Energy-Efficient Adaptive Dynamic Sensor Scheduling for Target Monitoring in Wireless Sensor Networks

Jian Zhang, Cheng-dong Wu,Yun-zhou Zhang, and Peng Ji

Due to uncertainties in target motion and randomness of deployed sensor nodes, the problem of imbalance of energy consumption arises from sensor scheduling. This paper presents an energy-efficient adaptive sensor scheduling for a target monitoring algorithm in a local monitoring region of wireless sensor networks. Owing to excessive scheduling of an individual node, one node with a high value generated by a decision function is preferentially selected as a tasking node to balance the local energy consumption of a dynamic clustering, and the node with the highest value is chosen as the cluster head. Others with lower ones are in reserve. In addition, an optimization problem is derived to satisfy the problem of sensor scheduling subject to the joint detection probability for tasking sensors. Particles of the target in particle filter algorithm are resampled for a higher tracking accuracy. Simulation results show this algorithm can improve the required tracking accuracy, and nodes are efficiently scheduled. Hence, there is a 41.67% savings in energy consumption.

Keywords: Wireless sensor networks, target monitoring, energy balance, node scheduling, particle filter.

I. Introduction

Wireless sensor networks (WSNs) have been widely used in many fields. One of the most significant and elementary applications is localization and tracking moving targets [1]. A major driver for localization within WSNs is driven by networks with mobile nodes [2]. The ability to track the targets, for example, vehicles, animals, or people, opens up a wide range of applications in transport management, agriculture [3], military, and health domains [4],[5]. Therefore, the applications of localization and tacking moving targets have been an important and growing research topic for WSNs [6].

The vast majority of previous works in localization within sensor networks has focused on theoretical and simulation approaches to validation of algorithms [7]-[12]. However, energy-based localization in actual implementation is necessarily considered by analyzing the consumption in the power of the incoming signal.

With the development of WSNs, selecting only a proper group of sensors from an available set to perform tracking is of research value [13] in the field of motion monitoring. In [14], large-scale sensor array management, from which a small subset of available sensors is selected to optimize tracking performance, is concerned to track multiple targets. The authors in [15] utilize one-step-look-ahead posterior Cramer-Rao lower bound to estimate the state error for target tracking by considering sensor selection with quantized data. A new sensor selection scheme for target tracking in binary sensor networks using auxiliary particle filter is proposed in [16]. Due to limitations of sensing regions of sensors, an adaptive energy-efficient multisensor scheduling scheme calculating the optimal sampling interval, selecting the cluster according to their joint detection probability (JDP), designating the cluster head is

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proposed for collaborative target tracking in [17]. In [18], an adaptive active region size algorithm based on the node density is proposed to select the optimal nodes taking part in localization. The authors in [19] propose a decentralized estimation approach considered in WSN using the extended information filter for target tracking and a cost function based on the geometrical dilution of precision for sensor selection.

Although sensor selection strategies mentioned above are proposed as far as the tradeoff between accuracy and energy consumption, the problem that nodes could be excessively scheduled in the active region is not considered for both localization and target monitoring. This leads to dramatic increases in energy consumption of these nodes. To overcome the limitations of existing works, this paper presents the implementation of energy-efficient adaptive sensor scheduling for target monitoring in WSNs.

The main contribution of this paper is a sensor scheduling strategy to balance energy consumption for target monitoring in randomly deployed WSNs. First, the decision function is applied to select candidate tasking sensor nodes. Second, an optimization strategy is proposed to determine which sensor node is eventually scheduled. Finally, a particle filter algorithm is used to localize the target. Therefore, we actually focus on three aspects: accuracy, energy effectiveness, and sensor node validity.

II. Models

In this section, we present the sensor model, sensor detection model, and particle filter algorithm used in the target localization.

1. Sensor Model

We assume that the sensor model of the system is denoted by

$$z_{i,t} = h_i(x_t, v_{i,t}),\ i = 1, 2, ..., N_t. \tag{1}$$

If there are N_t sensors at time t, and $S_t = \{s_1, s_2, ..., s_{N_t}\}$ is a set that involves those sensors taking part in measurement, then measurement vector from $z_t = \{z_{1,t}, z_{2,t}, ..., z_{N_t,t}\}$ is defined by

$$z_t = (z_{1,t}, z_{2,t}, ..., z_{N_t,t})^T, \tag{2}$$

where $z_{i,t}$ is the measurement of sensor s_i, $h_i(\cdot)$ denotes the measurement function of sensor s_i, and $v_{i,t}$ is the measurement noise. In this paper, the measurement function is specifically described by

$$z_{i,t} = \sqrt{(x_{1,t} - x_{1,s_i})^2 + (x_{2,t} - x_{2,s_i})^2} + v_{i,t}, \tag{3}$$

where (x_{1,s_i}, x_{2,s_i}) indicates that the coordinate of sensor s_i and $v_{i,t}$ is the observation noise which is a Gaussian distribution with mean 0 and variance $\sigma_{i,t}^2$ ($i = 1, 2, ..., N_t$, and N_t is the number of senor nodes at time t).

Several assumptions are made in this paper to resolve the problem that happens in the localization and motion monitoring system:

i) The process noise u_t and the measurement noise $v_{i,t}$ are assumed statistically independent of each other.

ii) $z_{i,t}$, $i = 1, 2, \cdots, N_t$ from sensors are independent of each other.

iii) Sensor nodes are aware of their own localization and modality.

iv) All sensors are homogeneous.

2. Sensor Detection Model

In most of the existing literature, the sensor detection model is a 0-1 model, that is, the transmitted signal is 1 as long as the target is within the detection region of a sensor. However, the probability that a sensor s_i detects a target does not equal 1 usually even though the target is within its detection region. Actually, the detection probability [17] is defined by

$$p_{s_i}(x_1, x_2) = \begin{cases} \alpha, & \text{if } (x_1, x_2) \in \psi_i, \\ 0, & \text{otherwise}, \end{cases} \tag{4}$$

where $\alpha \in [0, 1]$, (x_1, x_2) is the target location, and ψ_i is the detection region of sensor s_i.

The probability density function [20] of the target located at $X_p = (x_1, x_2)^T$ can be defined by

$$p(x_1, x_2) = \frac{1}{2\pi |\Sigma|^{1/2}} \cdot \exp\left(-\frac{1}{2}(X_p - E(X_p))^T \Sigma^{-1} (X_p - E(X_p))\right). \tag{5}$$

Therefore, the predicted detection probability of sensor s_i is presented as

$$\Pr(s_i) = \iint p_{s_i}(x_1, x_2) \cdot p(x_1, x_2) dx_1 dx_2. \tag{6}$$

If a target location denoted by (x_1, x_2) is covered by n sensors, that is, $s_{i_1}, s_{i_2}, ..., s_{i_n}$, its detection probability will be expressed as

$$p_{s_{i_1}, s_{i_2}, ..., s_{i_n}}(x_1, x_2) = 1 - \prod_{i=i_1}^{i_n} (1 - p_{s_i}(x_1, x_2)), \tag{7}$$

and the joint detection probability for these n tasking sensors is expressed as

$$\Pr(s_{i_1}, s_{i_2}, ..., s_{i_n}) = \iint p_{s_{i_1}, s_{i_2}, \cdots, s_{i_n}}(x_1, x_2) \cdot p(x_1, x_2) dx_1 dx_2. \tag{8}$$

III. Particle Filter

We start with a brief review of the recursive Bayesian

estimation method and present a resampling method not to suffer from degeneracy problem.

1. Review of PF

The purpose here is to recursively calculate the probability distribution of x_t given the measurement vector, which is denoted by $z_t = (z_{1,t}, z_{2,t}, \cdots, z_{N_t,t})^T$ up to time t. In Bayesian theory, the posterior probability density $p(x_t \mid z_{0:t})$ can be inferred from prior probability density $p(x_t \mid z_{0:t-1})$:

$$p(x_t \mid z_{0:t}) = p(z_t \mid x_t) \cdot p(x_t \mid z_{0:t-1}) / p(z_t \mid z_{0:t-1}), \quad (9)$$

where

$$p(z_t \mid z_{0:t-1}) = \int p(z_t \mid x_t) p(x_t \mid z_{0:t-1}) dx_t. \quad (10)$$

The Monte Carlo simulation method is used to approximate the posterior density by N particles

$$p(x_t \mid z_{0:t}) \approx \sum_{i=1}^{N} \omega_{t-1}^i \delta(x_{t-1} - x_{t-1}^i). \quad (11)$$

Usually,

$$\omega_t^i = \omega_{t-1}^i p(z_t \mid x_t^i).$$

The estimated state is finally approximated by

$$\hat{x} = \sum_{i=1}^{n} \omega_t^i x_t^i. \quad (12)$$

2. Method of Particle Resampling

Based on JDP, we assume that S_t is a set of measurements of sensors at time t, R_{s_i} presents the sensor region of node s_i, ω_0 is the threshold of resample, and R_{ω_0} denotes a circle whose center is the coordinate of target localization with radius ω_0.

Proposition. Suppose nodes $s_1, s_2, ..., s_N$ are tasking nodes at time t in the process of localization and motion monitoring. If the coordinate of the target meets

$$(x^j{}_{1,t}, x^j{}_{2,t}) \in (\bigcap_{i=1}^{N} R_{s_i}) \bigcup R_{\omega_0},$$

then $(x^j{}_{1,t}, x^j{}_{2,t}) \in (\bigcap_{i=1}^{N} R_{s_i}) \bigcup R_{\omega_0}$ is a resampled particle we need.

Proof. We utilize the cost function in [21] at time t to explain it. For the sake of simplicity, set q=1, N=3, then the cost function can be rewritten by

$$\begin{aligned} C_{t+1} &= C(x_{t+1} \mid z_{t+1}) \\ &= \|z_t - f_z(x_t)\| \\ &= [z_t^{s_1} - f_z(x_t^{s_1})]^2 + [z_t^{s_2} - f_z(x_t^{s_2})]^2 + [z_t^{s_3} - f_z(x_t^{s_3})]^2, \end{aligned}$$

where $f_z(x_t^{s_i}), i = 1,2,3,$ is the measurement function of $(x_{1,t}, x_{2,t})$ at time t. Let the measurement from sensor node s_2 satisfy $(x^j{}_{1,t}, x^j{}_{2,t}) \in \bigcup_{i=1}^{3} R_{s_i} \bigcup R_{\omega_0} - \bigcap_{i=1}^{3} R_{s_i}$, and the cost function is

$$\begin{aligned} C_{t+1,j} &= C_{t,j}(x_t \mid z_t) \\ &= \|z_t - f_z(x_t)\| \\ &= [z_{t,j}^{s_1} - f_z(x_{t,j}^{s_1})]^2 + [z_t^{s_2} - f_z(x_t^{s_2})]^2 + [z_t^{s_3} - f_z(x_t^{s_3})]^2. \end{aligned}$$

Owing to $[z_t^{s_1} - f_z(x_t^{s_1})]^2 < [z_{t,j}^{s_1} - f_z(x_{t,j}^{s_1})]^2$, $C_{t+1} < C_{t+1,j}$ is obtained. Similarly, the measurements from s_1 and s_3 are established. Therefore, $(x_{1,t}^j, x_{2,t}^j) \in \bigcap_{i=1}^{3} R_{s_i} \bigcup R_{\omega_0}$ is chosen as a resampled particle. □

IV. Adaptive Dynamic Sensor Scheduling

Active sensor nodes collect data from the monitoring region to localize the target, and others keep sleeping. To schedule nodes effectively to avoid from overusing and balance local energy consumption, some measures should be taken.

1. Sensor Selection Algorithm

In the process of target tracking, some sensor nodes are used by clusters in WSNs. This will lead to energy exhaustion and death of those sensor nodes. To avoid this problem, a decision function, which determines whether a node should be selected in the tracking cluster, is proposed to reduce the reused times according to the residual energy and times of a single node.

Set Ps is a decision function in the cluster at time t. It is denoted by

$$Ps(N) = \beta(N) \times \frac{E_r}{E_w}, \quad (13)$$

where E_r and E_w indicate the residual energy and the total energy [22] of a node, respectively. The times which a node has been used before is denoted by N. A monotonically decreasing function on N is described by $0 < \beta(N) \le 1$. With the increase of N and the decrease of E_r, the decision value of a node decreases, which means that the feasibility of node selection becomes lower.

In current dynamic monitoring region, every node owes its decision value. We descend all nodes according to these values and get a set $S_{t+1}^{'} = \{s_1, \cdots, s_N\}$.

If $\Pr_{s_1}(x_1, x_2) \ge \theta_d$, the selected set of nodes is

$$S_{t+1} = \{s_1\}.$$

Otherwise, $S_{t+1} = \{s_1, s_2\}$.

In a similar way, if $\Pr_{s_1,s_2}(x_1, x_2) \ge \theta_d$, the selected set of nodes is

$$S_{t+1} = \{s_1, s_2, s_3\}.$$

More sets will be calculated according to the same procedure until $\Pr_{s_1,s_2,\ldots,s_m}(x_1, x_2) \geq \theta_d$, and the tasking cluster for the next time t+1 is

$$S_{t+1} = \{s_1, s_2, s_3, \ldots, s_m\}.$$

In addition to the implementation of localization algorithm, the cluster head executes a task of scheduling between selected nodes. Let CH_t denote cluster head at time t. The cluster head CH_{t+1} is selected by

$$CH_{t+1} = \arg_{s_i} \min(| s_i^{\max(Ps(N))} - \mu_{t+1} |),$$

where $s_i^{\max(Ps(N))}$ denotes the node with the highest decision value Ps and μ_{t+1} is a predictive value of the tracked target.

2. Mathematical Formulation

We consider the energy balance based on decision function and sensor-detection probability model previously. At time t, the cluster head determines how tasking nodes should be selected to balance the local energy of the monitoring region, such that

$$\min(\max(E_{ri}) - \min(E_{rj})),$$

is subject to

$$Ps(N),$$

and

$$p_{s_1,s_2,\cdots,s_m}(x_1, x_2) \geq \theta_d .$$

According to (7), (8), and (13), this problem can be expressed as

$$\min(\max(E_{ri}) - \min(E_{rj})),$$

and is subject to

$$Ps(N) = \beta(N) \times \frac{E_r}{E_w},$$

and

$$\iint (1 - \prod_{i=1}^{m} (1 - p_{s_i}(x_1, x_2))) \cdot p(x_1, x_2) dx_1 dx_2 \geq \theta_d,$$

which means to minimize difference of energy consumption between nodes subject to both the decision function and JDP, where E_{ri} and E_{rj} are the residual energy of nodes, $i \neq j$.

V. Simulation Results

In 2D space, the dynamic system in [17] is expressed as

$$x_t = Fx_{t-1} + u_t,$$

where $x_t = (x_{1,t}, x_{2,t}, \dot{x}_{1,t}, \dot{x}_{2,t})^T$ is the target state vector at time t, $\dot{x}_{1,t}$ and $\dot{x}_{2,t}$ indicate the corresponding speeds of coordinates of $x_{1,t}$ and $x_{2,t}$, respectively. The system state transition matrix is F and can be defined by

$$F = [1\ 0\ T_s\ 0; 0\ 1\ 0\ T_s; 0\ 0\ 1\ 0; 0\ 0\ 0\ 1],$$

where T_s is the sampling interval. The process noise u_t is a Gaussian distribution with mean 0 and variance Q presented as $Q = Ddiag\{\sigma_x^2, \sigma_y^2\}D^T$, where D is defined by $D = [T_s^2/2\ 0; 0\ T_s^2/2; T_s\ 0; 0\ T_s]$.

In these simulations, we carry out the simulation section in MATLAB on a Lenovo Laptop with a 1.6 GHz Core2 Duo processor and 2 GB of RAM. Five hundred runs are taken for simulations. N=100 sensor nodes with sensor radius R=30 m and sampling interval T_s = 1 s are randomly deployed in a square field 150 m × 150 m. To facilitate comparison, we assume that the process noise variance in particle filter is $diag([0.125\ 0.125\ 0.5\ 0.5])$, and the measurement noise variance of each sensor node is 1. The sensor detection probability α and the threshold θ_d are 0.78 and 0.99, respectively. At time $t = 0$, the initial state is $x_0 = [0\ 0\ 2\ 2]^T$, and the target tracking time continues for 50 s. Two scheduling methods are considered. One is a general sensor selection algorithm (GSSA), which all sensor nodes are scheduled in a cluster at every time interval. The other is dynamic sensor selection algorithm (DSSA) proposed in this paper.

Comparisons of sensor scheduling between GSSA and DSSA are shown in Figs. 1 and 2. Generally, the number of nodes in DSSA is less than GSSA according to the decision function and JDP shown in section IV. In this process, the decision function guarantees that tasking sensor nodes are selected to eliminate redundant sensor nodes, and JDP is used to detect the target. For GSSA, all sensor nodes in a cluster are

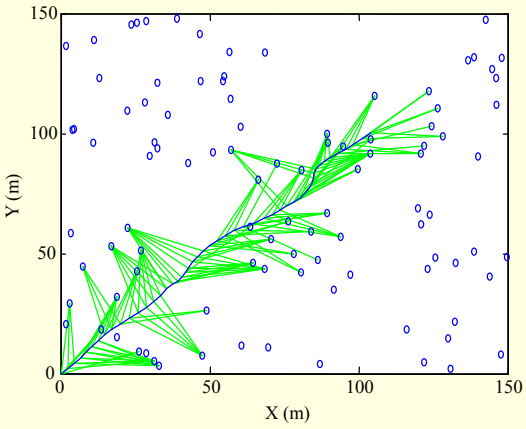

Fig. 1. Sensor scheduling of DSSA.

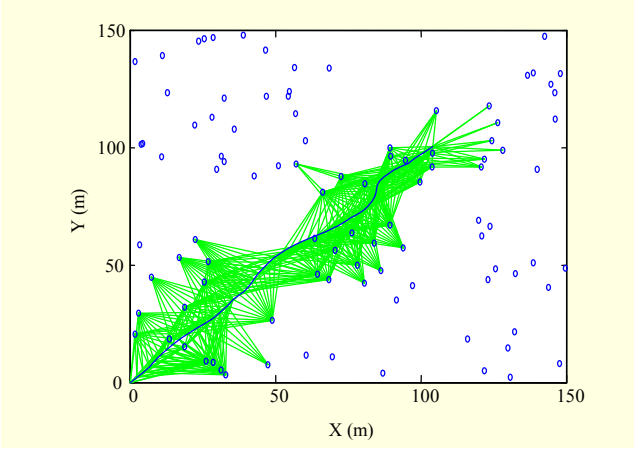

Fig. 2. Sensor scheduling of GSSA.

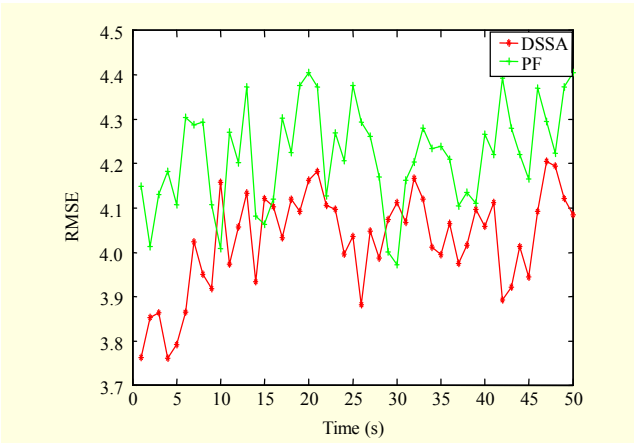

Fig. 3. Root mean square error of PF and DSSA.

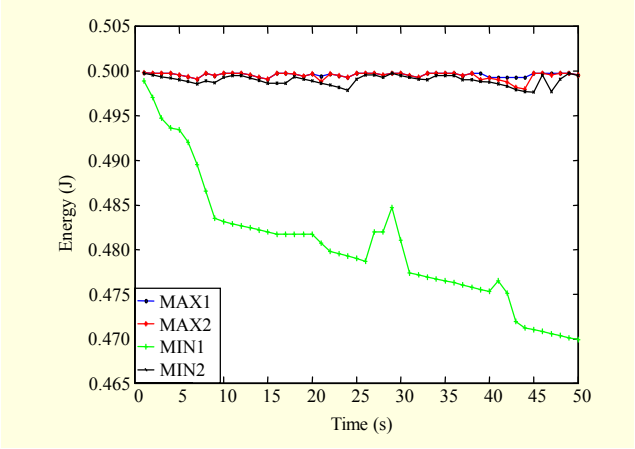

Fig. 4. Residual energy of DSSA and GSSA.

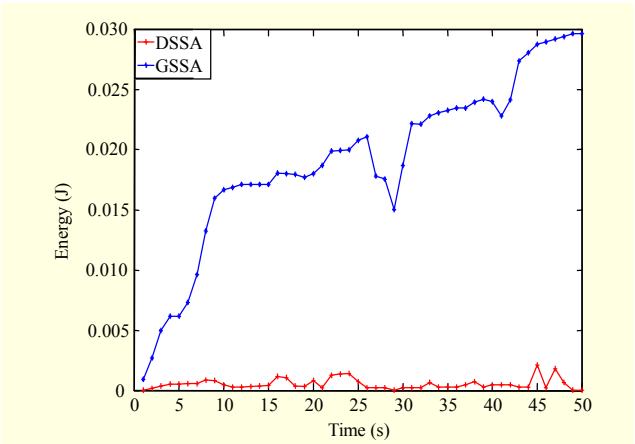

Fig. 5. Difference of residual energy of DSSA and GSSA.

scheduled in a cluster at every time interval. This reduces not only the redundant information to save channel bandwidth but also network cost. So, the performance of DSSA proposed in this paper is superior to GSSA.

Figure 3 describes the root mean square error utilizing standard PF and DSSA. The localization accuracy of DSSA is relatively higher than PF. The reason is that particles with higher threshold are easily chosen from the resampling method. Seen from Fig. 3, the error mean of DSSA is 4.0 and the one of PF is 4.2. In this sense, DSSA demonstrates a better result.

Comparison results in terms of energy consumption of GASS and DSSA are demonstrated in Fig. 4, where MAX1 and MIN1 are the maximal value and the minimal value of GSSA, respectively, and MAX2 and MIN2 are the maximal one and the minimal one of DSSA, respectively. Obviously, we can note that the energy consumption of individual node of GSSA is more than the one of DSSA, while the maximal values of GSSA and DSSA are almost equal in the tracking process. Especially, the green line varies between 0.47 and 0.5. In other words, some nodes are continuously reused during the monitoring time in GSSA. In this sense, the optimization strategy subject to the decision function and JDP determines energy consumption of sensor nodes in a cluster as far as DSSA. Hence, the proposed scheme presents superior performance in energy consumption for target tracking.

Figure 5 distinctly presents the residual energy difference between GSSA and DSSA. Due to the introduction of the scheduling strategy and the joint detection probability, sensor nodes are selected with an optimal solution to rid of sensor nodes which have been scheduled before. While reused sensor nodes are usually selected by GSSA, therefore, the residual energy difference of DSSA is no more than 0.0025 J, and the curve is smoother than GSSA whose residual energy difference is up to 0.029 J.

As shown in Fig. 6, the accumulated energy consumption of GSSA is 0.24 J, while the one of DSSA is 0.14 J in the monitoring process. Obviously, the total energy consumption of DSSA decreases by 41.67% compared with GSSA.

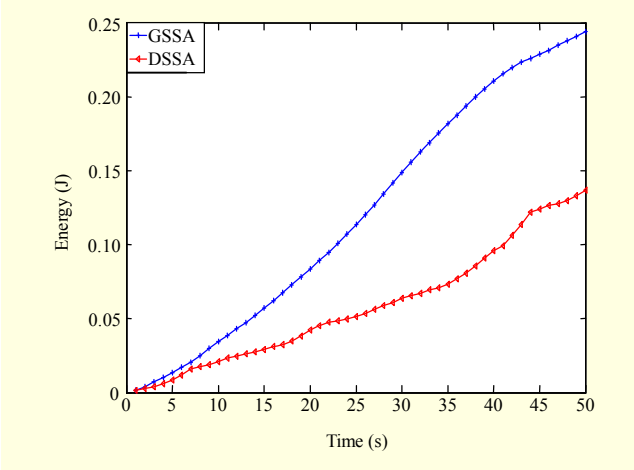

Fig. 6. Accumulated energy consumption of DSSA and GSSA.

VI. Conclusion

This paper proposed a motion monitoring algorithm based on energy balance in local monitoring region of WSNs. An improved particle filter algorithm for degeneracy is applied to localize the target. Due to the redundant information collected from sensor nodes in the cluster, a sensor selection method is essential. Then, the problem of sensor selection is exchanged into energy optimization subject to the decision function and the joint detection probability. Sensor nodes with higher decision value are selected under the condition of the joint detection probability, and superior performances (that is, tracking accuracy, residual energy of a sensor node, accumulated energy consumption, and lifetime of WSNs) for target tracking are demonstrated. As a result, the energy consumption saved is 41.67%.

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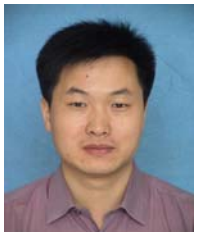

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