Routing in Delay-tolerant network Based on Nodes’ Sociality

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Abstract—To solve the problem of low ratio success delivery, long latency caused by the rapid dynamic change of network topology, limited node buffer, large amount of data transmission and large user population density in delay-tolerant network (DTN). This paper propose a routing algorithm in DTN based on nodes' sociality. In this paper, contact history was used to determine the node link quality; Markov model was used to predict the node position based on the nodes’ movement track; according to nodes’ social similarity to divide community, then calculated node betweenness centrality. Finally, the best forwarding nodes for message transmission were determined. Besides, to increase the ratio of successful delivery, message delivery probability in the relay node’s buffer was calculated. Experimental results show that compared with traditional routing algorithm, the proposed algorithm performs better on the delivery ratio and average end-to-end delay.

1. Introduction

Delay-tolerant Network (DTN) is a network architecture proposed by NASA Jet Propulsion Laboratory to solve the problem of interplanetary network (IPN) [1]. In the emergency communication network scenario, the traditional TCP/IP protocol cannot be used due to the mobility of nodes, and dynamic changes of network topology between nodes. Therefore, Kevin Fall introduces the bundle layer between the transmission layer and the application layer, and adopts the "store-carry-forward" mechanism to solve the problems of network intermittent connection, high delay and high bit error rate [2].

Burleigh proposed opportunistic CGR on the basis of contact graph routing (CGR), which uses the predictability of node contact to obtain the network topology, determine the contact graph, and determine the next hop node through the forwarding decision process [3]. In addition, the research of DTN routing algorithm can be divided into single-copy routing and multi-copy routing algorithms. There are some classical multi-copy routing algorithms include Epidemic [4], Spray and Wait [5], Prophet [6].

In order to improve the routing performance, Yu [8] propose a location prediction routing algorithm, which use Markov model to predict the next location of the node to make the best transmission path. In the stage of Spray, Yu et al calculate the connection time and delivery probability of nodes, selects the best nodes, then transmit the message to the relay nodes with high comprehensive utility value in the Wait stage.

According to the social attributes of nodes in routing algorithm. Jain and Yadav proposed BubbleRap algorithm in [9], which combined node activity and transmission history to determine the node ranking.
Lindgren [10] defined the degree of preference of nodes for different interests, allowing nodes to choose forwarding paths according to their own preferences.

According to the nodes’ social relationship, community can effectively improve the routing performance. In [11], the concept of community was introduced in DTN routing. Nodes are divided into different communities and numbered. Nodes in the same number community are selected for routing transmission, which effectively reduces the duplication of message copies. In [12], a new community partition method is proposed by calculating the similarity of social attributes of nodes. Newman [13] proposed the concept of betweenness centrality. If a node is located on multiple shortest paths of other nodes, then the node is the core node, which has greater betweenness centrality and closer relationship between communities, so it is preferred to be the relay node.

In addition, with the increase of routing data, Sakai et al firstly proposed data-intensive protocol [14] to solve the problem of how to route a large amount of data under the condition of limited buffer, considering the node contact frequency, connection time and node buffer, propose the DIR protocol which can effectively solve the problem of multi-hop data transmission under the data-intensive condition.

DTN has the following characteristics: there is no stable link in the network, and the topology changes dynamically; the node community has high aggregation degree, strong mobility, periodic and time-varying trajectory; the node buffer is limited. According to the characteristics of DTN network, this paper proposes a DTN routing algorithm CNS (routing algorithm in delay tolerant network based on nodes' Society), the contributions of this paper are as follows:

1. Determine node link quality. The link quality between nodes is calculated according to the contact history, the connection time and contact frequency, and combined with the historical meeting position of nodes.

2. Predict node location. According to nodes’ historical movement trajectory, the node position is predicted, and the probability of the destination node's region after the message forwarding delay is estimated, so as to prevent the possibility of message delivery failure caused by the node's movement and improve the message delivery ratio.

3. Divide node community. Through the reasonable community division of nodes and the selection of nodes with high betweenness centrality in the community, it is convenient for the transmission of messages between communities.

4. Determine the probability of message delivery in the node buffer. Because the relay node buffer is limited, the message transmission failure may be caused by cache overflow or message lifetime decrease to zero. Therefore, the probability of message delivery in the relay node buffer is defined to reduce the possibility of transmission failure.

Simulation results show that compared with Epidemic, Spray and Wait, Prophet routing, the CNS algorithm have some advantages in message delivery ratio and average end-to-end delay.

2. Systen model

2.1. Network Model
Contact history refers to a list generated by nodes connecting by mobile encounter and exchanging contact history information in DTN. Contact history includes contact message (contact time, contact node and contact area). According to contact history, nodes can build contact list with other nodes. $V = \{V_i | 1 \leq i \leq n\}$ represent $n$ node in network, list $(E_i, start_time(i), end_time(i), conn_time(i), R)$ separately store the contact history updated after the node $V_i$ contacts with $n$ nodes. In addition, edges $[e_{i1}, e_{i2}, \ldots, e_{in}] \in E_i$, an edge $e_{i,j}$ indicate the number of connections between node $V_i$ and $V_j$. whenever $V_i$ encounter $V_j$, $e_{i,j}$ value plus 1, the higher the value is, the more frequent the nodes are encounter.
**2.2. Link Quality**

Link Quality (LQ), is a metric to indicate the effectiveness of the connection between contacted nodes. During routing process, it’s helpful to improve the routing performance by choosing the node with long connection time, frequent encounter and high message delivery ratio. The contact process between node $V_i$ and $V_j$ is shown in Figure 1. The contact time of node is divided into connection time and non-connection time. $t_1$ and $t_2$ represent the start and end time of the first contact between node $V_i$ and $V_j$ separately. If two nodes contact at $t_1$, disconnect at $t_2$. $t_1= (, )_{ij}^{st}$, $t_2= (, )_{ij}^{et}$, $[t_1,t_2]= (, )_{ij}^{ct}$, $(, )_{ij}^{e}$ add 1 for each contact, update values in linked list. Due to the random motion of the node, there will be a second contact and a third contact...

![Fig.1 Node contact process](image)

We defined the link quality as Eq.(1), $N(i)$ indicate the total number of times node $V_i$ has established a connection to other nodes during routing process, $N(R,j)$ indicate that the node $V_i$ and $V_j$ establish a connection in the region $R$.

$$LQ_{(i,j)} = \frac{\sum_{t}^{N(i)} (ct_{(i,j)} + (st_{(i,j)} - et_{(i,j)}))^2}{2T \cdot e_{(i,j)}} \cdot \frac{N(R,j)}{N(i)}$$

(1)

**2.3. Node location prediction**

The purpose of node location prediction is to estimate the probability of the destination node’s area after the message forwarding delay, prevent the possibility of message delivery failure due to the node movement, and improve the message delivery probability. Therefore, the region of a node at the next time can be predicted by the historical trajectory with Markov model.

Each node in the network keep the last one month historical track of its own and other related nodes. It is assumed that the movement track of node $V_i$ has periodicity and time variability. The position of node at a certain time is related to the previous position. In the process of the location prediction, there are still a large number of aggregation nodes in the network, and have enough statistical data which can ensure the accuracy and accuracy of prediction. Therefore, Markov model is applied to predict the location.

We divide the 24 hours of a day(1440 min), into 32 time periods, $t \in [0,32]$. $G_i$ represent the historical track of node $V_n$. $G_i = \{H_1, H_2, \cdots \}$, $H_t = <A_t, Day_t, hour_t, Area_t>$. $G_i$ record will start from 0:00 every day to record the area where the node is and which time period in, then make a day mark for the track...
information of the day. When one node enter a certain area, the label of the area, the day mark, the enter time and leave time in the area, \( t_{enter}, t_{leave} \) will record.

Suppose that the \( m \)-th region of a node is related to its \( m-1 \)-th region, according to the definition of conditional probability, the node in the \( A_{u-1} \) status is \( u \), in \( A_{v} \) status is \( v \), then from \( A_{u} \) to \( A_{v} \) just like probability of transition from status \( u \) to \( v \),

\[
P_{uv} = P(A_{u-1} = u | A_{v} = v) = P(A_{u} / A_{v}) , \quad u \in [1, m], \quad v \in [1, m],
\]

the state transition matrix \( P_{uv} \) as follows:

\[
P_{uv} = \begin{pmatrix}
P_{u1} & P_{u2} & \cdots & P_{um} \\
P_{v1} & P_{v2} & \cdots & P_{vm} \\
\vdots & \vdots & \ddots & \vdots \\
P_{um} & P_{vm} & \cdots & P_{mm}
\end{pmatrix}
\]

\( P_{uv} \) meet the following conditions:

\[
0 \leq P_{uv} \leq 1 \quad (u, v = 1, 2, \ldots, m)
\]

\[
\sum_{v=1}^{m} P_{uv} = 1 \quad (u = 1, 2, \ldots, m)
\]

When the source node send a message to the destination node, the initial position of the destination node is determined according to the contact history. At this time, \( t = 0 \). After a period of time \( t \) move, the probability \( \pi_{v}(t) \) of the destination node at \( t \) time in \( A_{u} \) is expressed as:

\[
\pi_{v}(t) = \sum_{u=1}^{m} \pi_{u}(t-1) P_{uv} (v = 1, 2, \ldots, m) \sum_{v=1}^{m} \pi_{v}(t) = 1
\]

To get row vector \( \pi(t) = [\pi_{1}(t), \pi_{2}(t), \ldots, \pi_{m}(t)] \), According to the above formula, the recurrence formula of state probability can be calculated:

\[
\begin{align*}
\pi(1) &= \pi(0)P \\
\pi(2) &= \pi(1)P = \pi(0)P^2 \\
&\vdots \\
\pi(t) &= \pi(t-1)P = \pi(0)P^{t-1}
\end{align*}
\]

Among them:

\[
\pi(0) = [\pi_{1}(0), \pi_{2}(0), \ldots, \pi_{m}(0)]
\]

Therefore, it can be seen from the above formula that the initial state of the node is known, and the recursive formula can be used to predict the position of the node at the \( t \)-th time after the state transition at \( t-1 \)-th time. For convenience of calculation, Eigen decomposition of matrix \( P_{uv} \):

\[
\pi_{i}(t) = \pi(0)TD^tT^{-1}
\]

2.4. Community division based on social attributes of nodes

In DTN, because nodes have social attributes, nodes (people) have their own majors, classes, and their own circle of friends. Nodes in the circle of friends have common interests and hobbies. Therefore, we can divide nodes into communities. Nodes with the same social activities and personal preferences will be divided into communities first, at the same time, the betweenness centrality of nodes is calculated to get the nodes which are closely related to each other. The social properties of a node can be defined as Eq.(8):

\[
S_{x} = (I_{1}^{1}, I_{2}^{1}, \ldots, I_{x}^{1})
\]

\( x \) represent types of social activities, there are \( x \) species in total network, \( I_{1}^{1}, I_{2}^{1}, \ldots, I_{x}^{1} \) vector represent social attributes of nodes, for example, class, sports. At the same time in each vector \( I_{x}^{1} \) there are \( y \) sub-vectors, \( I_{y}^{1} = (a_{1}, a_{2}, \ldots, a_{y}) \), for example, if \( I_{y}^{1} \) represent community activities, \( (a_{1}, a_{2}, a_{y}) \) can be defined
as: guitar club, aviation model association, dance troupe or something else. If \( I_i^j \) on behalf of sports activities, then, \((a_1, a_2, a_3, \ldots)\) can be defined as: basketball, football, volleyball... to express more intuitive, if node \( V_i \) participate in the aviation model association and like play basketball, then \( I_i^j = (0, 1, 0) \), \( I_i^j = (1, 0, 0) \). Another example that if node \( V_j \) participate guitar club and dance group, like play football, then \( I_i^j = (1, 0, 1) \), \( I_i^j = (0, 1, 0) \).

According to [15], we can first define the similarity between node \( V_i \) and \( V_j \) in \( I_i^j \) by Eq.(9):

\[
\text{sim}_{ij}^\Phi = \frac{I_i^j + \Phi}{\text{max}(I_i^j)} \cdot \text{min}(I_i^j) - I_i^j \tag{9}
\]

\(|I_i^j|, |I_j^j|\) is module vector, for example \( I_i^j_{\text{max}} = (1, 1, 1, \ldots), \ 0 \leq \text{sim}_{ij}^\Phi \leq 1 \). Assume the weight of node \( V_i \) to \( x \) activities is \( w_{ix} \in [0, 1] \), the result show the preference degree of each node to different social activities, and the weight is equal to 1 set as Eq.(10). Based on the above information, we can get the social similarity \( s_{ij} \) of node \( V_i \) and node \( V_j \) by Eq.(11):

\[
w_{ix} = w_{ix} / (\sum_{i=1}^{m} w_{ix})
\]

\[
s_{ij} = \frac{\sum_{k=1}^{n} (\text{sim}_{ij}^k \cdot w_{ik} \times (\text{sim}_{ij}^k \cdot w_{jk} \cdot \text{w}_{jk}))}{\sum_{k=1}^{m} w_{ik}^2 \times (\sum_{k=1}^{n} w_{jk}^2)} \tag{11}
\]

It is assumed that the similarity threshold of social activities \( \text{thre} = 0.5 \), if \( s_{ij} \geq \text{thre} \), node \( V_i \) and \( V_j \) have similar social activity preferences, and they are divided into one community.

2.5. Centrality calculation of node betweenness

Node betweenness centrality indicate the popularity of a node in different communities. After dividing a node into communities, a node may be in different communities and have better contact opportunities with nodes in multiple nodes. Therefore, the selection of such nodes can reduce the number of interactions between nodes and reduce the network overhead on the basis of ensuring the message delivery ratio.

Node betweenness centrality in [13] can be defined as Eq.(12):

\[
BC_{(i,v)} = \sum_{(i,j)} (\sigma(i,j|v) / \sigma(i,j)) \tag{12}
\]

\( \sigma(i,j) \) is the number of shortest paths from node \( V_i \) to \( V_j \). \( \sigma(i,j|v) \) is the number of shortest paths from \( V_i \) to \( V_j \) passing through relay node \( v \). Here, the shortest paths from node \( V_i \) to \( V_j \) have the minimum hop number from the source node to the destination node. If the \( BC \) value of the current node is lower than other nodes, the message in the current node cache will be forward to other nodes.

2.6. Message forwarding in node buffer

Node buffer is responsible for the receiving, forwarding, discarding and maintenance of message queue. However, the buffer in the node is limited, the number of messages in the node, the lifetime and the message size all affect the routing performance of the node. Therefore, we define the delivery probability of the message in the node buffer. For a message in buffer, the higher the probability it is, it will be forwarded as soon as possible, so as to alleviate the buffer capacity of the node, improve the delivery rate of the message. We propose the concept of \( \text{val}_i \) by extended concept of \( MTT \) in [16]. Assume the \( i \)-th message forwarding probability in node \( V_i \) be \( \text{val}_i \), the number of messages in the node is \( K \),
\[ Val_i = \sum_{k=1}^{n} \left[ \theta_1 \cdot \left( 1 - \frac{TTL_i}{TTL_{total}} \right) + \theta_2 \cdot \left( 1 - \frac{st_{i,j}}{T_{sys}} \right) + \theta_3 \cdot \left( 1 - \frac{msg_{sys}}{msg_{total}} \right) \right] \] (13)

\( \frac{TTL_i}{TTL_{total}} \) represent the ratio of the \( TTL \) of the message \( l \) at the current time to the initial \( TTL \), \( \frac{st_{i,j}}{T_{sys}} \) represent the ratio of the start time of the \( c \)-th encounter of node \( Vi \) and \( Vj \) to the current system time, \( \frac{msg_{sys}}{msg_{total}} \) indicate the ratio of the current message size to the total number of messages in the buffer. The larger the ratio is, the longer the message exist in the node buffer, and should be forwarded as soon as possible. \( \theta \) indicate the influence of message lifetime and message receiving time on message sequence. We set \( \theta_1 = 0.4, \ \theta_2 = 0.4, \ \theta_3 = 0.2. \)

3. Performance evaluation
In this section, we evaluate the performance of CNS compared with three classical routing.

3.1. Simulation setup
The proposed CNS and compared routing algorithms are implemented using the Matlab R2017b. In order to show the advantages of CNS algorithm, we compare the CNS algorithm with Epidemic, Spray and Wait, Prophet in two aspects: message delivery ratio, average end-to-end delay. The main simulation parameters are shown in Table 1. The communication area is 4500m×4500m, which is divided into 25 equal regions, and the HCMM movement model was applied [17].

| Simulation parameter       | Value                  |
|----------------------------|------------------------|
| Simulation tool            | Matlab R2017b           |
| Mobility model             | HCMM                   |
| Communication area         | 4500m×4500m            |
| Geographic area            | 900m×900m              |
| Number of Nodes            | 550                    |
| Message TTL                | 60-300min              |
| Storage capacity of a node | 5M-50M                 |
| Speech range of a node     | 1-9m/s                 |
| Number of sub-vectors      | 5                      |
| Number of feature words    | 25                     |

The following two metrics are evaluated to show the effectiveness of the routing algorithms.
(1) Message delivery ratio: the ratio of the number of messages successfully received by the destination node to the total number of messages generated by the source node in the network.
(2) Average end-to-end delay: the average time a message takes from the source node to the destination node.

Algorithm CNS
1. Input: Contact history, source node, destination node.
2. Output: The best transmission path.
3. According to the node contact history, calculate the node link quality \( LQ(i,j) \).
4. Calculate node \( S_{i,j} \) if \( S_{i,j} \geq \text{thresh} = 0.5 \) then divide into one community.
5. Calculate node betweenness centrality \( BC \).
6. when transmit a message from \( Vi \) to \( Vd \).
7. Predict node position by using Markov model,
\[ \pi(0) = [\pi_1(0), \pi_2(0), \ldots \pi_n(0)], \pi_i(0) = \pi(0)T^\top T^{-1} \]
8. If \( V_j = V_d \), delete the message from \( V_i \) buffer after pass it to \( V_j \).
9. else
10. If \( V_i \) and \( V_j \) in the same community, \( (j,d)\pi_i(t) > (i,d)\pi_i(t) \), and \( V_j \) have high BC, pass messages to node \( V_j \).
12. else
13. Choose other nodes in community.
14. Determine message delivery probability in optimal relay node buffer.

3.2. Data overhead
As can be seen from the previous sections, because the CNS algorithm use a linked list to store information such as the contact history of the node, storing the linked list in the node will also cause a certain overhead. For \( n \) nodes in the network, after full contact, according to [18], Le et al use the following formula to calculate the number of edges, \( C_n = \frac{n(n-1)}{2} \). If there are 550 nodes in the network, there are at most 150975 edges in the node, each node needs to store at least ten items of data, so each node needs about 1474KB nearly 1.5M. With the support of the existing Bluetooth 5.0 technology, the transmission rate is about 1Mbps-2Mbps, the actual working distance is generally within 10m, and the theoretical transmission speed is about 1.7Mbps. Therefore, it takes about 6.7s to build the linked list. Therefore, the node generation overhead is acceptable to a certain extent.

3.3. Simulation Results
3.3.1. Routing performance with changing buffer size
The results of the experiments are shown in Figure 2, Figure 3. In Figure 2, at the beginning, due to the limited buffer, the delivery ratio of three classical routing algorithms is not high, the CNS algorithm can maintain a high delivery ratio, and the delivery ratio change little as the buffer size increase. The reason is because we using CNS to select the relay node and determine message delivery in the buffer, which improves the message delivery ratio. With the increase of buffer, the message delivery ratio of three routing algorithms increases gradually. Epidemic algorithm increase sharply because it does not limit the message copies, with buffer size increase, Epidemic have enough buffer to storage message. The Spray and Wait algorithm only produce a certain number of message copies, which can effectively avoid congestion but delivery ratio is not well.

As shown in Figure 3, the average end-to-end delay of the four algorithms vary different with changing buffer size. Epidemic have the highest delay and delay increase gradually, because Epidemic produce a large number of message copies, it’s easy to cause message congestion and reduce delivery performance. Spray and Wait have the same change trend as Epidemic, the different is that SnW limit the number of copies, so it’s delay lesser. CNS algorithm can determine the best relay node, reduce the number of forwarding hops, and improve the message delivery ratio, so the average delay is lower than the other three algorithms and have the trend to decrease with the changing buffer size.
3.3.2. Routing performance with changing TTL

The results of the experiments are shown in Figure 4, Figure 5. In Figure 4, with the increase of message lifetime, the message delivery ratio of Epidemic decrease, because there are a large number of nodes in network, and flood mechanism is easy to cause network congestion; Spray and Wait can keep a better performance with changing TTL; CNS algorithm can improve the efficiency of message forwarding and improve the ratio of message delivery when the message lifetime increases by determining the best relay node. Therefore, the message delivery rate is the highest.

Figure 5 show the change of the average end-to-end delay with changing message TTL. The four algorithms in the Figure 5 are all proportional to the growth of TTL, and the average end-to-end delay of CNS algorithm is relatively stable, because this algorithm selects relay nodes based on the social attributes of nodes, which can effectively reduce the message forwarding time of relay nodes.
In conclusion, compared with the other three algorithms, the CNS algorithm has some advantages in message delivery ratio, average end-to-end delay under different node buffer and message lifetime, which shows the effectiveness of the CNS algorithm.

4. Conclusion
This paper propose a CNS algorithm based on nodes’ social attributes to solve the problems of low data delivery ratio, high end-to-end delay caused by the dynamic changes of network topology, limited node buffer size, large amount of data transmission and large user population density in DTN. Firstly, node’s link quality was determined to pick up the suitable nodes. Secondly, to prevent message transmission failure due to node movement, we use Markov model to predict the location of nodes. Thirdly, we divide the communities according to nodes’ social attributes. Then, considering the problem of node buffer limitation, the message delivery probability in the node buffer is calculated. Experiments show that the CNS algorithm has some advantages in message delivery rate, average end-to-end delay. At the same time, because the CNS algorithm uses contact story to storage the nodes’ contact history, the overhead will become huge when the network scale is large, which reduce the efficiency of the CNS algorithm; the energy consumption of mobile nodes is not considered in this paper, the future work will focus on to improve routing performance.

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References

[1] Burleigh S, Hooke A, Torgerson L, et al. Delay-tolerant networking: an approach to interplanetary Internet [J]. IEEE Communications Magazine, 2003, 41(6):128-136.
[2] Fall, Kevin. A Delay-Tolerant Network Architecture for Challenged Internets[C]// 2003:27-34.
[3] Burleigh S, Caini C, Messina JJ, et al. Toward a unified routing framework for delay-tolerant networking. In: Proc. of the 2016 IEEE Int’l Conf. WiSEE. Piscataway: IEEE, 2016. 82–86.
[4] VAHDAT A, BECKER D. Epidemic Routing for Partially-Connected Ad Hoc Networks[R]. Durham N C: Duke University, 2000.
[5] Spyropoulos T, Psounis K, Raghavendra C S. Spray and wait: An efficient routing scheme for intermittently connected mobile networks[C]// ACM SIGCOMM workshop on Delay-tolerant networking. USC, 2005.
[6] Lindgren A, Doria A, Schelén, Olov. Probabilistic routing in intermittently connected networks [J]. ACM SIGMOBILE Mobile Computing and Communications Review, 2003.
[7] Wang X., Zhang L., Lin Y., Zhao R. (2018) A Routing Algorithm Based on the Prediction of Node Meeting Location in Opportunistic Networks. In: Li J. et al. (eds) Wireless Sensor Networks. CWSN 2017. Communications in Computer and Information Science, vol 812. Springer, Singapore. https://doi.org/10.1007/978-981-10-8123-1_25
[8] Yu C, Tu Z, Yao D, et al. Probabilistic routing algorithm based on contact duration and message redundancy in delay tolerant network[J]. International Journal of Communication Systems, 2015: n/a-n/a.
[9] Jain S, Yadav P. Controlled Replication Based Bubble Rap Routing Algorithm in Delay Tolerant Network [J]. 2017.
[10] Lin C J, Chen C W, Chou C F. Preference-aware content dissemination in opportunistic mobile social networks [J]. Proceedings IEEE Infocom, 2012, 131(5):1960-1968.
[11] Hui, P. and Crowcroft, J. How Small Labels Create Big Improvements. Proceedings of the Fifth Annual IEEE International Conference on Pervasive Computing and Communications Workshops, White Plains, 19-23 March 2007, 65-70. http://dx.doi.org/10.1109/percomw.2007.55
[12] Li D, Ma L, Yu Q, et al. An community detection algorithm based on the multi-attribute similarity[C]// International Conference on Communications. IEEE, 2013.
[13] M. E, J, Newman. A measure of betweenness centrality based on random walks [J]. Social Networks, 2005.
[14] Sakai K, Sun M T, Ku W S. Data-Intensive Routing in Delay-Tolerant Networks[C]// IEEE INFOCOM 2019 - IEEE Conference on Computer Communications. IEEE, 2019.
[15] Zhang Heng, Chen Zhi gang, Jia Wu et al. FRFR: A Fuzzy Reasoning Routing-Forwarding Algorithm using Mobile Device Similarity in Mobile Edge Computing-Based Opportunistic Mobile Social Networks[J].IEEE Access, 2019.
[16] Yong Zhang, Tao Zhang. Cache Management Strategy Based on Distributed Storage in Delay/Disruption Tolerant Network. [C]ICCT, 2019.
[17] J. Pak and Y. T. Song, “Health capability maturity model: Person centered approach in personal health record system,” in Proc. Americas Conf. Inf. Syst., San Diego, CA, USA, Aug. 2016, pp. 11–13.
[18] Le T. Multi-hop routing under short contact in delay tolerant networks [J]. Computer Communications, 2021, 165:1-8.