Position and Velocity Tracking in Mobile Cellular Networks Using the Particle Filter

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Abstract—**This paper presents a new method for tracking a mobile based on Aulin's wave scattering model. This model takes into account non line of sight and multipath propagation environments, which are usually encountered in wireless fading channels. According to Aulin's model, the received instantaneous electric field at the base station is a nonlinear function of the mobile location and velocity. A method based on particle filtering (sequential Monte Carlo methods) that copes with nonlinearities in order to estimate the mobile location and velocity is proposed. In contrast to standard target tracking literature we do not rely on linearized motion models, measurement relations, and Gaussian assumptions. Numerical results are presented to evaluate the accuracy of the proposed method. They demonstrate significant accuracy improvement over known algorithms.**

I. INTRODUCTION

THE need for an efficient and accurate mobile station (MS) positioning system is growing day by day. This has been stressed by a recent federal order issued by the federal communications commission (FCC), which mandates all wireless service providers to provide public safety answering points with information to locate an emergency 911 caller with an accuracy of 100 meters for 67% of the cases [1]. It is also expected that the FCC will tighten its requirements in the near future [2]. Many other applications, such as vehicle fleet management, location sensitive billing, intelligent transport systems, fraud protection, and mobile yellow pages have driven the cellular industry to research new and promising technologies for MS positioning.

The problem of estimating the location and velocity of a mobile subscriber by processing received information has been the subject of much research work over the last few years. The current literature and standards in estimating the location are based mostly on time signal information, such as Time Difference Of Arrival (TDOA), Enhanced Observed Time Differences (E-OTD), Observed Time Difference Of Arrival (OTDOA), Global Positioning System (GPS) etc., [3-7]. However, not all of these methods meet the necessary needs imposed by specific services. In addition, most of them require new hardware since localization is not inherent in the current wireless systems, for instance, GPS demands a new receiver and TDOA, E-OTD, OTDOA require additional location measurement units in the network [8]. Adding extra hardware means extra cost for implementation, which can be reflected on both consumers and operators. Researchers have also suggested several mobile location methods based on signal power measurements such as in [9] and [10], where a certain minimization problem is solved numerically to get an initial estimate of the mobile position, and then a smoothing procedure such as linear regression [9], or the Kalman filter [10] are applied to obtain a more accurate estimate.

In this paper, we propose a mobile tracking method using sequential Monte Carlo methods or particle filters [11], which employs the instantaneous electric field measurements based on the 3D multipath channel model of Aulin [12]. Aulin's model accounts for multipath and non line of sight (NLOS) characteristics of the wireless channel as well as the dynamicity of the mobile user. The received instantaneous electric field in this model is a nonlinear function of the position and velocity of the mobile user. Nonlinear models in state equation and measurement relation and non-Gaussian noise assumption may lead to non-optimal solutions for linearized methods, such as, the extended Kalman filter (EKF). The particle filter approximates the optimal solution numerically based on the physical model, rather than applying an optimal filter to an approximate model such as in the EKF. It also provides general solutions to many problems where linearization and Gaussian approximations are intractable or yield low performance. The more nonlinear model or the more non-Gaussian noise, the more potential particle filters have, especially in applications where computational power is rather cheap and the sampling rate is moderate. In this paper, the particle filter algorithm is implemented for the classical Bayesian bootstrap method [13].

Aulin's model postulates knowledge of the instantaneous received field at the mobile unit, which obtained through the circuitry of the mobile unit. The proposed algorithm takes into

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account NLOS condition as well as multipath propagation environments. Only one base station is required to estimate the mobile location and velocity instead of at least three base stations found in the literature [10] and [14]. Though with one base station the particle filter may take longer to converge. Particle filtering has been used in several tracking wireless applications [15-18], but the models used do not take into account the multipath properties of the channel. To the best of our knowledge, the utilization of particle filter together with the classical wireless channel model to extract the mobile location and velocity is new. Numerical results indicate that the proposed algorithm is accurate and can be implemented in real time.

The main contribution of this paper is to develop a method, which uses Aulin's 3D wave scattering model to estimate the mobile location and velocity based on particle filtering. The choice of this model is to account for the multipath properties and NLOS of wireless networks. This method supports existing network infrastructure and channel signaling. Moreover, as the simulation studies show, it achieves appropriate level of performance with respect to the standards imposed by FCC.

The paper is structured as follows: In Section II, we describe the mathematical models for the location and velocity estimation algorithm. The recursive Bayesian bootstrap-filtering algorithm is presented in Section III. In Section IV we present numerical results. Section V provides concluding remarks.

II. Mathematical Models

A. Aulin's Scattering Model

The basic wireless scattering channel model described in [12], which assumes that the electric field, denoted by $E(t)$, at any receiving point (x_0, y_0, z_0) is the resultant of P plane waves (see Figure 1), in which the receiver moves in the X-Y plane having velocity υ in a direction making an angle γ with the X-axis, is given by:

$$E(t) = \sum_{n=1}^{P} E_n(t) = \sum_{n=1}^{P} r_n \cos\left(\omega_c t + \omega_n t + \theta_n\right) + n(t) \tag{1}$$

where

$$\omega_n = {}^{2\pi\upsilon}\!/_{\lambda}\left(\cos(\gamma - a_n)\cos\beta_n\right) \tag{2}$$

$$\theta_n = -{}^{2\pi}\!/_{\lambda}\left(x_0 \cos a_n \cos\beta_n + y_0 \sin a_n \cos\beta_n + z_0 \sin\beta_n\right) + \phi_n \tag{3}$$

and a_n, β_n are spatial angles of arrival, ω_n is the Doppler shift, θ_n is the phase shift, λ is the wavelength, r_n is the amplitude of the nth component, $n(t)$ is a white Gaussian noise, ϕ_n is the phase of the nth component, and P is the total number of paths. It can be seen from (2) and (3) that the Doppler shift and phase shift depend on the velocity and location of the receiver, respectively.

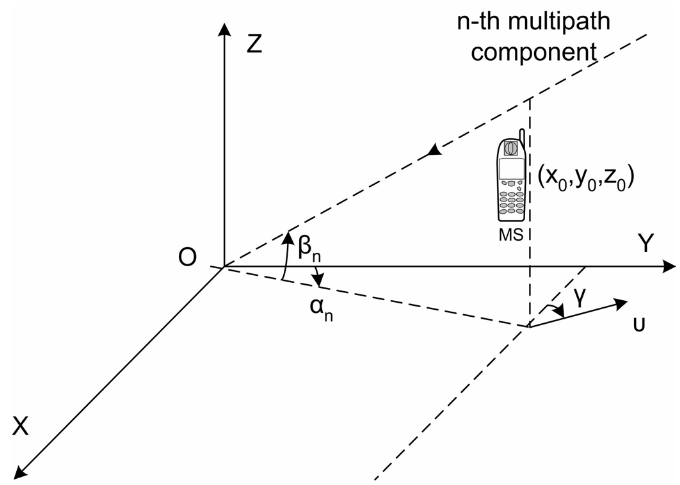

Fig.1. Aulin's 3D multipath channel model.

Clearly, (1) assumes transmission of a narrowband signal. This assumption is valid only when the signal bandwidth is smaller than the coherence bandwidth of the channel. Nevertheless, the above model is not restrictive since it can be modified to represent a wideband transmission by including multiple time-delayed echoes. In this case, the delay spread has to be estimated. A sounding device is usually dedicated to estimating the time delay of each discrete path (e.g., Rake receiver) [19].

It can be seen that the noisy instantaneous received field in (1) depends parametrically on the location and velocity of the receiver. Consequently, we can utilize this expression to estimate the MS location and velocity through particle filtering.

B. State and Measurement Models

Next, we formulate the location estimation as a filtering problem in state-space form [20]. The general form, once discretized, is given by

$$\begin{aligned} \mathbf{x}_k &= \mathbf{f}(\mathbf{x}_{k-1}, \mathbf{w}_{k-1}) \\ \mathbf{z}_k &= \mathbf{h}(\mathbf{x}_k, \mathbf{v}_k) \end{aligned} \tag{4}$$

where $\mathbf{f}(.,.)$ and $\mathbf{h}(.,.)$ are known vector functions, k is the estimation step, $\mathbf{z}_k$ are the output measurements at time step k, and $\mathbf{x}_k$ is the system state at time step k and must not be confused with location coordinates. Further, in (4) $\mathbf{w}_k, \mathbf{v}_k$ are the discrete zero-mean, independent state (process) and measurement noise processes, and Q, R are their covariance matrices, respectively, given by

$$\begin{aligned} E\left[\underline{w}(i)\underline{w}^T(k)\right] &= Q_i \delta_{ik} \\ E\left[\underline{v}(i)\underline{v}^T(k)\right] &= R_i \delta_{ik} \end{aligned} \tag{5}$$

where δ_{ik} is the Kronecker delta.

Now let $\mathbf{x}_k = [x_k, \dot{x}_k, y_k, \dot{y}_k]^T$ denote the state of the mobile at time k, where x_k and y_k are the Cartesian coordinates of the mobile, $\dot{x}_k$ and $\dot{y}_k$ are the velocities of the mobile in the X and Y directions, respectively. We choose the case when the velocity of the mobile is not known and is subject to unknown accelerations. Then the dynamics of the mobile can be written as [15]:

$$\begin{bmatrix} x_{k+1} \\ \dot{x}_{k+1} \\ y_{k+1} \\ \dot{y}_{k+1} \end{bmatrix} = \begin{bmatrix} 1 & \Delta_k & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & \Delta_k \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_k \\ \dot{x}_k \\ y_k \\ \dot{y}_k \end{bmatrix} + \begin{bmatrix} \Delta_k^2/2 & 0 \\ \Delta_k & 0 \\ 0 & \Delta_k^2/2 \\ 0 & \Delta_k \end{bmatrix} \begin{bmatrix} w_{k,1} \\ w_{k,2} \end{bmatrix} \tag{6}$$

where Δ_k is a (possibly non-uniform) measurement interval between time k and $k + 1$.

The measurement equation can be found from Aulin's scattering model in (1) which can be rewritten in discrete form as:

$$z_k = h(\mathbf{x}_k, v_k) = \sum_{n=1}^{P} r_{n_k} \cos\left(\omega_c t_k + \omega_{n_k} t_k + \theta_{n_k}\right) + v(t_k) \tag{7}$$

where

$$\omega_{n_k} = \frac{2\pi\sqrt{\dot{x}_k^2 + \dot{y}_k^2}}{\lambda}\left(\cos(\gamma_k - \alpha_{n_k})\cos\beta_{n_k}\right) \tag{8}$$

$$\theta_{n_k} = \frac{-2\pi}{\lambda}\begin{pmatrix} x_k \cos\alpha_{n_k} \cos\beta_{n_k} + \\ y_k \sin\alpha_{n_k} \cos\beta_{n_k} + z_0 \sin\beta_{n_k} \end{pmatrix} + \phi_{n_k} \tag{9}$$

Clearly, the measurement equation $h(.,.)$ is a non-linear function of the state-space vector, as observed in (7), (8) and (9). If we assume knowledge of the channel, which is attainable either through channel estimation at the receiver (e.g., GSM receiver), or through various estimation techniques (e.g., least-squares, Maximum Likelihood), then this problem falls under the broad area of non-linear parameter estimation from noisy data which can be solved using the particle filter, which is discussed in the next section.

III. Bayesian Bootstrap Filter Design

A. Recursive Nonlinear Bayesian Estimation

Consider the general discrete-time dynamical system model described in (4). Let the known probability density functions (PDFs) of the process noise $\mathbf{w}_k$ and the measurement noise $\mathbf{v}_k$ be $p(\mathbf{w}_k)$ and $p(\mathbf{v}_k)$, respectively. As usual, $\mathbf{w}_k$ and $\mathbf{v}_k$ are assumed to be mutually independent. The set of entire measurements from the initial time step to time step k is denoted by $\mathbf{Z}_k = \{\mathbf{z}_i\}_{i=1}^{k}$. The distribution of the initial condition $\mathbf{x}_0$ is assumed to be given by $p(\mathbf{x}_0 \mid \mathbf{Z}_0) = p(\mathbf{x}_0)$.

The recursive Bayesian filter based on Bayes rule is organized into the time-update stage and the measurement-update stage [11]. The time-update stage computes the PDF $p(\mathbf{x}_k \mid \mathbf{Z}_{k-1})$ via the Chapman-Kolmogorov equation as:

$$p(\mathbf{x}_k \mid \mathbf{Z}_{k-1}) = \int p(\mathbf{x}_k \mid \mathbf{x}_{k-1}) p(\mathbf{x}_{k-1} \mid \mathbf{Z}_{k-1})\, d\mathbf{x}_{k-1} \tag{10}$$

where $p(\mathbf{x}_{k-1} \mid \mathbf{Z}_{k-1})$ has been propagated from time step $k-1$. Note that in (10) the Markov property of the state model $p(\mathbf{x}_k \mid \mathbf{x}_{k-1}, \mathbf{Z}_{k-1}) = p(\mathbf{x}_k \mid \mathbf{x}_{k-1})$ has been used. The PDF $p(\mathbf{x}_k \mid \mathbf{x}_{k-1})$ is determined by the system model and the known PDF $p(\mathbf{w}_{k-1})$. The measurement-update can be carried out by applying Bayes rule:

$$p(\mathbf{x}_k \mid \mathbf{Z}_k) = \frac{p(\mathbf{z}_k \mid \mathbf{x}_k) p(\mathbf{x}_k \mid \mathbf{Z}_{k-1})}{\int p(\mathbf{z}_k \mid \mathbf{x}_k) p(\mathbf{x}_k \mid \mathbf{Z}_{k-1})\, d\mathbf{x}_k} \tag{11}$$

The PDF $p(\mathbf{z}_k \mid \mathbf{x}_k)$ is computed by the measurement model and the known PDF $p(\mathbf{v}_k)$.

In general, the above recursive Bayesian filter does not have a closed form solution, and therefore, has to be approximated numerically using the particle filter.

B. Bootstrap Filter Algorithm

Suppose we have a set of random samples $\{\mathbf{x}_k(j)\}_{j=1}^{N}$ drawn from the PDF $p(\mathbf{x}_k \mid \mathbf{Z}_k)$, where N is the number of bootstrap samples (or particles). The Bayesian bootstrap filter algorithm [13] performs the time-update and the measurement-update to these samples in order to obtain a set of samples $\{\mathbf{x}_{k+1}(j)\}_{j=1}^{N}$, which are approximately distributed as the PDF $p(\mathbf{x}_{k+1} \mid \mathbf{Z}_{k+1})$.

The time-update stage is performed by passing the random samples $\{\mathbf{x}_k(j)\}_{j=1}^{N}$ through the system model (6) to obtain the time-updated samples $\{\tilde{\mathbf{x}}_{k+1}(j)\}_{j=1}^{N}$. Namely, the time-updated samples are obtained by:

$$\tilde{\mathbf{x}}_{k+1}(j) = \mathbf{f}\left(\mathbf{x}_k(j), \mathbf{w}_k(j)\right) \tag{12}$$

where $\mathbf{w}_k(j)$ is a sample drawn from the PDF $p(\mathbf{w}_k)$ of the system noise. Then, the samples $\{\tilde{\mathbf{x}}_{k+1}(j)\}_{j=1}^{N}$ are distributed as the time updated PDF $p(\mathbf{x}_{k+1} \mid \mathbf{Z}_k)$.

The measurement-update stage can be performed by evaluating the following likelihood for each sample $\tilde{\mathbf{x}}_{k+1}(j)$ as:

$$q_j = \frac{p\left(\mathbf{z}_{k+1} \mid \tilde{\mathbf{x}}_{k+1}(j)\right)}{\sum_{j=1}^{N} p\left(\mathbf{z}_{k+1} \mid \tilde{\mathbf{x}}_{k+1}(j)\right)} \quad (13)$$

given the measurement sample $\mathbf{z}_{k+1}$ at time step k + 1. We define a discrete density over $\{\tilde{\mathbf{x}}_{k+1}(j)\}_{j=1}^{N}$ with probability mass q_j associated with each sample $\tilde{\mathbf{x}}_{k+1}(j)$. Then we get the measurement-update samples $\{\mathbf{x}_{k+1}(j)\}_{j=1}^{N}$ through a resampling process, such that $\Pr\{\mathbf{x}_{k+1}(i) = \tilde{\mathbf{x}}_{k+1}(j)\} = q_j$ for any i. This process performed by drawing a sample u_j from the uniform distribution over (0, 1]. Then, the sample $\{\tilde{\mathbf{x}}_{k+1}(M)\}$ is chosen as the updated sample $\mathbf{x}_{k+1}(j)$ if the random sample u_j satisfies the relation

$$\sum_{i=0}^{M-1} q_i < u_j < \sum_{i=0}^{M} q_i \quad (14)$$

where $q_0 = 0$. This resampling process is repeated for $j = 1, \ldots, N$. The key point with resampling is to prevent high concentration of probability mass at a few particles. Although the resampling step reduces the effect of the degeneracy problem, it may introduce another problem. That is particles that have high weights are statistically selected many times. This leads to a loss of diversity among the particles, as the resultant sample will contain many repeated points. This problem is called sample impoverishment, and can be reduced by introducing an additional noise in the samples. This technique is called roughening in [13] and jittering in [21].

In this paper, the so-called prior editing method mentioned in [13] is used to reduce the sample impoverishment problem. It can be described by delaying the estimation problem one time-step. The likelihood can then be evaluated at the next time step. The idea is to reject particles with sufficiently small likelihood values since they are not likely to be resampled. The update stage is repeated until a feasible likelihood value is received. The roughening method is applied before the update step. Finally, the estimate of the particle filter at time k + 1 is chosen to be the mean of the samples $\{\mathbf{x}_{k+1}(j)\}_{j=1}^{N}$.

In the next section, a numerical example is presented to illustrate the accuracy of the proposed method.

IV. Simulation Results

The wireless communication network in this numerical example has the following parameters:

- The envelope of the received signal for all paths, r_n's, are generated as Rayleigh independent identically distributed (iid) random variables (RVs) with parameter 0.5.
- a_n, β_n, and ϕ_n are generated as uniform iid RVs in [0, 2π], [0, 0.2π], and [0, 2π], respectively.
- The total number of paths P is 6, which represents urban environments.
- f_c = 2000 Hz for simulation reasons.
- The base station is located at the center of the cell and it is considered as the origin.
- The cell radius is 5000 meters.

The particle filter has the following parameters:

- Number of particles is 5000.
- Number of time steps (measurements) is 50 with $\Delta_k = 0.1$ seconds.
- 100 Monte Carlo simulations were performed.
- Process noise covariance Q and measurement noise variance R are $I_{2\times 2}$ and 0.01, respectively. Where $I_{2\times 2}$ is the two-dimensional identity matrix.
- The initial PDF of the mobile position is assumed to be uniform over the entire cell size. This represents the worst-case as far as choosing an initial PDF is considered.
- The initial PDF of the mobile velocity is Gaussian distributed with mean 65 meters/seconds and variance 10.
- The mean estimate of all particles is used as the final estimate.

In Figure (2) and (3) one realization is viewed illustrating the convergence of the particle filter to the real position and velocity of a moving MS, respectively. The initial actual mobile location and velocity are x=3000 meters, y=2000 meters, $\dot{x}$=50 meters/seconds, and $\dot{y}$=50 meters/seconds. The initial actual state can then be written as $(3000, 50, 2000, 50)^T$. The initial state is $(2500, 65, 1500, 65)^T$. As previously stated, we assume adequate channel knowledge, i.e., α_n, β_n, φ_n, r_n, and number of paths P are known. The relevant values are marked on the figures; these are the initial and the final estimate errors.

We observe that the estimator has excellent accuracy. Specifically, the accuracy is below 10 meters most of the time. The final error is 2.2 meters in the X-coordinate and 0.6 meters in the Y-coordinate in comparison to the initial error of 500 meters as shown in Figure (2). Also the mobile velocity is estimated with high accuracy as shown in Figure (3). As the initial speed estimate error is 15 meters/seconds for both X and Y directions, it reduces to 0.15 and 0.03 meters/seconds, respectively, in the final estimate error. This is due to the appropriateness of Aulin's channel model and the efficiency of the particle filtering in this particular application.

The position (or velocity) root mean square error (RMSE) is defined as:

$$\mathrm{RMSE}(k) = \sqrt{\frac{1}{100}\sum_{i=1}^{100}\left(\hat{\mathbf{x}}_k^i - \mathbf{x}_k^{\text{true}}\right)^T\left(\hat{\mathbf{x}}_k^i - \mathbf{x}_k^{\text{true}}\right)} \quad (15)$$

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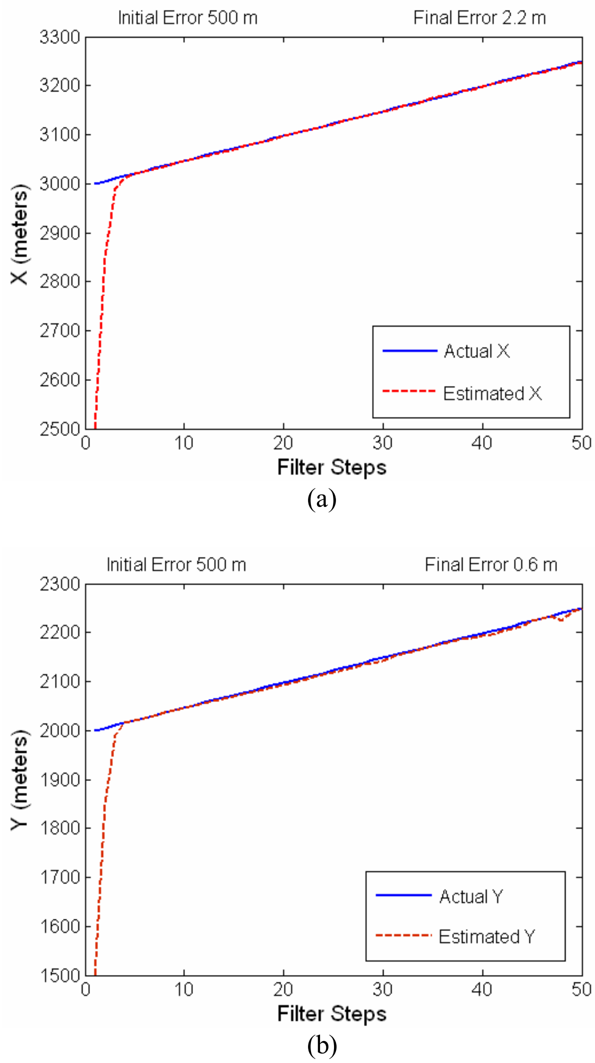

Fig. 2. Mobile location estimation in (a) X-coordinate, and (b) Y-coordinate.

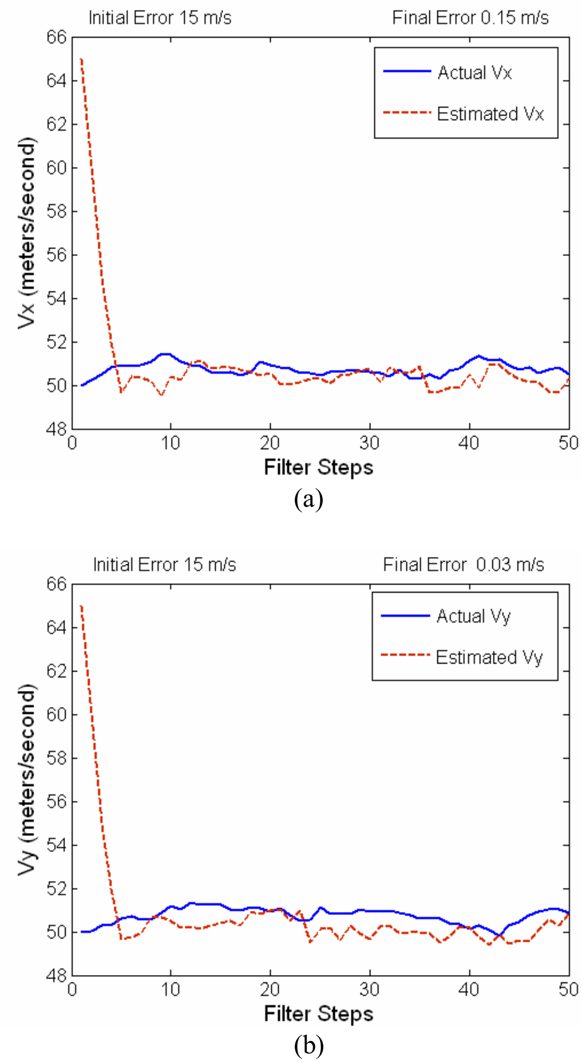

Fig. 3. Mobile velocity estimation in (a) X-direction, and (b) Y-direction.

where $\hat{\mathbf{x}}_k^i$ is the filter position estimate $(x, y)^T$ (or velocity estimate $(\dot{x}, \dot{y})^T$), at time k in Monte Carlo run i. Since it takes less than 5 iterations for the filter to converge near the actual value as shown in Figures (2) and (3), the RMSE (k) is calculated starting from the iteration k = 5. Figure (4) shows the position and velocity RMSE for each time according to (15). It can be seen from Figure (4) that the position and velocity RMSE is below 8 m and 2 m/sec, respectively, most of the time. The overall RMSE can be defined by:

$$\text{RMSE} = \sqrt{\frac{1}{L}\sum_{k=1}^{L}\frac{1}{100}\sum_{i=1}^{100}\left(\hat{\mathbf{x}}_k^i - \mathbf{x}_k^{\text{true}}\right)^T\left(\hat{\mathbf{x}}_k^i - \mathbf{x}_k^{\text{true}}\right)} \qquad (16)$$

where L is the total number of simulation time steps after the convergence of the filter (in our example $L = 46$). The overall position and velocity RMSE in our example (ignoring transients) using (16) are found to be 4.31 meters and 1.01 meters/second, respectively.

The high accuracy, consistency and performance of the proposed method, makes it suitable to be used in any location estimation applications, particularly those which require high accuracy, such as emergency services.

It is worth mentioning that when the particle filter is used in practice, we often wish to minimize the number of particles in order to reduce the computational burden. Therefore, this method can be implemented in real-time. Since our state model is linear, then Rao-Blackwellization procedure [22] can be used to reduce the number of particles. The idea is to use the Kalman filter for the part of the state space model (in our case the mobile velocity) and the particle filter for the other part (the mobile location). It is shown in [23] that Rao-Blackwellised particle filters lead

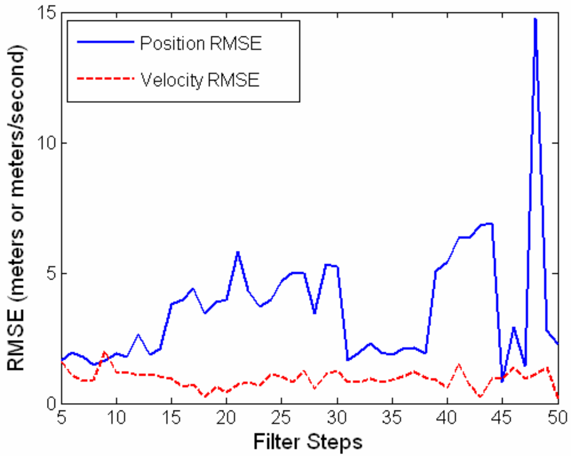

Fig. 4. Position and velocity RMSE (k) for the particle filter estimation.

to more accurate estimates than standard particle filter. This is of high importance for high-performance real-time applications, and is an on-going research project.

V. CONCLUSION

A new estimation method is proposed to track the position and velocity of a mobile in a cellular network. It is based on Aulin's scattering model and the particle filter. Since the instantaneous electric field is a nonlinear function of the mobile location and velocity, the particle filter is used for the estimation process. The results for typical simulations show that it is highly accurate and consistent. The use of nonlinear models and/or non-Gaussian noise is the main explanation for the improvement in accuracy over linear algorithms. The choice of state coordinates making the state equation linear is beneficial for computation time and opens up the possibility for Rao-Blackwellization. This procedure enables a significant decrease in the particle state dimension. The evaluation of the likelihood one step ahead before resampling (prior editing) is, together with adding extra state noise (roughening, jittering) crucial for avoiding divergence and implies that the number of particles can be decreased further. The assumptions are knowledge of the channel and access to the instantaneous received field, which are obtained through channel sounding samples from the receiver circuitry. Future work will focus on generating efficient channel estimation algorithms, to remove the assumption on complete knowledge of the channel. Finally, work on building a pilot application to test the performance of the proposed method in realistic conditions is on-going together with the incorporation of channel model parameters estimation algorithms.

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