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Design of a randomly distributed sensor network for target detection ☆

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Abstract

This paper explores the design and configuration of a sensor network for target detection. Subject to a budget limit for sensors, the network is required to secure a certain detection probability and to work for a reasonable long time. One novel model of randomly distributed network is presented to fulfill this requirement. A state switching scheme is developed for sensor to save energy. The functional relationships between detection probability and related parameters about sensor, network and target are analyzed. Moreover, a two-level optimization problem is formulated. At the lower level, we optimize the behavior of each sensor subject to its energy constraint and at the upper level, we maximize the lifetime of the network. Equilibrium solution of the two-level optimization problem is obtained by numerical method. An example is presented to illustrate the main results.

Keywords: Sensors; Networks; Detection; Probability; Optimization

1. Introduction

Recent advances in wireless communications and micro electromechanical system have enabled the development of low-cost, low-power, multi-functional sensors that are small in size and can communicate with each other from short distances (Akyildiz, Su, Sankarasubramaniam, & Cayirci, 2002). For example, the project "Smart Dust" at University of California, Berkeley aims to make small, light and cheap sensors and deploy such sensors on the ground, in the air, under water, on bodies, in vehicles, and inside buildings (Kahn, Katz, & Pister, 1999).

Sensor networks that consist of a large number of densely deployed sensors, have a wide range of applications such as military sensing, physical security, environment monitoring, traffic surveillance, etc. (Akyildiz et al., 2002; Chong & Kumar, 2003). For example, the project ExScal is designed as a sensor network platform for reliable detection, classification, and quick reporting of rare, random, and ephemeral events. It seeks to demonstrate a 10,000 sensors network capable of discriminating civilians, soldiers and vehicles, spread out over a 10 km^2 area (Dutta, Grimmer, Arora, Bibyk, & Culler, 2005).

When the environment of interest is inaccessible or located in a hostile area, sensors may be air-dropped from an aircraft or by other ways which results in a random placement (Clouqueur, Phipatanasuphorn, Ramanathan, & Saluja, 2003). For example, an aircraft sprinkles a number of cheap wireless magnetic sensors along a road; once they hit the ground, these sensors automatically form a network and begin to scan the environment for magnetic signals. When a vehicle rolls by, they can tell from its magnetic signature what kind the vehicle is, its speed and direction.

The wireless sensor usually can only be equipped with a limited power source (< 0.5 Ah, 1.2v) (Akyildiz et al., 2002). MICA2, as an off-the-shelf sensor model, has a full-duty lifetime of about one day with a battery capacity of 0.5 Ah

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(Rev, 2003). Replenishment of power might be impossible. Hence, power conservation and management are of great importance (Akyildiz et al., 2002). Power conservation protocol is commonly used to extend the lifetime of the network. Sensors can, of course, coordinate and negotiate to decide their working states with communication; however, randomly independent state switching schemes (SSSs) are also widely adopted (see e.g., Gui & Mohapatra, 2004; Pattem, Poduri, & Krishnamachari, 2003; Ren, Li, Wang, Chen, & Zhang, 2005) since it is simple and free of communication.

Our problem is to design a sensor network with a given budget for sensors, to monitor an area of interest for target detection with certain probability, e.g., 0.95, and make the network work for a reasonable long time, e.g., 10 days or longer. We present a *randomly distributed sensor network* (RDSN) model. Based on this model, we obtain detection probability as an *explicit* function of network parameters and optimize the behavior of the sensor network.

The rest of the paper is organized as follows. In Section 2, problem formulation is presented. In Section 3, related work is reviewed and comparison is made between the existing work and our work. Section 4 is devoted to the analysis and mathematical derivation of detection probability of the RDSN. In Section 5, a two-level optimization problem is formulated to optimize the behavior of sensor and maximize the lifetime of the RDSN subject to the requirement of detection probability and budget constraint. In Section 6, an illustrative example is provided. Finally, Section 7 concludes the paper.

2. Formulation of the problem

All sensors making up the RDSN are identical (in terms of sensing radius, energy as well as any other function and capability). Sensors are independently and identically distributed in the *area of interest* (AoI) following uniform distribution. More precisely, the probability density function of each sensor located at s is

$$\phi(s) = \begin{cases} \dfrac{1}{A}, & s \in \text{AoI}, \\ 0 & \text{otherwise}, \end{cases}$$

where A is the total area of the AoI. The AoI is something like a battle field. Target may enter the AoI by crossing its border or land on it directly. Any point in the AoI is possible entrance for target.

The main idea is using quantity (number of sensors) to trade for quality (detection probability). We let each sensor be ON/OFF randomly and independently. When being ON, a sensor can sense and communicate; when being OFF (or asleep), it can neither sense nor communicate and consumes no energy (or too little energy to be taken into account). In this way, each sensor can work longer so that the lifetime of the RDSN will be prolonged. Due to random placement and ON/OFF scheme for sensors, the RDSN likely fails to detect a target. *Detection probability* is defined as the probability that the RDSN detects a target within the entire course of the target moving in the AoI. Power conservation and the quality of target detection are conflicting requirements. The difficulties in this problem include: first, sensor needs to schedule its working time so that it can live as long as the life expectation for the network; second, the cooperative efforts of sensors should guarantee a predefined detection probability.

Passive sensors such as magnetometer sensor (detecting disturbance from automobiles) and infrared sensor (detecting moving objects) have sensing ranges. A sensor's sensed data may vary along its distance to the target. If its measurement is above a particular threshold, the sensor is assumed to detect the target. We assume a sensor's sensing area is a disc with the sensor as its center. This assumption is also commonly used in the study of sensing coverage (see e.g., Cardei & Wu, 2002; Chakrabary, Iyengar, Qi, & Cho, 2002; Slijepcevic & Potkonjak, 2001). The following parameters of sensors are assumed known.

E_o	Total energy which can be used by each sensor.
P_{on}	Average energy consumption per unit time for sensor when its state is ON.
e_s	Energy consumption for sensor switching from state OFF to ON each time.
r	Sensing radius of each sensor.
c	Price for a single sensor.

After being deployed, every sensor needs to first perform an initialization task to form a network. E_o represents the remaining energy of a sensor after the setup stage.

Detection probability depends not only on the RDSN but also the target's speed and path in the AoI. The related parameters are listed in the table below, where $\hat{P}$ and B are given and N and L_{sn} need to be optimized.

$\hat{P}$	Probability of detecting target for the RDSN.
B	Limit of budget for sensors in the network.
N	Number of sensors to be deployed in the AoI.
L_{sn}	Expected operating lifetime of the RDSN.
v	Target's speed when moving in the AoI.
L	The length of target's track within the AoI.

Generally, the AoI may be in various shapes. For convenience of analysis, it is first assumed as a unit square. The results based on this assumption can be easily applied to the AoI of different shapes.

2.1. State switching scheme (SSS)

To save energy, each sensor independently switches its state, ON and OFF, with probabilities a and $1-a$, respectively, and keeps its state at least for U_T before taking chance to change its state. SSS is a combination of randomized activation and duty-cycle. It has both advantages of randomness (from parameter a) and regularity (from parameter U_T). The behavior of each sensor or even the RDSN at large is mainly determined by (a, U_T). After setup stage, every sensor will follow SSS independently with the same value of (a, U_T).

More precisely, if $\{S_n,\ n \geqslant 0\}$ denotes the sequence of one sensor's states, where n represents its nth U_T, then

$$P(S_n = \text{ON}) = a, \quad P(S_n = \text{OFF}) = 1 - a, \quad \forall n \geqslant 0.$$

The probability for one sensor staying ON (or OFF) for the entire $k \times U_T$ time interval follows geometric distribution. That is

$$P(S_n = \text{OFF and } S_{n+i} = \text{ON}, 1 \leqslant i \leqslant k) = (1-a)a^k,$$

$$P(S_n = \text{ON and } S_{n+i} = \text{OFF}, 1 \leqslant i \leqslant k) = a(1-a)^k.$$

From the point view of each sensor, SSS lets each sensor stay ON for a portion of its life. From the point view of the RDSN, SSS also lets a portion of sensors in the RDSN being ON at any time. SSS can be easily implemented with the following three steps.

Step 1: When sensor is ON, its CPU generates a sequence of random numbers, $a(1), \ldots, a(k)$, where $a(i) \sim U(0, 1)$ for any $1 \leqslant i \leqslant k$ and $a(k)$ is the first number satisfying $a(k) \leqslant a$, i.e., $a(i) > a$ for any$1 \leqslant i < k$.

Step 2: If $k = 1$, the sensor will stay ON in the following U_T and repeat step 1.

Step 3: If $k > 1$, the sensor will be OFF in the following $(k-1) \times U_T$, then sensor will become ON for the kth U_T and repeat step 1.

Assumptions imposed in this paper are as follows:

Assumption 1. Sensors are homogeneous.

Assumption 2. Each sensor is independently and identically distributed in the AoI following uniform distribution.

Assumption 3. The AoI is a unit square.

Assumption 4. Sensor's sensing range is a disc with radius r.

Assumption 5. Sensor's total energy CANNOT afford it to be ON for the whole expected operating lifetime of the RDSN, i.e., $E_o < P_{on} L_{SN}$.

Assumption 6. SSS is used.

3. Related work

Target detection is closely connected to sensing coverage. Full sensing coverage is usually energy consuming and demanding on sensors' locations. Different centralized or locally coordinated algorithms for full coverage are developed (see e.g., Cardei & Wu, 2002; Chakrabary et al., 2002; Slijepcevic & Potkonjak, 2001).

Probabilistic or partial coverage aims to strike the balance between energy consumption and the performance of the network. Exposure is defined as how well an object moving on an arbitrary path can be observed by the sensor network over a period of time. Meguerdichian, Koushanfar, Qu, and Potkonjak (2001) has developed an algorithm for finding minimal exposure paths which provides valuable information about the worst case exposure-based coverage in sensor networks. Liu and Towsley (2004) defines three coverage measures, i.e., area coverage, node coverage and detectability to characterize the coverage properties of large-scale RDSNs. It shows that there exists a critical density for object detection, however, it does not incorporate any power conservation scheme for sensors and they need to be always ON. In Yan, He, and Stankovic (2003), based on coordination among sensors, different subsets of sensors can become active during separate time slots so that differentiated surveillance service for sensor networks is carried out. Pattem et al. (2003) addresses tracking strategies in which a small portion of the network is activated randomly and/or in a duty-cycled manner and evaluates the fundamental performance of these tracking strategies. In Gui and Mohapatra (2004), the network operates in surveillance and tracking states; the trade-off between power conservation and quality of surveillance and tracking is quantified .

Ren et al. (2005) presents a model to analyze object detection probability with respect to network conditions and sensor scheduling schemes. Its work is similar to the one of this paper (in Sections 2 and 4). In Ren et al. (2005), energy conservation protocol is called *random sensing schedule* (RSS). Its idea is that, within a sensing period, sensor will be ON for a short duration, and in the rest of time sensor will be OFF. The starting point of the active duration is randomly and independently decided by each sensor. There are noticeable differences between the model and analysis in Ren et al. (2005) and in this paper. Particularly, a comparison between RSS in Ren et al. (2005) and SSS is provided in the following table.

It is seen that SSS is more flexible and easy for implementation. More important, by choosing optimal value for (a, U_T), we can maximize the detection probability of an individual sensor. This is an essential way to prolong the lifetime of the network (see Section 5.1).

4. Analysis of detection probability

The aim of this section is to reveal the relationship between detection probability and the system parameters which are related to the RDSN and the target.

RSS	SSS
Parameters: sensing period, P, and active duration, H.	Parameters: the probability to be ON, a, and the shortest time interval for any state, U_T.
H is fixed. P is adjustable.	Both a and U_T are adjustable.
H is assumed lasting long enough.	To be shown that decreasing U_T can improve detection probability of individual sensor
ON–OFF transition energy cost is ignored.	ON–OFF transition energy cost (denoted as e_s) is taken into account.

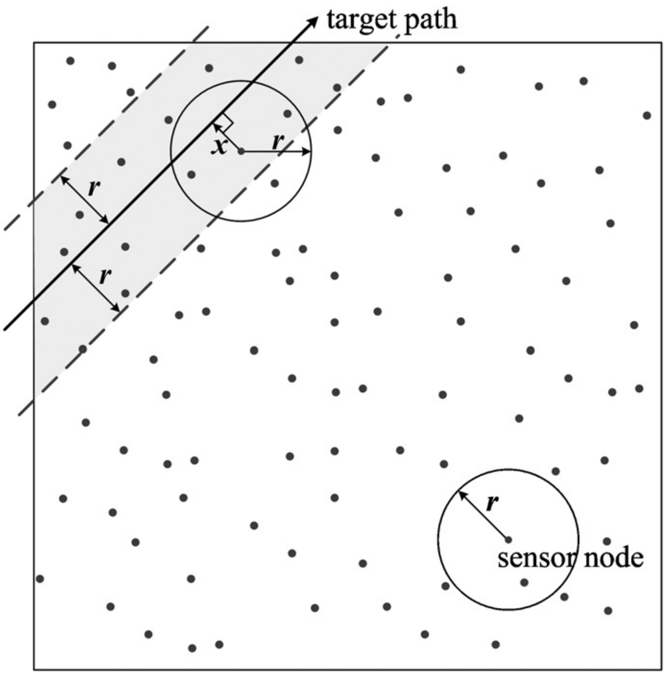

Fig. 1. Illustration of DZ and sensing area of sensor in the AoI.

Sensor needs to decide the starting point of H in every P.	No need to decide the state at the beginning of every U_T. When being ON, sensor decides how long it will stay OFF before it switches back to ON next time.

Comparing to the large area of the AoI, the target's size is assumed small enough and can be neglected. When a target moves in the AoI, only the sensors which are close to its path can sense it. A target's *detection zone* (DZ) is introduced as the area in which sensors have chance to detect it. Sensors located outside of a target's DZ cannot detect the target. For example, in Fig. 1, if the target moves along the solid line, its DZ is the area between the two dashed lines within the AoI.

4.1. Detection probability of an individual sensor

Suppose a and U_T are fixed and the target takes Δt to get through a sensor's sensing area. There exists a non-negative integer $k = \lfloor \Delta t/U_T \rfloor$ ($\lfloor x \rfloor$ means the maximal integer which is less or equal to x) such that $\frac{\Delta t}{U_T} - 1 < k \leqslant \frac{\Delta t}{U_T}$, or equivalently, $kU_T \leqslant \Delta t < (k+1)U_T$.

Two time axis shown in Fig.2 helps to illustrate the only two possible cases which may happen between Δt and sensor's state switching. Each interval between two vertical lines equals to U_T. Δt may start from any point in $[0, U_T)$. When its starting point in $[0, (k+1)U_T - \Delta t]$, Δt will end in the $(k+1)$thU_T as shown by the lower axis. Complementarily in the upper axis, when Δt starting from a point in $((k+1)U_T - \Delta t, U_T)$ it will end in the $(k+2)$thU_T. The probabilities for the two cases are $((k+1)U_T - \Delta t)/U_T$ and $(\Delta t - kU_T)/U_T$, respectively.

In the lower axis, Δt is totally covered by the first $(k+1)U_T$. If the sensor is continuously OFF for $(k+1)U_T$, it will fail to detect the target. The probability for such event is $(1-a)^{k+1}$. Similarly, in the upper axis, the probability for the sensor failing to detect the target is $(1-a)^{k+2}$. Therefore, the probability of the sensor failing to detect the target is

$$
\begin{aligned}
q_1(\Delta t) &= (1-a)^{k+2}\left(\frac{\Delta t - kU_T}{U_T}\right) \\
&\quad + (1-a)^{k+1}\left(\frac{(k+1)U_T - \Delta t}{U_T}\right) \\
&= (1-a)^{k+1}\left(1 - a\left(\frac{\Delta t}{U_T} - k\right)\right).
\end{aligned}
$$

Equivalently, replacing k with $\lfloor \Delta t/U_T \rfloor$, we have

$$
q_1(\Delta t) = (1-a)^{\lfloor \Delta t/U_T \rfloor + 1}\left(1 - a\left(\frac{\Delta t}{U_T} - \left\lfloor \frac{\Delta t}{U_T} \right\rfloor\right)\right).
$$

So the probability of an individual sensor detecting the target is $p_1(\Delta t) = 1 - q_1(\Delta t)$.

Suppose the perpendicular distance between the target's trajectory and the sensor is x as shown in Fig. 1, the length of the target's trajectory contained in the sensing disc of the sensor is $2\sqrt{r^2 - x^2}$. Then $\Delta t = 2\sqrt{r^2 - x^2}/v$. By Assumption 2, each sensor is uniformly distributed; the value of x obeys uniform distribution, i.e., $x \sim U(0, r)$; the mean of $q_1(\Delta t)$ is

$$
\begin{aligned}
q_1^* &= E_{\Delta t}\{q_1(\Delta t)\} \\
&= E_x\left\{(1-a)^{\lfloor \Delta t/U_T \rfloor + 1}\left(1 - a\left(\frac{\Delta t}{U_T} - \left\lfloor \frac{\Delta t}{U_T} \right\rfloor\right)\right)\right\} \\
&= (1-a)\int_0^r (1-a)^{\lfloor 2\sqrt{r^2-x^2}/(v\cdot U_T) \rfloor} \\
&\quad \times \left(1 - a\left(\frac{2\sqrt{r^2-x^2}}{v\cdot U_T} - \left\lfloor \frac{2\sqrt{r^2-x^2}}{v\cdot U_T} \right\rfloor\right)\right)\frac{\mathrm{d}x}{r} \\
&= (1-a)\int_0^1 (1-a)^{\lfloor 2r\sqrt{1-z^2}/(v\cdot U_T) \rfloor} \\
&\quad \times \left(1 - a\left(\frac{2r\sqrt{1-z^2}}{v\cdot U_T} - \left\lfloor \frac{2r\sqrt{1-z^2}}{v\cdot U_T} \right\rfloor\right)\right)\mathrm{d}z; \qquad (1)
\end{aligned}
$$

and accordingly, $p_1^* = 1 - q_1^*$.

Thus, p_1^*, the expected detection probability of a single sensor which lies inside a target's DZ, is obtained; in this case, there is no longer any random factor involved in p_1^*; now, both p_1^* and q_1^* are determined by parameters a, U_T, r and v. To make such dependence more noticeable, p_1^* can be re-written as

$$
\begin{cases}
p_1^*(a, U_T, r, v) = 1 - q_1^*(a, U_T, r, v), \\
q_1^*(a, U_T, r, v) \text{ is defined in (1).}
\end{cases} \qquad (2)
$$

It is obvious that larger a leads to a larger detection probability. If a target moves slower in the AoI, it is more likely that the

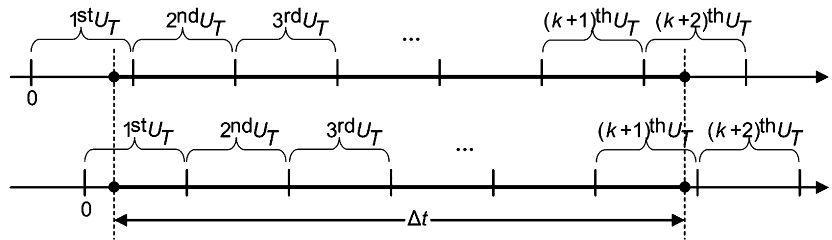

Fig. 2. Illustration of the two possible cases of Δt vs. U_T.

RDSN detects it. With shorter U_T, a sensor may switch its state more frequently so that it has more chances to detect the target.

Theorem 7. p_1^*, *the mean value of detection probability by a single sensor defined in* (2), *is monotonously increasing as* U_T *is decreasing* (*or* v *is decreasing*).

Proof. Since in (1) v appears in the equivalent place where U_T does, we only need to prove the case when U_T is decreasing.

Define two functions $f(U,z) = 2r\sqrt{1-z^2}/(v \cdot U_T)$ and $I(U,z) = \lfloor 2r\sqrt{1-z^2}/(v \cdot U_T) \rfloor$, then $0 \leqslant f(U,z) - I(U,z) < 1$. The integrand in (1) can be rewritten as

$$g(U,z) = (1-a)^{I(U,z)}[1 - a(f(U,z) - I(U,z))].$$

Suppose $U_1 > U_2 > 0$, then $f(U_1,z) < f(U_2,z)$. There are two possible cases for $I(U_1,z)$ and $I(U_2,z)$:

Case 1: $I(U_1,z) \leqslant I(U_2,z) - 1$, then

$$g(U_1,z) = (1-a)^{I(U_1,z)}[1 - a(f(U_1,z) - I(U_1,z))] > (1-a)^{I(U_1,z)+1}$$

and

$$g(U_2,z) = (1-a)^{I(U_2,z)}[1 - a(f(U_2,z) - I(U_2,z))] \leqslant (1-a)^{I(U_2,z)} \leqslant (1-a)^{I(U_1,z)+1}.$$

Therefore, $g(U_1,z) > g(U_2,z)$.

Case 2: $I(U_1,z) = I(U_2,z)$, then

$$g(U_1,z) = (1-a)^{I(U_1,z)}[1 - a(f(U_1,z) - I(U_1,z))] > (1-a)^{I(U_2,z)}[1 - a(f(U_2,z) - I(U_2,z))] = g(U_2,z).$$

In both cases, $g(U_1,z) > g(U_2,z)$ holds so that $p_1^*(U_1) < p_1^*(U_2)$ is proved. □

Further discussion on (2) is as follows.

Remark 8. $a=1$ means the sensor is ON always, then $p_1^* = 1$ suggests that any sensor in the DZ can detect the target for sure. On the opposite, even located in the DZ, a sensor cannot detect the target ($q_1^* = 1$) if the sensor is OFF all the time ($a = 0$).

Remark 9. When the target is essentially stationary (i.e., $v \to 0$), $p_1^* = 1$. In this case, any sensor in the DZ of the target path can detect the target. When the target moves through the AoI very fast (i.e., $v \to \infty$), any sensor in the DZ has no chance to switch its state. So it can detect the target with probability a. This coincides with the results of (2), i.e., $q_1^* = 1 - a$ and $p_1^* = a$, respectively.

Remark 10. For targets of interest, suppose their velocity range is known, say $0 < v \leqslant V_{\max}$. In (2), one conservative way is adopting $v = V_{\max}$ to guarantee the detection probability.

4.2. Detection probability with given target's path

When the target traverses the AoI along one line, multiple sensors may detect it, e.g., as shown in Fig. 1, all sensors within its DZ have chance to detect the target. As described in Section 2, N sensors form up the RDSN and each of them operates with SSS independently.

Theorem 11. *Suppose one target moves in the AoI along a line with speed* v *and* s *as its area of DZ. Let* $p_s(a, U_T, r, v, N)$ *denote the probability of the RDSN detecting the target*; *and* $p_s^*(a, U_T, r, v, N)$ *denote the mean of* $p_s(a, U_T, r, v, N)$, *then*

$$p_s^*(a, U_T, r, v, N) = 1 - (1 - sp_1^*)^N, \tag{3}$$

where p_1^* *is defined in* (2).

Proof. If there are i sensors located in the DZ of the target, only when all these i sensors fail to detect the target, then RDSN cannot detect the target. Notice that each sensor works independently. We have

$$\begin{aligned} &P(\text{RDSN detects the target}) \\ &\quad = 1 - P(\text{All the } i \text{ sensors fail to detect the target}) \\ &\quad = 1 - \prod_{j=1}^{i} P(\text{Sensor } j \text{ fails to detect the target}) \end{aligned}$$

and

$$\begin{aligned} &E[P(\text{All the } i \text{ sensors fail to detect the target})] \\ &\quad = \prod_{j=1}^{i} E[P(\text{Sensor } j \text{ fails to detect the target})] \\ &\quad = (q_1^*)^i. \end{aligned} \tag{4}$$

By Assumptions 2 and 3, the probability of one sensor located in such DZ is *the area of target's DZ/the total area of AoI* $= s/1 = s$, where $s < 1$. Due to the independence of sensor's location, the probability of i sensors located in the area s obeys binomial distribution $B(N, s)$, that is

$$P(i \text{ of } N \text{ sensors are located in an area of } s) = C_N^i (1-s)^{N-i} s^i. \quad (5)$$

Therefore,

$$\begin{aligned} p_s(a, U_T, r, v, N) &= P(\text{RDSN detect the target with } s \text{ as area of its DZ}) \\ &= 1 - \sum_{i=0}^{N} \{C_N^i (1-s)^{N-i} s^i \\ &\quad P(\text{All } i \text{ sensors fail to detect the target})\}. \end{aligned}$$

Taking expectation on both sides, using (4) and the formula $(a+b)^N = \sum_{i=0}^N C_N^i a^{N-i} b^i$, we can get (3) by simple calculation. The proof is completed. □

We can understand Theorem 11 more directly. Each sensor has probability s to fall in DZ and, if a sensor is in DZ, then it can detect the target with probability p_1^*. So each sensor has probability sp_1^* to detect the target. $(1-sp_1^*)^N$ is the probability that no sensor in the RDSN detects the target, and $1-(1-sp_1^*)^N$ is the probability that the RDSN detects the target. This theorem shows that as s increases $p_s^*(a, U_T, r, v, N)$ increases too. This is consistent with the fact that with larger DZ there are more sensors so the target is more likely to be detected.

Remark 12. It is not necessary to require the target enters the AoI from one edge and exits from another edge along one line. Target may take a curved path as well as a straight one. Of course, in the former case, it becomes a little complicated to calculate the corresponding area of the target's DZ. One efficient way is by using several line segments to approximate the curve and making summation accordingly. The fact is that, when target is taking a curved path, it is more likely to be detected because it spends more time in the AoI. The detection probability for straight line essentially provides a lower bound of such probability for curved path.

Remark 13. Another possible scenario is that the target drops in the AoI from the air and move around inside it. (3) is still applicable in this case.

Remark 14. Sensor which is located at the border of the AoI may detect the target when it is approaching the AoI but has not entered yet. However, DZ is defined to be within the AoI; therefore detection probability calculated according to (3) will be a little smaller than the real one. In reality, sensor's sensing radius is usually much small comparing to the width of the AoI, thus the approximation error incurred by (3) is very small and can be neglected.

In particular, when a target traverses the AoI in its inner part instead of on or close to its border, the area of its DZ can be calculated by $s=2Lr$, where L is the length of target's track. The following corollary is an immediate consequence of Theorem 11.

Corollary 15. *Suppose one target traverses the AoI along a line with speed v and its track length is L. Let $p_L^*(a, U_T, r, v, N)$ denote the mean probability of the RDSN detecting the target, then*

$$p_L^*(a, U_T, r, v, N) \approx 1 - (1 - 2Lrp_1^*)^N. \quad (6)$$

Moreover, let $p_{tL}^*(a, U_T, r, v, N, t)$ denote the mean probability of the RDSN detecting the target as the target has covered its first $t \in [0, 1]$ portion of track, then

$$p_{tL}^*(a, U_T, r, v, N, t) \approx 1 - (1 - 2Lrtp_1^*)^N. \quad (7)$$

When $t = 0$ (target not entering in the AoI), then $p_{tL}^*(a, U_T, r, v, N, 0)=0$ (the network cannot detect the target); when t increases (e.g., $t = \frac{1}{8}, \frac{1}{4}, \frac{1}{2}$, etc.), $p_{tL}^*(a, U_T, r, v, N, t)$ also increases. Thus, (7) is helpful for a better understanding of the behavior of the RDSN during the entire course of the target's movement in the AoI.

4.3. Overall detection probability

The previous analysis shows that s, the target's area of DZ, is crucial to the detection probability. With bigger s, the target is more likely to be detected. Overall detection probability, however, must be averaged over all possible s and cannot be the worst one (for example, the target may barely touches a corner of the AoI, i.e., length of path is effectively a single point). Otherwise the result is too conservative to be a practical solution. Target can also take a curved path. Based on (3), if the distribution of s is given, the mean of detection probability can be calculated with respect to s and be viewed as the overall detection probability. One crude but simple way to approximate overall detection probability is using the mean of track length, or some track length L^* which is of most concern of the RDSN. Suppose P_L^* denote such approximate overall detection probability. By Corollary 15, we have

$$P_L^*(a, U_T, r, v, N) = 1 - (1 - 2L^* rp_1^*)^N. \quad (8)$$

4.4. Detection probability of multiple sensors

On average, any single sensor which is located in a target's area of DZ can detect the target with probability p_1^* as defined in (2). However, in the course of target getting through the AoI, how many sensors can detect it? This part aims to explore the detection probability of multiple sensors.

Theorem 16. *Suppose one target moves in the AoI along a line with speed v and s as its area of DZ. Let $P_d(a, U_T, r, v, s, N, n)$ denote the probability that there are exactly n sensors in the*

RDSN detecting the target and $P_d^*(a, U_T, r, v, s, N, n)$ *denote the mean of* $P_d(a, U_T, r, v, s, N, n)$, *then*

$$P_d^*(a, U_T, r, v, s, N, n) = C_N^n(1 - sp_1^*)^{N-n}(sp_1^*)^n, \tag{9}$$

where p_1^* *is defined in* (2).

Proof. If there are i $(i \geqslant n)$ sensors in the area of DZ, then the probability of that n out of such i sensors detect the target but the rest $(i - n)$ sensors fail is

$$P(\text{Exactly } n \text{ of } i \text{ sensors detect the target}) = C_i^n \prod_{j=1}^{n} P(\text{Sensor } j \text{detects the target}) \times \prod_{j=n+1}^{i} P(\text{Sensor } j \text{ fails to detect the target}).$$

Moreover, by (5), we have

$$P_d(a, U_T, r, v, s, N, n) = \sum_{i=n}^{N} \{C_N^i(1 - s)^{N-i} s^i \, P(\text{Exactly } n \text{ of } i \text{ sensors detect the target})\}.$$

Since each sensor works independently, taking expectation on both sides of the above equation, we get

$$\begin{aligned} &P_d^*(a, U_T, r, v, s, N, n) \\ &= \sum_{i=n}^{N} \{C_N^i(1 - s)^{N-i} s^i C_i^n (q_1^*)^{i-n}(p_1^*)^n\} \\ &= C_N^n(sp_1^*)^n \left\{\sum_{i=n}^{N} \frac{(N-n)!}{(i-n)!(N-i)!}(1-s)^{N-i}(sq_1^*)^{i-n}\right\} \\ &= C_N^n(sp_1^*)^n \left\{\sum_{j=0}^{N-n} C_{N-n}^j(1-s)^{N-n-j}(sq_1^*)^j\right\} \\ &= C_N^n(sp_1^*)^n(1 - s + sq_1^*)^{N-n} \\ &= C_N^n(1 - sp_1^*)^{N-n}(sp_1^*)^n. \end{aligned}$$

We conclude the proof. □

Like Corollary 15 being derived from Theorem 11, Corollary 17 is from Theorem 16.

Corollary 17. *Suppose one target traverses the AoI along a line with speed* v *and its track length is* L. *Let* $P_{Ld}^*(a, U_T, r, v, N, n)$ *denote the mean probability of that there are exactly* n *sensors in the RDSN detecting the target, then*

$$P_{Ld}^*(a, U_T, r, v, N, n) = C_N^n(1 - 2Lrp_1^*)^{N-n}(2Lrp_1^*)^n. \tag{10}$$

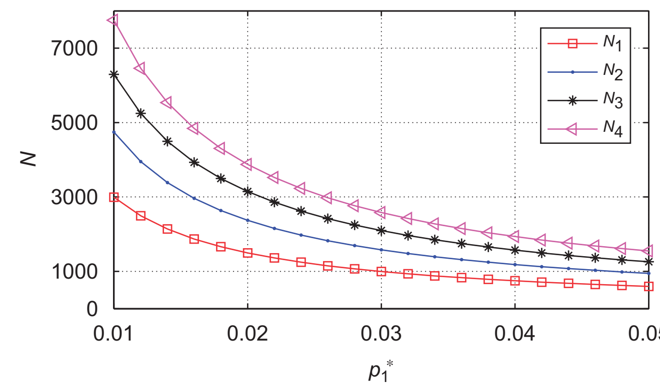

Fig. 3. N_i vs. p_1^*.

Moreover, let $P_{tLd}^*(a, U_T, r, v, N, n, t)$ *denote the mean probability of that there are exactly n sensors in the RDSN detecting the target as the target has covered its first* $t \in [0, 1]$ *portion of track, then*

$$P_{tLd}^*(a, U_T, r, v, N, n, t) = C_N^n(1 - 2Lrtp_1^*)^{N-n}(2Lrtp_1^*)^n. \tag{11}$$

The probability of multiple detection of the target can serve as one metric of confidence of detection. Like Corollary 15, Corollary 17 is useful for understanding the behavior of the RDSN in detecting the target.

The minimal number of sensors which guarantees certain detection probability is important for the RDSN. When sensing radius r is fixed, p_1^* represents the collective influence caused by a, U_T and v so that the minimal number of sensors is dependent on p_1^*. For example, suppose a target's track length $L = 1$ and $r = 0.05$ then $s = 2Lr = 0.1$. To have the target detected by at least i sensors with probability 0.95, from (10), the minimal number of sensors, N_i, is given by

$$N_i = \min\left\{N | 1 - \sum_{n=0}^{i-1} C_N^n(1 - 0.1p_1^*)^{N-n}(0.1p_1^*)^n \geqslant 0.95\right\}.$$

Four curves of N_i vs. p_1^*, where $i = 1, 2, 3, 4$, are plotted in Fig. 3. In fact, N_1 is the minimal number of sensors for the RDSN to detect the target with probability 0.95.

4.5. Impact of a single sensor

Suppose there are already N sensors in the AoI. When one more sensor is added to the RDSN, with (3), the contribution of this sensor to detection probability is

$$\Delta p_s = p_s^*(a, U_T, r, v, N + 1) - p_s^*(a, U_T, r, v, N) = (1 - sp_1^*)^N sp_1^*.$$

It is shown that, as N gets bigger, Δp_s becomes less noticeable. In other words, when the RDSN has enough sensors, one sensor becoming defunct can hardly reduce its detection probability dramatically. The RDSN *degrades gracefully* if sensor failure happens randomly and independently. This property is essential for the RDSN.

5. Optimization of the RDSN

Let $N_L(a, U_T, r)$ denote the number of sensors to guarantee detection probability $\hat{P}$ for the RDSN when target's speed is v^* and track length is L^*. With (8), we have

$$N_L(p, a, U_T, r) = \frac{\ln(1-\hat{P})}{\ln(1-2L^* r p_1^*)}, \tag{12}$$

where p_1^* is defined in (2) with $v = v^*$. From (2) and (12), with fixed (a, U_T), increasing r not only leads to p_1^* increasing but also enlarges the area of DZ. It seems that increasing r can reduce the number of sensors more effectively than increasing a or decreasing U_T (see Theorem 7) does. However, for a passive sensor, its r is rather determined by its physical property.

The pair (a, U_T) as design parameters are introduced in SSS and their value is adjustable. Choosing proper value for (a, U_T) to maximize p_1^* is an essential way to reduce the number of sensors and will provide a solid base for optimizing the performance of the RDSN.

5.1. Maximize p_1^* with given L_{sn}

By Theorem 7, p_1^* becomes bigger when U_T is smaller. However, for a real sensor, its sensing device needs some time to warm up before functioning normally. Thus sensor's state switching cannot happen too frequently. There exists $U_{\min}$, $U_{\min} > 0$, such that $U_T \geqslant U_{\min}$. On the other hand, U_T is limited by the total energy of a sensor. It is reasonable to assume that the feasible range of U_T satisfies

$$U_{\min} \leqslant U_T < \frac{E_{\mathrm{o}}}{P_{\mathrm{on}}} \leqslant L_{\mathrm{sn}}. \tag{13}$$

U_T is also related to the energy consumption of each sensor. When a sensor is ON, the energy it consumes per unit time (power) is P_{on} and sensor spends extra energy e_{s} to switch its state from OFF to ON each time. The average energy consumption per sensor within one U_T is $E(a, U_T) = aU_T P_{\mathrm{on}} + a(1-a)e_{\mathrm{s}}$; for per unit time the energy is $P(a, U_T) = E(a, U_T)/U_T = aP_{\mathrm{on}} + a(1-a)e_{\mathrm{s}}/U_T$. To ensure each sensor can work for the span of L_{SN}, sensor's total energy E_{o} cannot be less than $L_{\mathrm{sn}} P(a, U_T)$, that is, $E_{\mathrm{o}}/L_{\mathrm{sn}} \geqslant aP_{\mathrm{on}} + a(1-a)\frac{e_{\mathrm{s}}}{U_T}$, which implies the following two constraints on (U_T, a), which are

$$U_T \geqslant \frac{a(1-a)e_{\mathrm{s}} L_{\mathrm{sn}}}{E_{\mathrm{o}} - aP_{\mathrm{on}} L_{\mathrm{sn}}} \quad \text{and} \quad 0 < a < \frac{E_{\mathrm{o}}}{P_{\mathrm{on}} L_{\mathrm{sn}}}, \tag{14}$$

respectively. Combining (13) and (14) yields constraint on a

$$\frac{a(1-a)e_{\mathrm{s}} L_{\mathrm{sn}}}{E_{\mathrm{o}} - aP_{\mathrm{on}} L_{\mathrm{sn}}} < L_{\mathrm{sn}}, \quad a \in \left(0, \frac{E_{\mathrm{o}}}{P_{\mathrm{on}} L_{\mathrm{sn}}}\right). \tag{15}$$

Theorem 7suggests that U_T should be as small as possible. By (14), we have

$$U_T = \max\left\{U_{\min}, \frac{a(1-a)e_{\mathrm{s}} L_{\mathrm{sn}}}{E_{\mathrm{o}} - aP_{\mathrm{on}} L_{\mathrm{sn}}}\right\}. \tag{16}$$

Parameters e_{s}, E_{o} and $U_{\min}$ are determined by sensor's inherent property. Since L_{sn} is given, p_1^* merely depends on the value of a. The problem of choosing a to maximize p_1^* is formulated as follows:

$$\max_a \quad p_1^*(a, U_T, r, v^*) \text{ which is defined in (2)}$$
$$\text{s.t.} \quad \begin{cases} U_T \text{ satisfies (16)}, \\ a \text{ satisfies (15)}. \end{cases} \tag{$P1$}$$

Setting

$$U(a) = \frac{a(1-a)E_{\mathrm{s}} L_{\mathrm{sn}}}{E_{\mathrm{o}} - aP_{\mathrm{on}} L_{\mathrm{sn}}}, \tag{17}$$

we have its derivative as

$$\frac{\mathrm{d}U(a)}{\mathrm{d}a} = \frac{[E_{\mathrm{o}}(1-a)^2 + a^2(P_{\mathrm{on}} L_{\mathrm{sn}} - E_{\mathrm{o}})]e_{\mathrm{s}} L_{\mathrm{sn}}}{(E_{\mathrm{o}} - aP_{\mathrm{on}} L_{\mathrm{sn}})^2}.$$

By Assumption 5, $E_{\mathrm{o}} < P_{\mathrm{on}} L_{\mathrm{sn}}$, then $\mathrm{d}U(a)/\mathrm{d}a > 0$ such that $U(a)$ monotonously increases as a increases. When $U(a) > U_{\min}$, then $U_T = U(a)$. When a is small enough such that $U(a) \leqslant U_{\min}$, $U_T = U_{\min}$. Analytical solution for $(P1)$ may not be available. $(P1)$ can be solved numerically with the following algorithm. With maximum of p_1^* the behavior of the RDSN is optimized for target detection.

Algorithm 1. Solving problem $(P1)$.

Initialization
a_0 satisfies $U(a_0) = U_{\min}$ (a_0 *is the minimum of* a)
$\bar{a} = E_{\mathrm{o}}/(P_{\mathrm{on}} L_{\mathrm{sn}})$ ($\bar{a}$ *is an upper bound of* a)
$\Delta a = (\bar{a} - a_0)/K$, where K is a large integer
$a^* = a_0$, $U_T^* = U_{\min}$, $p^* = p_1^*(a_0, U_{\min}, r, v^*)$.
$j = 0$;
Repeat (*searching for* a^* *which maximize* p_1^*)
  $j = j + 1$;
  $a = \hat{a}_0 + j * \Delta a$, $U = U(a)$ with (17)
  Calculate $pp = p_1^*(a, U, r, v^*)$ with (2)
  if $pp > p^*$, then
    $p^* = pp$, $a^* = a$, $U_T^* = U$
  end if
until $j = K$.

The solution of $(P1)$, (a^*, U_T^*) eventually becomes a function of L_{sn}. Let $N(L_{\mathrm{sn}})$ denote the corresponding smallest number of sensors stipulated in (12), then

$$N(L_{\mathrm{sn}}) = \frac{\ln[1-\hat{P}]}{\ln[1 - 2L^* r p_1^*(a^*(L_{\mathrm{sn}}), U_T^*(L_{\mathrm{sn}}), r, v^*)]}. \tag{18}$$

To guarantee the detection probability $\hat{P}$ over the span of L_{sn}, a larger L_{sn} leads to a smaller p_1^* which makes the RDSN need a larger $N(L_{\mathrm{sn}})$ in return.

5.2. Maximize L_{sn} with budget limit

Even if a sensor is expected to be cheap in the near future, there is always a budget limit on the number of sensors one can deploy in a system. As $B$is the budget and c is the price of a single sensor, the problem of maximizing L_{sn} can be formulated as

$$\begin{aligned} \max \quad & L_{sn} \\ \text{s.t.} \quad & B \geqslant c \cdot N(L_{sn}). \end{aligned} \qquad (P2)$$

$(P1)$ and $(P2)$ together constitute a non-cooperative game which is known as a Stackelberg problem with L_{sn} as leader and (a, U_T) as follower; $(a(L_{sn}), U_T(L_{sn}))$ which is the solution for $(P1)$ is known as the response of (a, U_T) to L_{sn}, the decision of the leader (Aubin, 1993). Equilibrium $(a^*, U_T^*; L_{sn}^*)$ of the game is the solution to ($P1$ and $P2$). The algorithm of solving ($P1$ and $P2$) is as follows.

Algorithm 2. Solving problem ($P1$ and $P2$).

Initialization
$L_u = E_o/P_{on}$ (L_u is the minimum of L_{sn})
ΔL_u= a unit of lifetime (*e.g., one hour or one day*)
$L_{sn} = L_u$.
Repeat (*searching for the maximum of* L_{sn})
  With Algorithm 1 get solution $(a^*(L_{sn}), U_T^*(L_{sn}))$
  Calculate $N(L_{sn})$ with (18)
  $L_{sn} = L_{sn} + \Delta L_u$;
until $B < cN(L_{sn})$
$L_{sn}^* = L_{sn} - \Delta L_u$.

6. Illustrative example

An example is presented here to illustrate how to make a plan and design of the RDSN based on the results obtained in the previous sections.

Example. Suppose the AoI is 1 km × 1 km. One vehicle traverses across it with speed 18 km/h, and its track length is one kilometer. Budget $B = \$5000$. There are two sensor models. They share common U_{min} and e_s, i.e., $U_{min} = 5$s, $e_s = 0.005$ J, but differ in other parameters as shown below.

	E_o	P_{on}	r	c
Model 1	15 000 J	0.05 W	5 m	\$1.0
Model 2	10 000 J	0.025 W	3 m	\$0.8

If the network is required to detect such a vehicle with probability $\hat{P} = 0.95$, then which model should be chosen and how long the sensor network can work?

With Algorithms 1 and 2, we can obtain equilibrium solutions for these two sensor models separately. With one model, for any fixed L_{sn}, solving Problem $(P1)$, the optimal $(a^*(L_{sn}), U_T^*(L_{sn}))$ is obtained. Then calculate the number of sensors, $N(L_{sn})$, and the cost on sensors, $c * N(L_{sn})$. Increasing L_{sn} day by day and repeating the procedure deliver three sequences of a^*, N and $c * N$, respectively, with respect to L_{sn}. They are plotted separately in Fig. 4. The intersection point of the line of cost 5000 and the curve corresponding to model 1 suggests the RDSN made up by sensors of model 1

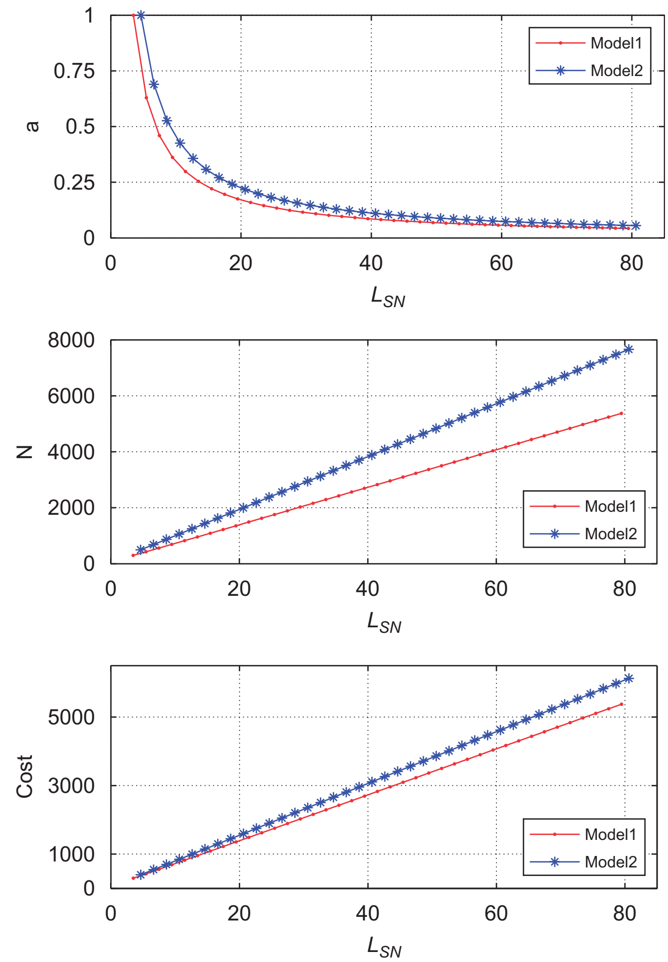

Fig. 4. Solutions of problem $(P1-2)$ for Models 1-2.

can have longer lifetime, i.e., 74 days. Thus, model 1 is the better option. Meanwhile, the optimal value for (a^*, U_T^*) is $(0.046, 5s)$ when $L_{sn}^* \approx 74$. The number of sensors of model 1 to make up the RDSN is 4972, accordingly.

7. Concluding remarks

In this paper, a novel model of RDSN is investigated. The AoI is assumed to be a unit square. So the number of sensors required by the RDSN can be viewed as the sensor density. Such density is applicable to any AoI with arbitrary shape and size. A state switching scheme, SSS, is developed for power conservation. It does not require sensors to coordinate their working schedule by communication so that sensors can save much energy. The randomness in state switching makes it hard to predict sensor's state and enables the RDSN to operate robustly. SSS fundamentally controls the behavior of sensors and the RDSN at large. It lets the RDSN have a good scalability as the number of sensors increases. SSS is easy to implement and its overheads are very small. Analysis and results in this paper uncover important features and provide deep insights and useful information for the design of randomly distributed networks, hence they are helpful for target tracking.

With this model, an immediate question is, when sensors detect a target, how to report this event to the base station so that some actions can be taken on time. As sensors switch their states between ON and OFF independently, the topology of the RDSN changes randomly and imposes a big challenge on routing. Although there are already a number of data transmission protocols developed for large scale and RDSN (see e.g., Chatzigiannakis, Nikoletseas, & Spirakis, 2005; Ye, Zhong, Lu, & Zhang, 2005; Zorzi & Rao, 2003), the RDSN demands an ad hoc protocol which can be well incorporated with SSS. We have developed a robust and flexible protocol for it (Chen, Ho, Zhang, & Bai, 2006).

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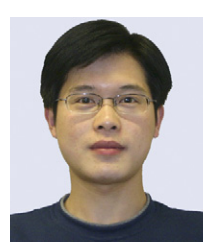

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