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Contents

Target Tracking Node Selection Algorithm in Wireless Sensor Network Zhike KUANG*······(1)
The Load Distribution Characteristics of The Cylindrical Roller Bearing Xuening ZHANG*
Applied Research of Fault-tolerant Monitoring Algorithm in Wireless Networks Haogui CHEN*
Multi-Project Management System of The Scientific Research Team in Universities based on Web Ruihong WANG*, Lianjie DONG······(20)
Task Scheduling of Firefly Algorithm based on Cloud Computing Shuaili WANG*
A Nonmonotone Wedge Trust Region Method with Self-correcting Geometry for Derivative-free Optimization Weili ZHENG, Qinghua ZHOU*
Research on Application of CGAR Algorithm in Network Routing Protocols Jianjun WU*
Non-monotone Trust Region Technique for Equality Constrained Optimization Xiao WU, Qinghua ZHOU*
Research on the tracking of public places based on pedestrian detection Hean LIU*, Zhike KUANG

Target Tracking Node Selection Algorithm In Wireless Sensor Network

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Abstract: Since target tracking node's selection in wireless sensor network has a significant impact on the life cycle of wireless sensor networks, therefore it proposes a tracking node selection algorithm with tracking quality assurance in this paper. First, it defines the sensory data error model which adequately quantifies sensor sensing node data errors and the probability of the node making the wrong decision within its perceived scope on the target. Secondly, it analyzes three elements wich have impact on residual energy of node lifetime, energy consumption of target tracking task execution and possibility of node sends false alarms. Finally, on this basis, it proposes target tracking algorithm with quality control. Under the premise of user given track quality assurance requirements, the algorithm selects a subset of nodes involved in target tracking and positioning tasks which maximizes the lifetime of the network, the algorithm ensures a given target tracking reliability requirements while optimizes the network lifetime. Experimental results show that: the proposed algorithm can prolong the lifetime of wireless sensor networks.

Keywords: Sensing Data; Energy; Routing; Node

1. Introduction

In recent years, target tracking based on wireless sensor network has attracted wide attention, and made effective tracking method and proposed target tracking mechanism based on node selection, by predicting the regional emergence of target or setting node classification rules to select some node to track target. Zhao F and so on put forward information-driven target tracking method, which consider node communication resources and computing resource constraints, integrates sensor nodes' collected data and receives data information of the neighbors and selects some nodes to collaboratively finish target tracking tasks [1]. Brooks R and so on put forward a distributed target classification and tracking methods [2]. Under the method, the sensor network monitoring area is divided into a plurality of sub-areas, so that potential nodes around the target track cooperatively detect target appears. When concerned goals appear, tracking process will be activated. Li D and so on put forward target tracking mechanism based on cooperative signal processing [3]. The proposed tracking method wakes the nodes in four corners of monitoring position to monitor potential targets. Liu L and so on divides the whole tracking process into target monitoring and targeting [4]. In the target monitoring phase, using density control algorithm to select the appropriate subset of nodes to monitor objectives. In the targeting phase, proposing a node with minimum energy consumption to ensure node selection and targeting methods.

Liu L researches network energy consumption and tracks the balance of quality and put forward data collection algorithm with information quality assurance [4]. The algorithm uses the triangulation method under the allowed track error condition to select a node in an active state. He T and so on designs and implemented a distributed target tracking system, which uses energy management mechanism which allows the sensor nodes to rotate between sleep and working conditions in order to save network energy consumption [5-7]. Meanwhile, in the process of objective monitoring, classification and tracking, this system takes a wake-up node and a packet aggregation policy mechanisms for tracking delay and energy savings balance. Jeong J [8], etc., gives a minimum contour tracking method. The method researches the kinematic characteristics of the target, the moving object area may be limited to a minimum contour line, the wake up the nodes within minimum contour line to take part in tracking tasks, thus minimizing the number of nodes involved in tracking [9]. However, this method requires all nodes within the contour lines continue to maintain working condition.

In many target tracking applications, users require that tracking system has a certain guarantee of reliability [10]. However, due to environmental interference and perceptual part accuracy limitations, sensor nodes' sensing data often exist error, especially when the node battery will be exhausted, the probability of erroneous data generated by the sensor will be significantly increased. Sensory data error adds to the difficulty of the quality-assured target tracking study. Obviously, trying to choose nodes with reliable sensory data to take part in tracking can improve targeting accuracy. However, since the energy consumption of each sensor node is different, therefore how to select a node in tracking tasks with good tracking quality while ensuring the survival of network optimization is a challenging problem. First, the sensor nodes' sensing range is limited, only the sensor nodes located around the target can perceive a moving target. The target trajectory is random, usually sensor nodes located in the region where the target appears more frequently need greater consumption. Secondly, the communication range of the sensor node is limited, nodes closer to Sink need to transit the packet of nodes which are farther from Sink the and consume more energy, which causes the network sensor node energy consumption imbalance, while the sensor network survivability is decided by energy depleted time of nodes which need larger energy consumption. Therefore, an effective tracking algorithm not only has a tracking quality assurance, but also to consider the network node energy savings and balance.

With the increase in the number of sensor nodes, network lifetime is significantly increased and can be applied to a variety of tracking targets with different speeds. When the number of tracking nodes varies between 5 to 6, the increased tendency of forwarding nodes is reduced, so that the increased trend of network energy consumption will be eased, as a result, the decreasing tendency of network lifetime become slow.Simulation results show that: the range in which each node sensing time more evenly, more conducive to balance node energy consumption, thereby extending the network lifetime.

2. Network Model

2.1. Hypothesis

Without loss of generality, assume that the sensor network is composed of m nodes, number node ID from $1 \sim$ m. All nodes have the computing, communications and sensing capabilities. Sensor nodes are usually battery powered, the energy, communication bandwidth and computing power are limited. In order to facilitate the description of the algorithm, the paper make the following two reasonable assumptions:

(1)Assuming sensor network nodes uniformly distributed in the monitoring area, these nodes can get their location coordinates via GPS or other location mechanisms.

(2)All of the sensing range of the sensor nodes are identical and can be approximated to disc region with R_s radius. All sensor nodes have the same communication range, the maximum communication distance is R_c . R_c is an integer multiple of R_s .

2.2. Sensory data error model

When the tracking target appears in the monitoring area of sensor network, sensor nodes located around the target will produce sensory data. Due to the limited accuracy of perception part and environmental interference, there are often a perception data errors. Use s_i represents the exact perception data collected by sensor node $i(1 \le i \le n)$, the actually perception data o_i collected by the sensor node *i* can be expressed as:

$$o_i = \begin{cases} \delta_i + s_i, \text{Target and node i distance} \le R \\ \delta_i, & else \end{cases}$$
(1)

Wherein δ_i is the perception data errors. Sensory data using Gaussian distribution describes the error, that is $\delta_i \square (o, o_2)$. Parameter *o* can be obtained through historical training data.

Given the sensing data threshold value T, if $o_i \ge T$, then node i can monitor the tracking target, which means the target appears in the sensing range of the node i. Use '1' to represent that node i make "monitor target tracking" decision, and "0" indicates that the node i to make "not monitored to track the target" decision. Since nodes in the network make decisions independently, so the sensor node i's decision p_i can be expressed as:

$$p_i = \begin{cases} 0, o_i \le T \\ 1, o_i \ge T \end{cases}$$
(2)

Because there are errors in the data-aware, sensor nodes may make the wrong decisions. For example: a moving target node *i* has entered the sensing range and it make a decision that node $p_i = 0$; or moving target is not in the sensing range of the node *i*, the node make decision that $p_i = 1$. We are usually more concerned about the likelihood of the latter's wrong decision, because in this case the resulting data will be involved in targeting operations, affecting the accuracy of targeting. The possibility of node making the wrong decisions will be given in the following.

2.3. Definition1 probability of false positives

When a moving target is outside the range of sensing nodes, probability of node *i* making decisions $d_i = 0$ is defined as the probability of false alarm, expressed by d_i , d_i can be expressed as:

$$d_{i} = d\left(p_{i} = 1 | s_{i} \prec T \land o_{i} \ge T\right) = y\left(\frac{T}{\gamma}\right)$$
(3)
$$h_{i}\left(0, \frac{\gamma}{T}\right) = \frac{1}{\left(2\pi\sigma^{2}/T\right)^{\frac{1}{2}}} \exp\left(-\frac{d_{i}T^{2}}{2\lambda^{2}}\right)$$
(4)
$$\vdots = \frac{\lambda}{T} \mathscr{G}\left(-\frac{Td_{i}}{\gamma}\right)$$

In order to further quantify the possibility of the sensor node sending out false alarms, we use the likelihood function to describe the probability of node *i* sending false alarms as:

Wherein γ is the probability density function of the standard normal distribution. Accordingly, d_i logarithmic likelihood function can be expressed as

$$LnL_{i} = \left(0, \frac{\gamma}{T} / d_{i}\right) = -\frac{1}{2} In\left(\frac{\gamma^{2}}{T^{2}}\right) In\left(\delta\left(-\frac{Td_{i}}{\delta}\right)\right)$$
(5)

Use

$$FA_i = LnL_i\left(0, \frac{\delta}{T} / d_i\right)$$

Quantify the possibility of false alarms provided by node i, the smaller the threshold values is, the more reliable the sensing data which is generated by node. Given false alarm threshold δ , when $FA_i \leq \delta$, we say decision made by node i is believable.

3. Network Topology

3.1. Build dynamic tracking sub-tree

When the target occurs within the monitoring area of the network, node *i* which monitors the target (node makes a decision that $d_i = 1$) calculates the value FA_i . If $FA_i \leq \delta$, then the node *i* found the target packets DT-Packet within the broadcast network. DT-Packet consists of a *tuple* $\langle FA_i, l_i \rangle$, wherein l_i is the expected lifetime of the node, the fourth section will define l_i . When father node j receives DT-Packet from the child node *i*, it conduct the packet processing, and then forwarded it to the parent node. All radio and DT-Packet forwarding nodes form a dynamic tracking sub-tree.

Any node j, collection of child nodes in dynamic tracking sub-tree can be represented as

$$d_i = \left\{ i \left| FA_i \le \delta, i \le R_s, 1 \le i \le m \right\}$$
(6)

3.1. Dynamic tracking sub-tree pruning

When father node receives its child node data, it performs a series of data processing operations. According to the received packet type, the father node's performed processing operation mainly includes two types: (1) choose child nodes to participate in tracking; (2) aggregate and forward data packets.

Definition 2 Discovered nodes

For any node *i*, if *i* can monitor goals, and meet the conditions $FA_i \le \delta$, we call that node *i* is found node.

Definition 3 Tracking node

Discovery node selected by the node selection algorithm to take part in target tracking is called a track node. After father node receives DT-Packet from children (found) node, then it calculates the number of received DT-Packet, if the received packet is greater than the number k (the minimum number of trace nodes, k is specified by the user or targeting algorithm needs), the father node will be prune the dynamic sub-tree's branches, namely through the execution node selection algorithm to select the candidate tracking node and unselected discovery nodes will be cut off. Otherwise, all discovered nodes as a candidate tracking node. Section B will give a specific node selection algorithm.

Father node gathers candidate tracking node information then forward to sink node, Sink node perform selection algorithm again on the candidate tracking node to determine the final tracking nodes. The selected nodes will monitor the tracking target node, and generates sensory data. Other non-tracking nodes leave the dynamic tracking sub-tree, these nodes can according to scheduling rules periodically fall into sleep mode to conserve energy. Father tracking node receives sensory data generated on the target, after gathering forwarded to Sink node, Sink node performs targeting algorithms. Most existing targeting algorithms can be applied to the proposed algorithm.

4. Target Tracking Node Selection Algorithm

When the target occurs within the monitoring area in sensor networks, all trace nodes and sensor nodes which transit tracking node data form a dynamic tracking subtree. Target tracking node collects the information and forward it to sink node to locate the target. In order to ensure the tracking quality while maximizing network lifetime, this section study the node selection problem which take optimizing the network lifetime as a goal. We first gives node lifetime definition in A, B gives node selection algorithm with assured tracking quality. This algorithm will select the nodes that participate target tracking from the a collection of discovery nodes to reduce the dynamic tracking sub-tree node number, thereby reducing energy consumption throughout the network. Table 1 shows the symbols used in the text and their meanings.

sign	Sense
М	The number of nodes in a sensor network
R_{s}	The sensor node communication radius
R_{e}	Digital radius of sensor nodes
W	Dynamic tracking digital internal node set
Ν	Tracking node set
\mathcal{E}_{i}	The node sensing data I error
l_i	Node I survival
d_i	Node I sends out the probability of false alarms

4.1. Ready knowledge

 FA_{r}

In order to improve the accuracy of target tracking system, we try to select a node with smaller FA value to join in target tracking. The smaller the threshold the higher reliability of the sensing data provided by the nodes. Users can specify the selected node set of false positives tracking threshold FAT, to define the possibility of false data by a set of tracking nodes.

For any given *FAT* value, the tracking nodes' selection result is not unique. Therefore, we can choose different trace nodes to balance network node's energy consumption. Try to choose smaller FA value tracking node as target tracking node can improve the reliability of these nodes, however, it will lead to excessive energy consumption, thereby reducing the network lifetime.

Without loss of generality, assuming that when possibility of false data of node *i* is FA_i , the possibility of this node is selected as tracking node is $h(FA_i)$, $h(FA_i)$ indicates the possibility of false positives $FA_i \leq \delta$. Obviously, $h(FA_i)$ is a non-increasing function. The node *i* energy consumption for each cycle can be expressed as:

$$B_i^{\text{cost}} = \begin{cases} h(FA_i) \cdot (B_i^s + B_i^a), & d_i = \sigma \\ h(FA_i) \cdot (B_i^s + B_i^a + b * B_i^r), |D| = b \end{cases}$$
(7)

Wherein $B_i^{\cos t}$ represents node *i* energy consumption per cycle during the process of sampling perception data, c is the number of tracking nodes of child nodes *i*.

Assuming the residual energy of the node *i* is B_i^1 , the expected lifetime of the node *i* can be expressed as

$$l_i = \frac{B_i^1}{B_i^{cost}} \tag{8}$$

The lifetime of the network is defined as time interval from network layout to a sensor node energy deplete. The proposed algorithm can be applied to q(q > 1)q covered by the network, namely any location of the network is covered by the q sensor nodes. In this case, q nodes in an arbitrary covered position can be treated as a node with greater energy, the energy of this node is the sum energy of q nodes.

Therefore, the lifetime of sensor networks can be expressed as

$$l_{network} = \min_{i \in \{1, 2, \dots, m\}} l_i \tag{9}$$

4.2. Tracking node selection algorithm

Definition 4 TQANS problem

Given found node set $N = \{n_1, n_2, ..., n | N |\}$, it is required to find a |N| element vector $(y_1, y_2, ..., y |N|)$, wherein $y_i \in \{0,1\}$. Satisfies the condition: (a) $\min_{i \in N \land Y_i \neq 0} y_i l_i$ value the largest

(b)
$$\sum_{i \in N} y_i F A_i \le \sum_{i \in N} y_i \ge k$$
(c)
$$\sum_{i \in N} y_i \ge k$$

In which, FA_t is given by the user or set according to actual application requirements. K is the minimum number of trace nodes, k is specified by the user or determined according to the target location algorithm's needs.

This section's presented two tracking node selection algorithm are: selection algorithm based on greedy heuristic and selection algorithm based on conditional replacement. Greedy heuristic algorithm greedily choose track nodes from a collection of nodes, with a low time complexity advantage. The condition-based replacement selection algorithm based on greedy heuristic algorithm adjusts the choice results according to the FA and attribute value of l_i to optimize the chosen results.

4.3. Greedy heuristic selection algorithm for tracking node

Selection algorithm based on greedy heuristic (G-TQANS) adopt well-known greedy strategy to incrementally choose track nodes from the collection of discovery nodes. In order to use greedy strategy, we define a revenue function g. G-TQANS each time selects nodes which can maximize the revenue function g. Given found node set $N = \{n_1, n_2, ..., n | N |\}$, the problem solved by the present section, the node n_i revenue function g is defined as follows

$$g\left(n_{i}\right) = l_{i} \tag{10}$$

According to equation (10) defined by greedy rules, the paper designs a greedy heuristic algorithm based on G-TQANS, as shown in Algorithm 1. During initialization, determine the set N of found nodes , and set the initial value of |N| element vector $(y_1, y_2, ..., y|N|)$ as 0 (statements 1-3). Next, the algorithm selects the current optimal node n_i and make its corresponding value y_i as 1 (statements 5-8). Thereafter, the algorithm enters a loop process, each time it selects from the remaining node set a node n_i which can maximize the revenue function g, and set its corresponding value y_i as 1 (statement 9 to 16). When the full condition (2) and (3) are met, out of the loop, then the algorithm ends. The node whose corresponding y_i is 1 in vector $(y_1, y_2, \dots, y|N|)$ the tracking node. It takes time O (1) to calculate $g(n_i)$, so the whole algorithm's time complexity is $o(|N|\log|N|)$.

4.4. Node selection algorithm of conditions replacement

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Node selection algorithm (G-TQANS) based on heuristic greedy each time makes the best choice currently does not guarantee overall optimality. And when FAT value is small, the algorithm may not find the solution which meet condition (3). Therefore, this section presents node selection algorithm S-TQANS based on conditional permutation , the algorithm replace the selection results according to node's FA and *l* attribute based on the G-TQANS .

S-TQANS firstly, order the found nodes in set N in accordance with the value of 1, making internal node N satisfies the condition $l_1 \ge l_2 \ge \dots, \ge l |N|$ (statement 1). Next, the algorithm selects the previous k nodes in N as a candidate tracking node added to the collection W, the value of each element in the vector (y_1, y_2, \dots, y_k) is set to 1. Sums up the value of tracking candidate nodes' FA values, if meet the condition

$$\sum_{i \in w} FA_i \le FA_T$$

Then the algorithm ends (statement 2 to 5). Otherwise, the algorithm enters a loop process, each time select node n_i with the greatest FA_i value, and use node j which with the greatest l in set N-w and meanwhile satisfy the condition $FA_i > FA_j$ to replace node n_j (Statement 9 to 20). When the following condition is satisfied, $\sum_{i \in w} FA_i \le FA_T$

Then exit the loop, the algorithm terminates. The time complexity of the algorithm is $o(|N|\log|N|+k_1)$.

Algorithm 2 S-TQANS algorithm

Input: Found nodes N, FA_i

Output: Satisfy FA_i the $l_{network}$ threshold condition and make largest |N| Element vector $(y_1, y_2, ..., y|N|)$

1) Within the N node according to the l values in des-

cending order;2) N in the first k node joining w;

3) FOR (i = 1 to k) DO;

- 4) $y_i = 1;$
- 5) END FOR;

6) FOR
$$(i = k + 1to |N|);$$

7)
$$y_i = o;$$

8) END FOR;

9) WHILE
$$\left(\sum_{i \in w} FA_i \text{ and } |N| \succ 0\right)$$
 DO;

10) Select *FA* from the w, n_i maximum value node; 11) $y_i = 0$;

12) Select N-W from the l, n_i maximum value node;

13) IF
$$\left(FA_i \succ FA_j\right)$$
 THEN;
14) $W = W_u \left\{n_j\right\} - \left\{n_i\right\};$
15) $y_1 = 1;$
16) ELSE;

5. The Simulation and Analysis

5.1. Experimental setup

We use VC + +6.0 language to develop wireless sensor network simulation environment. In the simulation environment, the sensor nodes are deployed in units of 1000 \times 800 screen area. As the number of sensor nodes is an important factor that affect tracking performance, given the size of the distribution area of nodes, the node number and the node density are directly related. In this experiment, we set the number of nodes varies from 1200 to 3000, the default number of sensor nodes as 1600. As the number of selecting track nodes will affect the node energy consumption thereby affect the survival of the entire network, the present study investigates the lifetime changes of the network when the number of tracking nodes varies between 3 and 6. The moving speed of the tracking target determines each successive node's length tracking time, therefore it is closely related to energy consumption with each node. We consider two cases in which the maximum moving speed of the target track are 10 and 20 units.

In the experiment, set node energy consumption model parameter, all the nodes' initial energy are the same, and is set to 50mJ. Nodes transmitting and receiving a byte respectively costs energy consumption of 0.0144mJ and 0.0057mJ. Each packet has a length of 32Bytes. The energy consumption for data collection and processing data is negligible, because the communication energy consumption is much higher than that of these two. In the experiment, the target respectively runs in accordance with lines and curves, the movement direction of the target is generated randomly when it conducts curvilinear motion. The proposed G-TQANS algorithm and S-TQANS algorithms run on the sensor node and Sink node.

5.2. Analysis

Figures 1 and 2 show experimental results of the proposed target tracking algorithm for linear motion tracking when the number of selecting track nodes is 3 and 4, and the number of nodes in the network is respectively 1200,1600,2500 and 3000. We can see from the figure, with the increase in the number of sensor nodes, network lifetime significantly increased. This is because the increase in the number of nodes in the network makes the network density increases, algorithm has more choices in selecting tracking node. It is more conducive to reducing average energy consumption of nodes. The proposed

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algorithm is designed to ensure balanced energy within the network nodes. When the network density increases, the number of discovered nodes increase, the average number of each node be selected to be trace nodes reduces, each node's average energy consumption reduces, resulting in increase in the lifetime of each node. The lifetime of the network is decided by the node with the shortest lifetime, the overall increase of the node will inevitably lead to increases of lifetime of the network.

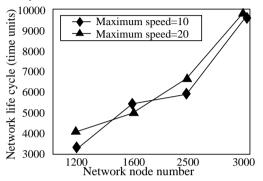


Figure 1. Target as linear motion, the number of tracking nodes=3, the impact of the number of nodes in the network on the network life cycle

Figures 2 and Figure 3 show experimental results of the proposed target tracking algorithm tracking curvilinear motion target when the number of selecting track nodes is 3 and 4, and the number of nodes ranges from 1200~3000. From the figure we can still see the dependence of the proposed algorithm's performance on network size. From the figure we can also see that in the case of setting the same parameters, the goal to make the curve movement, the network survival the algorithm provides is significantly lower than that of linear motion. When the goal makes the linear motion, the network lifetime maximum is about 9600 time units, while the goal makes the curve movement, the maximum network lifetime is about 4800 time units.

This is because when the target conducts curve movement, the randomness of moving direction may cause target node stay longer in some nodes' sensing area, resulting a large energy consumption of these nodes, which is not conducive to energy balance within the network, thereby reducing the entire network lifetime. While the goal makes linear motion, the time it stays in each node's perceived area is more evenly, so more conducive to balancing node energy consumption, thereby extending the network lifetime.

Can also be seen from the above chart, there is no obvious dependency between the target's movement speed and lifetime of the network. When the target moves slower, the time of target's average continuous staying in sensing range increase, but in the entire target tracking process, the average time of each node within perception tends to remain unchanged, so this will not affect the target of algorithm balancing node energy consumption within the network. The experiment also proved that the proposed algorithm can be applied to a variety of tracking targets with different speeds.

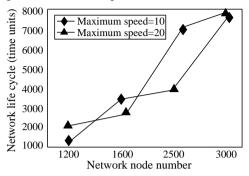


Figure 2. Goals as curvilinear motion, the number of tracking nodes = 3, the impact of the number of nodes within the network on the network life cycle

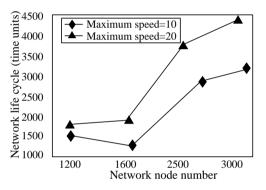


Figure 3. Goals as curvilinear motion, the number of tracking nodes = 4, the impact of the number of nodes within the network on the network life cycle

Figure 4 shows the network lifetime changes when an object moves in a straight line and a curve, and the tracking number of nodes is 3,4,5,6 respectively. In this set of experiments, the number of nodes within the network is 1600, the target's maximum speed is 10 units. As can be seen from the figure, when the tracking number of nodes increased from 3 to 5, the network lifetime reduces significantly. When the number of tracking nodes increase from 5 to 6, this decreasing trend shows. This is because the lifetime of the network is decided by the nodes which needs larger energy consumption, while the node with greater energy consumption comes mainly from intermediate nodes of tracking node and forwarding tracking node data. When the number of tracking nodes increases, not only number of nodes monitor target which collects sensing data increases, the number of forwarding nodes will be a correspondingly increase, which makes the average energy consumption of the network nodes significantly increase, therefore the network lifetime will be significantly reduced. When the number of forwarding

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nodes reaches a certain level, the rate of increase will be reduced. Therefore, when the number of nodes in track changes between 5 and 6, the increasing tendency of forwarding node reduces, therefore the network's trend of increased energy will be eased, so that the lifetime's decreasing trend of the network slows down.

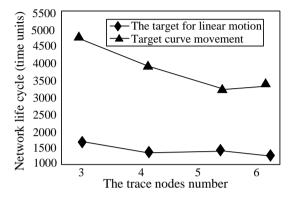


Figure 4. Goals as straight and curved motion, the impact of the number of tracking nodes on the network life cycle

6. Conclusion

In this paper, we research the node selection algorithm which with tracking quality assurance in target tracking application, considering the perception data error and the impact of energy consumption of nodes on tracking quality and node lifetime, and study network lifetime maximization problem on the premise of assured tracking quality, and puts forward valid node selection algorithm.

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