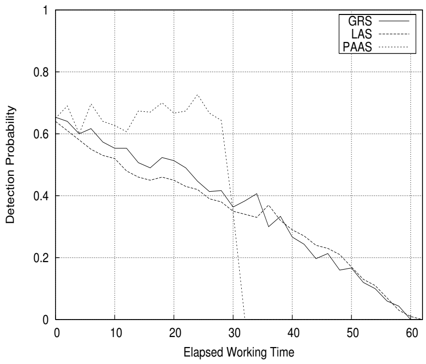

Fig. 4. DP Degradation with Time. The parameters are: $d = 0.2$, $R = 0.5$, $v = 5$, $t_a = 2$, $P = 1.1$, $f = 0.5$, $r = 3$ and $E_{max} = 30$.

vation interval t_a. As shown in Figure 1, we define the *active area* AA of this object as the oblong area, including the rectangle area with length vt_a and width of $2R$, and the two half disks with radius R attached to the rectangle. Consider a sensor at location (x_s, y_s), the segment length that the object trajectory intersects this sensor's sensing range is $l(x_s, y_s) = min(\frac{vt_a}{2}, x_b) - max(\frac{-vt_a}{2}, x_a)$.

Let $Pr(x_s, y_s)$ denote the probability this sensor can detect this object, we know (1) if $l(x_s, y_s) < (1-f)vP$, $Pr(x_s, y_s) = f + \frac{t}{P}$; (2) if $l(x_s, y_s) \geq (1-f)vP$, $Pr(x_s, y_s) = 1$, where $t = \frac{l(x_s,y_s)}{v}$. Let $\tilde{P}r$ denote the probability that one single sensor can detect this object within t_a, we have $\tilde{P}r = \frac{1}{AA}\int_{-R}^{R} \mathrm{d}y_s \int_{-\frac{vt_a}{2}-R}^{\frac{vt_a}{2}+R} Pr(x_s, y_s)\mathrm{d}x_s$. The expected probability that at least one sensor will detect this motion object is $Pr(all, rand) = 1 - e^{-\lambda \tilde{P}r}$, where $\lambda = d \cdot AA$.

2) Average Stealth Distance: The average stealth distance under random sensing scheme is $E(SD) = \int_0^{\infty} ve^{-\lambda \tilde{P}r}\mathrm{d}t_a$.

B. Synchronized Sensing Analysis

1) Detection Probability: Similar to the random sensing scheme, in a synchronized sensing scheme the active area *AA* is the set of periodically repeated areas. Denote $X_0 = (1-f)vP$. Let $IA(P)$ be the total covering area of two half disks in one sensing period P, then the active area in one intermediate sensing period P is $AA(P) = IA(P) + 2RvfP$, where (1) if $R \geq \frac{X_0}{2}$, $IA(P) = X_0\sqrt{R^2 - \frac{X_0{}^2}{4}} + 2R^2 \arcsin\frac{X_0}{2R}$; (2) if $R < \frac{X_0}{2}$, $IA(P) = \pi R^2$. Let t_a be multiple times of P, and $\lambda_s = d \cdot AA(t_a)$, then $Pr(all, syn) = 1 - e^{-\lambda_s}$.

2) Average Stealth Distance: The average stealth distance under synchronized sensing scheme is $E(SD) = \frac{vP}{d\cdot(IA(P)+2RvfP)}e^{-d(\pi R^2 - IA(P))}$.

C. Analytical Results and Simulation

Figures 2 and 3 show the comparison between the analytical results and the simulation results. The simulation results match the analytical curves well, which validates the correctness of our model. We find that the synchronized scheduling does not perform better than the random scheduling, which is consistent to our prediction, because the synchronized sensing has more overlapping sensing areas than the random sensing.

IV. Scheduling Algorithm Design

Based on our analysis, we can schedule sensors according to d to meet the object-tracking quality requirements. We propose a centralized algorithm (Global Random Schedule (GRS)) and a localized algorithm (Localized Asynchronous Schedule (LAS)) to estimate d and assign f and P to sensors. We simulate the algorithms and plot their performance degradations with respect to time. We observe that both algorithms achieve the requirement at the beginning when all nodes have abundant energy, as shown in Figure 4.

We also design a Power-Aware Asynchronous Schedule (PAAS) to make the time to the first node failure longer than the two previous algorithms. We assume $2R < (1-f)vP$, and fP is a constant. Considering the diversity of power capacity among nodes, given the sum of the power capacity $E = \sum_{i=1}^{n} E_i$ (where E_i is the initial power of node i), we can schedule a node that has the power capacity E_i with the sensing period $\frac{E}{nE_i}P$ to achieve the same object-tracking quality as that with the same P. As shown in Figure 4, for the PAAS, after its system lifetime, the *DP* directly drops to zero because all nodes are depleted of power. This indicates in PAAS all nodes have the same working time.

V. Conclusion

Under probabilistic coverage, we present an analytical model to fully investigate the object-tracking quality with respect to various network conditions and sensor scheduling schemes. Centered on the two object-tracking metrics — detection probability and stealth distance, the analytical model gives us more solid and thorough understanding on controlling the object-tracking quality, and provides guidelines for optimal sensor deployment and power conservation.

References

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