

Dividing Sensitive Ranges Based Mobility Prediction Algorithm in Wireless Networks

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Abstract

As wireless networks have been widely deployed for public mobile services, predicting the location of a mobile user in wireless networks became an interesting and challenging problem. If we can correctly predict the next cell to which the mobile users are going, the performance of wireless applications, such as call admission control, QoS and mobility management, can be improved as well. In this paper, we propose a mobility prediction algorithm based on dividing sensitive ranges. The division is in accordance with the cell transformation probability. Then different prediction methods are applied according to the sensitivity of the range to gain high precision. Simulations are conducted to evaluate the performance of the proposed scheme. As it turns out, the simulation results show that the proposed scheme can accurately predict the location for mobile users even in the situation of lacking location history.

Key Words: Wireless Network, Mobility Prediction, Dividing Sensitive Ranges, WiFi

1. Introduction

Wireless networks, including Worldwide Interoperability for Microwave Access (WiMAX) [1], Wireless Fidelity (WiFi) [2], Wideband Code Division Multiple Access (WCDMA) [3], High Speed Download Packet Access/High Speed Upload Packet Access (HSDPA/HSUPA) [4], and Wireless Sensor Network (WSN) [5–7], are rapidly being developed to achieve high-speed data transmission. Since the NGN (Next Generation Network) consists of heterogeneous networks and supports mobile/ubiquitous computing, developing efficient generalized *mobility management* for the NGN has become one of the key issues in the NGN research. In addition, the mobility management will be a very important function for wireless networks in future all-IP radio heterogeneous networks.

The aim of *mobility management* is to track where the mobile subscribers are located, so that calls (or links) and other mobile services can be delivered to them correctly. The *location update* and *paging* are two essential operations for mobility management. However, they require more signaling costs. In GSM (Global System for Mobile Communications) or UMTS (Universal Mobile Telecommunications System) network, there are many base stations, and each base station covers a small geographical area, called *cell*, which is a uniquely identified location area. By integrating the coverage of each base station, cellular networks can provide a wider radio coverage area. In cellular networks, the *location update messages* allow a mobile subscriber to be informed whenever it moves from one location area to the next cell. *Paging* is another process used in the cellular networks when we are trying to search a mobile subscriber. It sends polling signals to the neighbor cells closed to the last reported location of a mobile subscriber. However,

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when the micro-cell technique was applied to the cellular networks, the frequency of location update will be increased, so that higher location update frequency would cause more extra overhead in cellular networks. As a result, if we can precisely predict the next cell where a mobile subscriber will go, things will be different. With precise mobility prediction techniques, the frequency of location update can be reduced drastically.

Vertical handoff is another important mechanism to achieve continuous seamless transmissions in cellular networks. In contrast to the horizontal handoff, vertical handoff considers not only the received signal strength (RSS) but also the service-class mapping between entering and leaving networks. However, in comparison to horizontal handoff, vertical handoff is a more complex process, which requires lower delay, lower power, and the occupied bandwidth should be as small as possible. In addition, vertical handoff needs more complex wireless access technologies in terms of signal detection, channel distribution, and the optimization of radio resource management. In order to improve the quality of service (QoS) in heterogeneous networks, moreover, handoff delay, channel scanning and resource reservation should be implemented as well. An excellent discussion on the QoS for wireless networks can be found in [8].

Mobility prediction is very helpful in terms of the performance improvement in each aspect. If the prediction of the next cell for a mobile subscriber can be carried out more accurately, on one hand, we can reduce the required workload, handoff delay [9] and the number of channels which are needed to scan in handoff. On the other hand, we can negotiate with the next cell and reserve the resources for the mobile subscriber in advance so as to avoid the QoS from being degraded due to insufficient resources available. Thus mobility prediction plays a prominent role in wireless networks. In addition, mobility prediction also plays an important role in flow control and energy consumption in wireless networks [10], and can improve the efficiency of multicast protocols in ad hoc networks [11]. Besides, mobility prediction will play a decisive role in developing wireless multimedia applications and integrating various business activities.

In this paper, we propose the concept of dividing sensitive ranges in accordance with the probability of cell transformation, and then provide a mobility predic-

tion algorithm based on dividing sensitive ranges, in which different algorithms are designed in accordance with different sensitive ranges. Finally, a comprehensive simulation is conducted to evaluate the performance of the proposed scheme. The simulation results show that the proposed scheme has high accuracy and universality.

The remainder of this paper is organized as follows. Section 2 describes some of the related works about mobility prediction. Section 3 introduces our mobility prediction algorithm based on dividing sensitive ranges. Simulation and experimental results are given in section 4, followed by section 5 which concludes this paper.

2. Related Work

In [12], the authors provided a brief description of several algorithms used for location prediction, which broadly falls into the following two categories: (1) *domain-independent algorithms* which are derived from Markov analysis and text compression algorithms, and can be applied to mobility prediction. (2) *domain-specific algorithms* which consider the geometry information of user motion as well as the semantics of the symbols in the user's movement history. In what follows, we briefly mention other algorithms, and end with some concluding remarks.

It should be noticed that the use of mobility prediction to improve mobility management makes one primary assumption, that is, user's movements follow a pattern and display some regularity, despite actual user mobility patterns may not be well understood. In order to increase the accuracy rate of prediction, some researchers make a secondary assumption: the next cell crossing is a logical function of user's current position, velocity, and cell geometry. Mobile motion prediction algorithm is based on the user's movement history [13], and the movements consist of regular and random components, which can be either matched with circle/track patterns or simulated by the Markov chain model. Prediction is highly accurate with regular movements but decreases linearly with increasing random component.

Profile-based next-cell prediction algorithm is based on the user's movement history and the classification of locations [14]. Mobility can be purely random, almost random, purely deterministic, and mostly deterministic. The type of location can be office, corridor, or common

room. It provides advance reservation and adaptation in resource management. Prediction is highly accurate with fully predictable movements, 80% accurate for typically observed movements, and 70% for fully random movements.

Hierarchic position-prediction algorithm is based on the user's movement history and instantaneous RSSI (Received Signal Strength Indication) measurements of surrounding cells [15]. User's movement can be mapped into previous mobility patterns, with matching operations such as insertion, deletion and changing. Intercellular movements can also be estimated by current location, velocity and cell geometry. It sets up and reserves resources along a mobile's path, and plans quick handovers between base stations. This method minimizes the occurrence of location registration and update procedures. Prediction remains reasonably accurate (75%) despite the influence of random movements.

Adaptive user mobility prediction algorithm was derived from a probability distribution of all possible next moves [16]. If the first predicted cell does not contain a probability higher than the PCR (Prediction Confidence Ratio), one or more extra cells will be added to the group of cells in which resources will be reserved in advance and services will be pre-configured. This process will continue until the sum of their probabilities exceeds the PCR. But the value of PCR is different between different cells. Hence, it is difficult to obtain a correct PCR from certain networks, and thus its accuracy is not good enough.

In the future distance prediction scheme proposed in [17,18], a node predicts its own future position from its current position, speed, and direction. Model-based adaptive mobility prediction [19] uses the prediction scheme in [18] but with an enhanced future distance predictor which adaptively produces the coefficients of a specified estimator using learning automaton. Mobility prediction algorithm in [20] is similar with [13]. The major difference between the two schemes is that the motion prediction architecture is used to predict the mobile subscriber's next location in high speed environment where mobile subscriber moves with a very high speed. In [21], the authors propose a linear prediction algorithm, which divides time into multiple prediction windows, and each window is a prediction unit. They assume that the mobility behaviors of the nodes will not be modified during

adjacent prediction windows. This algorithm is adapted in underwater sensor networks.

Mobility prediction algorithm in [22] extrapolates the future positions according to the current position and their habits. They suggest a cache having mobile ID (a unique mobile identifier which includes pin code or MAC address), period (allows the distinction between a working day (0) and a public holiday (1)), source cell (indicates the cell from which the mobile came), destination cell (indicates the cell towards which the mobile is going), date (indicates the date at the moment the displacement is recorded), and then make prediction based on these history information in the cache. In fact, this method is a multiple state Markov model, and is difficult to be carried out.

Joint mobility prediction (JMP) algorithm [23] with differential accuracy requirements is applied to target tracking in wireless sensor network, which depends heavily on the cooperation between sink node and sensor node. Mobility prediction in [24] uses the order-2 Markov chain to capture user's movement history and carry out predictions. This is highly suitable for a campus environment because of its simplicity. However, the accuracy is not satisfactory. Mobility prediction algorithm in [25] uses a vector $([x_k, y_k, z_k, vx_k, vy_k, vz_k]^T)$ to denote the node's state at a time instance, where x_k, y_k and z_k specify the 3D position of the node, and vx_k, vy_k , and vz_k specify the velocity components on x, y , and z axes, respectively. Mobility prediction applies the current location information, the projected velocity, and the mobility pattern parameters to predicting the location at a future time instance.

3. Mobility Prediction Algorithm Based on Dividing Sensitive Ranges

In previous works, any location in a cell is treated equally in mobility prediction algorithms. In fact, such a setting may result in a low accuracy rate of prediction. Since the goal of mobility prediction is to predict the next cell or subnet that the mobile subscriber will enter, we are much concerned about the locations where the future cell may be different from the current one. In fact, the probability of moving from a cell to the next, called *cell transformation*, is different with respect to different locations in the cell. Hence, it is not reasonable to apply

the same mobility prediction to different locations. As a consequence, we propose a mobility prediction algorithm based on dividing sensitive ranges which does not need the location history. On one hand, our algorithm has the merit of putting predictive resources to rational use. On the other hand, the simulation results show that the accuracy rate achieves up to 100% (best case), and the average accuracy rate is about 93.4%. Furthermore, our algorithm can be widely employed by a variety of terminal units in wireless networks.

In what follows, we propose how to divide sensitive ranges. The probability of cell transformation is defined as *sensitivity*. When the probability of cell transformation is large (resp., small), the sensitivity is high (resp., low). If the probability is zero, the sensitivity is the minimum. In order to divide the range in a cell, if the minimum distance between the mobile subscriber and the border is greater than D , defined as follows, the range is called the number 1 range.

$$D = V_{\max} \times T \tag{1}$$

where V_{\max} is the maximum rate of the mobile subscriber; T is the period of mobility prediction, i.e., the location of the mobile subscriber is predicted every T seconds. Note that, if V_{\max} is unknown, it can be replaced by the upper limit rate supported by the networks.

According to the calculation of D , it is reasonable to assume the probability of cell transformation in the number 1 range to be zero, i.e., the sensitivity is zero. If the mobile subscriber is located within the number 1 range, it will still be in the same cell in T seconds. If the minimum distance between the mobile subscriber and the border is from d to D , in which d is defined as follows, this range is called the number 2 range.

$$d = \bar{v} \times T \tag{2}$$

where \bar{v} is the average rate of mobile subscriber. Apparently, compared to the number 1 range, the probability of cell transformation in the number 2 range is larger, and the sensitivity in the number 2 range is also higher. Finally, if the distance between the mobile subscriber and the border is from zero to d , this range is called the number 3 range. The probability of cell transformation considers not only the motion characteristics but also

the location of the mobile subscriber currently. Since the probability of cell transformation in the number 3 range will be larger than that in the number 2 range, the sensitivity in number 3 is the highest.

Take a regular hexagonal cell as an example. As illustrated in Figure 1, the area which is filled in black is the number 1 range and its sensitivity is lowest. The area which is covered with shadow is the number 2 range and its sensitivity is higher, as compared to the number 1 range. The number 3 range is filled in white and its sensitivity is the highest of all.

Generally, the complexity of algorithm is proportional to the accuracy. In order to use the predictive resources rationally, different algorithms with different complexity should be applied to different sensitive ranges. Therefore, two algorithms with different complexity (*average rate mobility prediction* and *polynomial regression mobility prediction*) are introduced as follows.

Average rate mobility prediction uses the following steps to predict the location of a mobile terminal unit. As shown in Figure 2, the last and current geographical locations of the mobile subscriber are denoted as $A(X_{i-1}, Y_{i-1})$ and $B(X_i, Y_i)$, respectively, and the predictive geographical location of the mobile subscriber is denoted as $C(X_{i+1}, Y_{i+1})$. First we calculate average rate \bar{v} between A and B , in which \bar{v}_x is the component of \bar{v} in direction x , and \bar{v}_y is the component of \bar{v} in direction y . Then we estimate the average rate between B and C which may be

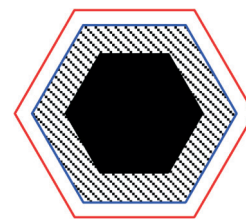


Figure 1. Sensitive divisions in a regular hexagonal cell.

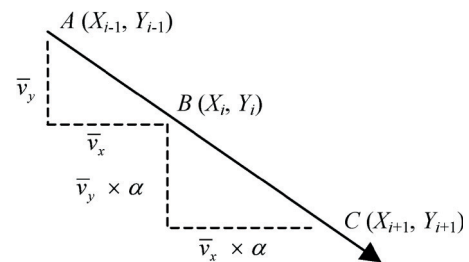


Figure 2. Average rate mobility prediction algorithm.

taken as $\bar{v} \times \alpha$. Initially, the value of α is assigned 1. Then α can be adjusted in accordance with the recent situation at regular intervals. By doing so, the future location of mobile subscriber can be predicted.

Polynomial regression mobility prediction [26] uses the following steps to predict the location of a mobile terminal unit.

Step 1 – Preprocessing step

In prediction, some previous locations are important for determining the next predictive location. Let the previous location data at H times compose an original data sequence $S(p)$ ($p = 1, 2, \dots, H$). To intensify the polynomial regression-based curve fitting, the preprocessing procedure of accumulated generating operation is adopted to achieve the accuracy of the prediction results. The preprocessing procedure generates a new data sequence $S'(n)$ by accumulating the previous n location data records, which are formulated by the following equation:

$$S'(n) = \sum_{p=1}^n S(p) \quad (3)$$

The purpose of the preprocessing procedure is to smooth the fitting curve. For instance, an original data sequence of $\{3, 6, 4\}$ becomes $\{3, 9, 13\}$ after preprocessing.

Step 2 – Mobility prediction step

After the preprocessing step, the new data sequence is used as the input data for curve fitting in the mobility prediction step. The predictive location in the new sequence is denoted as $S_{pre}'(n+1)$, which is computed as follows:

$$S_{pre}'(n+1) = P(t_{n+1}) \quad (4)$$

where $P(\cdot)$ is a polynomial function with $k+1$ unknown coefficients as follows:

$$P(t) = a_0 t^0 + a_1 t^1 + a_2 t^2 + \dots + a_k t^k \quad (5)$$

Let R_h be the location of the previous h -th process. Then, the sum of the square of the difference between actual R_h and predictive $P(t)$ of the previous n processes is defined as

$$D = \sum_{h=1}^H [R_h - (a_0 t_h^0 + a_1 t_h^1 + a_2 t_h^2 + \dots + a_k t_h^k)]^2 \quad (6)$$

To determine each coefficient a_i , each a_i in each polynomial can be treated as a variable. We take the partial differential of each a_i in equation (6), and then set each partial differential equation to zero. Then we can obtain the following equivalent polynomials:

$$\begin{cases} a_0 \left(\sum_{h=1}^H t_h^0 \right) + a_1 \left(\sum_{h=1}^H t_h^1 \right) + \dots + a_k \left(\sum_{h=1}^H t_h^k \right) = \sum_{h=1}^H t_h^0 R_h \\ a_0 \left(\sum_{h=1}^H t_h^1 \right) + a_1 \left(\sum_{h=1}^H t_h^2 \right) + \dots + a_k \left(\sum_{h=1}^H t_h^{k+1} \right) = \sum_{h=1}^H t_h^1 R_h \\ \vdots \\ a_0 \left(\sum_{h=1}^H t_h^k \right) + a_1 \left(\sum_{h=1}^H t_h^{k+1} \right) + \dots + a_k \left(\sum_{h=1}^H t_h^{2k} \right) = \sum_{h=1}^H t_h^k R_h \end{cases} \quad (7)$$

After determining all the summations of t in equation (7), we can simplify this matrix of polynomials to an upper triangle matrix of polynomials. Each coefficient a_i can be determined by the native Gauss elimination method, where $i = H, H-1, H-2, \dots, 0$. Consequently, the polynomial function of $P(t_{n+1})$ in equation (4) is obtained, i.e., the prediction of the pre-processed $S_{pre}'(n+1)$ is determined. Since $S_{pre}'(n+1)$ and $S'(n+1)$ can be computed by equation (4), the predictive location of the original sequence $S_{pre}(n+1)$ and $S(n+1)$ can be determined by the reverse transformation of equation (3).

$$S_{pre}(n+1) = S_{pre}'(n+1) - S'(n) \quad (8)$$

It is obvious that the complexity of average rate mobility prediction algorithm is less than that of the polynomial regression mobility prediction algorithm, but the prediction accuracy of the former is also less than the latter. When the mobile subscriber is located at higher sensitive ranges of cell, the probability of cell transformation is higher. For achieving higher prediction accuracy, the polynomial regression mobility prediction algorithm is applied, vice versa. By doing this, we can not only ensure the prediction accuracy but also reduce the complexity of operation.

Our proposed mobility prediction algorithm based on dividing sensitive ranges is described as follows. Firstly, we calculate the minimum distance between the current locations of the mobile subscriber and the border

to decide the sensitivity for the current location. If the sensitivity is the lowest in the cell, we will do nothing and directly predict that the next cell is still the same one as the current cell. If the sensitivity is the medium in the cell, we will use the average rate mobility prediction mentioned above to predict the next cell. Finally, we will use the polynomial regression mobility prediction mentioned above to predict the future cell if the sensitivity is the highest in the cell.

4. Simulations and Performance Evaluation

In this section, a simulation experiment is conducted to investigate the effect of our algorithm. In the simulation scenarios, 1000 mobile subscribers move randomly at a walking speed in a Wi-Fi environment with 400 hot points, in which 5000 cell records are selected randomly as the original data set. In the data set, each subscriber terminal unit has its own record, which contains the time and the cell in that time. Since the moving speed of the mobile subscriber has been considered in defining the dividing sensitive ranges, it would not affect the accuracy of the proposed prediction algorithm. The performance is analyzed in stationery and universality, where the length of prediction is the number of mobility prediction and can be measured by t/T (in which t is the total time spent by the mobility prediction; T is the period of mobility prediction, i.e., the mobility prediction is executed once every T seconds). The accuracy of prediction is related with T . In simulation, T is assigned 5 seconds, which are adapted according to the subscriber's walking speed. For comparison of performance, the order-1 Markov predictor [27] which has been verified to have better performance is taken as a contrast.

The order-1 Markov predictor can predict the location of mobile subscriber at next time from its current location context. Let the cell records which a mobile subscriber passes through be a_1, a_2, \dots, a_n , and let substring $L = a_1 a_2 \dots a_n$. The location of the mobile subscriber is regarded as a random variable X . Let $X(i, j)$ be a string X_i, X_{i+1}, \dots, X_j representing the sequence of random variables X_i, X_{i+1}, \dots, X_j for any $1 \leq i \leq j \leq n$. In the order-1 Markov predictor, X behaves as follows, $i \in \{1, 2, \dots, n\}$.

$$P(X_{n+1} = a | X(1, n) = L) = P(X_{n+1} = a | X_n = a_n) \quad (9)$$

$$P(X_{n+1} = a | X_n = a_n) = P(X_{i+1} = a | X_i = a_i) \quad (10)$$

Let A be the set of all possible locations. If $a \in A$, then $P(X_i = a_i | \dots)$ denotes the conditional probability where X_i takes the value a_i . These probabilities can be represented by a transition probability matrix M . The predictor scans the row of M corresponding to the current context a , choosing the entry with the highest probability for its prediction.

Since our algorithm adjusts a part of parameters, such as α , the initial performance is reduced shortly when the movement characteristics of the terminal unit are modified abruptly (see Figure 3). Since the order-1 Markov predictor is based on the location history, its performance is bad initially, but becomes better with the growth of the prediction length (see Figure 4). Finally, its performance becomes stationary when the length of prediction is about 4000 (see Figure 4). Figures 3 and 4 show that our algorithm performs well in stationery, especially when the length of prediction is larger than 100. The accuracy rate is up to 100% and the average accuracy rate is about 93.4%.

The mobility prediction algorithm based on dividing sensitive ranges predicts the future cell of a terminal unit according to its own real-time movement characteristics, so it is appropriate for most terminal units. The order-1 Markov predictor is based on the transition probability matrix, so it is not suitable for the terminal units whose movement characteristics are not marked. Figures 5 and

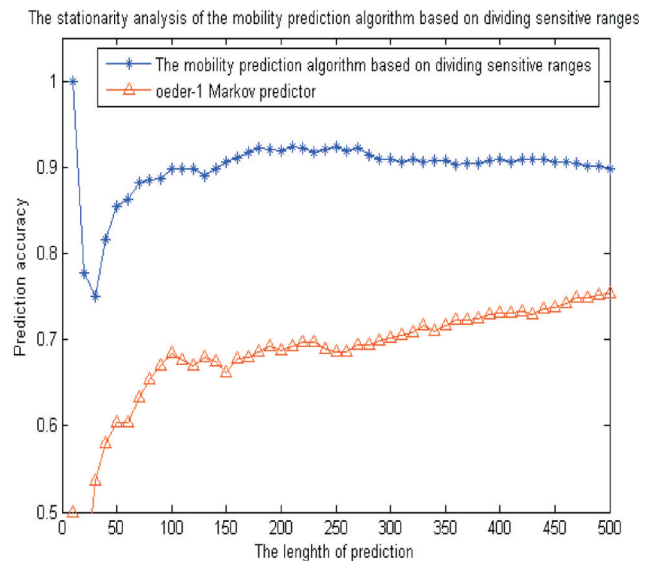


Figure 3. Algorithm efficiency in short length of prediction.

6 show that our algorithm performs well in universality, regardless of the length of prediction, in which the accuracy rate is concentrated between 92% and 95%.

To sum up, the mobility prediction algorithm based on dividing sensitive ranges introduces the concept of sensitive range. The complexity of algorithm is concentrated in the high sensitivity range, which makes the use of predictive resources more reasonable. The mobility prediction algorithm based on dividing sensitive ranges can perform better in accuracy with the same complexity. Through simulation and analysis, the mobility prediction algorithm based on dividing sensitive ranges also per-

forms well in both stationery and universality.

5. Conclusion

In this paper, we have proposed a new mobility prediction algorithm based on dividing sensitive ranges. The proposed scheme introduces the concept of sensitive ranges. The complexity of algorithm is concentrated in the high sensitivity range, which makes it more reasonable to use the predictive resources. In addition, our method can obtain better accuracy rate with the same complexity. The results of simulation confirm the remarkable performance improvement of our scheme. A line of future work is to consider the performance of our algo-

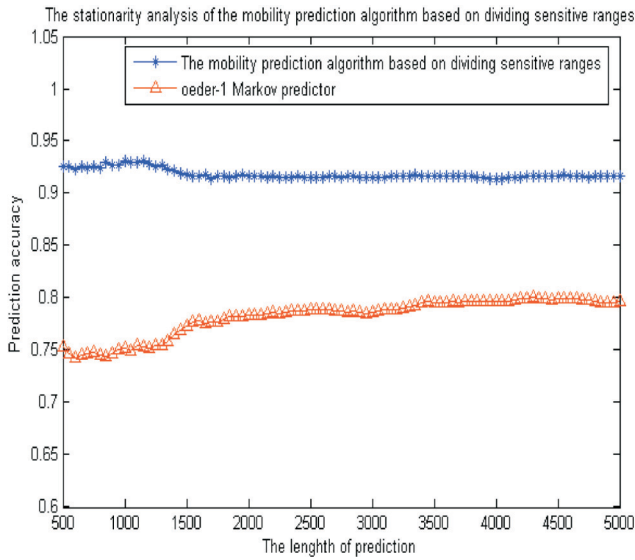


Figure 4. Algorithm efficiency in longer length of prediction.

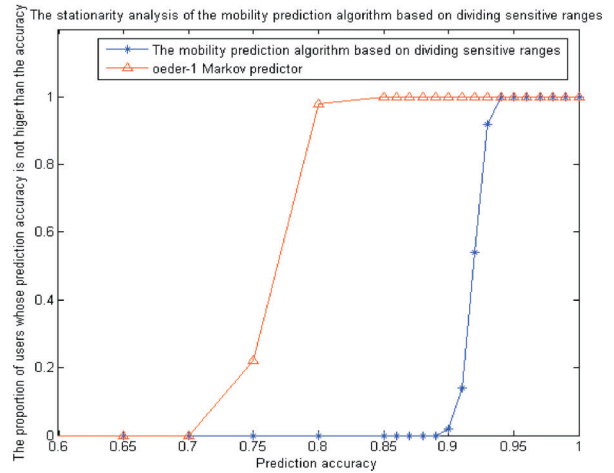


Figure 6. The universality of algorithm in medium length of prediction (the length of prediction is 5000).

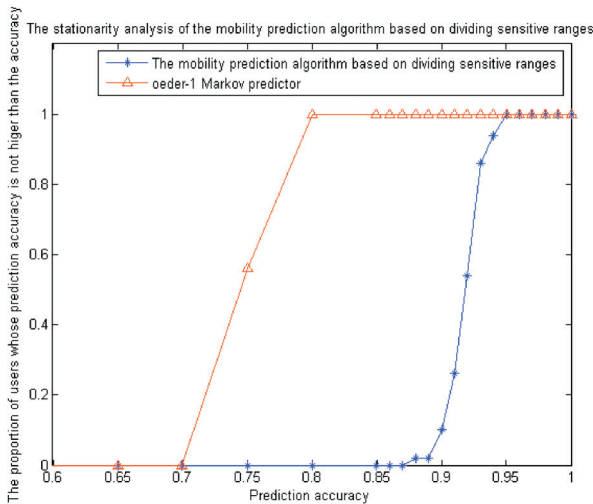


Figure 5. The universality of algorithm in short length of prediction (the length of prediction is 500).

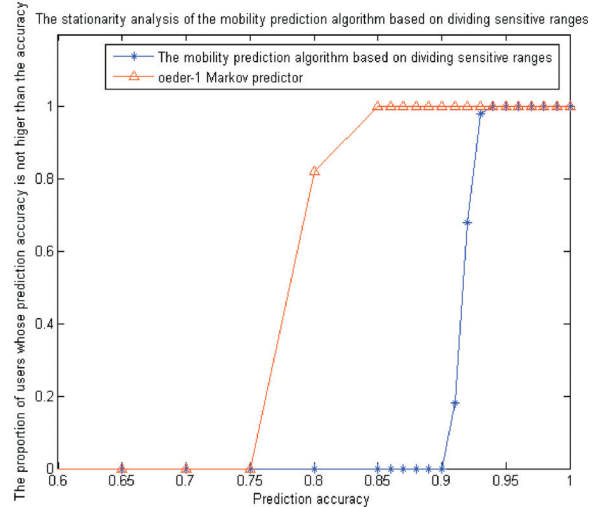


Figure 7. The universality of algorithm in long length of prediction (the length of prediction is 10000).

rithms in actual applications both in homogeneous networks and heterogeneous networks.

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