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Energy Balance-Based Tracking Strategy in Wireless Sensor Networks

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Abstract: This study studies the problems of tracking mobile targets in wireless sensor networks (WSNs). We propose a tracking strategy to achieve energy balance while improving the tracking performance. To this end, we first characterize the energy consumption of wireless sensor network with moving object tracking through theoretically analyze. Based on this result, we developed an approach to select tracking nodes by utilizing their remaining energy in different areas in the network. Our experiments demonstrate that the proposed approach significantly decreases the probability of unsuccessful tracking and transfers in comparison with previous approaches.

Key words: Wireless sensor network, tracking mobile target, energy-hole, energy balance, tracking performance

INTRODUCTION

Target tracking is an important application of wireless sensor networks (Gui and Mohapatra, 2004). Tradeoff between energy efficiency and tracking accuracy is a general solution. Many approaches modeled the trajectory of the tracked target as an sequence of straight line segments (He and Hou, 2005; Ghica *et al.*, 2010; Manohar and Manjunath, 2009). These works reduce the energy cost compared with the tracking algorithm (McErlean and Narayanan, 2002), which activates all nodes in sensor area and make them in working order. However, straight line segment based prediction of the actual position of target can cause deviations or even failure in tracking process for the upcoming frame. Zhou *et al.* (2012) presents a method called dead-reckoning-based particle filtering (DRPF) to recursively calculate the target's angular deflection, which can significantly reduce the communication overhead and computation complexity and improve reliability.

In wireless sensor networks, the sink as the gathering center of sensory data collects information transmitted from tracking nodes. It has been noticed that the sensors which close to the sink tend to deplete their energy faster than other sensors because they have to relay data for a large number of sensors, thus they run out of batteries very quickly. This area is known as the hotspots. Nodes in the hotspots die much faster than other sensors because of higher energy dissipation rate. This phenomenon is referred to as energy-hole (Ee and Bajcsy, 2004). Energy-hole phenomenon is widespread in tracking process and network lifetime largely depends on the nodes' remaining energy in hotspots.

In preliminary experiments we find that if the target tracking algorithm has a good prediction and selection mechanism, it can improve the tracking performance greatly. According to residual energy of node in wireless sensor networks, we propose an efficient energy balance consumption tracking strategy. In this paper we mainly focus on tracking mobile target which has continuous path and different directions of continuous change. Our study is different from other target tracking researches in following aspects:

- Although there are a number of proposed tracking algorithms and strategies, their common goal is only to reduce single tracking node computational overhead. While we are considering the tradeoff between energy efficiency and tracking accuracy, we think energy consumption situation of the whole networks.
- Therefore, our ultimate goal is balance of the all nodes' energy consumption and the improvement of tracking accuracy in wireless sensor networks.

The contributions of this paper can be summarized as following aspects:

- 1) We establish an elaborate energy consumption model to describe mobile target tracking and data collection process. We also use this model to compute energy consumption in different area of the network through theoretical analysis
- 2) Base on this energy consumption model we propose a energy balance tracking strategy

- 3) We present a large amount of simulation results to evaluate the proposed algorithm and which shows that our method gives a good tracking performance under a wide range of conditions

The rest of this study is organized as follows. Section 2 introduces related researches on the prediction and selection mechanisms. Section 3 depicts the structure of network model which is used in this paper and describes the questions we intend to solve. Section 4 discusses the computation of prediction and energy consumption of tracking. Section 5 describes the details of strategy which we proposed. Section 6 shows the simulation results. Section 7 concludes the paper.

RELATED WORK

Energy-hole phenomenon causes a lot of energy waste, especially the nodes which are located far away from sink area, as Lian *et al.* (2006) argues that by the time the network is out of function, some sensors in the network still have up to 90% initial energy. And once the network stops working, nodes' remaining energy could not be totally utilized. Therefore, in the tracking process, outer nodes have the ability to work for predicting target trajectory and fusing data. Accordingly, this method is feasible because that it could balance energy consumption and achieve better tracking performance. To better understand this issue, we first introduce some related research results in the wireless sensor networks field.

Target-state estimation: Prediction of the target motion trajectory is an important part of tracking algorithm. Many sensor selection proposals in target tracking have employed filtering methods and Bayesian theory to estimate the state of a target (Zou and Chakrabarty, 2006). Contrary to the more passive approaches, for instance, using acoustic sensors to estimate the location of the moving object during collaborative tracking (Rowaihy *et al.*, 2007), Zhou *et al.* (2012) propose a particle-filtering-based method which refers to as dead-reckoning-based particle filtering (DRPF). It is presented for recursively calculating the target's angular deflection, which, can significantly reduce the computation and communication overhead of state estimation. Armaghani et al. (2011) proposes a scheme that dynamically selects varying number of sensors at any time of tracking by using information utility and multivariate niche overlap of the sensors.

Energy-hole and analytical model: However, it has been noticed that the sensors close to the sink tend to deplete their energy faster than other sensors because they have to relay data for a large number of sensors and thus run out of batteries very quickly (Ee and Bajcsy, 2004). Li and Mohapatra (2007) presents an analytical model for the energy-hole problem in wireless sensor networks. They assume a uniform node distribution and discuss the validity of strategies such as hierarchical deployment, data compression, etc. Cheng *et al.* (2008) attempts to propose a general network lifetime and cost model to evaluate sensor network deployment strategies. Liu *et al.* (2013) think that the usual statement "around the sink" is too vague to guide the network deployment and optimization, so they accurately analyze the location and dimension of the energy-hole.

As far as we know, there is no research that comprehensively analyzes the impact of energy-hole on tracking target and collecting data. The previously mentioned researches about mobile target tracking do not take account of the effects of energy consumption asymmetric of node in network. In this paper, we establish model and propose an effective tracking strategy based on energy balancing to improve tracking performance.

NETWORK MODEL AND PROBLEM DEFINITION

Network model: In this study, we use a typical circular wireless sensor network scenario to investigate the problems (Lian *et al.*, 2004). The WSN is consisted of N homogenous static sensor nodes S_i , all sensor nodes are deployed in the circular network with R as the radius and the sink at the center of the circle.

We assume that all the nodes have identical communication range R_c and sensing range R_s . Each node is assumed that it only knows its own location and the locations of its one-hop neighbors. A given sensor node locates the target in its sensing area via some range-based methods, e.g., received signal strength indicator (RSSI) or time difference of arrival (Saxena *et al.*, 2008). Finally, we assume that the network is dense enough to ensure that a moving target can be tracked while it travels in the area of nodes' deployment (Zhou *et al.*, 2012).

The symbols used throughout the rest of this paper are summarized in Table 1.

Energy consumption model: We use Eq. 1 to calculate the communication overhead and the energy for tracking target through Eq. 2. We refer for more details of Mica2 Mote energy consumption (Zhou *et al.*, 2012).

Table 1: List of symbols

Symbol	Description
R	Network radius
S_i	Sensor node i
R_c	Communication range
R_s	Sensing range
$N(S_i)$	The one-hop neighborhood nodes of S_i
X_t	Target statue at time t
$Z_{0:t}$	The sequence of measurements $z_0, \dots, z_t$
$Z_t(S_i)$	Measurements of S_i at time t
L_t	Estimated 2D coordinates (x_t, y_t)
w_t^i	The weight of ith particle
φ_t	Angular deflection at t
v	The speed of target

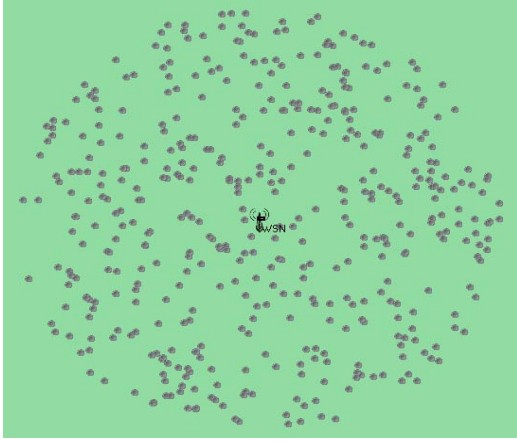


Fig. 1: Network model

$$\begin{cases} E_{\text{send}} = E_{RT} \cdot \text{data} \\ E_{\text{receive}} = E_{RR} \cdot \text{data} \end{cases} \quad (1)$$

$$E_{\text{sensing}} = E_{SA} \cdot \text{DATA} \quad (2)$$

If the distance between S_i and S_j is less than R_c , i.e., $\|S_i - S_j\| \leq R_c$, we use Eq. 1 to calculate nodes' communication overhead and use Eq. 2 to calculate sensing overhead.

Problem description: For a given sensor network shown in Fig. 1, we formalize the problem as: how to assign tasks to nodes in different areas in network at tracking process to increase the tracking accuracy under the premise of no reduction of network lifetime.

Definition 1

Tracking accuracy: It means the successful rate of targets tracking. For example, suppose the sum of the number of tracking is N and N_a is the number of successful tracking, then tracking accuracy $T_a = N_a/N$.

TARGET-STATE ESTIMATE USING PARTICLE FILTERING

Particle filtering algorithm: Particle filtering originates from Monte Carlo method. Its main idea is to use a number of dependent random variables called particles to represent the posterior probability. The posterior can be updated in time using the importance sampling method, which is based on target dynamics and the observation likelihood model (Chen, 2003). Particle filtering is constitutive of two processes, predict and update, which can be expressed as follows:

$$P(x_t | Z_{t-1}) = \int p(x_t | x_{t-1}) p(x_{t-1} | Z_{0:t-1}) dx_{t-1} \quad (3)$$

$$p(x_t | Z_{0:t}) = \frac{p(Z_t | x_t) p(x_t | Z_{0:t-1})}{p(Z_t | Z_{0:t-1})} \quad (4)$$

Equation 3 describes the predict process, calculates the prior distribution according to posterior distribution estimation in $t-1$ and $p(x_t | x_{t-1})$. The expression $p(x_t | x_{t-1})$ is target-state transition density. Eq. 4 indicates update process, calculates the posterior distribution of the target state. $p(Z_t | x_t)$ is the measurement equation and noise model, $p(x_t | Z_{0:t-1})$ is the knowledge of mobility model, $p(x_t | Z_{0:t-1})$ is a constant called evidence.

Direction deflection estimate with particle filtering: Our goal is to estimate the direction deflection of target at time t via particle filtering and the detailed discussion of the estimating processes as follows.

Sampling: By sampling from $p(x_t | x_{t-1}^i, Z_t)$ and evaluating $P(Z_t | x_{t-1}^i)$ using Eq. 5 (Doucet *et al.*, 2000) can we obtain the variance of importance weight w_t^i conditional upon x_{t-1}^i and $Z_{0:t}$.

$$P(Z_t | x_{t-1}^i) = \int p(Z_t | x_t) p(x_t | x_{t-1}^i) dx_t \quad (5)$$

Weight calculation: We assume a Gaussian error model for range measurements of each node. Then the weight w_t^i of particle x_t^i is calculated as Eq. 6.

$$w_t^i = w_{t-1}^i \prod_{j=1}^M \frac{1}{\sqrt{2\pi}\sigma_j} e^{-\frac{(z_t(s_j) - z_t^i(s_j))^2}{2\sigma_j^2}} \quad (6)$$

M is number of measurements. Calculation formula of importance weight is shown in Eq. 7.

$$\omega_t^i = \omega_{t-1}^i \cdot \frac{p(Z_t | x_t^i) p(x_t^i | x_{t-1}^i)}{q(x_t^i | x_{0:t-1}^i, Z_{0:t})} \quad (7)$$

The weight of particle can be normalized as follow:

$$\omega_t^i = \frac{\omega_t^i}{\sum_{k=1}^N \omega_t^k} \quad (8)$$

The location $\tilde{L}$ is updated as the centroid of all the weighted particles as follows (Zhou *et al.*, 2012):

$$\tilde{L}(\tilde{x}, \tilde{y}) = \left(\sum_{i=1}^N \omega_t^i \cdot x_t^i, \sum_{i=1}^N \omega_t^i \cdot y_t^i \right) \quad (9)$$

Finally, we can estimate φ_t according to the historical trajectory tracking coordinates information (x_{t-1}, y_{t-1}) and (x_{t-2}, y_{t-2}) as following expression.

$$\varphi_t = \arctan\left(\frac{\tilde{y} - y_{t-1}}{\tilde{x} - x_{t-1}}\right) - \arctan\left(\frac{y_{t-1} - y_{t-2}}{x_{t-1} - x_{t-2}}\right) \quad (10)$$

Resampling: Resampling is an important stage to solve the particle degradation. It can effectively remain the system more stable and resolve the problem that minority particles have almost all the mass.

Trajectory prediction: We can estimate the location $\tilde{L}$ and angular deflection φ_t of the target using Eq. 9 and Eq. 10, respectively:

$$\text{Traj}(k) = \begin{cases} \tilde{x}_{t+k} = \tilde{x}_t + v \cdot k \cdot \cos(\varphi_{t-1} + k \cdot \varphi_t) \\ \tilde{y}_{t+k} = \tilde{y}_t + v \cdot k \cdot \sin(\varphi_{t-1} + k \cdot \varphi_t) \end{cases} \quad (11)$$

Traj(k) means the location of target after time k, we assume that $\varphi_t = 0$ means the direction is on the left of φ_{t-1} .

SELECTION OF TRACKING NODES

Situation of energy consumption: Energy consumption depends on the amount of packets that nodes send and receive messages. First we can get the relationship between network radius R and communication radius R_c as follow:

$$\begin{cases} R = \alpha \cdot R_c + \beta \\ \alpha = \left\lfloor \frac{R}{R_c} \right\rfloor, \beta < R_c \end{cases} \quad (12)$$

Theorem 1: The amount of packets of node which distance from sink is L must relay is shown in Eq. 14.

$$L = i \cdot R_c + x, i \in (0, a), x \in (0, R_c) \quad (13)$$

Proof: Take an arbitrary node S_i in network whose distance from sink is $D_i = i \cdot R_c + x, i \in (0, a), x \in (0, b)$, the we take a segment of circle γ width of dx. So the area of it can approximate at $2\pi dx$ and the number of nodes in it is $2\pi \rho dx$:

$$\begin{cases} \text{Data}_i = \frac{1 + \left((a-i-1) \cdot x + \frac{(a-i-1) \cdot (i+a) \cdot R_c}{2} \right)}{(iR_c + x)}, \\ (i \in \{0, 1, \dots, a\}, x \in \{b \dots R_c\}) \\ \text{Data}_r = \frac{\left((a-i-1) \cdot x + \frac{(a-i-1) \cdot (i+a) \cdot R_c}{2} \right)}{(iR_c + x)}, \\ (i \in \{0, 1, \dots, a\}, x \in \{b \dots R_c\}) \\ \text{Data}_i = \frac{1 + \left((a-i) \cdot x + \frac{(a+i+1) \cdot (a-i) \cdot R_c}{2} \right)}{(iR_c + x)}, \\ (i \in \{0, 1, \dots, a\}, x \in \{0 \dots b\}) \\ \text{Data}_r = \frac{\left((a-i) \cdot x + \frac{(a+i+1) \cdot (a-i) \cdot R_c}{2} \right)}{(iR_c + x)}, \\ (i \in \{0, 1, \dots, a\}, x \in \{0 \dots b\}) \end{cases} \quad (14)$$

If the distance between S_i and sink is D, S_i is responsible for relaying the data from the area Ψ which is shown in Eq.15.

$$\begin{aligned} \Psi &= 2\pi((i+1) \cdot R_c + x) dx + \dots + 2\pi(aR_c + x) dx \\ &= 2\pi dx \left((a-i) \cdot x + \frac{(a+i+1)(a-i) \cdot R_c}{2} \right) \end{aligned} \quad (15)$$

We assume that in small area γ each node undertakes the same amount of packets, then, the amount of packet sent by each node in γ is:

$$1 + \frac{\left((a-i-1) \cdot x + \frac{(a-i-1)(a+i) \cdot R_c}{2} \right)}{iR_c + x}$$

Then the amount of packets received by each sensor node in γ is:

$$\left((a-i-1) \cdot x + \left(\frac{(a-i-1)(a+i) \cdot R_c}{2} \right) \right) / iR_c + x$$

Then, the amount of packets sent by γ as follow, $\bar{e}$ is node density:

$$\left(2\pi dx \left((a-i) \cdot x + \left(\frac{(a+i+1)(a-i) \cdot R_c}{2} \right) \right) + (2\pi i r + x) dx \right) \cdot \lambda$$

Then, the amount of packets received γ is:

$$2\pi dx \left((a-i) \cdot x + \left(\frac{(a+i+1)(a-i) \cdot R_c}{2} \right) \right) \cdot \lambda$$

Corollary 1: We use E_i to denote the energy consumption of node which distance from the sink is $D_i = i \cdot R_c + x$, then we use E_s to denote the node that tracking for $\tilde{N}$ times.

$$E_i = E_r + E_t = (E_{RR} + R_{RT}) \cdot \tau \cdot \text{Data}_i \quad (16)$$

$$E_s = \tilde{N} \cdot E_{\text{tracking}} \quad (17)$$

Proof: We can calculate E_i according to Eq.1, data is the amount of packets of node, i.e., $\text{data} = \tau \times \text{Data}_i$, then we can also get E_s according to Eq. 2.

From the above results, we can find that the amount of packets are reduced with the increasing of the distance from sink and this tendency is nonlinear, the closer nodes distance from sink the more the amount of packets nodes have to relayed. On the other hand, if the time of tracking is long enough and the trajectories of targets which enter tracking range of network are random, each node has the same $\tilde{N}$, i.e., the energy consumption of nodes for tracking can be considered to be the same. In other words, E_s has nothing to do with the distance between sink and nodes.

Energy balance tracking strategy: Through above analysis, we find that there is a huge difference between energy consumption of nodes in different areas. Network lifetime mainly depends on remaining energy of nodes which distance from sink less than communication range R_c . Based on these results, we propose an effective tracking approach called energy balance-based tracking strategy (EBTS).

We use a threshold δ to divide the network. Within the range of 0 to δ meter from sink, we use Deflection-

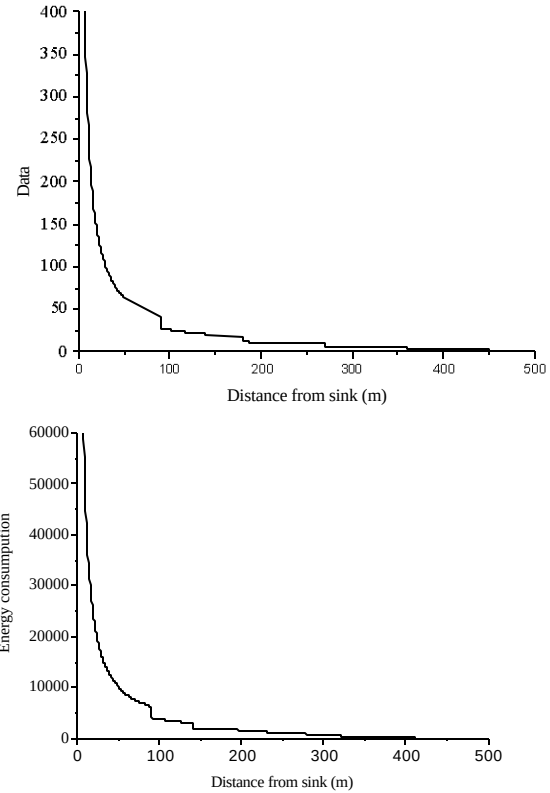


Fig. 2: The amount of packets and the energy consumption of nodes in different areas

Aware Selection (DAS) (Zhou *et al.*, 2012), which is proposed to select tracking-principal. Within the range of δ to R from sink, we use the energy balance-based sensor selection (EBS) to select next tracking node. More specifically speaking, the strategy can be divided into two parts: target tracking and data fusing, however, they proceed not at the same time. The pseudo-code of EBS is presented in Algorithm 1. A set of candidate of tracking nodes $\text{Cand}(S_n)$ can be got according to EBS. Data fusing is proceeded at next time. One node is selected to transmit data to sink from candidate.

Algorithm 1: Energy Balance-based Sensor Selection

Require: Current tracking node S_i , $N(S_i)$

Ensure: $\text{Cand}(s_n) \neq \text{NULL}$

1: Estimate φ with (10)

2: Calculate $\tilde{L} = \text{Traj}(\tilde{e})$, $\tilde{e} = 1$ with (11)

3: Time stamp $T \leftarrow t$

4: While $|S_i - \text{sink}| > \delta$ do

5: if $|\tilde{L} - S_i| > R_s$ then

6: for each $S_k \in N(S_i)$ do

7: if $|\tilde{L} - S_k| > R_2$ then

8: $N(S_i)$ remove (S_k)

9: end if

10: end for

11: end if

Algorithm 1: Continued

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12: Sort  $N(S_i)$  in ascending order
13: Cand  $(S_n) \leftarrow N(S_i)$ 
14: return Cand  $(S_n)$ ;
15: T=T+1;
16: end while
    
```

EVALUATION WITH SIMULATIONS

In this section, we provide examples to show the tracking performance of the proposed strategy and we compare our methodologies with algorithm proposed by Zhou *et al.* (2012). We adopted a modified random waypoint mobility model for moving target (Camp *et al.*, 2002).

Every simulation spanned 2000s. In addition, we conduct 40 random runs for each configuration to value the average performance of different plans, Initial Energy is 5J, $\delta = 90$.

In this study, the above specific parameters are listed in Table 2 as adopted from Zhou *et al.* (2012)

Improvement of tracking performance

- **Impact of target's speed:** Figure 3 demonstrates the unsuccessful tracking times of DAS and EBTS. It shows the more accurate tracking of EBTS compared with DAS. The faster the mobile target, the more tracking nodes are required. A fast moving object decreases the certainty of the prediction and node selection for both EBTS and DAS. EBTS achieves improvement by 12.83-32.92% over DAS. With the increase of speed, EBTS reduces a growing number of unsuccessful tracking times compared with DAS.
- **Impact of the node density:** Along with node density increases, the probability of unsuccessful tracking is decrease. However, EBTS reduces 15.72-22.08% compared with DAS. An important observation is that, a small numbers of neighbors can be sufficient to reach good performance.

Figure 4 and 5 show that the trend of EBTS is more stable than DAS. EBTS has a characteristic of little network factors affection.

In conclusion, the simulation results demonstrate that our strategy significantly better than DAS under a wide range of conditions.

Energy consumption: Figure 5 compares the energy consumption of EBTS to DAS. It is a great improvement of utilization rate of energy within the range of δ to R. It is precisely because EBTS makes nodes in that area do more tracking work, the tracking performance is better than

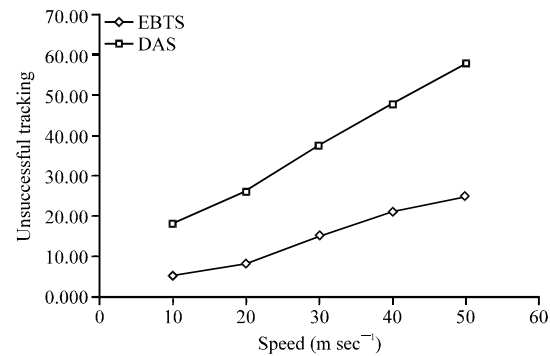


Fig. 3: Impact of target speed v

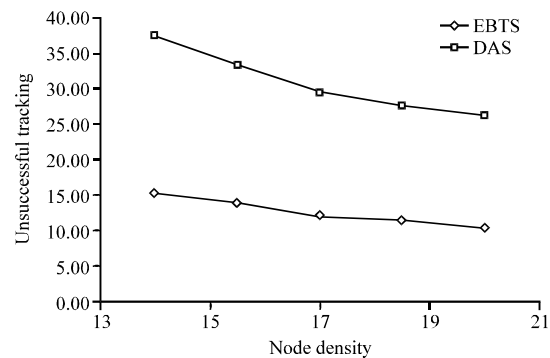


Fig. 4: Impact of node density λ

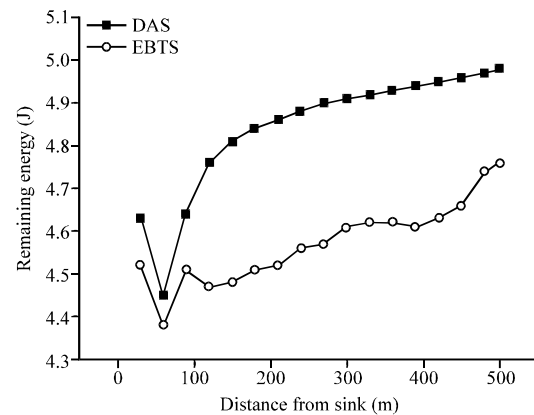


Fig. 5: Comparison of energy consumption

DAS. The results are shown in Fig. 3 and 4. As can be observed from Fig. 5, remaining energy of EBTS is less than DAS in the hotspots. In some sense, it can indicate the advance of tracking performance. Because the higher tracking accuracy is, the more data nodes in hotspots have to relayed, the more energy have to consumed.

DISCUSSIONS AND CONCLUSIONS

In this study we propose an energy balance-based tracking strategy. The main idea of EBTS is using different

tracking algorithms in different areas. Both theoretical analyses and simulation experiments, compared with existing tracking approaches, especially DAS, show that our strategy has a better performance in a wide range of scenarios. We plan to address augmenting our recent researches in the near future.

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