On Optimal Information Capture by Energy-Constrained Mobile Sensors

Shibo He* Jiming Chen* Youxian Sun* David K. Y. Yau† Nung Kwan Yip†
*State Key Lab. of Industrial Control Technology, Zhejiang University, Hangzhou 310027, China
†Purdue University, West Lafayette, IN, USA
ferrer@zju.edu.cn, jmchen@ieee.org, yxsun@iipc.zju.edu.cn, yau@cs.purdue.edu, yip@math.purdue.edu

Abstract

A mobile sensor is used to cover a number of *points of interest* (PoIs) where dynamic events appear and disappear according to given random processes. The sensor, of sensing range r, visits the PoIs in a cyclic schedule and gains information about any event that falls within its range. We consider the temporal dimension of the sensing as given by a *utility function* which specifies how much information is gained about an event as a function of the cumulative sensing or observation time. It has been shown in [1] that for Step and Exponential utility functions, the *quality of monitoring* (QoM), i.e., the fraction of information captured about all events, increases as the speed of the sensor increases. This work, however, does not consider the energy of motion, which is an important constraint for mobile sensor coverage. In this paper, we analyze the *expected information captured per unit of energy consumption* (IPE) as a function of the event type, the event dynamics, and the speed of the mobile sensor. Our analysis uses a realistic energy model of motion, and it allows the sensor speed to be optimized for information capture. We present extensively simulation results to verify and illustrate the analytical results.

Index Terms

Mobile sensor coverage, quality of monitoring, energy consumption, sensor network

I. Introduction

Wireless sensor networks are useful in a wide range of applications, such as environment monitoring, tracking of wild life, defense against natural hazards or malicious attacks, and social networks. In sensor network design, the *coverage problem* is concerned with the allocation of sensing resources to different parts of a deployment area for effective information capture about interesting events. The concept *"coverage"* is a measure of the quality of service (QoS) and is subject to a wide range of interpretations due to a large variety of applications.

Traditional work in sensor coverage can be classified into two broad categories [2], [3]. In a dense network, the problem is to optimally task subsets of the sensors, or to schedule the duty cycles of the sensors, in order to achieve area coverage (i.e., each point of the surveillance region is within range of at least one sensor) or area k-coverage (i.e., each point of the region is within range of at least k sensors), while maximizing the network lifetime before energy is depleted. In a sparse network, in which the sensor density is insufficient to provide significant redundancy of coverage, the goal is to optimally place the sensors so that the area of coverage or k-coverage is maximized.

More recently, the importance of mobile coverage is recognized [4], [5], [6], [7]. Support for programmed mobility is, for example, made feasible by advances in robotics which drive down deployment costs [8]. Mobile coverage is already the norm in certain existing applications, e.g., reconnaissance airplanes flying over enemy territories to collect intelligence, where the installation of an expansive static sensor network is out of the question. In other situations, real-life sensors (chemical, radiation, and biological sensors, among others) may have limited range. If there are insufficient sensors to cover a large geographical area all the time, mobility can be used to effect total coverage over time, while requiring a significantly smaller number of sensors. In this case, the cost savings of using fewer sensors have to be balanced against the costs of supporting the mobility, but the tradeoff is interesting, especially when the sensor mobility can be piggybacked onto that of an existing mobile entity, e.g., a patrol car.

In [9], the need for mobility is motivated for data collection from a number of data collection points in an underwater environment, where high signal attenuations preclude the communication of data over significant distances. To overcome the problem, a mobile device can be used to move among the data collection points, download the collected data, and carry the downloaded data to a data sink for analysis. Similar use of a mobile device for data collection in other "hard-to-access" environments (e.g., underground) is justified, given the extreme challenges of placing a connected set of wireless access points for long-haul movement of data.

The problem of capturing stochastic events that appear and disappear dynamically at given *points of interest* (PoIs) by mobile sensors has been studied in [9]. Each event at a PoI arrives probabilistically, stays for a random time drawn from a statistical distribution, and is followed by another event after a random event absent time drawn from another distribution. The goal is to design a mobile coverage schedule to maximize the number of events captured, where an event is captured if it falls within range of one or more sensors during its lifetime. In [1], the mobile coverage problem is augmented in two respects. First, the authors consider additionally a *temporal dimension* of the sensing, in which they recognize that a non-trivial sensing time is often needed to gain information about many real-world events. How the information gained about an event increases with additional sensing time is captured by an *event utility function* for the type of event. The optimization objective then becomes the maximization of the total information gained about all captured events, instead of simply the number of these events. Second, they consider the paradigms of periodic and proportional-share scheduling of the coverage time among different PoIs. The proportional-sharing objective, in particular, allows more important PoIs to be covered for a larger fraction of time.

Analysis is given in [1] about the rate of information captured by a mobile sensor moving among the PoIs in either a *linear periodic* or *general periodic* schedule. The results show how the information gained is affected by the event dynamics, the type of event, the proportional share of coverage time received by a PoI, and the fairness granularity over which the proportional share is acheived. Optimal mobile coverage algorithms are then designed to achieve given proportional shares while maximizing the QoM of the total system.

The prior work in [9], [1] does not consider the energy use of the mobile sensors. In real life, however, mobile sensors often run on limited batteries. When they deplete their energy budgets, they will need to be recharged or replaced, or they will simply stop contributing to the sensor network. Hence, there is the dual objective of ensuring the effective operation of a sensor (in terms of maximizing its ability to capture information) on the one hand, and prolonging the lifetime of the sensor (in terms of managing its energy use for mobility) on the other hand [10], [11]. In this paper, we quantify such dual performance of a mobile sensor. Our contributions are as follows.

- First, we use a realistic energy model to account for the cost of movement. This allows to quantify the tradeoff between increased QoM due to a finer grained sharing of the coverage time between PoIs achieved by a faster sensor, and increased lifetime of the sensor due to a lower rate of energy use by a slower sensor. The tradeoff is formally captured by a metric of *expected information capture per unit of energy consumption* (IPE). An optimal sensor speed v can be determined that maximizes the

IPE.

- Second, we illustrate how the IPE varies by different deployment parameters and the event dynamics. For example, we show that the IPE is a decreasing function of the average distance between PoIs (denoted by γ), while it is an increasing function of the event arrival rate. Our analytical results are supported by simulation experiments. The experimental evaluation also compares the performance of the mobile sensor relative to a stationary sensor, thereby quantifying the benefits of mobility for the sensing task.

II. Related Work

There has been substantial research on the coverage problem in sensor networks. Meguerdichian *et al.* [2] discuss different forms of the coverage problem, namely deterministic, statistical, and worst and best case coverage. Using computational geometry and graph algorithms, they provide optimal polynomial-time solutions for the coverage problem. Huang and Tseng [12] formulate the k-coverage problem as a decision problem, i.e., how to decide if every point in a service area is covered by at least k sensors. They present polynomial-time algorithms that can be realized via distributed protocols. Practical systems exist that apply solutions to the coverage problem. Chebrolu *et al.* [13] investigate the use of sensors to monitor the structural health of bridges and report when/where maintenance operations are needed.

The above work [2], [12], [13] considers the use of stationary sensors. Stationary sensors have some limitations. For example, a large number of sensors may be needed to fully cover a service area. Also, holes may exist after the death/failure of certain sensors, or after changes in the deployment environment. Mobility can be applied to ameliorate the operation of a sensor network. The coverage problem has been studied for hybrid mobile/stationary sensor networks [7]. Wang *et al.* show that the quality of coverage can be significantly improved by introducing a small fraction of mobile sensors. Liu *et al.* [5] define three measures of coverage for a mobile sensor network: area coverage, area coverage over a time interval, and detection time. They show that sensor mobility can be used to compensate for the lack of sensors and improve the coverage effectiveness. Eriksson *et al.* [4] describe an application of mobile sensing, namely detecting and reporting the surface conditions of roads. In [8], Singh *et al.* use a Gaussian Process model for the relationship between underlying physical phenomena. They present an efficient path planning algorithm to maximize the amount of information captured by a mobile sensor.

Since sensors often run on limited energies, power consumption can be a major consideration in sensor network design, beyond other performance metrics such as fairness, latency, and bandwidth utilization [14]. Because of the advantages and need for unattended operations, maximizing the energy lifetime of a sensor network is an important challenge. Many protocols have been designed at different network layers for power saving and prolonging the network lifetime [15]. Our goal in this paper is to investigate the tradeoff between performance and energy use of a mobile sensor. We extensively investigate such tradeoff problem [16]. Different energy models [10], [17], [18], [19] have been proposed for mobility under different operating conditions. They all recognize energy depletion due to outside forces such as friction. We adopt such an energy model in this paper.

III. Problem Statement

We consider n *points of interest* (PoIs) situated in a deployment region. The PoIs are connected by a circuit of length D. Stochastic events appear at each PoI. Each event stays for a random event *staying time*, drawn from some statistical distribution, and then disappears. Following the disappearance, a next event appears after another random event *absence time*, drawn also from some distribution. In this paper, we assume that the event staying and absence times at PoI i follow the Exponential distribution with means $\frac{1}{\lambda_i}$ and $\frac{1}{\mu_i}$, respectively. For simplicity, we further assume that $\lambda_i = \lambda$ and $\mu_i = \mu$, for $i = 1, \ldots, n$.

A mobile sensor, of sensing range r, completes identical rounds of the circuit until its energy is depleted. In each round, the sensor passes through each PoI once and only once. We assume that if there is an event present at a PoI, the sensor will gain information about the event while the event is within range. We further assume that different events are *identifiable*, i.e., when a sensor senses an event at a PoI, leaves, and later returns to the same PoI to sense the same event, it will recognize that it is the same event. Hence, the sensor will accumulate information about the event over a possibly non-contiguous interval of sensing. How the information increases with the sensing time is captured by a *utility function* for the type of event.

The utility function is monotonically increasing from zero to one, with zero meaning no information captured and one meaning full information captured about the event. In this paper, we consider two important forms of the utility function (see [1] for further forms of the function that have been proposed):

- Step function: $U_I(t) = 1, \text{ for } t > 0$. In this case, full information about an event is obtained as soon as the sensor detects the event. This function is useful, for example, if we are interested in counting the number of occurrences of an event whose presence can be detected quickly and unequivocally.
- Exponential function: $U_A(t) = 1 - e^{-At}$. This function models the law of diminishing returns that characterizes a wide range of real-world phenomena. According to the function, information is learned at a high rate during the initial observation. As more information is learned, however, the marginal gain in information decreases with additional sensing time. When the sensing time is long enough, full information is obtained.

We assume that the mobile sensor runs on limited battery and is therefore energy constrained. The *quality of monitoring* (QoM) of the sensor is the sum of the information it captures about all the events before it runs out of energy. We are interested in optimizing the sensor's movement for the highest QoM. Because of how it moves, the sensor will periodically visit a PoI, say i, for q_i time every T time, where T is the time taken by the sensor to complete a round of the circuit. Assume that the energy budget is such that the sensor can complete N rounds of the circuit. Let $Q_i^{(k)}$ denote the total expected information gained by the sensor at PoI i in the k-th round, for $k = 1, 2, \cdots, N$. The total information the sensor gains at i during its lifetime is given by $Q_i = \sum_{k=1}^{N} Q_i^{(k)}$. For all the n PoIs, the total amount of information the sensor gains during its lifetime (i.e., the QoM), is given by $Q = \sum_{i=1}^{n} Q_i$.

In general, the sensor controls q_i and T by controlling its speed during the mobile coverage. We know that the expected fraction of information captured about each event is a function of q_i, T, and the type of event. If the sensor moves at a fixed speed, say v, $q_i = 2r/v$, for $i = 1, \ldots, n$, and $T = D/v$, where D is the length of the circuit. For the Step and Exponential utility functions, it has been shown that the fraction of information increases as v increases, when the energy cost of the mobile coverage is ignored [1]. However, if the energy constraint of the sensor is important, increasing v will generally increase the rate at which energy is consumed to support the movement, so that the sensor can only complete fewer rounds of the circuit. In this paper, we are therefore interested in quantifying the expected information captured per unit of energy consumption (IPE) as a function of the sensor speed v.

IV. Expected Information Captured per Unit Energy

A. Energy models

To analyze the IPE of a mobile sensor, we need a realistic energy model for the sensor's motion. Energy consumption during travel can be complex [10], [11]. Existing energy models of motion [17], [18], [19] have generally considered the energy depleted due to friction, gravity, and other environmental factors. For a robot traveling on scope inclined at an angle of φ, according to [19] the energy cost of distance l is $mg(\kappa \cos(\varphi) + \sin(\psi)) \cdot l$. Here a ψ is gradient of the terrain face, κ is the friction coefficient between the mobile robot and the surface and mg is the weight of the robot. It is pointed out [19] that this formula was confirmed experimentally within 10% for wheeled vehicles on slopes of less than 20%. So when the mobile sensor travels with a velocity of v, the energy loss is $k_2 vt$, where $k_2 = mg(\kappa \cos(\varphi) + \sin(\psi))$. When the device travels in a fluid, such as water, the viscous force is $f = k_2 v$ [20]. Therefore, when the device travels at a speed of v during the time interval $[0, t]$, the energy cost equal to $k_2 v^2 t$. In other situations, the expression for the consumed energy may be different. In this paper, we use the expression $k_2 v^\alpha t$ for the energy consumption, for the sensor traveling at speed v during time interval $[0, t]$, where α is a constant parameter accounting for environmental factors.

Besides mobility, energy is needed for the sensing task. We assume that the sensing function operating continuously over time interval $[0, t]$ will consume $k_1 \times t$ amount of energy, where k_1 is a proportionality constant. For simplicity, we assume additionally that the sensing function is turned on all the time. Hence, considering both the mobility and sensing aspects, our sensor completing rounds of the circuit at speed v for t time will expend a total of $k_1 t + k_2 v^\alpha t$ energy during the deployment.

B. IPE analysis

We now analyze the IPE of a sensor covering n PoIs in a closed circuit moving at a fixed speed v. The analysis will allow us to optimize v to achieve the highest IPE.

The strategy of computing the IPE is as follows. Let E_* be the energy constraint, or the maximum energy available. The time needed for one round is $\frac{D}{v}$. By the above energy model, the energy used per round is $(k_1 + k_2 v^\alpha) \times \frac{D}{v}$. Hence the sensor can complete $N = \frac{vE_*}{D(k_1+k_2v^\alpha)}$ times of the circuit. Thus the total information captured *per unit energy* is given by:

$$\text{IPE} = \frac{v}{D(k_1 + k_2 v^\alpha)} \times \text{(QoM per event)} \times \text{(Total number of events per round).} \tag{1}$$

Now, the number of events in each round is given by

$$\text{(Number of PoIs)} \times \left(\frac{1}{\lambda} + \frac{1}{\mu}\right)^{-1} \times \frac{D}{v}. \tag{2}$$

Thus, the overall IPE is given by:

$$\text{IPE} = \left(\frac{n}{k_1 + k_2 v^\alpha}\right)\left(\frac{\lambda\mu}{\lambda + \mu}\right)\text{(QoM per event)}. \tag{3}$$

In particular, for a stationary sensor, energy is only consumed for the sensing of information but not for mobility, Hence the energy consumption is less than that of a mobile sensor. However, the gain of event information also becomes less. Quantitatively, from (3), in the case of only one stationary sensor, QoM = 1, n = 1 and $k_2 v^\alpha = 0$. Then the stationary sensor's IPE, denoted by IPE_s, is given by

$$\text{IPE}_s = \frac{\lambda\mu}{k_1(\lambda + \mu)} \tag{4}$$

The following paragraphs consider various forms of the QoM, and study its competition with the energy use and hence its effect on the overall IPE. The formulas for the QoM are taken from [1].

1) Step utility function:

Theorem 1: For the Step utility function, the IPE is given by

$$\frac{n}{k_1 + k_2 v^\alpha}\left(\frac{\lambda\mu}{\lambda + \mu}\right)\left[\frac{2r}{D} + \frac{v}{\lambda D}\left(1 - e^{-\lambda\left(\frac{D-2r}{v}\right)}\right)\right] \tag{5}$$

where n is the number of PoIs, and k_1 and k_2 are dissipation coefficients defined above for the energy model.

Proof: The proof follows directly from the formula of the QoM derived in [1, Theorem 2, Eqn. (3)]. The corresponding formula is computed explicitly here for the exponentially distributed event staying times:

$$\text{QoM} \;=\; \frac{q}{p} + \frac{1}{p}\int_0^{p-q} \Pr(X \geq t)\, dt, \tag{6}$$

where $q = \frac{2r}{v}$ and $p = \frac{D}{v}$ are the time during which the sensor is present at a PoI and the time taken to complete one round of the circuit. The random variable X is the event staying time which is exponentially distributed with parameter λ, so that $\Pr(X \geq t) = e^{-\lambda t}$. The key point of the formula is that an event can be captured if it occurs while the sensor is present at the PoI or if the sensor is absent, the event stays long enough for the sensor to come back. ■

We make the following observations about the above result.

(1) Note that the QoM derived above is an *increasing, bounded* function of v such that

$$\lim_{v\to 0^+} \text{QoM} = \frac{2r}{D} \quad \text{and} \quad \lim_{v\to +\infty} \text{QoM} = 1$$

On the other hand, the energy used per unit time is an *increasing, unbounded* function of v. Hence ultimately, the IPE will go to zero as $v \longrightarrow \infty$. In particular, we have

$$\lim_{v\to 0^+} \text{IPE} = \frac{n}{k_1}\left(\frac{\lambda\mu}{\lambda+\mu}\right)\frac{2r}{D} \quad \text{and} \quad \lim_{v\to +\infty} \text{IPE} = 0$$

(2) Let $Q(v) = \text{QoM}$ and $E(v) = (k_1 + k_2 v^{\alpha})$. Then we have:

$$\text{IPE}'(0) \propto \frac{E(0)Q'(0) - Q(0)E'(0)}{E^2(0)} \tag{7}$$

If $\text{IPE}'(0)$ is *positive*, the IPE function *initially increases* and then ultimately *decreases* to zero. Thus it will attain its *maximum* value at some *intermediate* v_*. We can analyze $\text{IPE}'(0)$ for different ranges of α as follows:

$$\lim_{v\to 0^+} \text{IPE}'(0) = \begin{cases} \frac{n\mu}{Dk_1(\lambda+\mu)} & \text{for } \alpha > 1 \\ \frac{\mu(k_1 - 2r\lambda k_2)}{k_1^2 D(\lambda+\mu)} & \text{for } \alpha = 1 \\ -\infty & \text{for } \alpha < 1. \end{cases} \tag{8}$$

For $\alpha > 1$, it is clear that $\text{IPE}'(0) > 0$. The optimal value v_* can be found by various numerical root-finding algorithms such as the Newton's Method. For $\alpha \leq 1$, $\text{IPE}'(0)$ can be negative. However, the experimental results in Section V explore the impact of α systematically, by plotting the IPE against v for a range of α values. The results show that the initial decrease in the IPE is not significant in practice, and the same numerical optimization method will work for $\alpha \leq 1$ as well.

(3) As mentioned before, k_2 is a parameter of the deployment environment. When k_2 increases, more energy is needed to support a certain speed of motion, which reduces the IPE. In the limiting cases,

$$\lim_{k_2 \to \infty} \text{IPE} = 0, \tag{9}$$

$$\lim_{v \to \infty, k_2 \to 0^+} \text{IPE} = \frac{n}{k_1} \left(\frac{\lambda\mu}{\lambda + \mu} \right). \tag{10}$$

Hence, under conditions of higher motion resistance, we should use a lower speed of the sensor for optimal performance. When the resistance is low, the sensor can run at a high speed for higher information gain.

(4) Denoting by $\gamma = \frac{D}{n}$ the average distance between sensors along the circuit, we note that the IPE is a decreasing function of γ, which can seen directly from Theorem 1.

2) Exponential utility function:

Theorem 2: When the exponential utility function is used, the IPE is given by

$$\text{IPE} = \frac{n}{k_1 + k_2 v^\alpha} \left(\frac{\lambda\mu}{\lambda + \mu} \right) Q. \tag{11}$$

Here, Q is from [1, Eqn. (6)]:

$$\begin{aligned} Q = {} & \frac{Aq}{(A+\lambda)p} - \frac{1 - e^{-\lambda q}}{\lambda p} + \frac{\lambda(1 - e^{(A+\lambda)q})}{(A+\lambda)^2 p} \\ & + \frac{(e^{\lambda q} - 1)^2}{\lambda p e^{\lambda q}(e^{\lambda p} - 1)} - \frac{\lambda(e^{(A+\lambda)q} - 1)^2 e^{-(A+\lambda)q}}{(A+\lambda)^2 p (e^{Aq+\lambda p} - 1)} \\ & + \frac{2(e^{\lambda(p-q)} - 1)}{p} \times \\ & \times \left[\frac{e^{\lambda q} - 1}{\lambda(e^{\lambda p} - 1)} - \frac{e^{(A+\lambda)q} - 1}{(A+\lambda)(e^{Aq+\lambda p} - 1)} \right] \\ & + \frac{(e^{Aq} - 1)e^{\lambda q}(e^{\lambda(p-q)} - 1)^2}{\lambda p (e^{\lambda p} - 1)(e^{Aq+\lambda p} - 1)}, \end{aligned} \tag{12}$$

where $q = 2r/v$ and $p = D/v$

The proof is omitted as it is easily obtained using the appropriate QoM function. Again, the optimal value v_* can be found numerically, just as in the case of the step utility function. The behavior is also illustrated in the simulation results presented in Section V-B.

C. Randomly distributed PoIs

So far we have made the assumption that the positions of the PoIs are known to be uniformlly spaced. This might not be practical as their actual locations may be irregular or even unknown. This motivates us to consider random placement of the PoIs. In this subsection, we assume that the PoIs are uniformly distributed along the circuit of length D. In this case, the distance of two PoIs may be less than $2r$. Here we assume that the sensor covering more than one PoI can capture events from the different PoIs at the same time.

To have a rough idea of how random placement affects the IPE, we consider the simple case of a stationary sensor. Here, the number of PoIs covered by the sensor is a random variable. It is given by the binomial distribution and its expected number $E(N)$ can be computed as:

$$E(N) = \sum_{i=1}^{n} i \frac{n!}{i!(n-i)!} (\frac{2r}{D})^i (\frac{D-2r}{D})^{n-i} = \frac{n2r}{D}.$$

Hence, analogous to formula (3), the expected value of the total IPE is given by

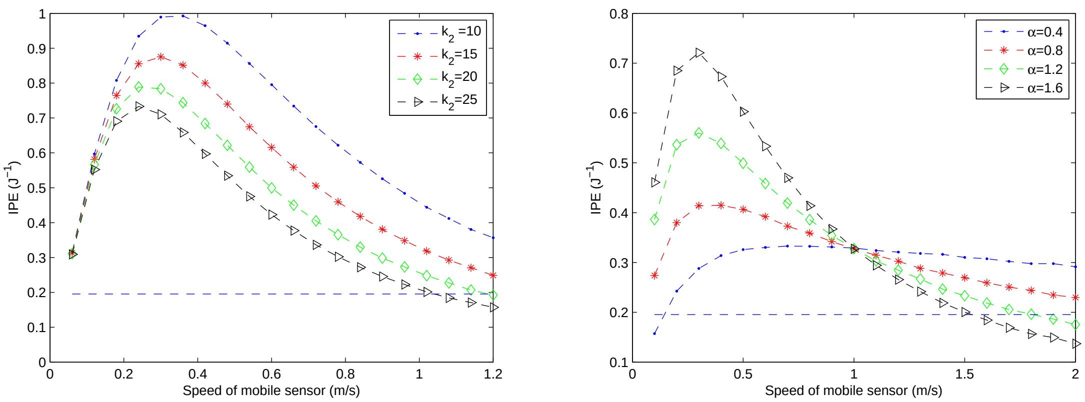
$$E(\text{IPE}) = \frac{n2r}{Dk_1} \left(\frac{\lambda\mu}{\lambda+\mu} \right) (\text{QoM}). \tag{13}$$

(Note that for a stationary sensor, $v = 0$ in the energy model.) Thus we see that the overall effect of random placement is to change the number of PoIs n to the new value $\frac{n2r}{D}$. For concrete examples, for the step utility function, the QoM equals one as full information about any event will always be captured, while for the exponential utility function U_A and exponential staying time distribution with parameter λ, the QoM equals:

$$\int_0^\infty U_A(t) \Pr(X = t)\, dt = \int_0^\infty (1 - e^{-At}) \lambda e^{-\lambda t}\, dt = \frac{\lambda}{\lambda + A}$$

V. Simulation Results

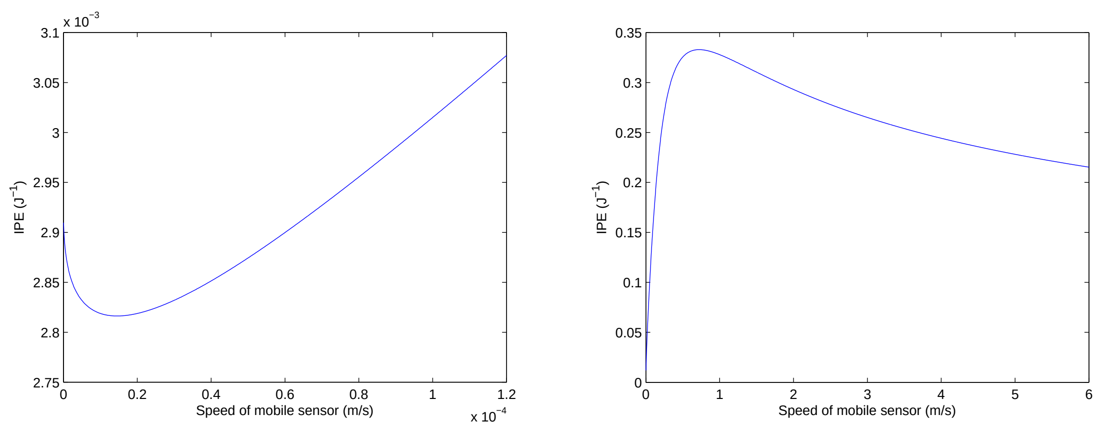
In this section, we present simulation results to illustrate the analysis in the previous section. Modeling the sensor with its internal energy consumption for computing, sensing, and communication as in [21], we set k_1 in the motion energy model to be 2.5585 J/h. For the energy budget, denoted by E_{energy}, we assume two batteries each of capacity 1350 mAh, so that E_{energy} = 29160 J.



(a) IPE as a function of v, for different k_2.

(b) IPE as a function of v, for different α.

Fig. 1. Impact of energy model on the IPE for events that have Step utility function.



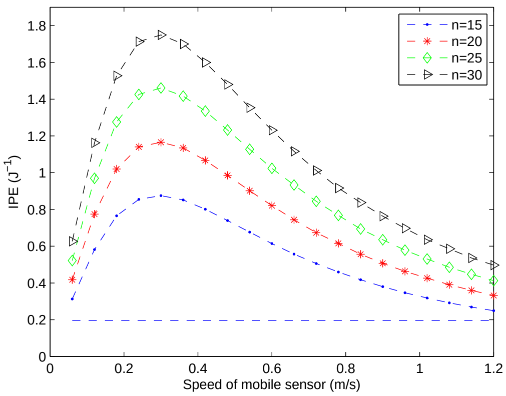
(a) IPE over a range of *low* sensor speed v.

(b) IPE over a broader range of sensor speed v.

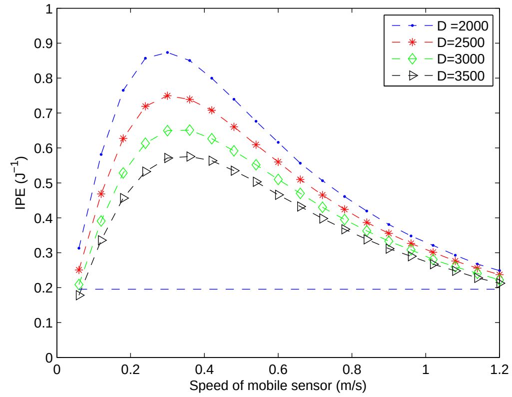
Fig. 2. Numerical results: Plot of IPE as a function of v, for α=0.4.

In the simulations, we measure the IPE as the total amount of information captured during the sensor's lifetime (i.e., before energy runs out), divided by E_{energy}. The reported results are averages over 500 independent runs. The large numbers of runs give standard deviations that are extremely small. We therefore do not report the standard deviations.

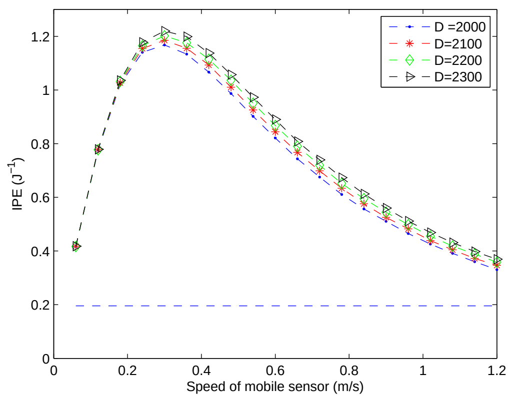
As in Section IV, we use both the Step and Exponential utility functions. Unless otherwise stated, the parameters in Section IV are set as follows: D = 2000 m, r = 1 m, $\lambda = \mu$ = 1/h, n = 15, k_2 = 15 J/h, and α = 2. The PoIs are placed uniformly on the circuit such that the distance between any two neighbors is the same. Unless otherwise stated, the starting point of the mobile sensor on the circuit is



(a) IPE as a function of v, for different n.

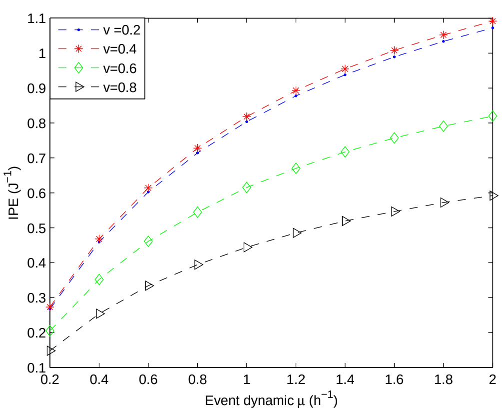


(b) IPE for as a function of v, for different D.

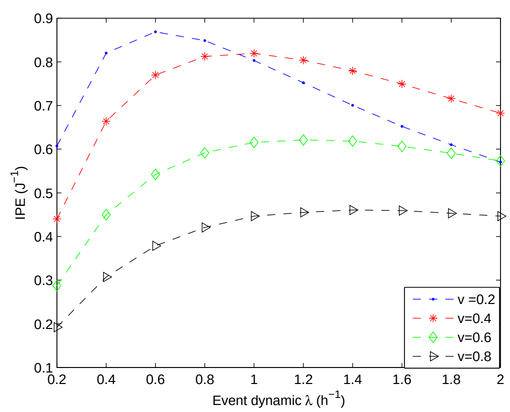


(c) IPE as a function of v, for different k_2 while fixing γ.

Fig. 3. Impact of PoI distribution on the IPE for Step utility function.



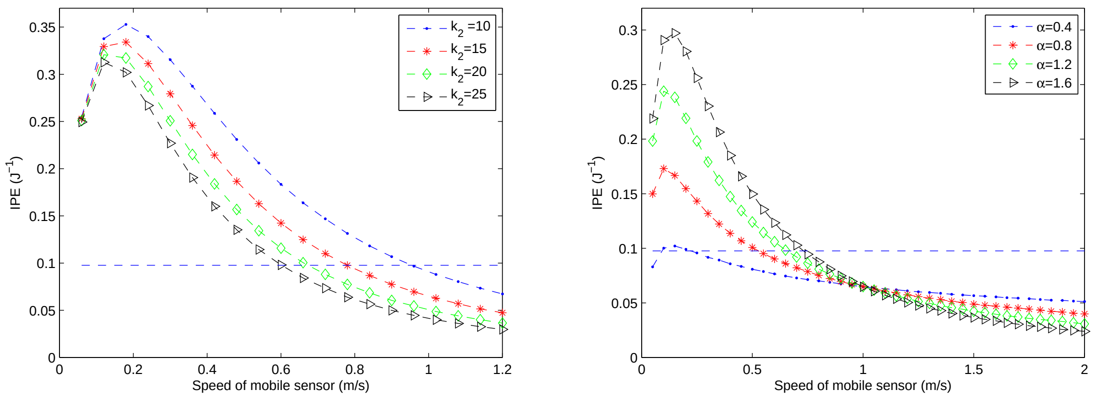
(a) IPE as a function of μ, for different v.



(b) IPE as a function of λ, for different v.

Fig. 4. Impact of event dynamics on the IPE for Step utility function.

chosen uniformly at random.



(a) IPE as a function of v, for different k_2.
(b) IPE as a function of v, for different α.

Fig. 5. Impact of energy model on the IPE for events that have Exponential utility function.

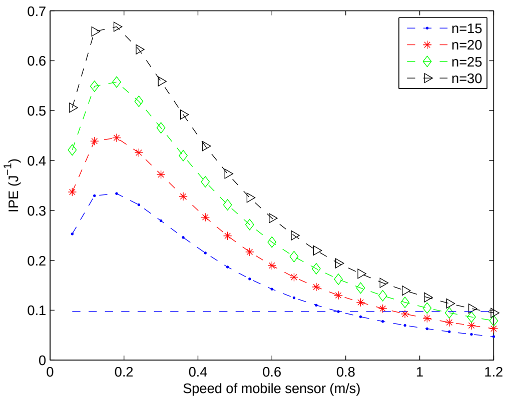
A. Step utility function

We first present results for Step utility. Fig. 1 illustrates the effects of the energy model on the IPE. We vary k_2 in the motion energy model to be 10, 15, 20, and 25 J/h, to correspond to different energy costs of the motion. Plots of the IPE against the speed of the sensor, for the different values of k_2, are shown in Fig. 1(a). In the figure, we also show, as the horizontal line, the IPE of a stationary sensor placed at one of the PoIs for comparison. (Notice that the stationary sensor IPE is different from the IPE of the mobile sensor at speed 0, since the stationary sensor is guaranteed to be located at a PoI.) From the figure, we see that mobility is beneficial most of the time, as long as the sensor is not moving too fast, so that not too much energy is consumed for motion. This is because for Step utility, all the information about an event is learned as soon as the event is detected. Even though the event stays, there is no motivation for the sensor to remain at the same PoI and observe the same event longer. Instead, the sensor gains information by moving elsewhere to look for new events. Hence, modulo the energy cost of motion, the rate at which information is captured increases with the sensor speed. When the energy cost is also considered, as in the experiments, there is a competitive effect between the increased rate of information captured and the higher rate of energy consumption for a faster sensor. Hence, the optimal IPE occurs at an intermediate speed. The optimal speed is in general smaller when the energy cost of motion is higher, i.e., when k_2 is larger.

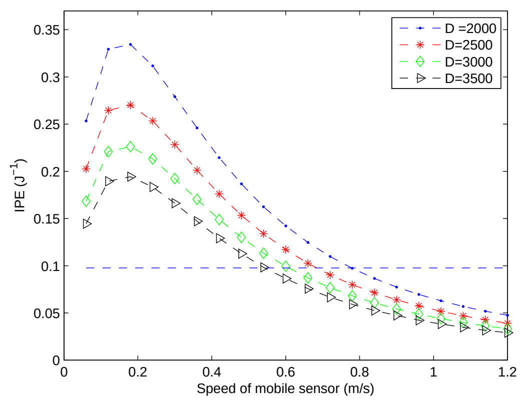
The effects of α on the IPE can be seen from Fig. 1(b), which plots the IPE against the sensor speed v for varying values of α. (In general, a higher α implies stronger environmental resistance against motion.) From the figure, note that when $v = 1$ m/s, the IPE is the same for the different α values. For $v > 1$ ms, the IPE decreases as α increases, while for $v < 1$ m/s, the IPE increases as α increases. All these results agree with Theorem 1. From Eqn. (8), we know that the IPE initially *decreases* for $\alpha < 1$. However, a numerical plot of the IPE in Fig. 2(a) shows that the initial decrease is quite brief and at a low sensor speed (< 0.2 m/s), the IPE again rises with v. The numerical plot in Fig. 2(b) shows that over a broader range of v, the IPE mostly increases in the beginning and then decreases afterwards. This general trend of the IPE is in agreement with the plots in Fig. 1(b) across the range of α values used, i.e., the IPE first increases and then decreases. Hence, the globally optimal IPE is reached at an intermediate v, and the numerical optimization of v discussed in Section IV-B can be applied even when $\alpha \leq 1$.

We present IPE results for different distributions of the PoIs. Fig. 3(a) shows plots of the IPE against v for different values of n, while the other parameters are kept the same as before. Fig. 3(b) shows the IPE plots against v for different values of D, while n is now fixed to be 15. The figures show that the IPE increases either as n increases or as D decreases, because of the increased density of information available for capture (per unit distance) on the circuit. Recalling $\gamma = D/n$, we show in Fig. 3(c) the IPE for different values of D but with the value of γ fixed. We can see that in this case, the IPE is not affected much as the value of D is varied to be 2000, 2100, 2200, and 2300 m.

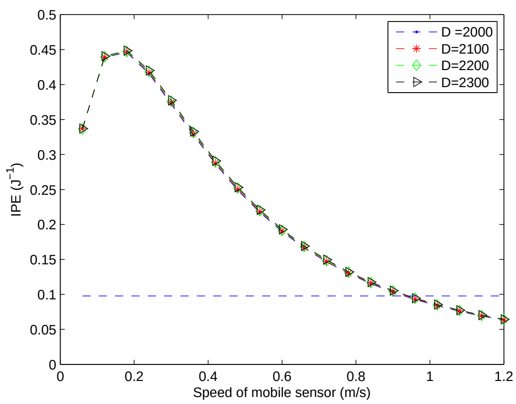
We now discuss the effects of the event dynamics μ and λ on the IPE. With the other parameters fixed, we vary v to be 0.2, 0.4, 0.6, and 0.8. For each v value, we show the IPE as a function of μ in Fig. 4(a). From Fig. 4(a), it can be seen that a larger μ will increase the IPE. This is because when μ is large, more events arrive per unit time, which increases the opportunities for the sensor to capture more information. Similarly, we plot the IPE against λ under different values of v. From Fig. 4(b), notice that the IPE first increases and then decreases as a function of λ. In the case of Step utility, the sensor captures full information about an event as soon as it detects the event. Hence, when λ is too small,



(a) IPE as a function of v, for different n.



(b) IPE as a function of v, for different D.



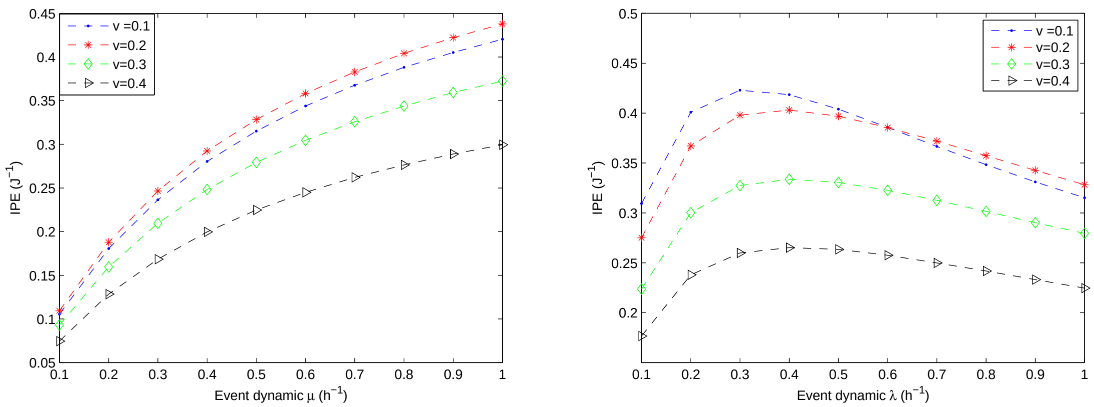
(c) IPE as a function of v, for different k_2 while fixing γ.

Fig. 6. Impact of PoI distribution on IPE for Exponential utility function.

meaning that events will last for a long time on average, the number of events available per unit time decreases, although it is highly likely that each event will be captured (i.e., the QoM is high). When λ is too large, meaning that events will appear only briefly, many events at a PoI will disappear before the sensor returns to the PoI (i.e., the QoM is low), so that the IPE will be small. Hence, as λ increases, the IPE first increases and then decreases.

B. Exponential utility function

We now present corresponding simulation results for the Exponential utility function. The sequence of experiments reported and their parameter settings are identical to the case of Step utility in Section V-A. From Figures 5 and 6, we can see that the Exponential utility results show similar trends as the Step



(a) IPE as a function of μ, for different v.

(b) IPE as a function of λ, for different v.

Fig. 7. Impact of event dynamics on the IPE for Exponential utility function.

utility results. However, there are two differences. First, the IPE for Exponential utility is smaller than that for Step utility. This is because for Exponential utility, a longer sensing time is needed before full information can be captured. Moreover, some of the events may not stay long enough for them to be captured at their full information. Second, the optimal v to maximize the IPE is in general smaller than that for Step utility, indicating a less strong motivation for mobility in the case of Exponential utility. This is because for Exponential utility, the sensor that detects an event at a PoI may continue to gain some more useful information by staying at the PoI and observing the event longer. Hence, relative to Step utility, there is a somewhat less strong case for the sensor to move elsewhere. However, it is still true that, for Exponential utility, the rate of information captured increases as the sensor speed increases [1]. But, as before, the increased rate of information captured must be balanced against the increased rate of energy consumption for the optimal IPE, and the balance is shifted towards a lower speed for Exponential utility relative to Step utility.

Effects of the event dynamics λ and μ on the IPE are shown in Fig. 7 for Exponential utility. The plots are similar to those for Step utility (Fig. 4), and we shall omit our comments.

VI. Conclusions

We have analyzed the expected information captured per unit of energy consumption (IPE) for a mobile sensor repeatedly covering n PoIs in a circuit of length D. Our analysis quantifies the effects of the event dynamics (i.e., statistical distributions of the event staying and absent times), the type of event as captured by either the Step or Exponential utility function, the sensor speed v, and the density of the PoIs given by $\gamma = D/n$. The analytical results have allowed us to optimize v for the highest IPE. In addition, we have compared the performance of mobile coverage against the use of a stationary sensor in two situations. First, the locations of the PoIs are known, and the stationary sensor is optimally placed to cover a PoI for maximum information capture. Second, the PoIs are uniformly distributed at random along the circuit and a stationary sensor is likewise placed at a random location. We analyze conditions when the mobile coverage can perform better than the static coverage in terms of the IPE. We have also illustrated and verified our analytical results by simulation experiments.

Our analysis can be extended in several ways. First, the sensor may vary its speed along the circuit, for example, it may slow down while covering a PoI compared with while it is traveling between PoIs. Second, the sensor can be turned off when it is known not to be covering any PoI. This strategy will reduce the energy expense of sensing, but it may require energy to transit between the on- and off-states. Third, different trade-offs can be characterized according to the energy due to of sensing in relative to that of mobility.

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