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A Similarity-Based Method for Base Station Selection in 5G Networks

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***Abstract*—Mobile devices face the problem of handover signal sources in mobile communication networks. It is particularly difficult to address this problem in 5G networks, because the coverage area of 5G base stations is smaller than that of traditional mobile communication networks, e.g., 4G networks. Therefore, when a device is moving, it needs to frequently handover base stations to maintain the connection with the network in the 5G network. Given that 5G networks have high requirements for low latency and high reliability, new methods need to be proposed to optimize the selection of gNBs for devices. The prediction of the UEs' trajectory can reduce redundant handovers between devices and base stations. However, the prediction of the UEs' movement trajectory requires sufficient user movement data to achieve the desired prediction accuracy. For users with less trajectory data, inaccurate predictions may cause negative effects and even increase the number of handovers. In this paper, we propose a gNB handover model based on user similarity. The evaluation results show that our method can reduce the number of handovers by 50% compared with existing related solutions, which means that the proposed method will effectively reduce the transmission delay and enhance the robustness of the gNB.**

***Index Terms*—5G, gNb handover, trajectory prediction, user similarity**

I. Introduction

The generation NodeB (gNB) has the characteristics of low delay with big data [1]. This has promoted the development of a number of date-oriented industries, such as Internet of vehicles, telemedicine, and mobile smart devices [2]–[5]. Mobile devices that require low latency may be prone to accidents due to the delay caused by handover when mobile devices are moving [6]. In addition, the high bandwidth of millimeter microwaves will allow 5G networks to provide high-precision positioning, and User-Equipment (UE) has become increasingly intelligent and will carry high-precision GPS positioning capabilities. There is a trend to combine artificial intelligence with the network [7]–[10], such as deep learning for Internet of Things security [11], [12] and network resource scheduling [13], [14].

Mobile prediction can improve the performance of 5G networks by sensing the location of communications, computing tasks, and UE mobility in 5G edge networks [15], [16]. For example, mobile load balancing of the cell [17]. The introduction of mobility prediction into 5G network can effectively avoid the delay caused by handover and improve the mobility management and robustness of the network [18], [19]. However, a big challenge for mobile prediction to be utilized in base station handover is that the handover results heavily relies on the prediction accuracy. Once the accuracy of the prediction is not high, it will have a negative impact on the mobile system generated by the network. Moreover, UE in 5G will handover far more frequently than 4G networks [20]. Therefore, how to achieve efficient handover between base stations is a challenging problem for UEs in 5G networks.

Handover is one of the basic elements of mobility management in wireless networks. It allows UEs to roam between wireless networks, making the UEs associated with the base station handover to the next base station or handover between sectors without interrupting the session [21]. Therefore mobility, security, high Quality of Service (QoS), and user reliability all depend on this seamless handover. When the UE is moving at high speed, it will increase the difficulty of handover selection in the wireless network, and reasonable handover will become a key factor for efficient data transmission. The 4G networks mainly relies on hard handover, that is, disconnect first and then connect. The current 5G network use soft handover, and some equipment disconnected for tens of milliseconds may cause damage, such as unmanned vehicles. When the UE is handover from the serving cell to the target cell, the generating force of the handover process depends on the appropriate time and precision of the measurement control variables that maintain the data correlation in the handover decision step. Therefore, if the quality of the measured variable is not good or the time is not right, it will cause unnecessary handover [22].

The 5G base station has high frequency and weak signal penetration, and the coverage range of 5G base station is only about 200m-500m [23]. Frequent handover will cause a sharp increase in the cost of the base station, and the handover failure rate will also increase [24]. One of the effective ways to address this problem is to introduce the user mobility prediction into the wireless network. The handover of the target cell depends on the mobile prediction of UEs, which can reduce the unnecessary handover and the measurement of the neighbor cell. The prediction of UE movement trajectory can help terminal devices to realize proactive handover, avoid the disadvantage of reactive handover, and realize intelligent connection of base stations. 5G base stations have edge computing function, which can analyze user behavior and predict user trajectory ability [15]. The accuracy of user

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trajectory prediction directly affects the handover performance and overhead of base station. At present, many studies are based on a large amount of data of a single user to make trajectory prediction [24], [25]. However, for new users or new locations, previous single-user prediction models often have large deviations, which makes it difficult to give satisfactory results.

In recent years, some studies have focused on the default of sufficient user movement trajectory data [24] or other information, such as Received Signal Strength (RSS) [26] or past handover information [21]. However, for users who seldom pass through the base station area, there are problems such as low accuracy of prediction and unreasonable handover planning. In view of the above problems, we make the following contributions:

- We use similarity to address the unpredictable problem of user with insufficient trajectory data, and extract user data in the form of grid to better mine user similarity.
- We propose a gNBs model assisted by UE similarity to optimize the handover efficiency of gNBs, which can optimize 5G small cells handover and reduce the handover times.

The rest of this paper is organized as follows. In Section II, we discuss the related work. Then, in Section III, the detail problem is described. Section IV introduces the proposed system model in detail. Section V presents the experimental results and Section VI concludes the paper.

II. Related Work

There are two main categories of research. The first type is the handover algorithm without the deep learning or machine learning. The second type is handover algorithm with deep learning or machine learning.

A. Methods Without Machine Learning

We mainly focus on the research of introducing user movement trajectory prediction into base station handover. Mandour et al. proposed a handover scheme based on Reference Signal Received Power (RSRP), Reference Signal Receiving Quality (RSRQ), UE parameters and their movement direction [27]. This scheme selects the most appropriate target flight network among numerous candidate cellular networks, which can reduce the number of redundant handover times of LTE and improve the success rate of UEs handover. The disadvantage of LTE-A hard handover (i.e., the UE handover speed is not fast enough) may cause the UE to be disconnected from the Internet. In order to solve this problem, Ahmad et al. proposed an LTE-A connection scheme based on user history and user movement direction [21]. When user closer to the handover point, gNB will look at history, according to the user to connect records to select target base stations. If the UE does not record the handover base station, then the user will choose the cosine function and distance to select the target base station. Tao et al. in [28] proposed an intelligent handover mode based on the mobile mode of the user terminal, which can intelligently determine the next base station access point to be visited by the user terminal through the mobile information history of the user terminal. This technology can effectively reduce the number of handover, handover delay and ping-pong handover [29], but its mobile decision complexity is relatively high.

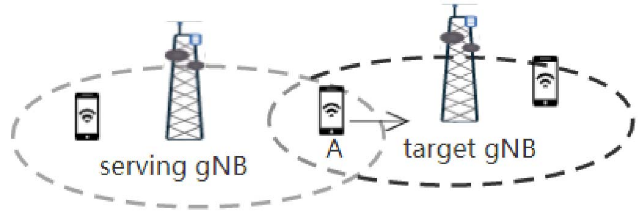


Fig. 1. The scenario of handover

B. Methods With Machine Learning or Deep Learning

In [30], the authors proposed a prediction model of 5G mobile system based on the combination of neural network and Markov chain. The data results show that in the Internet of vehicles, the prediction accuracy of mobile terminals within 4 seconds before handover can reach 88%. The traditional base station handover model rarely consider the hotspots. Deng et al. [24] put forward a kind of heterogeneous based on HMM cellular mobile user behavior prediction model which adopt the SLAW model to simulate the hot spots in the user mobile path. The results showed that the model can improve the accuracy of user behavior prediction in hot spots and can make effective preparation for the upcoming handover requests. Ulan et al. considered the prediction of user mobility to improve handover strategy in 802.16am broadband wireless access, and proposed two strategies of active handover and passive handover to reduce the possibility of signal loss and handover times respectively [22].

In [25], Hasan et al. proposed an energy saving framework for 5G ultra-dense network based on user mobility prediction. The trajectory was generated through SLAW trajectory and input to discrete time Markov model for user movement trajectory prediction. Meanwhile, optimization was discussed in this paper when the accuracy of user trajectory prediction reached 55%. The accuracy below 55% would be an increase in the power consumption of the base station. In [26], Li et al. proposed two base station different handover algorithm by introducing Multi-Armed Bandit(MAB) to reduce unnecessary handover by carefully deciding the next base station to which the user should handover, therefore the handover UE could connect for as long as possible.

To sum up, the current research predicts the mobile trajectory of UEs based on the trajectory data of large amount of data. If the user is a new user or new location data, the prediction behavior will have a negative effect and increase the cost of the base station.

III. Problem Description

A. Handover Scene

As shown in Fig.1, the gNB handover scenario of 5G network is briefly described. The handover is triggered by the degradation of the signal quality caused during the movement of UE (device A) . The UE will frequently scan the RSRP or RSRQ or Signal to Interference plus Noise Ratio (SINR) of the serving cell, and the handover process will be triggered when the UE measurement value is below the threshold. When the UE moves from the serving gNB to the target gNB, the RSRQ and RSRP of the UE serving gNB gradually decrease, and the RSRP and RSRQ of the corresponding target gNB gradually increase. When the UE enters the public area, the handover is triggered by the specific threshold set according to the event occurs within the Time to Trigger (TTT) period cycle. UEs can set thresholds to trigger handover within the TTT time, effectively avoiding ping-pong effect [29]. Meanwhile, TTT can be set according to the user's moving speed [31].

When the UE sends the quality inspection report to the serving gNB, the corresponding measurement values of all neighborhood gNBs will be sent to the serving gNB. Then, the handover process starts and selects the target gNB to be switched from the list of neighborhood gNBs, and then the handover is executed. The UE establishes a new connection with the new serving cell, and the target gNB and the serving gNB realize resource synchronization to complete the handover. But the UE cannot handover to the target gNB within a certain period of time, the UE will fail to handover.

Handover Process: The measurement reporting defines six events (A1, A2, A3, A4, A5, and A6) and two events (B1, B2) for the 5G NR network to trigger the handover [32]. Compared with LTE, the 5G NR network adds A6 events, that is, when the neighboring cell is higher than the serving cell's Cell Individual Offset (CIO). Handover procedures are divided into collection of information, handover request and handover execution.

As shown in Fig. 2, when the UE completes access or handover, the serving cell will send the measurement control information to the UE. The gNB will issue the updated measurement information over the Radio Resource Control (RRC) connection when the measurement configuration information is updated. The first step is to trigger the measurement. When the UE detects the wireless channel and meets the measurement conditions (A1-A6, B1 and B2), the user will send the measurement report to gNB. The trigger of the user measurement event can be RSRP, RSRQ or SINR, then the handover decision will be activated, which constitutes the second step. In the third step, the serving gNB will select the appropriate target gNB according to the quality measurement report of the neighborhood cells to send the handover request, apply for the application and allocation of resources. The target gNB has the right to refuse or accept the handover request of the serving gNB. In the fourth step, the target gNB sends the confirmation information to the serving gNB. Finally, the serving gNB sends the handover command to the UE, and the UE executes the handover command to handover to the target gNB and disengage from the serving cell [33].

IV. The Proposed Model

Although human activity areas and turnover patterns are highly free and diverse, the trajectories of users will also show structural patterns due to geographical and social restrictions. Human beings experience a periodic trajectory movement, which is related to their social relations, hobbies, geographical restrictions, etc., so the trajectory information of users is predictable [34].

In previous UEs movement prediction research, Although some studies are based on deep learning or machine learning, but these models are based on the large amount of trajectory data [24], [30]. However, when the amount of data of UE in the active area is small, the prediction results of user movement behavior are often not accurate. Therefore, we use the UE data set to find the most similar UE with the target UE in this paper, and uses the mobile behavior of similar UE to assist the prediction of the UE. When there is no historical track record and handover record of this place in the historical track of the target UE, we can use the user-aided prediction of similar UE can be used to give a prediction result. Since the movement behavior of similar UE is similar to that of the target base station, the prediction result of similar UEs can be used as the prediction result of the target UE in this location.

Humans experience a combination of periodic movements that are geographically limited and seemly [34]. Therefore we put forward the key of the target user mobile patterns as its movement characteristics, and find the target UEs the most similar to help predict target UEs next track points. It can help solve the problems of the base station less target UE data. By accessing user track records of intelligent devices at the UEs, it can provide UEs with high-quality services and improve the quality of network communication and the robustness of the network system.

A. UEs Similarity

We define similarity mining for base station user data, and location history is a record of locations visited by entities in geospatial space over a period of time. As shown in Fig. 3, the historical trajectory point of the user data can be defined as $g_i =< x_{t_i}, y_{t_i} >$. x_{t_i}, y_{t_i} denote the longitude and latitude of the i track point of the user. History of base station users u_k sequence can be expressed as $T_{uk}=\{(t_0, g_0), (t_1, g_1), (t_2, g_2), ..., (t_n, g_n)\}$. Firstly, we grid the areas visited by base station users, define the grid visited by base station users as k, and record the time period of each visit. The red track on the left is converted to the red track in the grid on the right. The track with different colors represents the track points that the user visits in this area at different times. We set a reasonable length L of each grid. Different sizes of L can adjust the size of the geographical location area. We can adjust the size of L to divide the user's access area hierarchically. If the user has continuous track points in a grid and only records one point, then the key movement mode

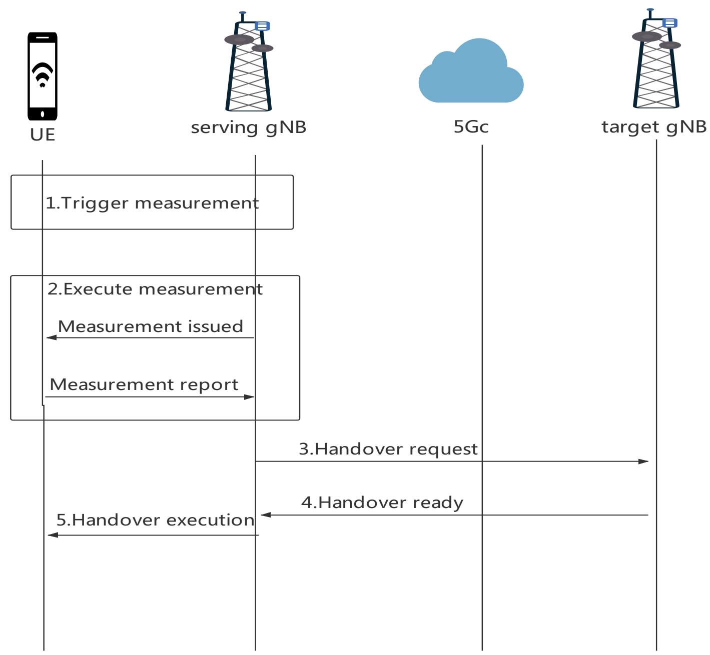


Fig. 2. The process of 5G handover

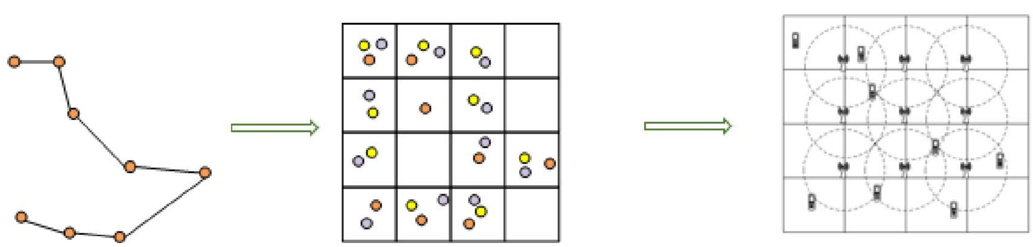


Fig. 3. The overview of user trajectory data mapping into network

is extracted, denoted as $k_i = < k_1, k_2, k_3, ..., k_n >$, where i represents the movement track of the user in the i_{th} base station, and n represents the length of the user's movement mode.

In this paper, the similarity of key modes is measured by cosine similarity and the length of the maximum common substring of key modes, and the similarity of different users is quantified. Among them, the similarity of users measuring key modes based on the maximum substring is calculated as follows:

$$sim(m_i, n_j) = \frac{2 * lcx(m_i, n_j)}{len(m_i) + len(n_j)} \tag{1}$$

where m_i and n_j represent the i_{th} and j_{th} movement modes of base station user m respectively, where $lcx(m_i, n_j)$ represent the longest common substring of the two key modes of user m and n, $len(m_i)$ and $len(n_j)$ represent the length of the key modes of user m and n.

B. Prediction Model Based on the Similar UEs

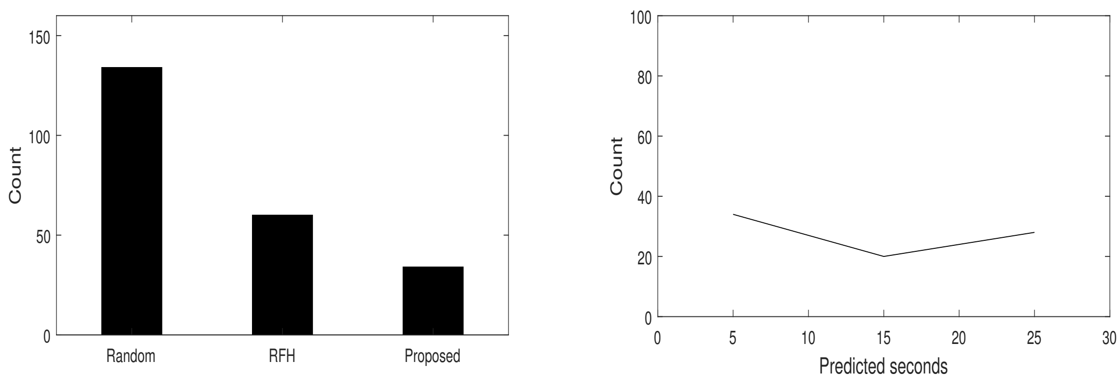
The predicted values of the above models and the actual trajectories of target UEs are input into the evaluate model of the network base station, and the target UEs are taken as the actual mobile trajectories of the UE.

As shown in Fig. 3, we input the UEs' actual trajectory and predicted UEs trajectory points into the network evaluate in this paper. The coverage radius of 5G base station is about 200m [23]. In this model, we select the appropriate base station for handover according to the trajectory points predicted by users and their directions. In this model, we select the appropriate base station for handover according to the trajectory points predicted by UEs and their trajectory directions. If the predicted point can connect to multiple base stations, select the base station with low load. The specific algorithm is shown in Algorithm 1.

Algorithm complexity analysis: Assuming that there are n old UE trajectory data, we first need to traverse the first K

TABLE I
NETWORK SIMULATION MODEL PARAMETER SETTING

Parameter	Values or description
Number of 5G gNBs	25
Coverage of single 5G gNBs	200 m
gNBs layout	The gNBs are evenly distributed in the vehicle's activity area. The inter-site distance is 250 m.
User mobility	We input the trajectory of the real user, made up of GPS trajectory points with movement. GPS trajectory points are mapped to the experiment.
Simulation time	180s
Vehicle speed	The average speed of the user is measured by the distance from the next track point
Handover rule	We define three kinds of users in different ways to connect the gNBs. First is to connect the Rate-First handover (RFH). The second is random handover, and the third is that we propose gNBs handover based on user trajectory.



(a) The comparison of handover count

(b) The handover-count with the predicted seconds

Fig. 4. Experiment results

Algorithm 1 Handover Algorithm

input: $predicate\_Trajectory, gNB\_list, Candidate_list$
output: $gNBs\_selected$
$max\_dist \leftarrow max$
$gNBs\_selected \leftarrow NULL$
$most\_simuser \leftarrow NULL$
$point\_List \leftarrow NULL$
$point\_list.add(ue.point)$
$most\_simuser = search(pont\_list\_add, point\_list)$
$next\_point = most\_simuser.find(p)$
while $gNB! = NULL$ **do**
    $dist = disatance(gNB.point, next\_point)$
    if $dist < min\_dist$ **then**
        $min\_dist \leftarrow dist$
        $gNB\_selected = gNB$
    end if
end while
$return\ gNBs\_selected$

trajectory data to find the old UE most similar to this UE. Suppose the number of trajectory points of each old UE is n_{u_k}. Therefore, the time complexity of finding similar trajectory segments is $O(num_{u_k})$. The time complexity of finding the most similar UE is $O(n_{u_k} * n)$. Finally, the time complexity of choosing the most appropriate gNB algorithm from m gNBs in the switchable list is $O(n_{u_k} * n * m)$. The spatial complexity of the algorithm is mainly related to the length of the trajectory data stored by the user, whih is $O(n * n_k)$.

C. The Theoretical Analysis

We search the UE u_k that is most similar to the target UE $simu_k$, through the track of UE $simu_k$ predict the position $p_k = \{x_k, y_k\}$ after the time k, and the next tuple information of the target user is expressed as $\{C_N^0, T_{HO}\}$. T_{HO} is the location of the gNB C_N^0. We seek to find the cell closest to p_k within the cell tuple as the target cell of the next handover. If the target user can accurately predict the probability p of the next location by the algorithm presented. In this paper, there may be a certain error which will not change the accuracy of handover. The error is set to ε, then the handover accuracy can be $p+\varepsilon$, and $p+\varepsilon < 1$. If the probability of user error is $1-p-\varepsilon$, a negative gain effect may occur. The UE handover count N_{u_k} can be presented as:

$$N_{u_K} = \begin{cases} C - N_2(p) & P = \rho + \varepsilon \\ C + N_1(p) & P = 1 - \rho + \varepsilon \end{cases} \tag{2}$$

where the C is the handover count of default algorithm, and the $N_1(p)$ and $N_2(p)$ are the negative gain effect and gain effect generated by the predicted result, the handover counts of the UE can be expressed as $total(N) = (p+\varepsilon) * (C -$

$N_2(p)) + (1 - p - \varepsilon) * (C + N_1(p))$. The more accurate the prediction, the more significant the gain.

V. Performance Evaluation and Analysis

A. Dataset

We use the Geolife-Trajectory-Dateset, which contains a 5-year GPS trajectory data set with a history of 182 users to evaluate our model [35]. In this evaluation, we preprocess the user trajectory data firstly. Deleting data record fewer users. We set the time span is not more than 5s between two adjacent trajectory point. We remove the discontinuous user record and select users with continuous time span of the GPS data. In order to better predict the UEs' next points, meet the demands of the design of experiment gNBs scene a small scale, we select the Beijing center to the user in a small area as the experimental data, the precision of GPS in the diameter of [39.8, 40.0] and latitude [116.3, 117.4]. We take new users with small data as input data, and users with large data as old UE. Through user similarity analysis, the trajectory of new users can be predicted based on the mobile behavior of old UE.

B. Results Analysis

In order to evaluate the performance of our algorithm, we design a simulation experiment, the key system parameter settings in TABLE I.

The simulation results are shown in Fig. 4(a) and Fig. 4(b). We look for the UEs trajectories that are most similar to users with less data or to new users, and use the similarity of user trajectories to help predict target users. As shown in Fig. 4(a), random handover and Rate-First handover methods are used for comparison, and the handover times of similar users are predicted after 5 seconds. As shown in Fig. 4(b), when the user specifies a number of seconds to predict the UEs' trajectory, the prediction increases gradually after 15 seconds, because the accuracy of the prediction decreases after 15 seconds when the UE is moving.

VI. Conclusion

With the rapid development of 5G networks, the efficient handover of UEs between base stations has attracted more and more attention. In existing studies, the prediction of UEs requires a large amount of data to achieve a certain accuracy or the trajectory data generated through simulation experiments, but the simulation lacks objectivity. In this paper, we propose a base station handover algorithm based on user trajectory similarity, which can make up for the prediction of new users or the small amount of user data, aiming at the shortcomings of previous studies that require a large amount of user trajectory data to improve the accuracy. The experimental results show that compared with the standard scheme and the reference scheme, the proposed algorithm can reduce the handover times and improve the performance of the network system.

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