Mobile User Tracking Algorithm via Velocity Estimation for Microcellular Urban Environment

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***Abstract*—A novel tracking algorithm for mobile user based on velocity estimation in microcellular urban environment is proposed in this paper. The Short-Time Fourier analysis of received signal strength is employed to estimate mobile speed. Utilizing user's mobility model and a bank of extended Kalman filters, the algorithm tracks the mobile user by switching to the suitable extended Kalman filter based on the velocity and average received power estimates. The proposed tracking algorithm shows a good ability to predict user mobility behavior in urban area with multipath fading and shadowing phenomena.**

Keywords- Mobile tracking; mobility model; local mean estimation; corner detection; extended Kalman filter

I. INTRODUCTION

Information of position and velocity of mobile stations plays an important role on offering efficient network controlling mechanisms and variety of offered services in cellular networks. A reliable mobility tracking algorithm is desirable to reduce the number of handovers and waste of bandwidth due to unnecessary signaling. In addition to an efficient resource planning, user locating and tracking provides helpful services for immediate assistance in emergency situations. In this paper, we present a method to track mobile user in noisy urban environment by using a bank of extended Kalman filters. The tracking algorithm chooses the suitable extended Kalman filter from the bank of filters by switching between them based on the proposed velocity estimation and corner detection algorithms. Although different algorithms have been proposed for velocity estimation [1, 2, 3], they have considered line of sight (LOS) or constant velocity situations that do not match to user mobility behavior in urban areas. Based on periodogram of the received signal strength (*RSS*), a novel user velocity estimation algorithm is proposed which is suitable for time varying, non line of sight (NLOS) and complex structure of urban areas. In [4, 5, 6] several mobility models have been proposed that are applicable to high maneuvering users in simple structure environments. By utilizing velocity estimator, in our proposed tracking algorithm, the user mobility model is derived in an online manner which is appropriate for possible maneuvering user in microcellular urban structure.

The paper is organized as follows. In section II, a propagation model is presented. The mobility tracking algorithm is proposed in section III. Section IV determines relevant parameters and presents performance results of the proposed tracking algorithm and section V includes conclusions.

II. PROPAGATION MODEL

The propagation model discussed here takes into account three effects that are present in many microcellular wireless environments: correlated multipath fading, correlated log-normal shadowing, and a distance dependant trend [1]. A model for the received signal (*RS*), $\gamma(t)$ is given by:

$$\gamma(t) = \sqrt{s(t)} \cdot r(t) + \eta(\mathrm{t}) \tag{1}$$

Where $r(t)$ is the complex envelop due to multipath propagation and user mobility, which contains the mobile's Doppler amplitude information and $s(t)$ is average received power at the mobile station and $\eta(\mathrm{t})$ is AWG noise with zero mean and variance of σ_n^2 which is added to the *RS*. $r(t)$, $s(t)$ and $\eta(\mathrm{t})$ are mutually independent. $r(t)$ is defined by [8]:

$$r(t) = \frac{1}{\sqrt{k}} \sum_{i=1}^{K} a_i e^{j(2\pi f_d \cos(\theta_i)t + \varphi_i)} \tag{2}$$

Where f_d is the Doppler frequency, θ_i and φ_i are mutually independent random variables uniformly distributed within the range $(-\pi, \pi]$, a_i is the gain of ith scatter and *K* is the number of independent scatters (usually *K*=20 is sufficient to provide good approximation). The process $s(t)$ is a wide-sense stationary log-normal random process, which contains distance dependent trend and log-normal shadowing. We denote its mean and variance by μ_s and σ_S^2, respectively. Shadow fading process is assumed to have the exponential correlation function (a first order autoregressive [AR(1)]) model proposed by [8] based on the measured autocovariance function of $s(t)$ in urban environments. Path loss which is a mean of $s(\mathrm{t})$, (μ_s) decreases monotonically with distance from the base station. Path loss for microcellular structure, at position *d* is modeled by [8]

$$\mu_s = \begin{cases} P_0 - 20\log_{10}(\frac{d}{x_0}) - \frac{10}{\chi}\log_{10}(1 + (\frac{d}{x_c})^{(\zeta-2)\chi}) & 0 < d_1 < d_c \\ P_L(d_1)10^{\frac{-\Delta S(d)}{10y_0}} & d_c < d < y_0 \\ P_L(d_2) - 20\log_{10}(\frac{d}{y_0}) - \frac{10}{\chi}\log_{10}(1 + (\frac{d}{y_c})^{(\eta-2)\chi}) & d_2 < y_0 \end{cases} \tag{3}$$

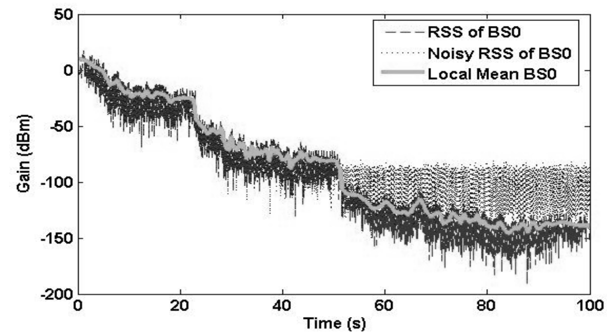

Figure 1. Example of RSS for a variable mobile speed, recived by base station (BS0 in Fig. 3). long term SNR = 20 dB for noisy *RS*.

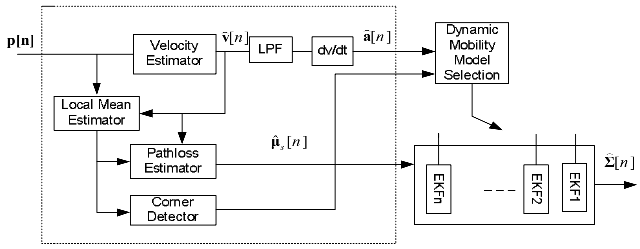

Figure 2. Overall block digaram of tracking algorithm. **P**[n] is recived signal strength (*RSS*) .

According to [8], dimensionless parameter x_0, the distance parameters x_c, y_0, y_c and exponents ζ, η, χ are introduced. Corner effect could cause ΔS dB signal drop, in y_0 meters. P_0 is a constant that accounts for transmitted power and antenna gain. To suppress noise and interference terms, $\gamma(t)$ is passed through a low-pass filter with a bandwidth $BW > f_{max}$; since we are only interested in the Doppler power spectrum, which is narrowband and variable between (0 - f_{max} (Hz)) in microcellular structure. f_{max} is maximum possible Doppler frequency of channel. Note that shadow fading $s(t)$ varies very slow in comparison with $r(t)$. After that we consider $\gamma[n]$ - which is discrete form of $\gamma(t)$ with the sampling rate of $1/2BW$, where:

$$\gamma[n] = \sqrt{s[n]}r[n] + \eta[n] \tag{4}$$

An example of *RSS* in a microcellular environment is plotted in Fig. 1, for variable mobile speed when long-term *SNR* is 20 dB. As it is seen, short term *SNR* is high near base stations. Long-term *SNR* is considered for 100 seconds observation.

III. Tracking Algorithm

The structure of the proposed tracking algorithm is shown in fig. 2. Velocity, local mean and pathloss estimation and corner detection are done in the preprocessor block. The outputs of preprocessing block are fed to the mobility model selection block and extended Kalman filter bank (*EKF*). In the following subsection, we describe each part of the tracking algorithm that has been shown in Fig. 1.

A: Velocity Estimator

Due to time-varying nature of mobile communication environment, the signal properties include (amplitude, frequencies, and phases) will change with time. In cases where the signal can be modeled by sum of sinusoids (like received band-pass signal at a mobile (base) station) the Fourier transform of finite-length segments of received signal yields valuable information about signal characteristics. Therefore, we consider using time-dependent Fourier transform also referred to as the short-time Fourier transform (*STFT*) to estimate the power density spectrum of the *RS*. The *DFT* of finite-length time segments of the *RS* is obtained by banks of rectangular filters such that, each filter has different duration. The Fourier transform of segmented input V_i is given by:

$$V_i(e^{j\omega}) = \Im\{\gamma_i[n]\} = \Im\{w_i[n]\gamma[n]\} = \sum_{n=0}^{L_i-1} w_i[n]\ \gamma[n]\ e^{-j\omega n} \tag{5}$$

Where $w_i[n]$ is the i^{th} window with the length L_i. An estimate of power spectrum *PSD* would be:

$$PSD_i(\omega) = \lim_{L_i \to \infty} \frac{1}{L_i \Delta t F}\ E\ \left\{ \left| V_i(e^{j\omega}) \right|^2 \right\} \approx \frac{1}{L_i \Delta t F} \left| V_i(e^{j\omega}) \right|^2 \tag{6}$$

Where Δt is sampling period and the constant F anticipates for normalization to remove bias in spectral estimate [9]. This approximation is valid for large L_i. If the rectangular window is used, the estimator for the *PSD* is called periodogram. Because explicit transform of the *PSD* estimate can be carried out only in discrete frequencies, we have:

$$PSD_i(\omega_k) \approx \frac{1}{L_i F}\left\{ \left| V_i[K] \right|^2 \right\} \Rightarrow \omega_k = \frac{2\pi K}{N}\ \ for\ K = 0,1\ \ldots, N-1 \tag{7}$$

$V_i[k]$ is N-point *DFT* of $w_i[n]\gamma[n]$, if N is chosen to be greater than L_i the appropriate zero-padding would be applied to the sequence $w_i[n]\gamma[n]$. Maximum of $PSD_i(\omega)$ takes place in maximum Doppler frequency which is proportional to mobile velocity. ($\hat{v} \propto \hat{f}_d \cdot \lambda$) in which λ is wave length.

$$\hat{\omega}_d = \arg \underset{\omega}{Max} \{PSD_i(\omega)\} \tag{8}$$

Thus, the mobile velocity can be obtained from $\hat{\omega}_d$.

B: Local Mean Estimator

Because of slow variation of shadow fading and path loss, they are present only in *DC* component of the estimated power spectrum of the *RS*. In other words, local mean of the *RS* is *DC* component of estimated *PSD*. For variable mobile speed, the duration of observation window (L_i) must be constantly adapted and the rate of adaptation is critical for performance of speed and power estimators. To solve this problem, as it is mentioned, we used bank of observation windows for periodogram estimation which enables us to adapt length of smoothing window to the speed of mobile user. *DC* component of estimated *PSD* is adaptively extracted from different filters.

$$\hat{s}_i \simeq \frac{1}{L_i t F} E\left\{ \left| V_i(e^{j\omega}) \right|^2 \right\} |_{\omega=0} = \frac{1}{L_i t F} \left| \sum_{n=0}^{L_i-1} w_i[n]\gamma[n] \right|^2 \tag{9}$$

where $\hat{s}_i$ is the estimated local mean. Active smoothing window is switched to another window in which its duration is selected proportional to inverse of estimated velocity for each iteration.

C: Corner Detection Algorithm

Corner detection method uses estimated velocity and average received power to detect corner effect in urban propagation environment. The corner effect, refers to a sudden change in the average received power when a mobile station makes a turn at an intersection. It seems that when there is no considerable noise (multipath fading fluctuations is mitigated), Differentiation between successive samples (*DSS*) of estimated local mean have corners information. Corner is detected when we have considerable differences (at least more than T_c) at least for α samples. In which α is selected proportional to practical corner width in propagation area. This procedure is based on measurements of one base station. But detection can be performed via measurements of all surrounding base stations. In this case, corner is detected if all of surrounding base stations detect the corner by means of above algorithm. In addition, we can improve performance of corner detection algorithm based on velocity estimation scheme discussed in subsection *A*. The idea is, in order to change direction or turn in intersection of streets; mobile user must reduce its velocity or stop in some scenarios, which can be traffic light, for instance. So information from speed estimator can be used to improve performance of corner detection method. Corner is detected if estimated (*DSS*) is more than T_c from surrounding base stations and if user is classified as a slow one. Because instantaneous velocity is not needed in the act of corner detection, we could use a velocity threshold T_v to change instantaneous velocity to velocity's condition.

D: Dynamic Mobility Model

Performances of Kalman based tracking algorithms are dependant on accuracy of mobility model. Due to urban propagation environment, users have some constraints in their movements so their movements can not be modeled by Gauss-Markovian model [5, 6]. Thus a velocity profile based on specifications of propagation environment, limitations of user and traffic condition is considered. We modified the profile proposed in [1] such that it could be used as a mobility model. This model can capture wide range of realistic user mobility patterns in urban area. It is calculated by:

$$v(t)=\begin{cases} v_s & t_{s_1}<t<t_{e_1} \\ v_{max}\cdot\omega\left(\frac{t-t_{e_1}}{\Delta t_2}\right) & t_{s_2}<t<t_{e_2} \\ v_{max} & t_{s_3}<t<t_{e_3} \\ v_{max}\cdot\omega\left(\frac{t_{e_4}-t}{\Delta t_4}\right) & t_{s_4}<t<t_{e_4} \\ v_e & t_{s_5}<t<t_{e_5} \end{cases} \tag{10}$$

$$\text{Where}\quad \Delta t = t_e - t_s \qquad t_{e_i} = t_{s_{i+1}}$$

$$\omega(t)=\begin{cases} 0 & t<0 \\ 3t^2-2t^3 & 0<t\leq 1 \\ 1 & t\geq 1 \end{cases}$$

Where $v(t)$ is in kilometer per hour (km/h), v_s is initial velocity, v_{max} is maximum applicable velocity in urban area, v_e is ultimate velocity in period of Δt and t is in seconds. The mobile station's state at time t is defined by a vector:

$$\Sigma(t)=[x(t),\dot{x}(t),\ddot{x}(t)] \tag{11}$$

where $x(t)$ denotes the position, $\dot{x}(t)$ specifies the velocity and $\ddot{x}(t)$ stands for the acceleration. The user movements within the system are assumed to be one-dimensional. This assumption is considered to reduce the computational burden and also due to the fact that length of streets is much longer than width of streets. The acceleration is assumed to be a Gaussian process that its statistical specifications are calculated from samples of estimated acceleration by means of velocity estimation algorithm discussed in subsection *A*. Observation models are discussed in section II for microcellular propagation area. Note that fading and shadowing have been modeled as a Gaussian noise in [5, 6] for observations. It's clear that this model is not appropriate for dense urban area. Further more, due to variable nature of velocity of mobile users in system, a fixed length filtering can not remove fluctuations of multipath fading [1]. In order to improve the accuracy of tracking algorithm, observations from neighboring base stations are considered but tracking with measurements from only one base station is possible. The observation vector from three BSs becomes:

$$\mathbf{O}[n]=[p_1[n],p_2[n],p_3[n]]^T=\mathbf{h}(\mathbf{\Sigma}[n])+\mathbf{S}[n]+\mathbf{R}[n]+\mathbf{\Gamma}[n] \tag{12}$$

where p[n] is *RSS*, $\boldsymbol{h}(\mathbf{\Sigma}[n])$ is pathloss model which is mentioned in equation (3), $\mathbf{S}[n]=10\log_{10}[\sqrt{s_1[n]},\sqrt{s_2[n]},\sqrt{s_3[n]}]^T$ stands for shadowing vector, $\mathbf{R}[n]=10\log_{10}[r_1[n],r_2[n],r_3[n]]^T$ specifies multipath fading and $\mathbf{\Gamma}[n]$ defines power of additive Gaussian noise of channel respectively. Observations are processed by means of local mean estimation algorithm discussed in subsection *B* in order to mitigate multipath fading fluctuations. Also in order to obtain, estimate of pathloss ($\hat{\mu}_s$) which is essential for tracking algorithm, we must smooth shadow fading by means of adaptive windowing scheme in which duration of smoothing filter is adaptively chosen proportional to inverse of estimated velocity. Because of the fact that short term *SNR* is low far from base stations, specially after corners of streets, we use corner detection algorithm to switch to suitable observations in tracking algorithm. After conversion of observations from dB to linear, we have:

$$\hat{\boldsymbol{\mu}}_s[n]=\mathbf{h}(\hat{\mathbf{\Sigma}}[n])+\mathbf{H}[n]\Delta\mathbf{\Sigma}+\mathbf{\Psi}[n] \tag{13}$$

where $\hat{\mathbf{\Sigma}}[n]$ is state vector estimate, $\Delta\mathbf{\Sigma}$ is state estimation error, and $\mathbf{\Psi}[n]$ is residual of multipath and shadowing fluctuations and $\mathbf{H}[n]$ is given by:

$$\mathbf{H}[n]=\left.\frac{\partial h}{\partial \mathbf{\Sigma}}\right|_{\mathbf{\Sigma}=\hat{\mathbf{\Sigma}}} \tag{14}$$

E: Extended Kalman Filter

By means of mobility model discussed in subsection *D* the *EKF* is modified as follows: The state estimate at time n is defined by $\hat{\mathbf{\Sigma}}[n|n]$, with the initialization step $\hat{\mathbf{\Sigma}}[0|-1]=\mathbf{0}$, where

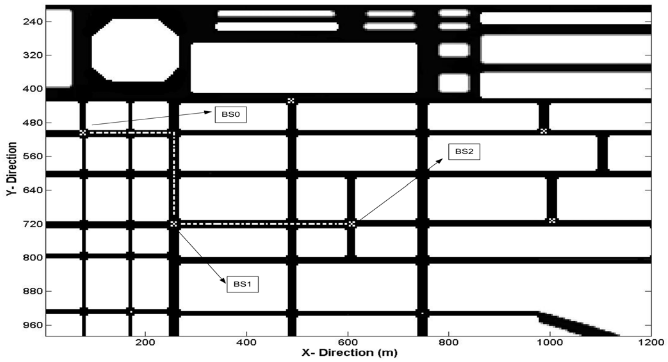

Figure 3: simulation area

$\mathbf{0}$ is a 3×1 vector of zeros. The Kalman gain matrix is denoted by $\mathbf{K}[n]$. $\mathbf{M}[n \mid n-1] \equiv Cov(\boldsymbol{\Sigma}[n] | \widehat{\mathbf{O}}_{n-1})$ is the covariance matrix and it is initialized by $\mathbf{M}[0 \mid -1] = \mathbf{I}_3$. The recursion step for *EKF* at time *n* is:

$$
\begin{aligned}
&\widehat{\boldsymbol{\Sigma}}[n \mid n-1] = \mathbf{A}\boldsymbol{\Sigma}[n-1 \mid n-1] \ \ (prediction\ step) \\
&\mathbf{M}[n \mid n-1] = \mathbf{A}\mathbf{M}[n-1 \mid n-1]\mathbf{A}^T + \mathbf{Q} \\
&\mathbf{K}[n] = \mathbf{M}[n \mid n-1]\mathbf{H}^T[n]\left(\mathbf{C} + \mathbf{H}[n]\mathbf{M}[n \mid n-1]\mathbf{H}^T[n]\right)^{-1} \\
&\widehat{\boldsymbol{\Sigma}}[n \mid n] = \widehat{\boldsymbol{\Sigma}}[n-1 \mid n-1] + \mathbf{K}[n]\times \\
&\qquad \left(\hat{\boldsymbol{\mu}}_s[n] - h_{lin}(\widehat{\boldsymbol{\Sigma}}[n-1 \mid n-1])\right) \ (correction\ \ step) \\
&\mathbf{M}[n \mid n] = \left(\mathbf{I} - \mathbf{K}[n]\mathbf{H}[n]\right)\mathbf{M}[n \mid n-1]
\end{aligned} \qquad 15)
$$

Where $\mathbf{A}$ is the state transition matrix, which defined by mobility model, $\mathbf{Q}$ is the covariance matrix of our mobility model and $\mathbf{C}$ is the sample covariance vector of observations.

$$
\mathbf{A} = \begin{bmatrix} 1 & T & \frac{T^2}{2} \\ 0 & 1 & T \\ 0 & 0 & 1 \end{bmatrix}, \qquad
\mathbf{Q} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & \sigma_a \end{bmatrix}, \qquad
\mathbf{C} = \begin{bmatrix} \sigma_{\hat{o}_1} \\ \sigma_{\hat{o}_2} \\ \sigma_{\hat{o}_3} \end{bmatrix}
$$

Where *T* is sampling duration, σ_a is sample variance of estimated acceleration. σ_a is updated in accordance with specifications of user's mobility and C is updated by means of $\hat{\boldsymbol{\mu}}_s[n]$. When estimated acceleration changes significantly then matrix $\mathbf{Q}$ and vector C are updated in *EKF*. By means of corner detection algorithm discussed in subsection C, when corner is detected, the suitable *EKF* is reinitialized in kalman filter bank.

IV. Parameter Selection and Simulation Result

To evaluate the performance of the proposed velocity and local mean estimation, corner detection and tracking algorithms, a simulator for radio wave propagation in cellular system for complex urban structure is developed. The basic input data fed to the program is 1) processed map of simulation environment and 2) cellular network configuration. The software is capable of simulating radio wave propagation in micro - cellular structure based on Berg model by taking into account of shadowing and multipath fading [8, 9]. Figure (3) shows a map which is used in simulation. In our numerical

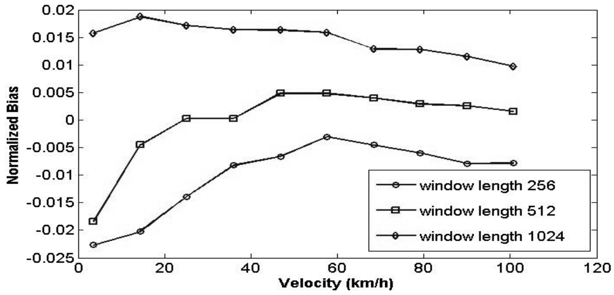

Figure 4: Normalized Bias of speed Estimation. Corner effect-Constant speed scenario for long term $SNR = 20dB$

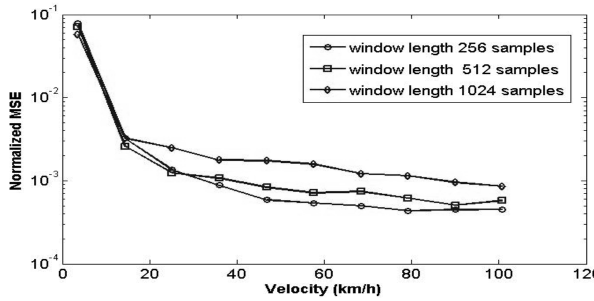

Figure 5: Normalized MSE of speed Estimation. Corner effect-Constant speed scenario for long term $SNR = 20dB$

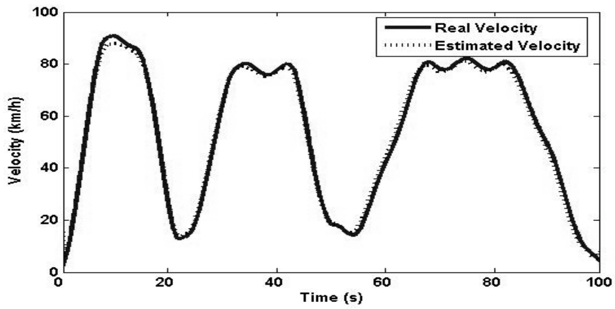

Figure 6: Velocity tracking performance comparison with *SNR-balancing* for long term $SNR = 20dB$

experiments LOS and NLOS scenarios are simulated by means of proposed simulation test bed for constant and variable speed. Typical Maximum Doppler frequencies are considered within the range of 0-100 Hz. The normalized bias $E\{(\hat{v}-v)/v\}$ and mean square error (*MSE*) $E\{((\hat{v}-v)/v)^2\}$ of the speed estimates are investigated as *SNR* varies in LOS and NLOS scenarios. The carrier wave length $\lambda = 1/3m$, the correlation distance of log-normal Shadowing $x_c = 20m$ and path loss parameters are set according to [9]. As it is seen in Fig (4) and Fig (5), estimation error is negligible for *SNR* more than 20dB. To track the velocity profile, the proposed method which is mentioned in section II, is used. Due to the fact that short term *SNR* is high near BSs, We proposed *SNR-balancing* method to reduce the estimation error in situations that *RSS* from more than one base station is at hand. So the estimated velocity of each base station is weighted according to its *SNR*. This technique significantly improves the performance of proposed method. Therefore the estimated velocity

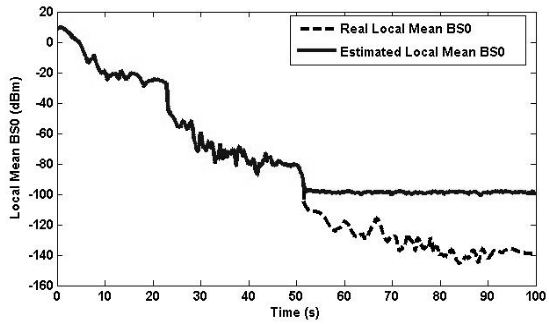

Figure .7 Local mean estimation results for long term $SNR = 20dB$.

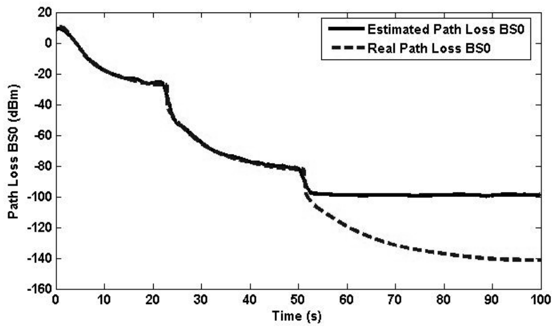

Figure .8 path loss estimation results for long term $SNR = 20dB$.

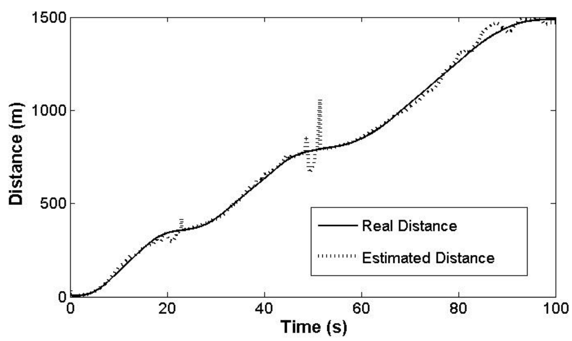

Figure .9 Tracking result estimated distance vs real distance .

is:

$$\hat{v}[n] = \sum_{i=1}^{N_{BS}} \alpha_i \cdot \hat{v}_i[n] \qquad (16)$$

where N_{BS} denotes the number of surrounding BSs, $\hat{v}_i[n]$ is estimated velocity from i^{th} base station and α_i is weighing coefficient, which is calculated by:

$$\alpha_i = \frac{P_i[n]}{\sum_{j=1}^{N_{BS}} P_j[n]} \qquad (17)$$

Fig. (6) shows the estimated velocity from three base stations at *SNR=20* dB (note that *SNR* is long term). Local mean and pathloss estimation results for BS0 are given in fig. (7) and fig. (8). As it is seen the estimation error is negligible, even in situations with low *SNR* (20dB). The corner detection algorithm is evaluated using proposed simulation test bed. The *std* of shadow fading is considered different when mobile user makes a turn at an intersection. This value is selected in range of 4dB to7dB. Results are given in table. I. In our simulations, sampling interval is set to 1*ms*. Estimated distance is specified in fig. (9), in which mobile user receives observations from three BSs simultaneously. The total length of tracking trajectory is about 1.5 Km and the detection delay is measured in meters (m).

TABLE I. CORNER DETECTION PERFORMANCE

Detection Threshold (T_d)	***False Detections***	***Missed Detections***	***Mean Detection Delay (m)***
0.1	4	0	2.45
0.2	3	0	2.60
0.3	1	0	2.75
0.4	0	0	3.00
0.5	0	0	3.15
0.6	0	1	3.25
0.7	0	2	3.50

V. CONCLUSIONS

New technique for mobile user tracking is presented in this paper for urban environment with multipath fading and shadowing. The proposed algorithm has been developed based on the mobility model which is capable of capturing large range of mobility behaviors of mobile users within urban area. The tracking algorithm chooses the suitable *EKF* from Kalman filter bank based on velocity estimation and corner detection algorithms. Simulation results show that the proposed algorithm achieves a good performance in tracking mobile users within urban area with complex structure.

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