2022 21st International Symposium on Distributed Computing and Applications for Business Engineering and Science (DCABES)

RIS-Aided Channel Construction in Random Opportunistic Networks

Fei Gao
School of Computer Science and Artificial Intelligence
Wuhan University of Technology
Wuhan, China
e-mail: 413242540@qq.com

Xin Yan
School of Computer Science and Artificial Intelligence
Wuhan University of Technology
Wuhan, China
e-mail: yanxin@whut.edu.cn

***Abstract*—Random opportunistic networks are dynamic, resulting in nodes not being able to sense the state of the network, and the network topology of nodes changes all the time. Therefore, this paper proposes a RIS-aided channel construction algorithm, which can be used to maintain and change the topology of random opportunistic networks. A machine learning algorithm with spatio-temporal feature fusion is first used to predict the current position of the node, and finally the RIS-aided channel construction is implemented based on the predicted position. The simulation experiments show that the algorithm can find the optimal path between the target node and the source node in the presence of errors in the target node.**

Keywords-graph convolutional neural; long short-term memory ;RIS

I. INTRODUCTION

Random opportunistic network are opportunistic networks that relies on the movement of nodes to forward messages, thus enabling communication between source and destination nodes[1].Random opportunistic networks are flexible in networking, not constrained by infrastructure, and more suitable for communication needs in network resource-constrained scenarios. However, there are still some problems with random opportunistic networks. The network topology of stochastic opportunistic networks varies over time, the network has intermittent connectivity, and communication latency is high.Reconfigurable Intelligent Surfaces[2] (RIS) is a communication technology with passive and low-cost characteristics. The implementation of RIS-aided channel construction in random opportunistic networks can maintain the topology of the network, solidify the network structure, or change the structure of the network. Second, it can strengthen the communication links and extend the duration of network communication. Furthermore, it can assist in the deployment of distributed systems such as federated learning.

Abdullah et al.[3,4] investigated a collaborative system composed of RIS and decode-and-forward relay in both half-duplex and full-duplex modes of operation, respectively, and showed that the collaborative system composed of RIS and relay can significantly improve the communication performance, whether operating in half-duplex or full-duplex mode. To improve the bottleneck of existing O2I (Outdoor-to-Indoor) millimeter wave communication, Nemati et al.[5] used RIS to design a smart wall for intelligent signal conversion from outdoors to indoors. Buzzi et al.[6] studied a multi-user wireless network aided by RIS and gave a resource allocation algorithm for several cases. Zeng et al.[7] developed a RIS layout optimization problem by optimizing RIS direction and horizontal distance to maximize cell coverage .Liu et al.[8] introduced RIS into unmanned aircraft (UAV) systems to jointly optimize UAV trajectories, RIS passive beamforming, and maximize the average downlink throughput.

The rest of the structure of this paper is as follows. The second part proposes a node motion position prediction algorithm based on spatiotemporal feature fusion, and the third part proposes a RIS-aided channel construction algorithm. The fourth part is the simulation experiment, and the fifth part summarizes and proposes future work.

II. TARGET COORDINATE ESTIMATION

In random opportunistic networks, nodes can only obtain their own location information, while information about other nodes cannot be obtained in real time. To address this problem, we can sample the location information of node movement and compose discrete time series, then we can use the time series scheme to model it and then achieve prediction. This can not only improve the resource utilization of the network to a certain extent, but also reduce the network control consumption.

A. Problem Description

If we use the adjacency matrix to represent the topology of a random opportunistic networks, then this adjacency matrix can be represented as a dynamic graph. Usually, a dynamic graph can be divided into the set of static graphs with different moments. Mathematically, the dynamic graph is represented as:

$$\Gamma = (G^1, G^2, \cdots, G^T) \tag{1}$$

$$G^t = ((V^t, X^t, A^t)) \tag{2}$$

Where G^t denotes the graph at time t, the V^t is the set of N nodes on the network, and $A^t \in R^{N\times N}$ is an adjacency matrix, representing the connectivity of the nodes. X^t denotes the feature matrix of each node. Then the prediction problem is formed as learning a function $f(\cdot)$ that maps the P historical graph signals to graph signals at the future moment.

$$X_{t+1} = f(\Gamma; (X_{t-P}, \cdots, X_{t-1}, X_t)) \tag{3}$$

B. Experimental data

In this paper, the simulated random waypoint movement model (RWP) is used to generate the dataset of node movement. The RWP model is set to 50 nodes with a communication radius of 2 m. In a circular area with an active radius of 10 m, the movement speed is [1,6] (m/s), the abscissa and ordinate of the motion coordinates of a

2473-3636/22/$31.00 ©2022 IEEE
DOI 10.1109/DCABES57229.2022.00069

node at 1000 moments with a dwell time of [1,6] (s) are shown in Figure 1.

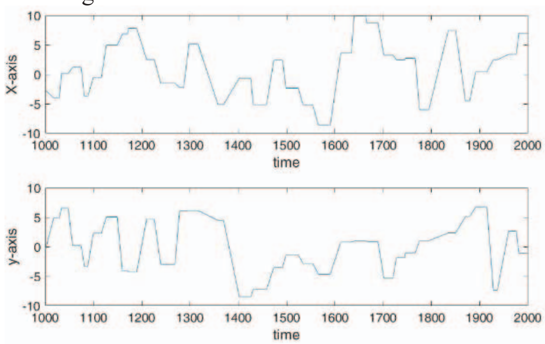

Figure 1. RWP model data

C. Spatial-Temporal Features Extraction Module

Given the adjacency matrix A and the identity matrix X, the GCN[9] model constructs a Fourier domain convolution kernel. This convolution kernel can act on the nodes of the graph and it uses convolution to extract features of the graph structure type data and propagates them in the form of equation (4).

$$H^{(l+1)} = \sigma\left(\widetilde{D}^{-\frac{1}{2}}\tilde{A}\widetilde{D}^{-\frac{1}{2}}H^{(l)}\theta^{(l)}\right) \tag{4}$$

Where $\tilde{A} = (A + I)$,I is the unit matrix and $\widetilde{D}$ is the $\tilde{A}$ the degree matrix of $\widetilde{D} = \sum_j \tilde{A}_{ij}$, and H represents the input features of each layer, and σ represents the nonlinear activation function, and $\theta^{(l)}$ represents the l the parameter values of the layers.

In this study, a two-layer GCN model is chosen to obtain the spatial correlation, which can be expressed as

$$f(X, A) = \sigma\big(\hat{A}Relu\big(\hat{A}XW_0\big)W_1\big) \tag{5}$$

where $\widetilde{D}^{-\frac{1}{2}}\hat{A}\widetilde{D}^{-\frac{1}{2}}$ denotes the preprocessing step, and$W_0 \in R^{P\times S}$ denotes the weight matrix from the input to the hidden layer, and P denotes the length of the feature matrix, the S denotes the number of hidden cells, and $W_1 \in R^{S\times T}$ denotes the weight matrix from the hidden layer to the output layer. $f(X, A) \in R^{N\times T}$ denotes the prediction length of T of the output, and $ReLU(\cdot)$ represents the corrected linear unit, which is the commonly used activation layer in current deep neural networks.

D. Temporal Feature Extraction Module

Temporal relationship is a key feature to be considered in node movement coordinate prediction. RNN can be used to extract them from sequential data, but it cannot be used directly due to the vanishing gradient problem. In this case, this paper uses the LSTM network, the LSTM network [11] follows the RNN network structure, but the structure of each unit is different from that of the RNN. Since there is only one Tanh in each unit of the RNN, the unit structure of the LSTM is modified to three weight gates, namely input gate, output gate and forget gate. The input controls the receipt of the input of the unit, the output gate controls the receipt of the output of the unit, and the forget gate controls the forgetting of the internal state of the unit.

E. Model structure

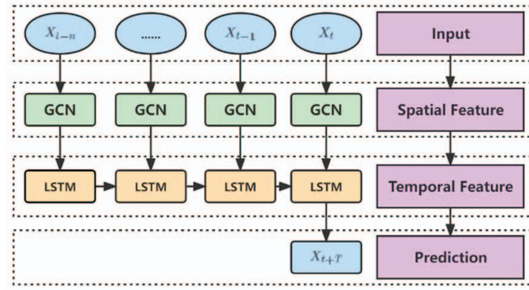

Figure 2. GCN-LSTM Structures

This part uses the method of processing dynamic graph convolutional neural network (GCN) and long short-term memory network (LSTM) to predict the coordinates of its nodes based on historical data. Specifically, GCN is used to learn the topology of the network to obtain spatial correlation, while LSTM is used to learn the dynamic changes of data to obtain temporal correlation. The GCN-LSTM model used in this paper is shown in Figure 2. The 2-dimensional coordinate information of 50 nodes and 10 time steps is used as the slice data {X} and the adjacency matrix {A} corresponding to each moment, and sent to the GCN layer for extraction Spatial features, the number of neurons in GCN is 16. The shape of the GCN output data is changed through the reshape layer, and then input to the two-layer LSTM to extract time-related trend features. The number of neurons in each layer of LSTM is 32. Then it goes through the dropout layer. The last is a fully connected layer, and uses the Timedistributed layer to transform the output single-step prediction results.

III. RIS-Aided Channel Construction

In the previous section, we can obtain the predicted location of the current target node. Usually, RIS devices can be conveniently arranged on the surface of buildings due to their easy deployment. We can achieve the channel construction between the target node and the source node by selecting an optimal reflection path among the RIS devices arranged in advance. The specific RIS channel construction schematic is shown in Figure 3 below.

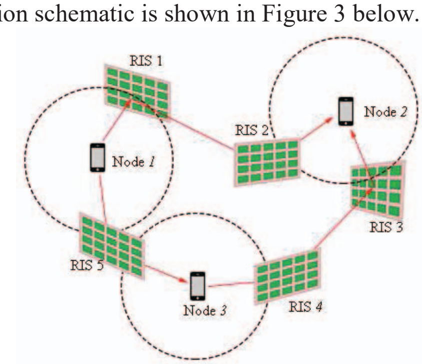

Figure 3. RIS-Aided channel construction structure

A. RIS Power Model

We consider a general RIS-aided single-input, single-output wireless communication system, where we place the RIS device in the $X - Y$ in the plane, and we first establish the power radiation pattern[11] visualizing the location where the antenna transmits or receives the maximum power. The normalized power radiation function $F(\theta)$, where θ is the elevation angle from the antenna to the particular transmit/receive direction. When $\theta = 0$, it represents that the corresponding antenna has the maximum gain.

$$F(\theta) = \begin{cases} cos^3\theta & \theta \in \left[0, \frac{\pi}{2}\right] \\ 0 & \theta \in \left[\frac{\pi}{2}, \pi\right] \end{cases} \tag{6}$$

We denote the reflection coefficient of the RIS by X, which usually depends on the properties of the RIS, the polarization of the radio waves, and the angle of incidence. Then, the received (noise-free) baseband signal can be represented as equation (7):

$$r(t) = \frac{\lambda}{4\pi}\left(\frac{R\times e^{-\frac{j2\pi r}{\lambda}}}{r}\right)x(t) \tag{7}$$

Assume that $x(t)$ the transmitting power of P_t and λ is the wavelength, and r is the distance between the transmitter and the receiver, and d_x , and d_y is the RIS cell size in horizontal and vertical coordinates. We consider at this point the received power of a single RIS cell as follows.

$$P_{n,m}^r = F(\theta)P_t\left(\frac{\lambda}{4\pi r}\right)^2 d_x d_y \tag{8}$$

Assume that the peak radiation direction of both the transmitting and receiving antennas point to the center of the RIS, and M, N are the number of reflecting units in the horizontal and vertical coordinates of the IRS device, respectively. Then the received power of each RIS is related to the transmitted power of the previous device.

$$P_{cur} = F(\theta_{pre})\left(\frac{\lambda}{4\pi r}\right)^2 P_{pre}MNd_x d_y \tag{9}$$

B. RIS-Aided Channel Construction Algorithm

After we obtain the need to connect the starting node to the destination node, we can construct a communication channel between the starting node and the destination node by means of reflection from the RIS devices arranged in the active range. It should be noted that due to some errors in the predicted node locations, the reflection of the last RIS reflecting surface before reaching the node needs to be changed so that it uses a broadcast to the target node searched. We choose the power loss of the system as the cost, and the specific steps of its RIS channel construction algorithm are shown below.

1) First, we initialize the source node and the nodes of the RIS device as the set $\{R\}$ that predicts the target nodes$s$. The distance matrix between the nodes$m$, the pow array records the power of each node initialized to 0, as well as records the previous node of the current optimal path node pre array.

2) The set $\{R\}$ and iterate through the set of $\{R\}$ the vertex that consumes the least power$r$ and from the set $\{R\}$ remove the node r .

3) Use the node u as the intermediate point of signal transmission, modify pow the power of each node in the array. The power is updated using the cost update formula of (10).

$$pow[r] = max(F(\theta,\varphi)(\frac{\lambda}{4\pi r})^2 pow[u]MN, pow[r]) \tag{10}$$

4) Repeat steps 2) and 3) until all vertices have been traversed.

5) Add the predicted target node S into it, and traverse the set {R} each node in the node as an intermediate node through equation (9) to update the node S After finding the node with the optimal path, determine whether the real node can be reached S If it can be reached, the final path is output. Conversely, the intermediate node is excluded and the suboptimal node is found. The improved RIS channel construction algorithm pseudo code is shown in Table 1 below.

TABLE I. RIS-AIDED CHANNEL CONSTRUCTION ALGORITHM

Input: Node Set U, Distance matrix m, Power matrix, Target Node s, **Output**: Path arrays

$R', R \leftarrow U - s$
while R is not empty:
  $r \leftarrow$ element in R with max $pow[u]$
  Remove r from R
  for each neighbor u of r still in R :
    $pow[r] = max(F(\theta,\varphi)(\lambda/4\pi r)^2 pow[u]MN, pow[r])$
  End for
End while
for each neighbor x of s in R' :
  $te[x] = pow[s]F(\theta,\varphi)(\lambda/4\pi r)^2 MN$
End for
Sort(te)
for each x in te:
  if (true)
  Insert x into the pre
  Break;
  End if
End for
Traverse pre output path

C. Algorithm Analysis

The RIS-aided channel construction algorithm in this section uses Dijkstra's algorithm[12], whose model can be abstracted as a graph structure consisting of n vertices and m edges, so its time complexity is $O(n^2 + m)$ On the basis of this, the target node is taken out, and the vertex set is traversed once before the update judgment, Therefore, the time complexity of the RIS channel construction algorithm is $O(n^2 + n + m)$.

IV. SIMULATION RESULTS

Table II provides the simulation parameters below.

TABLE II. SIMULATION SCENARIO SETTINGS

Simulation Parameters	*Values*
operating frequency f	4.25GHZ
Wavelength λ	0.07m
Size of element $d_x = d_y$	0.01m
number of element $N = M$	10
Number of RIS	10
Angle of RIS	$[0^\circ, 360^\circ]$
RIS Communication radius	10m
Transmit power P	20dBm

A. Experiment of GCN-LSTM

In this paper, the common evaluation metrics used in the experimental evaluation phase with regression models are: root mean square error (RMSE), mean absolute error (MAE), and accuracy, and in the training process, we set the learning rate to 0.001, use Adam optimizer to optimize automatically, set the batch size to 32, set the number of iterations to 600, dropout ratio is set to 0.3 and the prediction sliding window is 10, and we do single-step prediction. The experimental results are as follows.

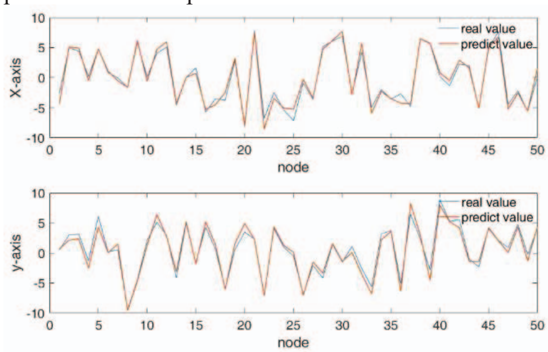

Fig. 4. Node coordinate predicted value and true value

The experimental results are given in Figure 4, where the yellow line is its true value and the blue line is the predicted value. The algorithms HA (Historical average), ARIMA (Autoregressive Integrated Moving Average Model), LSTM, and LSTM-GCN proposed in this paper were also selected. As shown in Table 3, the prediction results of GCN-LSTM proposed in this paper are more accurate, which can prove the effectiveness and feasibility of the algorithm.

TABLE III. NUMERICAL RESULTS

Models	RMSE	MAE	Accuracy
HA	1.5078	1.2294	38.7%
ARIMA	1.0506	0.8468	58.3%
LSTM	0.6823	0.4521	71.9%
GCN-LSTM	**0.5761**	**0.3345**	**79.6%**

As can be seen from the above table, GCN-LSTM based on rate-temporal features is more effective than methods that only consider rate-temporal features.

B. *Experiment of RIS-Aided Channel Construction*

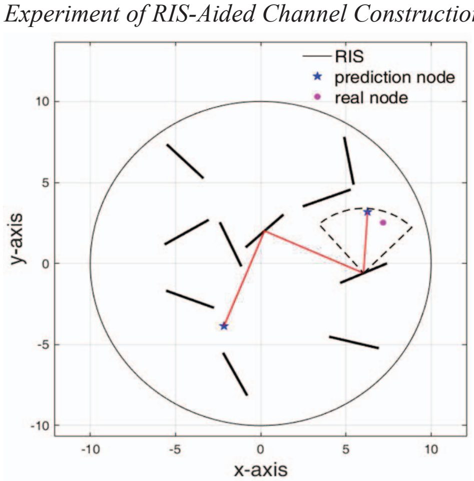

Fig.5. RIS-Aided channel construction result

According to the prediction of network nodes by GCN-LSTM algorithm, we can get the approximate location of the target node, set up ten random RIS devices with random angles in an active range. The experimental results are shown in Figure 5 above, where the node first finds the previous RIS reflection surface where its predicted node is located by the RIS channel construction algorithm after the coordinates of the predicted node are known. The RIS reflection method is modified so that it can search for the real target node within a sector. Eventually, the purpose of connecting the source node to the real target node is achieved.

V. CONCLUSIONS

In this paper, we propose a node prediction method considering spatio-temporal characteristics for the problem of unavailability of random opportunistic networks nodes, and propose a RIS-aided channel construction algorithm, which is used to find the optimal path between the target node and the source node, even if there is some error in the location of the target node. This algorithm can be used to maintain and update the topology of random opportunistic networks, which is significant for congestion control, route optimization memory load balancing of random opportunistic networks.

ACKNOWLEDGMENT

This work is supported by the National Natural Science Foundation of China (grant no. 61771354).

REFERENCES

[1] P. Kosmides and L. Lambrinos, "Intelligent Routing in Mobile Opportunistic Networks," 2018 Global Information Infrastructure and Networking Symposium (GIIS), 2018, pp. 1-4 .

[2] MD Renzo, Debbah M , Phan-Huy D T , et al. "Smart Radio Environments Empowered by AI Reconfigurable Meta-Surfaces: an Idea Whose Time Has Come". EURASIP Journal on Wireless Communications and Networking, 2019(1) MAY 2019.

[3] Z. Abdullah, G. Chen, S. Lambotharan and J. A. Chambers, "A Hybrid Relay and Intelligent Reflecting Surface Network and Its Ergodic Performance Analysis ," in IEEE Wireless Communications Letters, vol. 9, no. 10, pp. 1653-1657, Oct. 2020 .

[4] Z. Abdullah, G. Chen, S. Lambotharan and J. A. Chambers, "Optimization of Intelligent Reflecting Surface Aided Full-Duplex Relay Networks," in IEEE Wireless Communications Letters, vol. 10, no. 2, pp. 363-367, Feb. 2021 .

[5] M. Nemati, B. Maham, S. R. Pokhrel and J. Choi, "Modeling RIS Empowered Outdoor-to-Indoor Communication in mmWave Cellular Networks," in IEEE Transactions on Communications, vol. 69, no. 11, pp. 7837-7850, Nov. 2021 .

[6] S. Buzzi, C. D'Andrea, A. Zappone, M. Fresia, Y.-P. Zhang and S. Feng, "RIS Configuration, Beamformer Design, and Power Control in Single- Cell and Multi-Cell Wireless Networks," in IEEE Transactions on Cognitive Communications and Networking, vol. 7, no. 2, pp. 398-411, June 2021 .

[7] S. Zeng, H. Zhang, B. Di, Z. Han and L. Song, "Reconfigurable Intelligent Surface (RIS) Aided Wireless Coverage Extension: RIS Orientation and Location Optimization," in IEEE Communications Letters, vol. 25, no. 1, pp. 269-273, Jan. 2021 .

[8] X. Liu, Y. Yu, F. Li and T. S. Durrani, "Throughput Maximization for RIS-UAV Relaying Communications," in IEEE Transactions on Intelligent Transportation Systems .

[9] T. N. Kipf and M. Welling, "Semi-supervised classification with graph convolutional networks," 2016.

[10] M. Yu, F. Xu, W. Hu, J. Sun and G. Cervone, "Using Long Short-Term Memory (LSTM) and Internet of Things (IoT) for Localized Surface Temperature Forecasting in an Urban Environment," in IEEE Access, vol. 9, pp. 137406-137418, 2021 .

[11] W. L. Stutzman and G. A. Thiele, Antenna Theory Design, 3rd ed .New York, NY , USA: Wiley, 2012.

[12] D.-D. Zhu and J.-Q. Sun, "A New Algorithm Based on Dijkstra for Vehicle Path Planning Considering Intersection Attribute," in IEEE Access, vol. 9, pp. 19761-19775, 2020.