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LEACH-MTC: A Network Energy Optimization Algorithm Constraint as Moving Target Prediction

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Abstract: When some nodes cooperatively track moving targets in a wireless sensor network, some things including network working node selection and network energy consumption are influenced. Thus, this paper proposes an improved algorithm LEACH-MTC (LEACH with Moving Target Constraint) based on low energy adaptive clustering hierarchy protocol (LEACH). First, based on the two-step linearization of the nonlinear dynamic model, the state of the nonlinear moving target is predicted by the extended Kalman filter (EKF). Second, combining the state prediction of the moving target and the performance of collaborative monitoring, this paper constructs an ellipse monitoring area of some working nodes to consist with the direction of the target movement. Subsequently, the node sleep strategy corresponding to the state prediction of moving target is designed. Finally, the cluster head selection strategy is proposed based on energy balance utilizing the state prediction of the moving target. Simulation results show that the proposed LEACH-MTC algorithm can not only ensure the real-time consistency between the changing direction of area and the direction of target movement, but also increase the number of working nodes' survival and reduce the network energy consumption.

Keywords: wireless sensor network; state prediction; node sleep strategy; cluster head selection; energy optimization

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1. Introduction

Wireless sensor networks (WSNs) are intelligent communication networks composed of a large number of sensors in a multi-hop and self-organizing manner. WSNs have many advantages including flexible deployment, low price, low power consumption, and high accuracy of information acquisition. Thus, they are widely used in military fields [1–3], environmental monitoring [4–6], industrial control [7–9], and so on. However, as network nodes are usually deployed in complex, dangerous places, it is difficult to maintain them frequently, and the energy carried by the node is limited. Once the energy of nodes is exhausted, they are die, and as a result, they cannot be guaranteed to detect and track targets, which leads to the subsequent decline of the monitoring performance of the network [10–12]. Therefore, how to effectively reduce nodes' energy consumption and prolong the lifetime of WSNs is of great significance.

1.1. Related Work

Sharma et al. proposed the LEACH-DBCH (LEACH-Distance-Based Cluster Head) algorithm to relieve the high energy consumption of the classical LEACH algorithm [13]. The LEACH-DBCH algorithm designs a new threshold function in cluster head selection stage. The new function comprehensively involves some factors related to cluster head selection including remain energy of node, distance between node and base station, and distance between node and cluster head. Simulations show that, compared with the classical LEACH algorithm, the LEACH-DBCH algorithm can effectively prolong lifetime of WSNs. According to requirement of target monitoring quality, Guo et al. propose the LEACH-RARE (LEACH-Reduced Area REporting) algorithm to save energy of WSNs by restricting the number of nodes related to target monitor and the amount of data related to cluster head [14]. Based on the distance from the cluster member nodes to the cluster head, Nguyen et al. propose a cluster head selection algorithm to prolong network lifetime by optimizing the number of cluster heads [15].

Lu proposed an efficient adaptive node selection algorithm named ANSTT (Adaptive Node Scheduling for Target Tracking) [16], which combined the network node's perception of moving targets and the relative residual energy of network nodes to develop a working node selection mechanism. It effectively reduced network energy consumption and extended the network life cycle. Zhang proposed an efficient and energy-efficient adaptive network nodes scheduling algorithm [17]. By prioritizing the decision function, the algorithm used the nodes with higher value as the working nodes to balance the local energy consumption of dynamic clustering. The node with the highest value became the cluster head, and the particle filter algorithm was used to track the target whose motion model is nonlinear. Research shows that Zhang's algorithm solved the problem of unbalanced network energy consumption, which is caused by the uncertainty of target motion modeling and the randomness of cluster head selection. Moreover, Zhang's algorithm can also effectively schedule network nodes and improve the tracking accuracy of moving targets.

Harizan et al. proposed a node scheduling method based on an improved genetic algorithm. The fitness function of the improved genetic algorithm was constructed by some factors including the least number of nodes, the selected node coverage, and the remaining energy [18]. In addition, this algorithm constructs the set of working nodes by selecting some nodes close to the target, thus leading to reduced number of nodes and enhanced network efficiency. Although the above methods can effectively reduce network resources and balance network energy consumption, some factors including network environment, static/dynamic target, and so on, which were not considered to influence working nodes selection, cluster head selection, energy consumption modeling, and so on. When the wireless sensor network nodes cooperatively track the moving target, the target motion state (for example, the motion trajectory, speed, and direction) will affect the selection of the network working nodes and the network energy consumption.

1.2. Contributions

In this paper, an improved algorithm named LEACH-MTC (LEACH with Moving Target Constraint) is proposed. This algorithm constructs a time-varying ellipse area in which the nodes are working nodes, these nodes format work node set and are used to monitor moving target. The proposed network node dormancy strategy considers the distance between the working node and the focuses of ellipse area. The proposed cluster head selection threshold considers the distance factor between the working node and the moving target. As a result, for the actual cooperative tracking environment, the proposed LEACH-MTC is more feasible for the realization of the moving target cooperative tracking system. Overall, the main contributions of this paper can be summarized as follows.

(1) This paper timely constructs an ellipse monitoring area with the direction changing of the moving target, which constitute a work node set to monitor the moving target. Because it uses a two-step linearization method to linearize nonlinear dynamic system, and utilizes extended Kalman filter (EKF) to predict the moving target state, the shape and size of the ellipse area and the number of nodes contained in the area can all be changed in real-time. This can reduce the number of work nodes, thus reducing the network energy consumption caused by redundant nodes.

(2) To reduce the number of working nodes, an improved network node dormancy strategy is proposed to construct working node set under the moving target tracking environment. Besides, according to the network node's own attributes and monitoring

environment factors, some network monitoring accuracy indicators are reconstructed. Thus, the monitoring efficiency of system is improved.

(3) Based on the working node set and the state prediction of moving target, a new cluster head selection threshold is proposed. Because the number of working nodes is considered to vary in real-time, the above cluster head selection strategy can be adaptively used to select the cluster head to transmit the collected data.

(4) The simulations of this paper are carried out based on the MATLAB platform. To better describe the feasibility and effectiveness of LEACH-MTC, we designed a simulation to verify the monitoring accuracy by difference working node selection strategies, the number of node survivor, the network residual energy, and so on. We can conclude that the proposed LEACH-MTC yields better performance than traditional methods.

1.3. Paper Organization

The rest of this paper is organized as follows. In Section 2, the target nonlinear dynamic model and the target state prediction model are described. In Section 3, the new network node dormancy strategy, improved cluster head selection strategy, and network monitoring accuracy criterion are designed; additionally, the LEACH-MTC algorithm based on moving target constraints is proposed. In Section 4, the feasibility and effectiveness of the improved algorithm are simulated and analyzed in terms of saving the number of working nodes and reducing the network energy consumption. The conclusions of this paper are given in the final section.

2. System Model and Conventional Method

In the WSNs, some nodes collaborative observing target may obtain more information. For example, take a typical example of WSNs applied to smart urban planning [19]. We awaken some nodes in WSNs based on the state prediction of target to coordinate to observe the target. In this section, we present the target motion model, target measurement model, energy consumption model of sensor nodes, and prediction mechanism of target state.

2.1. Nonlinear Motion Model of Target

In a two-dimensional monitoring area, target motion model is as follows:

$$\begin{bmatrix} x(k+1) \\ y(k+1) \\ \theta(k+1) \end{bmatrix} = \begin{bmatrix} x(k) \\ y(k) \\ \theta(k) \end{bmatrix} + \begin{bmatrix} \Delta t & 0 & 0 \\ 0 & \Delta t & 0 \\ 0 & 0 & \Delta t \end{bmatrix} \begin{bmatrix} cos\theta(k) & 0 \\ sin\theta(k) & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \mathrm{v}(k) \\ \omega(k) \end{bmatrix} \tag{1}$$

where $x(k)$ and $y(k)$ are the coordinates of the target in x and y direction at time k, respectively, and $\theta(k)$ is the angle between the target and the horizontal direction at time k. Δt is the sampling time. $v(k)$ is the speed of moving target, and $\omega(k)$ is the angular velocity of moving target at time k. Assuming that the target motion is disturbed by external environmental disturbance noise, above model can be simplified as follows:

$$X(k+1) = f(X(k)) + W(k) \tag{2}$$

where $X(k) = [x(k)y(k)\theta(k)]^T$ is the state of moving target at time k. $f(\cdot)$ is the nonlinear state transition function, which is consist in $x(k)$, $y(k)$, $\theta(k)$. $W(k)$ is the target state Gaussian noise, and it satisfies $W(k) \sim N(0, Q(k))$. $Q(k)$ is the noise covariance matrix.

2.2. Measurement Model of Target

Assume that in the monitoring area, the deployment coordinate of the network node s_i is (x_i, y_i), and the effective communication coverage area is a circular area with the radius of the center of the network node itself as r_i. When the moving target appears within the coverage, $h_i(X(k)) = \sqrt{(x(k) - x_i)^2 + (y(k) - y_i)^2}$ can be used to express the distance between the moving target t with the position $(x(k), y(k))$ and the deployed node s_i with the position (x_i, y_i). Assuming that the sensor measurement of the target is disturbed by external environmental disturbance noise, the measurement of the network node s_i at time k can be modeled as

$$Z_i(k) = h_i(X(k)) + U_i(k) \tag{3}$$

where $X(k)$ is the state of moving target at time k. $U_i(k)$ is the measurement noise of the network node s_i at time k, which is a Gaussian white noise with a mean of zero and a variance of $R_i(k)$.

2.3. Two-Step Linearization of Target State Prediction

The motion model of target and the measurement model of target are represented as Equations (2) and (3), and they constitute a nonlinear detection system. They are nonlinear functions, thus the standard Kalman filter (KF) is no longer applicable, and the nonlinear filtering problem needs to be approximated as a linear filtering problem, so that a sub-optimal solution is obtained [20,21]. Therefore, the Extended Kalman Filter (EKF) can be considered to predict or estimate the target state [22].

In the above nonlinear system, as the nonlinear system needs to be linearized, that is, the Taylor series expansion is used to approximate the nonlinearity, which is transformed into the process of calculating the Jacobian matrix of the nonlinear functions $f(\cdot)$ and $h(\cdot)$, that is, the state transition matrix $F(k)$ and the observation matrix $H(k)$ are obtained. Therefore, the linearized system model can be obtained after linearization:

$$\begin{cases} X(k+1) = F(k)X(k) + W(k) \\ Z(k) = H(k)X(k) + U(k) \end{cases} \tag{4}$$

where

$$F(k) = \left. \begin{bmatrix} 1 & 0 & -\theta(k) \\ 0 & 1 & \frac{3}{2} - \theta(k) \\ 0 & 0 & 1 \end{bmatrix} \right|_{\theta(k)=\hat{\theta}(k|k-1)} \tag{5}$$

$$H(k) = \left. \begin{bmatrix} x(k) - x_1 & y(k) - y_1 & 0 \\ x(k) - x_2 & y(k) - y_2 & 0 \\ \vdots & \vdots & \vdots \\ x(k) - x_n & y(k) - y_3 & 0 \end{bmatrix} \right|_{X(k)=\hat{X}(k|k-1)} \tag{6}$$

Note that Equation (6) is obtained using two-step linearization. x_i and y_i are defined as the X-axis and Y-axis of node s_i, respectively.

Based on the nonlinear system models (2) and (4), and the linearized system model (5), the state of moving target can be estimated or predicted by the Kalman filter. The main steps are as follows:

$$\hat{X}(k+1|k) = f\big(\hat{X}(k|k)\big) \tag{7}$$

$$P(k+1|k) = F(k)P(k|k)F^T(k) + Q(k) \tag{8}$$

$$K(k+1) = P(k+1|k)H(k) \cdot \Big[H(k)P(k+1|k)H^T(k) + R(k)\Big]^{-1} \tag{9}$$

$$\hat{X}(k+1|k+1) = \hat{X}(k+1|k) + K(k+1)\big[Z(k+1) - h\big(\hat{X}(k+1|k)\big)\big] \tag{10}$$

$$P(k+1|k+1) = (I - K(k+1)H(k))P(k+1|k) \tag{11}$$

2.4. Energy Consumption Model of Sensor Nodes

We use the first-order model described in [23] to model energy consumption of WSNs. Considering data in each data packet, this paper describes the energy consumption of the node related to receiving and transmitting one data packet as follows.

$$E_{TX}(l,d) = E_{TX-elec}(l) + E_{TX-amp}(l,d) = \begin{cases} lE_{elec} + l\varepsilon_{fs}d^2 & d \leqslant d_0 \\ lE_{elec} + l\varepsilon_{fs}d^4 & otherwise \end{cases} \tag{12}$$

$$E_{RX}(l) = E_{RX-elec}(l) = lE_{elec} \tag{13}$$

where $E_{TX-elec}$, $E_{RX-elec}$, and E_{TX-amp} are energy consumption of transmitter, energy consumption receiver, and energy consumption amplifier, respectively. ε_{fs} and ε_{mp} are coefficient amplify of free space and coefficient amplify of multi-path, respectively. E_{elec} is energy consumption of one bit data processing, l is amount of data, d describe the distance between transmitter and receiver, $d_0 = \sqrt{\varepsilon_{fs}/\varepsilon_{mp}}$ is effective communication distance between nodes.

3. Method: LEACH-MTC Based on Moving Target State Prediction

In WSNs, when some network nodes cooperatively track a target, although the network monitoring performance is improved, the addition of a large number of working nodes will cause redundant measurement information of the target, and also cause waste of the node resources. In order to improve the utilization of nodes and reduce the energy consumption of the network, this section proposes an improved algorithm called LEACH-MTC based on the prediction information of moving targets, and its flow chart is shown in Figure 1.

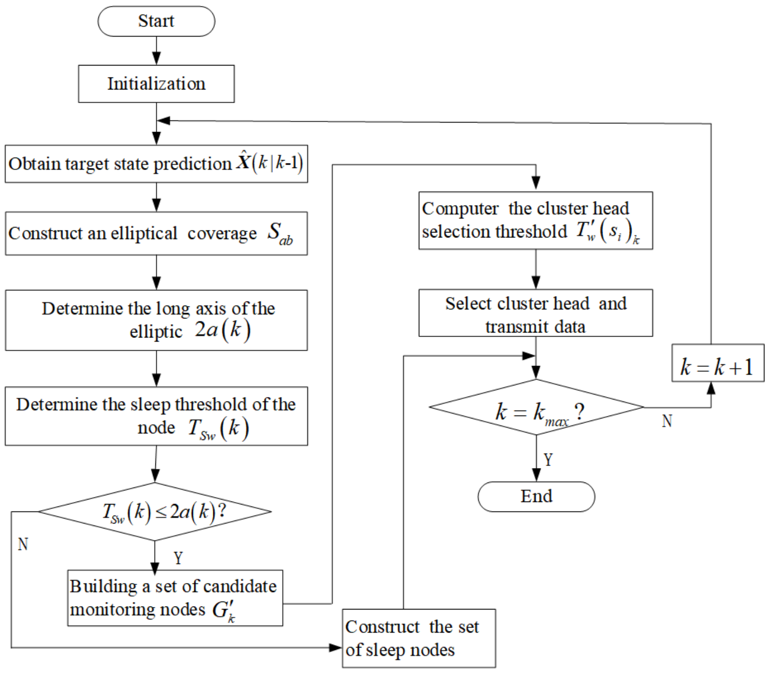

Figure 1. LEACH-MTC algorithm flow chart.

Based on the LEACH protocol, the LEACH-MTC algorithm uses EKF to obtain the state prediction of moving targets in a nonlinear system. Based on the current position state and the position state prediction of the moving target, an elliptical coverage area which is related to the state prediction is designed to determine the working nodes. Besides, the improved node sleep strategy and the improved cluster head selection strategy are designed under the constraints of moving targets, respectively. Subsequently, three improvements—elliptic coverage construction, node sleep strategy, and cluster selection strategy—are introduced under some constraints of moving targets.

3.1. Classical LEACH Algorithm

The LEACH algorithm is the earliest clustering routing algorithm, which is mainly based on the process wheel and node clustering [24,25]. This algorithm regards a work cycle as a round and divides the work process into several rounds; this algorithm periodically executes the work process. Each round contains two instances of processing: the node cluster and the data transfer. In the processing of node clustering, cluster heads of network nodes should be selected first, and a cluster head set should be constructed. Then, cluster heads with hierarchical structured should be formed by each cluster head node and non-cluster head nodes.

Whether some nodes become cluster heads can be judged by the threshold $T(s_i)$, which is as the Equation (14). Assume that the value generated by node s_i is $T_{rand}(s_i)$, if $T_{rand}(s_i) \leq T(s_i)$, s_i is selected as cluster head node; otherwise, s_i is non-cluster head node.

$$T(s_i) = \begin{cases} \frac{p}{1-p[r \bmod (1/p)]} & s_i \in G \\ 0 & others \end{cases} \tag{14}$$

where p is the ratio of the number of expected cluster head nodes selected to the total number of nodes in the monitoring area. r is the current network running time (i.e., the number of running rounds). G is the node set that has not been selected as cluster head in the latest round $1/p$.

In the cluster stage, each cluster head node sends signals to the network in the form of broadcast. According to the received signal strength, each non-cluster head node chooses the cluster head to join. In order to reduce network energy consumption, non-cluster head nodes are usually added to the nearest cluster head. When all the non-cluster head nodes are added to the corresponding cluster head, all the nodes complete the cluster forming.

In the data transmission stage, cluster member nodes send some monitoring data to the cluster head according to the timing schedule. Then, the cluster head fuses the received data and transmits the fusion results to the base station.

3.2. Construction of Elliptical Area Based on State Prediction

Intuitively, reasonably choosing work nodes close to target can effectively reduce redundant information related to observed target, thus enhancing energy efficiency of WSNs. Therefore, we can pre-awaken sleeping nodes nearby the direction of the moving target to perform monitor work. Specifically, to make sure working nodes (i.e., awakened sleeping nodes) are located in direction of the moving target, the coverage area of the awakened sleeping nodes is defined as an ellipse whose major axis coincides with the direction of target moving.

According to the network monitoring performance parameter C_w and the target state prediction, an elliptical coverage area can be constructed. The size of the coverage area can be represented by an elliptical area S_{ab} as follows:

$$S_{ab} = \pi ab = \frac{C_w S_M}{m} \tag{15}$$

where a and b represent the long semi-axis and the short semi-axis of the elliptical coverage area, respectively. C_w represents the monitoring performance of network. S_M represents the monitored area, and represents the total number of nodes deployed in the network. The schematic figure based on the motion trajectory of moving target and the elliptical coverage area of the working node is shown in Figure 2.

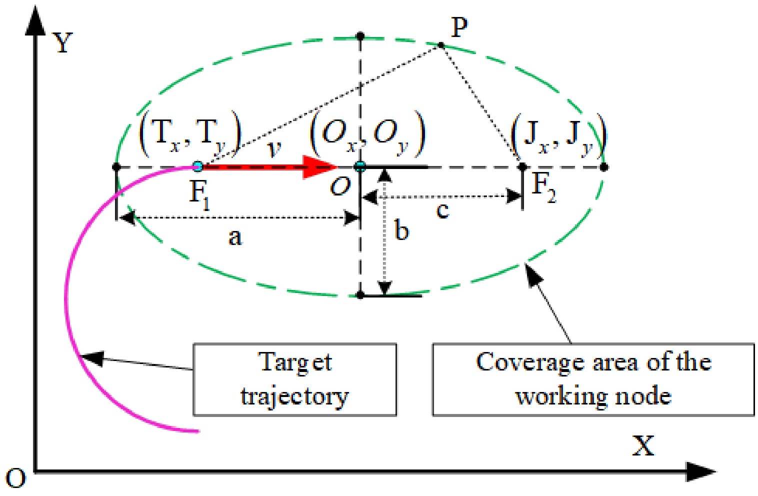

Figure 2. Target motion trajectory and elliptical area.

In Figure 2, the nodes inside the ellipse are in the working state, while the nodes outside the ellipse are in the sleep state. $O(O_x, O_y)$ is the coordinate of the elliptical center. $F_1(T_x, T_y)$ is the back focus of the ellipse, and it represents the current position of the moving target. The long axis of elliptical is in the direction of the target motion, and v represents the current speed of the moving target, and its direction is the tangential direction of the target moving trajectory. $F_2(J_x, J_y)$ is the front focus of the ellipse and it represents the prediction position of the moving target. a is the long semi-axis of the ellipse, b is the short semi-axis of the ellipse, and c is the semi-focal length of the ellipse. If P is any point on the elliptic curve, it satisfies the sum of the distances to the two focal points equal to the long axis, which is Equation (16):

$$|PF_1| + |PF_2| = 2a \tag{16}$$

otherwise, if P is any point inside the ellipse, it has the Equation (17):

$$|PF_1| + |PF_2| < 2a \tag{17}$$

where $|PF_1|$ is the distances between the point P and the focal point F_1, and $|PF_2|$ is the distance between the point P and the focal point F_2.

According to Equations (16) and (17), this paper determines whether the network node in the working state or in the sleep state. The distribution of network nodes as shown in Figure 3.

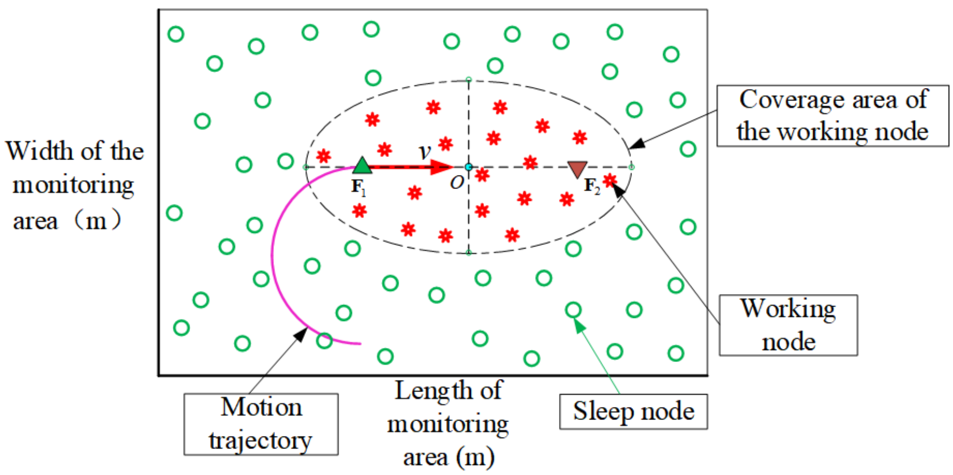

Figure 3. Distribution of working nodes and sleep nodes.

In Figure 3, the elliptical area is the area of the coverage area formed by the working node, where F_1 is the current position of the moving target and F_2 is another focus about the center O of ellipse.

Based on the Figure 2, at time k, we assume that the coordinate of the elliptical center is $O(O_x(k), O_y(k))$, the two focal coordinates of the ellipse are $F_1(T_x(k), T_y(k))$ and $F_2(J_x(k), J_y(k))$, respectively. According to the state prediction of the moving target, the predicted position coordinate can be received as $(T_x(k+\delta_t), T_y(k+\delta_t))$ at time $k+\delta_t$. Thus, the magnitude of speed $v(k)$ as follows:

$$|v(k)| = \frac{\sqrt{(T_x(k+\delta_t) - T_x(k))^2 + (T_y(k+\delta_t) - T_y(k))^2}}{\delta_t} \tag{18}$$

This paper assumes that the shape of the elliptical coverage area formed is related to the target motion velocity, then the semi-focal length of the ellipse $c(k)$ is received by the Equation (19).

$$c(k) = \frac{1}{2}|\mathrm{F_1F_2}| = \lambda|v(k)| \tag{19}$$

where λ is the weight coefficient. According to the relation between the axis and the focal length of the ellipse, the relation is $a(k)^2 = b(k)^2 + c(k)^2$. Combining the elliptical coverage area $S_{ab}(k)$ in the Equation (14), the ellipse long semi-axis $a(k)$ and the short semi-axis $b(k)$ are obtained as follows, respectively:

$$a(k) = \sqrt{2}S_{ab}(k) \Bigg/ \left(\pi\sqrt{\frac{\sqrt{(\lambda|v(k)|)^4\pi^2 + 4S_{ab}(k)}}{\pi} - (\lambda|v(k)|)^2}\right) \tag{20}$$

$$b(k) = \frac{\sqrt{2}}{2}\sqrt{\frac{\sqrt{(\lambda|v(k)|)^4\pi^2 + 4S_{ab}(k)}}{\pi} - (\lambda|v(k)|)^2} \tag{21}$$

Thus, based on the moving target's current position F_1 and the velocity $v(k)$, the position of the front focus $F_2(J_x(k), J_y(k))$ and the center $(O_x(k), O_y(k))$ of the ellipse can be obtained:

$$\begin{bmatrix} O_x(k) \\ O_y(k) \end{bmatrix} = \begin{bmatrix} T_x(k) \\ T_y(k) \end{bmatrix} + \lambda|v(k)|\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}\begin{bmatrix} cos\tilde{\theta}(k) \\ sin\tilde{\theta}(k) \end{bmatrix} \tag{22}$$

$$\begin{bmatrix} J_x(k) \\ J_y(k) \end{bmatrix} = \begin{bmatrix} O_x(k) \\ O_y(k) \end{bmatrix} + \lambda|v(k)|\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}\begin{bmatrix} cos\tilde{\theta}(k) \\ sin\tilde{\theta}(k) \end{bmatrix} \tag{23}$$

where $\tilde{\theta}(k)$ is the predicted of $\theta(k)$, which is the angle between the target and the horizontal direction at time k.

In summary, the shape and size of the elliptical coverage area constructed can be determined by the ellipse area $S_{ab}(k)$, the long semi-axis $a(k)$, the short semi-axis $b(k)$, the focal point F_2, and the ellipse center $O(k)$. According to the coverage area of the ellipse, nodes in the ellipse should be awakened and nodes out of ellipse should be kept sleeping.

3.3. Node Sleep Strategy Under Moving Target Constraint

In ellipse, based on the back focus $F_1(T_x, T_y)$ and the front focus $F_2(J_x, J_y)$, the sleep threshold $T_{Sw}(k)$ of the network node $s_i(x_i, y_i)$ can be defined at time K:

$$T_{Sw}(k) = \sqrt{(x_i - T_x(k))^2 + (y_i - T_y(k))^2} + \sqrt{(x_i - J_x(k))^2 + (y_i - J_x(k))^2} \tag{24}$$

Therefore, a strategy of sleep node is developed which can select working nodes more effectively and cost-effectively, and reduce the number of working nodes and network energy consumption:

(a) If $T_{Sw}(k) \leq 2a(k)$, the node s_i inside the elliptical coverage area, it is in working state and performs the monitoring task, at the same time, this node s_i is added to the working node set G'_k.
(b) If $T_{Sw}(k) > 2a(k)$, the node s_i is not in the elliptical coverage area; it is in a sleep state and does not perform any monitoring task.

3.4. Cluster Head Selection Strategy Based on Equilibrium

In this section, round is defined as a base unit related to data transmission in network. In each round, after the working node set G'_k is formed, cluster head selection is performed for all working nodes. In the cluster head selection stage, in order to reduce the probability that nodes with little residual energy or far from the base station become cluster heads, an improved strategy is designed. This strategy takes into some factors including target movement state, the distance between working node and the target, the residual energy rate of working node, and the distance between working node and the base station. Assuming s_i is a working node, we can obtain its the cluster head selection threshold $T'_w(s_i)_k$ at time k:

$$T'_w(s_i)_k = \begin{cases} \kappa * p_k + \mu * \Delta p_k & s_i \in G' \\ 0 & others \end{cases} \tag{25}$$

$$\Delta p_k = \Delta T(s_i)_k - \frac{1}{n_k}\sum_{i=1}^{n_k} \Delta T(s_i)_k \tag{26}$$

$$\Delta T(s_i)_k = \alpha E_{avg}(s_i)_k + \beta(1 - \omega_{st}(s_i)_k) + \gamma(1 - \omega_{ss}(s_i)_k) \tag{27}$$

where p_k and Δp_k represent the expected probability and the compensation probability at which the node s_i becomes the cluster head, respectively. n_k represents the number of surviving nodes in the working node set G'_k. $E_{avg}(s_i)_k$ represents the residual energy rate of the node s_i. $\omega_{st}(\mathrm{s}_i)_k$ and $\omega_{ss}(s_i)_k$ represent the distance factor of the node s_i to the target, the node s_i to the base station, respectively. $\kappa, \mu, \alpha, \beta$ and γ represent the weighting coefficient of the cluster head selection threshold, respectively.

Therefore, after the cluster head selection threshold is determined using the Equation (25), the cluster can be formed by the LEACH protocol framework. Every cluster with working nodes which is self-organized, and the monitoring data of the nodes are processed and transmitted by the cluster head nodes.

3.5. Network Monitoring Accuracy

It is assumed that the position of the moving target is $T(x_T(k), y_T(k))$ at time k, every working node s_i inside the elliptical area has its own measurement $Z_{s_i}(x_{Ti}(k), y_{Ti}(k))$ for the moving target. As the node measurements are subject to environmental interference during the monitoring process, and as the distance $d_{Ti}(k)$ between the working node and the moving target increases, the interference effect becomes more serious. Therefore, the measurement of working node s_i can be expressed as follows:

$$Z_{s_i}(x_{Ti}(k), y_{Ti}(k)) = T(x_T(k), y_T(k)) + f(\varepsilon, d_{Ti}(k)) + V(k) \tag{28}$$

$$d_{Ti}(k) = \sqrt{(x_i - x_T(k))^2 + (y_i - y_T(k))^2} \tag{29}$$

where the position of the working node s_i is (x_i, y_i) which is fixed deployment. $f(\cdot)$ is a function of the working node monitoring accuracy and distance; here, ε is a weighting factor. $V(k)$ is Gaussian white noise.

In order to ensure high monitoring accuracy, it is necessary to enable multiple nodes to work simultaneously. Thus, more state information of the moving target can be obtained. However, in order to select the appropriate number of working nodes to reduce network resource, the network monitoring accuracy can be developed by the difference between the actual and the expected value of the selected working node. Besides, $\Delta Z_T(k)$ represents the measurement error of the working node, and it is as follows:

$$\Delta Z_T(k) = \frac{\left\| \frac{1}{m}\sum_{i=1}^{m} Z_{s_i}(x_{Ti}(k), y_{Ti}(k)) - T(x_T(k), y_T(k)) \right\|_2}{\| T(x_T(k), y_T(k)) \|_2} \times 100\% \quad (30)$$

where m represents the number of working nodes at time k.

According to the size of the network monitoring area and the monitoring environment, it can be set that the network monitoring accuracy error can meet the monitoring accuracy requirements as long as it satisfies $\Delta Z_T(k) \leq \Phi\%$; here, $\Phi\%$ is the threshold of accuracy.

4. Simulation Results and Discussion

4.1. Simulation Background and Parameters

Assume that WSNs composed of m sensor nodes were randomly distributed in the monitoring area S_M. When multiple nodes monitor the moving target, some network nodes in the vicinity of target are selected to perform monitoring tasks. These working nodes need to consume energy for tasks such as information collection, data processing, and communication transmission. Once the remaining energy of one working node is less than zero, it is considered dead and loses itself monitoring ability. Network nodes that are inactive can be considered dormant, and they do not consume their own energy.

In this section, performances of proposed method are verified by comparative experiments on MATLAB simulation platform. The main parameters of simulation are shown in Table 1. Besides, the proposed algorithm LEACH-MTC is compared to three other LEACH-based algorithms: LEACH [24], LEACH-DBCH [13], and LEACH-RARE [14], and conducts performance analysis from the aspects of the working nodes selection, nodes survival number, network residual energy and network monitoring accuracy, and so on.

Table 1. Simulation parameters.

Parameter Name	Symbol	Value
Network monitoring area	S_M	300 m $\times$ 300 m
Number of network nodes	m	100
Base station location	(x_{BS}, y_{BS})	$(150, 150)$
Initial energy of the node	E_0	1 J
Transmitting circuit energy consumption	E_{TX}/E_{RX}	$50n$ J/bit
Signal amplification energy consumption in unit data free space	ε_{fs}	$10p$ J/bit/m^2
Signal amplification energy consumption under unit data multipath attenuation	ε_{mp}	$0.0013p$ J/bit/m^2
Data fusion energy consumption	E_{DA}	5 nJ/bit/packet
Control signal size	l_1	100 bit
Signal amplification energy consumption in unit data free space	l_2	4000 bit
Expected probability of cluster head	p_{ex}	0.1
Maximum number of running rounds	k_{max}	1300
Threshold weight	k	0.8
Threshold weight	μ	0.2
Threshold weight	α, β, γ	$10, 0.01, 0.01$

4.2. Verification of Proposed Algorithm

In the comparative simulation, the distribution of network nodes and working nodes corresponding to the four algorithms of LEACH, LEACH-DBCH, LEACH-RARE, and LEACH-MTC is shown in Figure 4.

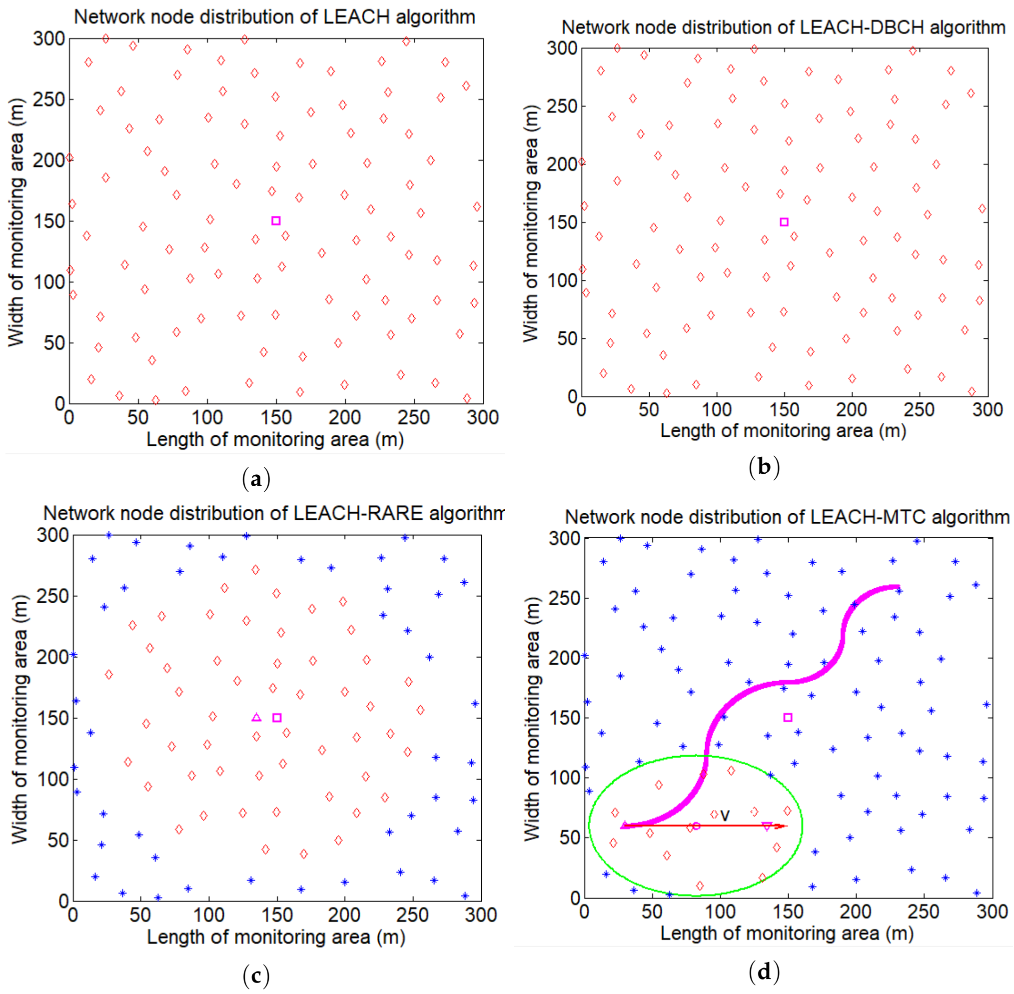

Figure 4. Node distribution of four algorithms.

In Figure 4, □ stands for base station, △ stands for moving target, ♢ stands for working node, ∗ stands for sleep node, curve stands for target trajectory, the target velocity at the current moment is v, and the direction is horizontal. In Figure 4a,b, the network nodes in the monitoring area corresponding to the LEACH and LEACH-DBCH algorithms are all in working state. As the two algorithms do not consider the factor of the moving target, all nodes in the network are working nodes. They all need to collect data, process data, and transmit data. However, in Figure 4c, the nodes closer to the target in the LEACH-RARE algorithm are in the working state, while the nodes farther from the target are in the dormant state, and there are 52 working nodes and 48 sleep nodes. In Figure 4d, the nodes inside the elliptical area are in working state, and their number is 14; the nodes outside the elliptical area are in the dormant state; and as the position of the moving target changes, the shape and size of the ellipse area also changes.

4.2.1. Working Node Selection and Monitoring Accuracy

As the target moves, the network nodes that are working are constantly changing. Figure 5 shows the change of the target position and the working node when the LEACH-MTC algorithm is running in the 1th round, 300th round, 600th round, and 800th round, respectively.

In Figure 5, □ stands for base station, △ stands for moving target, ♢ stands for working node, ∗ stands for sleep node, curve stands for target trajectory. In Figure 5a,c, when the number of network running rounds is in the 1th round and the 600th round, the number of nodes that are in the working state is 15, and the remaining nodes are in a dormant state. In Figure 5b,d, when the number of network running rounds is 300th round and 800th round, the number of nodes that are in working state is 16. The above results indicate that as the target position changes, the long axis, the short axis, and the shape of the ellipse also change, besides, the number of working nodes that are in the ellipse area is constantly changing.

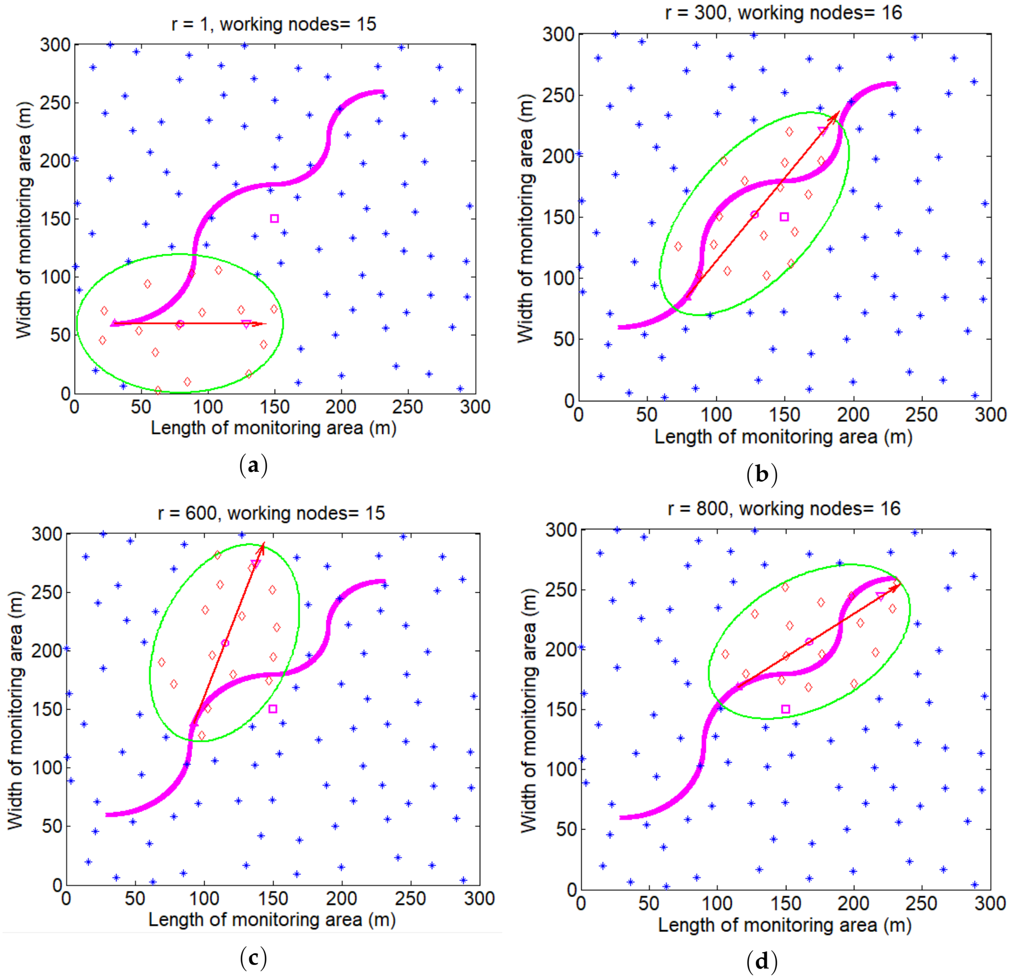

Figure 5. Change of target position and working node selection.

Assume that the elliptical area are formed by the working node is $S_{ab} = 14,400m^2$, and all the working nodes in this area can meet the monitoring accuracy requirements. According to Equations (18)–(21), the long semi-axis a, the short semi-axis b, and the half-focal length c of the ellipse area can be obtained. The network monitoring accuracy is shown in Table 2.

Table 2. Ellipse parameters and network monitoring error.

Run Time Parameter	Round 1	Round 300	Round 600	Round 800
Number of working nodes	15	16	15	16
long semi-axes a	79.1984 m	96.6545 m	86.9920 m	82.9734 m
short semi-axes b	57.8757 m	47.4232 m	49.3975 m	51.7899 m
Half focal length c	54.0629 m	84.2208 m	71.6066 m	64.8259 m
Network monitoring error	1.85%	2.10%	1.73%	1.65%

From Table 2, it can be seen that the number of running rounds is the 1th round, the 300th round, the 600th round, and the 800th round, respectively; the number of working nodes in the elliptical area is not the same, which indicates that as the target position changes; and the ellipse area also changes. It can be seen from the changes of the long semi-axes, the short semi-axes, and the semi-focal lengths in Table 2. This indicates that as the target position changes constantly, the shape of the ellipse area also changes. The analysis of the monitoring accuracy of the network at four moments shows that the monitoring error is less than, which can meet the requirements of network monitoring accuracy.

4.2.2. Number of Node Survivor and Network Residual Energy

The working nodes need to constantly obtain the moving target state, and as the amount of data processing increases gradually, the energy consumption of the working nodes increases continuously, and their residual energy decreases gradually. When the residual energy of the working node is less than 0, it is regarded as the dead state, which leads to the reduction of the number of surviving nodes. The amount of time from network start running to first nodes death is defined as the life cycle of the network. Figure 6 shows the changes of the number of the surviving nodes corresponding to the four algorithms.

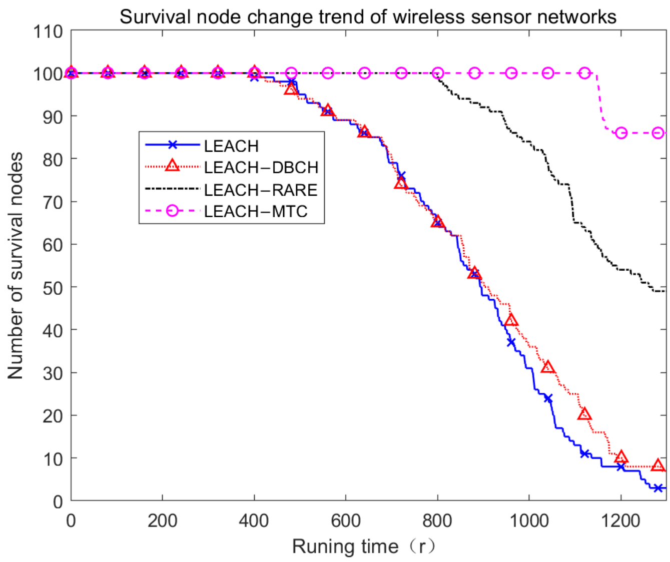

Figure 6. The number of network surviving nodes.

In Figure 6, when the network starts running, there are 100 surviving nodes corresponding to the four algorithms. As the network running time is extended, the energy consumption of the working nodes increases, and the remaining energy of the working nodes will gradually decrease. It can be seen from this figure that when the run-time corresponding to the four algorithms run to 407, 365, 814, and 1142, respectively, the four corresponding curves begin to decline, that is, the death nodes begin to appear in the network. By comparing the time of death of the first node of the four algorithms, it can be seen that the LEACH-MTC algorithm has the longest time to the appearance of the first dead node. Therefore, the LEACH-MTC algorithm can effectively extend the time of the first dead node by constructing an ellipse monitoring area of some working nodes. When the number of running rounds is the same, the curve corresponding to the LEACH-MTC algorithm is above the curve corresponding to the other three algorithms in the whole process, which indicates that the LEACH-MTC algorithm has the largest number of network surviving nodes when the running time is the same. When the network runs to the maximum number of running rounds, i.e., the number of surviving nodes in the network corresponding to the four algorithms is 4, 4, 51, and 87, respectively. In summary, the LEACH-MTC algorithm makes the number of surviving nodes higher than that of other three algorithms; it effectively increases the number of nodes surviving. Accordingly, Figure 7 shows the variation trend of the total residual energy of network nodes with the working time.

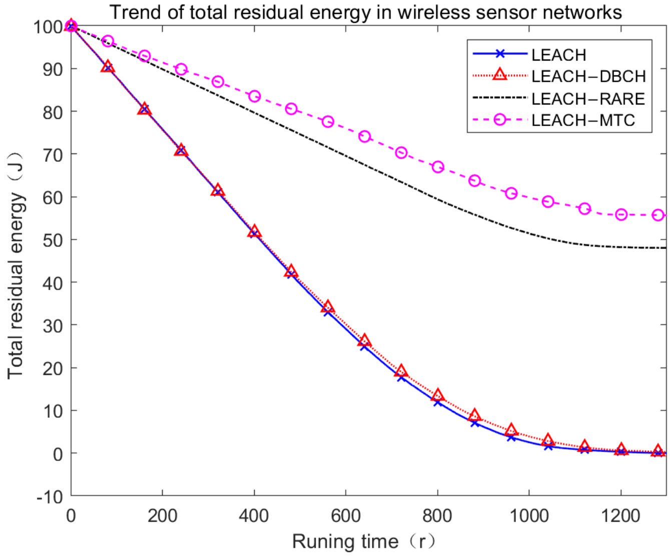

Figure 7. The variation of network residual energy.

In Figure 7, the total initial energy of the four algorithms is 100 J. As the network running time increases, the energy curves corresponding to the four algorithms all have a downward trend. When the number of running rounds is the same, the curve of the LEACH-MTC algorithm is obviously above the other three curves, which means that the network residual energy of the algorithm is larger than the other three algorithms. When the network runs to the maximum running rounds, i.e., the remaining energy of the network nodes of the algorithms LEACH, LEACH-DBCH, LEACH-RARE, and LEACH-MTC are 0.0807 J, 0.2345 J, 48.0405 J, and 55.6336 J, respectively. It can be seen that the total residual energy of the LEACH-MTC algorithm is higher than that of the other three algorithms. The simulation results show that the residual network energy corresponding to the four algorithms decreases with the increase of running time, but the residual network energy corresponding to LEACH-MTC algorithm is higher than the other three algorithms, which can save network energy more effectively and prolong the network's life cycle.

5. Conclusions

The proposed LEACH-MTC algorithm combines the state prediction of moving target and the network monitoring performance parameters, and meets the network monitoring accuracy requirements. This paper constructs a time-varying ellipse monitoring area with the direction changing of the moving target, and it determines the working nodes set. Combined the working node set and the state prediction of moving target, this paper gives a new cluster head selection threshold to construct the cluster head strategy. The LEACH-MTC algorithm increases the number of network nodes to survive, reduces network energy consumption, and prolongs the network life time.

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