An Adaptive Handover Trigger Strategy for 5G C/U Plane Split Heterogeneous Network

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***Abstract*—Fifth-generation (5G) control/user (C/U) plane split heterogeneous network may cause more serious handover problems than traditional networks, especially for the inter-macrocell handover. In addition, the mobility behavior of mobile node (MN) may also result in improper handover triggers. In this paper, an adaptive handover trigger strategy (AHTS) is proposed to predict the received signal strength indicator (RSSI), to guarantee that handover trigger is accurate and timely when the MN is moving. First, the fast dynamic time warping (FastDTW) algorithm as well as the density-based spatial clustering of applications with noise (DBSCAN) algorithm are used for clustering trajectories to discover the mobility patterns of MN. Then multiple hidden markov models (HMM) are trained based on the results of clustering. Finally, according to the HMM model which is selected based on the similarity between test trajectory and each cluster center, an adaptive RSSI predication (ARP) algorithm is implemented to predict the values of the RSSI. Simulation results show that our strategy outperforms the existing schemes in terms of the handover probability and the handover success probability.**

I. Introduction

5G networks [1], which has been considered as a new direction in the research of future cellular networks, provide high quality wireless service for mobile node. 5G networks propose an idea of effectively improving the network capacity and spectrum efficiency by independently addressing the coverage and capacity issues, which can be realized through an architecture where C-plane and U-plane split among different evolved node Bs (eNBs), as shown in Fig.1. However, comparing with traditional cellular architectures, this architecture makes handover more complex by increasing the type of handover, which can lead to intolerable handover failure.

To address these issues, many handover trigger schemes have been proposed to improve the handover performance in the C/U split architecture by handover parameters optimization or handover predication, but not consider the mobility of MN [2], [3]. For mobility issues, a formula between handover parameters and velocity was proposed for handover trigger based on the assumption that the velocity is fixed when the MN is moving [4], [5], while it cannot be applied in real environments. As can be seen, most of these schemes are based on the linear mobility of MN. However, the MN usually takes the Random Walk model in real environments, where the MN moves following no certain rules, or the direction of movement is often motivated by the wants and goals [6]. In such a case that the MN changes the speed and direction while moving towards the new neighbour network, which may have a negatively impact on the accuracy and timeliness of handover trigger, resulting in a handover failure.

Therefore, we propose a handover trigger strategy that can adapt to the mobility behavior of MN in the C/U plane split architecture. Using the FastDTW algorithm [7] and the Hidden Markov Model predication technique [8], we predict the received signal strength of current network and target network, which can be used to make handover trigger decision. The major contributions can be summarized as follows:

- Analyzing the characteristics of 5G networks and the mobility behavior of MN, we solve the handover trigger problem by providing an adaptive handover trigger strategy, which is used to make a handover trigger decision. This strategy focuses on the scenario in which a MN is traversing its serving cells at a varying velocity and direction, and is handed over to its next target cell.
- Comparing with the existing schemes [3], [9], simulation results show that our strategy can effectively increase the accuracy of predication, the handover probability as well as the handover success probability. Thus our work can be used as a potential candidate for handover trigger in future 5G networks.

The rest of this paper is organized as follows: Section 2 describes the detailed adaptive handover trigger strategy. Section 3 analyzes the complexity of the proposed strategy. Section 4 reports the experiments and discusses the simulation results. Finally, Section 5 draws the conclusion.

II. Adaptive handover trigger Strategy

The proposed adaptive handover trigger strategy (AHTS) occurs in the stage of handover preparation and initiation. This strategy can be used to predict the values of the received signal strength indicator (RSSI) to trigger a proper handover. In this strategy, considering that the change of velocity and direction can affect the accuracy of the predicted values, we use the fast dynamic time warping (FastDTW) algorithm and the adaptive RSSI predication (ARP) algorithm based on the HMM model

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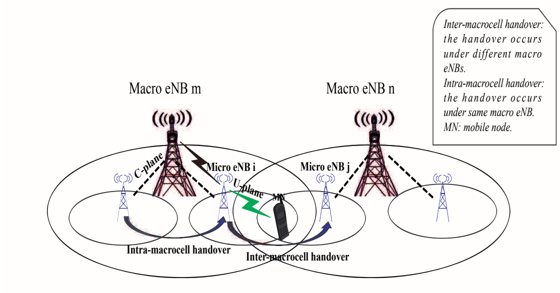

Fig. 1. 5G C/U plane split architecture

to maintain the precision of the predicted values, as shown in Fig 2. It consists of the following four processes:

A. Similarity measurement

Using the trajectories of MN with spatio-temporal information, we can calculate the similarity between the trajectories of MN via the FastDTW algorithm [7]. The trajectory similarity is the optimal alignment between the two trajectories which may vary in time or velocity. The FastDTW algorithm calculates the similarity of two trajectories in linear time, and distinguish between trajectories on the same path but oriented in opposite directions. The features of the algorithm make it suitable for measuring the similarity of trajectories.

B. Trajectory clustering

Based on the similarity measurement results obtained from above stage, we can identify similar mobility patterns of MN via the DBSCAN algorithm [10]. This algorithm is used to discover trajectory clusters of arbitrary shapes as well as to distinguish abnormal trajectories without specifying the number of clusters. The details of this algorithm can refer to [10]. Finally, each cluster contains a set of similar trajectories and the obtained results as the input of the next stage.

C. Building a HMM model

For each cluster, we train a HMM model to model the mobility patterns of MN, from which we're able to infer the most probable trajectory based on observational data.

Definition of a HMM: HMM[Q] is a six tuple, ie, $Q = \{C, H, O, \pi, A, B\}$. The parameters of the model are as follows:

C is a set of trajectories in an arbitrary trajectory cluster.

O is a set of observation symbols and can be represented as $\{o_i | i = 1, 2, \dots, m\}$, where m is the total number of observation states. In this HMM model, O represents the grids, which is obtained by dividing the trajectories into grids.

H is a set of hidden states and can be expressed as $\{h_i | i = 1, 2, \dots, n\}$, where n corresponds the total number of hidden states. In this HMM model, H represents the trajectory segments divided by the grid size.

$\pi = \{\pi_i\}$ represents the initial state of the HMM model.

$A = \{a_{ij}\}$ describes the transition probability matrix, Where $a_{ij} = P\{H(t+1) = h_j | H(t) = h_i\}$ represents the probability from hidden state h_i to h_j.

$B = \{b_{ik}\}$ describes the transition probability matrix, where $b_{ik} = \{P(O(t) = o_k) | H(t) = h_i\}$ represents the probability from the hidden state h_i to the observation state o_k.

In this HMM model, the first step is to decide the values of the observation states and the hidden states for training the model. The observation states O can be obtained by transforming the trajectories into grid sequences. The grids are the result of partitioning the digital map into a series of conjoined grids. The hidden states H can be formed by partitioning training trajectories into segments, and the size of it is determined by the size of grids. The reason for this setting is to avoid the hidden state discontinuities. Using the grids to replace the trajectory points can simplify the trajectory representation and improve the predication efficiency of the HMM model.

For ease of use, this HMM model is denoted as $\lambda = (\pi, A, B)$. The parameters in the model can be determined by the Baum-Welch algorithm [11]. This algorithm can be iteratively used to adjust λ to maximize the model likelihood probability $\log P(O \mid \lambda)$ based on the initial parameter λ_0, the hidden states H and the observation states O. For more details about HMM training, the readers can refer to [11].

D. Adaptive RSSI prediction (ARP) algorithm using HMM

When given a trajectory D, we can choose the proper HMM model according to the maximum similarity. The maximum similarity can be determined by calculating the distance between the trajectory D and each cluster center. Then we can predict the values of the RSSI via the ARP algorithm. In the forecast process, we consider the difference of interval between the trajectory points due to the change of velocity. If the distance of the trajectory points is greater than twice the size of the grid, this can result in the hidden state chain being discontinuous. If the distance of the trajectory points is less than the size of the grid, this can lead to a state retention problem [8]. This can affect the accuracy of the predicted values of the RSSI, and lead to improper handover triggers. In order to address this problem, we need to calculate $MinDis$, which represents the minimum distance of the trajectory points in the test trajectory, and then zoom the test trajectory until $MinDis$ is less than $Size_g$ (the size of grids). However, the distance between points is amplified when the test trajectory is zoomed in a 2-D space. Therefore, a linear insertion method is used to address this problem in the process of prediction. The details procedure of the ARP algorithm is presented as follows.

As shown in Algorithm 1, our goal is to predict the location at the (n+1)-th time based on the values of the previous n points, and calculate the RSSI values of the predication position. This algorithm consists of the following steps: 1) get the minimum distance of the trajectory points in the test trajectory ($MinDis$) (line 2); 2) check whether $MinDis$ meets the requirements of HMM model (lines 3-5); 3) traverse

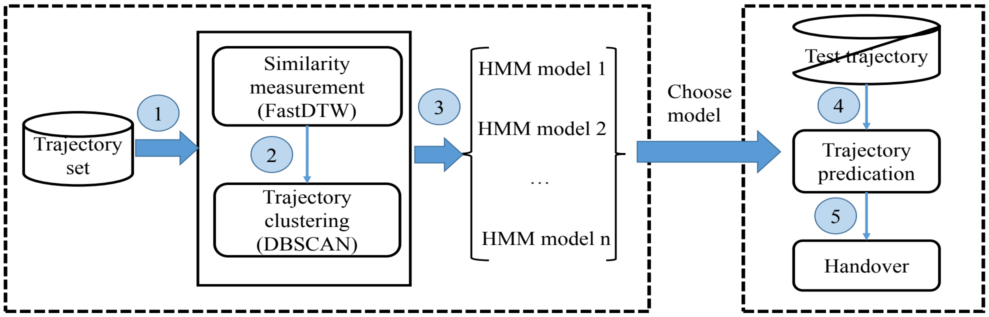

Fig. 2. Adaptive handover trigger strategy

1 Adaptive RSSI predication algorithm

Input: Trajectory D, the size of grids $Size_g$, HMM model h
Output: the values of the RSSI received at the predicted location$(x_{n+1}, y_{n+1}, t_{n+1})$

```
1:  while true do
2:      MinDis = Mindistance(D);
3:      if MinDis < Size_g then
4:          Zoom(D);
5:      end if
6:      for i < D.length do
7:          dis = GetDistance(D_i, D_{i+1})
8:          if dis > gridSize × 2 then
9:              newTrajectory D' ⟵ insertPoint(D)
10:         end if
11:     end for
12:     PreState = Forward(h, D')
13:     (x_{n+1}, y_{n+1}, t_{n+1}) = Center(PreState)
14:     According to WINNER2 model to calculate the values
        of the RSSI and return the results
15: end while
```

each point (line 6), get the distance of the trajectory points (dis) (line 7) and check if the distance meets the amplify requirements (lines 6-11); 4) the forward algorithm is used to calculate the maximum probability (N+1)-th state, and the center point corresponding to this state as the predicted point (lines 12-13); then 5) the RSSI values of the macro eNBs and the micro eNBs at the predicted target point can be calculated by the WINNER2 model [12], and can be used to trigger handover (line 14).

III. Complexity analysis

This section provides a simple analysis of the proposed strategy. In the future we will deploy it to the real network environment, and will further consider the complexity of the real network environment. The AHTS strategy consists of four stages, the first three stages used to train HMM model can work offline, the last stage is the main reason leading to time consumption in the procedure of prediction. Through the analysis of the last stage, we found that the required predication time is mainly incurred by the Forward algorithm. In the algorithm, using the probability of the observed sequence $\{S_1, S_2, \ldots, S_k\}$ at time k, we need to calculate the most likely observation sequence at time $k+1$.

$$a_k(i) = P(S_1, S_2, \ldots, S_k, q_k = H_i|\lambda) \tag{1}$$

where $a_k(i)$ is the probability of the joint event that $\{S_1, S_2, \ldots, S_k\}$ are observed, and the state at time k is H_i; $i \in [1, N]$, N represents the total number of hidden states in the selected HMM model λ; $k \in [1, T]$, T is the length of the observation sequence.

The state H_j can reach at time $k+1$ by calculating the product $a_k(i)a_{ij}$. Since state H_i has N possible, we need to sum the product which results in the probability of H_j at time $k+1$. Once this is done, the probability $a_{k+1}(j)$ is obtained by multiplying the sum of the product $a_k(i)a_{ij}$ and $b_j(S_{k+1})$. $b_j(S_{k+1})$ represents the probability of generating an observed value S_{k+1} at state H_j.

$$a_{k+1}(j) = P(S_1, S_2, \ldots, S_k, S_{k+1}, q_{k+1} = H_j|\lambda) \tag{2}$$

For state H_j also has N possible, it has to calculate for all states H_j, $j \in [1, N]$. By analyzing the Forward algorithm, the procedure of complexity calculation can be expressed as:

$$\begin{aligned} O(k \to k+1) &= O(\sum_{j=1}^{N} a_{k+1}(j)) \\ &= O\{\sum_{j=1}^{N}[(\sum_{i=1}^{N} a_k(i)a_{ij}) * b_j(S_{k+1})]\} \\ &= O(N^2) \end{aligned} \tag{3}$$

Since the length of observation sequence is T, so we need iterated it for $k = 1, 2, \ldots, T$. Thus, the complexity of the Forward algorithm is $O(N^2 \times T)$.

IV. Simulation

A. Experimental setup

The performance of the AHTS is analyzed by simulation with Matlab. The simulation model of 5G networks consists of two macro eNBs, and two micro eNBs controlled by the macro eNBs, as shown in Fig 1. In that figure, eNB m and eNB i are

TABLE I
SIMULATION PARAMETERS

Parameters	Value
Macro Cell radius R	1.7Km
Micro Cell radius r	0.8Km
Macro antenna height	30m
Micro antenna height	5m
Macro overlapped areas	0.8km
Micro overlapped areas	0.6km
Macro Cell carrier frequency	2GHz
Micro Cell carrier frequency	6GHz
Macro transmit power	43dB
Micro transmit power	33dB
Macro shadow fading deviation	4dB
Micro shadow fading deviation	3dB
sample time	500ms
outage threshold γ	-68dB
handover hysteresis threshold τ	3dB
direction of movement θ	$(-\frac{\pi}{2}, \frac{\pi}{2})$
speed of movement threshold v	(5, 30) m/s

the source eNBs, eNB n and eNB j are the target eNBs where the MN needs to establish a connection. x_m = 0 km, x_i = 0.8 km, x_j = 1.7 km, x_n = 2.5 km are the eNB locations in X-axis respectively. The detailed simulation parameters and their values are shown in table I. To simulate a wireless channel for cellular connection in a network model, we use the WINNER2 model [12]. The path loss of macro eNB m and micro eNB i at the Z point can be calculated as follows:

$$PL(m, Z_m)[dB] = 26\log_{10} Z_m + 39 + 20\log_{10}\frac{f_{cm}}{5} + \varepsilon(m, Z_m) \quad (4)$$

$$PL(m, Z_i)[dB] = 22.7\log_{10} Z_i + 41 + 20\log_{10}\frac{f_{ci}}{5} + \varepsilon(i, Z_i) \quad (5)$$

Where Z_m and Z_i represent the distance between the Z point and the eNB m and i, respectively; f_{cm} and f_{ci} are the carrier frequency of eNB m and eNB i; $\varepsilon(m, Z_m)$ and $\varepsilon(i, Z_i)$ represent shadow fading and can be regarded as a Gaussian distribution with zero mean and standard deviation σ.

Based on the network model, we need to simulate the trajectories of MN according to the random walk model. For the MN to move to the target eNB, the probability density of direction can be set as $f(\theta) = \frac{1}{2\pi}, (-\frac{\pi}{2} < \theta < \frac{\pi}{2})$. Additionally, we set the velocity of MN moves constantly from 5 to 30 m/s. Since the special architecture of 5G networks, the inter-macrocell handover is more complex than the intra-macrocell handover, we only analyze the performance of the inter-macrocell handover. In this paper, we use the following metrics to evaluate the predication effect of the AHTS:

Hit rate: Given an RSSI sample sequence $R = \{r_1, r_2, \ldots, r_k\}$ and a predicted RSSI sequence $T_p = \{p_1, p_2, \ldots, p_k\}$. Then calculate the Euclidean distance $dist(r, p)$ between points r and q. The formula $dist(r_i, p_i) < \theta$ implies one time of hit in RSSI predication, θ is a distance threshold. The hit rate can be calculated by Eq.6:

$$H(r_i, p_i) = \begin{cases} 0 & if\ dist(r_i, p_i) > \theta \\ 1 & if\ dist(r_i, p_i) < \theta \end{cases} \quad (6)$$

Predication accuracy: Given an RSSI sample sequence R, and a predicted RSSI sequence T_p, the predication accuracy can be calculated as follows :

$$Accuracy = \frac{\sum_{i=1}^{n} H(r_i, p_i)}{|T_p|}, r_i \in R, p_i \in T_p \quad (7)$$

where $|T_p|$ represents the length of the predicted RSSI sequence.

B. Effect analysis of the size of grids

As we know, the predication accuracy of RSSI is effected by the historical location error. In the real environment we can obtained the historical trajectories through the WIFI or GPS, which can be as accurate as 5-10 meters [13].

In this simulation experiment, we randomly generate 200 trajectories through the random walk model and employ the AHTS to evaluate the effect of the size of grids (denoted as α). The prediction accuracy of the values of the RSSI is greatly affected by α. Figure 3 illustrates the relationship between the size of grids and the prediction accuracy, in which the blue line denotes the prediction accuracy of the RSSI values of the source macro m, the red line denotes the prediction accuracy of the RSSI values of the target macro n. Figure 3 shows the predication accuracy usually rise before $\alpha = 18$. But after $\alpha = 18$, the prediction accuracy decreases gradually. We can concluded that the predication accuracy can be guaranteed to achieve the optimal accuracy value when $\alpha = 18$.

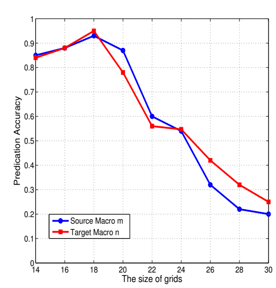

Fig. 3. Predication accuracy under different size of grids

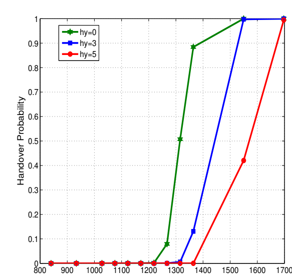

Fig. 4. Handover probability under different hysteresis thresholds

C. Effect analysis of the hysteresis thresholds

Figure 4 shows the relationship between the handover probability and the distinct handover hysteresis thresholds τ dB. As can be seen, the handover probability increases as the MN moves through the coverage area of its serving cell. In addition, the handover probability decreases with increasing hysteresis threshold. In order to ensure the quality of service of handover and the timely trigger of handover, then $\tau = 3$ dB will be adopted in the following simulations.

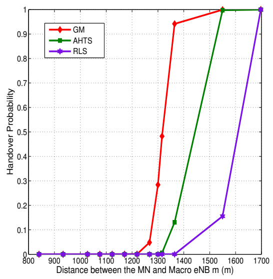

Fig. 5. Handover probability

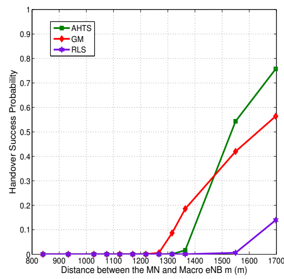

Fig. 6. Handover success probability

D. Performance Comparison

In order to prove the effectiveness of our approach, we compare with two predication-based handover trigger schemes [3], [9] in aspects of the handover performance. Since the inter-macrocell handover only occurs in the overlapping regions of eNBs, it only needs to analyze the performance of the overlapping regions [3].

1) Handover probability analysis: Figure 5 shows the relationship between the handover probability and the distance between the MN and the source eNB m, in which the green line denotes the AHTS strategy, the red line denotes the GM strategy, the purple line denotes the RLS strategy. It can be seen that the predication via the GM strategy can cause the handover to be triggered too early, and through the RLS strategy forecast can lead to the handover to be triggered too late. This is due to the error of RSSI predication caused by the mobility of MN. The RLS strategy and the GM strategy are only applicable in scenarios where historical data have high correlation. Clearly, our approach used to trigger a handover is more applicable.

2) Handover success probability analysis: Figure 6 shows and compares the handover success probability of the AHTS strategy, the RLS strategy and the GM strategy, denoted by the green line, the purple line and the red line, respectively. For the RLS strategy, the handover success probability is basically zero due to the trigger is too late. For the GM strategy and the AHTS strategy, at the early stage, the GM strategy is slightly better than the AHTS strategy due to the GM strategy trigger a handover is earlier than the AHTS strategy, but as the increase in the number of predictions, the probability of handover success of AHTS strategy is better than the GM strategy.

V. Conclusion

In this paper, which is aimed at exploring the characteristics of 5G networks, and the mobility behaviour of MN, we proposed an adaptive handover trigger strategy to determine when to trigger a handover. This strategy combined the FastDTW algorithm and the adaptive RSSI predication algorithm based on the HMM model. The FastDTW algorithm was used to calculate the trajectory similarity to distinguish between trajectories on the same path but oriented in opposite directions. The adaptive RSSI predication algorithm for predicting the values of the RSSI can adapt to the velocity change. Analytical and simulation results demonstrated that our strategy outperformed the existing schemes in terms of the handover probability and the handover success probability.

In the future, we will further improve the predication efficiency of the AHTS strategy and consider the interference impact caused by the dense deployment of micro cellular in C/U plane split architecture.

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