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Multi-objective optimization sensor node scheduling for target tracking in wireless sensor network①

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Abstract

Target tracking in wireless sensor network usually schedules a subset of sensor nodes to constitute a tasking cluster to collaboratively track a target. For the goals of saving energy consumption, prolonging network lifetime and improving tracking accuracy, sensor node scheduling for target tracking is indeed a multi-objective optimization problem. In this paper, a multi-objective optimization sensor node scheduling algorithm is proposed. It employs the unscented Kalman filtering algorithm for target state estimation and establishes tracking accuracy index, predicts the energy consumption of candidate sensor nodes, analyzes the relationship between network lifetime and remaining energy balance so as to construct energy efficiency index. Simulation results show that, compared with the existing sensor node scheduling, our proposed algorithm can achieve superior tracking accuracy and energy efficiency.

Key words: wireless sensor network (WSN), target tracking, sensor scheduling, multi-objective optimization

0 Introduction

Wireless sensor network (WSN) is a multi-hop network formed by a large number of miniature, inexpensive, and low-power sensor nodes which are deployed in or around the monitoring area via wireless communication[1]. WSN has developed rapidly in recent years and been applied gradually in military and civilian fields[2]. Target tracking, as a basic and typical application of WSN, has always received extensive attention.

Due to limited power, computation and communication, target tracking in WSN must rely on sensor node management to achieve superior performance in terms of energy efficiency, network lifetime, tracking accuracy, etc. Hintz first applied an information theory to sensor management in Ref. [3]. Subsequently information utility[4], information-driven querying[5], entropy-based heuristic approach[6] etc. are successively introduced into the sensor node management in WSN.

It is observed that a small number of sensor nodes are sufficient to achieve desired tracking accuracy. Ref. [7] studies how to choose a certain amount of nodes so as to minimize the error in estimating the position of a target. It focuses on improving the tracking performance but neglects energy consumption. An energy-efficient multi-sensor scheduling scheme based on calculated target detection probabilities is developed in Ref. [8]. The scheme doesn't deal with network lifework and only satisfies a threshold of tracking accuracy.

In order to maximize the network lifetime, the remaining energy after tracking at each time step should be balanced so that no sensor would die of premature energy depletion. Therefore, the network lifetime can be prolonged from the perspective of remaining energy balance. Ref. [9] investigates the maximization of the coverage time for a clustered WSN by optimal balancing of power consumption among cluster heads. Ref. [10] builds a cluster of tasking nodes according to the pre-specified tracking accuracy and selects the node with the greatest remaining energy as the cluster head aiming at energy balance within the cluster. However, not only the node inside cluster but also the ones waken but not scheduled and the cluster head at previous time step should be also involved.

To overcome the limitations of existing work, the

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paper develops a multi-objective optimization sensor node scheduling algorithm aiming at optimal tradeoff among energy consumption, network lifetime and tracking accuracy. With this algorithm, cluster head and members are determined according to the multi-objective optimization function proposed in this paper.

1 Sensor node scheduling for target tracking

It is assumed that every sensor node is equipped with only one sensor and keeps the location information of its neighboring nodes. They are normally in sleeping mode and will be woken once triggered.

The scenario of target tracking in WSN is shown in Fig. 1. When a target moves randomly in the monitoring area, at each time step, a subset of sensor nodes from the set of woken nodes are scheduled to constitute a tasking cluster and sense the target collaboratively. A tasking cluster consists of a cluster head (CH) and several cluster members (CMs). Under this configuration, each CM senses data of the target and transmits it to the CH for further processing. The CH is responsible for estimating the target position and error based on the sensing data, waking all the nodes in the sensing range for the predicted target, selecting previously the CH and CMs at next time step, and then transmitting the prediction state and error to the next CH.

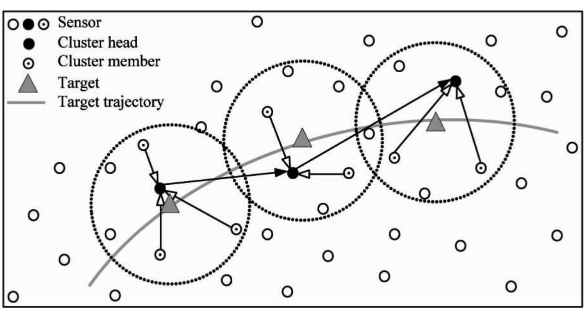

Fig. 1 Target tracking scenario

2 UKF algorithm and tracking accuracy

In this paper, a distributed single-target tracking problem is considered and the UKF algorithm is used to estimate target state and tracking error because of its superior performance on nonlinear estimation.

The discrete target motion model in this paper is assumed as

$$X_{k+1} = F_k X_k + G_k W_k \tag{1}$$

where X_k is the state vector of the target at the k^{th} time step, $X_k = [x_{c,k}, x_{v,k}, y_{c,k}, y_{v,k}]^{\mathrm{T}}$, where $x_{c,k}$ and $y_{c,k}$ are x- and y-coordinates of the target, $x_{v,k}$ and $y_{v,k}$ are the velocities of the target along x- and y-directions at the k^{th} time step, W_k is the white Gaussian process noise with covariance matrix $\boldsymbol{Q}_k$ and $\boldsymbol{F}_k$ and $\boldsymbol{G}_k$ are the transition matrices of target state and process noise respectively, beside

$$\boldsymbol{F}_{k-1} = \begin{bmatrix} 1 & t & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & t \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad \boldsymbol{G}_k = \begin{bmatrix} t^2/2 & 0 \\ t & 0 \\ 0 & t^2/2 \\ 0 & t \end{bmatrix}$$

where t is the sampling interval between two successive time steps.

The measurement of tasking node s_i at k^{th} time step is formulated as following:

$$z_k^i = h^i(X_k) + v_k^i \tag{2}$$

where $h^i(\cdot)$ is the measurement function of s_i with $h^i(X_k) = \sqrt{(x_k^i - x_{c,k})^2 + (y_k^i - y_{c,k})^2}$, (x_k^i, y_k^i) is the coordinate of s_i at k^{th} time step; v^i is the zero-mean Gaussian measurement noise with variance σ_i^2, which are decided by the characteristics of the sensor node and the environment, and independent of W_k. Then measurement model of the network is given by

$$Z_k = H(X_k) + V_k = \begin{bmatrix} h^1(X_k) \\ h^2(X_k) \\ \vdots \\ h^{L_k}(X_k) \end{bmatrix} + \begin{bmatrix} v_k^1 \\ v_k^2 \\ \vdots \\ v_k^{L_k} \end{bmatrix} \tag{3}$$

where $Z_k = [z_k^1, z_k^2, \cdots, z_k^{L_k}]^{\mathrm{T}}$ is the measurement vector consisting of the measurements of L_k tasking nodes. $H(\cdot)$ and V denote respectively the vector forms of $\{h^i(\cdot)\}_{i=1}^{L_k}$ and $\{v^i\}_{i=1}^{L_k}$. The covariance matrix R_k of measurement noise V_k is represented as

$$R_k = \operatorname{diag}(\sigma_1^2, \sigma_2^2, \cdots, \sigma_{L_k}^2) \tag{4}$$

Based on the motion model and measurement model, UKF algorithm is depicted as follows:

1) State prediction

$$\hat{X}_{k+1|k} = F_k \hat{X}_{k|k} \tag{5}$$

$$P_{xx,k+1|k} = F_k P_{xx,k|k} F_k^T + G_k Q_k G_k^T \tag{6}$$

2) Sigma points selection

$$X_{0,k+1|k} = \hat{X}_{k+1|k}, \quad l = 0 \tag{7}$$

$$X_{l,k+1|k} = \hat{X}_{k+1|k} + \alpha(\sqrt{nP_{xx,k+1|k}})_l, \quad l = 1, 2, \cdots, n \tag{8}$$

$$X_{l,k+1|k} = \hat{X}_{k+1|k} - \alpha(\sqrt{nP_{xx,k+1|k}})_l, \quad l = n+1, \cdots, 2n \tag{9}$$

where α is an adjusting parameter, and $(\sqrt{n\hat{P}_{xx,k+1|k}})_l$ denotes the l^{th} column of the matrix square root.

3) Measurement prediction

$$\hat{Z}_{k+1|k} = \sum_{l=0}^{2n} \eta_l Z_{l,k+1|k} = \sum_{l=0}^{2n} \eta_l H(X_{l,k+1|k}) \tag{10}$$

$$P_{zz,k+1|k} = \sum_{l=0}^{2n} \eta_l (Z_{l,k+1|k} - \hat{Z}_{k+1|k})(Z_{l,k+1|k} - \hat{Z}_{k+1|k})^{\mathrm{T}} + R_{k+1} \quad (11)$$

$$P_{xz,k+1|k} = \sum_{l=0}^{2n} \eta_l (X_{l,k+1|k} - \hat{X}_{k+1|k})(Z_{l,k+1|k} - \hat{Z}_{k+1|k})^{\mathrm{T}} \quad (12)$$

where $\eta_l = 1 - \frac{1}{\alpha^2}$, if $l = 0$; $\eta_l = \frac{1}{2n\alpha^2}$, if $l = 1, 2, \cdots, 2n$.

4) State update

After the real measurement Z_{k+1} for the target is obtained, the following update could be implemented:

$$\hat{X}_{k+1|k+1} = \hat{X}_{k+1|k} + K_{k+1}(Z_{k+1} - \hat{Z}_{k+1|k}) \quad (13)$$

$$P_{xx,k+1|k+1} = P_{xx,k+1|k} - K_{k+1} P_{xz,k+1|k} \quad (14)$$

$$K_{k+1} = P_{xz,k+1|k}(P_{zz,k+1|k})^{-1} \quad (15)$$

In this paper the tracking accuracy index is established with the trace of state covariance matrix $P_{xx,k+1|k+1}$:

$$\Phi_1 = \mathrm{trace}(P_{xx,\ k+1|k+1}) \quad (16)$$

where function trace(·) is to get the trace of a matrix.

3 Multi-objective optimization sensor node scheduling scheme

The lifespan in this paper is defined as the duration from the beginning of tracking process to the appearance of a first node which doesn't keep sufficient energy to perform a task.

Network lifetime relies heavily on the lifetime of each node that constitutes the network[11]. And the lifetime of a sensor node mainly depends on two factors: how much energy it consumes over time, i. e. energy consumption quantity; and how much energy is available for future use, i. e. remaining energy. In this paper, two factors are depicted synthetically using a terminology of energy efficiency. If a target frequently maneuvers in a certain region of interest, it might cause a fact that the energy of some sensor nodes in the network is easier to deplete, which results in network disconnection, energy hole, information loss, and ultimately premature ending of the network lifespan[12]. However, under the same quantity of energy consumption, it would prolong the network lifetime observably to keep the remaining energy of each sensor node balance.

It is assumed that energy consumption by s_i for sensing data of b bits is $E_s(s_i) = e_s b$ and that for transmitting b bits to s_j is $E_t(s_i, s_j) = [e_t + e_d \mathrm{Dis}^v(s_i, s_j)]b$, where e_t and e_d are determined by the specifications of transmitter s_i, Dis(· , ·) is the Euclidean distance function and v depends on the channel characteristic. Energy for receiving data of b bits by s_j is $E_r(s_j) = e_r b$[10].

In order to build the next tasking cluster, it is needed to predict the energy consumption and remaining energy of each candidate node as well as the error covariance in UKF. The specific operations are described as follows:

1) Based on the state prediction estimation $\hat{X}_{k+1|k}$, all the nodes in the sensing range for predicted target position constitute a candidate node set

$$G_{k+1} = \{ g_{k+1}^i \mid Dis(g_{k+1}^i, \hat{X}_{k+1|k}) \leqslant r \}_{i=1}^{N_{k+1}} \quad (17)$$

where r is the sensing radius of a sensor node; and N_{k+1} is the number of candidate nodes.

2) Sensor node scheduling is practically to search an optimal combination $C'_{k+1} = \{ c'^{l}_{k+1} \}_{l=1}^{L_{k+1}}$, $c'^{l}_{k+1} \in G_{k+1}$ in set G_{k+1}. Supposing that CH'_{k+1} is the cluster head in candidate cluster C'_{k+1}, the set of cluster members can be represented as:

$$CM'_{k+1} = \{ C'_{k+1} - CH'_{k+1} \} = \{ cm'^{j}_{k+1} \}_{j=1}^{L_{k+1}-1} \quad (18)$$

3) Energy cost by current cluster head CH_k is for transmitting predicted target state and error covariance to the candidate cluster head at the next time step.

$$E_{CH_k} = [e_t + e_d \mathrm{Dis}^v(CH_k,\ CH'_{k+1})] b_1 \quad (19)$$

where b_1 is the bit number of the data transmitted from CH_k.

4) Every cluster member needs to sense data of b_2 bits about the target and transmit it to its cluster head. So energy consumption by each candidate cluster member is predicated as

$$E_{cm'^{j}_{k+1}} = e_s b_2 + [e_t + e_d \mathrm{Dis}^v(cm'^{j}_{k+1},\ CH'_{k+1})] b_2 \quad (20)$$

5) Energy consumption by candidate cluster head CH'_{k+1} includes: receiving the predicted target state and error covariance sent from current cluster head CH_k; sensing the data about the target; and receiving the sensing data from all candidate cluster members.

$$E_{CH'_{k+1}} = e_r b_1 + e_s b_2 + \sum_{j=1}^{L_{k+1}-1} e_r b_2 \quad (21)$$

6) Predict total energy consumption in tasking region:

$$E_{k+1} = E_{CH_k} + \sum_{j=1}^{L_{k+1}-1} E_{cm'^{j}_{k+1}} + E_{CH'_{k+1}} \quad (22)$$

7) Predict the remaining energy of different tasking node:

$$R_{CH_k,k+1} = R_{CH_k,k} - E_{CH_k} \quad (23)$$

$$R_{cm'^{j}_{k+1},k+1} = R_{cm'^{j}_{k+1},k} - E_{cm'^{j}_{k+1}}, \quad j = 1, 2, \cdots, L_{k+1} - 1 \quad (24)$$

$$R_{CH'_{k+1},k+1} = R_{CH'_{k+1},k} - E_{CH'_{k+1}} \quad (25)$$

8) Compute the standard deviation of remaining energy of all tasking nodes:

$$\sigma_{k+1} = \mathrm{std}(\{R_{CH_k,k+1}, \bigcup_{l=1}^{L_{k+1}} R_{c'^{l}_{k+1},k+1}\}) \tag{26}$$

It is clear that the smaller σ_{k+1} is, the better the energy balance level is.

9) The energy efficiency index is constructed by weighing energy consumption quantity and remaining energy balance degree.

$$\Phi_2 = \varepsilon_1 E_{k+1} + (1 - \varepsilon_1)\sigma_{k+1} \tag{27}$$

where $\varepsilon_1 \in [0,1]$ is a weight parameter used to tradeoff energy consumption quantity and energy balance degree.

The design objectives of sensor node scheduling scheme are low energy consumption, balanced remaining energy and high tracking accuracy, which is indeed a multi-objective optimization problem and could be formulated as follows:

$$\begin{cases} \min \Phi_1 \\ \min \Phi_2 \\ \text{s. t. } R_{CH_k,k+1}, R_{c'^{l}_{k+1},k+1} \geqslant \theta \end{cases} \tag{28}$$

To ensure current cluster head and all candidate nodes have enough energy to complete next tasks, a constraint is made that their remaining energy must be larger than or equal to θ, whose value is computed according to the required energy for performing a task.

By transforming the above multi-objective optimization problem to a single-objective optimization problem, a multi-objective optimization function for cluster node selection is formulated as following:

$$\Phi = \varepsilon_2 \Phi_1 + (1 - \varepsilon_2)\gamma \Phi_2 \tag{29}$$

where $\varepsilon_2 \in [0,1]$ is a weight parameter, and γ is a matching factor that makes the value of energy efficiency index have the same order of magnitude with tracking accuracy index. The candidate cluster enabling Φ minimal is determined to be the real tasking cluster, and the candidate cluster head and members in it are determined to be the real tasking cluster head and members.

$$C_{k+1} = \arg_{C'_{k+1}} \min \Phi, C'_{k+1} \subset G_{k+1} \tag{30}$$

$$CH_{k+1} = \{CH'_{k+1} \mid CH'_{k+1} \in C_{k+1}\} \tag{31}$$

$$CM_{k+1} = \{cm'^{j}_{k+1} \mid cm'^{j}_{k+1} \in C_{k+1}\}_{j=1}^{L_{k+1}-1} \tag{32}$$

4 Simulation and analysis

In order to seek the optimal combination of tasking cluster, Genetic algorithm with elitism reservation strategy[13] is employed to solve this optimization problem with the reciprocal of Φ in Eq. (29) as the fitness function. If $G_{k+1} = \varnothing$, where $\varnothing$ denotes an empty set, then $C_{k+1} = \{CH_k\}$, and the target position and error covariance are determined as the prediction estimation of current cluster head CH_k. If $G_{k+1} \neq \varnothing$, Genetic operations begin. The flow chart of multi-objective optimization sensor node scheduling scheme based on Genetic algorithm is schematized as Fig. 2:

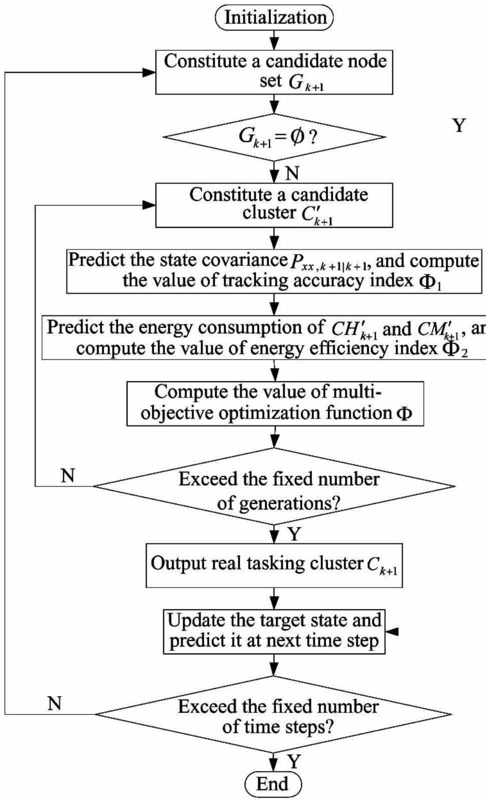

Fig. 2 Flow chart of multi-objective optimization sensor node scheduling scheme

In Genetic algorithm, the evolutionary population with μN_{k+1} chromosomes is encoded into a $\mu N_{k+1} \times N_{k+1}$ binary matrix, where μ is an adjusting factor which adjusts the size of the population to improve the convergence rate of Genetic algorithm. Each chromosome represents a candidate cluster C'_{k+1} and each gene $ge^{i}_{k+1}, i = 1, 2, \cdots, N_{k+1}$ in it responds to a candidate node whose value indicates whether it belongs to C'_{k+1}.

$$ge^{i}_{k+1} = \begin{cases} 0, \text{ responding node doesn't belong to } C'_{k+1} \\ 1, \text{ responding node belongs to } C'_{k+1} \end{cases}$$

In order to prove the superiority of our proposed sensor scheduling scheme based on energy efficiency and tracking accuracy (SEETA), a comparison with following three different sensor scheduling schemes is made.

a. SSECQ (Sensor scheduling scheme based on energy consumption quantity): to minimize the energy consumption quantity, i.e. the case of $\varepsilon_1 = 1$ in Eq. (29);

b. SSMNN (Sensor scheduling scheme based on maximal number of cluster nodes): to select all the sensor nodes which satisfy the constraints in Eq. (28) in the sensing range for the target as cluster nodes;

c. SSEKF (Sensor scheduling scheme based on Extended Kalman Filtering): to employ EKF algorithm to estimate target state and error covariance, rather than UKF algorithm used in the above three schemes.

4.1 Simulation setup

The proposed scheme is tested in a single-target tracking scenario. The monitoring area is a 100m × 100m rectangular region with 60 sensor nodes disseminated randomly inside and forming a sensor network. Assume that all the sensor nodes have the same sensing radius r_s = 20 and the same measurement noise variance σ_i^2 = 2. To construct an energy imbalanced network, the initial energy of all nodes is set to 0.5J except that of the 7th and 44th nodes to 0.1J. The whole simulation lasts for 40 time steps. The other parameters and their values are listed in Table 1.

Table 1 Parameters in the simulation

Parameter	Value	Parameter	Value
Num	60	t	0.2s
e_t	45×10^{-6} J/bit	e_d	10×10^{-9} J/bit · m^2
e_s	50×10^{-6} J/bit	e_r	135×10^{-6} J/bit
b_1	264 bit	b_2	16 bit
ε_1	0.5	ε_2	0.3
υ	2	θ	0.074 J
γ	10	μ	5

In UKF, the initial state and covariance matrix are assumed respectively to be $X_0 = \hat{X}_{0|0} = [0, 5, 70, 25]^{\mathrm{T}}$ and $P_{xx,0|0} = 0.01I_4$, where I_4 is a 4 × 4 identity matrix. The covariance of process noise W_k is $Q_k = I_2$.

In Genetic operations, the crossover probability and mutation probability are set to 0.8 and $0.7/N_{k+1}$ respectively. All the simulation figures are average results of 50 experiments except Fig. 3 and Fig. 5.

4.2 Results and Analysis

Fig. 3 shows the real and estimated trajectories of the target with aforementioned four sensor scheduling schemes. The number labeled on each sensor node is its identification number. The nodes that are selected as cluster heads are linked to the target position at that time step. From Fig. 3 we find the estimated trajectories with SEETA, SSECQ, SSMNN schemes are very close to the real trajectory, but the estimated trajectory with SSEKF scheme has deviated obviously in latter half of the path, which demonstrates that when there is significant change in target motion, the estimation performance of EKF declines obviously in contrast with UKF. However, using the same state estimation algorithm of UKF, SSMNN scheme which schedules all energy-sufficient sensor nodes and SEETA scheme which selects a part of optimal nodes almost take on equal tracking accuracy.

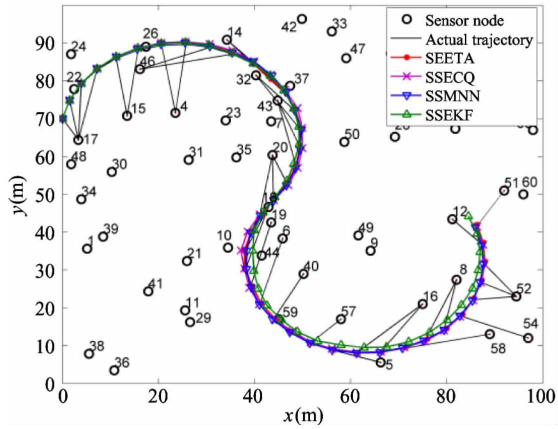

Fig. 3 Target trajectories and cluster heads

The distance between real and estimated positions of the target is taken as the tracking error. From Fig. 4, for the four sensor scheduling schemes, the tracking error of SSEKF is larger than others, which further illustrates that the estimation performance of UKF is superior to that of EKF when the target moves with high randomness. Among SSECQ, SEETA and SSMNN, the tracking error of SSECQ is the largest because in order to minimize energy consumption quantity it schedules fewer nodes in the selection of cluster nodes.

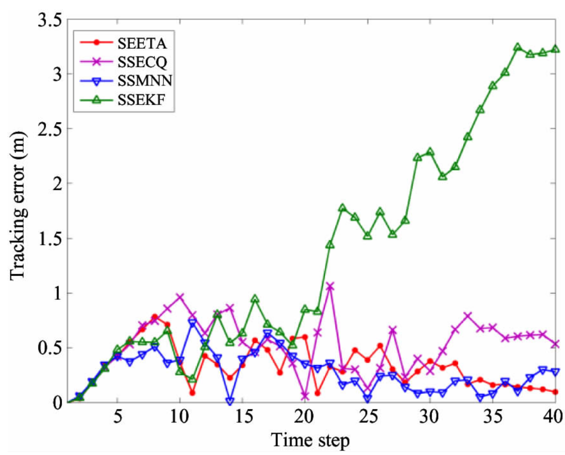

Fig. 4 Tracking error

From the above comparison it is known that in terms of tracking accuracy, SSEKF scheme works worst among the four schemes while SSMNN and SEETA schemes do best. However, the cluster length (the number of tasking nodes in a cluster, i. e. L_k) with SSMNN scheme is much longer than that with other schemes as shown as Fig. 5. That's because with the SSMNN scheme all woken and energy-sufficient sensor nodes are scheduled to work.

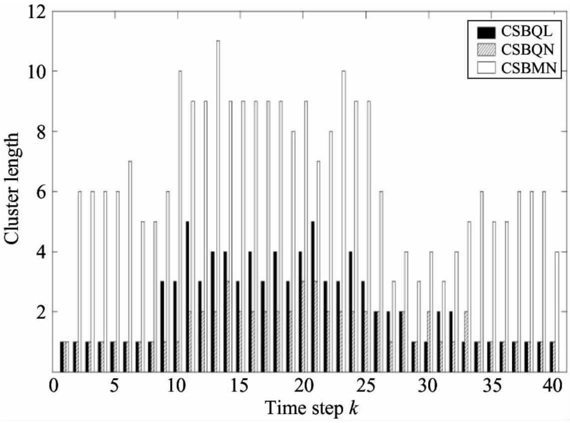

Fig. 5 Cluster length

In terms of energy efficiency, some parameters about network energy and lifetime are listed in Table 2. For the SSMNN scheme, without the effect of energy efficiency index, the energy consumption is much more than other three schemes. From the perspective of energy balance, which SSMNN and SSECQ haven't considered, the standard deviations of their remaining energy are both larger than others. Final remaining energy of every node is also shown in Fig. 6. With the SSMNN scheme, the remaining energy of the nodes located in the region of target frequent motion, such as 7^{th}, 16^{th}, 20^{th}, 32^{nd}, 44^{th}, 46^{th}, 57^{th} node etc., is less than that of other nodes. With the SSECQ scheme, the nodes close to the target, such as 7^{th}, 14^{th}, 16^{th}, 35^{th}, 44^{th} node, have obviously less remaining energy than that with SEETA and SSEKF schemes. On the contrary, in order to optimize the distribution of remaining energy, the SEETA and SSEKF schemes may discard the nodes that close to target but without sufficient remaining energy and select those a bit farther but energy-sufficient nodes. For example, the 7^{th} and 44^{th} nodes whose initial energy (0.1J) is lower than others are rarely scheduled though they are very close to the target. So SEETA and SSEKF schemes prevent a fraction of nodes from coming to a premature death effectively, and their network lifespan gets prolonged.

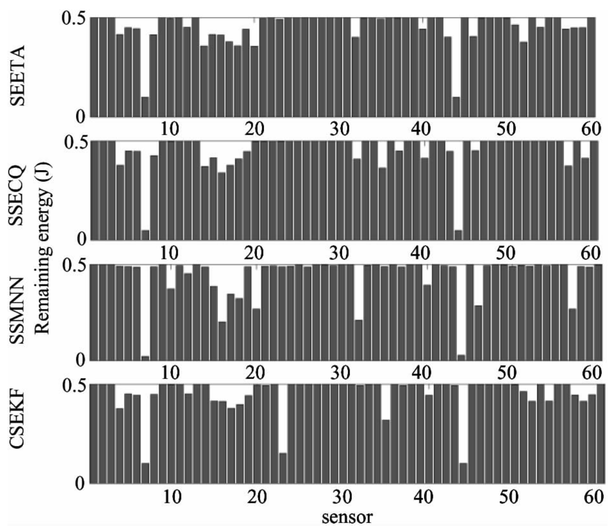

Fig. 6 Final remaining energy

Table 2 Parameters about network energy and lifetime after tracking process

Scheduling scheme	Energy consumption (J)	Remaining energy (J)	Standard deviation	Network lifespan (Time step)
SEETA	1.8648	27.3352	0.0800	>40
SSECQ	1.7361	27.4639	0.0888	19
SSMNN	2.4005	26.7995	0.1095	16
SSEKF	1.8158	27.3842	0.0886	>40

5 Conclusions

A multi-objective optimization sensor node scheduling algorithm is designed aiming at improving energy efficiency and tracking accuracy. The trace of error covariance in UKF algorithm is determined as tracking accuracy index. An energy efficiency index considering comprehensively energy consumption quantity and remaining energy balance is established.

Our next work will extend the application of multi-objective optimization sensor node scheduling algorithm to multi-target tracking by selecting disjoint tasking clusters. And state estimation algorithms with higher accuracy will be used.

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