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SMTS: a swarm intelligence-inspired sensor wake-up control method for multi-target sensing in wireless sensor networks

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Abstract

The different number of targets in wireless sensor networks (WSNs) leads to different detection effects. Because of the existence of multiple targets in the detection area, excessive nodes wake up to detect each target in most cases. This process will consume too much energy and lead to the early failure of the network. We propose an algorithm named sensor wake-up control method for multi-target sensing (SMTS) inspired by swarm intelligence. In SMTS, we first construct the stochastic switching model based on a sliding window mechanism to distinguish single-target or multi-target scenarios. We further research wake-up strategy optimization for dynamic targets to solve the problem associated with excessively awakened nodes. The simulations demonstrate that SMTS significantly reduces the number of wake-up nodes around the intersections of multiple targets, effectively saves energy, and prolongs the service lifetime of WSNs while ensuring detection efficiency and accuracy.

Keywords Swarm intelligence · Wireless sensor network · Multi-target sensing · Wake-up strategy optimization · Energy saving

1 Introduction

There is a variety of sensors with different functions, which are extensively applied in the industry. Sensors are used to monitor the status of roads in the traffic sector [1, 2], monitor underwater pollution [3], and monitor overhead transmission line [4]. In many real applications, wireless sensors appear in the form of sensor networks, which contain a certain number of sensor nodes deployed in specific areas to finish the scheduled tasks in a certain way.

Currently, many methods are being employed for target detection in WSNs. We propose a distributed sensor wake-up control method based on the ant colony algorithm [5]. This method does not require the position of nodes, which is suitable for sensor networks in complex geographic environments. Instead, it flexibly applies the idea of the ant colony algorithm, which adaptively adjusts the wake-up probability of nodes and controls the status of the nodes through cooperation and information sharing among neighbors. In addition, this algorithm is distributed with strong robustness inspired by swarm intelligence and does not need a cluster leader; therefore, situations, such as the failure of the leader causing a too large deviation, can be avoided.

In sensor networks, nodes are usually powered by their own energy. Therefore, depletion of energy will lead to the failure of the node. Furthermore, when the total number of failure nodes reaches a certain threshold, the whole

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network will no longer be able to complete the task and lose the ability to work. Therefore, how to reasonably utilize the limited energy and prolong the service lifetime of the network with timely detection and accurate tracking targets becomes an important research problem.

Previously, we proposed a distributed sensor wake-up control method based on the ant colony algorithm named BSWC (biologically-inspired sensor wake-up control method) [5]. The BSWC does not consider the impact of different number of targets. Regardless if single-target or multi-target scenario, the BSWC determines the node state in the same way. However, in a multi-target scenario, a large number of nodes wake up in locations in which multiple targets are close to each other. The pheromone content of these nodes is too high and the wake-up probability is too large because they receive multiple pheromones from neighbors that have detected targets. These nodes are in a wake-up state but not close to the target and cannot detect the target. This mean that they are redundant and invalid. At the same time, the pheromone content of these nodes cannot rapidly decay to a normal level, which causes these nodes to continuously wake up within a period of time after the targets have passed. These issues lead to the waste of energy.

Regarding the problem mentioned, we propose a swarm-intelligence-based node sleep scheduling algorithm, which is adjusted by pheromones: SMTS. This algorithm first determines whether a node is in a single-target or multi-target scenario and then adaptively adjusts the pheromone reception probability. The SMTS can effectively reduce the number of invalid wake-up nodes, improve the node utilization rate, and save energy. The contributions of this paper can be summarized as follows:

1. We put forward a distributed wake-up control method inspired by swarm intelligence, which does not require information about the physical location of the nodes. The wake-up probability is calculated according to the pheromone content of the nodes to adjust the node state.
2. A stochastic switching model is used for multi-target sensing to distinguish single-target from multi-target scenarios. The pheromone reception probability is then adaptively adjusted and the corresponding algorithm automatically switches.

The remainder of this paper is organized as follows. Section 2 introduces the work performed at home and abroad. Section 3 presents the idea of this algorithm. The simulation experiment and analysis results are presented in Sect. 4 and conclusions are provided in Sect. 5.

2 Related work

In WSNs, target detection can be devided into two classes: single-target detection and multi-target detection. In the single-target scenario, sensors are used to detect the target appearing alone in the sensing range. In the multi-target detection scenario, the number of the targets appearing in the sensors sensing range can be larger than 1 or the target appears in the sensing range continuously.

We categorize multi-target detection into three main areas: target detection, target localization and cost optimization. Target detection detects a target if exist or not. Target localization reports the target position. And Cost optimization aims to make the energy efficient for sensors network.

Target detection Currently, many methods are being used for multi-target detection in WSNs. Most of them have the aim to accurately determine the number of targets based on the detection process conditions. The appropriate method is selected based on the different number of targets to achieve significant detection effects.

Different targets can be distinguished using sensor node measurements [6–9]. The tracking of the targets is modeled as the problem of target state estimation [7]. When the targets are close to each other, a single sensor node may detect multiple targets. This means that its measurements may contain information from multiple targets. Therefore, the measurements need to be decomposed into submeasurements associated with different targets. Meanwhile, a single target may be simultaneously detected by multiple sensor nodes. And submeasurements associated with the target from these nodes need to be fused together to correctly estimate the target state. The sensor nodes are designed to wake up and sleep periodically. The nodes join different clusters and some nodes are cluster heads. This means that it uses the two-layer network structure to solve the problems related to information fusion and data association. The detection method and the network structure are different from our algorithm.

Target localization Problems associated with the localization of multiple targets are considered in [10–14]. In [10, 11, 14], the localization problem is transformed into a sparse vector recovery problem by utilizing the sparsity of the space position of the target. The targets are considered to be distributed in a two-dimensional area with N grids. There is a N-dimensional vector. A vector value of 1 means that a target is located in a grid. Different targets are located in different grids. Therefore, the target number is the number of 1 in the vector. The locations of the targets are the two-dimensional coordinates of the corresponding grids. By using the compressive sensing theory and RSS (received signal strength) values of the grids, the algorithm recovers the value of each element of the sparse vector to obtain the number and locations of multiple targets.

Cost optimization Liu et al. [15] proposes a method which uses a minimum number of sensors to minimize the cost of the WSNs. So that all targets can be continuously monitored for at least m time long, and monitored data can be collected by the base station. However, if the base station is not working well, the entire sensor network can be trapped in a serious mistake. In [10], the energy consumption is reduced by deploying fewer sensors. In [11], the sensor node decides whether to activate based on the activation probability received from the sink node. Each activated node sends the RSS values from the targets to the sink node. The sink node performs the algorithm to obtain the number and locations of the targets. Before the beginning of the next cycle, the sink node recalculates the activation probabilities to activate the nodes close to any estimated target with a greater probability. The calculation of the node activation probability depends on the activation probability of the previous cycle and the distance between each node and estimated target. When the estimated target status is stable, the sink node reduces the activation probabilities of the nodes around the target to save energy. It is different from the SMTS in that this algorithm requires the sink node and location information of the nodes. In addition, it cannot avoid sink node failures causing a big deviation. Subir and Sipra [16] proves that the density of nodes plays a significant role in network lifetime. In order to meet the requirement of energy balancing, it proposes a probability density function(PDF) and implements a node deployment algorithm based on PDF to control the lifetime of WSN. Imon introduces an algorithm RaSMaLai [17] to gather data in the sensors network. In RaSMaLai, a tree structure rooted at the sink is defined and used to keep the energy efficient. Another idea [18] is to use a new asynchronous duty cycling MAC protocol, called demand sleep MAC(DS-MAC), which could adaptively adjust the sleeping time of the node according to the amount of packets received. When the energy stored in the sleep state can not support for nodes changing between the sleeping and the active state, the node will not get into sleep state to save energy. When the amount of data packet received by the node is less than a threshold value, the node increases its resting time to avoid energy wasting. But this protocol is asynchronous in time, and it requires time synchronization in the application of some sensor networks.

In [19], the tracking of targets is considered as a dynamic task assignment problem. Different targets are distinguished according to the signal processing algorithm [19]. For example, a unique *ID* is assigned to each detected target. A cluster head (CH) node and several cluster member (CM) nodes are assigned to each target. These nodes are responsible for the detection of the target. The CM sends its measurements to the CH and the CH performs an algorithm to estimate the target locations. Based on the distance between the node and the target and the node's remaining energy, the benefit of a certain node for a certain target is quantified. The node's task (CH or CM) is then finally determined. Because of the movement of the target, reassignment of tasks is necessary. In [20], nodes are divided into different groups according to the region in which they are located to detect if each target enters or leaves the region. Within each group, the leader node sends an activation message to activate other nodes and these nodes send the detection data to the leader node. However, both algorithms [19, 20] are based on static deployed nodes and a multi-layer network structure (CH and leader node), which does not apply to our situation. Moreover, information on the location of the nodes and their neighbors is required in [19].

In [21, 22], the target k-coverage is focused on. In [21], each target is covered by k sensor nodes. The nodes close to the target form a cluster with a cluster head. The k nodes in the cluster remain in working mode to detect the target. Before these k nodes run out of energy, the next set of k nodes is randomly assigned. Nodes that detect multiple targets at the same time are assigned to different clusters to balance the size of each cluster. The cluster boundary is fixed for static targets. For dynamic targets, the cluster boundary is dynamically adjusted according to the change of the target location. In [21], the sensor nodes are stationary and the nodes are grouped into different clusters with a cluster head. However, our algorithm is distributed, and does not need a cluster head. Reference [21] does not apply to networks with a single-layer structure.

3 SMTS algorithm

We propose an algorithm named sensor wake-up control method for multi-target sensing (SMTS) inspired by swarm intelligence, which accurately and timely detects the target, even without node localization. However, as mentioned before, the BSWC fails to save energy by reducing the number of invalid wake-up nodes around the intersections of the target trajectories. Therefore, the new algorithm is designed as follows.

3.1 Algorithm outline

3.1.1 Basic definition

We selected the detect scene of the sensor network to be a square area of $L \times L$ in which N sensor nodes are randomly distributed. The definition is as follows:

1. All sensor nodes are the same and have the same configurations, where R_c is the communication radius of the node, R_s is the sensing radius, and P_d is the detection probability. The communication range of a node is a circle with radius R_c. The sensing range of a node is a circle with radius R_s.
2. The initial energy of all nodes is equal.
3. Synchronization is guaranteed by the S-MAC [23] synchronization protocol.
4. Each node has an operation cycle named T, which is divided into two parts. The first part is responsible for detecting the target and determining the node state. During the second part, the node will communicate with the neighbors. Note that wake-up and communication require a certain amount of energy.
5. The pheromone of a node is uniformly released to all neighbors once it detects the target; the detection requires some energy.
6. The stochastic switching model is used to distinguish between single- or multi-target scenarios. The probability of the nodes receiving neighbor pheromones is then dynamically adjusted.
7. Once a node's energy is exhausted, it turns into an invalid state and no longer works.

3.1.2 SMTS algorithm design

Inspired by swarm intelligence, SMTS uses the stochastic switching model to distinguish between single- and multi-target. It then adaptively adjusts the pheromone reception probability to ease the problem of redundant nodes waking up around the crossings of targets and thus to save energy. Based on the illustration above, our algorithm is divided into three stages, namely, wake-up of nodes, target detection, and pheromone control. Figure 1 is a block diagram of our algorithm.

In the wake-up stage, the node is modeled as an ant. The set of nodes in a sensor network is defined as $A = \{A_j\}(j = 1, \ldots, N)$ and the initial pheromone content of each node is at its minimum I_j^{min}. The calculation is introduced in [5]. The wake-up probability of a node is calculated based on the pheromone content to determine the next state of the node. The awakened nodes search the target within the sensing range. The indicators are defined as follows:

$$Ser(j,k) = \begin{cases} 1, & A_j \text{ is on search duty in the k-th step} \\ & j = 1, \ldots, N \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

where j is the number of nodes and k is the current step of the target.

The wake-up of nodes consumes a certain amount of energy, which is set to e. The energy value of the sensor node j in the k-th step is defined as $Energy(j, k)$. Thus, $Energy(j, k)$ will be reduced by e.

In the target detection stage, the awakened nodes try to detect the target. This process also consumes energy. Therefore, $Energy(j, k)$ will also be reduced by e. The target moves during this process. Only the target exists, the node can detect the target.

The indicator of the target existence is defined as follows:

$$Exi(k) = \begin{cases} 1, & \text{target exists in sensing area in the k-th step} \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

The indicator of the node detecting the target is defined as follows:

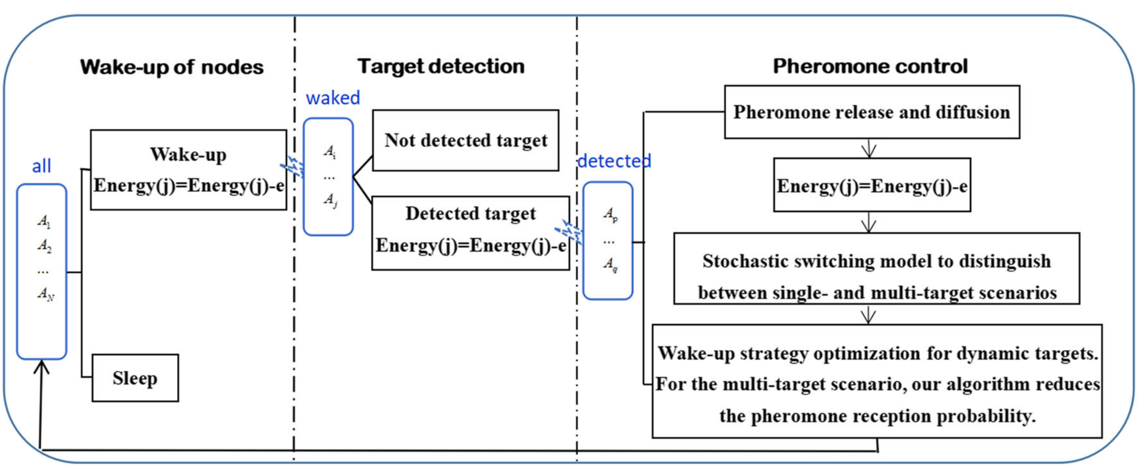

Fig. 1 SMTS algorithm block diagram

$$Det(j,k) = \begin{cases} 1, & A_j \text{ detects the target in the k-th step} \\ & j = 1,\ldots,N \\ 0, & \text{otherwise.} \end{cases} \tag{3}$$

In the pheromone control stage, the node that has detected the target uniformly releases a certain amount of pheromones to other nodes within its communication range (neighbor nodes). "Pheromone release and diffusion" schema obeys the definitions (3), (4) and (5) that mentioned in Sect. 3.1.1. First, a sensor j detects the target presented in its sensing range and then converts this event into pheromone. Second, j signals the pheromone to its neighbor set *neighbor*(j) that have the same sleep scheduling through S-MAC protocol. The release of pheromones also consumes energy.

The neighbor set of the j-th node is defined as:

$$neighbor(j) = \{i | 0 \le |l_i - l_j| \le Rc, \quad i,j = 1,\ldots,N\}. \tag{4}$$

where l_i and l_j represent the space position of the i-th and j-th node. For convenience, we assume that nodes are in two-dimensional space.

The released pheromone increment of the j-th node is the following:

$$\tau(j,k) = \begin{cases} 1, & Det(j,k) = 1, \quad j = 1,\ldots,N \\ 0, & \text{otherwise.} \end{cases} \tag{5}$$

when a node receives pheromones from its neighbors, it first determines if it is in a multi-target scenario or not. It then calculates the corresponding pheromone reception probability and randomly receives pheromones according to the reception probability. Note that the amount of pheromones decreases over time at a certain rate. The wake-up probability of the next cycle is calculated according to the current pheromone value. The accumulation of pheromones includes previous residual pheromones and the receival from newly released pheromones. The reception amount of pheromones depends on the pheromone reception probability is discussed in the next subsection.

3.2 Stochastic switching model

Based on the sliding window mechanism, we constructed the stochastic switching model to determine whether there are multiple targets in the detection area. The detailed description of the model is provided below.

If a node continuously discovers the target m times or more in n times detection, we can consider that there are multiple moving targets in the sensing range of the node. This means that the node currently is in a multi-target scenario.

The probability of a node to detect the target is set as P_{det}. If there is only one target in the sensing range, the detection probability of the node is set to P_s. Any of the targets appearing in the node's sensing range is independent. If there are multiple targets in the sensing range, the detection probability of the node is set to P_m. The relationship between the two detection probabilities is as follows:

$$P_m > P_s. \tag{6}$$

If P_{det} is given as:

$$P_{det} = \begin{cases} P_s, & \text{single-target} \\ P_m, & \text{multi-target.} \end{cases} \tag{7}$$

The probability of a node detecting targets m times or more in n times detection is:

$$P = C_n^m P_{det}^m (1 - P_{det})^{n-m} + C_n^{m+1} P_{det}^{m+1} (1 - P_{det})^{n-m-1} + \cdots + C_n^n P_{det}^n. \tag{8}$$

If (7) is substituted into (8):

$$P_{single} = C_n^m P_s^m (1 - P_s)^{n-m} + C_n^{m+1} P_s^{m+1} (1 - P_s)^{n-m-1} + \cdots + C_n^n P_s^n. \tag{9}$$

$$P_{multi} = C_n^m P_m^m (1 - P_m)^{n-m} + C_n^{m+1} P_m^{m+1} (1 - P_m)^{n-m-1} + \cdots + C_n^n P_m^n. \tag{10}$$

Taking a value of m close to n, the limits of (9) and (10) are $P_{single} = P_s^n$ and $P_{multi} = P_m^n$. Therefore, $P_{multi} > > P_{single}$ because $P_m > P_s$. If the values of n and m are very close to each other, this method is feasible to distinguish between single- and multi-target scenarios. We use $n = 4$ and $m = 3$ for the simulation.

We use a sliding window with a fixed size $n = 4$ in this study. Sensor nodes store the detection statuses of the last four cycles. If the target is detected by a node, the status of this node is set to 1; otherwise, it is set to 0. Four detection cycles before the current form a sliding window with a fixed size. Figure 2 shows that the current window consists

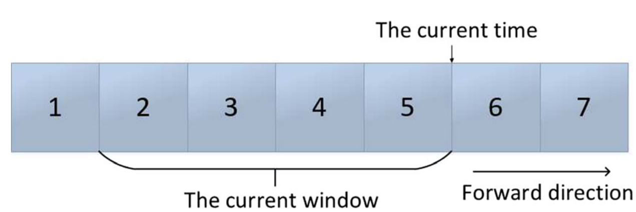

Fig. 2 Sliding window diagram

of four cycles (2, 3, 4, and 5). If a node continuously detects the target three times in the four cycles, the statuses of three consecutive cycles will be 1. For example, the status for each cycle in 3, 4, 5 would be 1 if the node detected a target. Therefore, we can consider that the node is currently in the multi-target scenario; otherwise, it is in the single-target scenario. After the test is completed, the sliding window moves forward by a unit of time and enters the next test. During the next test, the sliding window includes the other four cycles (3, 4, 5, and 6).

Based on the stochastic switching model, we can determine if a node is in a multi-target scenario or not. Subsequently, the pheromone reception probability is adjusted and the corresponding algorithm automatically switches.

3.3 Wake-up strategy optimization for dynamic targets

Firstly, we calculate the pheromone reception probability. The pheromone reception probability of the i-th node is set to $W(i, k)$ in the k-th step. Because of the regular communication and exchange of data between the nodes, each node knows if its neighbors are in the multi-target scenario. For the single-target scenario, $W(i, k)$ should be 1. When multiple targets appear at the same time, the neighbors of the i-th node continuously wake up several times. These neighbors have enough pheromones with large wake-up probabilities; they can complete the detection task. Thus, the pheromone reception amount of the i-th node can be appropriately reduced to reduce its wake-up probability. This means that $W(i, k)$ should be less than 1.

Based on the above-mentioned analysis, the pheromone reception probability is calculated as follows:

$$W(i,k) = 1 - \frac{num}{|f\_neighbor(i)|}. \tag{11}$$

where num is the number of nodes that are neighbors of the i-th node and have detected multiple targets. The parameter $|f\_neighbor(i)|$ is the total number of nodes that are neighbors of the i-th node and have detected single or multiple targets. Thus, if the neighbors of the i-th node detect multiple targets, $W(i, k)$ will be less than 1. Therefore, the pheromone reception amount of the i-th node will decrease.

The pheromone of a node is uniformly released to all neighbors once the target is detected by it. For example, the pheromone amount $I(i, k)$ released by the i-th node to each neighbor in the k-th step is as follows:

$$I(i,k) = \frac{\tau(i,k)}{|neighbor(i)|}. \tag{12}$$

where $|neighbor(i)|$ is the total number of neighbors of the i-th node.

The pheromones in the sensing range of node A_j are uniform and there are two sources of pheromone accumulation $I_j(k)$:

1. The newly released pheromone $\Delta I_j(k)$ of A_j and its neighbors in the k-th step:

$$\Delta I_j(k) = \sum_{i \in neighbor(j)} (I(i,k)). \tag{13}$$

2. The residual pheromones of the previous $k-1$ steps. The pheromone decays with time, with a certain proportion ρ ($\rho \in [0,1]$); the residual pheromone is $(1-\rho)I_j(k-1)$.

Therefore, the final value of the pheromone is calculated as follows:

$$I_j(k) = W(j,k) \times \Delta I_j(k) + (1-\rho)I_j(k-1). \tag{14}$$

The wake-up probability of a node in next cycle is:

$$P_j(k+1) = max\left\{\frac{I_j^{min}}{I_j^{max}}, min\left\{1, \frac{I_j(k)}{I_j^{max}}\right\}\right\}. \tag{15}$$

where I_j^{max} is the maximum pheromone content and I_j^{min} is the minimum content. Detailed proof of these two factors is given in [5]. Note that a sensor node will wake up at the minimum probability I_j^{min}/I_j^{max} when the target does not appear in the detection region. This ensures that the least energy is used to detect the target. Based on the stochastic switching model, we can successfully distinguish between single- and multi-target scenarios. Subsequently, the pheromone reception probability is adjusted. Therefore, the pheromones of the node decrease and the wake-up probability decreases. Finally, the algorithm can achieve the purpose of saving energy.

3.4 Algorithm implementation

The working process of the sensor nodes in this study is as follows. Figure 3 is the algorithm flow chart.

If a node still has energy, its state will be determined by a random number in the range of 0 to 1. If the random number is smaller than the wake-up probability, the node will wake up to search the target. Otherwise, the node will sleep. If the k-th node detects the target, it will release a certain amount of pheromones to the other nodes within its communication range. This process consumes some energy. If the target is not detected by the node, the pheromone increment is set to 0 and no energy will be consumed.

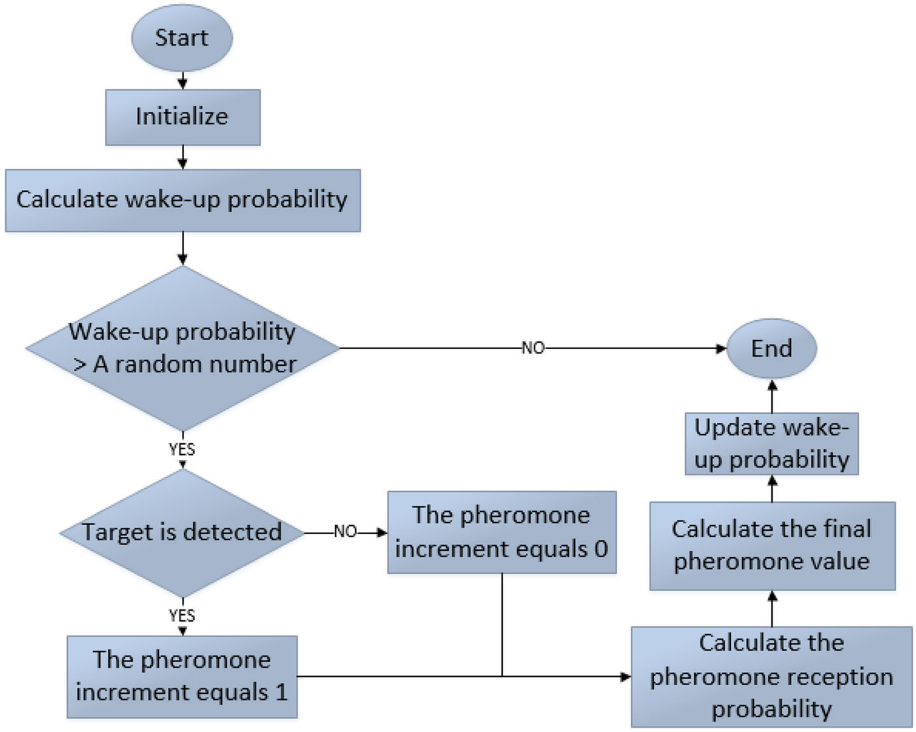

Fig. 3 SMTS algorithm flow chart

Based on the method described above, each node determines whether it is currently in the single- or multi-target scenario and dynamically adjusts the pheromone reception probability according to (11). The wake-up probability of the next cycle can then be calculated using (15).

The pseudo-code used in this paper is as follows:

Algorithm 1 SMTS Algorithm

```
Initialize pheromone content I_j(1) = I_j^min, Energy = E, and P_j(1) = I_j^min / I_j^max
for k = 1 → steps do
   for j = 1 → N do
      Generate a random number rand(j) in the range of 0 to 1
      if rand(j) < P_j(k) then
         Wake up the j-th node in the k-th step
         Energy(j,k) = Energy(j,k) − e
      end if
   end for
   if Target is detected then
      Pheromone release and diffusion
      Energy(j,k) = Energy(j,k) − e
   end if
   Calculate W(j,k)
   Calculate I_j(k)
   P_j(k+1) = I_j(k) / I_j^max
end for
```

4 Simulation and analysis

4.1 Simulation environment setting

We use the MATLAB tool to carry out Monte Carlo simulations of our algorithm. The detailed description is provided below.

We select the detection area to be a square of 200 m × 200 m in which 500 sensor nodes are randomly scattered.

All sensors are the same. Initially, the energy value of each node is 1000. When the energy value reaches 0, the node will stop working. The simulation parameters are shown in Table 1.

There are two types of simulation scenarios. One is the single-target scenario. This means that there is only one target whose parameters are the same as that of Target 1 in Table 2. The other type is the multi-target scenario. There are two targets whose parameters are shown in Table 2. During a single round, the target moves 50 steps from the starting point, which takes 50 s.

The simulation scenarios are shown in Figs. 4 and 5, respectively. The straight lines show the trajectories of the targets, the arrows indicate the movement directions of the targets, and the red dots represent randomly distributed sensor nodes. To maintain the effectiveness of detection and tracking, we set up the rule that the whole network will not be working if the target is not discovered during the continuous movement of 10 steps. This means that the WSN fails.

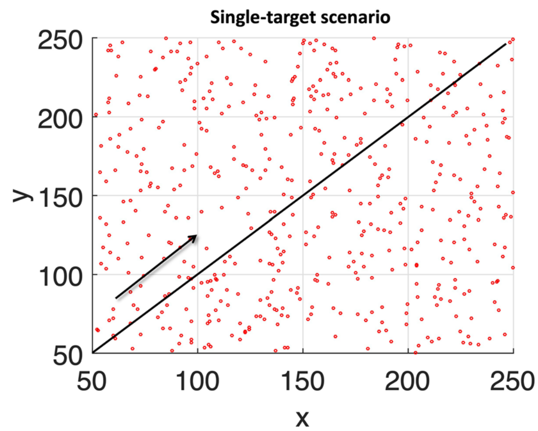

Fig. 4 Single-target scenario

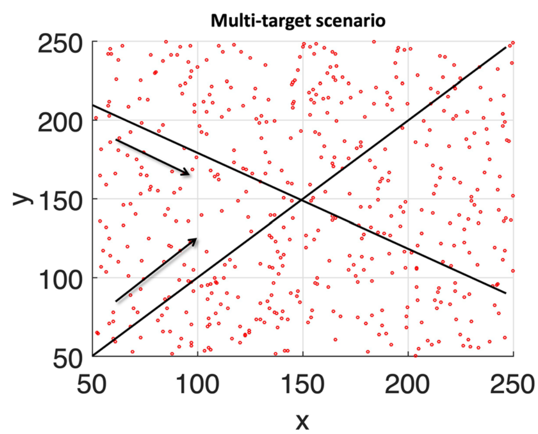

Fig. 5 Two-target scenario

4.2 Performance indicator setting

In WSNs, it is important to determine how to effectively save energy and prolong the lifetime of the whole network during practical application under the premise of ensuring the timely detection and accurate tracking of targets. To better illustrate the performance of our algorithm, we design the following performance indicators to test the optimization of this work.

Table 1 Simulation parameters

R_s	R_c	P_d	P_f	$P_{\min}$	E	e	α	β
15 m	30 m	0.9	0.05	0.3	1000	1	0.05	0.9

Table 2 Target movement parameters

	Starting point	Speed (m/s)	Slope	Movement time (s)
Target 1	[50, 50]	5.66	1	50
Target 2	[50, 210]	5	− 3/5	50

4.2.1 Detection probability

$P_A(t)$ is the probability of the target that is found by the WSN when it is in the t-th step. In addition, this value can indicate the detection effect of the WSN for this target for a certain step. Therefore, the higher the detection probability is, the better is the detection performance.

Define events: The parameter B_t indicates that the target is found in the t-th step and $B_{t,k}$ indicates that the target is found by sensor A_k in the t-th step. The derived equations are as follows:

$$
\begin{aligned}
P_A(t) &\equiv P(B_t) \\
&= 1 - \overline{P(B_t)} \\
&= 1 - P(\overline{B_{t,1}}, \overline{B_{t,2}}, \ldots, \overline{B_{t,sensor(i)}}) \\
&= 1 - P(\overline{B_{t,1}})P(\overline{B_{t,2}})\ldots P(\overline{B_{t,sensor(i)}}) \\
&= 1 - \prod_{k \in sensor(i)} P(\overline{B_{t,k}})
\end{aligned} \tag{16}
$$

$$
=1 - \prod_{k \in sensor(i)} (1 - P_d). \tag{17}
$$

In the simulation, the detection probability is set to 0.9. Therefore, if the target is simultaneously detected by two nodes, the probability is 0.99. At this time, we assume that the target is found by the WSN.

4.2.2 Total number of wake-up nodes

This indicator is used to indicate if SMTS effectively reduces the number of wake-up nodes in the multi-target scenario.

4.2.3 Node utilization rate

This is the ratio of the total number of nodes that detected the target to the total number of wake-up nodes. The rate to a certain extent reflects the effective utilization of energy. A larger value of this indicator indicates that more wake-up nodes participated in the task and detected the target.

4.2.4 Detection steps of the target

We assume that the target is detected as soon as two or more sensors discover the target. This index can be used to measure the detection delay. Fewer steps indicate a shorter delay.

4.3 Simulation results analysis

To effectively evaluate the performance and optimization of SMTS, we compared our algorithm with the BSWC and random activation algorithm in the single- and two-target scenarios, respectively.

We chose three different wake-up probabilities for the RA (random activation) algorithm. The algorithms with wake-up probabilities of 1, 0.5, and 0.077 (minimum wake-up probability) are called RA1, RA0.5, and RA0.077. The same parameters of the five algorithms take the same values. In all algorithms, the experiments are repeated 200 times. The results represent the average values of 200 experiments.

Figures 6 and 7 show that there is almost no difference in the detection probability of a single round between SMTS and BSWC in the single- and two-target scenarios. This shows that the detection effect of the target is unaffected after considering the multi-target sensing mechanism. Because of the larger propagation amount of pheromones around the intersections of multiple target trajectories, the reduction of the pheromone reception amount of the nodes allows to maintain the wake-up probability at a normal level. Meanwhile, the detection probabilities of SMTS, BSWC, and RA0.5 increase to 0.95. However, the detection probability of RA0.077 is below 0.4, which means that the target cannot be detected in most cases.

Figures 8 and 9 show the trend of the total number of wake-up nodes in a single round. As shown in Fig. 8, SMTS and BSWC have essentially the same total number of wake-up nodes. This indicates that the proposed algorithm does not affect the target detection of the sensor networks in the single-target scenario. At the same time, the total number of wake-up nodes of SMTS is greater than that of RA0.077. The wake-up probability of all nodes is maintained at 0.077 before the target appears. After the target appears, the amount of pheromones of the nodes

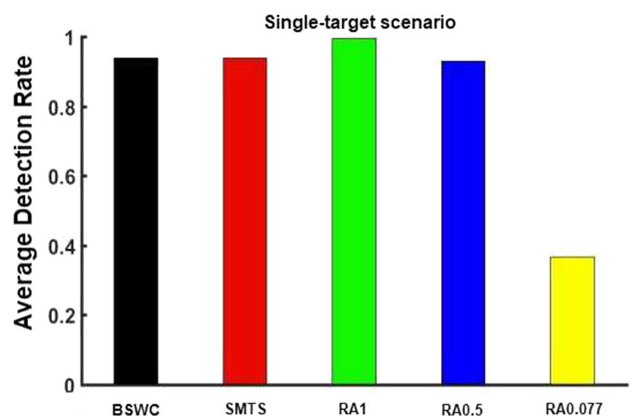

Fig. 6 Average detection rate for the single-target scenario

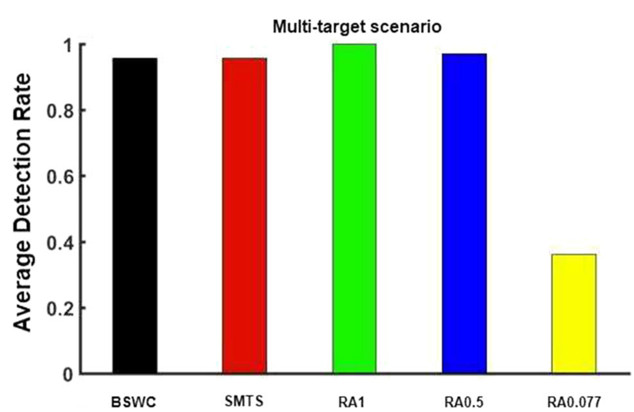

Fig. 7 Average detection rate for the two-target scenario

around the target increases due to the propagation of the pheromones. The wake-up probability of these nodes increases. The total number of wake-up nodes in SMTS is less than that of RA0.5, which is approximately half of that of RA0.5. Because of the dynamic adjustment of pheromones in SMTS, the number of wake-up nodes is very small at locations at which the target does not appear. Therefore, the total number of wake-up nodes is smaller. At the same time, the rapid increase of the total number of wake-up nodes also shows that SMTS can wake up the nodes around the target in time.

Figure 9 shows the trend of the total number of wake-up nodes in the two-target scenario. Based on Fig. 5 and the movement speed of the targets, some nodes receive multiple pheromones from their neighbors that detected different targets after the target moves forward approximately 13 steps. After the two targets cross, the total number of wake-up nodes in SMTS is notably smaller than that in BSWC and remains steady (Fig. 9). This indicates that our algorithm effectively reduces the number of redundant wake-up nodes by alleviating the situation of excessive pheromone receival. Our algorithm saves energy.

Figures 10 and 11 show the trend of the number of nodes that detected the target in a single round. The total number of nodes that detected the target in SMTS is almost equal to that of RA1 and significantly greater than that of RA0.5 and RA0.077. This indicates that SMTS always has more nodes detecting the target and the detection effect is remarkable. At the same time, Fig. 9 shows that SMTS does not prevent the nodes around the target from performing detection tasks, although it reduces the total number of wake-up nodes. This means that SMTS almost only reduces the number of invalid wake-up nodes.

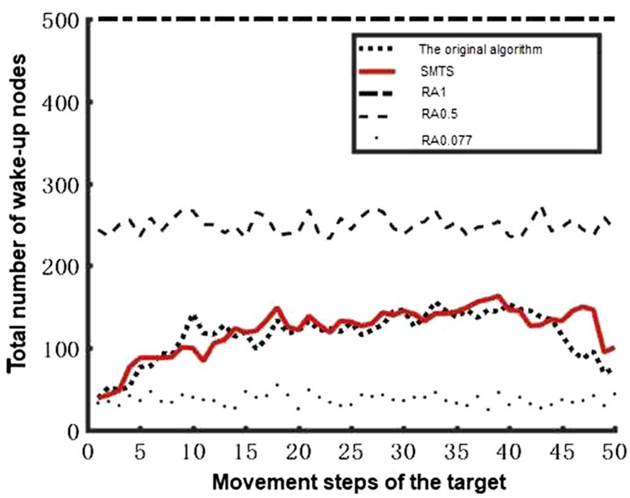

Fig. 8 Total number of wake-up nodes for the single-target scenario

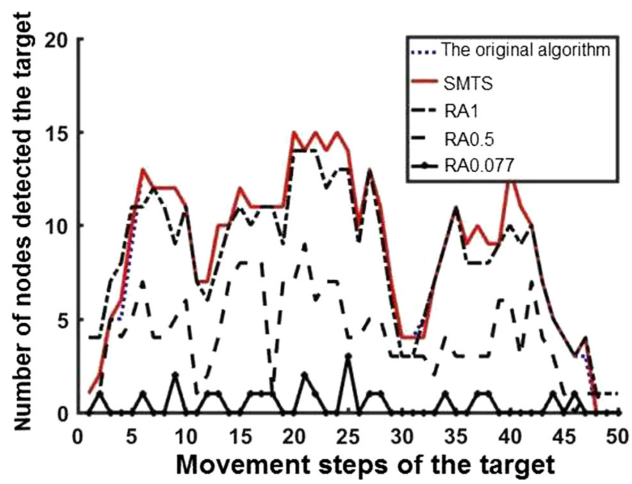

Fig. 10 Number of nodes that detected the target in the single-target scenario

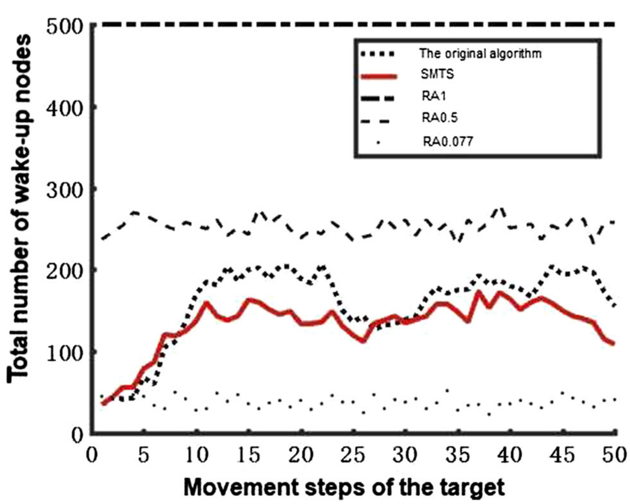

Fig. 9 Total number of wake-up nodes for the two-target scenario

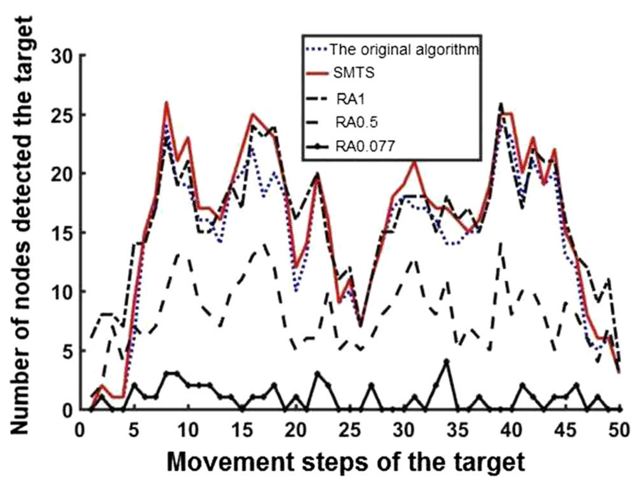

Fig. 11 Number of nodes that detected the target in the two-target scenario

Figures 12 and 13 show the trend of the node utilization rate in a single round. As shown in Fig. 12, SMTS and BSWC have essentially the same node utilization rate. It is significantly larger than that of RA1, RA0.5, and RA0.077. The larger node utilization rate indicates that the proportion of the nodes that detected the target of the total number of wake-up nodes is larger. Based on Fig. 8, SMTS achieves the greater node utilization rate. Thus, SMTS successfully reduces the energy consumption.

The node utilization rate associated with two targets in the detection region is shown in Fig. 13. The node utilization rate in SMTS is significantly greater than that of BSWC. The SMTS reduces the number of invalid wake-up nodes by adjusting the pheromone reception probability. Meanwhile, the total number of nodes that detected the target is not reduced in SMTS (Fig. 11). Therefore, the node utilization rate in SMTS increases.

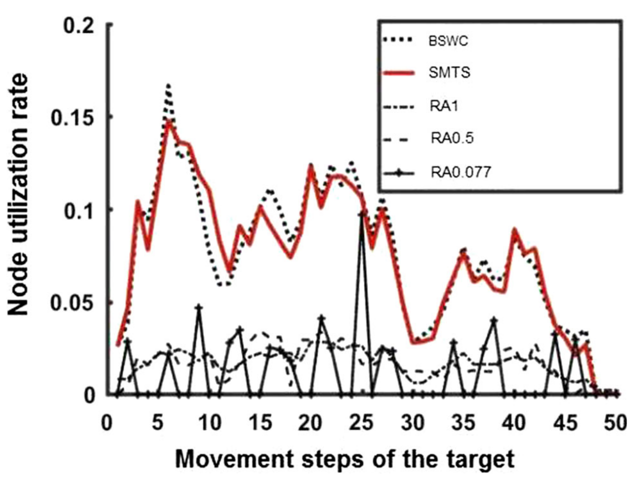

Fig. 12 Node utilization rate for the single-target scenario

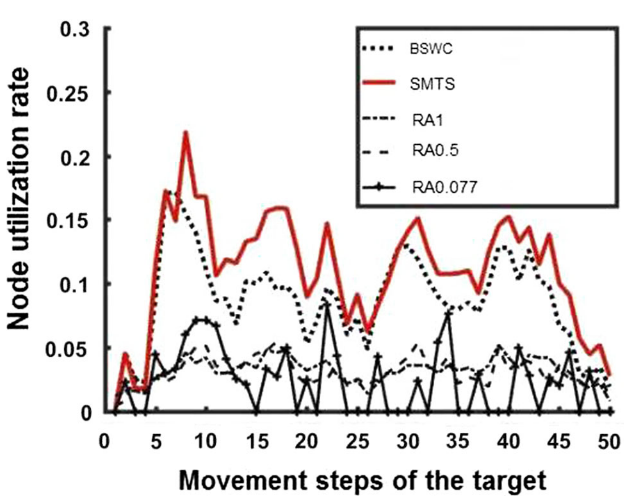

Fig. 13 Node utilization rate for the two-target scenario

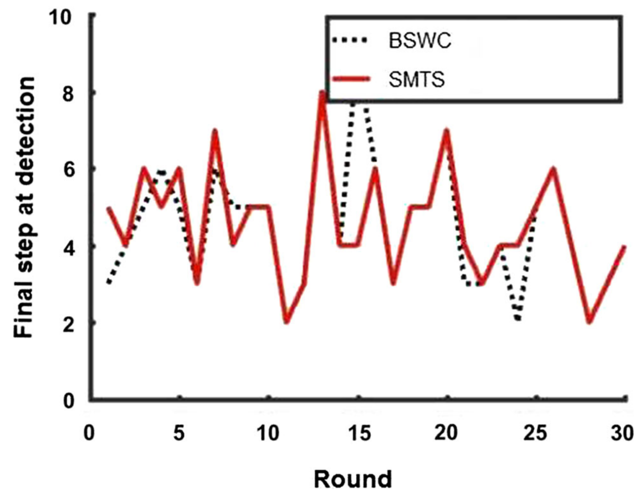

Fig. 14 Final step at detection for the single-target scenario

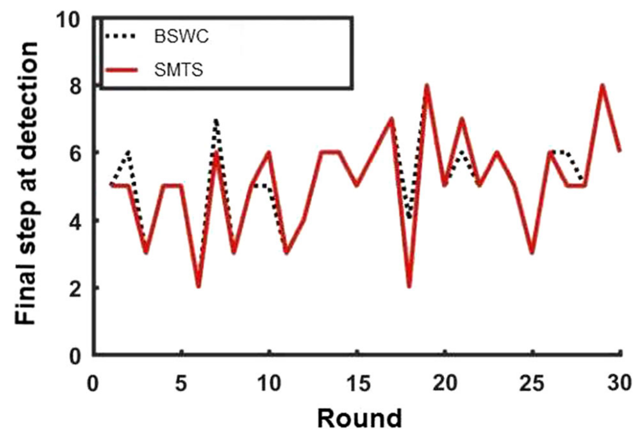

Fig. 15 Final step at detection for the two-target scenario

Figure 14 shows that the target has moved roughly four steps when it is detected in SMTS and BSWC in the single-target scenario. The detection speed of the targets in SMTS is roughly the same as that in BSWC when there are two targets (Fig. 15). Therefore, SMTS can quickly detect the target.

Based on the above-mentioned analysis, SMTS effectively reduces the number of wake-up nodes around the intersections of different target trajectories and notably saves energy at these locations while ensuring detection efficiency and accuracy.

5 Conclusion

In this paper, we propose a multi-target sensing mechanism, which uses the stochastic switching model to distinguish between single- and multi-target scenarios. If a node continuously discovers the target m times or more in

n times detection, we can consider that there are multiple targets in the sensing range of the node. We first put forward the method to calculate the pheromone reception probability to reduce the pheromone content of the nodes and keep it at a normal level around multiple target crossings. Subsequently, we add this factor to the calculation of the wake-up probability to wake up fewer nodes and save energy. The simulations demonstrate that SMTS fully considers the impact of different numbers of targets. Moreover, it prolongs the service lifetime of the WSN while ensuring detection efficiency and accuracy.

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