Flow Identification of Intelligent Wireless Communication Network Based on Optimal Symbol Output Control

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Abstract: Markov decision model is the most suitable decision algorithm for random dynamic system based on Markov process theory. Through its decision set at each node, the path that meets the requirements is selected as the allowed decision set for data forwarding, and it does not completely depend on the historical moment of the entire system. Since multiple paths may be included in the allowed decision set, further optimization is required to select the optimal path. In the paper, Markov routing decision model is applied to comprehensively consider the communication distance matrix, node transfer probability, and the number of node neighbors in the network. Equipped with different weights according to actual application scenarios, the nodes within the communication range are evaluated, and the evaluation results are used as the basis for the optimal symbol output to control the optimal path, thereby improving the identification of wireless communication network traffic, extending the network life cycle, and achieving global routing optimal strategy selection.

1. Introduction
When data is forwarded in a wireless communication network, if only a few or one parameter in the network transmission process is considered, it cannot adapt to the development characteristics of the future Internet of Things. Therefore, it is an inevitable choice to consider multiple parameters of link quality, node remaining energy and number of node neighbors to reflect network performance. Comprehensively adopt multiple parameters and dynamically adjust the balance between parameters according to different network requirements. This is neither a one-sided emphasis on one or two of the parameters, nor the average of multiple parameters, which requires necessary decisions on link establishment. Ant colony algorithm is a simulated evolutionary algorithm used to find the optimal path in graph theory. Its algorithm refers to the ant colony foraging process to select the global optimal strategy for the Internet of Things routing link to make the network run in an optimal state.

In the paper, a data forwarding link optimization algorithm based on Markov ant colony decision is proposed. The algorithm enhances the ability to find the optimal next-hop network node in the communication process, and uses Markov properties to reduce the possible adverse effects of early node selection. Markov decision model is an optimal decision model of random dynamic system based on Markov process theory. It can use its decision set at each node to select a path that meets the requirements as the allowed decision set for data forwarding, and do not depend on the historical moment of the system. Facing the decision set may contain multiple paths to select the optimal path. The method comprehensively considers multiple parameters such as link quality, node remaining energy and number of node neighbors, and dynamically adjusts the balance between the parameters according to differentiated network requirements, and selects the transmission path that meets the conditions as the data forwarding decision set. And the ant colony foraging process is referred to select the global optimal strategy for the Internet of Things routing link to make the network run in an optimal state.
2. Markov ant colony decision process
In the decision process based on Markov ant colony, the Markov decision model is the optimal decision model of random dynamic system based on Markov process theory. It can use its decision set at each node to select the path that meets the requirements as the allowed decision set for data forwarding, and it does not depend on the historical moment of the system. Since multiple paths may be included in the allowed decision set, further optimization is required to select the optimal path. First, Markov node should be screened. Then, based on the remaining node settings, and it is used as a starting point to evolve from generation to generation through the ant colony algorithm, until the set optimization goal is met.

The Markov decision process is shown in Figure 1.

![Figure 1. Markov decision process](image1)

When the source node sends data to the target node, the process of establishing the communication link between the source node and the target node is regarded as the process of ants looking for food, the source node is used as an ant nest, and the destination node is used as food. The node calculates the transition probability of the allowed decision set within the communication range, and selects the optimal path through the transition probability. Since the direct transmission of data packets will increase network delay and energy consumption, it is proposed to use forward ants to find the optimal path before data transmission. The route selection process is shown in Figure 2.

![Figure 2. The foraging routing process of the ant colony for the Internet of Things network based on the Markov decision model in the t stage](image2)
In Figure 2, Given that the node $a$ as the source node, that is the ant nest, and the node $b$ as the destination node, that is food. Sending forward to ants is done during route discovery, and forwarding to ants is done during route confirmation. The purpose of the forward ant is to search for available paths and select the optimal link before sending data, and the purpose of the backward ant is to update the link, determine the optimal link, and transmit data according to the link. When the source node has data to send to the destination node, the source node first checks the routing table. If there is an entry to the destination node, data transmission is performed according to the existing route. If there is no existing route, the Markov routing decision process is adopted. According to the application background, the weight of multiple parameters such as link quality, node remaining energy and number of node neighbors is weighed to evaluate the path within the communication range and calculate the evaluation function value $V_i(a)$ of the path that meets the requirements within the node communication range at the current stage. The pheromone concentration is obtained according to the evaluation function value, and the transition probability $p_i(a)$ of the decision set allowed within the communication range of the node at the current stage is calculated, and the path corresponding to the maximum transition probability is found as the forward direction of the ant. When the forward ant arrives at the destination node, the destination node selects the link with the smallest number of hops and passes the backward ants backward according to the path, updates the routing table of each node along the road until the ant nest, and announces the death of the backward ant, and the link is established until completing the process.

The basic steps of Markov ant colony decision-making operation to solve the problem are as follows:

Step 1: The initial environment of network survival, the number of sensor nodes, and setting source and destination nodes are defined;
Step 2: Whether there is a destination node, if not, the next step should be performed;
Step 3: Markov decision is used to evaluate the state of the node;
Step 4: Reconfiguring the network is done for the nodes after the evaluation;
Step 5: The ant colony algorithm selects the best routing path;

The basic flow diagram of Markov ant colony decision-making is shown in Figure 3.

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**Figure 3** The basic flow diagram of Markov ant colony decision-making
As a new type of cluster intelligent optimization algorithm, GWO algorithm imitates the population behavior of ant colony, and compares the process of ant colony tracking and surrounding prey to the optimization process, so as to achieve the purpose of obtaining the optimal solution. The cluster head optimization problem of WSNs is mapped to GWO. The position of the ant colony represents the position of the sensor, and the position where the prey is hunted is the position of the cluster head, which is also the position of the optimal solution described in this paper. In the ant colony algorithm, \( a \) ant, \( b \) ant, and \( s \) ant respectively represent the first dominant node, the second dominant node, and the third dominant node in the wireless sensor network. They are located at the top of the population and have the best decision-making ability compared to ordinary ant colonies. Compared with the three sensor nodes with the highest priority, other ant colonies must obey the instructions of the first dominant node with the highest priority. According to the existing algorithm, the GWO algorithm is divided into two main processes: encircling the prey and hunting. The distance between the prey and the ant colony needs to be ascertained during the encircling process. The expression is as follows:

\[
b = c \left| - \frac{1}{x_p} \right|
\]

(1)

Where \( X \) is the position of the prey when iterating to \( x_p \), \( x^1 \) is the position of the ant colony at the moment, and \( c \) is a constant factor:

\[
C = 2 \times r_c \ (r_c \in [f(D, 2)])
\]

(2)

Then, based on the surrounding prey information, the next specific direction of the ant colony can be calculated. The next step of the ant colony hunting direction is:

\[
x'^{r+1} = |x' - SD'|
\]

(3)

S is the convergence factor expressed by the following formula:

\[
S = 2 \cdot S \cdot T_2 - s(TO_2 \in [0, 2])
\]

(4)

In the hunting process of the traditional algorithm, the three ants with the highest priority will directly determine their final position. The expression is substituted into formula 2 which its form is:

\[
x_{a+1} = x_a - 1_b
\]

(5)

\[
x_{a+1} = x_a - \frac{1}{b} \cdot D_a
\]

(6)

\[
X_{a+1} = X_a - 1_a \cdot D_a
\]

(7)

Finally, the position of the prey can be obtained:

\[
x^{-1} + 1 = \frac{x^{-1}x^{-1} + x^{-1}x^{-1} + x^{-1}x^{-1}}{3} + \frac{x^{-1}x^{-1}}{3}
\]

(8)

3. Algorithm improvements

3.1 The ant colony fitness function model based on energy and distance

The greater the distance between the node and the base station, the greater the energy consumed by the node. The main basis for whether the current node has a chance to become the cluster head is the remaining energy of the current node. Choosing nodes with high remaining energy helps to improve the survival time of the network and prevent the occurrence of energy holes. Therefore, in the paper, a fitness function is designed based on the remaining energy of the node and the communication distance between the node and the base station, as follows:

\[
E = \begin{cases} 
\frac{E}{F} + \frac{A}{D} \cdot \frac{D_A}{D}, & E_b = 0 \\
0, & E_b \neq 0
\end{cases}
\]

(9)
In formula 10, other losses during the transmission process are ignored, and it is assumed that whether it becomes a cluster head has only the influence of distance and energy, and $D_{Avg}$ is the average distance between nodes in the current cluster and the base station. Meanwhile, in order to emphasize the first advantage node, the second advantage node, and the third advantage node of the wireless sensor network, the optimal weight factor is reset in the process of determining the position of the cluster head node for the entire heterogeneous network. The improved best cluster head position is as follows:

$$E = \sum_{i=1}^{n} F_i \quad (E_i \geq 0)$$

(10)

In formula 10, $E_i$ is the energy of the i-th node, $F_i$ is the fitness value of the i-th node, and $n$ is the number of nodes. The improved best cluster head position is obtained by maximizing the energy of the cluster head node.

$$x^{v+1} = F_{x_a}^v x_a + F_{x_b}^v x_b + F_{x_c}^v x_c$$

(11)

In formula 11, $x_a$, $x_b$, and $x_c$ are the first, second, and third advantages, respectively, and each of the weighting factors is:

$$f_u = \frac{f_u}{f_u + f_b + f_s}$$

$$f_b = \frac{f_b}{f_u + f_b + f_s}$$

$$f_s = \frac{f_s}{f_u + f_b + f_s}$$

(12)

3.2 An improved adaptive adjustment strategy of convergence factor

According to the calculation method of the algorithm, the convergence rate of the function is faster at the initial stage of the iteration. As the number of iterations increases, the algorithm iteration rate gradually decreases. It can be seen that the iteration factor $s$ plays a key role in the convergence of the algorithm. Based on the traditional GWO algorithm, the paper adopts a non-linear adjustment strategy of the cosine function, and uses the non-linear reduction characteristic of the cosine function on $[0, \frac{\pi}{2}]$ to expand the original interval $s \in [0, 2]$ to:

$$s = 2 \cos \left( \frac{t}{t_{max}} - \frac{\pi}{2} \right)$$

(13)

In formula 13, $t_{max}$ is the maximum number of iterations, and $t$ is the current number of iterations. From the fitness value in formula 11, the fitness value of each wireless sensor network node in each cluster can be obtained. Each fitness value $f_i$ is compared with the average fitness value. If its fitness value is higher than the average fitness value, it is judged that the individual is close to the hunting prey, and the forward direction of the population should be adjusted in time. Otherwise, the influence range of the control parameters should be expanded and the global search interval should be enhanced, as follows:

$$s = \begin{cases} 2 \cos \left( \frac{t}{t_{max}} \right), & f_i \geq f_{Avg} \\ -2t + i, & f_i \leq f_{Avg} \end{cases}$$

(14)

4. Simulation experiment and analysis

The number of iterations to 1000 in MATLAB is set, the nodes are filtered that meet the conditions...
according to Markov, are also selected that meet the conditions, and the final path optimization is completed. Figure 4 shows the randomly generated node graph, and randomly sets the initial network configuration for the node, and specifies the maximum communication radius DDD of the node. The specific parameter settings are shown in Table 1.

| Parameter                  | Value             |
|----------------------------|-------------------|
| Network range              | \{100 m\}        |
| Number of nodes            | 30                |
| Alpha initial pheromone    | 0.76              |
| Tau initial pheromone matrix | Tau=ones(25,25) |
| Rho Pheromone Evaporation Coefficient | Rho=ones(25,25) |
| Pheromone increase intensity factor | 0.3 0.3 \times 10^{-i} |

Figure 4. The randomly generated node graph

To realize the dynamic balance of the Internet of Things link establishment, it is necessary to comprehensively consider the three factors of the link quality in the network, the remaining energy of the node, and the number of node neighbors. The Markov routing decision model is used to evaluate the nodes within the communication range of the nodes, and the evaluation results are used as the basis for the ant colony to find the optimal path, thereby improving the overall performance of the network. The result of Markov decision to node optimization is shown in Figure 5.
Figure 5. Node optimization of Markov

Figure 6 shows that in the same network environment, the time delay in the Markov decision network is compared with the traditional ant colony algorithm. The simulation results show that the information transmission process of the network has lower delay transmission.

Figure 6. Time delay and cost of Markov ant colony decision-making

In the initial state, the node is affected by the location and the number of neighbor nodes, the uncertainty in the network transmission process causes the robustness of the network to decrease, and the living space is greatly weakened. The blue line in Figure 6 is the algorithm proposed by the paper, and the black line is the traditional ant colony algorithm. Experimental results show that the proposed method effectively reduces the delay and cost of the network. Compared with the traditional ant colony algorithm routing method, the cost is saved by 46%, and the delay is saved by about 54.3%.

5. Conclusion
In the paper, starting from the link quality in the network, the remaining energy of the node and the number of neighbors of the node, it is equipped with different weights to achieve equilibrium according to the actual application environment, and the equilibrium result is used as the evaluation standard of the evaluation function in the Markov routing decision model. The multi-group Markov routing decision model is constructed based on the Internet of Things, and the allowed decision set of the node is obtained through the value iteration process, that is, the data forwarding path set. The ant colony foraging process for route selection is imitated, the transition probability of nodes is calculated in the decision set, and the transition probability is used to complete the establishment of the optimal data transmission path for the Internet of Things link, so that can improve the overall performance of the network.

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