An Optimal Self-Learning Estimator for Predicting Inter-Cell User Trajectory in Wireless Radio Networks

Tong Liu[1], Paramvir Bahl[2], *Member, IEEE*
Imrich Chlamtac[3], *Fellow, IEEE*

Abstract—**Prediction of the next-crossing cell is an important issue for mobility and connection management in wireless radio networks. In this paper, we propose a new approach to modeling inter-cell user mobility, and develop an optimum self-learning estimator for trajectory tracking and next-crossing cell prediction. The dynamic states of movement, in terms of speed and position, are obtained by modeling the user's acceleration as a time-correlated, semi-Markovian process, and by passing subsequent signal-strength measurements to neighboring base stations through an Extended, Self-learning Kalman filter. Prediction of next-crossing cell is obtained by evaluating user dynamic states with cell geometry. Analysis and simulation results show that our prediction algorithm is robust in the presence of pass loss, shadow fading , and random movement, being able to predict the position, speed, and direction-of-travel of the mobile user with a high degree accuracy.**

Keywords—**Location and Mobility Management**

I. Introduction

The key differentiater between wireline and wireless (cellular) networks is the latter's ability to maintain connectivity even as the end nodes move between cells. Unfortunately, due to lack of prior knowledge of the mobile user's trajectory, lifetime connectivity is not always possible and on-going network connections are often broken prematurely due to lack of resources in the cell entered by the mobile. Algorithms that rely on simple heuristics for predicting the mobile user's trajectory, so that the system may reserve resources in advance, have been proposed previously but these generally fall short when the user's movement pattern is random[1][2].

In this paper, we propose a novel method which facilitates efficient mobility management through user trajectory prediction in situations which have previously been thought to be unpredictable [2]. Our method is useful for the case when the subscriber's current movement pattern does not match any pattern known to the system. It is thus complimentary to the pattern matching methods and when combined with these is able to achieve robust prediction. Our approach is based on viewing the trajectory prediction problem as a filtering problem, extracting the necessary mobility information from practically available measurements such as the RF signal strength. Thus, trajectory estimation is obtained from real-time observations and a high degree of prediction accuracy is guaranteed even when the system has no prior information about the user's mobility history. An optimum filter, implemented as an Extended, Self-learning Kalman filter, adaptively tracks the user's trajectory and predict her dynamic states in terms of speed and position. This information together with cell geometry is used to predict the next cell to be crossed. The rest of this paper is organized as follows: In Section II we describe a user mobility model. In Section III we propose an adaptive optimum filter for tracking mobile users. In Section IV we develop an algorithm for predicting the next cell in the path of the mobile user, and finally in Section V, simulation results are presented.

[1] Tellabs Wireless Systems Division, 30 North Avenue, Burlington, MA 01803-3398, USA; Phone: (617) 273-1400, Fax: (617) 273-4160, tliu@wireless.tellabs.com

[2] Microsoft Research, One Microsoft Way, Redmond, WA 98052-6399 USA; Phone: (425) 936-1021, Fax: (425) 936-7329, bahl@microsoft.com

[3] Erik Jonsson School of Engineering and Computer Science. The University of Texas at Dallas, P.O. Box 830688 MS EC33, Richardson,TX 75083-0688 Phone: (972) 883-6295 Fax: (972) 883-2710 chlamtac@utdallas.edu

II. Simulating User Mobility

Our motivation for User Mobility modeling is based on the observation that the seemingly random choice of inter-cell movement is actually a logic function of the user's position, velocity, moving direction and cell geometry. However, User Mobility models found in the literature assume straight line movement and constant speed [3][4], which are can not reflect real situations.

In order to track time-varying movement, we model a moving user as a linear, dynamical system, on which linear minimum mean-square estimator can be built in real time to estimate and predict the dynamic states in two-dimensional Cartesian coordinates.

The basic modeling idea is shown in Figure 1-(a). In real situations, a moving user has a wide acceleration range. Traffic light and turns of the road may cause abrupt changes of speed in x and y directions respectively. In order to follow such sudden changes quickly and in the mean time be able to keep tracking slow variations . The driving input to the dynamic systems is modeled as a combination of a semi-Markov process $U(t)$ and a time-correlated random process $r(t)$. The states $S_1, S_2, ...S_m$ are discrete levels selected to cover the whole acceleration range $[-A_{\max}, A_{\max}]$, as shown in Figure 1-(b). Transition from one state to another corresponds to the dramatic change of moving behavior. Random acceleration $r(t)$ has Gaussian distribution, with zero mean and variance chosen to cover the "gap" between adjacent states. This modeling idea was once successfully applied in tactical weapon systems for maneuvering target tracking[5][6].

Observation of the output of the moving dynamics directly is expensive and infeasible. In practical systems, the position and velocity can be non-linearly related to some practical available measurement, such as signal-strength measurement from reachable base stations, which may be further corrupted by random shadowing.

The following two sub-sections describe the corresponding mathematical model in terms of dynamic equations and observation equations.

A. Dynamic Equations for a Moving User

Based on the model mentioned above, the continuous-time dynamic equation for a moving user is given by:

$$\underline{\dot{x}}(t) = F\underline{x}(t) + E\underline{u}(t) + G\underline{r}(t) \quad i = 1, \ldots, m \qquad (1)$$

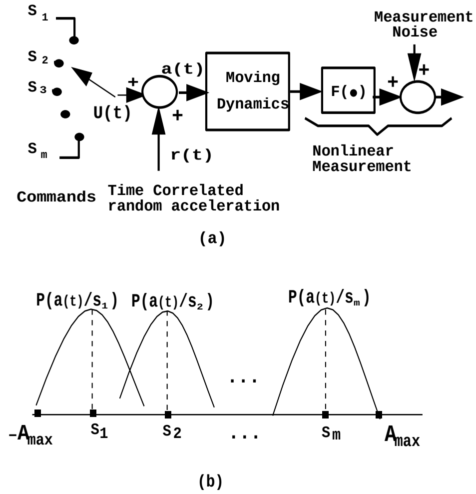

Fig. 1. User Mobility Model

$$\text{where } F = \begin{bmatrix} \Theta & 0 \\ 0 & \Theta \end{bmatrix} \qquad E = G = \begin{bmatrix} \Phi & 0 \\ 0 & \Phi \end{bmatrix}$$

$$\text{with } \Theta = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \qquad \Phi = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

For the problem being considered, $\underline{x}(t) = [x(t), \dot{x}(t), y(t), \dot{y}(t)]^T$ with $x(t)$ and $y(t)$ as rectangular coordinates. $\underline{u}(t) = [u_x(t), u_y(t)]^T$, $u_x(t)$ and $u_y(t)$ are independent semi-Markovian process which may take m possible discrete values respectively $s_1, s_2, ..., s_m$. Random acceleration $\underline{r}(t) = [r_x(t), r_y(t)]^T$ is correlated in time; namely if a moving object is accelerating at time t, it is likely to be accelerating at time $t+\tau$ for sufficiently small τ. A typical representative model of the correlation function is [5]:

$$R_r(\tau) = E[r(t)r(t+\tau)] = \sigma_m^2 e^{-\alpha|\tau|}, \alpha \geq 0 \tag{2}$$

where σ_m^2 is the variance of the random acceleration, and α is the reciprocal of random acceleration time constant. Such random process can be obtained by passing a white Gaussian process $w(t)$ to a one-pole shaping filter:

$$\dot{r}(t) = -\alpha\, r(t) + w(t) \quad \text{with} \quad \sigma_w^2 = 2\alpha\sigma_m^2\delta(\tau) \tag{3}$$

Combining Eq.1 and Eq.3, and applying the state-space method, we obtain the discrete-time dynamic equation:

$$X_{n+1} = AX_n + BU_n + W_n \tag{4}$$

$$\text{where } X_n = [x(n) \;\; v_x(n) \;\; r_x(n) \;\; y(n) \;\; v_y(n) \;\; r_y(n)]^T$$

$$U_n = \begin{bmatrix} u_x(n) \\ u_y(n) \end{bmatrix} \qquad W_n = \begin{bmatrix} w_x(n) \\ w_y(n) \end{bmatrix}$$

A and B are the state and disturbance transition matrices, W_n is discrete time Gaussian white noise with $w_x(n)$ and $w_y(n)$ uncorrelated.

B. Measurement and Linearization

In current cellular systems, the movement related measurement is the power level of RF signals transmitted from base stations. The measured signal strength to a base station at distance d is proportional to $\frac{10^{\xi/10}}{d^r}$. Alternatively, this expression can be represented as the summation of deterministic path loss component and a statistical shadowing component. The logarithm of the shadowing component ξ is found, in typical land mobile radio environments, to be a zero-mean Gaussian random variable with a standard deviation $4-7dB$. Since the shadowing is caused by blockage of local obstacles surrounding the mobile station, it is generally independent of distance [7]. The signal strength (in dB) of the received signal can be expressed by:

$$p = p_o - 10r\log d + \xi \tag{5}$$

where d is the distance between the mobile station and base station, r is a slope index (typically r = 2 for highways and r = 4 for microcells in a city). p_o is a constant determined by transmitted power, wavelength and antenna gain.

The distance to a particular Cell$_i$, d_i, can be expressed in terms of the position (x_n, y_n) of the mobile station at time t_n and the location of base stations (a_i, b_i):

$$d_i = [(x(n) - a_i)^2 + (y(n) - b_i)^2]^{1/2} \tag{6}$$

The subscript i is the cell index with six neighbor cells indexed from 1 to 6 anti-clockwise beginning from the cell in the north direction. The current residence cell is indexed by 0.

In order to track the mobile station in two dimensional domain, at least three independent measurement data are needed. For this case, we select the three largest measurements to form the observation vector, Z_n, which is non-linearly related to dynamic states X_n:

$$Z_n = h(X_n) + \xi_n \tag{7}$$

The linearized observation equation becomes:

$$Z_n = HX_n + \xi_n \quad \text{with} \quad H = \frac{\partial h}{\partial x}\Big|_{X=X_n^*} \tag{8}$$

where X_n^* is the optimal estimate of X_n.

III. Adaptive Optimum Filter Design

We are now in a position to develop a linear minimum mean square filter based on the linear discrete-time model developed in the last section. Observing the fact that the trajectory of a moving user is non-stationary, Kalman filter is the best candidate, which can also be easily implemented by simple software programming or DSP chip. However, conventional Kalman filter cannot resolve our problem, because the deterministic input U_n is a semi-Markovian process with m possible states. Such hidden randomness requires a bank of m filters with each filter operating on a possible state. Fortunately, when certain practical assumptions are made, as discussed in [8], the filter bank can be reduced to a single Kalman filter augmented by a recursive technique of estimating U_n. The adaptive state estimator then becomes:

$$\hat{X}_{n+1} = A\hat{X}_n + B\hat{U}_n + K_{n+1}(Z_{n+1} - HA\hat{X}_n - HB\hat{U}_n) \tag{9}$$

where

$$\hat{U}_n = \sum_{i=1}^{n} U_n(S_i) P(S^i_{n+1}/Z_{n+1}) \tag{10}$$

Here K_{n+1} is the standard Kalman gain matrix, and $\hat{U}_n$ is an estimate of U_n. The recursive technique for computing $\hat{U}_n$ was developed in detail by Moose [8], the final results of which are given by the following equations:

$$\hat{U}_n = \sum_{i=1}^{n} U_n(S_i) P(S^i_{n+1}/Z_{n+1}) \tag{11}$$

$$\begin{aligned} P(S^i_{n+1}/Z_{n+1}) &= (\text{const}) f(z_{n+1}/S^i_{n+1}, Z_n) \\ &\quad \sum_{\alpha=1}^{m} \theta_{\alpha i} P(S^i_n/Z_n) \end{aligned} \tag{12}$$

where the following are true:

1. Probability density function $f(z_{n+1}/S^i_{n+1}, Z_n)$ has a Gaussian distribution with mean $H_{n+1}AX_n(s_i) + H_{n+1}BU_n(s_i)$ and variance $H_{n+1}[AM_{n/n}A^T + Q_n]H^T_{n+1} + R_n$; $M_{n/n}$ is the state estimation matrix; R_n is the measurement error covariance matrix and Q_n is the Gaussian disturbance covariance matrix.
2. Probability $\theta_{\alpha i}$ = P($U_n = S_i | U_{n-1} = S_\alpha$) is obtained from semi-Markov considerations. This parameter can be approximated by a value p near unity for $i = \alpha$ and $(1-p)/(m-1)$ for $i \neq \alpha$ for many tracking situations.
3. The constant (const) is evaluated from $\sum_{i=1}^{m} P(S^i_n/Z_n) = 1$.

Based on this result, we are able to complete the adaptive optimum filter to estimate and predict the dynamic states from the received signal strength measured at the mobile station. The resulting algorithm turns out to be very simple:

Prediction:

$$X_{n+1/n} = AX_{n/n} + B\hat{U}_n \tag{13}$$

Minimum Prediction MSE Matrix:

$$M_{n+1/n} = AK_{n/n}A^T + Q \tag{14}$$

Kalman Gain Matrix:

$$\begin{aligned} K_{n+1} &= M_{n+1/n} H^T_{n+1} \\ &\quad [R_{n+1} + H_{n+1} M_{n+1/n} H_{n+1}] \end{aligned} \tag{15}$$

Correction:

$$\begin{aligned} \hat{X}_{n+1/n+1} &= \hat{X}_{n+1/n} + K_{n+1}[Z_{n+1} \\ &\quad - h(\hat{X}_{n+1/n})] \end{aligned} \tag{16}$$

Deterministic input update:

$$\hat{U}_n = \sum_{i=1}^{n} U_n(S_i) P(S^i_{n+1}/Z_{n+1}) \tag{17}$$

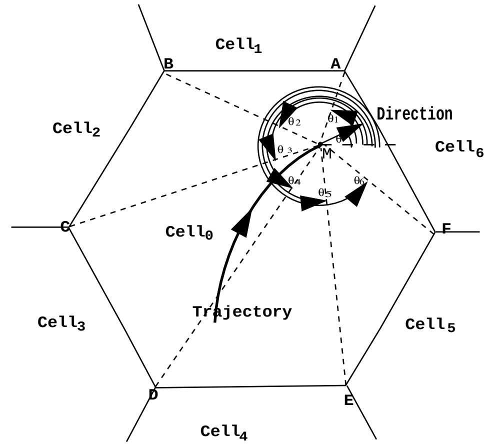

Fig. 2. Geometry for calculating cell-crossing probability

Minimum MSE matrix update:

$$M_{n+1/n+1} = [I - K_{n+1}H_{n+1}]M_{n+1/n} \tag{18}$$

where

$$H_{n+1} = \left.\frac{\partial h}{\partial X_{n+1}}\right|_{X_{n+1} = \hat{X}_{n+1/n}} \tag{19}$$

$P(S^i_{n+1}/Z_{n+1})$ for $i = 1, \ldots, m$ can be obtained using the recursive equation Eq.12.

IV. Next Cell Prediction

Prediction of the next crossing cell is performed when the mobile station moves close to the cell boundary, where we assume there is no chance left for the mobile station to make a dramatic change in its moving direction and speed. Such area is called *Correlation Area*. The cell-crossing probability given the dynamic state X_n, $P(\text{Cell}_i/X_n), i = 1, \ldots, 6$ can thus be calculated based on the position of the user $(x(n), y(n))$, moving direction θ and bearings of the cell vertex θ_i, $i = 1, \ldots 6$, as shown in Figure 2. Moving direction, θ can be simply obtained from the velocity in x and y direction, $v_x(n), v_y(n)$. Defining $f(X_n)$ as the probability density function (pdf) of the dynamic state X_n and $f(\theta/X_n)$ as the pdf of the moving direction given X_n, $P(\text{cell}_i/X_n)$ can be calculated by:

$$P(\text{Cell}_i/X_n) = \int_{\theta_i}^{\theta_{i+1}} f(\theta/X_n) d\theta \quad \text{with} \quad i = 1, 2, \ldots, 6 \quad \theta_7 = \theta_1$$

Prediction of the next crossing cell becomes:

$$\text{Next Cell}/X_n = \text{argmax}_i\{P(\text{Cell}_i/X_n)\} \quad i = 1, \ldots, 6$$

Calculation of $P(\text{Cell}_i/X_n)$ is not trivial in general, since θ is nonlinearly related to the dynamic state X_n, i.e.,

$$\theta = g(V_n) = \tan^{-1}\frac{v_y(n)}{v_x(n)} \tag{20}$$

where $V_n = [v_x(n), v_y(n)]^T$ is the velocity vector. Since V_n is part of X_n, it also has Gaussian distribution with mean $\mu_{V[n]}$ and variance Σ_V. If $\mu_{V[n]} \approx 0$, this is the case when the speed of the mobile station is very slow, $f(\theta/X[n])$ becomes a simple uniform distribution over $[0, 2\pi)$, in this case,

$$P(\text{cell}_i/X(n)) = \frac{\theta_{i+1} - \theta_i}{2\pi}, \quad \text{with} \quad i = 1, \ldots, 6, \quad \theta_7 = \theta_1 \tag{21}$$

In the general case, numerical method have to be used to calculate $f(\theta/X_n)$. However, if the variance of θ is small, $f(\theta/X_n)$ can be approximated by a Gaussian distribution. We achieve this by assuming that within the Correlation Area, there is only small change of velocity, then Eq.20 can be linearized as:

$$\theta \approx g(V^*) + G(\Delta V) \tag{22}$$

where

$$G = \left.\frac{\partial g}{\partial V}\right|_{V=V^*} = \left[\begin{array}{cc} \frac{-v_y(n)}{v_x^2(n)+v_y^2(n)} & \frac{v_x(n)}{v_x^2(n)+v_y^2(n)} \end{array} \right] \tag{23}$$

$$\Delta V = V(n+s) - V(n)$$

ΔV is the change of velocity between time t_n and t_{n+s} with $s \geq 1$. Since ΔV has Gaussian distribution with mean $\mu_{\Delta V}$ and covariance $\Sigma_{\Delta V}$, $f(\theta/X_n)$ becomes:

$$f(\theta/X(n)) \sim N(\mu_\theta, \Sigma_\theta) \quad \theta \in [\mu_\theta - \pi, \mu_\theta + \pi] \tag{24}$$

with

$$\mu_\theta = g(V^*) + H\mu_{\Delta V}; \quad \Sigma_\theta = H\Sigma_V H^T$$

Notice that for small Σ_θ, we assume $f(\theta/X[n]) \approx 0$, if $\theta \notin [\mu_\theta - \pi, \mu_\theta + \pi]$, then the cell crossing probability can be represented by a Q-function, i.e.,

$$P(\text{Cell}_i/X_n) = Q\left[\frac{\theta_{i+1} - \mu_\theta}{\Sigma_\theta}\right] - Q\left[\frac{\theta_i - \mu_\theta}{\Sigma_\theta}\right] \quad \text{with} \quad i = 1, \ldots, 6, \quad \theta_7 = \theta_1 \tag{25}$$

θ_i can be easily calculated from cell geometry. For example:

$$\theta_1 = \tan^{-1}\left(\frac{R\cos 30^\circ - (y(n) - b)}{R/2 - (x(n) - a)}\right) \tag{26}$$

Where R is cell radius, $(x(n), y(n))$ is the position of mobile station, (a, b) is the location of the base station of current cell.

Prediction of the next crossing cell can be combined with User Mobility Pattern (UMP) to predict the remaining cell sequence in her current journey[1]. The significance of trajectory tracking-based next cell prediction is that a kind of looking-ahead mode can be enabled in UMP classification. In this mode, the decision about the matched UMP is postponed until we look ahead at the prediction of subsequent cell based on trajectory tracking. As a result, UMP classification error can be greatly reduced, especially in the cell where there are multiple possible leaving UMPs and the crossed cell sequence is not enough to identify current UMP, for example, as shown in Figure 3.

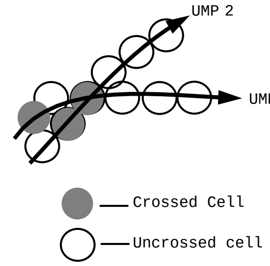

Fig. 3. A practical situation necessitates looking-ahead mode for UMP identification

Parameters	Comments
$T = 0.5s$	Sampling interval
$\sigma_m^2 = 0.5m/s^2$	Variance of random acceleration
$A_{\max} = 10m^2/s$	Maximum acceleration
$V \in [30, 60]$ miles/hr	Speed range
$1/\alpha = 10s$	Random acceleration constant
$\sigma_\xi = 5dB$	Standard deviation of random shadowing
$p_0 = 20w$	Base station transmission power
$g_b = 6dB$	Power gain of base station
$g_m = 1dB$	Power gain of mobile station
λ	Wavelength of RF signal
$R = 2km$	Radiance of cell

TABLE I
SIMULATION PARAMETERS

V. SIMULATION AND RESULTS

To illustrate and demonstrate the prediction performance of the adaptive optimum filter, three moving users are simulated in the conventional hexagon cell environment, who are able to move to any cell in the network along unknown trajectories with non-constant speed. On-line mobility related information are signal-strength measurement to neighboring base stations. Parameters involved in the simulation are summarized in Table I . In order to cover the range of dynamic acceleration $[-A_{max}, A_{max}]$, five levels $(0, \pm 2.5, \pm 7.5) m/s^2$ are selected as the states of the deterministic driving input.

The result of trajectory tracking is shown in figure 4, with the dashed curves as the actual trajectories, and solid curves indicating the predicted trajectories. Figure 5 demonstrates the result of time-varying velocity prediction. As we can see the proposed algorithm demonstrates a good estimation performance. The initial value of the dynamic state is estimated from the averaged RSS value with position error up to 1000m and speed error up to 5 m/s. Because of the strong "Pull in" power of the filter, it turns out that the adaptive filter is relatively insensitive to the initial conditions. The result of prediction of the next crossing cell is summarized in the Table II with prediction ratio =75%, 80%, 100% for User 1, 2 and 3 respectively. Here, the prediction ratio is defined as the ratio of the number of cells correctly predicted to the total number of cells need to be predicted in the path.

On analyzing the prediction result together with users' trajectory tracking, we find that a high degree of prediction accuracy is achieved once the Kalman filter becomes stable, and the error caused by the initial instability is limited to the prediction of the first-crossing cell at the beginning of the journey, as in the case of User 1. In the stable state, the prediction accuracy is related to the

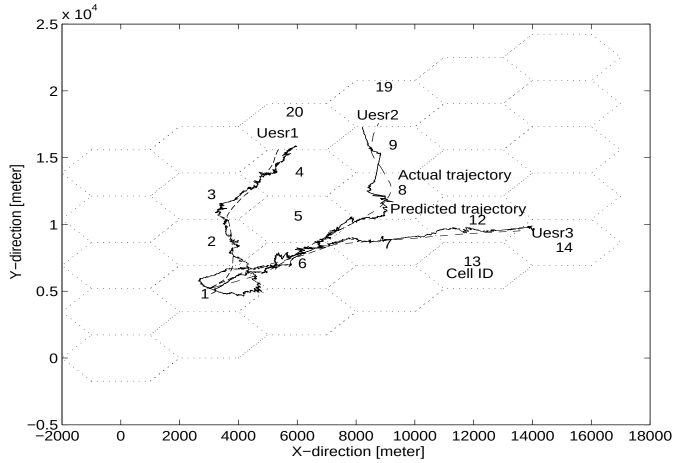

Fig. 4. Actual and predicted user trajectory

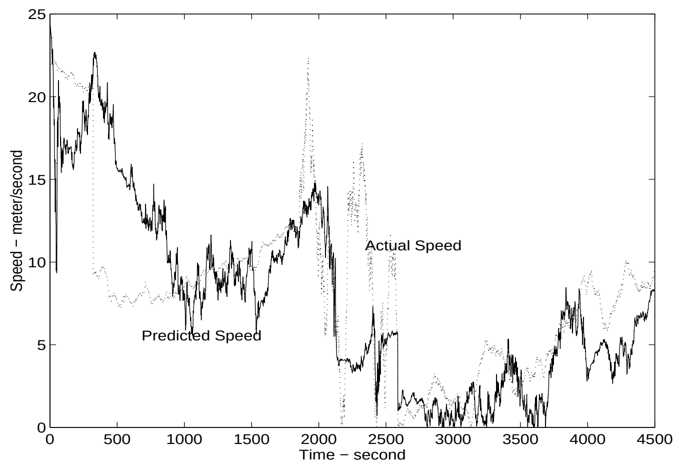

Fig. 5. Trajectory tracking and speed prediction

geometric relation of user trajectory and cell boundary. For example, if a user runs along cell boundary, the uncertainty will be high as to which is the next cell. In this case, cell geographic limitation and User Mobility Pattern may be used to help choose the next most probable cell. In addition to this special case, the tracking-based prediction doesn't assume any prior knowledge of the users' mobility – which is especially valuable for UMP identification and prediction in the case of random movement.

VI. Conclusion

In this paper, we recognize the fact that the dynamic states and trajectory of a mobile user play an important role in the prediction of the next cell crossing and in the identification of the user's current movement pattern. With this as motivation, we propose a new approach for user mobility modeling, in which we apply classical statistical signal processing techniques to extract user mobility information from noisy measurement. Analysis and simulation results prove that with such a system in place, the cellular network can obtain a high degree of prediction accuracy even in the absence of any prior information about the user's mobility history - which in turn can lead to significant improvement in the network's connection quality.

User1	Current Cell	1	2	3	4	20	
	Predicted Cell	6	3	4	20		
User2	Current Cell	1	6	5	8	9	19
	Predicted Cell	6	5	7	9	19	
user3	Current Cell	1	6	7	12	14	
	Predicted Cell	6	7	12	14		

TABLE II
PREDICTION RESULT OF NEXT CELL CROSSING.

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