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Research Article

A Routing Algorithm for the Sparse Opportunistic Networks Based on Node Intimacy

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Opportunistic networks are becoming more and more important in the Internet of Things. The opportunistic network routing algorithm is a very important algorithm, especially based on the historical encounters of the nodes. Such an algorithm can improve message delivery quality in scenarios where nodes meet regularly. At present, many kinds of opportunistic network routing algorithms based on historical message have been provided. According to the encounter information of the nodes in the last time slice, the routing algorithms predict probability that nodes will meet in the subsequent time slice. However, if opportunistic network is constructed in remote rural and pastoral areas with few nodes, there are few encounters in the network. Then, due to the inability to obtain sufficient encounter information, the existing routing algorithms cannot accurately predict whether there are encounters between nodes in subsequent time slices. For the purpose of improving the accuracy in the environment of sparse opportunistic networks, a prediction model based on nodes intimacy is proposed. And opportunistic network routing algorithm is designed. The experimental results show that the ONBTM model effectively improves the delivery quality of messages in sparse opportunistic networks and reduces network resources consumed during message delivery.

1. Introduction

In the early days, wireless networks used fixed infrastructure for communication. The infrastructure is called a wireless access point, which can receive wireless signals and connect to a wired network. The wireless communication terminal is connected to the AP. When the wireless communication terminal communicates with other nodes, the message must be routed through the AP. Although the terminal has achieved wireless access to the network, the terminal can only move within the signal coverage area of the infrastructure, and the network topology is stable. In this wireless network, although the communication terminal can move as a node, the nodes communicating with each other still requires infrastructure, such as a cellular network or a wireless local area network with the help of infrastructure (such as a wireless router).

In order to solve the terminal's reliance on infrastructure and use wireless network technology in a wider field or a harsh environment, researchers have proposed a wireless MANET (mobile ad hoc network). MANET has good adaptability to changes in topology and does not need to build infrastructure. When the node wants to communicate, other wireless nodes forward messages hop by hop to complete the communication task, and the nodes that pass through during forwarding form a wireless communication link. This technology is often used for communications in military environments and harsh environments. In wireless mobile ad hoc network, one or more stable links need to be established between communicating nodes, that is, the network is basically connected within a period of time.

However, under more severe conditions, all nodes in the network are mobile. Not only does the network have no infrastructure to use, but also, it has no basic connected links. The nodes are in multiple disconnected areas, and these areas are connected by the mobile nodes over a period of time. In this kind of network, people move randomly, there is no stable connection between nodes, which causes the topology of the network to change all the time, and there is almost no link between the two nodes. In this case, if the traditional wireless mobile ad hoc network routing algorithm is used for message transmission, the communication success rate is very low. Since it is necessary to wait for the establishment of a connected link during routing, the communication delay is greatly increased and the communication opportunity is lost.

For solving the above-mentioned problem of intermittent network connectivity, researchers proposed the concept of opportunistic networks [1]. Opportunistic network evolved from wireless MANET, which is not same as the traditional wireless MANET. In opportunistic networks, because communication nodes are mobile and signals are frequently interrupted by interference, there are no stable communication links between nodes, and the network is divided into multiple disconnected subnetworks [2–4]. Therefore, in traditional wireless ad hoc networks, message routing strategies based on end-to-end links cannot be applied in opportunistic networks. In opportunistic networks, an opportunistic network routing strategy of "storage-carry-forward" is adopted [5, 6]. That is, when the split network cannot be connected, the message is stored locally; when the split network is bridged by the mobile node, the message is forwarded.

2. Related Work

Routing algorithm is the focus of research in the field of opportunistic network. A detailed description of the opportunistic network routing algorithm is as follows.

There are two types of opportunistic network routing algorithm [7]. One is zero-message, including flooding mechanism [8], direct forwarding mechanism [9], two-hop forwarding mechanism [10], and fixed backup mechanism [11, 12]. The other is message-assisted, including routing algorithms based on data attributes [13, 14], routing algorithms based on node information [15–17], routing algorithms based on topology information [18, 19], and routing algorithm for information fusion [20, 21]. In recent years, some researchers studied opportunities networks using methods such as sensor networks, machine learning [22–24], and social networks in many different kinds of scenes. For example, wireless sensor networks (WSNs) [25–27] is used to analyse opportunities networks. What is more, some researchers [28–31] established models based on machine learning for optimal routing in the opportunistic network. However, the time series and sociality are more important to improve the message transmission quality [32–34]. In recent years, some scholars have integrated opportunistic network routing algorithms with Internet of Vehicles and edge computing to promote the development of the two fields [35–37].

Opportunistic networks have high utilization value for future communication networks, Internet of Things [38, 39], wireless sensor networks, etc. By studying the information of the nodes in the last time slice, the existing history-based opportunistic network routing algorithms predict the probability that nodes will meet in the next time slice. However, due to vast territory and small population in rural and pastoral areas, few nodes and encounters existed in the opportunistic network. Therefore, the existing opportunistic network routing algorithms obtained little encounter information in previous time slices and cannot accurately predict whether there are encounters between nodes in subsequent time slices, which will decrease the success rate of message delivery and result in an increase in delivery latency. Due to the existing history-based opportunistic network, routing algorithms are not fit to applied in rural and pastoral areas, that is to say, it is not suitable for the opportunistic network environment with sparse nodes of pedestrians. Therefore, this paper studies the node intimacy model, and the opportunistic network routing algorithm is provided. The proposed algorithm improves the efficiency of data forwarding in the sparse opportunity network composed of pedestrians.

There are two challenges for the algorithm based on history behavior of nodes: formal representation of encounter records and the way for converting into encounter state; classification of node encounter state.

In this paper, the main contributions include the following:

(1) According to characteristics of node behavior, contact duration, and encounter interval, we quantify the encounter records of nodes

(2) We constructed the probabilistic model of node encounter state for dynamic social relationship and classified the encounter state by using support vector machine. Based on the encounter state, the node intimacy calculation model is established

(3) An opportunistic network routing algorithm ONBTM is proposed to forward messages in the network

(4) The final results show that the ONBTM algorithm can achieve higher message delivery quality with less resource consumption than other routing algorithms, including epidemic, spray and wait, and prophet algorithm.

In this paper, the rest of the sections are organized as follows. Some preliminary knowledge are provided in "Problem Definition." In "Opportunistic Network Routing Algorithm Based on Node Intimacy," we introduced the algorithm in detail. Simulation experiments and some useful results are obtained in "Experiments." The main work of this paper is concluded in "Conclusion."

3. Problem Definition

We firstly give several preliminary knowledge, including time series, initial state of node encounter, marked state of node encounter, node intimacy, and node intimacy based on time series.

Definition 1. Time series. Let $R_i = \{T_0, T_1, \cdots, T_k\}$, where T_k denotes the kth time slice and R_i is a time series. In the opportunistic network, time series is used to analyse the periodic laws of node movement models, social relationships, encounter timings, and changes of communication state.

Definition 2. Initial state of encounter. Let $R_c = \{C_{ij} | 0 \le i \le n, 0 \le j \le n\}$, n is the node number, and C_{ij} denotes initial state when the node i and the node j encounter with each other. TE_{ij} describes the communication time of the node i and the node j, and TC_{ij} denotes the time required for nodes i and j to transmit a valid data. $P(C_{ij}, T_k)$ describes the state of the nodes i and j which meet in the kth time slice, where $C \in (0, 1)$. The initial state of encounter indicates the time that node remains within the range of communication, where $C_{ij} = TC_{ij}/TE_{ij}$.

Definition 3. Marked state of encounter. In the opportunistic network, encounter state can be divided into two types: valid encounter state and invalid encounter state. A valid encounter indicates that there may be some correlation between nodes, which can be used for data transmission. Invalid encounter represents that there is no association between nodes. Because C_{ij} is uncertain, it is necessary to map the encounter state to valid state or invalid state to indicate whether the encounter of nodes i and j is valid. The mapped encounter state is represented by $C\_Sat_{ij} = \{C\_Sat_{ij|0}, C\_Sat_{ij|1} | C\_Sat_{ij|0} = 0, C\_Sat_{ij|1} = 1\}$.

Let $R_{C\_Sat} = \{C\_Sat_{ij} | 0 \le i \le n, 0 \le j \le n\}$ represent the set of marked states that nodes meet each other in the opportunistic network, where C_Sat_{ij} is the encounter state after node i and node j are mapped and n denotes the node number.

For analysing the existence of encounter relationship between nodes, the initial encounter state needs to be mapped to marked state. R_c indicates that the initial state set of nodes meets any element in the set $C_{ij} \in [0, 1]$. It is necessary to map initial state C_{ij} to marked state C_Sat_{ij} by using the mapping function $F(C_{ij}) = C\_Sat_{ij}$. The mapping model of encounter state is defined by $F(R_C \to R_{C\_Sat}) = f(C_{ij} \to C\_Sat_{ij})$, where $C_{ij} \in R_C, C\_Sat_{ij} \in R_{C\_Sat}, i \in [0, n], j \in [0, n]$ and n represents node number in the network.

$$\begin{aligned} f : R_C \to R_{C\_Sat}, R_t &= f(C_{\text{if}} \to C\_Sat_{\text{if}} | T_x, 0 \le x \le \alpha) \\ &= \sum_{x=0}^{\alpha} w_x \cdot \phi(T_x) + b, \end{aligned} \tag{1}$$

where K is called the latest time slice in the time slice series, w_x is the complexity of mapping, T_x is the time slice, $\Phi(T_x)$ is mapping function, and b is mapping factor. The model of Equation (1) describes support vector regression model for mapping the initial state into marked state. The optimization problem of Equation (1) can be abstracted into minimum loss model of min $E(w)$:

$$minE(w) = \frac{1}{2}(w \cdot w) + C\left(\sum_{x=\alpha+1}^{k} \left| T_x - f(C_{ij} \to C\_Sat_{ij} | T_x, 0 \le x \le \alpha) \right|_{\varepsilon}\right). \tag{2}$$

In the model of Equation (2), $w \cdot w$ describes the complexity of function $\sum_{x=\alpha+1}^{k} |T_x - f(C_{ij} \to C\_Sat_{ij} | T_x, 0 \le x \le \alpha)|_{\varepsilon}$ in Equation (1) which represents the average loss on the training set; constant C is used to reduce the complexity $f(x)$ and decrease the average loss. Equation (2) is used to optimize Equation (1). Equation (3) is optimized by Equation (2).

$$\begin{cases} \min\limits_{w,\xi_x,\xi_x^*,b} & \frac{1}{2}(w \cdot w) + C \cdot \frac{1}{k}\sum\limits_{T=1}^{k}(\xi_x + \xi_x^*) \\ s.t. & (w \cdot \phi(X_T) + b) - C_{Sat_{ij}} \le \varepsilon + \xi_x \\ & C_{Sat_{ij}} - (w \cdot \phi(T_x) + b) \le \varepsilon + \xi_x^*, \end{cases} \tag{3}$$

where $\xi_x, \xi_x^* \ge 0$.

$$\begin{cases} \max\limits_{\beta_x,\beta_x^*} & \sum\limits_{x=1}^{k} \beta_x^* \left[\left(C_{Sat_{ij}} - \varepsilon\right) - \beta_x\left(C_{Sat_{ij}} + \varepsilon\right) \right] \\ & -\frac{1}{2}\sum\limits_{x=1}^{k}\sum\limits_{y=1}^{k}(\beta_x - \beta_x^*)\left(\beta_y - \beta_x^*\right)K\left(\beta_x, \beta_y\right) \\ s.t. & \sum\limits_{x=1}^{k} \beta_x - \beta_x^* = 0, 0 \le \beta_x, \beta_x^* \le \frac{c}{k}. \end{cases} \tag{4}$$

In Equation (4), $K(\beta_x, \beta_y) = \phi(\beta_x)\phi(\beta_y)$ denotes the kernel function, and we use it to predict the experimental results, (β, β^*) is the solution. In order to map the initial encounter state to marked state, state mapping model is constructed with Equation (1). In Equation (1), parameter b is uncertain. Equation (5) is derived from Equations (1), (3), and (4).

$$f\left(C_{ij} \to C\_Sat_{ij} | T_x, 0 \le x \le \alpha\right) = \sum_{x=0}^{\alpha}\left(\overline{\beta_x} - \overline{\beta_x^*}\right)K\left(\beta_x, \beta_y\right) + \bar{b}. \tag{5}$$

By using Equation (5), we can obtain the mapping factor $\bar{b}$.

$$\bar{b} = C_{Sat_{ij}} - \sum_{y=0}^{\alpha}\left(\beta_y - \beta_x^*\right)K\left(\beta_x, \beta_y\right) - \varepsilon, \beta_x \in \left(0, \frac{c}{k}\right). \tag{6}$$

Based on above analysis, the initial encounter state is first established between the nodes. And then, the initial state is mapped to the marked state using the node state mapping model.

Based on marked encounter state of nodes, opportunistic network probabilistic routing based on node intimacy is designed, which relies on the prediction of likelihood of nodes encountering. In order to calculate the probability of nodes meeting, node intimacy model is proposed.

Definition 4. Node intimacy. Node intimacy represents the intimacy of social relationships between nodes. The higher the intimacy, the bigger possibility that the nodes meet with each other. In the opportunistic network, the node intimacy of any two nodes u and v is calculated by Equation (7):

$$Coh(u, v) = \frac{1}{2n_c} \sum_{u=1}^{c} \sum_{v=1}^{c} A_{uv} P_{uv}, \tag{7}$$

where c is the node number in the opportunistic network topology, P_{uv} denotes the historical encounter probability of nodes, and A_{uv} describes the social network topology of the opportunistic network.

Definition 5. Node intimacy based on time series. Let $\text{Pr\_coh}(u, v)$ denote the probability of intimacy between nodes a and b. $\text{Pr\_coh}(u, v)_{old}$ denotes the probability of intimacy in previous time slice between nodes u and v. Pr_coh_{init} is the initialization constant between nodes, which is computed by Equation (7). For all nodes in the opportunistic network, the probability $\text{Pr\_coh}(u, v) = \text{Pr\_coh}(u, v)_{old} + (1 - \text{Pr\_coh}(u, v)_{old}) * \text{Pr\_coh}_{init}$ generally takes initial intimacy of any two nodes u and v. The initial intimacy values on possible worlds of opportunistic networks are denoted by $OptN$. By using intimacy of the last time slice node u and node v, we can calculate the intimacy $\text{Pr\_coh}(u, v)$ of nodes a and b under the current time. $\text{Pr\_coh}(u, v)$ is susceptible to the frequency of node encounters in the current time slice, which may cause the calculated node intimacy to have jumps in different time slices. In order to overcome the sensitivity of $\text{Pr\_coh}(u, v)$ to the frequency of node encounters in different time slices, we define new intimacy probability $\text{Pr\_coh}(u, v)_{new}$ from node u to node v on the opportunistic networks named $OptN$.

$$\text{Pr\_coh}(u, v)_{new} = \frac{\text{Pr\_coh}(u, v)_{old} * last\_time}{cur\_time} + \frac{\text{Pr\_coh}(u, v)_{old} * (cur\_time - last\_time)}{cur\_time}. \tag{8}$$

For all the node $u \in V(N)$, we can compute the $\text{Pr\_coh}(u, v)_{new}$ by Equation (8). The last_time is the time slice that recently updated the probability value of node intimacy, and cur_time is time since the opportunistic network has been running.

4. Opportunistic Network Routing Algorithm Based on Node Intimacy

Let node intimacy describe the valid encounter of nodes. Node intimacy can predict the encounter probability of nodes in a future time slice. Based on the fusion of historical encounter probability and time series, the method of calculating node intimacy is proposed.

Algorithm 1 calculates the node intimacy of nodes u and v, and $\text{Pr\_coh}(u) = \text{Pr\_coh}(v) = \text{Pr\_coh}(u, v)$.

By calculating node intimacy, opportunistic network routing algorithm based on node intimacy is proposed. The routing algorithm balances resource consumption, delivery latency, and delivery success rate. And it is a multicopy replication propagation routing algorithm, which is message-limited. In Algorithm 1, when node A carrying message M meets node B, they exchange their message list. If there is no message M in node B' message list, B obtains the permission to transmit the message M. Then node A and node B compare their transmission predictions $\text{Pr_coh}(OptN)$new. If $\text{Pr\_coh}(\text{B}) \geq \text{Pr\_coh}(\text{A})$, node A copies the carried message M to node B. In opportunistic network topology, messages are always propagated in the direction that has a higher probability of reaching the target node.

In Algorithm 2, S.request() is the request sent by node S to node A. The request message contains the id and size of the message M, and destination node. A.service_confirm() is receiving service confirmation sent to A when node A receives node S. Node S sends the message after receiving the confirmation from node A, finally updating the intimacy of node A and node S.

5. Experiments

We conducted several experiments to evaluate proposed algorithms. The experimental results are as follows.

5.1. Experimental Setting. The experiments were run on a Thinkpad T440p with 2.5GHz Intel Core i5 CPU and 16GB of RAM, and Windows 10 is installed on the machine.

By using the famous simulation platform ONE (Opportunistic Networking Environment) [2], we simulated a sparse opportunistic network with pedestrians as nodes. In the network, the node speed is the walking speed, and the node storage size is set to a smaller value. We also simulated the opportunistic network routing algorithm based on node intimacy. Then, the proposed algorithm are compared with several well-known routing algorithms, for example, prophet, epidemic, and spray and wait. For the purpose of making the experimental environment more stable, it is necessary to generate message after simulation platform runs for 1000 seconds. The parameter settings are shown in Table 1.

5.2. Experimental Results and Analysis

5.2.1. Experimental Results

(1) Average Buffer Time. It is used to represent that the occupancy of the node buffer when the opportunistic network routing strategy forwards message. The average buffer time of $nodes = \sum_{i=1}^{destinationnode} \tau_i / messagesreceivedbydestinationnode$, and τ_i represents the total buffer time of message i at each node in opportunistic network. In the experiment, we compared the average buffer time of opportunistic network routing algorithm ONBTM and other three algorithms. The node number is varied from 0 to 180. Figure 1 reports the effects of average buffer time of nodes in different node numbers. The experimental results indicate that ONBTM is a very effective

for all $u \in V(OptN)$ **do**
    $\Pr\_coh_{init} \leftarrow \text{random}(0,1)$
end for
for all $v \in V(OptN)$ **do**
    $\Pr\_coh(u,v) \leftarrow \Pr\_coh(u,v)_{old}$
      $+(1-\Pr\_coh(u,v)_{old}) * \Pr\_coh_{init}$
    cur_time ← get_current_slice_time()
    last_time ← get_last_slice_time()
    $\alpha \leftarrow \{\Pr\_coh(u,v)_{old} * \text{last\_time} + \Pr\_coh(u,v) * (\text{cur\_time} - \text{last\_time})\}/\text{cur\_time}$
    $\Pr\_coh(u,v)_{new} \leftarrow \alpha$
end for
return $\Pr\_coh(OptN)_{new}$

Algorithm 1: $\Pr\_coh(OptN)_{\text{new}}$.

$S \in V(OptN)$
for all $A \in V(OptN)$ **do**
    A ← S. request ()
    if $\Pr\_coh(A) \geq \Pr\_coh(S)$ **then**
        S ← A.service_confirm()
    end if
    if S.get(A.service_confirm()) **then**
        A.buffer() ← S.send(M)
    end if
end for
update $(\Pr\_coh(S,A)_{new})$
return $\Pr\_coh(S,A)_{new}$

Algorithm 2: ONBTM.

algorithm. Compared with epidemic and prophet algorithms, algorithm proposed by this paper shows a steady downward trend as the nodes number increases.

(2) Delivery Probability. It indicates the ability that the opportunistic network routing strategy transmits messages to the target node. What is more, the delivery probability can measure the performance of the routing strategy.

$$deliveryprobability = \frac{messagesreceivedbydestinationnode}{messagesreceivedbysourcenode}. \tag{9}$$

In the experiment, we compared delivery success rate of ONBTM, prophet, epidemic, and spray and wait. From Figure 2, we have some observations:

(i) When the nodes are less than 60, all algorithms have similar delivery probability

(ii) When the node number is greater than 60, ONBTM is significantly better than epidemic and prophet. Our algorithm ONBTM shows a steady upward trend as the node number increases

(iii) Compared with the spray and wait algorithm, ONBTM has a slightly lower delivery probability. But ONBTM has much lower average buffer time than spray and wait. That is, ONBTM achieves a higher delivery success rate than epidemic and prophet with lower resource consumption and a slightly lower delivery success rate than spray and wait.

(3) Average Hop Count. It represents the consumption of resources when messages are transmitted in the network.

$$averagehopcount = \frac{\sum_{i=1}^{destinationnode} S_i}{number of\, messagereceivedbydestinationnode}. \tag{10}$$

S_i represents the relay nodes that message i passes before reaching the destination node in the opportunistic network.

In the experiment, we examined the average hop count of ONBTM, prophet, epidemic, and spray and wait. There are some observations from Figure 3:

(i) In the opportunistic network, the node number ranges from 20 to 180. Compared with the other three algorithms, epidemic has the highest average hop count, because messages are forwarded as long as the nodes meet, which results in high resource consumption, high cost of message forwarding, and message congestion in the network. In terms of average hop counts, the ONBTM and the prophet show similar trend, but the spray and wait is lower than the other three algorithms. As the node number increases, the average hop of epidemic strategy increases fastest. This is because as the nodes number increases, network congestion will increase. The average hop count of ONBTM, prophet, and spray and wait grows slowly as the nodes increases, and when nodes increase to 150, the average hop count tends to be stable

Table 1: The parameter of simulation scenario.

Category	Parameter (unit)	Values
Scenario settings	Simulation time (s)	43200
	Simulation region (m)	4500 ∗ 3400
Group characteristics	Group movement model	Shortest path map-based movement
	Buffer size (MB)	5
	Wait time (s)	0~120
	Speed (m/s)	0.5~1.5
	msgTtl (m)	300
Message characteristics	Events.nrof	1
	Events1.class	MessageEventGenerator
	Events1.interval	25~35
	Events1.size (kB)	500~1000
	Events1.hosts	0~29

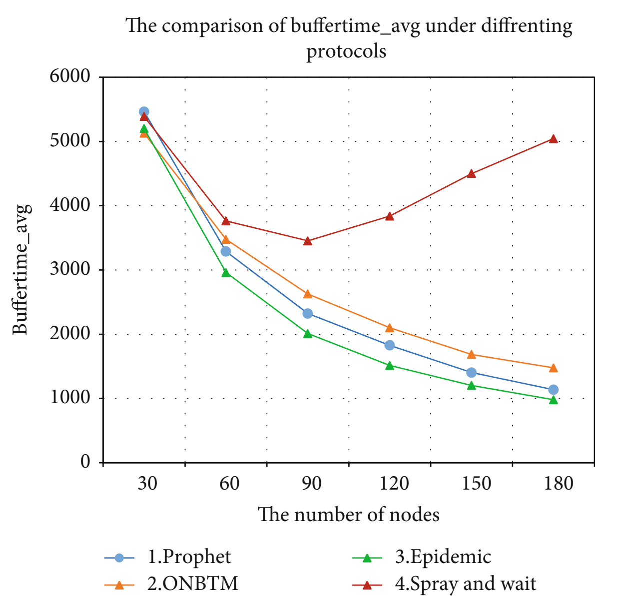

Figure 1: The comparison of buffertime_avg under different routing protocols.

(ii) The ONBTM algorithm has higher average hop than spray and wait. However, the algorithm ONBTM has much lower average buffer time than spray and wait. It indicates that ONBTM obtains a lower average hop count and delivery resource consumption with a smaller resource consumption.

(4) Average Latency. It represents the time that message from generation to successful delivery. It is used to measure the timeliness of the opportunistic network routing strategy in delivering the message.

$$averagelatency = \frac{\sum_{i=1}^{messagesreceivedbydestinationnode} t_i - t_{i0}}{messagesreceivedbydestinationnode}. \quad (11)$$

t_{i0} is the produced time of message i, and t_i is the time that message i reaches the destination nodes.

In this experiment, we tested the average latency of ONBTM, prophet, epidemic, and spray and wait. Some observations from Figure 4 are as follows:

(i) In the experiment, the nodes ranged from 20 to 180. When the node number is greater than 60, the average latency obtained by ONBTM, prophet and epidemic shows similar trends. As the nodes increase to 60, the average latency of all routing algorithms shows a different degree of decline. The average latency obtained by ONBTM is close to epidemic, both are slightly better than prophet, and spray and wait has the fastest decline rate. It also can be seen that the four routing algorithms have similar average latency when running in a sparse opportunistic network.

5.2.2. Analysis. Firstly, we compared the average buffer time of nodes by using four different routing algorithms. ONBTM, prophet, and epidemic are relatively similar to each other in average buffer time, but spray and wait is much larger than the above three algorithms. With the increase of nodes, our algorithm ONBTM performs well than spray and wait, which shows that our algorithm has a better control over network resource consumption.

Secondly, we compared the delivery success rate of messages by using four different routing algorithms. Compared with prophet and epidemic, ONBTM has a large increase in the sparse and dense opportunistic network. Although spray and wait performs slightly better than ONBTM, it occupies more network resources and increases the energy consumption. Algorithm ONBTM has a good balance between network resource consumption and delivery probability.

Thirdly, we compared the average hop count of message delivery by using four different routing algorithms. Algorithm epidemic has a higher average hop count for message delivery, especially when the node number is more than 80. As the nodes increase from 20 to 180, ONBTM and prophet

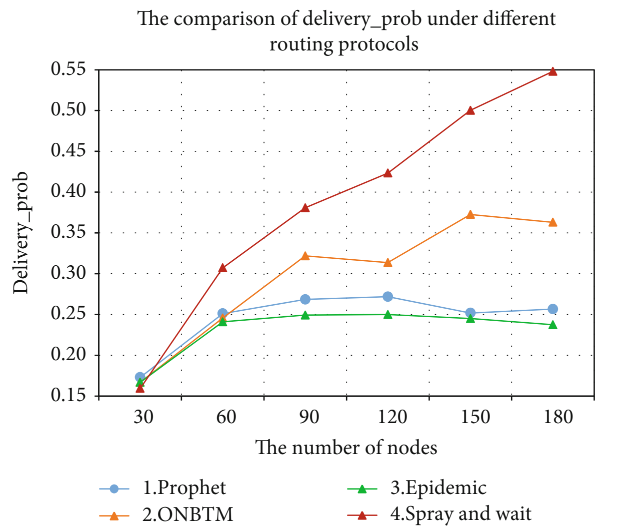

Figure 2: The comparison of delivery_prob under different routing protocols.

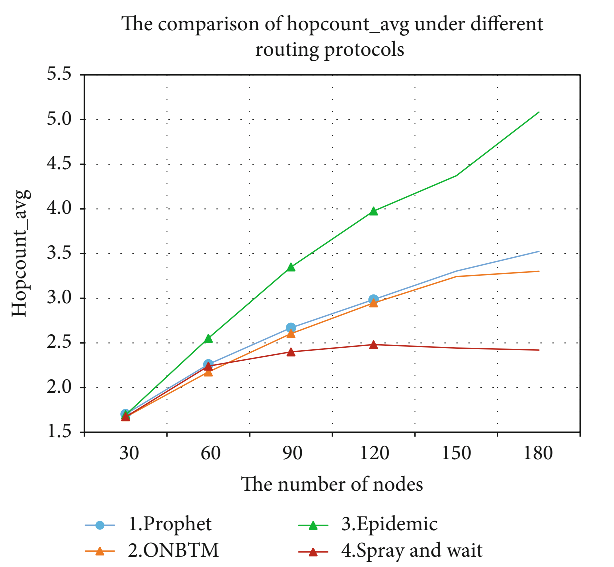

Figure 3: The comparison of hopcount_avg under different routing protocols.

get similar average hop. When the nodes exceed 80, the spray and wait obtains smaller average hop; this is because the spray and wait algorithm gets smaller average hop count with more persistent network resources.

Finally, we compared the average latency of the four different routing algorithms. As the nodes increase from 20 to 180, the ONBTM, epidemic, prophet, and spray and wait algorithms all show a steady downward trend. However, the prophet and epidemic algorithms consume a higher average latency in the opportunistic network. When the nodes are less than 60, the ONBTM algorithm and the spray and wait algorithm have similar average latency. In the opportunistic network where nodes increase from 60 to 180, the average latency of the spray and wait is lower than ONBTM. The reason is that when the message is delivered using spray and

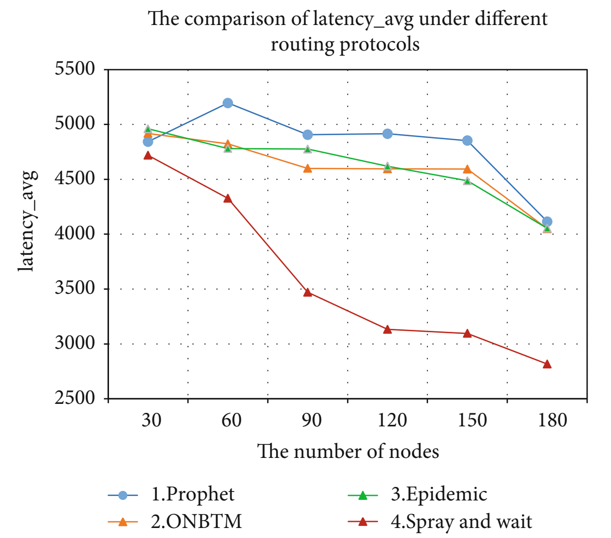

Figure 4: The comparison of latency_avg under different routing protocols.

wait, the message takes up more network resources for a longer time.

In summary, compared with existing opportunistic network routing algorithms, ONBTM proposed in the paper has a smaller network resource occupation and consumption, smaller delivery latency and average hop count, and higher delivery success rate. What is more, ONBTM algorithm achieves a good balance between message delivery and resource consumption, thus achieving higher quality of message delivery with low resource usage.

6. Conclusion

The paper defined some concepts related to node intimacy and proposed the ONBTM algorithm. Unlike the existing opportunistic network routing algorithms, ONBTM has strong adaptability and stability, especially suitable for sparse opportunistic networks. Experimental results show that ONBTM and optimization technique proposed in the paper are effective and efficient. To lay foundations for node intimacy, we study the ONBTM in the sparse opportunistic network. Through comparing four different routing algorithms with different numbers of nodes, we find that the ONBTM algorithm is more effective and efficient.

Data Availability

The data used in this study are generated by the famous simulation platform ONE (Opportunistic Networking Environment).

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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References

[1] L. Pelusi, A. Passarella, and M. Conti, "Opportunistic networking: data forwarding in disconnected mobile ad hoc networks," *IEEE Communications Magazine*, vol. 44, no. 11, pp. 134–141, 2006.

[2] A. Keränen, J. Ott, and T. Kärkkäinen, "The ONE simulator for DTN protocol evaluation," in *International Conference on Simulation Tools & Techniques*, pp. 2–6, Rome, Italy, 2009.

[3] P. Juang, H. Oki, Y. Wang, and M. Martonosi, "Energy-efficient computing for wildlife tracking: design tradeoffs and early experiences with ZebraNet," in *ACM SIGPLAN Notices*, vol. 37, pp. 96–107, San Jose California, 2002.

[4] B. Hull, V. Bychkovsky, Y. Zhang, and K. Chen, "CarTel: a distributed mobile sensor computing system," in *Proceedings of the 4th international conference on Embedded networked sensor systems*, pp. 125–138, Boulder Colorado, USA, 2006.

[5] C. Sengul, A. C. Viana, and A. Ziviani, "A survey of adaptive services to cope with dynamics in wireless self-organizing networks," *ACM Computing Surveys*, vol. 44, no. 4, pp. 1–35, 2012.

[6] P. Hui, J. Crowcroft, and E. Yoneki, "Bubble rap: social-based forwarding in delay tolerant networks," *IEEE Transactions on Mobile Computing*, vol. 10, no. 11, pp. 1576–1589, 2011.

[7] H. D. Ma, P. Y. Yuan, and D. Zhao, "Research progress on routing problem in mobile opportunistic networks," *Journal of Software*, vol. 26, no. 3, pp. 600–616, 2015.

[8] A. Vahdat and D. Becker, "Epidemic Routing for Partially Connected Ad Hoc Networks," *Handbook of Systemic Autoimmune Diseases*, Elsevier, 2000.

[9] R. C. Shah, S. Roy, S. Jain, and W. Brunette, "Data MULEs: modeling and analysis of a three-tier architecture for sparse sensor networks," *Ad Hoc Networks*, vol. 1, no. 2-3, pp. 215–233, 2003.

[10] W. Zhao, M. Ammar, and E. Zegura, "A message ferrying approach for data delivery in sparse mobile ad hoc networks," in *Proceedings of the 5th ACM international symposium on Mobile ad hoc networking and computing*, pp. 187–198, Roppongi Hills, Tokyo Japan, 2004.

[11] P. Yuan and H. Ma, "Hug: Human gathering point based routing for opportunistic networks," in *IEEE Wireless Communications and Networking Conference (WCNC)*, pp. 3024–3029, Roppongi Hills, Tokyo Japan, 2012.

[12] J. Wu, M. Xiao, and L. Huang, "Homing spread: community home-based multi-copy routing in mobile social networks," in *Proceedings IEEE Infocom*, pp. 2319–2327, Turin, Italy, 2013.

[13] A. T. Prodhan, R. Das, H. Kabir, and G. C. Shoja, "TTL based routing in opportunistic networks," *Journal of Network and Computer Applications*, vol. 34, no. 5, pp. 1660–1670, 2011.

[14] M. Xiao, J. Wu, C. Liu, and L. Huang, "TOUR: time-sensitive opportunistic utility-based routing in delay tolerant networks," in *2013 Proceedings IEEE Infocom*, pp. 2085–2091, Las Vegas Nevada, USA, 2013.

[15] A. Mtibaa and K. A. Harras, "Fairness-related challenges in mobile opportunistic networking," *Computer Networks*, vol. 57, no. 1, pp. 228–242, 2013.

[16] D. Zhao, H. Ma, P. Yuan, and L. Liu, "Differentiated probabilistic forwarding for extending the lifetime of opportunistic networks," in *Wireless Communications and Networking Conference (WCNC)*, pp. 3002–3007, Paris, France, 2012.

[17] E. Bulut and B. K. Szymanski, "Exploiting friendship relations for efficient routing in mobile social networks," *IEEE Transactions on Parallel and Distributed Systems*, vol. 23, no. 12, pp. 2254–2265, 2012.

[18] W. Gao and G. Cao, "On exploiting transient contact patterns for data forwarding in delay tolerant networks," in *The 18th IEEE International Conference on Network Protocols*, pp. 193–202, Kyoto, Japan, 2010.

[19] X. Tie, A. Venkataramani, and A. Balasubramanian, "R3: robust replication routing in wireless networks with diverse connectivity characteristics," in *Proceedings of the 17th annual international conference on Mobile computing and networking*, pp. 181–192, Las Vegas Nevada USA, 2011.

[20] D. Gunawardena, T. Karagiannis, A. Proutiere, E. S. Neto, and M. Vojnovic, "Scoop: decentralized and opportunistic multicasting of information streams," in *Proceedings of the 17th Annual International Conference on Mobile Computing and Networking*, pp. 169–180, Las Vegas Nevada, USA, 2011.

[21] U. G. Acer, P. Giaccone, D. Hay, G. Neglia, and S. Tarapiah, "Timely data delivery in a realistic bus network," *IEEE Transactions on Vehicular Technology*, vol. 61, no. 3, pp. 1251–1265, 2012.

[22] A. Bemani, A. Baghban, S. Shamshirband, A. Mosavi, P. Csiba, and A. R. Varkonyi-Koczy, "Applying ann, anfis, and lssvm models for estimation of acid solvent solubility in supercritical co2," *Computers, Materials & Continua*, vol. 63, no. 3, pp. 1175–1204, 2020.

[23] F. Bi, X. Fu, W. Chen, W. Fang, and B. Assefa, "Fire detection method based on improved fruit fly optimization-based svm," *Computers, Materials & Continua*, vol. 62, no. 1, pp. 199–216, 2020.

[24] Z. Zhou, Q. M. J. Wu, Y. Yang, and X. Sun, "Region-Level visual consistency verification for large-scale partial-duplicate image search," *ACM Transactions on Multimedia Computing, Communications, and Applications*, vol. 16, no. 2, pp. 1–25, 2020.

[25] X. Fu, G. Fortino, W. Li, P. Pace, and Y. Yang, "WSNs-assisted opportunistic network for low-latency message forwarding in sparse settings," *Future Generation Computer Systems*, vol. 91, pp. 223–237, 2019.

[26] B. Billet and V. S. Issarny, "Spinel: an opportunistic proxy for connecting sensors to the Internet of Things," *ACM Transactions on Internet Technology (TOIT)*, vol. 17, no. 2, p. 21, 2017.

[27] H. Saidi, D. Gretete, and A. Adnane, "Opportunistic routing in wireless sensors networks," in *ICCWCS'17 Proceedings of the 2nd International Conference on Computing and Wireless Communication Systems*, pp. 1–5, Larache Morocco, 2018.

[28] P. Kosmides and L. Lambrinos, "Intelligent routing in mobile opportunistic networks," in *2018 Global Information Infrastructure and Networking Symposium (GIIS)*, pp. 1–4, Greece Thessaloniki, 2018.

[29] V. Vashishth, A. Chhabra, and D. K. Sharma, "GMMR: a Gaussian mixture model based unsupervised machine learning approach for optimal routing in opportunistic IoT networks," *Computer Communications*, vol. 134, pp. 138–148, 2019.

[30] D. K. Sharma, S. K. Dhurandher, D. Agarwal, and K. Arora, "KROp: k-means clustering based routing protocol for opportunistic networks," *Journal of Ambient Intelligence & Humanized Computing*, vol. 10, no. 4, pp. 1289–1306, 2018.

[31] A. Gupta, A. Bansal, D. Naryani, and D. K. Sharma, "CRPO: cognitive routing protocol for opportunistic networks," in *Proceedings of the International Conference on High Performance Compilation, Computing and Communications*, pp. 121–125, Kuala Lumpur Malaysia, 2017.

[32] C. Borrego, J. Borrell, and S. Robles, "Hey, influencer! Message delivery to social central nodes in social opportunistic networks," *Computer Communications*, vol. 137, pp. 81–91, 2019.

[33] N. Aschenbruck, H. Döring, C. Heiden, and M. Schwamborn, "Stationarity for the small world in motion mobility model," in *Proceedings of the 22nd International ACM Conference on Modeling, Analysis and Simulation of Wireless and Mobile Systems*, pp. 13–17, Miami Beach FL USA, 2019.

[34] P. Du, S. Yoo, Q. Zhao, M. Chen, and M. Gerla, "Towards opportunistic resource sharing in mobile social networks: an evolutionary game theoretic approach," in *Eighteenth ACM International Symposium*, pp. 308-309, Los Angeles CA USA, 2018.

[35] Z. Du, C. Wu, X. Chen, X. Wang, T. Yoshinaga, and Y. Ji, "A VDTN scheme with enhanced buffer management," *Wireless Networks*, vol. 26, no. 3, pp. 1537–1548, 2020.

[36] C. Wu, Z. Liu, F. Liu, T. Yoshinaga, Y. Ji, and J. Li, "Collaborative learning of communication routes in edge-enabled multi-access vehicular environment," *IEEE Transactions on Cognitive Communications and Networking*, vol. 6, no. 4, pp. 1155–1165, 2020.

[37] C. Wu, T. Yoshinaga, D. Bayar, and Y. Ji, "Learning for adaptive anycast in vehicular delay tolerant networks," *Journal of Ambient Intelligence and Humanized Computing*, vol. 10, no. 4, pp. 1379–1388, 2019.

[38] J. Zuo, Y. Lu, H. Gao, R. Cao, Z. Guo, and J. Feng, "Comprehensive information security evaluation model based on multi-level decomposition feedback for iot," *Computers, Materials & Continua*, vol. 65, no. 1, pp. 683–704, 2020.

[39] L. Kou, Y. Shi, L. Zhang, D. Liu, and Q. Yang, "A lightweight three-factor user authentication protocol for the information perception of iot," *Computers, Materials & Continua*, vol. 58, no. 2, pp. 545–565, 2019.