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JOINT TIME AND LOCATION MOBILITY PREDICTION ALGORITHM FOR HETEROGENEOUS WIRELESS NETWORKS

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ABSTRACT

Mobility prediction algorithm is the significant aspect to improve QoS (Quality of Service) for heterogeneous wireless networks because it can accurately predict user' s trajectory, decrease handoff latency and preserve resources in arriving cell for user. Considering inaccurate description of existing mobility prediction algorithms for mobile user's location in heterogeneous wireless networks, this paper proposes that overlay coverage zone (OCZ) can be used to precisely describe user's location, flexibly depict the mobile user's characteristics and vertical handoffs among different wireless networks. As existing algorithms highly depend on cell boundary estimation and suffer from low time prediction accuracy, the phase-type distribution is introduced to model user's residence time in OCZ to improve classical Markov predictor, and then a novel joint time and location mobility prediction algorithm is proposed. Simulation results show that, compared with Markov mobility prediction algorithm, the prediction accuracy of the proposed algorithm is highly increased.

Keywords: *Mobility Prediction Algorithm, Heterogeneous Wireless Networks, QoS, Overlay Coverage Zone, Joint Time and Location*

1. INTRODUCTION

Driven by technological developments and industrial interests, existing wireless networks are featured by different access technologies, networking modes, resource allocation, client groups and commercial backgrounds, leading to these networks being difficult to replace each other. Therefore, the future wireless communication networks will be open and distributed heterogeneous networks comprised of different wireless networks. In such an environment, communication services are highly developed and the number of mobile users is drastically increasing resulting in growing shortage of spectrum resources [1]. Meanwhile, mobile users are more eager for seamless and continuous services with strictly guaranteed QoS [2].

Mobility management can coordinate interactions across heterogeneous wireless networks and guarantee the receipt of consistent services for mobile users even when their location continuously changes in heterogeneous wireless networks. Mobility prediction is a crucial aspect of mobility management because it can predict user's motion trajectory and then preserve resources required by user in the arriving cells in advance to avoid degrading QoS due to insufficient resources. In addition, mobility prediction can partially complete the functions of horizontal or vertical handoffs to reduce handoff latency and signaling overhead when user's location is updating. Therefore, well-designed mobility prediction algorithms are highly significant for guaranteeing QoS and maximizing spectrum efficiency.

So far, existing mobility prediction algorithms have been derived from the ones for homogenous networks. Factually, since there are overlay coverage zones (OCZs) formed by multiple wireless networks within heterogeneous networks,

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the prediction of user's location in OCZ the key to mobility prediction for heterogeneous networks. Based on existing mobility prediction algorithms, in the light of the low time prediction accuracy of Markov model based mobility prediction algorithm, OCZ is used to precisely depict the user's location and the phase-type distribution is utilized to describe the residence time of user in OCZ, and then a novel joint time and location mobility prediction algorithm is proposed. Simulation results show that, compared with the classical Markov model based prediction algorithm, the proposed algorithm in this paper achieves higher prediction accuracy.

2. RELATED WORK

Depending on whether GPS (Global Positioning System) is used, mobility prediction algorithms in wireless networks can be classified into two types [3]. The first type uses GPS to get user's coordinate as UMH (User Mobile History) information, and then utilizes different fitting algorithms to predict user's coordinate or location in the next time. At length, by means of cell boundary estimation algorithm, the cell that user will visit can be determined. Apparently, the performances of the first type of prediction algorithms are highly dependent on the effects of boundary estimation algorithms (i.e. estimation of the shape and the size of cells). However, since there are few well-performed boundary estimation algorithms, much attention has been paid to the second type of mobility prediction algorithms without GPS.

The second type is without GPS, which uses history ID (identification) information sequence of cells passed by user as UMH and utilizes Markov predictor, data mining or model matching to predict user's trajectory. In comparison, such algorithms are independent of cell boundary estimation. In fact, above two mobility prediction algorithms are quite different from the application conditions and backgrounds; especially, they are mutually complementary and very difficult to replace each other.

In recent years, some mobility prediction algorithms of the second type have appeared [4-12]. In [4], Yu and Leung introduced data compression (For instance, Ziv-Lempel) into mobility prediction, but it is highly difficult to get Ziv-Lempel tree from mobile history information. In [5], Cleary and Teahan proposed a local matching algorithm based on fixed order, but the fixed order cannot well adapt to user's time-varying mobility resulting in deteriorated prediction. In view of the flaw of fixed order, Jacquet and Szpankowski proposed an extended local matching prediction algorithm in which the matching order is flexible [6]. In [7], the authors proposed that user's common information including its location and corresponding time should be incorporated in mobility prediction, however, as this information involves much personal privacy more often than not, such approach is difficult to be applied in open and public network environment. [8] compares Markov model based and other mobility prediction algorithms and points out the former has the advantages of simple implementation, high prediction accuracy and small data storage. By means of real trace data collected by Dartmouth College, [9] and [10] validate that multi-order Markov model is suitable for describing mobile use's trajectory. In [11], Song et al. presented a k-order Markov model based predictor and tested it using real trace data leading to poor time prediction accuracy for lower order k; however, higher-order Markov predictor not only depends on a large amount of UMH information, but has poor performance for insufficient UMH information as well. To cope with this situation, Sun and Blough gave out an adaptive k-order Markov based predictor with feedback in [12]; when it works badly for a certain order k, a lower order k will be automatically fed back to the predictor. However, it still suffers from low time accuracy.

So far, most of existing mobility prediction algorithms for heterogeneous wireless networks has been derived from the ones for homogeneous wireless networks, but the difference between heterogeneous and homogeneous wireless networks has not been taken into their consideration. On the other hand, how to describe user's location is the basis and premise of mobility prediction algorithms because a well-performed prediction algorithm would be deteriorated due to inaccurate location information. In addition, it is very apparent from above literature review that Markov model based mobility prediction algorithms are simple and easily-implemented relative to other algorithms. The only imperfection is that their improved versions always suffer from low time prediction accuracy.

In this paper, overlay coverage zone (OCZ) is proposed to describe user's location in heterogeneous wireless networks and phase-type distribution is applied to Markov predictor to model user's residence time, and then a novel joint time and location mobility prediction algorithm for heterogeneous wireless networks is proposed.

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Simulation results show that compared with other algorithm, the proposed algorithm has higher prediction accuracy.

3. JOINT TIME AND LOCATION MOBILITY PREDICTION ALGORITHM

3.1 Joint Time And Location Mobility Prediction Algorithm

Traditionally, user's trajectory is described using cell ID in homogeneous wireless networks because the services and the bandwidth required by the user is independent of the exact location of user in the cell. Therefore, the residence time and the IDs of cells can be used to describe the user's mobility. However, the cell coverage of different wireless networks is quite different form each other, for instance, the cell radium is about 1.5 km for WCDMA networks while the cell radium is roughly 60 m for WLAN (Wireless Local Area Network). As a result, the traditional methodology based on cell ID is not suitable for description of user's location in heterogeneous wireless networks. In view of the disadvantage, OCZ is introduced to depict user's location in this paper that the user's trajectory can be modeled as a series of OCZ' IDs. The classification of OCZ is according to the type of wireless networks that the OCZ covers. In this paper, three-layer OCZ system is used, including cellular networks, WMAN (Wireless Metropolitan Area Networks) and WLAN. In this condition, four types of OCZ can be demonstrated as shown in Fig.1.

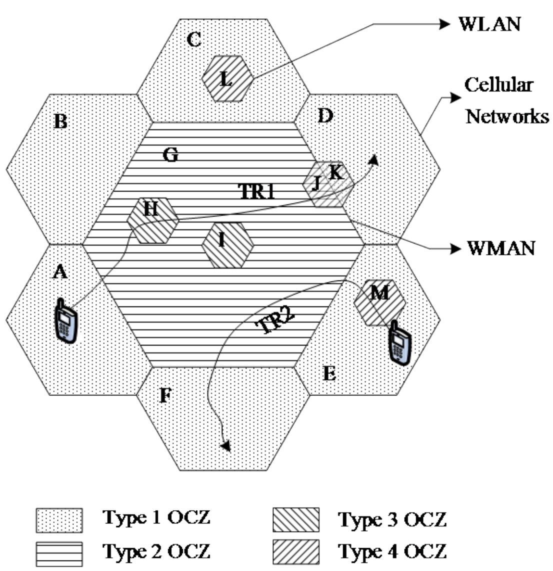

Figure 1. Overlay Coverage Zone

Type 1: OCZ only covered by cellular networks;

Type 2: OCZ covered by both cellular networks and WMAN;

Type 3: OCZ covered by cellular networks, WMAN and WLAN;

Type 4: OCZ covered by both cellular WLAN;

It is worthy to note that there is a WLAN cell divided into J and K parts in Fig.1 where part J is together covered by cellular networks, WLAN and WMAN, while part K is covered by both cellular networks and WLAN. The user's trajectory can be represented by a series of OCZ's IDs, for instance, trajectory 1 (TR1) is represented as A-G-H-G-J-K-D, while TR2 is denoted as E-M-E-G-F.

The advantages of using OCZ to describe user's mobility in heterogeneous wireless networks are specially manifested in three aspects.

First, OCZ is able to adapt to different wireless networks that different people are locate in and flexibly describe the mobile scenes of the terminals. Specifically, WLAN is often deployed according to hot spot in city of which features are high user density, slow speed, for example, the zones I and H shown in Fig.1. WMAN mainly covers whole city where its user has faster speed and slower direction change, for instance, the zone G demonstrated in Fig.1. In contrast, the zone B usually corresponds to highway of which features are relatively the lowest population density, highest speed and slowest direction change. In general, even though a user consistently goes through the same network, for instance, the user moves along trajectory TR1 passing by A-G-H-G-J-K-D in turn, it experiences different mobile scenes including cellular networks, WLAN and WMAN. Therefore, OCZ can differentially tackle different mobile scenes to improve prediction accuracy.

Second, OCZ can well depict vertical handoffs and resource allocation among different wireless networks. From the perspective of radio resource management, all of resources in heterogeneous wireless networks can be partitioned according to OCZs while resources in each OCZ can be shared by all different networks that compose the OCZ. Therefore, as long as there are preserved resources in an OCZ for all cross-OCZ users, handoff dropping can be avoided.

Third, since mobile terminals tend to be multi-mode [13] with the fast development of software radio, their favorable sensing to electromagnetic environment is the solid foundation of deploying

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OCZ. The electromagnetic environment above mentioned means the type and number of networks that user terminals access. When user terminal senses electromagnetic environment changed, the user terminal is entering a new OCZ, and then it sends the entrance time and the IDs of the cells that compose current OCZ to network management center for the information being recorded.

3.2 Markov Model Based Mobility Prediction Algorithm

Markov model based mobility prediction algorithm is simple and easily-implemented only without time information, resulting in low prediction accuracy. The basic idea of Markov model based algorithm is recounted as follows. Symbol sequence $(a_1, a_2, \cdots a_n)$ serves as history data and the next symbol can be predicted according to the recent k symbols $(a_{n-k+1}, \cdots, a_n)$ [11]. Given history data $H = a_1 a_2 \cdots a_n$, $H(i,j) = a_i a_{i+1} \cdots a_j$ represents a subset of H, where any i and j satisfy $1 \le i \le j \le n$. Y is a random variable, and $Y(i,j) = Y_i Y_{i+1} \ldots Y_j$ stands for a sequence comprised of variables $Y_i, Y_{i+1}, \ldots Y_j$. Define $c = H(n-k+1, n)$ as the context and A as a subset of all of possible symbols. If Y follows k-order steady-state Markov distribution, for all $a \in A$ and $i \in \{1, \cdots, n-k\}$, its distribution satisfies

$$\begin{aligned} &\Pr(Y_{n+1} = a \mid Y(1,n) = H) \\ &= \Pr(Y_{n+1} = a \mid Y(n-k+1, n) = c) \\ &= \Pr(Y_{i+k+1} = a \mid Y(i+1, i+k) = c) \end{aligned} \qquad (1)$$

where $i \ne n$ and $i \ge k-1$.

For any time t, current history information H and k symbols of the context c can be used to estimate the following transition probability

$$\Pr(Y_{n+1} = a \mid H) \approx P(Y_{n+1} = a \mid H) = \frac{N(ca, H)}{N(c, H)} \qquad (2)$$

where $N(s', s)$ means the number of occurrence of sub-sequence s' in sequence s.

Markov model based mobility prediction algorithm predicts the next best possible symbol as follows

$$Y_{n+1} = \arg\max_{a \in A} (P(Y_{n+1} = a)) \qquad (3)$$

3.3 Residence Time In Ocz

To determine the distribution of user's residence time in OCZ is the most important aspect of mobility prediction algorithm. As exponential distribution is simple and easily-analyzed, existing literature is mainly focuses on exponentially distributed residence time. In fact, user's movement is highly dynamic and irregular in many cases, leading to its residence time does not follow exponential distribution [14], and such a hypothesis brings about inaccurate prediction.

Fortunately, phase-type distribution is a highly effective stochastic model and can be used to approach arbitrary and non-negative variables [15]. In this paper, phase-type distribution is used to model user's residence time in OCZ, and EM (Expectation Maximization) is used to estimate the parameters of phase-type distribution. The introduction to phase-type distribution is omitted here and can be referred to some mathematics manuals.

PHASE-TYPE DISTRIBUTION

Consider a continuous-time Markov process with $m+1$ states, where $m \ge 1$, such that the states $1, \cdots, m$ are transient states and state 0 is an absorbing state. Further, let the process have an initial probability of starting in any of the $m+1$ phases given by the probability vector $(\alpha_0, \boldsymbol{\alpha})$, where α_0 is a scalar and $\boldsymbol{\pi}$ is a $1 \times m$ vector.

The phase-type distribution is the distribution of time from the above process's starting until absorption in the absorbing state. This process can be written in the form of a transition rate matrix,

$$Q = \begin{bmatrix} 0 & \mathbf{0} \\ \mathbf{t}^0 & \mathbf{T} \end{bmatrix} \qquad (4)$$

where $\mathbf{T}$ is a $m \times m$ matrix and $\mathbf{t}^0 = -\mathbf{T1}$. Here $\mathbf{1}$ represents a $m \times 1$ vector with every element being 1.

The distribution of time X until the process reaches the absorbing state is said to be phase-type distributed and is denoted PH($\boldsymbol{\pi}$, $\mathbf{T}$). The distribution function of X is given by

$$F(x) = 1 - \boldsymbol{\pi} \exp(\mathbf{T}x)\mathbf{1} \qquad (5)$$

and the probability density function (PDF) is

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given by

$$f(x) = \boldsymbol{\pi} \exp(\mathbf{T}x)\mathbf{t}^0 \quad (6)$$

for all $x > 0$, where $\exp(\cdot)$ is the matrix exponential. It is usually assumed the probability of process starting in the absorbing state is zero (i.e. $\pi_0 = 0$). The moments of the distribution function are given by

$$E[X^n] = (-1)^n n! \boldsymbol{\pi} \mathbf{T}^{-n} \mathbf{1} \quad (7)$$

PARAMETER ESTIMATION FOR PHASE-TYPE DISTRIBUTION

The history data for parameter estimation of phase-type distribution can be gotten from simulation results or real trace data, including the ID of OCZ that user enters and the residence time in the OCZ. Presently, some literature pays attention to parameter estimation of phase-type distribution [16,17], where EM estimation is the most effective approach. The main idea of EM approach will be illustrated below.

EM algorithm is an iterative method for finding maximum likelihood or maximum a posteriori (MAP) estimates of parameters in statistical models, where the model depends on unobserved latent variables [18]. The EM iteration alternates between performing an expectation step (E-step), which creates a function for the expectation of the log-likelihood evaluated using the current estimate for the parameters, and a maximization step (M-step), which computes parameters maximizing the expected log-likelihood found on the E-step. These parameter-estimates are then used to determine the distribution of the latent variables in the next E-step.

Suppose $Y = u(X)$ is observed with the PDF g_γ, where u is a many-to-one mapping, X is large numbers of unobserved results and f_γ is the PDF of X. In the $(n+1)$-th step of EM algorithm, γ_{n+1} which maximizes the following formula should be solved, i.e.

$$\gamma \to \mathrm{E}_{\gamma_n}\left[\log f_\gamma \,|\, u(X) = y\right] \quad (8)$$

where y is the observed data, γ_n is the estimate after n iterations.

Let E-step and M-step denote the solving conditional expectation and maximization likelihood. In EM algorithm, the complete data set for solving the maximum likelihood estimate of $(\boldsymbol{\pi}, \mathbf{T})$ from the observed results is given by

$$\mathbf{y} = (y_1, \ldots, y_n) = (s_0^{[1]} + \ldots + s_{m[1]-1}^{[1]}, \ldots, s_0^{[n]} + \ldots + s_{m[n]-1}^{[n]}) \quad (9)$$

The probability density function of $\mathbf{x}$ is

$$f(\mathbf{x}; \boldsymbol{\pi}, \mathbf{T}) = \prod_{i=1}^{p} \boldsymbol{\pi}^{B_i} \prod_{i=1}^{p} \exp\{t_{ii} Z_i\} \prod_{i=1}^{p} \prod_{\substack{j=0 \\ j\neq 1}}^{p} t_{ij}^{N_{ij}} \quad (10)$$

where B_i the number of Markov process starting from state i; Z_i is the total time in state i; N_{ij} the total number from state i to state j. The expressions of B_i, Z_i and N_{ij} are presented below

$$B_i = \sum_{v=1}^{p} \mathbf{1}_{\{I_o^{[v]} = i\}} \qquad (i = 1, \ldots, p) \quad (11)$$

$$Z_i = \sum_{v=1}^{n} \prod_{k=0}^{m[v]-1} \mathbf{1}_{\{I_k^{[v]} = i\}} S_k^{[v]} \qquad (i = 1, \ldots, p) \quad (12)$$

$$N_{ij} = \sum_{v=1}^{n} \sum_{k=0}^{m[v]-1} \mathbf{1}_{\{I_k^{[v]} = i, I_{k+1}^{[v]} = j\}} \quad (i \neq j, i, j = 1, \ldots, p) \quad (13)$$

The probability density function $f(\mathbf{x}; \boldsymbol{\pi}, \mathbf{T})$ is a multi-parameter exponential family with sufficient statistics being expressed

$$\mathbf{S} = \left((B_i)_{i=1,\ldots,p}, (Z_i)_{i=1,\ldots,p}, (N_{ij})_{i=1,\ldots,p,\, j=0,\ldots,p,\, i\neq j} \right) \quad (14)$$

The maximum likelihood estimate of $\mathbf{x}$ is given by

$$\begin{cases} \hat{\pi} = \dfrac{B_i}{n} & \hat{t}_{ij} = \dfrac{N_{ij}}{Z_i} \\ \hat{t}_i = \dfrac{N_{i0}}{Z_i} & \hat{t}_{ii} = -(\hat{t}_i + \sum_{j=1}^{p} \hat{t}_{ij}) \end{cases} \quad (i, j = 1, \ldots, p) \quad (15)$$

When iteration is performed, E-step is the start of every iteration. E-step computes the conditional expectation of the sufficient statistics $\mathbf{S}$ according to the observed $\mathbf{y}$ and the estimate $(\boldsymbol{\pi}, \mathbf{T})^{(k)}$ of the current $(\boldsymbol{\pi}, \mathbf{T})$. Then, M-step maximizes likelihood estimate of (10) using above conditional expectation of $\mathbf{S}$ as the observed data of (14), specifically, the new estimate $(\boldsymbol{\pi}, \mathbf{T})^{(k+1)}$ in (15) can be derived from the conditional expectation of $\mathbf{S}$.

4. ALGORITHM SIMULATION AND ANALYSES

To validate the proposed mobility prediction algorithm, mobile history data in real heterogeneous wireless networks should be provided, but so far,

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accessible mobile history traces data has been only restricted to homogeneous networks without traces data for heterogeneous networks, for example, the trace data for cellular networks collected by Stanford University and the trace data for WLAN from CRAWDAD (Community Resource for Archiving Wireless Data at Dartmouth). Therefore, the required mobile history data should be gotten from modeling and simulation. The simulation scene of heterogeneous wireless networks is the same as shown in Fig.1, including 7 WCDMA cells, 1 WiMax cell and 20 WLAN cells. The cell radiuses of above three wireless networks are 1500m, 750m and 60m, respectively. WLAN cells are randomly distributed within the coverage of 7 WCDMA cells. A Wrap-around technique is adopted to form cell edge region.

To model user's mobility in different scene, the 2-D Gauss-Markov model [19] is introduced of which the expressions are given below

$$s_n = \alpha_v s_{n-1} + (1-\alpha_v)\bar{s} + \sqrt{(1-\alpha_v^2)} s_{x_n-1} \quad (16)$$

$$d_n = \alpha_v d_{n-1} + (1-\alpha_v)\bar{d} + \sqrt{(1-\alpha_v^2)} d_{x_n-1} \quad (17)$$

where s_n is the speed at time n; d_n represents the direction at time n; α_v stands for memory factor ($0 \le \alpha_v \le 1$); $\bar{s}$ and $\bar{d}$ are the means of speed and direction, respectively; $s_{x_n\text{-}1}$ and $d_{x_n\text{-}1}$ are Gaussian distributed random variables.

This model can simulate various types of mobile scenes between random-walking and constant flow movement by adjusting memory factor α_v. The larger α_v is, the lower the randomicity is. $\alpha_v = 1$ means constant flow movement, while $\alpha_v = 0$ stands for random-walking. Therefore, different mobile characteristics can be depicted by means of different α_v. In addition, in order to describe different mobile characteristics of different users in the same zone, α_v is randomly selected in a specified interval for every simulation scene. These intervals are [0.7 1] for OCZ of type 1, [0.4 0.7] for OCZ of type 2 and [0 0.4] for OCZ of type 3, respectively.

Though the proposed joint time and location mobility prediction algorithm is independent of the information of cell boundary, the information is necessary for getting mobile history data. In real wireless environment, the size and the shape of cell is dynamic and affected by many factors, such as traffic load distribution. In contrast, this paper assumes the cell is hexagonal mainly because the focus of this paper is on the ID and residence time of OCZ where user is located. As a result, the assumption about the shape and the size of cell does not influence validation of the proposed algorithm.

Fig. 2 shows the transition probability that a user transits from OCZ_i to OCZ_A, OCZ_C and OCZ_F. From Fig.2, it is can be seen that the transition probability predicted by proposed algorithm is related to time unlike Markov model based prediction algorithm with constant probability. Specifically, the former is increasing and approaching the probability that the latter achieves over time. When $t \to \infty$, they are equal to each other. This is mainly because Markov model based mobility prediction algorithm does not include time information that it considers all transitions as the same for all time, leading to low prediction accuracy.

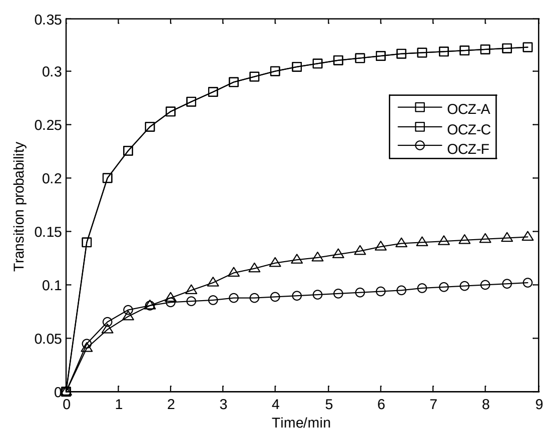

Figure 2. Transition Probabilities vs. Time

An accuracy factor (AF) is introduced to precisely evaluate the prediction performances of two algorithms. AF is defined as

$$\phi_p = \frac{\sum_{m=1}^{M} \delta_m}{M} \quad (18)$$

where δ_m is successful prediction indicator; M is the number of predictions.

If the predicted OCZ and the predicted time that transition happens are right, δ_m is set to 1; otherwise, δ_m is set to 0. When it comes to 'right' time, if the difference between the predicted time and the real time is less than a certain ΔT, the predicted time can be called right. In this paper, the prediction complexity and interval are taken into consideration to set ΔT = 1min.

Fig. 3 and Fig.4 demonstrate the average accuracy distribution of the proposed algorithm and the Markov model based algorithm. It is obvious from the results that the number of users in the interval of high average prediction accuracy is more than the Markov model based algorithm. Furthermore, the average prediction accuracy for all users of the proposed algorithm is 46.7% from Fig.3, while the same metric of the Markov model based algorithm is only 28.2% from Fig.4. Compared with the latter, the proposed mobility prediction algorithm increases accuracy by 65.6%.

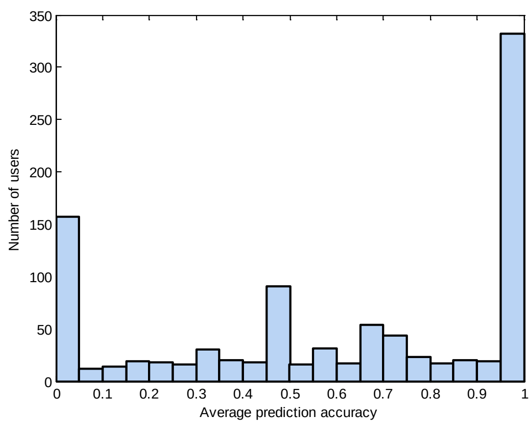

Figure 3. Distribution of the Average Prediction Accuracy of Joint Time Location Mobility Prediction Algorithm

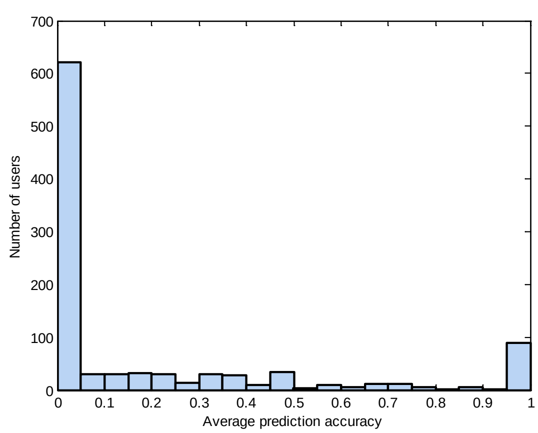

Figure 4. Distribution of the Average Prediction Accuracy of Markov Model Based Mobility Prediction Algorithm

5. CONCLUSIONS

Mobility prediction is a crucial aspect of mobility management and QoS. This paper analyzes the difference between heterogeneous and homogeneous wireless networks and proposes overlay coverage zone (OCZ) to depict user's location in heterogeneous wireless networks. In view of the Markov model based mobility prediction algorithm suffering from low time prediction accuracy, phase-type distribution is introduced to model residence time in OCZ. Based both on residence time and OCZ (location), a novel joint time and location mobility prediction algorithm is proposed. Simulation results show that, compared with the classical Markov model based mobility prediction algorithm, the proposed algorithm has higher prediction accuracy.

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