Filtering Techniques for Coarse Timescale Power Prediction in Wireless Networks

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***Abstract*—A wide range of wireless channel models have been developed to predict variations in received signal strength. In contrast to vast majority of prior work, which has focused primarily on channel modeling on a short, per- packet timescale (millisecond), we adopt filtering techniques (Kalman Filter(KF), Extended Kalman Filter(EKF), Unscented Kalman Filter(UKF), Particle Filter(PF)) to capture coarse timescale power variation occurring due to path loss and shadowing , particularly in mobile scenarios. The state variables of the system are the received power and the sender-receiver distance. The effect of shadowing is captured as the noise occurring the system equations. The received power is related to the shadowing and path loss by a non-linear stochastic difference equation. We model the speed of a client to change linearly between successive time slots.**

We collect signal strength and location measurements on a WiMAX (802.16e) network and test the effectiveness of these filtering methods. We observe that advanced filtering techniques surprisingly only provide marginal improvement over a simple Kalman Filter for predicting fluctuations in received power on a coarse timescale. We identify small variations in distance (at the timescales of interest) to be the main factor for the comparable performance of the different techniques. We are currently working on exploiting the temporal correlation of shadowing and obtaining independent measurements for shadowing to improve prediction results.

I. Introduction

Predicting and modeling received power variations over a wireless channel is challenging and the earliest work addressing this issue dates back to the Gilbert and Elliot two-state Markov channel [1], [2]. The inherent difficulty of the problem stems from the fact that there are multiple phenomena affecting the received power. Broadly, there are three factors causing received power variations over a wireless channel; they are multipath fading, path loss and shadowing. Among them, fading caused by the constructive or destructive interference of multipath waves effects the received power in the milliseconds timescale. On the other hand, path loss and shadowing model the variations in received power in the order of seconds. Path loss is the deterministic distance-dependent component of the received power, while shadowing captures the randomness in the received signal caused by changes in the environment (buildings, foliage and obstacles).

Each of the above mentioned phenomena has been studied individually [3], yet a holistic approach considering all the factors and leveraging their properties to predict power changes is largely missing. Most related work has modeled the effect of multipath fading on the received power [4]. Though some prior work [5], [6] exists, the joint effect of path loss and shadowing on the received power (the main factors in mobile scenarios) is still largely unexplored.

The goal of this paper is to predict received power variations over the wireless channel on a coarse timescale (order of seconds) in mobile networks and hence we focus on modeling the effect of path loss and shadowing in this work. The received power is related to the path loss and shadowing by a non-linear stochastic difference equation which makes it amenable to classic prediction techniques like the Kalman filter and its variants (Extended and Unscented Kalman filters). The variation in the received power being non-linear when the receiver is mobile (there is a change in distance), we propose using an EKF, UKF or PF to predict future signal strength values. We note here that a simple Kalman filter modeling the variation in received power as a linear system has been proposed in [7].The authors evaluate this simplistic model for short timescale power prediction in a static sensor wireless network. Filtering techniques can be used in analyzing performance of wireless network protocols (e.g., for route adaptation, or for video transmission) that adapt their behavior in response to link-level changes at the timescale of seconds.

The main contributions of our work are as follows. We propose using filtering techniques such as KF, EKF, UKF and PF to predict received power variations over the wireless channel. We assume time to be divided into slots. The duration of a time slot is in the seconds timescale. The goal is to predict the received power at time t, given state measurements till time $t-1$. The received power at any time t is modeled as a non-linear function of the transmitter-receiver distance at time $t-1$ along with some additive Gaussian noise resulting due to shadowing. We model the speed to vary linearly between two successive time slots i.e., the distance change between time instants t and $t-1$ is linearly dependent on the distance variation between time $t-1$ and $t-2$ subject to some noise.

The implementation of these filtering requires measurements for each of the system variables. We assume that receivers are capable of collecting signal strength measurements. Further, we also assume that the receivers are equipped with a GPS and thus can estimate the sender-receiver distance. We perform experiments in a WiMAX (802.16e) network and collect signal strength and GPS measurements under varying levels of user mobility (pedestrian and vehicular). Surprisingly, we observe that sophisticated filtering techniques perform similar to a simple Kalman filtering even in mobile scenarios. We identify limited variation in distance in one second to be the primary reason for the comparable performance.

The rest of paper is organized as follows. We discuss related work in Section II and provide a brief overview of the different filters in Section III. We state the problem in Section IV and describe our filtering models in Sections V and VI. The experimental results are presented in Section VII and we finally conclude the paper in Section IX.

II. Related Work

Predicting and modeling power variation over wireless networks is well studied with the earliest work in this area being the simple, two-state model proposed by Gilbert and Elliot [1], [2]. Much of the modeling work in this domain has been focused on constructing Markov chain models for wireless channels. In [8] a range of signal-to-noise ratio (SNR) values represents a state in the Markov chain. Based on this assumption the authors provide analytical expressions for the state transition probabilities and error probabilities in each state. In [9] the authors investigate the accuracy of a first-order Markov model for the success/failure of data blocks. A detailed survey of various channel models along with a description of their evolution over time is available in [4].

All the above channel models concentrate on modeling the effects of multipath fading on the received power and typically operate on the milliseconds timescale. To capture channel variations at a much coarser time granularity, typically in the order of a few seconds, in our previous work [6] we constructed a Markov chain model based on shadowing to model its effect on the received power. We validated our model using data collected via real world experiments in a variety of different settings. The Markov model does not capture the effect of path loss on the received power and hence can be used for received power prediction only in scenarios where the path loss is assumed to be constant in the time period of interest. In contrast to this, in our current work we adopt filtering approaches to capture the effect of both path loss and shadowing on the received power. This work aims to provide a more holistic view and can be readily utilized by applications which rely on power prediction on a coarse time granularity.

Kalman filtering approaches for modeling the received power over the wireless channel have also been explored previously [7], [10]. Senel *et.al,* propose a Kalman filter for link quality estimation in wireless sensor networks [7]. They focus on stationary nodes and adopt a simple linear model for the received power. The authors in [5] exploit the exponential autocorrelation assumption of shadowing to construct a Kalman filter to model its effect on the received power. They then perform simulations to show how this approach performs better than window-based schemes. In [10], the authors use UKF and PF to perform signal-strength based tracking of RFID tags and rely on matlab simulation and traces collected from static zigbee testbed to evaluate the effectiveness of their model. Models based on Kalman filters have also been used for power control by predicting interference in wireless networks [11], [12]. Apart from this, there is a large body of literature which has relied on received power measurements to track and predict mobility patterns in different types of wireless networks [13], [14], [15]. Our work differs from the above mentioned works in the sense that we are interested in predicting variations in received power in mobile scenarios on coarse timescales. We model the system using a non-linear set of equations and use filtering techniques to evaluate the performance. Further, we test the performance of the filters with data collected via experiments performed over a WiMAX network, which is absent in majority of prior work.

III. Background

This section provides a brief review of the basics of Kalman filter, its limitations and the EKF, UKF and PF. This background is provided to help the reader better understand the adoption of these techniques for our power prediction problem.

A. Kalman Filter

Kalman filters are widely used in tracking and prediction and a detailed description is available in [16]. Let x_t denote the true state of the system at time t, where x_t is a vector if there are multiple state variables. Let z_t be the measurement of state x_t at time t. Although the state and measurement variables are random processes, for ease of representation we will consider their variation at any given time t and treat them as random variables.

The Kalman filter is used to estimate the state of a discrete time process which can be represented by a linear stochastic difference equation [16]. ie. x_t, the state of the system at time t is a linear function of x_{t-1} along with some additive process noise w_{t-1}. z_t is also modeled to vary linearly with x_t with an additive measurement noise v_t. The state space and measurements are governed by (1) and (2) respectively.

$$x_t = A_t x_{t-1} + B_t u_t + w_{t-1} \tag{1}$$

$$z_t = H_t x_t + v_t \tag{2}$$

where w_t and v_t are assumed to be independent and Gaussian white. At any given time t, $w_t \sim N(0, Q_t)$ and $v_t \sim N(0, R_t)$. A_t and H_t relate current state x_t to the previous state x_{t-1} and measurement z_t to current state x_t. u_t is the optional control input to the system and B_t captures the dependence of x_t on u_t.

The Kalman filter estimates the linear process by using feedback control. The Kalman filter obtains *a priori* estimates of the state x_t using *a posteriori* estimates of the state x_{t-1}. Let $\hat{x}_t^-$ and $\hat{x}_t$ denote *a priori* and *a posteriori* estimates of x_t. The *a posteriori* estimate ($\hat{x}_t$) is obtained from z_t. The *a priori* and *a posteriori* error covariances P_t^- and P_t of the state estimates at time t are also updated at every time step. This recursive approach prevents state space explosion as more observations are obtained and therefore has low computational overhead. The Kalman filter is the optimal predictor if the underlying noise is white and the covariances are known.

B. Extended and Unscented Kalman Filter

If the process cannot be modeled as a linear function and (or) the relationship between the measurement and process is non-linear, a Kalman filtering approach cannot be used for prediction purposes. The extended Kalman filter [16] and the unscented Kalman filter [17] relax the linearity assumption. We will describe the EKF in detail and provide a flavor about the working of UKF.

The EKF linearizes the non-linear dynamics about the current mean and variance. Let the state vector x_t and the measurement vector z_t be governed by non-linear functions f and h as shown in (3) and (4) respectively.

$$x_t = f(x_{t-1}, u_t, w_{t-1}) \tag{3}$$

$$z_t = h(x_t, v_t) \tag{4}$$

The EKF also works in the same recursive manner as the Kalman filter. Using *a posteriori* estimates ($\hat{x}_{t-1}$), *a priori* estimates ($\hat{x}_t^-$) are obtained. Similarly P_t^- is also estimated from P_t. This leads to the time update equations shown below.

1) **Time Update Equations**

$$\hat{x}_t^- = f(\hat{x}_{t-1}, u_t, 0) \tag{5}$$

$$P_t^- = A_t P_{t-1} A_t^T + W_t Q_{t-1} W_t^T \tag{6}$$

Once, z_t is obtained, the estimates for x_t are updated. The Kalman gain of the filter (K_t) is also updated at this stage along with the state error covariance. These are formally represented by the measurement update equations below.

1) **Measurement Update Equations**

$$K_t = P_t^- H_t^T (H_t P_t^- H_t^T + V_t R_t V_t^T)^- 1 \tag{7}$$

$$\hat{x}_t = \hat{x}_t^- + K_t(z_t - h(\hat{x}_t^-, 0)) \tag{8}$$

$$P_t = (I - K_t H_t) P_t^- \tag{9}$$

In the time and measurement update equations, A_t is the Jacobain matrix of of partial derivatives of f with respect to x, W_t is the Jacobain matrix of of partial derivatives of f with respect to w, H_t is the Jacobain matrix of of partial derivatives of h with respect to x and V_t is the Jacobain matrix of of partial derivatives of h with respect to v. A_t, W_t, H_t and V_t are given by (10, 11, 12, 13) respectively.

$$A_{ij} = \frac{\partial f_{[i]}}{\partial x_{[j]}}(\hat{x}_{t-1}, u_t, 0) \tag{10}$$

$$W_{ij} = \frac{\partial f_{[i]}}{\partial w_{[j]}}(\hat{x}_{t-1}, u_t, 0) \tag{11}$$

$$H_{ij} = \frac{\partial h_{[i]}}{\partial x_{[j]}}(\hat{x}_t^-, 0) \tag{12}$$

$$V_{ij} = \frac{\partial h_{[i]}}{\partial v_{[j]}}(\hat{x}_t^-, 0) \tag{13}$$

where i and j correspond to the i^{th} row and j^{th} column of the matrix. Equations (10 -13) are a result of the linearization of the non-linear state and measurement equations. By iteratively applying the time and measurement update equations, the EKF can be directly used for the one-step prediction.

The Unscented Kalman Filter belongs to larger family of filters called the sigma-point Kalman filters. EKF is somewhat an ad-hoc extension of the Kalman filer for non-linear systems. The linearization requires the calculation of Jacobian matrices which can be hard for certain highly non-linear systems. In UKF, the posterior state distribution is approximated by using a minimal set of carefully chosen sample points. The sigma points are propagated through the non-linear process equations to obtain the transformed points and the prior mean and covariance are determined as the weighted average of these transformed points. The expected performance of the UKF is higher than EKF [17].

C. Particle Filter

The particle filter falls in the category of sequential Monte Carlo (MC) filters and it implements a Bayesian filter by MC sampling. In particle filter the posterior distribution of the states is approximated as a weighted average of the samples obtained by MC sampling. In PF as the samples are obtained using MC sampling in comparison to UKF where the samples are obtained deterministically, in general PF requires a large number of samples or particles. The state estimation performance of PF improves as the number of particles increases, but the computational time also increases drastically. Details about the particle filter (including the different sampling techniques, the degeneracy problem and resampling) is available in [18].

IV. Problem Definition

In this section, we describe the power prediction problem that we are addressing in this work. Consider a wireless network, where a mobile client (the receiver) is communicating with the sender. The sender can either be the base station (in case of a WiMAX/4G network) or another client (in case of the an ad-hoc network). We assume time is divided into slots, with the slot duration being in the order of seconds. At the beginning of each time slot, the receiver collects signal strength measurements. We also assume that the client is equipped with a GPS to collect location information.

Signal strength is considered to be a measure of the link quality between the sender and receiver. The client is interested in coarse timescale channel prediction and wants estimates of the sender-receiver link quality at future time instants. Hence, the problem can be defined as:
Given a series of signal strength and location measurements till time $t-1$, predict the signal strength at time instants t.

We discuss some applications to help motivate the application of the results of this work. The most compelling application is the scheduling of multiple video streams over a 4G/WiMAX network with the objective of minimizing the number of playout jitters [19]. Let us assume a simple time slotted scheme in which a video stalls if there is not enough data to play out in a time slot. Such a model would require channel estimation from one timeslot to the other. Further to facilitate a smooth viewing experience the time slots should be in the order of seconds instead of milliseconds to avoid experiencing large number of small glitches. Rate control on a block of data is gaining popularity and a successful implementation of a block based scheme would require a coarse timescale channel model to predict channel variations from one block to the next (a block can take 1-2 seconds to be transmitted) coupled with a fine grained tracking of signal strength fluctuations within a block [20].

V. System and Measurement Model

The objective of this work is to predict received power changes over a wireless channel. Previous theoretical and practical studies indicate that the average received power varies logarithmically with the distance between the transmitter and receiver; this is the deterministic path loss component of the received power and is popularly known as the pathloss. Superimposed on the pathloss is lognormally distributed random shadowing, which takes into account the fact that the received signal strength at the same transmitter-to-receiver separation can vary due to changes in the environmental surroundings.

We begin by modeling the received power variation. Let d, α, d_0 be the transmitter-to-receiver separation, the path loss coefficient and the close-in reference distance respectively. The received power $p_r(d)$ in [dBm] is given by

$$p_r(d)[dBm] = \bar{p_r}(d_0) - 10\alpha \log \frac{d}{d_0} + s \tag{14}$$

where $\bar{p_r}(d_0)$ is the average received power at the reference distance d_0, the second term reflects the logarithmic dependence of received power on distance, and s is the shadowing and is assumed to be Gaussian random process with an exponential autocorrelation function [21], [22], [23]. Therefore, at any given time t, s_t is $\sim N(0, \sigma^2)$ in [dB].

Let p_t and d_t denote the received power and the sender-receiver distance at time t. From (14) we can write the following relation.

$$\begin{aligned} p_t &= p_{t-1} - 10\alpha \log \frac{d_t}{d_{t-1}} + s_t - s_{t-1} \\ &= p_{t-1} - 10\alpha \log \frac{d_t}{d_{t-1}} + w^p_{t-1} \end{aligned} \tag{15}$$

where w^p_t is the noise in the power measurements at t as a result of shadowing and is modeled as $\sim N(0, \sigma^2_{w^p_t})$. We next consider the variation in d_t. We model the velocity to vary by a factor β between two consecutive time slots subject to a noise (16) i.e., the difference between d_t and d_{t-1} is equal to β times the difference between d_{t-1} and d_{t-2}, where $0 < \beta < 1$. This is a reasonable assumption for both vehicular and pedestrian mobility, as the time slot duration is small. The noise w^d_{t-1} models the fact that the direction of motion could be altered due to turns and the winding of the road.

$$d_t - d_{t-1} = \beta(d_{t-1} - d_{t-2}) + w^d_{t-1} \tag{16}$$

where w^d_t is assumed to be $\sim N(0, \sigma^2_{w^d_t})$ and is independent of d_t.

Let us consider a new variable m_t which we define as

$$m_t = d_{t-1} \tag{17}$$

We model velocity in (16) and thus introduce a dependence of d_t on d_{t-2}. As the application of these filters requires a system model where its current state depends only the previous state, we introduce m_t which is simply the distance at the previous time instant i.e., d_{t-1}. Using the above relations, we first rewrite (16 and 15) in the following way, as shown in (18) and (19) respectively.

$$d_t = (1+\beta)d_{t-1} - \beta m_{t-1} + w^d_{t-1} \tag{18}$$

$$\begin{aligned} p_t &= p_{t-1} - 10\alpha \log \frac{(1+\beta)d_{t-1} - \beta m_{t-1} + w^d_{t-1}}{d_{t-1}} \\ &\quad + w^p_{t-1} \end{aligned} \tag{19}$$

We consider the state vector $x_t = [p_t, d_t, m_t]$. The system behavior is thus modeled by a non-linear set of difference equation given by (19,18 and 17). The process noise vector is given by $w_t = [w^p_t, w^d_t, 0]$. The non-linear dynamics of the system mandates the use of advanced filters such as EKF, UKF and PF to predict future values of the system state vector.

Further it is necessary that the state variables be observable. The measurement vector corresponding to x_t is given by $z_t = [p'_t, d'_t, m'_t]$. We assume that receivers are capable of collecting signal strength measurements using their wireless cards. Further, we also assume that the receivers are equipped with a GPS. The GPS device provides latitude and longitude information, which was then converted to 2D-Cartesian coordinates. If the coordinates (latitude and longitude) of the sender are known, then the transmitter-to-receiver distance can be calculated from this information.

$$p'_t = p_t + v^p_t \tag{20}$$

$$d'_t = d_t + v^d_t \tag{21}$$

$$m'_t = m_t + v^m_t \tag{22}$$

As all measurement noise is also assumed to be independent and Gaussian with zero mean.

VI. Determining the Parameters

A. Model Parameters

In order to use these filters it is first necessary to estimate the parameters of the filter namely, α, $\sigma^2_{w^p_t}$, β and $\sigma^2_{w^d_t}$. Linear regression is used to determine the values of α and β. We plot the signal strength measurements with the logarithm of the transmitter-receiver distance and use linear regression on the power samples to estimate α as suggested in [3]. The shadowing samples (s_t) are then extracted by observing the deviation of the received power samples from the log distance relation. $\sigma^2_{w^p_t}$ is just the variance of the difference between successive shadowing samples. Having determined d_t at the different time instants t from the GPS measurements, we plot the values of $(d_t - d_{t-1})$ with $(d_{t-1} - d_{t-2})$ (16). Linear regression is then used to determine β and $\sigma^2_{w^d_t}$.

It is also necessary to determine the variance of the measurement noise. For our calculations we consider $\sigma^2_{v^p_t} = 1sq$

dBm. The variance of the error in distance estimates from GPS measurements ($\sigma^2_{v^d_t}$) is taken as $100 sq.m$ [24], [25], [26].

The next step is to determine the covariance matrices Q_t (23) and R_t (24), which in our case do not change over time.

$$Q_t = \begin{pmatrix} \sigma^2_{w^p_t} & 0 & 0 \\ 0 & \sigma^2_{w^d_t} & 0 \\ 0 & 0 & 0 \end{pmatrix} \quad (23)$$

$$R_t = \begin{pmatrix} \sigma^2_{v^p_t} & 0 & 0 \\ 0 & \sigma^2_{v^d_t} & 0 \\ 0 & 0 & \sigma^2_{v^d_t} \end{pmatrix} \quad (24)$$

B. Filter Parameters

The next step is to determine the parameters for the different filters. For EKF we need to determine the Jacobian matrices A_t, H_t, V_t and W_t using (10-13). Both H_t and V_t are equal to I, the identity matrix. W_t and A_t are given by (25 and 26) respectively.

$$W_t = \begin{pmatrix} 0 & -\frac{10\alpha}{(1+\beta)\hat{d}_{t-1}} - \beta\hat{m}_{t-1} & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{pmatrix} \quad (25)$$

$$A_t = \begin{pmatrix} 1 & -\frac{10\alpha(1+\beta)}{\hat{d}_{t-1}(1+\beta)-\beta\hat{m}_{t-1}} + \frac{10\alpha}{\hat{d}_{t-1}} & \frac{10\alpha(1+\beta)}{\hat{d}_{t-1}(1+\beta)-\beta\hat{m}_{t-1}} \\ 0 & 1+\beta & -\beta \\ 0 & 1 & 0 \end{pmatrix} \quad (26)$$

It is clear that W_t and A_t need to be computed at each step of the filter operation.

Since UKF does not compute the Jacobian, the calculation of A_t and W_t is not required. We have to set 3 additional transformation parameters: α which determines the spread of the sigma points around the mean is set to 10^{-3}, κ which is the secondary scaling parameter is set to 0 and β which is used to incorporate the prior knowledge is set to 2 for Gaussian distribution.

PF uses MC techniques and hence initial distribution plays a crucial role. The initial distribution of the states (x_0) was set to multivariate gaussian distribution with mean centered around the first observation sample and covariance matrix Q. All particles in the initial distribution was assigned equal weights. Multinomial sampling technique was used for Resampling. The basic idea of resampling was to eliminate particles that have small weights and to retain only the particles with large weights.

The initial value of the error covariance P_0 and the initial state x_0 which remain common across all the filters, also needs to be determined. As the initial value of P_0 is unavailable, the common practice is to use Q_0 as the initial guess of P_0 [7]. The initial value of x i.e., x_0 also needs to be determined. We use the first two distance measurements to determine the value of d_0 and m_0. p_0 is taken to be equal to the second signal strength measurement and s_0 is calculated from p_0 and d_0. One can then start using the filter after the third time slot. This is a reasonable assumption from an implementation perspective.

VII. Data Collection

In the preceding sections we proposed filtering techniques to predict variations in received power over the wireless channel on the seconds timescale. In this section our goal is to conduct experiments, collect signal strength and GPS measurements and test the effectiveness of the filtering approaches. We collected data under varying levels of user mobility (pedestrian and vehicular) for experiments carried out over a 802.16e (WiMAX) network. Channel quality measurements were taken by continuously transmitting data from a base station and receiving them on a laptop. The WiMAX measurements were carried out outdoors for pedestrian and vehicular mobility cases. Stationary outdoor measurements were also taken but changes in signal strength were found to be confined to a 4 dBm range. This implies that the channel essentially remains invariant and thus of little interest to us. Hence we do not explore this case any further here.

The WiMAX experiments were carried out at WINLAB in New Jersey, where the base station is mounted on the roof of a WINLAB building. The frequency of transmission for WiMAX is 2.59 GHz and its range is approximately 500m. We note that the diversity of our measurements would have increased if the experiments were conducted in different physical locations, as shadowing is dependent on the environment. But with only one WiMAX base station available, all measurements were taken within the campus. We look forward to future studies that will build on this initial modeling and measurement work.

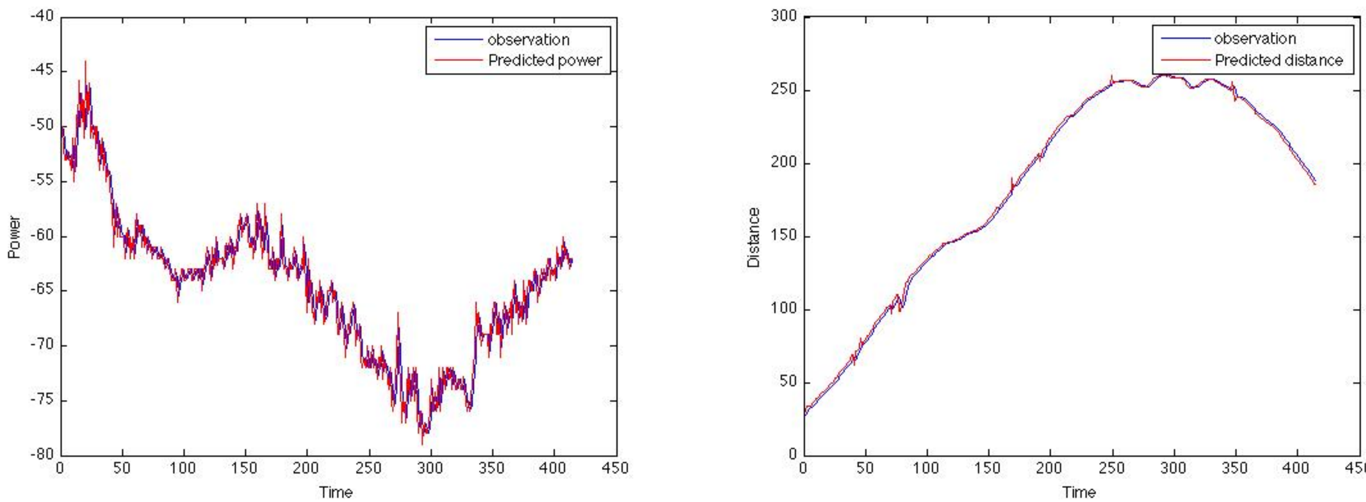
The distance variation from the outdoor base station was captured using a GPS device attached to the laptop. The GPS device provided latitude and longitude information, which was then converted to 2D-Cartesian coordinates. The height of the base station from the ground was also measured and the transmitter-to-receiver distances calculated from this information.

We obtain signal strength quality one second apart from each another. To eliminate any fast fading effects, we consider the average signal strength at the beginning of each second. The average signal strength at the beginning of each second is obtained by averaging approximately 5 received power samples during a 50 ms period centered around the integer-values time (second) value. In all, three vehicular and two pedestrian traces were collected, each having a duration of approximately 8 minutes.

To eliminate bias we partition the data into two different sets for both the vehicular and pedestrian mobility cases . We use one of the sets determine the parameters of the models described in Section VI. We then evaluate the performance of the filtering techniques on the other data set.

VIII. Evaluation

We compare with different filtering approaches in terms of the Mean Squared Error of 1-step prediction (Table I). Note that we evaluate the MSE of state prediction at time t and not state estimation at some time t, given the measurements at time t. Usually in most scenarios one would expect the MSE for EKF, UKF and Particle Filter to be higher than a simple



(a) Power

(b) Distance

Fig. 1. MSE curve showing the performance of Particle Filter by varying number of particles.

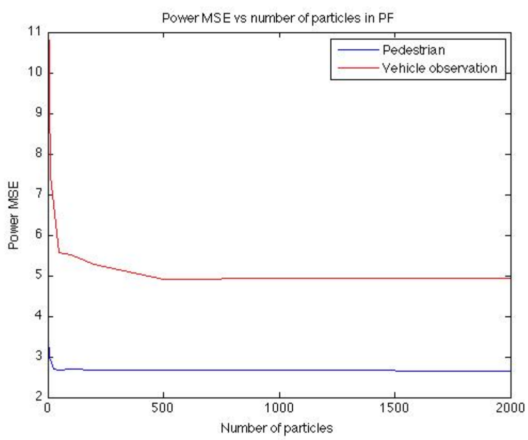


Fig. 2. MSE curve showing the performance of Particle Filter by varying number of particles.

Kalman Filter. Surprisingly however, in our evaluation we observed that the EKF, UKF and Particle Filter only marginally outperform the Kalman filter.

Further investigation revealed that under the current mobility model pattern, the term capturing the logarithmic dependence of distance on the received power in (19) did not contribute significantly to the received power. A back of the envelope calculation shows that the absolute value of this term for this data set is around 0.3. Since the distance model is the only non-linear part of the process dynamics, it makes the equations approximately linear and we do not gain much by using non-linear extensions of the Kalman Filter for the data set explored. This explains why we see only a minor decrease in the MSE as we move from simple Kalman towards the Particle Filter.

Figures 1(a) and 1(b) are graph of observed(true) power/distance measurements and predicted power/distance measurements respectively for the particle filter. The purpose of these graphs is to demonstrate that our predictions follow the measurements very closely. The main reasons for this behavior are 1) the power measurements have low variance and 2) the change in distance between successive time instants is small. Because of these reasons we do not get much improvement by using more sophisticated filtering techniques.

We also performed experiments to investigate the performance (MSE) of PF by varying the number of particles and the results are are shown in Figure 2 for both pedestrian and vehicle dataset. According to the figure, we can clearly see that PF performance increases (low MSE) as we increase the number of particles. But, PF reaches a saturation point after which, increasing the number of particles does not have any effect on the performance.

TABLE I
MINIMUM MEAN SQUARE (MSE) OF ONE STEP PREDICTION FOR WIMAX DATASET

	Vehicle	Pedestrian
KF	5.11	2.81
EKF	5.02	2.73
UKF	5.01	2.79
PF	4.87	2.6

IX. CONCLUSION

In this project, we considered the problem of coarse time scale power prediction in wireless networks. It is well known that the received power over a wireless channel is dependent on shadowing and sender-receiver distance (popularly known as shadowing). We propose a simple mobility model to capture variations in distance. We then leverage the above mentioned facts to model continuous variations in received power over a wireless network in mobile scenarios. We adopt different filtering techniques (namely Kalman filter, Extended Kalman Filter, Unscented Kalman Filter and Particle Filter) for power prediction using our proposed model.

We collected signal strength and location measurements over a WiMAX (802.16e) network and observed that advanced filtering techniques surprisingly only provide marginal improvement (in terms of MSE) over a simple Kalman Filter. We identified small variations in distance (at the timescales of interest) to be the main factor for the comparable performance of the different techniques.

In future we will work on improving our model for capturing power variation in mobile scenarios. One way might be to leverage the fact that shadowing is modeled as an AR(1) process [21] which will tell us how shadowing varies from one time step to the other. The biggest hurdle in incorporating this is to obtain an independent measurement for shadowing (i.e., not derived using the distance and power measurements). One approach might be to map a location (i.e., latitude and longitude) to a shadowing value.

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