Discrete Mobile User Tracking Algorithm via Velocity Estimation for Microcellular Urban Environment

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Abstract— **A novel discrete tracking algorithm for mobile user based on velocity estimation in microcellular urban environment is proposed in this paper. By partitioning the mobile path and defining each partition as a state, the proposed algorithm tracks the mobile user based on Hidden Markov Model (HMM). The Short-Time Fourier analysis of the received signal strength is employed to estimate the mobile speed. Based on averaged received power (local mean), pathloss, velocity estimation and using dynamic programming technique, the proposed algorithm predicts the next state of the mobile user. The proposed tracking algorithm shows good ability to predict user mobility behavior in urban area with multipath fading and shadowing phenomena.**

Index Terms— **Mobile Tracking, Dynamic Programming, Mobility Model, Corner Detection.**

I. INTRODUCTION

Information of position and velocity of mobile stations plays an important role in offering efficient network controlling mechanisms and a variety of offered services in cellular networks. A reliable mobility-tracking algorithm is desirable to provide necessary positioning information and location-aware controlling mechanisms. In hot spots, information of user mobility can effectively reduce number of handovers and reduce waste of bandwidth due to unnecessary signalling. By means of mobility information, an efficient planning and usage of resources is possible in transport systems. Also, in case of a car breakdown or an emergency call, automatic monitoring of the position would be of great help for immediate assistance. Two quantities can be used to obtain distance and speed information; the received signal strength measured at the mobile station and corresponding propagation time. Both parameters are subject to strong irregular variations caused by multipath and shadow fading. In a tracking algorithm, mobility characterization model is needed. Construction of mobility patterns for analysis and simulation has attracted considerable attention in recent years [1-3]. Some of these models are based on Markov, semi-Markov model [1, 3], random walk or Brownian motion [1]. These methods can be useful for scenarios with high direction change which is not appropriate for urban environment. In which users are bounded to city buildings and tracking algorithms suffer from corner effect. In this paper, by using dynamic programming technique, a new tracking algorithm for noisy urban environment is proposed. By utilizing proposed averaged received power, pathloss, velocity estimation and corner detection algorithms [4], the proposed tracking algorithm estimates the location of mobile user.

The paper is organized as follows. In section II, a propagation model is presented. The discrete 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 correlated multipath fading, correlated lognormal shadowing and a distance dependant trend [5]. A model for the received signal (*RS*), $\gamma(t)$ is given by

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

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 the average received power (local mean) at the mobile station and $\eta(t)$ is AWG noise with zero mean and a variance of σ_n^2 which is added to the *RS*. $r(t)$, $s(t)$ and $\eta(t)$ are mutually independent. $r(t)$ is defined by [6]

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

where f_d is the Doppler frequency, θ_i and φ_i are mutually independent random variables uniformly distributed over $(-\pi, \pi]$, 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 [6] based on the measured auto covariance function of $s(t)$ in urban environments. Pathloss, μ_s, which is the mean of $s(t)$, decreases monotonically with distance from the base station. Pathloss for microcellular structure at position d is modelled by [6]

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

According to [6], 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 and f_{max} 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

$$\gamma[n] = \sqrt{s[n]} r[n] + \eta[n] \qquad (4)$$

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. DICRETE TRACKING ALGORITHM

In the discrete tracking algorithm, mobile user's trajectory can be modelled by means of hidden Markov model. In this case, mobile trajectory is divided into partitions with different lengths. Then each partition can be defined as an HMM state. By this assumption, each user has its own chain of HMM states. The probability of existence of user in each state is calculated by means of dynamic programming. As it was mentioned before, the information that is available from different observations (estimated velocity, acceleration, local mean, pathloss and corners positions) can be utilized for next state probability calculation. The structure of the proposed tracking algorithm is shown in Fig. 2. In the proposed method, the pre-processing block provides velocity, local mean, pathloss estimates and corner information. The outputs of pre-processing block are fed into HMM block to predict next partition (N) of mobile user location. In the following subsections, we describe each part of the tracking algorithm that has been shown in Fig. 2.

A. Velocity Estimator

Due to the time-varying nature of mobile communication environment, the signal properties (amplitude, frequency, and phase) will change with time. In cases where the signal can be modelled by sum of sinusoids like received band-pass signal at a mobile (base) station, the Fourier transform of finite-length segments of the received signal yields valuable information regarding signal characteristics. Therefore, we use time-dependent Fourier transform, also referred 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

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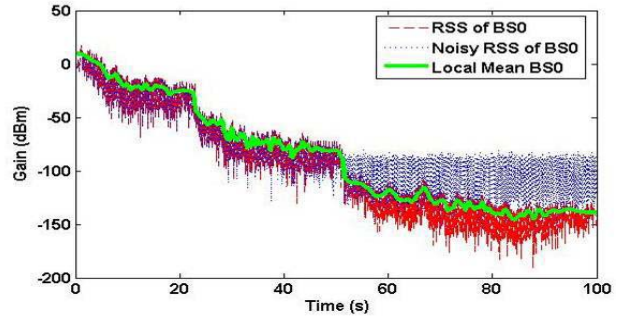

Fig. 1. Example of RSS for a variable mobile speed, recived by base station (BS0 in Fig. 4). long term SNR = 20 dB for noisy RS.
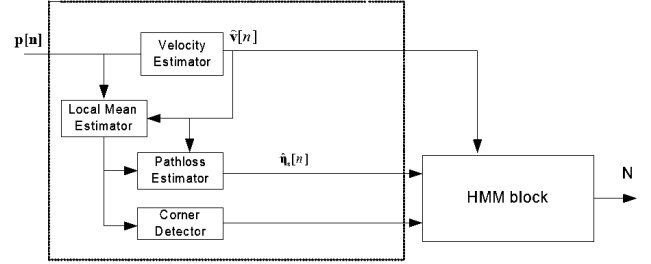

Fig. 2. Block digaram of tracking algorithm. **P**[n] is the recived signal strength (RSS).

where $w_i[n]$ is the ith window with the length L_i. An estimate of power spectrum PSD would be

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

where Δt is sampling period and the constant F is used for normalization to remove bias in spectral estimate [7]. This approximation is valid for large L_i. If a 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

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

where $V_i[k]$ 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 $w_i[n]\gamma[n]$. The maximum of $PSD_i(\omega)$ takes place of the maximum Doppler frequency, which is proportional to the mobile velocity ($\hat{v} \propto \hat{f}_d \cdot \lambda$) in which λ is the wavelength.

$$\hat{\omega}_d = \arg \underset{\omega}{Max}\left\{PSD_i(\omega)\right\} \qquad (8)$$

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

B. Averaged Received Power Estimator

Because of the slow variation of shadow fading and pathloss, 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 the 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, a bank of observation windows is used 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.

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

where $\hat{s}_i$ is the estimated averaged power (local mean). Active smoothing window is switched to another window and duration of window is selected proportional to the inverse of estimated velocity.

C. Corner Detection Algorithm

The proposed corner detection method uses estimated velocity and average received power to detect corner effect in urban propagation environments. The corner effect refers to a sudden change in the average received power when a mobile station turns at an intersection. It seems that when there are no considerable fluctuations (multipath fading fluctuations are mitigated), differentiation between successive samples (*DSS*) of estimated local mean has corners information. Corner is detected if there is a considerable difference (more than T_c) at least for α samples. α is selected proportional to actual corner width in the propagation area. This procedure is based on measurements of one base station. But detection can be performed via measurements of surrounding base stations. In this case, corner is detected if all of the surrounding base stations detect the corner by means of the proposed algorithm. In addition, we can improve the performance of corner detection algorithm based on velocity estimation scheme discussed in subsection *A*. The idea is, in order to change direction or turn at intersection of streets; the 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 the performance of the corner detection method. Corner is detected if estimated *DSS* is more than a threshold (say 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 the velocity state.

D. Velocity Profile

A velocity profile based on specifications of propagation environment, limitations of user mobility and traffic properties is considered. The profile proposed in [5] is modified, such that it can be used as a velocity profile. This profile can capture a wide range of realistic user mobility patterns in urban areas. The velocity profile is calculated by

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

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

$$\omega(t) = \begin{cases} 0 & t \leq 0 \\ 3t^2 - 2t^3 & 0 < t \leq 1 \\ 1 & t \geq 1 \end{cases} \qquad (10)$$

where $v(t)$ is in km/h, v_s is initial velocity, v_{max} is maximum applicable velocity in urban areas, v_e is the ultimate velocity in period of Δt and t is in seconds. The user movements in streets are assumed one-dimensional. This assumption is made because the length of street is much longer than its width and to decrease computational burden. Note that in other literature [2, 3], multipath fading and shadowing are modelled as an additive Gaussian noise. It is clear that this kind of assumption or modelling is not appropriate for dense urban areas. Further more, due to variable nature of mobile velocity, a fixed length filtering cannot remove fluctuations of multipath fading [5]. In order to improve the accuracy of tracking algorithm, observations from neighbouring base stations are considered but tracking with measurements from only one base station is possible. The observation vector from three BSs becomes

$$\mathbf{O}[n] = [p_1[n], p_2[n], p_3[n]]^T = \boldsymbol{\mu}_s + \mathbf{S}[n] + \mathbf{R}[n] + \boldsymbol{\Gamma}[n] \qquad (11)$$

where p[n] is *RSS*, $\boldsymbol{\mu}_s$ is pathloss model given by Eq. (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 $\boldsymbol{\Gamma}[n]$ defines power of additive Gaussian noise of channel. 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 an 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 the inverse of estimated velocity. Because of having low short term *SNR* for far base stations, specially after corners of streets, we use corner detection algorithm to switch to suitable observations in tracking algorithm.

E. HMM Block

The goal of discrete tracking process is to find the highest probable location (partition) from a set of surrounding locations (partitions). For this purpose HMM is used to model the tracking path. This means that tracking path is partitioned and each partition can be considered as a state of HMM. Movement of mobile user along the tracking path, results in sequence of states. Discrete tracking algorithm aims to find the optimum sequence of states. In order to find the optimum sequence dynamic programming technique is used.

Estimating the state transition matrix of HMM which determines the transition probability of discrete components is important. Effective parameters in determination of matrix dimensions are user mobility specifications, sampling period, corner position information and partition length. The observations of HMM model are estimated velocity and pathloss (which is obtained from the estimated local mean). In each decision-making stage, the probability of user being in each partition is obtained, with respect to the pre-mentioned criteria. The partition with the highest probability is the most reliable location at which, user can be found for the next sampling period. The simulation area in tracking is shown in Fig. 4. The tracking path has three parts: A, B and C. Regarding to pathloss estimation and corner detection algorithm for each three parts of the tracking path, estimation of next partition is being done separately. This is, because of the fact that, before reaching any corner, the probability of user being present at partitions of other paths is zero. According to the velocity profile and presumed size of partitions, the number of states is defined N_{state}. $P_{s_i}[k]$

shows the probability of occurrence of each state in k^{th} moment of ith state with sampling step t_s and

$$\sum_{j=1}^{N_{state}} P_{ij} = 1 \qquad (12)$$

Probability of being in i^{th} state can be calculated from transition matrix. The HMM chain model is shown in Fig. 3. The transition matrix is:

$$\begin{bmatrix} P_{S_1}[k] \\ \vdots \\ P_{S_{N_{state}}}[k] \end{bmatrix} = \begin{pmatrix} p_{11}[k] & \cdots & p_{1N_{state}}[k] \\ \vdots & \cdots & \vdots \\ p_{N_{state}1}[k] & \cdots & p_{N_{state}N_{state}}[k] \end{pmatrix} \cdot \begin{bmatrix} P_{S_1}[k-1] \\ \vdots \\ P_{S_{N_{state}}}[k-1] \end{bmatrix} \qquad (13)$$

IV. SIMULATION RESULTS

To evaluate performance of 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 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, shadowing and multipath fading [8]. Fig. 4 shows the map which is used in simulation. In our numerical experiment, LOS and NLOS scenarios are simulated by means of proposed simulation test bed for constant and variable speed. Typical maximum Doppler frequencies are considered in 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 lognormal shadowing $x_c = 20m$ and path loss parameters are set according to [8]. Because 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 available. So the estimated velocity of each base station is weighted according to its SNR. This technique significantly improves the performance of proposed method. So estimated velocity is calculated by

$$\hat{v}[n] = \sum_{i=1}^{N_{BS}} \alpha_i \cdot \hat{v}_i[n] \qquad (14)$$

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

$$\alpha_i = P_i[n] \Big/ \sum_{j=1}^{N_{BS}} P_j[n] \qquad (15)$$

The estimated velocity from three base stations at $SNR=20$ dB (note that SNR is long term) is plotted in Figs. 5-7. As it is seen in Figs. 5-7, estimation error is negligible for SNR more than 20dB. Fig. 8 shows effect of proposed SNR-balancing method. Averaged received power (Local mean) estimation results are given in Fig. 9-11. As it is seen estimation error is negligible, even in situations with low SNR (20dB). The *std* of shadow fading is changed, when mobile user turns at an intersection. This value is selected from the range of 4dB to 7dB. In simulations, sampling
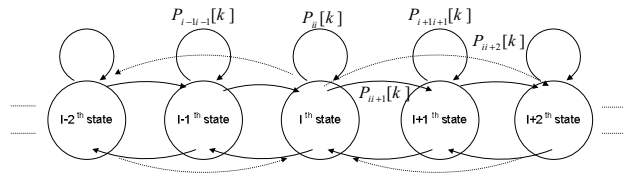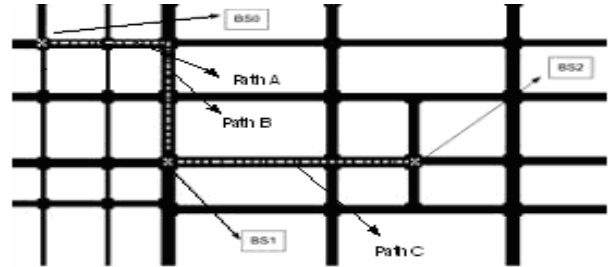

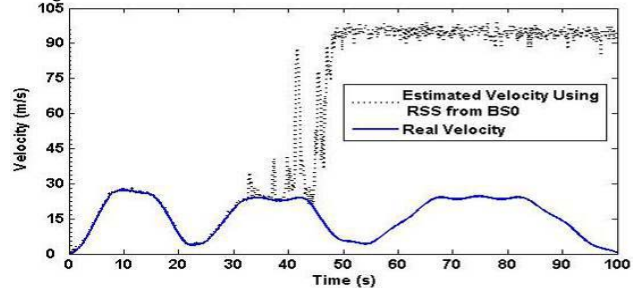Fig. 3. Hidden Markov model chain of states

Fig. 4. Simulation area

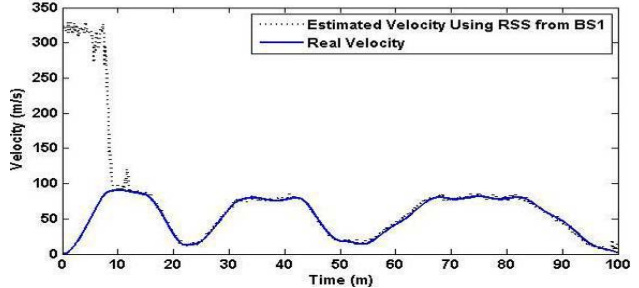Fig. 5. Velocity estimation for path A based on *RSS* of BS0.when long term *SNR= 20 dB*.

Fig. 6. Velocity estimation for path B based on *RSS* of BS1 when long term *SNR= 20 dB*.
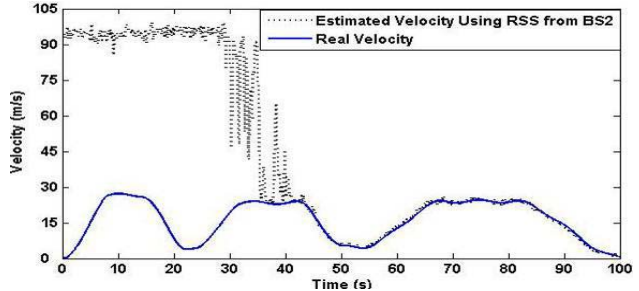

Fig. 7. Velocity estimation for path C based on *RSS* of BS2 when long term *SNR= 20 dB*.

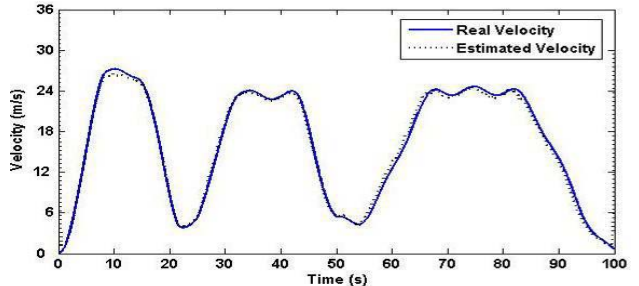

Fig. 8. Velocity tracking performance using *SNR-balancing* technique for long term *SNR= 20 dB*.
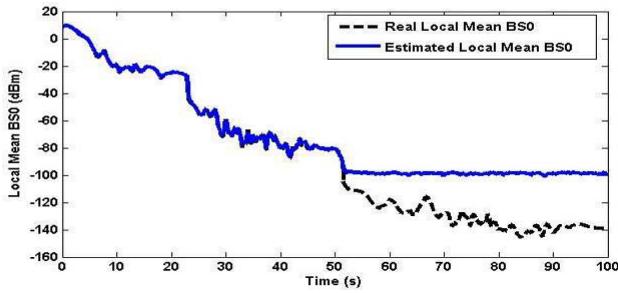
Fig. 9. Local mean estimation for path A based on *RSS* of BS0 when long term *SNR= 20 dB*.
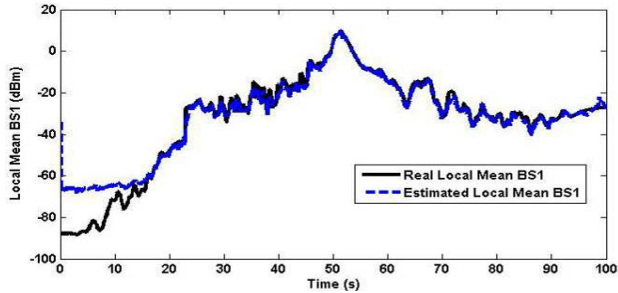

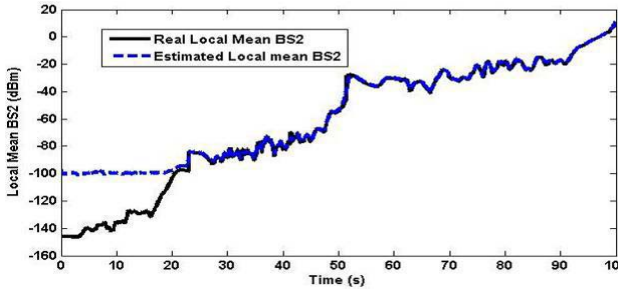Fig. 10. Local mean estimation for path B based on *RSS* of BS1 when long term *SNR= 20 dB*.

Fig. 11. Local mean estimation for path C based on *RSS* of BS2 when long term *SNR= 20 dB*.
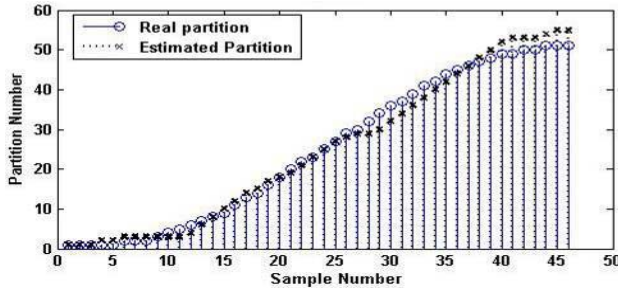

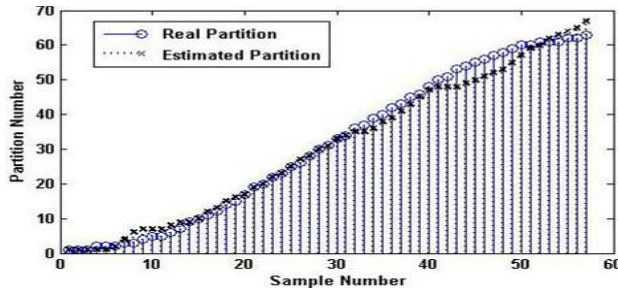Fig 12: Tracking performance for path A.

Fig .13. Tracking performance for path B.

interval is set to 1*ms*. The total length of tracking trajectory is about 1.5*km* and the detection delay is measured in meters (m). In simulations, HMM observations sampling interval is set to 0.5 *s*. The length of each partition is considered 7m,
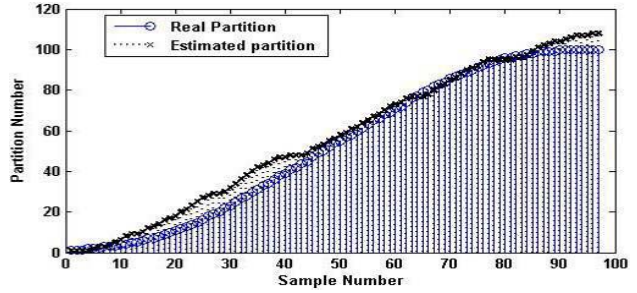

Fig .14. Tracking performance for path C.

which is optional and can be defined according to the desired level of accuracy or to computational burden. In case of more accuracy, size of partitions can be shortened. Path A (350m), B (450m) and C (700m) are divided to 50, 65 and 100 partitions, respectively. According to partition length (7m) and maximum speed for mobile user in urban area (30 m/s), the transition matrix is 5×5. That means, in next decision making stage, presence of mobile user only in 5 partitions is probable. As it is shown in Fig. 3, the possible states can be remaining in the same partition, two partitions ahead and two partitions backwards. The estimated partitions for each part of tracking path are shown in Figs. 12-14.

V. CONCLUSIONS

A new technique for discrete mobile user tracking is presented in this paper for urban environment considering multipath fading and shadowing. The proposed algorithm has been developed based on the velocity profile which is capable of capturing large range of mobility behaviors in urban areas. Employing dynamic programming, the tracking algorithm predicts the next partition of mobile user (location) based on proposed velocity estimation and corner detection algorithms. Simulation results show that the proposed algorithm achieves good performance in tracking mobile users in urban areas with complex structure.

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