Mobile Target Detection in Wireless Sensor Networks With Adjustable Sensing Frequency

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Yanling Hu, Mianxiong Dong, Kaoru Ota, Anfeng Liu*, Minyi Guo

Abstract-How to sense and monitor the environment with high quality is an important research subject in the Internet of Things (IOT). This paper deals with an important issue of the balance between the quality of target detection and lifetime in Wireless Sensor Networks (WSNs). Two target monitoring schemes are proposed. One is TDSFK (Target Detection with Sensing Frequency *K*) which distributes the sensing time that currently is only on a portion of the sensing period into the entire sensing period. That is, the sensing frequency increases from 1 to *K*. The other scheme is TDASF (Target Detection with Adjustable Sensing Frequency) which adjust the sensing frequency on those nodes which have residual energy. The simulation results show that the TDASF scheme can improve the network lifetime by more than 17.4%, and can reduce the weighted detection delay by more than 101.6%.

***Index Terms*—wireless sensor networks (WSNs), moving target detection, sensing frequency, delay, network lifetime.**

I. Introduction

Internet of Things (IOT) is a worldwide network of interconnected objects based on standard communication protocols, and it is commonly accepted as the next generation of internet [1]. A Wireless Sensor Network (WSN) is composed of a large number of cheap sensor nodes that deployed in the monitoring area and communicate with each other to sense and measure the surrounding environment. A WSN is an important form of the underlying network technology of IoT. An important application in WSNs is to sense and monitor the moving target intelligently.

Although there have been many studies of target detection, most of them focus on how to optimize the duty cycle of node to optimize the target detection quality [2-7]. The quality of target detection mainly includes the delay for detection, the probability of missing target and network lifetime. Wu et al. [5] pointed out that in WSNs, node wakes up periodically to detect the target, receive or send data to the sink or the next-hop node. After that, it will re-enter the sleep mode. Therefore, a nodal cycle consists of wake and sleep states. Generally speaking, the duty cycle of nodes should be relatively small in order to save energy. Thus the nodes will go through a short wake time after the long sleep state. When a node is in sleep, the target will not be detected, that leads to a blind period in the detection. The sensing frequency of this scheme is 1 in a perceived cycle. We call it Target Detection with Sensing Frequency One (TDSFO) scheme. To improve the target monitoring quality, a new intelligent solution called Target Detection with Sensing Frequency *K* (TDSFK) scheme is proposed. The main idea of the TDSKF is to divide the sensing duty cycle into small pieces within the wake state of nodes so that there is no long sleep state for nodes. The quality of target detection is thus enhanced. However, the TDSFK scheme has to pay the energy consumption for the state transition which is given less consideration by the previous studies. The authors of [5] noticed that the processors and sensors for the state transition need certain energy. They also pointed out that the Mica mote sensor requires 4 ms to start [5]. Hence, how to optimize the given sensing frequency of node to increase the lifetime and improve the monitoring quality is an important research issue. We also propose a method called Target Detection with Adjustable Sensing Frequency (TDASF) scheme which is based on adopting different sensing frequency in distinct regions of the network. TDASF scheme can further improve the quality of target detection. The main contributions in this paper are as follows:

(1) We first analyze the relationship between the sensing frequency of nodes and sensing quality of the network, and the relationship between the energy consumption of a node and its sensing frequency. Then, a tradeoff optimization scheme between detecting quality and network lifetime is given.

(2) Based on the above optimization, an optimized method of unequal sensing frequency is put forward, which can improve monitoring quality of network greatly.

A novel measurement framework, called the Weighted Quality of Target Detection (WQTD) is also proposed for evaluating the quality of target detection. Nodes from area to area have different duty cycles, so the quality of the target detection is also different with their distances to sink. In this paper, we measure the overall quality of target

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detection by the weighting method. As the WQTD considered the uneven nature of the system, it can be effectively used to evaluate the quality of target detection and the performance of the detection scheme.

(3)Through our extensive theoretical analysis and simulation study, we demonstrate that for such systems, both target detection performance and energy-efficient can be achieved simultaneously. We also demonstrate that our scheme has significantly improved both from a single quality indicator and the overall performance indicators. This is difficult to be achieved in the study of the past.

The rest of this paper is organized as follows: In section Ⅱ, the related works are reviewed. The system model is described in section Ⅲ. In section Ⅳ, a novel TDASF scheme is presented. Performance analysis is provided in section Ⅴ. Section Ⅵ is experimental results and comparison. We conclude in section Ⅶ.

II. Related Work

There have been many studies of target detection. Huang et al. [8] studied the optimal placement of sensors with the goal of minimizing the number of installed devices, while ensuring coverage of target points, and wireless connectivity among sensors. There were some researchers who took a different approach by choosing proper nodes from the deployed network to compose coverage and connectivity so as to play a monitoring role [9]. Liu and Towsley [10] evaluated coverage quality when sensors are distributed according to a 2-D Poisson point process. Different from the previous research, Rout and Ghosh [11] introduced and studied the problem of designing WSNs for the detection of mobile targets traversing a sensitive region along specific paths.

On one hand, the sensing range of sensor nodes has to cover the monitoring area. On the other hand, due to the energy of sensor nodes is very limited, if a node has been always in active state, the energy consumption of the node is considerably high although the targets within the scope of coverage can be detected. Hence, the method used by most studies on target detection makes the nodes work and sleep periodically to save energy. Due to the sensor nodes often have redundancy when deployed, the monitoring quality still can be achieved at a higher standard even if the duty cycle is little, and the network lifetime will be greatly prolonged. Therefore, most researchers focus on how to optimize the duty cycle of node (nodes' wake-up strategies) to optimize the target detection quality [2-7, 11-13]. The sensor node consists of sensing and communication device. Sensing device is for target detection, and communication device is used for data communication. The total energy of the node is certain and there is a tradeoff optimization relations between energy consumption used for detection and for communication: if assign more energy to sensing device, the monitoring quality is high. On the contrary, if assign more energy to communication device, the internal nodes are at the working state with high probability when the external nodes have data to be transmitted in the route. Then the delay for data getting to sink will be less. Based on the above analysis, the main design goals of [2, 7] is to maximize the operational lifetime of the system while ensuring high target detection performance and short response time. They put forward a cross-layer optimization method between sensing (for detection) and communication layers.

There are many optimization algorithms. However, the duty cycle of nodes is often in connection with the network load. So we need a method with adaptive duty cycle that can meet the monitoring quality when adopt the minimum duty cycle, so as to maximize the network lifetime. Based on the above ideas, Ref. [14, 15] proposed a control-based approach to the duty cycle adaptation through the queue management to achieve high-performance under variable traffic rates for wireless sensor networks. To have energy efficiency while minimizing the delay, they design a feedback controller, which adapts the sleep time to the traffic change dynamically by constraining the queue length at a predetermined value.

In conclusion, the current research has two shortcomings: (a) the entire network adopts the same node duty cycle. This results in the unbalance of energy consumption. The residual energy of non-hotspots nodes in the network will be wasted. (b) The nodes in active state were arranged in a continuous period of time. It leads to a longer perceived gap, and then affects the monitoring quality. In this paper, we propose two target monitoring schemes TDSFK and TDASF to intelligently adjust the sensing frequency, thus overcome these two shortcomings.

III. The system model and Problem statement

A. Network model

Our network model is similar to Ref. [2, 7]. In this network, a large number of acoustic sensors are deployed with density ρ to monitor the activities and locations of the animals in a natural habitat continuously [16-18]. As soon as the trends of endangered species (incoming targets) are detected, the corresponding source nodes nearby will report data periodically to the sink node [19]. WSNs can also keep monitoring when hunter enters the protected area. Once the hunter appears, an alert message will be sent to sink. In this way, the message sent for the control center outside the network protects the endangered species from hunters [20].

The network radius is R. All the targets are randomly distributed in the network. So the probabilities of the targets monitored by each sensor node are equal. Likewise, the probabilities of generating data are equal as well.

B. Problem statement

Mobile target detection is a problem of multiple targets optimization. The goal here is to maximize the network lifetime and at the same time to minimize the probability of missing target. Just like in Ref. [2, 7], the target detection of a WSN can be characterized by several performance indicators as explained below:

(1) Delay for detection (denoted as $D_{\det}$). $D_{\det}$ refers to the time from the ingoing moment of target to being detected by any sensor for the first time.

(2)The probability of missing a single incoming target (denoted as P_{md}). P_{md} refers to the probability of not being detected by any sensor node when the target goes through the monitoring area.

(3)The probabilities of missing all incoming targets (denoted as P_{ma}). P_{ma} refers to the probability of all the targets node not be detected when passing by the monitoring area.

(4) The probabilities of missing at least one of the incoming targets (denoted as P_{mo}). P_{mo} refers to the probability of at least one target not being detected by the sensor node when multiple targets go through the monitoring area.

(5) Lifetime (denoted as ℓ). Like Ref. [21], lifetime is defined as the death time of the first node in the network.

Obviously, the goal of target detection can be stated as follows:

$$\begin{cases} \min(D_{\det}),\ \min(P_{md}) \\ \min(P_{ma}), \min(P_{mo}), \max(\ell) \\ s.t.\ D_{\det} \le D_{\det}^{\Theta},\ P_{md} \le P_{md}^{\Theta} \\ \quad P_{ma} \le P_{ma}^{\Theta},\ P_{mo} \le P_{mo}^{\Theta} \end{cases} \tag{1}$$

In Eq. (1), $D_{\det}^{\Theta}$, P_{md}^{Θ}, P_{ma}^{Θ}, P_{mo}^{Θ} represent the minimum requirements of monitoring performance thresholds $D_{\det}$, P_{md}, P_{ma}, P_{mo} in applications. The goal of Eq. (1) is to minimize the monitoring performance $D_{\det}$, P_{md}, P_{ma}, P_{mo}, and keep them not less than the minimum requirements of the application performance. Meanwhile, maximize the lifetime as much as possible.

In the previous studies [2], the authors assume that all sensor nodes have the same values of network parameters and sensing frequency. This strategy is referred to as TDSSF (target detection with same sensing frequency) in this paper. Therefore, the monitoring performances of nodes are equal everywhere in the network. As indicated before, if using the same monitoring parameters, the non-hotspot area will have a lot of residual energy. In this paper, the non-hotspot nodes are set with greater sensing frequency for higher monitoring performances. Thus, the target detection performance of different regions of the network will be unequal. In order to evaluate the uneven monitoring performance better, a novel measurement framework WQTD is proposed. The monitoring performance of WQTD is represented as follows:

$$f_i^{\,w} = \sum_{j \in \Omega} \left(f_i^{\,j} \bullet \frac{n_j}{n} \right) \tag{2}$$

In Eq. (2), $f_i^{\,w}$ represents the performance indicators of node i after weighted (refers to $D_{\det}, P_{md}, P_{ma}$ and P_{mo}. Lifetime ℓ is not included, because it means the death time of the first node). $f_i^{\,j}$ represents the performance index order of the i^{th} node is j. n is the total number of nodes in network. n_j is the number of indicator in j indicators.

In the scheme of TDASF, increasing the sensing frequency of the non-hotspot nodes uses their remaining energy. The monitoring performances are different from area to area because the energy is often not equal. Let the delay for detection be $D_{\det}^{x}$ for nodes at x m away from the sink. The delay in the entire network is given by:

$$D_{\det}^{w} = \int_0^R \int_0^{2\pi} D_{\det}^{x} \cdot x \cdot dx \cdot d\theta \tag{3}$$

Similarly, other weighted monitoring performance indicators can be given as: P_{md}^{w}, P_{ma}^{w}, P_{mo}^{w}.

The network lifetime ℓ depends on the node that spends the most energy. The energy consumption of node i consists of: (a) communication energy. For instance, e_i^{t} and e_i^{r} are used for transmitting and receiving data, (b) sensing energy consumption e_i^{sen}, (c) the consumption in the Low-Power-Listening (LPL) state, e_i^{LPL}, and (d) the consumption in the sleep state, e_i^{s}. Because of the death time of the first node is defined as lifetime, minimizing the energy consumption of the node spends the most can be expressed as the following formula:

$$\max(\ell) = \min\ \max_{0<i\le n}(e_i^{t} + e_i^{r} + e_i^{sen} + e_i^{LPL} + e_i^{c}) \tag{4}$$

In conclusion, the design of TDASF is prolonging system lifetime to meet application requirements. The goal of TDASF proposed in this paper can be obtained:

$$\begin{cases} \min(D_{\det}^{w}), \min(P_{md}^{w}), \min(P_{ma}^{w}), \min(P_{mo}^{w}) \\ \max(\ell) = \min\ \max_{0<i\le n}(e_i^{t} + e_i^{r} + e_i^{sen} + e_i^{LPL} + e_i^{s}) \\ s.t.\ \max(D_{\det}^{x}) \le D_{\det}^{\Theta} \\ \max(P_{md}^{x}) \le P_{md}^{\Theta}, \max(P_{ma}^{x}) \le P_{ma}^{\Theta}\ , \max(P_{mo}^{x} \le P_{mo}^{\Theta}) \end{cases} \tag{5}$$

Eq. (5) is the same as Eq. (4) for lifetime ℓ. As for other monitoring performances, it means to optimize the weighted performances, and make the maximum performance indicators meet the required thresholds of application.

C. WSN model

A sensor node is composed of two major units: sensing device and communication sub-unit. Ideally, each unit can have separate power control [2]. The communication sub-unit does not necessarily have the same duty cycle with the sensing device [21]. In order to reduce the energy consumption of the system, the sensing part as well as communication sub-unit can be periodically switched off, according to a normalized duty cycle. The duty cycle of sensor node is defined as its active/working period. Every unit has its own duty cycle since the two major units control their status independently.

For sensing device, its duty cycle called sensing duty cycle is denoted as ς_{sen} in Eq. (6), and the other called communication duty cycle denoted as ς_{com} in Eq. (7) below:

$$\varsigma_{sen} = t_{sen}^{a} / t_{sen} = t_{sen}^{a} / (t_{sen}^{a} + t_{sen}^{off} + t_c) \tag{6}$$

where t_{sen} is the time length of a unit sensing cycle, t_{sen}^{a} is the valid sensing time by sensing device. While t_{sen}^{off} is the time that sensing device lasts when it is off in a cycle. t_c is the time for the transition from the sleep state to the sensing state (In Fig. 1, $t_c = \varepsilon$).

$$\varsigma_{com} = t_{com}^{a} / t_{com} = t_{com}^{a} / (t_{com}^{a} + t_{com}^{off}) \tag{7}$$

where t_{com} is a communication cycle time. t_{com}^{a} is the duration when the communication sub-unit is active. And t_{com}^{off} is the time length when the communication sub-unit is in sleep. The duty cycle starts over between two consecutive periods.

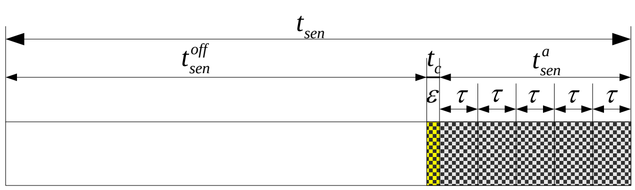

Fig. 1 TDSFO scheme (sensing frequency is 1)

The main notations and values adopted in this paper are concluded in Table 1.

Table 1 Main notations and values adopted in this paper

Symbol	Description	Value
t_{com}	Communication period of duration	250ms
t_{sen}	Sensing period of duration	15s
r_s	Perceived radius	20m
ε_c	Conversion power consumption	0.005W
ε_{sen}	Sensing power consumption	0.0036W
ω_R	The power used by a node to receive a packet;	Calculation-specific
ω_T	The power used to transmit an alert packet	Calculation-specific
ε_t	Transmission power consumption	0.0511W
ε_r	Reception power consumption	0.0588W
ε_s	Sleep power consumption	2.4*10^{-7}W
P_d	The target detection probability	0.1
N_{tar}	The number of times that a target appears during a reference period	10
ω_s	The power when node is in sleep	Calculation-specific
S_p	Preamble duration	0.26ms
S_{al}	Ack window duration	0.26ms
S_d	Packet duration	0.93ms
ε_s	Sleep power consumption	2.4*10^{-7}W

IV. THE DESIGN OF TDSFK SCHEME

A. *Proposal of target detection with sensing frequency k scheme*

In the previous studies [7], researchers divided the sensing cycle of a node into two states, one is the sensing state, and the other is the sleep state. The change from the sleep state to sensing state lasts for ε (i.e. t_c), the energy consumption for state transition is e_c. The minimum time slot for a node to sense once is τ. If the node in the sensing state is composed of k minimum time slots, then $t_{sen}^{a} = k\tau \mid k \geq 1$. In such a strategy, a duty cycle is composed of a continuous sleep time (t_{sen}^{off}), the transition time from sleep to sensing state (t_c), and a continuous sensing time (t_{sen}^{a}), as shown in Fig. 1. In this strategy, a duty cycle has only one continuous sensing period, namely the sensing frequency is 1. It is called TDSFO (Target Detection with Sensing Frequency One) scheme.

In TDSFO, if a node is in the sleep state for a long period of time t_{sen}^{off} and cannot detect the target, it may miss the target. Here, we illustrate the performance of TDSFO scheme by a simple example. Suppose that in a linear network such as shown in Fig. 2, the target accesses the network from the left, and try to pass through the network. The movement speed of target is v (m/s). The sensing cycle time of node is T (s), and the sensing duty cycle is ς_{sen} (%). Suppose the target is intelligent and able to enter the network just when the first node (n_1) begins to change over to the sleep state. Then, when the target passes by a node (n_1), it is able to move for a distance $L_1 = vT(1-\varsigma_{sen})$ without being detected. If $L_1 < 2ds$ (the monitoring range of n_1), the overall moving distance of not being detected is L_1. On the contrary, if $L_1 > 2ds$, the target can move to n_2's monitoring range. The target can still be undetected and move some distance in a certain probability. Fig. 3 is given when v=15m/s, T=15s, the distance that the target is able to move when ς_{sen} increases from 10% to 90% and the probability of missing target is less than 60%.

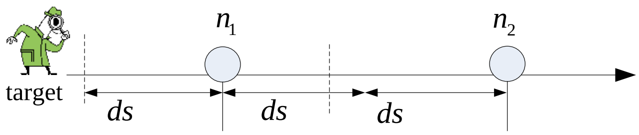

Fig. 2 Schematic diagram of target detection in linear network

It can be seen from the above discussion that in TDSFO, the nodes stay in the sleep state over a period of time. Therefore, it is possible that a target passes by a node just when the node is in the long period of sleep state, and the performance monitoring of network worsens in this way. For this reason, a scheme named Target Detection with Sensing Frequency K (TDSFK) is proposed. In TDSFK scheme the sensing period is dispersed throughout the whole cycle t_{sen}, as shown in Fig. 4. Nodes are first converted from sleep state to the sensing state, after the sensing time τ and then returned back to the sleep state. They run in circles like this, until the sensing cycle is complete. In this way, the sensing frequency of nodes is k, which avoids the shortage of long sleep time in a period. So the target is difficult to be undetected. Fig. 3 shows the performance of TDSFK. It is thus clear that under the same power consumption, the moving distance of target is almost only $1/k$ of the original in TDSFK, which greatly enhances the network monitoring performance.

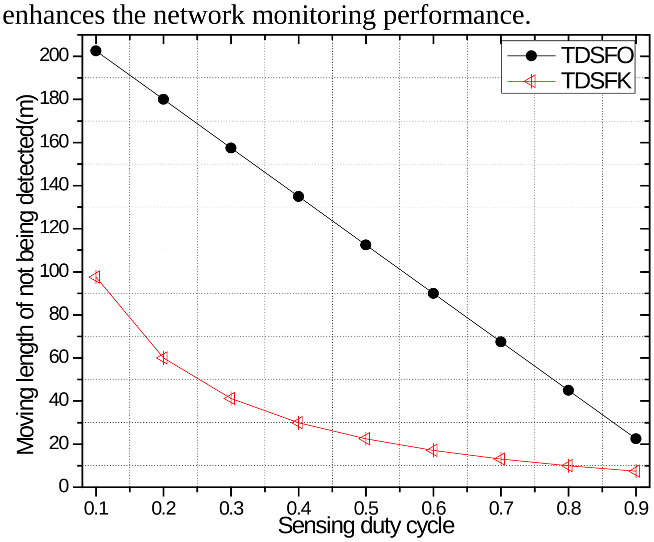

Fig. 3 Moving distances in different sensing duty cycles

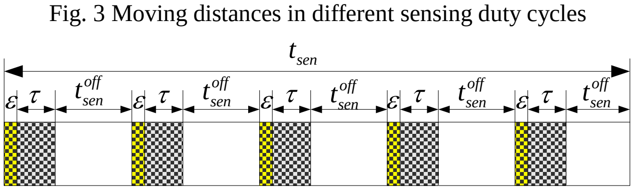

Fig. 4 TDSFK scheme (sensing frequency is k)

B. The calculation of sensing frequency k

Firstly, the calculation method of the sensing frequency k is presented in this section when adopting the TDSFK scheme instead of TDSFO and the energy consumption of nodes remains unchanged. As in the TDSFO scheme, the state transition is 1 time, and in the TDSFK scheme, it is k times, and each time need to consume energy, its energy consumption for state transition is higher than that of TDSFO scheme. So in TDSFO scheme, when the nodes are in the sensing state with sensing frequency k_1, sensing slot number τ, and converted into TDSFK scheme, if the sensing frequency is k_2, there is $k_1 \le k_2$. The calculation method of k_2 is given in the following Theorem 1.

Theorem 1. Assume that the TDSFO scheme changes state only once in a sensing cycle t_{sen}, the sensing time can be divided into k_1 blocks (sensing frequency is actually 1). When keeping the same total energy consumption, the greatest sensing frequency of TDSFK scheme is

$$k_2 \le \frac{k_1\tau\left(\varepsilon_{sen}-\varepsilon_s\right)+\varepsilon_c t_c}{\tau\left(\varepsilon_{sen}-\varepsilon_s\right)+\varepsilon_c t_c} \quad (8)$$

Proof. Eq. (6) provides the calculation formula of sensing duty cycle. Set the $t_{sen}^{a} = k_1\tau$, after optimization, $t_{sen}^{a\,'} = k_2\tau$.

If keeping the total energy consumption of sensing data unchanged, then $e_c^{k_1} + e_{sen}^{k_1} = e_c^{k_2} + e_{sen}^{k_2} \Rightarrow$

$$\varepsilon_c t_c + \left[\frac{k_1\tau}{t_{sen}}\varepsilon_{sen} + \varepsilon_s\left(1-\frac{k_1\tau}{t_{sen}}\right)\right]t_{sen} \ge k_2\varepsilon_c t_c + \left[\frac{k_2\tau}{t_{sen}}\varepsilon_{sen} + \varepsilon_s\left(1-\frac{k_2\tau}{t_{sen}}\right)\right]t_{sen}$$

That is, $\varepsilon_c t_c + k_1\tau\left(\varepsilon_{sen}-\varepsilon_s\right) \ge k_2\varepsilon_c t_c + k_2\tau\left(\varepsilon_{sen}-\varepsilon_s\right)$, where $k_2 \le \dfrac{k_1\tau\left(\varepsilon_{sen}-\varepsilon_s\right)+\varepsilon_c t_c}{\tau\left(\varepsilon_{sen}-\varepsilon_s\right)+\varepsilon_c t_c}$.

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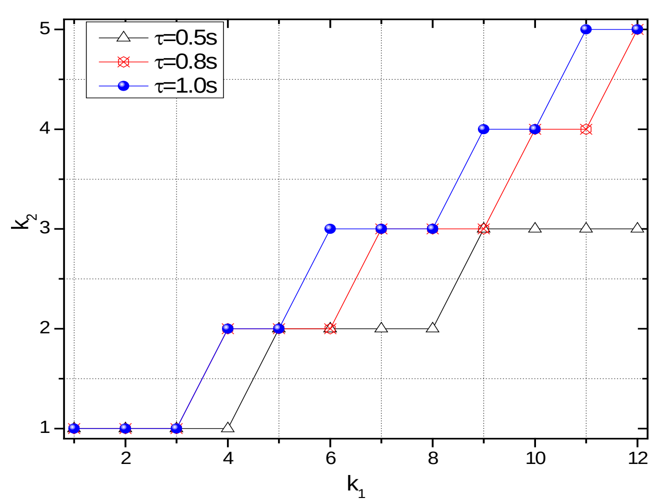

Fig. 5 The corresponding k_2 when the initial sensing frequency is 1

Fig. 5 shows the maximum k_2 corresponding to k_1 when the initial sensing frequency is 1. It can be seen from the figure that k_2 increased with the increase in k_1. When taking different τ, the growth of k_2 is also different. It follows that the relationship between k_1, k_2 and τ in Eq. (8) is correct.

C. Performance analysis of TDSFK scheme

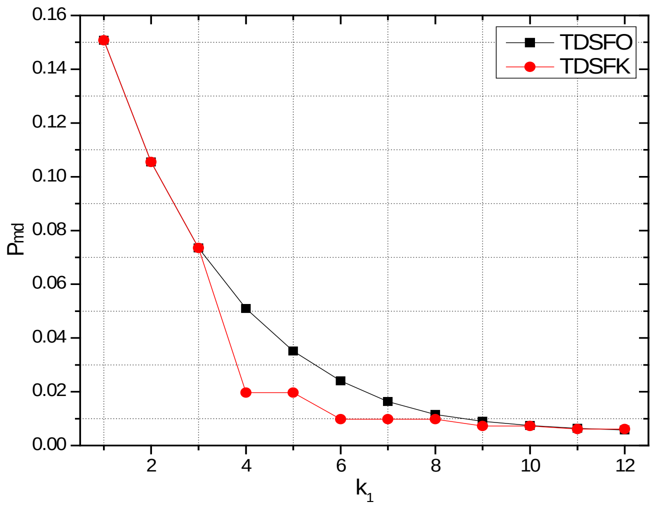

Fig.6 The corresponding maximum P_{md} when the initial sensing frequency is 1

When the sensing frequency increases to k_2, the time that sensor in the sleeping state declines with the increase of the sensing duty cycle. The time of monitoring lengthens and the probability of missed target detection becomes less. As Fig. 6 shows, TDSFK scheme improve the performance of P_{md} after the frequency is dispersed. When the frequency is divided into 4, the performance is improved the most.

Theorem 2. In TDSFK scheme, the probability of missed target detection of nodes with sensing frequency k_2 is as follows:

$$P_{md}(k_2) \geq \left\{1-\left[\frac{k_2\tau}{t_{sen}}+(1-\frac{k_2\tau}{t_{sen}})P_\partial(k_2)\right]\frac{r_s}{R}\right\}^N \quad (9)$$

$$where \;\; P_\partial(k_2)=\begin{cases}\dfrac{4r_s}{\pi\eta(k_2)v} & if \; \dfrac{2r_s}{v}<\eta(k_2)\\ \dfrac{4r_s-2\sqrt{4r_s^2-\eta(k_2)^2v^2}}{\pi\eta(k_2)v}+1-\dfrac{2a\sin\left(\dfrac{\eta(k_2)v}{2r_s}\right)}{\pi} & else\end{cases}$$

$$where \;\; \eta(k_2)=t_{sen}/k_2-\tau-t_c$$

Proof. According to the Theorem (8) in Ref. [2], the probability of missing a target within a circular region can be expressed as: $P_{md}\geq\left\{1-\left[\varsigma_{sen}+(1-\varsigma_{sen})P(\varepsilon_1)\right]\frac{r_s}{R}\right\}^N$

If $2r_s/v>c$,

$$P\{\varepsilon_1\}=\frac{4r_s-2\sqrt{4r_s^2-c^2v^2}}{\pi cv}+1-\frac{2a\sin\left(\dfrac{cv}{2r_s}\right)}{\pi},$$

else if $2r_s/v<c$, $P\{\varepsilon_1\}=\dfrac{4r_s}{\pi cv}$

Among them, r_s is the sensing radius of each node, R is the radius of the whole monitoring area, $c=(1-\varsigma_{sen})t_{sen}$.

Due to $\varsigma_{sen}=k\tau/t_{sen}$ and ς_{sen} varies with the change of k, therefore, let $\eta(k_1)$ and $\eta(k_2)$ substitute for c in the above formula, when sensing frequency is 1, we have $\eta(k_1)=t_{sen}-\left(k_1\tau+t_c\right)$. In TDSFK scheme, due to the increase in frequency, the times of state transition increases from 1 to k_2, so $\eta(k_2)=t_{sen}/k_2-\tau-t_c$.

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Theorem 3. In TDSFK scheme proposed in this paper, the delay for detection of nodes with sensing frequency k_2 is as the following formula:

$$D_{\det}(k_2)=\begin{cases}\dfrac{(2\bar{q}_{\max}r_s-\pi R^2)^{N+1}}{2\pi^N R^{2N}r_s(N+1)v} & if \; \frac{L}{v}>\eta(k_2)\\ \dfrac{\int_0^{\bar{q}_{\max}}\sum_{i=0}^{N}\left(1-\dfrac{2qr_s}{\pi R^2}\right)^{N-i}\left(\dfrac{2qr_s^2}{\pi R^3}(\dfrac{1}{k_2}-\dfrac{\tau}{t_{sen}})(1+P_\partial(k_2))\right)^i dq}{v} & else\end{cases} \quad (10)$$

Proof. According to Theorem 9 in Ref. [2], if $\dfrac{L}{v}>\eta(\varsigma_{\text{sen}}^x)$, $P\left\{\varepsilon_{SoT},\bar{\varepsilon}_{\det}\right\}=0$, $D_{\det}(\varsigma_{\text{sen}}^x)=E(Q)/v=$
$\dfrac{(2\bar{q}_{\max}r_s-\pi R^2)^{N+1}}{2\pi^N R^{2N}r_s(N+1)v}$,

else if $\dfrac{L}{v}\leq\eta(\varsigma_{\text{sen}}^x)$, $D_{\det}(\varsigma_{\text{sen}}^x)=E(Q)/v=$

$$\frac{\int_0^{\bar{q}_{\max}}\sum_{i=0}^{N}\left(1-\dfrac{2qr_s}{\pi R^2}\right)^{N-i}\left(\dfrac{2qr_s^2}{\pi R^3}(1\text{-}\varsigma_{sen}^x)(1+P_\partial(\varsigma_{\text{sen}}^x))\right)^i dq}{v}$$

In TDSFK scheme, the frequency is k_2. Replace ς_{sen}^x in the above formula with $\varsigma_{sen}=k_2\tau/t_{sen}$, and other values remain unchanged. Now Eq. (10) is proved.

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From Eq. (10) we see that, the more the divided frequency, the more times the node will sense. It is easier to be detected after the target enters the network, so the delay will be smaller. Fig. 7 shows that the performance is improved after the frequency being divided into several fragments. And, when the frequency is 6, performance improved the most.

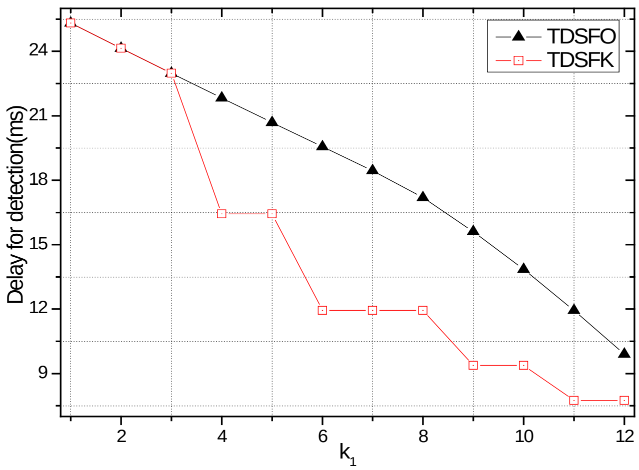

Fig. 7 The corresponding maximum D_{det} when the initial sensing frequency is k_1

V. TARGET DETECTION WITH ADJUSTABLE SENSING FREQUENCY SCHEME

A. *Presentation of questions*

As mentioned above, we have proposed TDSFK scheme. The uniform dispersion of sensing time slot in sensing cycle can improve the monitoring quality of the network. But according to our findings, actually, the monitoring quality of network can be further optimized. Therefore, the Target Detection with Adjustable Sensing Frequency (TDASF) scheme is presented in this section. Its main idea is: the "many to one" model is applied in WSNs to collect data, and then all the data is finally sent to sink. In this way, a region (i.e. hotspots) around the sink is formed and its energy consumption is higher than other regions, which leads to an early death of the network. This phenomenon is called the "energy hole". Many studies indicate that, when the sensor network dies in advance because of the "energy hole", there still remains as much as 90% energy. Thus, TDASF scheme makes full use of the remaining energy by increasing the sensing frequency energy of nodes in no-hotspots region. Generally speaking, the farther the node is away from the sink, the more its residual energy, the higher sensing frequency is needed, and vice versa. So this kind of scheme using different sensing frequency in different areas is called Target Detection with Adjustable Sensing Frequency scheme.

B. *The calculation of adjustable sensing frequency*

The main idea of TDASF scheme is to improve the sensing frequency of nodes far away from the sink by using their residual energy, which can improve the quality of monitoring. Therefore, we first calculate the energy consumption of the nodes in different regions at different distances from sink. The information can help to calculate the remaining energy consumption of nodes in different places, and then the sensing frequency of different nodes can also be computed. The following Theorem 4 gives the energy situation of nodes at different distances from the sink.

Theorem 4. At the region x m away from sink, the energy consumption of the nodes is as follows:

$$\omega_{tot}^{x} = \omega_{sen}^{x} + \omega_{LPL}^{x} + \omega_{R}^{x}\ \delta_{r}^{x} + \omega_{T}^{x}\ \delta_{t}^{x} + w_{c}^{x} \tag{11}$$

Proof. With the different distances to sink, the data amount of node varies from area to area, hotspot nodes have to receive and forward more data packets.

ω_{tot}^{x} denotes the total power consumed by sensing and communication operations of the nodes at x m away from sink in a communication cycle t_{com}. According to the description of the X-MAC protocol in Ref. [6], there are four possible states in the energy consumption ω_{tot}^{x}: (i) transmission, (ii) reception, (iii) sleep, and (iv) LPL. ω_{sen}^{x} denotes the power consumption for sensing in an activity duration t_{sen}. ω_{LPL}^{x} is the required power of the LPL operations. Suppose that the node at x m apart from sink has δ_{t}^{x} packets to be transmitted in a communication cycle t_{com}, and δ_{r}^{x} packets to be received. ω_{R}^{x} is the power used for receiving a packet. ω_{T}^{x} is the power for transmitting an alert packet. w_{c}^{x} is the power consumed for state transition. Summing up the above, ω_{tot}^{x} can be computed by Eq. (11).

■

Theorem 5. Suppose that all the residual energy are used to increase the sensing frequency, then the sensing frequency of the nodes at the smallest distance is denoted as $k^{x_{\min}}$, those at x m away from sink is denoted as k^{x}, the relationship between $k^{x_{\min}}$ and k^{x} can be expressed as follows:

$$k^{x} = k^{x_{\min}} - \frac{\left(\tau_{t}^{x_{\min}} - \tau_{t}^{x} + \tau_{r}^{x_{\min}} - \tau_{r}^{x}\right)t_{com} + \omega_{T}\left(\delta_{t}^{x} - \delta_{t}^{x_{\min}}\right) + \omega_{R}\left(\delta_{r}^{x} - \delta_{r}^{x_{\min}}\right)}{(\varepsilon_{sen} - \varepsilon_{s})\tau + \varepsilon_{s}t_{\varepsilon}} \tag{12}$$

Proof. The largest energy consumption comes from the nodes nearest sink node. From Theorem 4, we can arrive at when $x = x_{\min}$, its energy consumption is

$e_{tot}^{x_{\min}} = e_{c}^{x_{\min}} + e_{sen}^{x_{\min}} + e_{LPL}^{x_{\min}} + e_{T}^{x_{\min}} + e_{R}^{x_{\min}}$ where

$e_{c}^{x_{\min}} = k^{x_{\min}}\varepsilon_{c}t_{c}$, $e_{sen}^{x_{\min}} = \varepsilon_{sen}k^{x_{\min}}\tau + \varepsilon_{s}\left(t_{sen} - k^{x_{\min}}\tau\right)$,

$e_{LPL}^{x_{\min}} = \left[\varepsilon_{r}\varsigma_{com} + \varepsilon_{s}(1-\varsigma_{com}) - \tau_{t}^{x_{\min}} - \tau_{r}^{x_{\min}}\right]t_{com}$,

$e_{T}^{x_{\min}} = \omega_{T}\ \delta_{t}^{x_{\min}}$, $e_{R}^{x_{\min}} = \omega_{R}\ \delta_{r}^{x_{\min}}$.

Supposing that the nodes nearest sink and those at x m away from sink have equal energy consumption, so there is $e_{tot}^{x_{\min}} = e_{tot}^{x}$, namely,

$$e_{sen}^{x_{\min}} - e_{sen}^{x} + e_{c}^{x_{\min}} - e_{c}^{x} = e_{LPL}^{x} + e_{T}^{x} + e_{R}^{x} - (e_{LPL}^{x_{\min}} + e_{T}^{x_{\min}} + e_{R}^{x_{\min}})$$

$$\Rightarrow (\varsigma_{sen}^{x_{\min}} - \varsigma_{sen}^{x})(\varepsilon_{sen} - \varepsilon_s)t_{sen} + \left(k^{x_{\min}} - k^x\right)\varepsilon_c t_c = \left(\tau_t^{x_{\min}} - \tau_t^x + \tau_r^{x_{\min}} - \tau_r^x\right)t_{com}$$

$$+ \ \omega_T\,(\delta_t^x - \delta_t^{x_{\min}}) + \omega_R\,(\delta_r^x - \delta_r^{x_{\min}})$$

$$\Rightarrow k^{x_{\min}} - k^x = \frac{\left(\tau_t^{x_{\min}} - \tau_t^x + \tau_r^{x_{\min}} - \tau_r^x\right)t_{com} + \omega_T\left(\delta_t^x - \delta_t^{x_{\min}}\right) + \omega_R\left(\delta_r^x - \delta_r^{x_{\min}}\right)}{(\varepsilon_{sen} - \varepsilon_s)\tau + \varepsilon_c t_c}$$

■

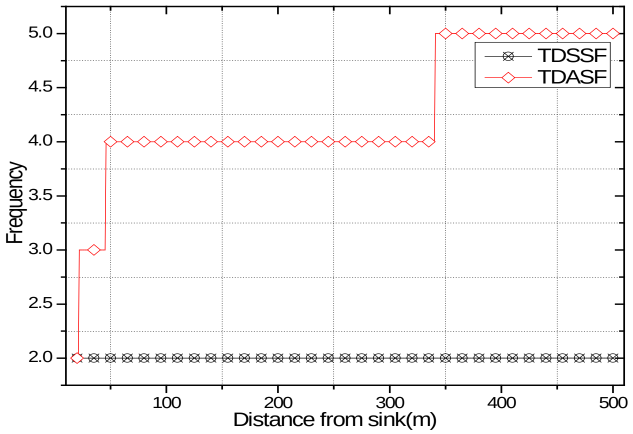

Fig. 8 The sensing frequency in different distances from sink

Fig. 8 shows the variation of sensing frequency in different areas in network. It adopts TDASF scheme and the sensing frequency of hotspots region is 2. Here we can see from Fig. 8 that, the sensing frequency that TDASF scheme adopts in most of the region in the network is more than 2 times that of TDSSF (Target Detection with Same Sensing Frequency). It means TDASF scheme can improve monitoring quality of the network significantly.

C. Performance analysis

1) Probability of missed target detection

a) Single target detection

Theorem 6. In TDASF scheme, the probability of missing target detection of the nodes at x m away from sink is as follows:

$$P_{md}(k^x) \ge \left\{1 - \left[\frac{k^x\tau}{t_{sen}} + (1 - \frac{k^x\tau}{t_{sen}})P_\partial(k^x)\right]\frac{r_s}{R}\right\}^N \quad (13)$$

$$where\ P_\partial(k^x) = \begin{cases} \dfrac{4r_s}{\pi\eta(k^x)v} & if\ \dfrac{2r_s}{v} < \eta(k^x) \\ \dfrac{4r_s - 2\sqrt{4r_s^2 - \eta(k^x)^2v^2}}{\pi\eta(k^x)v} + 1 - \dfrac{2a\sin\left(\dfrac{\eta(k^x)v}{2r_s}\right)}{\pi} & else \end{cases}$$

$$where\ \ \eta(k^x) = t_{sen}/k^x - \tau - t_c$$

Proof. In the network, the nodes near sink have a larger load than the far. In order to use the residual energy of the external nodes in the network effectively, we define the sensing frequency k of nodes increases with their distance to sink. Therefore, the probability of target detection $P_{md}(k^x)$ becomes a related function with x. The rest proof is the same as Theorem 2.

■

Theorem 7. In this paper, the probability of weighted missing target detection of the whole network is as follows:

$$P_{md}^w \ge \int_0^R \int_0^{2\pi} P_{md}(k^x)\cdot x \cdot dx \cdot d\theta \quad (14)$$

Proof. Let k^x be the sensing frequency of the nodes at x m away from sink. k^x varies with different x. So if only the weighted average of $P_{md}(\varsigma_{sen}^x)$ is calculated, and then the probability of missed target detection of the whole network can be obtained.

In the place whose distance from the network center is $x \mid x \in \{0,\ldots,R\}$, we take a fraction of fan-shaped ring ϕ with an angle $d\theta$ and a width of dx. The area of this region is $x\cdot dx\cdot d\theta$. The probability of missed target detection of the entire network can be expressed as $x\cdot dx\cdot d\theta\cdot P_{md}(k^x)$.

Eq. (12) shows the probability of missed target detection at x m away from sink. Integral to the entire region, the weighted probability of missed target detection can be obtained as:

$$P_{md}^w \ge \int_0^R \int_0^{2\pi} P_{md}(k^x)\cdot x \cdot dx \cdot d\theta$$

■

According to Theorem 7, Fig. 9 shows the probability of missed target detection at x m away from sink. With the increase of distance, P_{md} of TDASF is getting to less and less while the other line keeps horizontal. It is obvious that TDASF scheme can significantly decrease the P_{md} of external nodes.

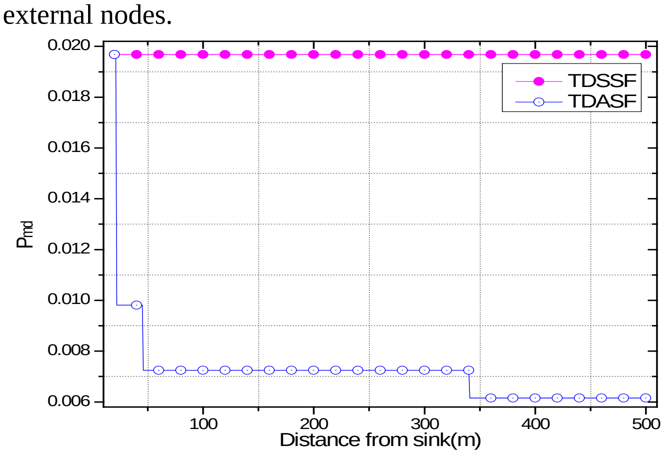

Fig. 9 P_{md} at different distances from sink

b) Multi target detection

Similar to Ref. [2], the probability of missed target detection of the node at x m away from sink is denoted as $P_{md}(k^x)$. So the probability of missing all and at least one out of N_T incoming targets detection are given respectively:

$$P_{ma}(k^x) = (P_{md}(k^x))^{N_T}$$

$$P_{mo}(k^x) = 1-(1-P_{md}(k^x))^{N_T}$$

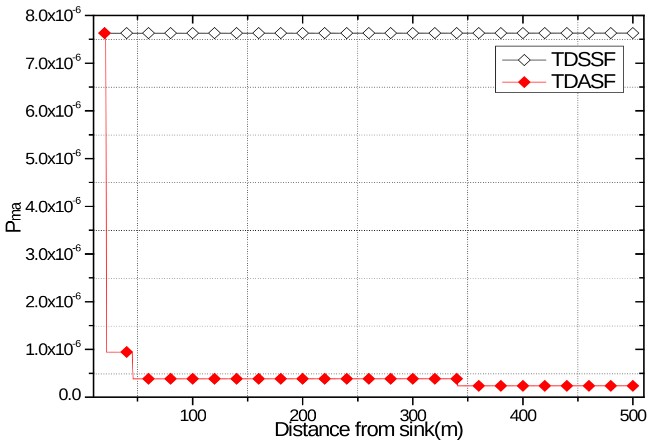

Fig. 10 Probability of missed multiple-target detection (P_{ma})

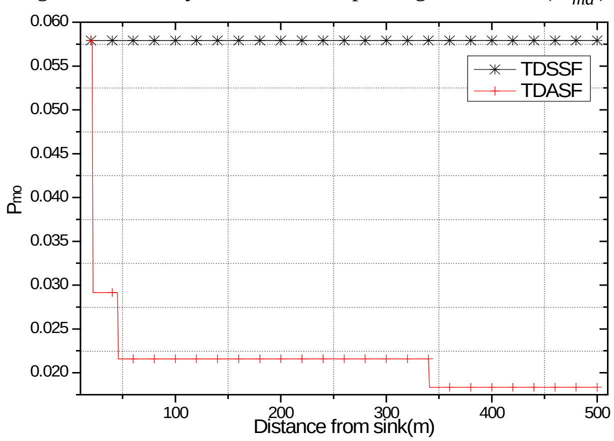

Fig.11 Probability of missed multiple-target detection (P_{mo})

Figs. 10 and 11 were given the probability of missing all and at least one out of N_T incoming targets detection under TDASF strategy and TDSSF strategy respectively. From the figures it can be seen that P_{ma} and P_{mo} of TDASF scheme are markedly less than those of TDSSF scheme.

Theorem 8. In TDASF, the probability of missed all incoming targets detection and the probability of missing at least one out of incoming targets detection of the entire network are as follows:

$$P_{ma}^{w} = \int_0^R \int_0^{2\pi} P_{ma}(k^x)\cdot x\cdot dx\cdot d\theta$$

$$P_{mo}^{w} = \int_0^R \int_0^{2\pi} P_{mo}(k^x)\cdot x\cdot dx\cdot d\theta \tag{15}$$

Proof. In the place whose distance from the network center is $x \mid x \in \{0,\ldots,R\}$, we take a fraction of fan-shaped ring ϕ with an angle $d\theta$ and a width of dx. The area of this region is $xdxd\theta$. The probability of missed targets detection of the network can be expressed as $x\cdot dx\cdot d\theta\cdot P_{ma}(k^x)$ and $x\cdot dx\cdot d\theta\cdot P_{mo}(k^x)$.

Integral to the entire region, the weighted probabilities of missed targets detection are as follows:

$$P_{ma}^{w} = \int_0^R \int_0^{2\pi} P_{ma}(k^x)\cdot x\cdot dx\cdot d\theta$$

$$P_{mo}^{w} = \int_0^R \int_0^{2\pi} P_{mo}(k^x)\cdot x\cdot dx\cdot d\theta$$

■

2) Delay for detection

Theorem 9. Based on the proposed weighted approach, the delay for detection at x m away from sink can be calculated as

$$D_{\det}(k^x) = \begin{cases} \dfrac{(2\bar{q}_{\max} r_s - \pi R^2)^{N+1}}{2\pi^N R^{2N} r_s (N+1) v} & if\ \frac{L}{v} > \eta(k^x) \\ \dfrac{\int_0^{\bar{q}_{\max}} \sum_{i=0}^{N} \left(1-\dfrac{2qr_s}{\pi R^2}\right)^{N-i} \left(\dfrac{2qr_s{}^2}{\pi R^3}\left(\dfrac{1}{k^x}-\dfrac{\tau}{t_{sen}}\right)(1+P_{\partial}(k^x))\right)^{i} dq}{v} & else \end{cases} \tag{16}$$

Proof. In the network, the nodes near sink have a larger load than the far. In order to use the residual energy of the external nodes in the network effectively, we define the sensing frequency k of nodes increases with their distance to sink. Therefore, the probability of target detection $D_{\det}(k^x)$ becomes a related function with x. The rest proof is the same as Theorem 3.

■

According to Theorem 9, Fig. 12 shows the delay for detection at x m away from sink. With the increase of distance, $D_{\det}$ of TDASF is getting to less and less while the other line keeps horizontal. It is obvious that TDASF scheme can significantly decrease $D_{\det}$ of the external nodes.

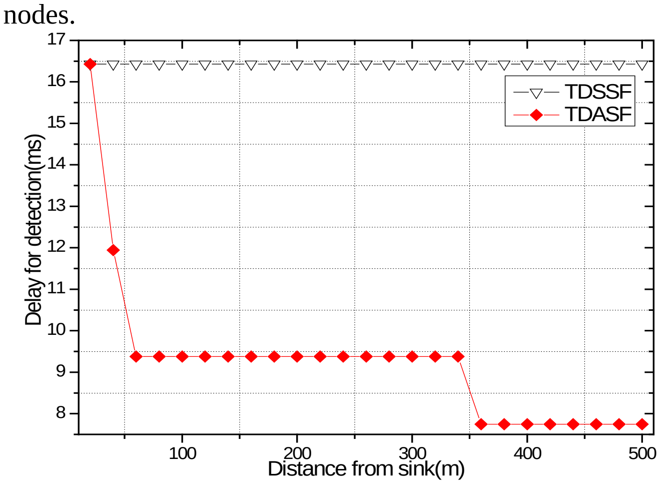

Fig.12 Detection delays at different distances from sink

Theorem 10. The delay for detection of the entire network in this paper can be obtained as:

$$D_{\det}^{w}=\begin{cases}D_{\det}(k^{x}) & if\ \frac{L}{v}>\eta(k^{x})\\ \int_{0}^{R}\int_{0}^{2\pi}D_{\det}(k^{x})\cdot x\cdot dx\cdot d\theta & else\end{cases} \tag{17}$$

Proof. If $L/v>\eta(k^{x})$,

$D_{\det}(k^{x})=\dfrac{(2\overline{q}_{\max}r_{s}-\pi R^{2})^{N+1}}{2\pi^{N}R^{2N}r_{s}(N+1)v}$. This formula has nothing to do with x, so the expression is constant.

Else if $L/v<\eta(k^{x})$, we take the position whose distance from the network center is $x\,|\,x\in\{0,\dots,R\}$, then a fraction of fan-shaped ring ϕ with an angle $d\theta$ and a width of dx. The area of this region is $xdxd\theta$. The probability of missed target detection can be given by $D_{\det}(k^{x})\cdot x\cdot dx\cdot d\theta$.

Integral to the entire region, the weighted delay for detection $D_{\det}^{w}=\int_{0}^{R}\int_{0}^{2\pi}D_{\det}(k^{x})\cdot x\cdot dx\cdot d\theta$.

■

3) Network lifetime

Theorem 11. According to the TDASF scheme, when the sensing frequency of the hotspot is $k^{x_{\min}}$, the lifetime of the network can be calculated as:

$$\ell=\frac{E_{init}}{e_{sen}^{x_{\min}}+e_{LPL}^{x_{\min}}+e_{T}^{x_{\min}}+e_{R}^{x_{\min}}+e_{c}^{x_{\min}}} \tag{18}$$

where $e_{sen}^{x_{\min}}=\varepsilon_{sen}k^{x_{\min}}\tau+\varepsilon_{s}\left(t_{sen}-k^{x_{\min}}\tau\right)$, $e_{LPL}^{x_{\min}}=\left[\varepsilon_{r}\varsigma_{com}+\varepsilon_{s}(1-\varsigma_{com})-\tau_{t}^{x_{\min}}-\tau_{r}^{x_{\min}}\right]t_{com}$, $e_{T}^{x_{\min}}=\omega_{T}\ \delta_{t}^{x_{\min}}$, $e_{R}^{x_{\min}}=\omega_{R}\ \delta_{r}^{x_{\min}}$, $e_{c}^{x_{\min}}=k^{x_{\min}}\varepsilon_{c}t_{c}$.

Proof. In TDASF, the calculation of the energy consumption is based on the maximum consumption of the hotspot nodes. The nodes nearest sink consume the most energy. Eq. (11) shows the power consumed in a state cycle. Network lifetime means the maximum energy consumption, that is, the initial energy E_{init} divided by the average energy consumption taking the state cycle as a unit.

■

VI. EXPERIMENTAL RESULT

OMNET++ is used for experimental verification [20]. If not specified, the network parameters are set to: R=500m, r=80m, the number of nodes is 1000. Other experimental parameters and symbols see Table 1.

A. Energy consumption

Figs. 13 and 14 show the energy consumption of network under different schemes. As can be seen from the figures, the energy consumption of TDSFK is basically balanced when the lifetime is not lower than TDSFO. This represents that the new scheme has efficiently balanced the energy of the whole network.

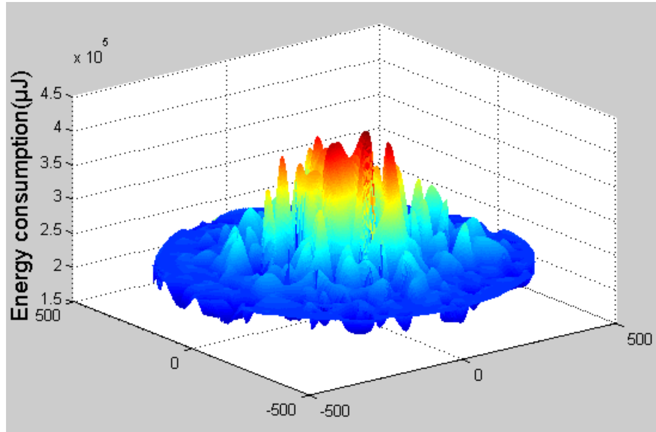

Fig. 13 Energy consumption of TDSFO scheme (lifetime=9 rounds)

Fig. 15 is the total energy consumption of all the operations, which includes data communication, sleep state, energy for conversion and LPL operations. It seems obvious that in TDSFK the energy line of network is much more balanced than below. This fully testifies to the necessity of new scheme.

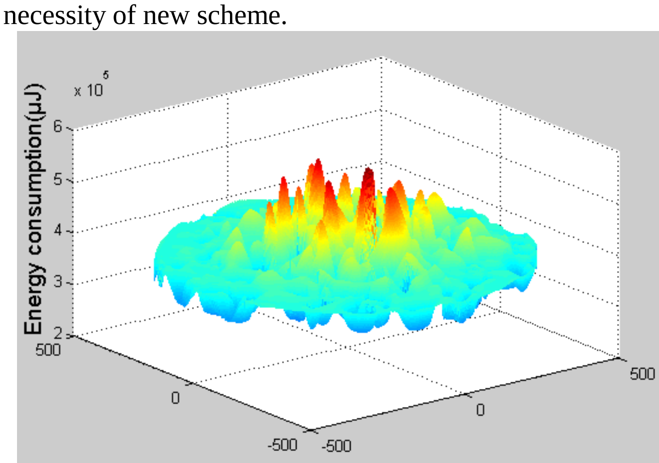

Fig. 14 Energy consumption of TDSFK scheme (lifetime=9 rounds)

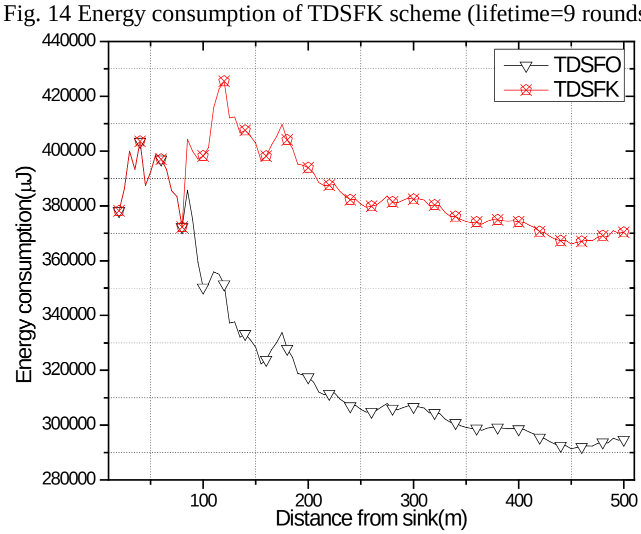

Fig.15 Total energy consumption

B. Network lifetime

This section mainly compares the lifetime of TDASF and TDSSF schemes under the same monitoring performance requirements. The comparative results below make use of the same weighted performance in order to ensure fairness. In the next place, the following experiment is the monitoring performances of TDASF compared to TDSSF when they share the same lifetime.

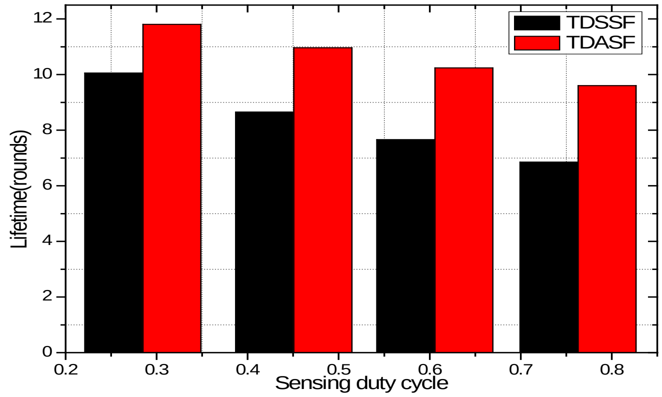

Fig. 16 Comparative lifetime of different schemes under the same weighted sensing duty cycles

Fig. 16 shows the comparative lifetime in different schemes when adopting the same weighted sensing duty cycles. TDASF can improve the network lifetime by 17.4%-40.1% in the figure.

C. Probability of missed target detection

Fig. 17 shows the weighted probability of missed target under different network radius R. In this figure, the line in red that denoted the value of weighted probability of missed target is much less than the other one. And with the increasing of network radius, the growth is slower. The weighted probability of missed target detection of TDSSF is 2.6 times to 4.8 times the value of TDASF. This illustrates that TDASF is more suitable for the large-scale network.

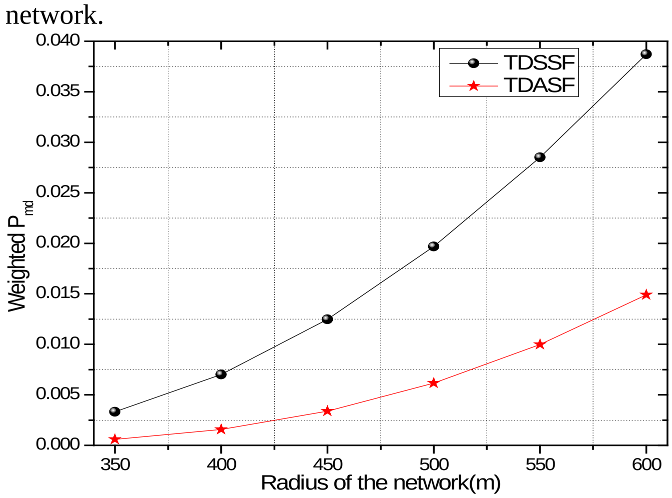

Fig. 17 Weighted probability of missing target detection under different network radius R

As shown in Figs. 18 and 19 respectively, the weighted probability of missing all and at least one out of the N_T incoming targets detection are given under the different network radius R. This shows that P_{ma}^{w} and P_{mo}^{w} of TDASF are much less than those of TDSSF.

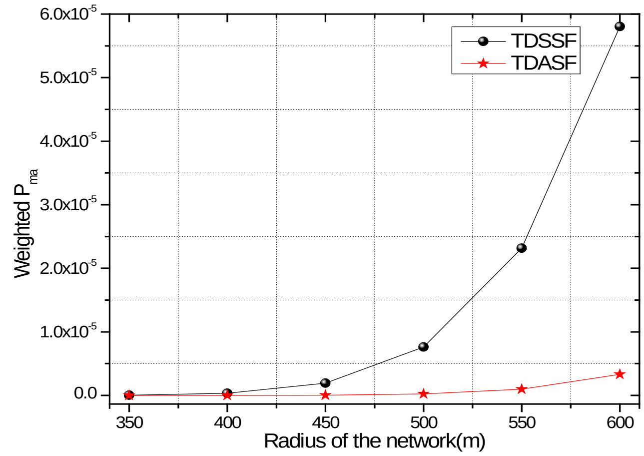

Fig.18 Weighted P_{ma} under different network radius R

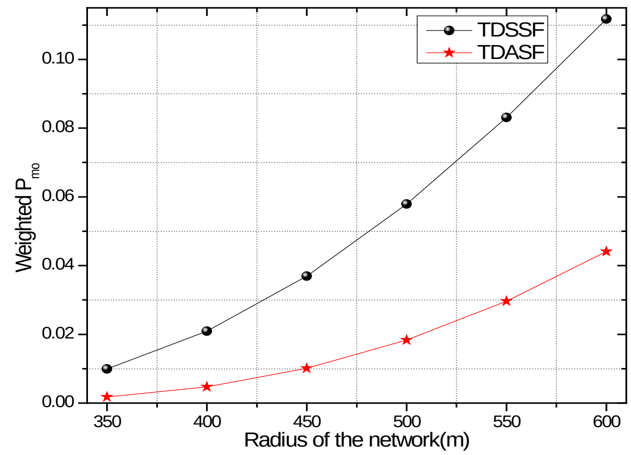

Fig.19 Weighted P_{mo} under different network radius R

D. Delay for detection

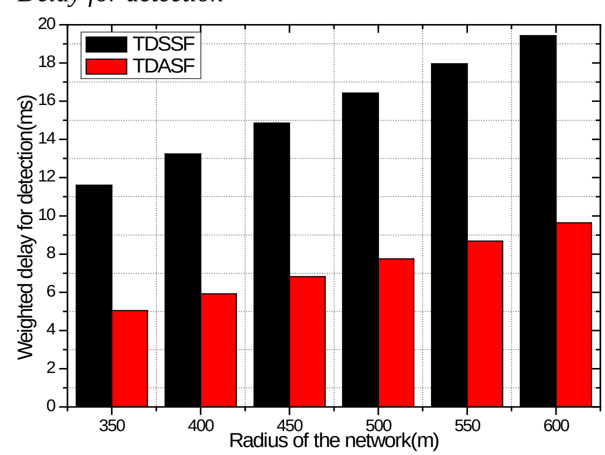

Fig. 20 Weighted delays for detection

According to Theorem 10, the comparison of weighted delay for detection between TDSSF and TDASF can be obtained. You can see from the Fig. 20 that under the same $\varsigma_{\text{sen}}^{x_{\min}}$ and different network radius, the weighted detection delays were reduced by 101.6%-130%. This illustrates the effectiveness of the TDASF strategy.

VII. CONCLUSION

In this paper, we have proposed an intelligent adjustable sensing frequency for mobile target detection based on the monitor quality optimization. Two schemes named TDSFK and TDASF are proposed. In the first scheme, the unequal sensing frequency in different regions is used to improve the monitor quality by taking the advantages of the residual energy throughout the network. The second scheme provides the method for the calculation of proper frequency value. The evaluation of the performances of the proposed schemes was made with three parameters: probability of missed target, delay and lifetime. Computer simulation results show that, the TDASF scheme can improve the network lifetime by more than 17.4%, and can reduce the weighted detection delay by more than 101.6%. The algorithm proposed in this paper is for the static sink WSNs, which is not suitable for mobile sink networks. Therefore, our further work is to explore the optimization problem of target detection in mobile sink network.

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