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Optimization Method of Opportunistic Network Routing Based on Deep Reinforcement Learning

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Abstract

The conventional routing optimization method of opportunistic networks mainly solves the problem of network breakage, which can not meet the communication conditions of nodes in complex environment. Therefore, an opportunistic network routing optimization method based on deep reinforcement learning is designed. Optimize the routing mechanism of opportunistic network, use routing protocol to obtain the next node, and transmit network data with three hop paths, and control the communication overhead ratio by reducing the number of data copies, thus ensuring the data transmission efficiency. Based on deep reinforcement learning, the opportunistic network congestion-aware probabilistic routing protocol is selected, and the redundancy of packet forwarding and caching is managed according to the contact probability of opportunistic network nodes and the action value of packet state, thus alleviating the congestion problem of long-term storage nodes of packets. The simulation results show that the optimization effect of this method is better and can be applied to real life.

Keywords*: Deep reinforcement learning; Opportunity network; Routing; Optimization method.*

Introduction

The split, connection and interruption of wireless network are the guarantee of data processing. When wireless interruption is not handled well, the network performance will decline, and even the whole network will be paralyzed [1-3] . Whether it is wireless sensor networks, WSN or mobile Ad Hoc networks, there is a lack of effective solutions to deal with data interruption in wireless networks, which affects the effect of network data transmission. Under this condition, the opportunity network came into being [4-6] . Opportunistic network nodes are constantly moving, and there is no routing path between nodes. The initial position of nodes is not fixed, and the routing path between source nodes and destination nodes is uncertain. Opportunistic network nodes transmit node data by constantly moving and meeting. This communication process will not be affected by network disconnection, and the transmission effect is better [7-9]. At the same time, the nodes of the opportunistic network are not single, and all kinds of wireless communication devices can transmit data to ensure the data transmission effect.

Opportunistic network can be used in complex network environment, and the problem of network data transmission interruption can be solved by node movement, so that the application scope of opportunistic network can be extended to military and civil fields [10-12]. In an opportunistic network, when a moving node meets the next node, the nodes exchange information with each other, store the

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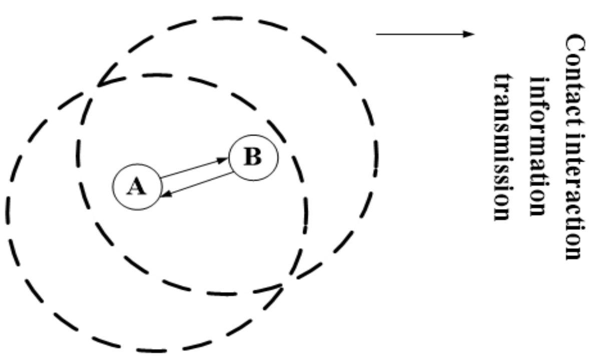
exchanged information in the nodes, and transmit it again when meeting the next node. In this process, routing protocol blessing is needed. Choosing an appropriate routing protocol can determine whether the data needs to be further transmitted when transmitting information, including the transmission validity period of the data, the data cache and the reply received by the node [13-15] . By judging the threshold of node cache, the transmission probability of data is determined. Therefore, based on deep reinforcement learning, this paper designs an optimization method of opportunistic network routing.

Methodology

Optimize the opportunistic network routing mechanism.

In opportunistic networks, the path between nodes is difficult, and there is a certain delay in data transmission due to the uncertainty of node movement. There are few connections between nodes in the opportunistic network, and under the condition that the route is known, the nodes in the opportunistic network have certain additional transmission range [16-18] . In order to transmit valid data, a node stores the data itself until it meets a suitable node and transmits the stored data to a suitable node. The process of information interaction when nodes contact is shown in Figure 1 below.

Figure 1: process diagram of information interaction when nodes contact.



As shown in Figure. 1, after the peer-to-peer connection is established between Node A and Node B, the behavior of the node itself is similar to that of the router, and the route is selected through the centralized unit [19-20]. Routing in the network is controlled by routing protocol. In this paper, the routing optimization method is divided into two parts: routing mechanism and routing protocol. In the optimization of routing mechanism, the next node is obtained by using routing protocol, and the network data is transmitted by three hop paths. The communication overhead ratio is controlled by reducing the number of data copies, thus ensuring the data transmission efficiency.

Selecting opportunistic network congestion-aware probabilistic routing protocol based on deep reinforcement learning.

Opportunity contact caused by node movement in opportunistic networks, the number of data packets is limited, and the transmission capacity of nodes is limited. FUDLU (Forwarding Utility Deep Learning Update) utility learning model of deep reinforcement learning is used to make the information generated by node contact interact, thus completing the update of node state-action value [21-23] . According to the contact probability of opportunistic network nodes and the action value of packet state, the redundancy of packet forwarding and caching is managed, thus alleviating the congestion problem of long-term storage nodes of packets. Opportunistic network routing protocols are shown in Table 1 below.

Table 1: Opportunistic Network Routing Protocol

Field	Illustrate
node ID	The identification number of the packet receiving node
data packet ID	The identification number of the data packet received by the node
Time	Time of receiving data packets
Q value	The state action value corresponding to the maximum introduced contact probability of the data packet at the receiving node
	Fill the field data into the receive confirmation message, with a blank Q value, and send it to node A
	Node A receives the confirmation message and parses and extracts the field data of the confirmation message
Q-value list	$\{(d_1, maxQ), (d_2, maxQ),\ldots,(d_n,maxQ)\}$
Contact freshness list	Set of freshness coefficients in contact with other nodes

As shown in Table 1, the transformation of node ID, the update of node state-action value and the selection of opportunistic network routing protocol are obtained in this paper. Among them, (d_n,maxQ) represents a data unit of node interaction content, and the maximum value of contact probability Q [24] is introduced from the destination node data packet d_n. By obtaining the Q value and Q value list, the node can complete the basic update. At this time, the d_n return value function and discount factor function are replaced by the average value, and different learning coefficients are adopted in the updating process, thus ensuring the effectiveness of routing [25]. In order to analyze the congestion degree of nodes in routing, the buffer idle ratio coefficient of node A is defined, and the formula is as follows:

$$F_a^A = \frac{B_a^A}{B_t^A} \quad (1)$$

In the formula (1),$F_a^A$is the buffer idle ratio coefficient of node A;$B_a^A$is available cache space for point A;$B_t^A$is the initial cache space of node A. Define the congestion coefficient of node A, and the formula is as follows:

$$C_A = e^{-K+F_a^A} \quad (2)$$

In the formula (2),$C_A$is the congestion coefficient of node A;$K$is a constant;e is the base.$K$is an indicator of regulation sensitivity of$C_A$toF_a^A. When$K$ =1, the sensitivity of$C_A$to$F_a^A$is weak; When K=5, the threshold corresponding to the node is 0.9, and when the remaining cache space exceeds half of the total cache space, the congestion problem is not considered; When K=10, the threshold corresponding to the node is 0.5,F_a^A< 0.5, the closer to 0, the more sensitive the change is for$C_A$rightF_a^A. Therefore, the congestion coefficient of node A in the adjacent area is:

$$CN_A = \frac{1}{|N_A|}\sum_{y\in N_A} CF_b \quad (3)$$

In the formula (3),$CN_A$is that congestion coefficient of node a in the adjacent area;$N_A$is the number of neighbor nodes of node A;CF_bIs the regional congestion coefficient of node B. Opportunistic network nodes constantly choose the next hop node, and the limited routing protocol also includes the distribution of data packet copies. According to the source node'sCN_A, get the network resource allocation agreement, the formula is as follows:

$$L_A = \left[L_c - \frac{1}{2}L_c(P'_{s,A} + CN_A)\right] \quad (4)$$

In the formula (4), L_A is allocating protocols for network resources; L_c is the constant value of opportunistic network packet copy; $P'_{s,A}$ is the contact probability between the source node and the destination node. By adjustment L_A, reducing the occupation of network resources by redundant data, thus improving the performance of the whole network. According to the routing protocol, calculate the data delivery rate of network nodes, and the formula is as follows:

$$DDR = \frac{P_z}{P_m} \quad (5)$$

In the formula (5), DDR is the data delivery rate; P_z is the total amount of data sent for that source node; P_m is the total number of data received for the destination node. The average routing overhead rate is calculated as follows:

$$ARO = \frac{W_m - P_m}{P_m} \quad (6)$$

In the formula (6), ARO is the average routing overhead rate; W_m is the amount of data successfully forwarded in the opportunistic network. When the data packet is successfully transmitted to the destination node, calculate DDR、 ARO input each data into the packet ID transmission list, determine the best route, and alleviate the congestion problem of network nodes to the maximum extent.

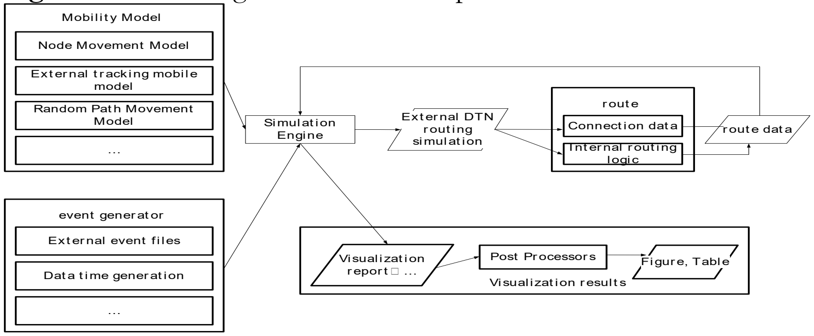
Simulation experiment

In order to verify whether the method designed in this paper meets the requirements of opportunistic network routing optimization, a simulation experimental platform is built, and the above methods are simulated and analyzed. The final experimental results are presented in the form of comparison between the conventional opportunistic network routing optimization method based on neural network, the conventional opportunistic network routing optimization method based on feedback neural network and the opportunistic network routing optimization method designed in this paper. The specific experimental preparation process and experimental results are as follows.

Experimental preparation

The ONE simulation platform is selected in this experiment, which has good visualization service and is more suitable for network environment analysis. The classic routing algorithm is embedded in the platform, and the network simulation software developed for java can better meet the needs of this experiment. As a simulation engine, The ONE simulation platform models the node status and data transmission of opportunistic networks, and each simulation node has undergone a series of updates and optimizations to achieve real network simulation results. The data generated on this platform, after Matlab processing tools, completes the platform visualization. The basic framework of the simulation platform is shown in Figure 2 below.

Figure 2: Frame diagram of simulation platform



As shown in Figure 2, this simulation platform includes mobile model, event generator, simulation engine, external routing simulation, routing, data, visualization results and other modules. The mobile model is used to determine the moving route, electromechanical position information, communication range and other attributes of the simulation node. The event generator generates data, and the routing module determines the data transmission path. The task of visualization results is to process the data in the simulation process and display the simulation data in the form of actual data, thus ensuring the effectiveness of the experiment. In this experiment, network size, node movement model, node communication mode, transmission range, data generation interval, number of nodes, movement rate, data size, transmission speed, buffer size and Tcast are selected as simulation parameters, and three sets of simulation parameter values are obtained respectively for three sets of simulation experiments. The simulation parameters are shown in Table 2 below.

Table 2: Simulation Parameter Table

Parameter	First set of values	Second set of values	Third set of values
network size	1000m×1000m	1000m×1000m	1000m×1000m
Node Movement Model	Random Way Point	Random Way Point	Random Way Point
Node communication method	Bluetooth	Bluetooth	Bluetooth
Opportunity Network Node Data Transmission Range	10m	30m	60m
Data generation interval	25s~35s	25s~35s	25s~35s
Number of Opportunity Network Nodes	30~300 each	30~300 each	30~300 each
Node Movement Rate	0.5m/s~1.5m/s	0.5m/s~1.5m/s	0.5m/s~1.5m/s
Opportunity Network Node Transmission Data Size	100KB~200KB	500KB~1MB	2MB~5MB
Transmission speed	2Mbps	2Mbps	2Mbps
Cache size	50Mb	50Mb	50Mb
Tcast	50s~170s	/	/

As shown in Table 2, three groups of simulation parameters are selected in this experiment, and each group of simulation parameters is tested once, and the average value of the experiment is taken as the final result of this experiment, thus ensuring the authenticity and effectiveness of this experiment. The simulation time of the first group of experiments is 21000 s and TTL is 150min. The simulation time of the second group of experiments is 43200 s and TTL is 300min. The simulation time of the third group of experiments is 62430 s and TTL is 450min.

Results and Discussion

Under the above experimental conditions, this paper randomly selects 30~300 opportunistic network nodes, and takes data delivery rate (DDR), average routing overhead rate (ARO) and average delay (AED) as the optimization performance indicators of the opportunistic network routing optimization method. When other conditions are known, the optimization performance of the conventional opportunistic network routing optimization method based on neural network, the conventional opportunistic network routing optimization method based on feedback neural network, and the optimization performance of the opportunistic network routing optimization method designed in this paper are compared. The specific experimental results are shown in Table 3 below.

Table 3: Experimental results

Number of Opportunity Network Nodes	Conventional neural network-based optimization method for opportunistic network routing selection			A Conventional Optimization Method for Chance Network Routing Based on Feedback Neural Networks			The optimization method for opportunistic network routing based on deep reinforcement learning designed in this article		
	***DDR*/%**	***ARO*/%**	***AED*/ms**	***DDR*/%**	***ARO*/%**	***AED*/ms**	***DDR*/%**	***ARO*/%**	***AED*/ms**
30	84.32	32.47	1927	84.36	21.62	1536	96.24	9.62	921
60	72.47	43.56	1864	85.67	25.48	1422	97.28	12.54	836
90	65.34	49.67	1542	88.42	28.72	1345	95.63	13.67	762
120	58.42	58.92	1361	86.54	34.21	1221	98.74	15.36	654
150	51.54	67.34	1136	87.33	37.54	1058	99.99	18.72	543
180	50.62	72.45	948	85.61	42.47	985	98.95	21.54	422
210	48.36	83.62	921	88.72	45.65	916	97.67	25.36	314
240	45.47	88.77	856	86.47	49.58	852	96.32	26.41	208
270	42.94	95.43	847	87.22	52.36	763	98.88	28.74	156
300	39.44	98.21	832	85.43	55.47	624	99.99	29.36	94

As shown in Table 1, DDR is the data delivery rate of opportunistic networks. The greater the DDR value, the higher the correctness of data transmission between nodes of opportunistic networks and the better the routing optimization effect of opportunistic networks. ARO is the average routing overhead rate of opportunistic network nodes during data transmission. The smaller the ARO value, the smaller the routing overhead of nodes for correctly transmitting data, and the less network resources are consumed for each successful data transmission, which plays an important role in improving network robustness. AED is the end-to-end average delay in the process of data transmission of opportunistic network nodes. The smaller the AED value, the shorter the average time required for data to be received by the destination node, which means that the opportunistic network has stronger routing ability, higher transmission efficiency, less network resource occupation and higher resource utilization, and can adapt to the scene that needs rapid data transmission and ensure the data transmission quality. In this experiment, 30~300 nodes were selected. The more nodes, the larger the ARO value and the smaller the AED value. Only when the ARO value, DDR value and AED value all meet the optimization requirements, the data transmission effect of opportunistic routing can be ensured.

When other conditions are the same, the DDR value changes in the range of 39%~85% after using the conventional opportunistic network routing optimization method based on neural network, and the data delivery rate is relatively low; The ARO value varies from 32% to 99%, and the routing overhead rate is relatively high. The AED value varies from 830 ms to 2000 ms, and the average delay is relatively high. It can be seen that after using this method, the routing ability of opportunistic network selection is weak, the data transmission efficiency is low, and the network resources occupied by each data transmission increase accordingly, which can not meet the demand of opportunistic network reason selection optimization. After using the conventional opportunistic network routing optimization method based on feedback neural network, the DDR value changes in the range of 84%~89%, and the data delivery rate is relatively stable, and it does not decrease with the increase of nodes, which can meet the basic needs of data delivery. The ARO value varies from 21% to 56%, and the routing overhead rate is better than the conventional optimization method based on neural network. AED value varies in the range of 620ms~1600ms, and the average delay is reduced. Thus, after using this method, the routing has been optimized and the performance of data transmission has been improved. However, this method is more inclined to increase transmission nodes, and the routing overhead increases accordingly. The more nodes, the greater the overhead, which cannot meet the requirements of routing overhead optimization and needs to be further optimized. After using the routing optimization method of opportunistic network based on deep reinforcement learning designed in this paper, the DDR value changes in the range of 95%~100%, and the DDR value is relatively stable, and when the number of nodes is 150 and 300, it infinitely approaches 100%, and the success rate of data delivery is higher. The ARO value varies in the range of 9%~30%, and the routing overhead rate is relatively small, so the resources consumed by correctly transmitting data between nodes are reduced and the data value is higher. The AED value varies from 90 ms to 950 ms, and the average time delay is lower than that of the above two methods. Thus, using the method designed in this paper, the data transmission quality of opportunistic networks is higher, and the routing optimization effect is better, which can adapt to various network environments and provide higher quality data transmission guarantee for opportunistic networks.

Conclusion

In recent years, wireless network technology has gradually penetrated into people's lives, providing convenient and fast data services for people's work and life. Opportunistic networks constantly move through nodes to complete data transmission. There is no need to choose a routing path between the source node and the destination node, thus improving the data transmission efficiency. In order to meet the transmission effect of opportunistic network data in complex network environment, this paper combines the advantages of deep reinforcement learning, and designs an optimization method of opportunistic network routing. From two aspects of routing protocol and routing mechanism, the optimal route is selected, so that the task of the highest delivery success rate can be completed with the lowest overhead in the data transmission process of the opportunistic network, and the use quality of the opportunistic network is really improved.

References

Sharma A. An Observable Network Route Support on Interpretation of Cloud Computing[J]. International Journal of Innovative Technology and Exploring Engineering, 2021, 9(8):336-339.

Sharma P, Shukla S, Vasudeva A. Trust-Based Opportunistic Network Offloaders for Smart Agriculture[J]. International Journal of Agricultural and Environmental Information Systems, 2021, 12(1):37-54.

Zhang S, Liu H, Chen C,et al.Activity-based routing algorithm in opportunistic mobile social networks:[J].International Journal of Distributed Sensor Networks, 2021, 17(9):e4860-2988.

Ji M, Cui X, Li J, et al.A Routing Algorithm Based on Network Connectivity Assessment for Maritime Opportunistic Networks[J].Procedia Computer Science, 2021, 187(2):200-205.

Lu Y, Chang L, Luo J, et al.Routing Algorithm Based on User Adaptive Data Transmission Scheme in Opportunistic Social Networks[J].Electronics, 2021, 10(10):1138.

Rashidibajgan S, Hupperich T, Doss R, et al.Secure and privacy-preserving structure in Opportunistic Networks[J].Computers & Security, 2021, 104(17):102208.

Yu Y, Yu J, Chen Z, et al.A Universal Routing Algorithm Based on Intuitionistic Fuzzy Multi-Attribute Decision-Making in Opportunistic Social Networks[J].Symmetry, 2021, 13(4):664.

Koumaras H, Makropoulos G, Batistatos M, et al.5G-Enabled UAVs with Command-and-Control Software Component at the Edge for Supporting Energy Efficient Opportunistic Networks[J]. Energies, 2021, 14(5):1480.

Derakhshanfard N, Soltani R. Opportunistic routing in wireless networks using bitmap-based weighted tree[J]. Computer Networks, 2021, 188(2):107892.

Ri M G, Han Y S, Pak J. a distributed energy-efficient opportunistic routing accompanied by timeslot allocation in wireless sensor networks: [J]. International Journal of Distributed Sensor Networks, 2022, 18(5):660-700.

Rao N, Hua X U, Zisen Q I, et al.Allocation method of communication interference resource based on deep reinforcement learning of maximum policy entropy[J].Journal of Northwestern Polytechnical University, 2021, 39(5):1077-1086.

Zhang D, Zhao J, Zhang Y, et al.Intelligent train control for cooperative train formation: A deep reinforcement learning approach:[J].Proceedings of the Institution of Mechanical Engineers, Part I: Journal of Systems and Control Engineering, 2022, 236(5):975-988.

Envelope B H *, Envelope E Y *, Envelope T H, et al.Dynamic and Interpretable State Representation for Deep Reinforcement Learning in Automated Driving[J].IFAC-PapersOnLine, 2022, 55(24):129-134.

Obert J, Trevizan R D, Chavez A .Efficient Distributed Energy Resource Voltage Control Using Ensemble Deep Reinforcement Learning[J].International Journal of Semantic Computing, 2023, 17(02):293-308.

Mao Y, Tu Z, Xi F, et al.TAPP: DNN Training for Task Allocation through Pipeline Parallelism Based on Distributed Deep Reinforcement Learning[J].Applied Sciences, 2021, 11(11):4785.

Shahbazi Z, Byun Y, Kwak H Y. Smart Home Gateway Based on Integration of Deep Reinforcement Learning and Blockchain Framework[J]. Processes, 2021, 9(9):1593.

Huang Y, Mu Z, Wu S, et al.Revising the Observation Satellite Scheduling Problem Based on Deep Reinforcement Learning[J].Remote Sensing, 2021, 13(12):2377.

Yan Q, Deng Q, Zhang J, et al.Low-latency deep-reinforcement learning algorithm for ultrafast fiber lasers[J].Photonics Research, 2021, 9(8):1493.

Hovell K, Ulrich S. Deep Reinforcement Learning for Spacecraft Proximity Operations Guidance[J]. Journal of Spacecraft and Rockets, 2021, 58(2):1-11.

Beyer K, Beckmann R, Geiendrfer S, et al.Adaptive Online-Learning Volt-Var Control for Smart Inverters Using Deep Reinforcement Learning[J].Energies, 2021, 14(7):1991.

Farazi N P, Zou B, Ahamed T, et al.Deep reinforcement learning in transportation research: A review[J].Transportation Research Interdisciplinary Perspectives, 2021, 11(12):100425.

Pawar S, Maulik R. Distributed deep reinforcement learning for simulation control[J]. Machine Learning: Science and Technology, 2021, 2(2):025029 (15pp).

Chen M, Liu W, Wang T, et al.Edge Intelligence Computing for Mobile Augmented Reality with Deep Reinforcement Learning Approach[J].Computer Networks, 2021, 195(2):108186.

Lver J, Gjrum V B, Lekkas A M. Explainable AI method on a deep reinforcement learning agent for automatic docking[J]. IFAC-PapersOnLine, 2021, 54(16):146-152.

Li X T, Cui C G, Yang N, etal. Temperature Control and Energy Saving of HVAC System Based on Reinforcement Learning [J]. Computer Simulation, 2021, 38(4):6.