Handoff Prediction for Femtocell Network in Indoor Environment Using Hidden Markov Model

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Abstract. With the explosive growth of indoor data traffic, the indoor communication performance has become a popular research area in the future wireless network. Femtocells have been deployed to improve the network capacity and coverage in indoor environment. The complex building topology and user behavior may result in frequent handover and transmission interruption. Thus, we propose a mobility prediction scheme to optimize the handoff process in indoor environment using Hidden Markov Model (HMM). In this scheme, we set up the prediction model to find the optimized handoff Femtocell Access Point (FAP). A typical case of office scenario is studied as example. Considering the user behaviors, we divide the whole prediction time into several periods according to the working schedule and study the movement characteristics in each period. With the complex building topology, we generate all possible trajectories and predict the user's movement paths in these trajectories to improve the prediction accuracy. With the wall penetration loss influence, we revise the probability of connecting to FAP at the positions where have walls between FAP and connecting point. Eventually, we propose a mobility prediction scheme using HMM to forecast the next optimized handoff FAP. Simulation results show that the proposed scheme achieves a better performance compared with exiting schemes in terms of the handoff numbers and dwell time.

Keywords: Handoff prediction · Indoor environment · Femtocell
Hidden markov model

1 Introduction

With the explosive growth of mobile data traffic, it is predicted that mobile data traffic will be 49 exabytes per month by 2021, and most of them emerge at indoor environment [1–3]. It has become an important and interesting research area in future wireless network. The tradition cellular network has the bandwidth limitation and coverage issues in indoor environment. Therefore, femtocells have

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been proposed as a key solution to meet indoor users' requirements for providing a large variety of applications with better quality of service (QoS) [4]. Due to its short transmit-receive distance, femtocells can greatly lower transmit power and achieve a higher SINR. But with the short range coverage, there are many handoffs occured when user moves from the coverage of one Femtocell Access Point (FAP) to another. For optimizing the handoff process, researchers have paid great deal of attentions to the handoff optimization problem.

In indoor environment, unplanned deployment of femtocells usually suffers abrupt signal drop due to multi-path propagation, wall penetration loss, and shadowing. Unnecessary handoffs and ping-pong effects may happen frequently [5]. One of the effective solution is to predict the indoor users' accurate movement trajectories and the dwell time to find the next optimized FAP, which can reduce the unnecessary handoff numbers to provide the users with consistent service and high performance. However, the complex building topology and flexible user behavior make it difficult to accurately predict the movement.

In tradition cellular network, existing works mainly focus on speed and direction of the users to predict the paths. In [6], the authors propose a speed and service-sensitive handoff algorithm. It predicts the speed of mobile stations using Gauss-Markov mobility model to reduce unnecessary handoff for hierarchical cellular networks. In heterogeneous network, researchers have paid attention on handoff between macrocell and femtocell. In [5], the authors propose a self-adaptive handoff decision algorithm to address the issues of both macro-to-femto and femto-to-macro handoff. It is based on the user location history to assist the handoff decision-making. In indoor environment, the authors in [7] have used a standard markov chain model to predict the next location. But its prediction system is limited to the current state and current action to determine the next state, so the performance will degrade with increasing random movement. The authors in [8] propose a handoff framework using Hidden Markov Model (HMM), which adopts current and historical movement information of the users to predict the next location. However, the authors ignore the effect of time factors on the moving trajectory and use the random Way Point Mobility. It will not be suitable for indoor environment where users usually move along corridors. The authors in [9] propose a HMM based-tracking algorithm to accurately estimate the user's movement trajectory. The algorithm assumes that users move just along straight-line or circular path, which cannot reflect a real user movement behavior. Based on the discussion above, we note that existing works mainly use random way point model to predict the movement trajectory. But the complex building topology and user behavior will influence the user paths in indoor environment, so we consider the effect of space-time factors on the moving trajectory to improve the prediction accuracy.

In this paper, we focus on the user mobility prediction to optimize handoff process in indoor environment. The user behavior has different characteristics at different times and spaces. Taking the office environment as an example, we study the user movement. Then we propose a mobility prediction scheme based on users' behavior and movement information to optimize the handoff scheme

(MPOHS). In this scheme, we take the building topology and user behavior characteristics into account and divide the prediction time into several periods, according to the working schedule. In each period, we compute the state transition probability for accurate prediction. Then, we generate all possible trajectories to avoid non-existent predicted paths. And we divide the whole coverage area into grids to compute the connect probability to the FAP. Eventually, we propose the prediction scheme using HMM to forecast the optimized handoff FAP based on the history of the users' movement information. The proposed scheme is compared with existing schemes by simulation. The obtained results show that our scheme has a better performance in the terms of the handoff numbers and dwell time.

The rest of this paper is organized as follows. Section 2 describes the system scenario. In Sect. 3, we propose our handoff prediction scheme using HMM and compute the two probability matrixes. In Sect. 4, we give a detail description of our mobility prediction model to optimize the handoff process. Section 5 presents the simulation results and analysis, and Sect. 6 concludes our work.

2 System Description

We consider an indoor environment deployed with a set of N femtocells designated by F_i as depicted in Fig. 1 [10]. We divide the area into 2D-grid and each femtocell is installed in the center point of the grid, ensuring the signal can cover the whole area. At the initial state, the UEs are connected to one of the FAPs F_i. We can get the location of the UE at time t while it moving from one place to another by the localization system as a coordinate(x(t), y(t)). The handoff

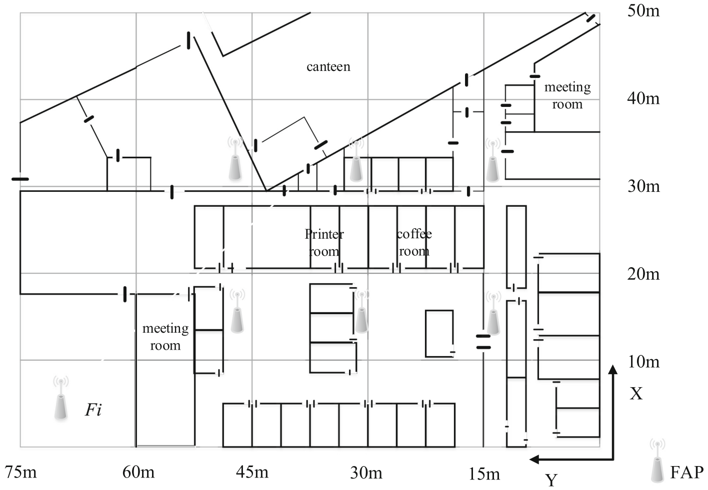

Fig. 1. Indoor environment map

occurs when UE moves from one area covered by F_i to another area covered by F_j during a communication.

Our purpose is to predict the optimized next FAP according to the previous and current positions of the UE. We can only observe the UE's position and have no information of which FAP the UE is connected to. Hence, we use the HMM as the most appropriate tool to solve the problem. We assume that all FAPs in the area are open access mode and have enough resource in the next FAP to confirm the handoff execution. In following section, we propose a scheme to predict the optimized next FAP using HMM.

3 Handoff Module Based on User Mobility Prediction

3.1 Hidden Markov Model

In this section, we give a brief overview of the HMM [11] and the method we used to solve the problem of handoff prediction. The HMM consists of a finite set of states (hidden variables), a sequence of emissions (observable variables), a finite set of state transition probabilities and a set of emission probabilities. In this model, the sequence of state transitions are hidden and can be only estimated through the sequence of emitted symbols. We can define the HMM as follows:

$S = \{S_1, S_2, S_3, ..., S_N\}$ is the set of hidden states in the system. Each state S_i represents a F_i which deployed at the center point of the grid.

$O = \{O_1, O_2, O_3, ..., O_T\}$ are the values of the observed sequences which defines the users' movement history.

$A = \{a_{i,j}\}$ are the state transition probabilities where $a_{i,j}$ denotes the probability of moving from state i to j.

$B = \{b_{ik}\}$ are the observation state probabilities where b_{ik} is the probability of emitting symbol O_k at state i.

$\Pi = \{\pi_i\}$ are the initial state probabilities where π_i indicates the probability of starting at state S_i.

For ease of use, this model is denoted as $\lambda = (\Pi, A, B)$.

3.2 State Transition Probability Distribution

The matrix A consists of the state transition probabilities, where $A = \{a_{i,j}\}$ is defined in above.

$$a_{i,j} = P(t_k == S_j | t_{k-1} == S_i) \tag{1}$$

where $a_{i,j}$ denotes the probability that the UE moving from the state S_i to the state S_j at next time slot. The indoor scenario is shown in Fig. 1. There are some popular areas such as coffee room, meeting room, printer room and canteen. The users' movement shows regularity according to the working schedule along the whole day. We assume that meeting usually takes place in the morning, the users move to canteen at noon, there will be another meeting takes place in the afternoon, and some other activities take place according to the schedule. The state transition probabilities will change at different time. So we divide the whole day into five periods, computing the matrix A at each period, as shown in Table 1. The division is suitable for most indoor office scenario. So we process the handoff prediction at different period using the appropriate matrix to improve the prediction accuracy.

Table 1. The state transition probability at each period

Period	Time interval	State transition probability matrix
t1	8:00–11:30	A1
t2	11:30–14:00	A2
t3	14:00–17:30	A3
t4	17:30–20:00	A4
t5	20:00–22:30	A5

3.3 Observation Probability Distribution

The matrix B consists of the observation probabilities, where B = $\{b_{ik}\}$ is defined in above.

$$b_{ik} = P(O_k | t_k == S_i) \tag{2}$$

where b_{ik} denotes the probability that the UE at geographical position O_k is connected to the FAP F_i, in state S_i at time t_k. The signal strength received by the UE changes according to the distance from observation to FAP. We divide the area covered by the FAP into grids, each grid represents an observation position. The authors in [8] distinguish the cover area into four signal level areas: high signal level area, medium signal level area, low signal level area and out of coverage area. It is reasonable and simple for calculating the observation probability. We refer to this coverage division idea.

It is important to notice that in indoor scenario, there are walls and other obstacles in the coverage area. The observation probability changes at different observations that belongs to the same signal level area. So we adjust the special positions observation probabilities to make it more accurate. As depicted in Fig. 2, the observation O_i and O_j belongs to Low signal level area, but there is a wall between O_i and FAP F_i, so the signal strength received at O_j is stronger than that at O_i. For that the grids we divide is small, so we assume that the walls only appear at the medium signal level area and low signal level area.

$$P_{O_k \epsilon M_{wb}} = b_{ik} \cdot \alpha \quad (0 < \alpha < 1) \tag{3}$$

$$P_{O_k \epsilon L_{wb}} = b_{ik} \cdot \beta \quad (0 < \beta < 1) \tag{4}$$

In (3) $P_{O_k \epsilon M_{wb}}$ denotes the probability connect to the FAP at the medium signal level area behind the wall. The parameter α is the coefficient to adjust the walls' influence. The same definition in (4) denotes the probability connect

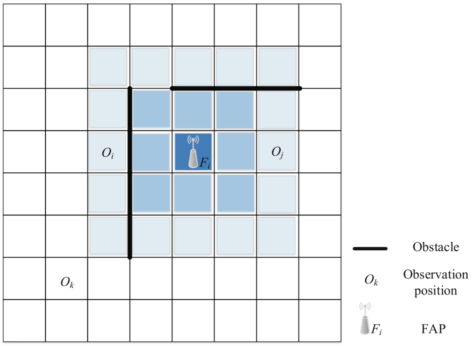

Fig. 2. The coverage of FAP and obstacle in the area

to the FAP at the low signal level area behind the wall, and the parameter β is the coefficient to adjust the walls' influence.

Now, we define all the parameters of the prediction system, the state transition probability matrix A, the observation probability matrix B, and the observation sequence of UE O. It is worth to notice that HMM can provide solution to three different problems [11]: calculating observation probability from observation sequence, decoding state sequence from observation sequence and adjustment of the HMM model to maximize the probability of the observation sequence. Our purpose is to select the optimized FAP, which we use the observation sequence of UE and the two matrixes we define in above to get the optimal state. Our problem is suitable to use the second scheme of HMM solutions, which decoding the most likely state sequence according to our observation sequence. The problem can be solved using the Viterbi algorithm.

4 Optimizing Handoff Based on Mobility Prediction Scheme

In this section, we introduce our mobility prediction based on users' behavior and movement information to optimize the handoff scheme (MPOHS). Our scheme predicts the user's next position based on the history movement information, combined with the indoor signal strength distribution to decide which optimized FAP to connect, to reduce the unnecessary handoff numbers. The MPOHS contains three major steps: initialization phase, prediction phase and handoff decision phase. In the initialization phase, we compute the two probability matrixes based on the training data. When a user comes to the coverage area, the prediction phase is activated to predict the user's next position. With the obtained prediction position, we can decide which FAP to connect in handoff decision phase.

4.1 Initialization Phase

The initialization phase is used to generate the state transition probability matrix A and the observation probability matrix B. In this phase, we generate the indoor scenario paths to train the users' movement trajectory according to the working schedule as defined in Table 1. In each period, we calculate the matrix A_i using (1), so we can acquire the needed five state transition probability matrixes. To calculate the observation probability matrix B, first we determine the values at signal level area where have no walls between FAP. Then we calculate the values at the signal level area behind the walls according to (2). Now we have the two probability matrixes and combine the history of users' movement information to predict the user's next movement position.

4.2 Prediction Phase

The prediction phase is activated at the time when a user comes to the coverage area, we add the current position to observation sequence. We calculate all the next possible position probabilities based on the two probability matrixes and the user's observation sequence using Viterbi algorithm. Then, we choose the maximum probability of all the next positions and output the position as the predict one.

4.3 Handoff Decision Phase

The handoff decision phase is used to decide which FAP to connect when we get the predict next position, we choose the optimized handoff FAP according to the observation probability matrix, which contains all position probabilities connect to the neighbor FAPs. If the predict optimized handoff FAP is the same with current connecting FAP, the user will still connect to the current FAP and go back to prediction phase. Otherwise, we execute the handoff process and handoff to the optimized FAP and then go back to prediction phase. The detail steps about our scheme is described at Algorithm 1.

5 Simulation Results and Discussions

In this section, we evaluate the performance of our handoff prediction scheme using HMM. We first describe the simulation scenario. Then we get the value of coefficient α and β through the simulation. We compare the benefits of our Scheme (MPOHS) with the OHMP [10] and Handoff to Nearest-neighbor Femtocell (HNF). The OHMP scheme optimizes handoff using HMM. It uses the random Way Point Mobility and ignores the walls' influence in the observation area. The HNF scheme chooses the nearest FAP to connect without any prediction procedures. We run multiple simulations and calculate the mean value of performance metrics.

Algorithm 1. Mobility Prediction to Optimize the Handoff Scheme(MPOHS)

Input:
the transition probabilty matrix A=$\{A_1, A_2, A_3, A_4, A_5\}$
the observation probability matrix B
the current trajectory of the user,
P=$< (O_1, t_1), (O_2, t_2), ...(O_k, t_k), ...(O_i, t_i) >$
the current state FAP F_i
Output: predicted handoff FAP F_j
for $t = t_1, \cdots, t_i$ **do**
  choose matrix $A_i \epsilon A$
end for
T=1
while user is still in area **do**
  F_j=hmmviterbi(P,A,B)
  if $F_i == F_j$ **then**
    continue
  else
    handoff to F_j
  end if
  T=T+1
end while

5.1 Simulation Scenario

In our simulation scenario as depicted in Fig. 1, the FAPs are distributed in this 50 m * 70 m area. The users' movement in this scenario during the whole day is simulated. They move along the corridor from one position to the other with velocity that varied from 0.2 m/s to 1m/s. There are distributed 6 FAPs that has a transmission range of 15 m. In our mobility prediction scheme, we consider the walls influence. We compare the Received Signal Strength(RSS) in low signal level area and medium signal level area where behind the walls according to the RSS trace file [9]. We set the α to be 0.2 and the β to be 0.5

5.2 The Performance of Handoff

The handoff happens when the user moves from one FAP F_i area to the other FAP F_j area. We evaluate the handoff numbers in different periods according to the work schedule. Figure 3 shows that the handoff numbers increase when time goes on. Our handoff prediction scheme handoff numbers are less than the other two schemes, which we can find that our scheme average handoff number is 15, compared to 18 for OHMP and 27 for HNF. The handoff numbers increase with time goes on and our prediction scheme always has less handoff numbers. Figure 4 shows that the average handoff number in each period, and all the five periods show that our scheme is better than the other two scheme on handoff numbers. So that we can conclude that our prediction scheme reduces more unnecessary handoffs compared to OHMP and HNF. For that we consider the walls influence in indoor environment and the users' movement behavior along the whole day, it could get more accurate prediction information about the users' communication environment compared to OHMP, and more geographic position information to HNF. So we can get the optimized next handoff FAP, which can help to reduce the unnecessary handoffs.

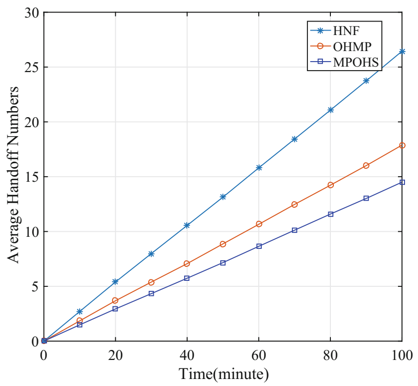

Fig. 3. Average handoff numbers

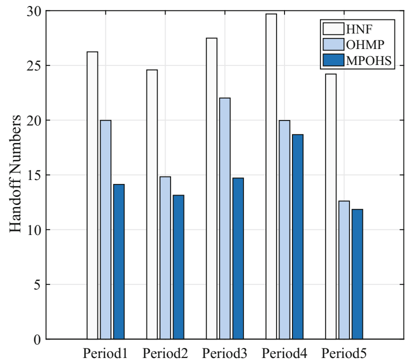

Fig. 4. Average handoff numbers in each period

5.3 The Performance of Dwell Time

The dwell time represents the amount time that user stays in a cell, where in this paper it means that user stays at the same FAP coverage area at continuous time slots. Figure 5 shows the dwell time at different period. It's obvious that our handoff prediction scheme enhance the dwell time compared to the other two schemes. At period 1 and 3, our scheme enhances the dwell time to 52.4%

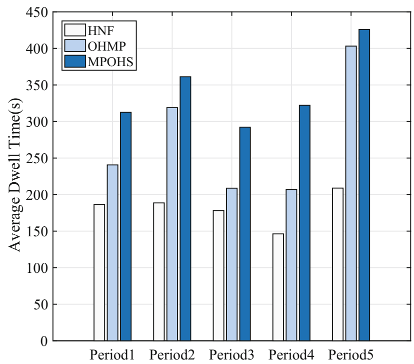

Fig. 5. Average dwell time

and 64.2% compared to HNF, and enhances the dwell time to 29.9% and 40.5% compared to OHMP. At period 2 and 4, our scheme enhances the dwell time to 173 s and 176 s compared to HNF, and enhances the dwell time to 43 s and 115 s compared to OHMP. At period 5, the dwell time is longer than the other periods, and our scheme enhances the dwell time to 217 s to HNF and 22 s to OHMP. We can conclude that our prediction scheme enhance the dwell time compared to the other two schemes. For that our scheme can have a good prediction of the user's movement and reduce unnecessary handoff, so it can enhance the time that users stay in the same coverage area.

6 Conclusion

In this paper, we propose a handoff prediction scheme using HMM. The HMM models FAP position as hidden states and the user's position as observation states. We consider the user's behavior along the whole day and compute five state transition probability matrixes at different period. Furthermore, we consider the walls influence at different signal level area and computing the observation probability matrix B. Then we use the users' movement information to predict the optimized FAP. The simulation results show that our prediction scheme has a better performance compared to HNF and OHMP, which reduces unnecessary handoff numbers and enhances the dwell time.

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