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A Hibernation Scheduling Method for Opportunistic Network Nodes Based on Convolutional Neural Network

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Abstract

The conventional scheduling method is mainly based on the path scheduling of source nodes and destination nodes, and the failed nodes and redundant nodes affect the final scheduling effect. Therefore, a hibernation scheduling method of opportunistic network nodes based on convolutional neural network is designed. The dormant scheduling model of opportunistic network nodes is constructed, and the dormant network nodes in the overlapping areas of perception are fused to reduce the energy consumption of data transmission and ensure the efficiency of network message transmission. Based on convolutional neural network, the cross-layer scheduling residual of dormant opportunity network nodes is eliminated, the message characteristics of nodes scheduled in the previous layer are mapped to the current scheduling layer, and messages are propagated back to the previous layer during the scheduling process, thus alleviating the problem of network data gradient disappearing. The simulation results show that the scheduling effect of this method is better and can be applied to real life.

Keywords: *Convolutional neural network, Opportunistic network node, Hibernation scheduling method.*

Introduction

Wireless sensor network nodes are mainly based on the planning of sensing range, which connects the source node and the destination node into multiple paths, and changes one path when congestion occurs, thus improving the data transmission efficiency. Sensor nodes use limited energy, artificial node replacement or energy supplement [1-3]. Under the condition of ensuring the normal work of the network, it is the key to judge the excellent network quality to optimize the node life and ensure the integrity and effectiveness of data transmission by using the node energy. In general, when sensor nodes are idle, listening to data changes consumes most of the energy [4-6] . Therefore, transforming idle nodes into dormant nodes can effectively reduce the energy consumed by data transmission.

The deployment of dormant nodes in the target area has a certain scale, and the sensing areas of nodes overlap, which will lead to high redundancy of data and affect the data transmission effect. On the basis of ensuring the data transmission performance, it is necessary to schedule the node's dormant state or wake-up state [7-8] . Putting different nodes into dormant and wake-up state can not only eliminate redundant data, but also reduce channel interference, thus effectively improving energy consumption. Opportunistic network does not need a complete path from the source node to the destination node and can realize data transmission [9-11] by taking advantage of the opportunities brought by node movement. By using the "store-carry-forward" mechanism to transmit messages, even in disconnected

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networks, messages can be sent, which is more suitable for practical self-organizing networks. Opportunistic network is mainly a routing and forwarding mechanism and a node movement model, which can solve the problem of message transmission with disconnected networks. The dormant scheduling of opportunistic network nodes can reduce the traffic of nodes, thus completing data transmission [12-14] on the premise of saving energy. In order to make the data transmission effect better meet the data transmission requirements of opportunistic networks, this paper designs a hibernation scheduling method for opportunistic networks by using convolutional neural networks.

Methodology

Build An Opportunistic Network Node Hibernation Scheduling Model

In the process of network nodes' movement, they are all in awake state and dormant state. When node I meets node J, there are two opportunities: effective meeting and missed meeting [15-17]. Only when they meet effectively can node I and node J complete data transmission. In this paper, according to the exponential distribution of contact time interval between opportunistic network nodes, the next meeting time of opportunistic network nodes is predicted, so as to avoid the problem that dormant scheduling network nodes miss opportunities and effectively improve the success rate of message delivery. Suppose that there are n dormant nodes in the opportunistic network, and each node i∈N runs periodically at low speed, and its operation mechanism is expressed as:

$$S_i = \langle w_i, T_i, \Delta_t \rangle \quad (1)$$

In the formula (1), S_i is the operation mechanism of the ith dormant node; w_i is the dormant state of node I; T_i is the period length; Δ_t for w_i time. When node I and node J reach the chance of meeting, the meeting time is calculated as follows:

$$t_x = \frac{\sqrt{R^2 - d_c^2}}{w_i(V_i + V_{\max}) + w_j(V_j + V_{\max})} \quad (2)$$

In the formula (2), t_x is the meeting time of node I and node J; R is that communication radiu of the dormant node; d_c is the distance between the meeting node and the nearest dormant node; V_i is the movement rate of node I; $V_{\max}$ is the movement rate of dormant nodes when they meet; V_j is the motion rate of node J. According to the encounter analysis mechanism of data delivery, the dormant state of nodes is adjusted, and the wake-up time of dormant nodes is prolonged or shortened, thus avoiding extra energy consumption [18-19]. Thus, a hibernation scheduling model is constructed, and the expression is as follows:

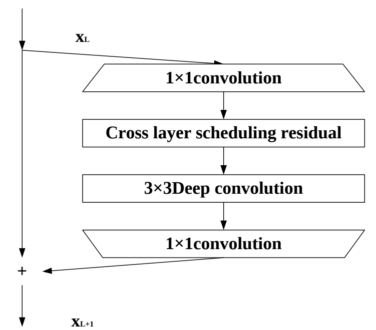
$$EV_i(m) = \sum_{1 \le j \le N, j \ne 1} f(m) \frac{t_x r_{ij}^m}{U_{ij}} \quad (3)$$

In the formula (3), $EV_i(m)$ is scheduling a time slot for the dormant of the i-th dormant node in the m-th dormant cycle; $f(m)$ is a periodic function; r_{ij}^m is the wake-up time slot of node I and node J in cycle m; U_{ij} Is the contact time between node I and node J during the movement. After constructing the hibernation scheduling model, this paper adjusts the data transmission mode according to the node hibernation state. And clear other channel interference before waking up the node to avoid data transmission congestion, reduce network throughput, data loss and other problems.

Eliminating Cross-Layer Scheduling Residual of Dormant Opportunity Network Nodes Based on Convolutional Neural Network

In the whole process of hibernation scheduling, opportunistic network nodes are affected by different hierarchical structures of convolutional neural networks, and redundant data transmission exists [20-22]. When the number of data transmission of dormant nodes in the residual module is more than the number of dormant nodes in the original convolution kernel, reducing the number of layers in the network reduces the network depth. At the same time, the widening factor affects the total parameters of the dormant scheduling model, thus improving the overall performance of the model. In order to eliminate the cross-layer scheduling residual in opportunistic network nodes, this paper takes redundant data as scheduling residual data, and uses convolutional neural network to map the data characteristics of nodes scheduled in the previous layer of the network to the current scheduling layer, and maps the data characteristics of the latter layer to the previous layer in the form of back propagation, which makes the whole data transmission process more complete, thus alleviating the problem of network data gradient disappearing. The elimination of residual module is shown in Figure 1 below.

Figure 1: Schematic diagram of residual module elimination



As shown in Figure 1, the scheduling residual X [23-24] of dormant nodes is subjected to 1×1 convolution, 3×3 convolution and 1×1 convolution to obtain an inverted residual structure X L+1. If X L+1 is re-input into the dormant scheduling model for secondary scheduling, X [23-24] can be eliminated, and the data on X [23-24] can be retained to ensure the data of network nodes. By using convolutional neural network, the overlapping areas of dormant nodes' perception range are fused to reduce the energy consumption of data transmission and avoid the problem of network data redundancy, thus ensuring the efficiency of network message transmission [25]. In the process of network data transmission, this paper uses hibernation scheduling $EV_i(m)$ as a standard, calculate the success rate of data delivery, and the formula is as follows:

$$R = \frac{M}{K} \quad (4)$$

In the formula (4), R is the success rate of data delivery; M is the amount of data successfully delivered to the destination node for the dormant node; K is the total amount of data generated for opportunistic networks. The calculation formula of average energy consumption rate of data transmission is as follows:

$$\overline{E} = \frac{\sum_{i=1} D_i}{E} \times 100\% \quad (5)$$

In the formula (5), $\overline{E}$ is the average energy consumption rate of data transmission; D_i is the energy consumed in transmitting data for the ith dormant node; E is the total energy of network data transmission. The calculation formula of data average outage rate is as follows:

$$\overline{L} = \frac{L}{F} \quad (6)$$

In the formula (6), $\overline{L}$ is the average interruption rate of data; L is the number of data transmission failures caused by connection interruption; F is the total number of data transmissions in the network. Take R 、 $\overline{E}$ 、 $\overline{L}$ as judgment index of dormant schedule effect. The bigger the R is, the better the hibernation scheduling effect is; The smaller the $\overline{E}$ is, the better the hibernation scheduling effect; The smaller the $\overline{L}$ is, the better the hibernation scheduling effect is.

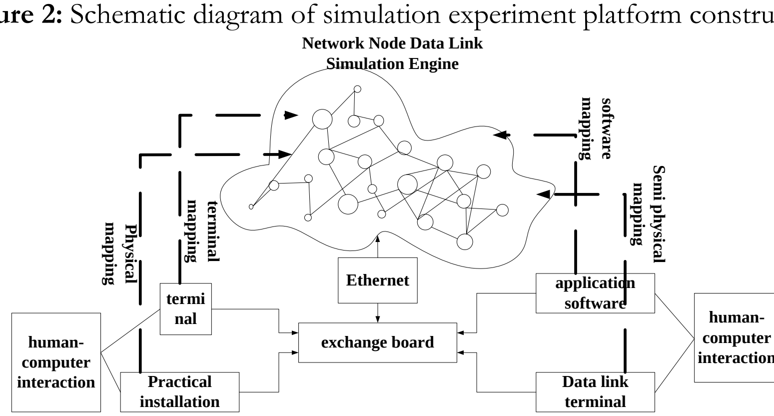
Simulation Experiment

In order to verify whether the method designed in this paper meets the hibernation scheduling requirements of opportunistic network nodes, this paper builds a simulation network scene and makes experimental analysis on the above methods. The final experimental results are presented in the form of comparison between the conventional opportunistic network node hibernation scheduling method based on reinforcement learning, the conventional opportunistic network node hibernation scheduling method based on clustering topology and the opportunistic network node hibernation scheduling method designed in this paper. The specific experimental preparation process and experimental results are as follows.

Experimental Preparation

In this experiment, an opportunistic network simulation tool is used to build a simulation platform, and the dormant state of opportunistic network nodes is simulated by using the network node data link simulation engine. Through terminal mapping, physical mapping, software mapping, hardware-in-the-loop mapping and other forms, the simulation data are interacted. 5min order to facilitate node scheduling, the cycle length is set to 5 minutes, and each cycle is divided into 10 30-second time slots to meet the test requirements. The construction of the simulation experiment platform is shown in Figure 2 below.

Figure 2: Schematic diagram of simulation experiment platform construction



As shown in Figure 2, this simulation experiment platform includes a network node data link simulation engine, which transmits the data of opportunistic network nodes to the installation through physical mapping and to the terminal through terminal mapping; It is transmitted to the application software through software mapping and transmitted to the data link terminal through hardware-in-the-loop mapping. Terminal and installation fuse data in the form of man-machine interaction, application software and data link terminal fuse data in the form of man-machine interaction, and finally fuse data through switch, so that the final data can meet the experimental requirements. After the simulation experiment platform is built, the simulation parameters are set, as shown in Table 1 below.

Table 1: Simulation Parameter Setting Table

Simulation parameters	**Parameter value**	**Simulation parameters**	**Parameter value**
Mobility Model	Random WayPoint	Data transmission rate	250kBps
Map size	600×400	Node Movement Rate	0.5m/s~1.5m/s
Routing method	Epidemic	Propagation radius	10m
Simulation time	12h	Data reduction	1MB~5MB
Initial number of nodes	25 each	Energy consumption for generating/receiving data	0.08J/s
Number of final nodes	250 each	Idle energy consumption	0.02J/s
Number of message nodes	25~250 each	Hibernation scheduling time slot	10 each /30s/cycle
Stop time when nodes transmit data	0s~120s	Warm-up time	1000s

As shown in Table 1, Random WayPoint is used to build a simulation network scene movement model, and 500 mobile nodes are randomly distributed in an area of 600m2×400m2. 250 nodes are regarded as hibernation scheduling nodes, and the initial moving speed of each node is 0.5m/s, and the moving speed of nodes is increased or decreased according to the urgency of data transmission. The minimum moving speed of nodes is not less than 0.5m/s and the maximum is not more than 1.5m/s The initial energy of the node is 3000J, and a data to be transmitted is generated every 25s, which is transmitted to the dormant node by Epidemic, and then transmitted to the final position through the mutual transmission of dormant nodes, so as to meet the data transmission requirements of network nodes.

Results and Discussion

Under the above experimental conditions, this paper randomly selects 250 dormant nodes, and the number of dormant nodes increases from 25 to 250, to judge whether the opportunistic network nodes can complete data transmission under the dormant condition during the dormant scheduling process. The success rate of data delivery, the average energy consumption rate of data transmission and the average interruption rate of data are used as the indicators to determine the data transmission effect of the scheduling method. The data transmission indexes of the conventional opportunistic network node dormancy scheduling method based on reinforcement learning, the conventional opportunistic network node dormancy scheduling method based on clustering topology and the data transmission indexes of the opportunistic network node dormancy scheduling method designed in this paper are compared respectively. The specific experimental results are shown in Table 2 below.

Table 2: Experimental results

Number of nodes/piece	Data transmission metrics for conventional reinforcement learning based opportunistic network node hibernation scheduling methods			Data transmission metrics for conventional cluster based opportunistic network node hibernation scheduling methods			The data transmission indicators of the opportunistic network node hibernation scheduling method based on convolutional neural networks designed in this article		
	Success rate of data delivery /%	Average energy consumption rate of data transmission /%	Average data interruption rate /%	Success rate of data delivery /%	Average energy consumption rate of data transmission /%	Average data interruption rate /%	Success rate of data delivery /%	Average energy consumption rate of data transmission /%	Average data interruption rate /%
25	88.26	15.62	17.56	86.32	12.63	12.12	96.23	2.36	1.12
50	86.42	20.36	21.32	85.43	14.56	11.36	98.72	3.45	1.03
75	85.63	24.42	22.47	85.21	16.28	10.94	97.36	5.32	0.96
100	83.21	28.36	24.96	86.37	19.36	13.61	99.62	6.74	1.14
125	81.56	35.73	26.75	87.52	21.54	14.52	98.56	8.96	1.56
150	78.36	41.56	28.54	88.14	25.32	11.14	99.14	9.21	1.43
175	75.42	55.43	31.28	89.54	26.43	12.23	98.35	9.36	1.21
200	74.37	68.96	35.47	90.41	28.36	15.46	99.99	9.48	1.08
225	72.12	75.24	38.92	85.58	29.42	11.33	98.96	9.55	0.84
250	69.36	86.32	42.63	86.32	29.83	12.47	99.43	9.82	1.15

As shown in Table 2, this experiment takes the success rate of data delivery, the average energy consumption rate of data transmission and the average interruption rate of data as the effect indicators of the scheduling method. Among them, the success rate of data delivery indicates that the opportunistic network node can transmit data correctly in the dormant state; The higher the success rate of data delivery, the more times the opportunistic network node correctly transmits data in the dormant state, and the better the hibernation scheduling effect. The average consumption rate of data transmission indicates the energy consumed by opportunistic network nodes in the dormant state when transmitting data correctly; The lower the average consumption rate of data transmission, the less energy the opportunistic network node consumes when it delivers data correctly, and the better the hibernation scheduling effect. The average interruption rate of data indicates the interruption of opportunistic network nodes when they deliver data correctly in the dormant state. The lower the average data interruption rate, the fewer the interruption times and the better the hibernation scheduling effect. All other things being equal, after using the data transmission index of the conventional opportunistic network node dormancy scheduling method based on reinforcement learning, the success rate of data delivery changes in the range of 68%~89%, and decreases with the increase of dormant nodes, so the data delivery effect is not good. The average energy consumption rate of data transmission varies from 15% to 87%, and increases with the increase of dormant nodes, and the data transmission consumption is relatively high. The average data interruption rate varies from 17% to 43%, and increases with the increase of dormant nodes, and the number of data transmission interruptions is relatively high. It can be seen that after using this method, the data transmission effect of dormant nodes is not good, and the hibernation scheduling level decreases accordingly.

After using the data transmission index of the conventional opportunistic network node dormancy scheduling method based on clustering topology, the success rate of data delivery changes in the range of 85%~91% and does not decrease with the increase of dormant nodes, with small fluctuation and relatively high data delivery times. The average energy consumption rate of data transmission varies from 12% to 30% and increases with the increase of dormant nodes. The data transmission consumption is higher than that of the conventional reinforcement learning-based scheduling method. The average data interruption rate varies from 10% to 16%, and the number of data transmission interruptions is improved compared with the reinforcement learning scheduling method. However, on the whole, the data transmission index still cannot meet the demand of opportunistic network scheduling, which affects the final data transmission effect and needs to be further optimized. However, after using the hibernation scheduling method of opportunistic network nodes based on convolutional neural network designed in this paper, the success rate of data delivery changes in the range of 96%~100%, and there is no problem of decreasing with the increase of dormant nodes, so the data delivery effect is more advantageous. The average energy consumption rate of data transmission varies from 2% to 10%. Although it increases with the increase of dormant nodes, the energy consumption of data transmission is always within 10%, and the energy consumption of data transmission is even less. The average data interruption rate varies from 0.8% to 1.6%, and the data transmission interruption times are relatively few or negligible, so the data transmission effect is better. It can be seen that the method designed in this paper has higher data transmission efficiency and lower energy consumption under hibernation scheduling, which meets the data transmission requirements of opportunistic networks.

Conclusion

In recent years, wireless sensor network has become the key to life and production by taking advantage of its data transmission. Data transmission nodes in wireless sensor networks complete data transmission through the path established by the source node and the destination node. However, in the actual transmission process, the nodes are more mobile, the energy limit is greater, and the data transmission power changes accordingly, so it is easy to have failed nodes and affect the data transmission effect under the interference of various factors. Opportunistic network does not need a complete path, but can transmit data by the mechanism of storage, carrying and forwarding, thus avoiding the problem of data transmission failure. In order to reduce the energy consumed by nodes during data transmission, this paper designs an opportunistic network node hibernation scheduling method by using convolutional neural networks. From the aspects of wake-up time, scheduling model and scheduling residual, the effect of node hibernation scheduling's improved, and the effective data transmission is guaranteed.

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