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The Enhanced User History-Based Prediction In 5G

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Abstract – Achieving seamless, mobile access is a major challenge in the next generation networks due to the huge traffic growth for mobile multimedia applications such as VoIP where the end-to-end delay is considerably big. By predicting where the users are moving, the resource allocation can perform prior to the actual handover, thus can reduce delays in resource allocation and finally can reduce the handover latency. This paper is aims to achieve an accurate user history-based by adding Temporal Prediction scheme for similar routes to eliminate the scanning overhead and unnecessary handoffs incurred in next generation networks. This is achieved by considering multiple characteristics of mobile users, and captures short-term and periodic behavior of mobile users to provide accurate next-cell predictions. The result shows 17% improvement in the accuracy compared to essential schemes.

Keywords— handover, Long Term Evolution, Femtocells, Mobility Prediction, scanning.

I. *Introduction*

Due to wide spread of streaming video, gaming and other social media, there is a prediction of an explosive growth in traffic demand over the coming years .The next generation (5G) of telecommunication networks, in Fig.1, has received un precedent attention from the researchers and the industrial fields whose starting to fund projects that looking for technologies that cope with traffic growth of 1000 times, besides the demand of extremely high data rate, efficient coverage, and user experience [1].

The third generation partnership project (3GPP) was introduced the Advanced Long Term Evolution (LTE-A) that support small cell technology as an integral part of International Mobile Telecommunication IMT- standard. Reducing the cell radii , increased the efficiency of spectral through higher frequency reuse[3]. Femtocell is a small cell with a Home-(enhanced) NodeB (H(e)NB) as its base station, incorporates the functionality of a base station and a radio network controller (RNC). The femtocells can be deployed either by the network operator in Mobile Core Network(MCN) or by the users themselves forming a two-tier network.[4]

Handover (HO) in the presence of femtocell considered one of the most challenging issues in the next generation of telecommunication networks. Aachieving seamless, mobile access is a major challenge because of large handoff delay incurred scanning for available access points (APs) when a mobile station (MS) switches connection from one AP, or cell, to another. Recent studies found that passively scanning for APs during a handoff can be as much as a second and actively scanning for APs requires 350-500 ms [5]. This becomes a major concern for mobile multimedia applications such as VoIP where the end-to-end delay is recommended to be not greater than 50 ms [6]

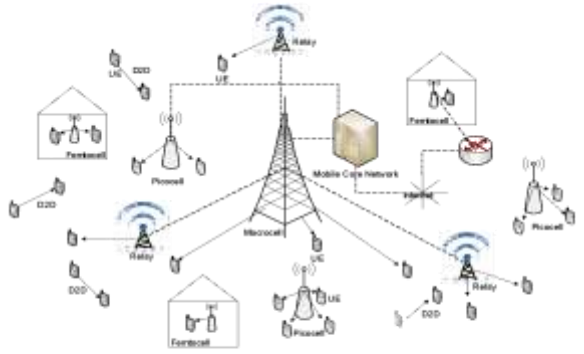

Figure 1. Heterogeneous Networks

Mobility prediction, based on the concept of the user history, creates user movement pattern. User's movement can be predicted via Markov Chains with input of user's mobility history, the prediction is more accurate when the user moves more regularly, the current studies are not satisfactory because of lack of investigating simultaneously spatial and temporal attributes of data, not taking into account that the spatial attributes of the mobile station is changed over time; resulting in increasing the probability of miss-prediction. Therefore, there is a high demand for more accurate prediction scheme considering the time constraints between locations.

The proposed mobility prediction based on the user movement behavior for 5G technology applications with enhanced properties such as groups and time of day. This information is useful to a network to achieve seamless handover and to reduce the user's mobility history data so that the memory space to store the data can be minimized.

II. *The State of Art*

This section focuses on the most recent trends followed by the researchers in mobility prediction. Current literature on handover (HO) algorithms includes many HO decision criteria and parameters that widely used on the decision making and resource allocations. the most widely used is the

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Received Signal Strength (RSS), that when mobile user moving between two base stations, signal strength from both base stations are measured, when current signal strength is below than threshold, the HO is trigged. [7]. Most RSS recent algorithms prioritize femtocell over macrocell access and incorporate other femtocell-specific criteria as well. These approaches suffer from signal attenuation, that's lead, the handoff prediction probability to be decreased.

The MS speed is another criterion [5] and it compared to absolute thresholds; which mostly arbitrary choose; to decrease the HO probability for medium to high speed users. Speed based algorithm incorporate other HO criteria as well, like RSS, the traffic type, and the available bandwidth of the target AP. Also the HO decision is taken depending on wide parameters within single cost function, e.g., battery lifetime, traffic type, cell load, RSS, and speed. The existing approaches integrate a multi-parameter function [4],[2] or use a weighted summation[9],[10]. The use of cost function and the weights related to the cost function enables sophisticated HO decision while signaling overhead need more investigation.

The Interference aware algorithms, account for the impact of co-tire and cross tire interference at the MS or the AP[11]. The main parameters in this class include the Received Signal Quality (RSQ), the Received Interference Power (RIP), the RS transmit powers, and the interference constraints at the cells. However the incorporation of these parameters need more complicated network signaling procedures.

Energy efficient algorithms aim energy utilization uses as criterion the battery power of the user equipment(UE), the expected UE energy consumption, or the mean UE transmit power. These algorithms closely related to the interference- aware algorithms because the energy consumption strongly depends on the interference at the network node.

III. *Related Work*

A. *The Global Positioning System (GPS) prediction approaches:*

This approach is depends on deciding the definite MS areas to anticipate the objective AP lead that MS could handover itself. In [11] the author propose to minimize the handoff latency, however the initialization phase delay was increased due to GPS response time to be maximum 60ms. This obviously not suited to real-time application. Also this method may prove erroneous if the MS follows a haphazard trajectory in which we cannot get a clear estimate of its future position even if we know the present an accurate prediction of the target AP. Although this methodology give a precise expectation of the targeted AP yet are still inadequate for specific cases regarding high cost, long time procedure, and high power utilization. Also the method is mostly used for outdoor networks and not suitable for indoor networks.

B. *User History-Based Prediction*

There are methods of various handover schemes and algorithms considering the MS history to provide the next AP, but these methods tend to be general and do not consider the special characteristic of Femtocells like the highly overlapped cell coverage, Mac contention, and variation in link quality. However, we take a unique approach to address the challenges by using a set of predictive method that combines various link, network and application layer. Many studies have shown that people often using similar routes and the routes are highly predictable [8,12,13]. The related mobility prediction techniques can be classified into the following two categories:

1) **Prediction based on data mining user's mobility history:**

in which for a better prediction result, collecting much history of location to initiate to the database and mine typical trajectory. But, the draw backs with data-mining techniques are consuming large storage and need fast processors to extract and analyze the long-term mobility history. Also the randomness of MSs leads to low utilization of the resources, because the data not available into the database for the new locations to be visited by users, the information mining systems used in [4, 8].

2) **Prediction based on markov chain:**

which depend on the way that the likelihood of the future result will be In light of the current What's more previous conclusions [2]. Typically, a Markov mobility predictor maintains the historical locations of MSs and extract the next locations of MSs based on the value of the most frequent visited location by MSs[5].

In markov chain methods that is used for regular movement only, the problem is when two routes have the same probability the schemes chose the next AP randomly that will affect accuracy. Fig 2.However, the suggested improved markov chain intended to fill in seamlessly with those 802. 11 MAC layer protocol. Furthermore could be used to improve these techniques and expand the exactness by acknowledging short-term mobility patterns utilizing time-series Investigation.

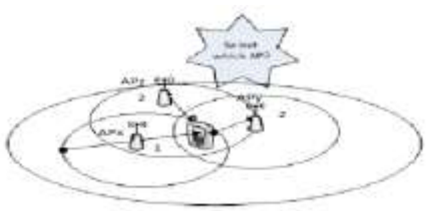

Figure 2. *The random selection for the same weighted routes*

From the literature review, the two main problems with the existing methods represent in unrealistic simplicity of the mobility models, besides treating the movement of the mobile node either regular or random but not both. In the next section, we propose hybrid method for both type of movement, taking into account several parameters to enhance the accuracy of the prediction.

IV. The Enhanced User History-Based prediction Technique

First step in data mining process is to create log report as in Table I. Data contained in a log file are date, location, time and transport. The user information, also contain the group to whom the user belongs to. The log information, by tracking the past associated APs, is analyzed, to exploit the regular patterns of movement of MS toward recognizing the specific user behaviors. Eventually utilization this information (location, the time of day, group, Furthermore duration) [2] will perform portability predictions to decrease those handoff delay.

TABLE I. LOGGING REPORT

	Date	Time (am/pm)	Location	Duration	Type of transport(walk, car, ...etc)
1					

TABLE II.

TABLE III. HHT FOR N= 3

PATTERNS	AP OF S=3			FREQUENCY N	HANDOFFS
	PAST	CURRENT	NEXT		
1	AP4	AP27	AP3	15	30
2	AP3	AP27	AP4	15	30
3	AP4	AP3	AP9	15	30
4	AP9	AP3	AP4	15	30
5	AP3	AP15	AP3	5	10
6	AP3	AP4	AP5	5	10
7	AP5	AP4	AP3	5	10
TOTAL					150

A. Handoff History Table (HHT)

Second step, the Handoffs history gathered in Table II, in a Handoff History Table (HHT), and used to predict the next upcoming future movements of the MS. The information of the present AP is needed as well as s−1 past-APs in order to keep track of an MS's handoff history of an s-entry. Table II illustrates HHT for s=3. The table has a null entry for the user that joining the network for the first time, and thus MS is maintained its movement most likely using the GPS predictor.

B. The ordinary Markov chain predictor

The mobility prediction based on the HHT can be represented by an order-k Markov process.

$$(X_{s+1} = c_{s+1} \mid X(s\text{-}k+1,s) = (c_{s\text{-}k+1}\ldots\ldots\ldots, c_s)) \quad (1)$$

Where, X_{s+1} is the prediction of the next point of attachment $k = l - 1$, L is the overall observed history of mobility patterns.

C. The Prediction Algorithm

Thirdly, the enhanced algorithm is created, when the MS associates with an AP, its information is queued in HHT. During each subsequent handoff, the MS sends to the server a route request containing route sequence as part of an authentication request. When the server receives Path requests from MSs, a history of all the handoffs in the network is maintained in the Path-Cache, where each entry contains a Cache Key represented by Current-AP and k−2 past-APs, next-AP, and a counter indicating the number of hits on this entry.

TABLE IV. THE CASE OF TWO EQUAL NUMBER OF HITS

	AP1	AP2	AP3
AP1	0	1	1
AP2	3	0	1
AP3	1	1	0

If two access point have the same probability , see Table III, and same number of hits the time of day is added to filter the selection see Table IV& V.

TABLE V. TIME INTERVALS TABLE

Time	Interval	Time	Interval
t_1	0:00 - 1:59	t_7	12:00 - 1:59
t_2	2:00 - 3:59	t_8	14:00 - 3:59
t_3	4:00 - 5:59	t_9	16:00 - 5:59
t_4	6:00 - 7:59	t_{10}	18:00 - 7:59
t_5	8:00 - 9:59	t_{11}	20:00 - 9:59
t_6	10:00 - 11:59	t_{12}	10:00 - 11:59

TABLE VI. HIT TABLE WITH TIME OF DAY PARAMETER

t_5	AP1	AP2	AP3
AP1	0	0	1
AP2	3	0	1
AP3	0	1	0
t_6	AP1	AP2	AP3
AP1	0	1	0
AP2	3	0	0
AP3	1	0	0

D. The Exponential Weighted Moving Average based prediction model (EWMA).

Exponential Weighted Moving Average (EWMA) is equivalent to general Auto Regressive Integrated Moving Average (ARIMA) model, ARIMA (0, 1, 1) [9, 14]. It used

to monitor the mean of the normally distributed process that may experience shift away from the target value.
The predicted frequency of each HS for the next period t+1;t+1 , can be obtained by the following EWMA:

$$\hat{z}_{t+1} = (1 - \lambda) + \lambda \hat{z}_t \quad (2)$$

Where z_t is the frequency of the handoff sequence during the current period t; t is the predicted frequency of the handoff sequence in the current period t, and is the smoothing factor 0<. t represents the minimum time interval for the time series data (i.e., t = 1 min). The parameter k determines the characteristic of the EWMA model and is typically chosen experimentally.

E. The Temporal Weighted Prediction Patterns

For the accuracy of prediction, the recent route patterns have a assigned weight of Hit Sequence Window(HSW) related to temporal attribute. This means that the recent history patterns is prioritizes more than the old patterns. The assigned values are calculated by:

$$weight\,(HSW) = \frac{R_{Date} - MinDate}{MaxDate - MinDate} \quad (3)$$

Where MinDate and MaxDate are the start and the end dates on the log file. R_{Date} is the last time date the specific patterns are hit.

TABLE VII. THE ROUTE WEIGHT

Cache-Route	Hits	Weight
AP1_AP10_AP12	5	33
AP1_AP3_AP1	3	50
AP3_AP2_AP5	2	70
AP5_AP3_AP2	7	20
AP1_AP10_AP5	5	50

V. Evaluation of Performance

In this section the performance evaluated in term of accuracy of predictions. The results are compared with those in [6] Fig 4. The results show superior improvement against the mentioned schemes.

A. Simulation Environment

In this study, we use 3 groups of real user mobility traces in UTM, which are undergraduate students, post-graduate students and staff. The numbers of APs in the simulated coverage area are 13 APs (see Fig 3). The total number of handover in this experiment 1200, With pre-process on the original data to extract the behavior of walker MS, the mobility trace denotes associated behavior- history of each user's group by the cell number in the network under a simple mobility model assumption. Based on this model, we propose temporal history- based mobility prediction algorithm. We used the Enhanced Markov predictor to predict future locations, especially in the case of similar routes probabilities.

B. The simulation result

(2)

The simulation is done using Mat lab simulator. Figure 4 shows the comparison of the accuracy in average between the pre-scanning scheme, the MCP and our proposed method. As can be seen, our method achieved a pretty much accuracy enhancement. In figure 5 the accuracy is checked for the three subjected groups. The undergraduate group and staff group tends to have accuracy higher than postgraduate, this is because of the regularity of their movement , since it is related to the lectures schedules. Figures 6 and 7 represent the histogram of the prediction after adding the time of day parameter, primary result shows that adding of the time of day parameter enhance the prediction accuracy by 17% in average for all groups.

Figure 3. *The simulation area in kfe bulidings in UTM.*

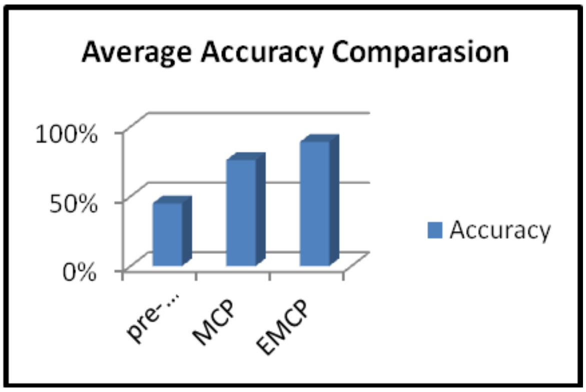

Figure 4. *Prediction Accuracy Average Based On EMCP Compared To Pre-scanning and MCP*

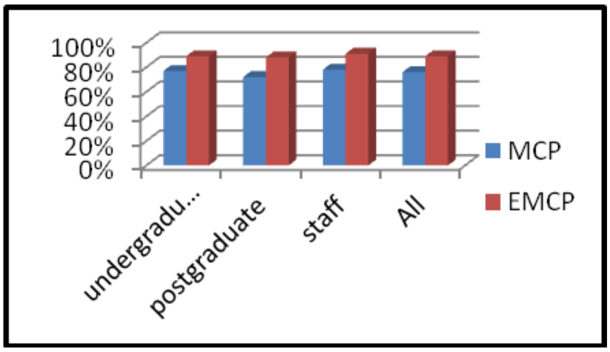

Figure 5. *Prediction Accuracy Of Groups Based On EMCP Compared To MCP*

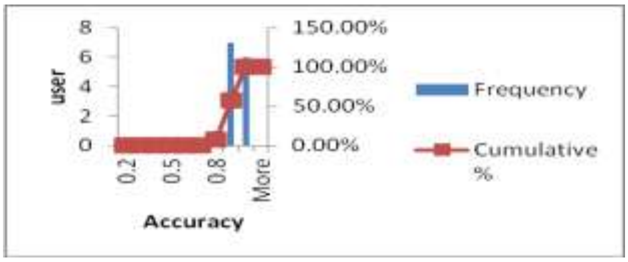

Figure 6. *Histogram Of Prediction With Time Of Day Parameter*

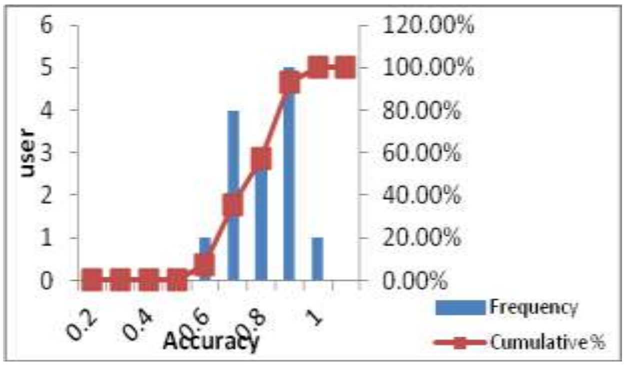

Figure 7. *Histogram Of Prediction Without Time Of Day Parameter*

VI. Conclusion

This paper presented the EMCP technique to enhance mobility prediction in the next generation mobile networks. The proposed method based on extracting the behavior patterns of three groups of users. The added factors, like time of day factor, result in improve the accuracy of the next cell prediction by17%. Our simulation study shows that the prediction is better when the movement of MSs is more regular results in much lower delay and good QoS.

For future work, we plan to investigate other factors influence the seamless mobility like the interferences and load balance.

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