Kalman Filtering for Power Estimation in Mobile Communications

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***Abstract*—In wireless cellular communications, accurate local mean (shadow) power estimation performed at a mobile station is important for use in power control, handoff, and adaptive transmission. Window-based weighted sample average shadow power estimators are commonly used due to their simplicity. In practice, the performance of these estimators degrades severely when the window size deviates beyond a certain range. The optimal window size for window-based estimators is hard to determine and track in practice due to the continuously changing fading environment. Based on a first-order autoregressive model of the shadow process, we propose a scalar Kalman-filter-based approach for improved local mean power estimation, with only slightly increased computational complexity. Our analysis and experiments show promising results.**

***Index Terms*—Fading channel, handoff, Kalman filtering, local mean, multipath, power estimation, shadowing.**

I. Introduction

MOBILITY-INDUCED fading is a serious impairment in mobile wireless communications. Due to the motion of the mobile station (MS), the received signal strength fluctuates with two multiplicative forms of fading, namely, shadowing (local mean, local power) and multipath. Shadowing, a slowly varying large-scale path loss, is caused by obstacles in the propagation path between the MS and the base station (BS). The rapidly varying small-scale multipath is due to varying Doppler shift along the different signal paths and the time dispersion caused by the multipath propagation delays. As one primary indicator of channel quality, the power of the slowly varying shadow component is important for handoff decisions and power control. For example, it has been shown that a 1-dB reduction in local power estimation error enables accommodating five more users in a system for a fixed outage probability, under a variety of power control schemes [1]. Most existing handoff algorithms [2]–[5] assume that multipath fluctuations can be adequately filtered and base handoff decisions on local mean power estimates.

Recently, several adaptive modulation techniques have been proposed [6], [7]. These techniques adapt the signal constellation according to both the instantaneous received signal power *and* the local mean (shadow) power. In order to fully exploit the capacity of the wireless channel, these approaches require accurate shadow power estimation and prediction [8].

A simple type of window-based estimators, namely weighted sample average estimators of local mean power, is currently deployed in many commercial communication systems such as GSM [9], and the Motorola Personal Access Communication System (PACS) [10]. Various other window-based estimators have been proposed in [11] and [12]. These window-based estimators work well under the assumption that the shadow process is constant over the duration of the averaging window, in which case their performance improves as the window size increases. In practice, however, the shadow process varies with time (albeit slowly relative to the fast-fading process), and this variation must be considered since both analysis (developed herein) and experiment shows that the mean square error (MSE) performance of these window-based estimators deteriorates severely when the window size increases beyond a certain value. Therefore, tools for choosing the optimal window size are required for these window-based estimators. The optimal window size depends not only on the vehicle velocity v, but also on the sampling period T_s and other shadow fading characteristics. To the best of our knowledge, no closed-form expression has been derived in the literature for the optimal window size as a function of system and propagation parameters, with the exception of a few empirical results [13], [14]. Although the analysis developed herein will provide a formula which can be used for computing the optimal window size numerically, estimates of certain key parameters (like velocity and shadow fading characteristics) are needed to calculate the optimal window size. These require separate nontrivial estimation.

In this paper, we propose a novel Kalman-filtering (KF)-based estimator for the local mean power and explore how KF compares with window-based estimators, like the sample average (SM) estimator [13], the uniformly minimum variance unbiased (UMVU) estimator of [12], and the maximum likelihood (ML) estimator of [11]. It will be shown that KF always meets or exceeds the performance of window-based estimators in the MSE sense and provides a host of other side benefits as well.

This paper is organized as follows. In Section II, we present the signal model and state the problem of local mean power estimation. The conventional window-based causal estimators are discussed in Section III. Section IV proposes the KF-based approach for local power estimation. Performance analysis, simulations, and discussion are presented in Section V, and conclusions are drawn in Section VI.

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The notation is as follows: $\log(\cdot)$ denotes base-10 logarithm; $\ln(\cdot)$ denotes base-e logarithm; $E[\cdot]$ denotes the mathematical expectation with respect to all the random variables within the brackets. For a generic real stationary stochastic process $x(t)$, we use $r_x(\tau) := E[x(t)x(t+\tau)]$ to denote its correlation function and use $c_x(\tau) := r_x(\tau) - (E[x(t)])^2$ for the covariance function at lag τ.

II. Signal Model and Problem Statement

The widely accepted[1] multiplicative model for the received power $p(t)$ at a mobile station in a wireless cellular radio environment is given by

$$p(t) = |h(t)|^2 s(t) \tag{1}$$

where $|h(t)|^2$ is the fast power fluctuation due to multipath, $s(t)$ is the slow power fluctuation due to shadowing, and the two processes are assumed to be statistically independent. In general, if $E[|h(t)|^2]$ is constant, then it can be absorbed into $s(t)$, yielding a scaled $s(t)$. This scale can be accounted for via mean removal in the log domain, which is tantamount to automatic gain control (AGC). We therefore assume that $E[|h(t)|^2] = 1$ for simplicity.

In digital systems, power measurements collected at the output of a log amplifier are provided in the form of discrete time real-valued samples in decibels (dB), since this allows for a wide dynamic range of power levels. The corresponding log-domain model derived from (1) is

$$P(t) = S(t) + H(t) \tag{2}$$

where $P(t) := 10\log[p(t)]$, $S(t) := 10\log[s(t)]$, and $H(t) := 10\log[|h(t)|^2]$. The focus of this paper is on the latter model since most handoff algorithms, as well as various system functions, like channel access and power control, rely on estimates of shadow power in decibels.

The problem can then be stated as follows.

Given $\{P(t)\}_{t=0}^{t_0}$, estimate $S(t_0)$. In the discrete-time domain, we are interested in estimating $S(n) := S(nT_s)$ on the basis of $P(i) := P(iT_s)$, $i = 0, 1, \ldots, n$, where T_s is the sampling period.

To solve this problem, the statistical properties of $H(t)$ and $S(t)$ are needed. In practice, the following model for the multipath $h(t)$ is usually adopted [15]:

$$h(t) = \lim_{R\to\infty} \frac{1}{R} \sum_{r=1}^{R} b_r e^{j(\omega_D \cos(\theta_r)t + \phi_r)} \tag{3}$$

where $\omega_D := 2\pi v/\lambda$ is the Doppler spread, λ is the wavelength corresponding to the carrier frequency, v is the magnitude of the mobile velocity [15], R is the number of independent scatterers (usually, $R = 20$ is sufficient to provide good approximation), b_r are the gains, $\{\theta_r\}_{r=1}^{R}$ are the angles between the incoming waves and the mobile antenna, assumed to be i.i.d., uniformly distributed over $(-\pi, \pi]$, and $\{\phi_r\}_{r=1}^{R}$ are i.i.d. phase random variables, also uniformly distributed over $(-\pi, \pi]$.

[1]Accurate measurement of the received power is a premise of most local power estimation approaches [6], [12], [13]. In practice, the effects of additive measurement noise can be alleviated by averaging over a few closely spaced power estimates and subtracting noise power, which is assumed known at the receiver.

It can be shown [4] that the model in (3) implies that the marginal probability density function (pdf) of the envelope of $|h(t)|$ is Rayleigh, and the pdf of $H(t)$ is given by [12]

$$f_H(x) = \frac{\ln(10)}{10} \exp\left(\frac{\ln(10)}{10}x - \exp\left(\frac{\ln(10)}{10}x\right)\right). \tag{4}$$

The mean of $H(t)$ can be computed from (4) as (cf. [13], [12])

$$\overline{H} := E[H(t)] = \frac{10\gamma}{\ln(10)} \tag{5}$$

where $\gamma = 0.577\,216\cdots$ is Euler's constant. Using (3), the covariance of $H(t)$ is given by (cf. [16])

$$c_H(\tau) := E[H(t+\tau)H(t)] - \overline{H}^2 = \left(\frac{10}{\ln(10)}\right)^2 \sum_{k=1}^{\infty} \frac{J_0^{2k}(\omega_D\tau)}{k^2} \tag{6}$$

where $J_0(\cdot)$ is the zeroth-order Bessel function of the first kind, and the variance of $H(t)$ is thus given by $\sigma_H^2 := [10/\ln(10)]^2(\pi^2/6)$. Although (6) only suggests that the sampled multipath process $H(nT_s)$ can be assumed approximately uncorrelated with a relatively large sampling period T_s, the following stronger assumption is usually made.

Assumption A: The sampled multipath process $H(nT_s)$ is i.i.d. with a marginal pdf given by (4) and independent of the shadow process $S(nT_s)$.

One of two alternative assumptions is usually adopted for the shadow process.

Assumption B: The shadow process $S(n)$ is constant over the duration of the averaging window.

Assumption C: The shadow process $S(n)$ adheres to a first-order autoregressive (AR) model.

In practice, Assumption C is more realistic and subsumes Assumption B, since a constant $S(t)$ can be regarded as an extreme case of the AR model corresponding to $a = 1$, and $\sigma_S = 0$.

A first-order autoregressive [AR(1)] model for the shadow process was suggested in [17]–[19] based on the measured autocovariance function of $S(t)$ in urban and suburban environments

$$c_S(\tau) = \sigma_S^2 \exp(-v|\tau|/X_c) \tag{7}$$

where σ_S denotes the shadow variance and X_c is the effective correlation distance, which is a key attribute of the wireless environment. It can be shown that [18]

$$X_c = -\frac{D}{\ln(\varepsilon_D)} \geq 0$$

where ε_D is the correlation coefficient of the shadow process between two points separated by distance D. X_c is usually in the range between 10 m (urban environments) and 500 m (suburban areas). The value of σ_S also depends on the environment. In suburban areas, a typical value is 8 dB [15], [18], whereas in urban environments it is roughly 4 dB [18].

The AR(1) model for the shadow process is given by [18]

$$S(n) = aS(n-1) + \phi(n) \tag{8}$$

where $S(n) := S(nT_s)$, $\phi(n)$ is zero mean white Gaussian noise with variance $\sigma_\phi^2 = (1-a^2)\sigma_S^2$, and $S[0] \sim N(\mu_S, \sigma_S^2)$. The coefficient a is given by

$$a := \exp(-vT_s/X_c).$$

Thus, [20]

$$E[S(n)] = a^n \mu_S;$$

$$c_S(n+k, n) = a^{2n+k}\sigma_S^2 + \sigma_\phi^2 a^k \sum_{l=0}^{n-1} a^{2l}, \qquad k \geq 0;$$

$$Var(S(n)) = c_S(n, n) = a^{2n}\sigma_S^2 + \sigma_\phi^2 \sum_{l=0}^{n-1} a^{2l}. \tag{9}$$

Note that the mean $E[S(n)]$ decreases monotonically as n increases. The parameter set $(\sigma_S^2, T_s, v, X_c)$ determines the second-order statistics of the shadow process. For simplicity, we assume that $\mu_S = 0$, thus

$$E[S(n)] = 0.$$

As $n \to \infty$, we have

$$c_S(n+k, n) \to \sigma_S^2 a^k := c_S(k) = r_S(k), \qquad k \geq 0. \tag{10}$$

III. Local Power Estimators

In this section, the conventional window-based estimators for the shadow process $S(t)$ are briefly reviewed, and some pertinent performance analysis is carried out.

A. Sample Average Estimator

Due to the rapidly changing character of the multipath process $H(n)$, an estimate of local mean power can be obtained by averaging the samples $P(n)$ and removing the true mean $\overline{H}$ in (5). Under Assumption B, several sample average-based estimators [21], [22], and more generally, linear filter-based local power estimators have been proposed in the literature [13], [14]. Under Assumption B, the performance of these estimators improves as the window size increases. In practice, especially in the urban scenario, Assumption B is not realistic, and the shadow variation must be taken into account. In [13], an integrate-and-dump (ID) filter and a first-order RC filter were investigated for the case of time-varying shadow. It is argued in [13] that the estimation error $\hat{S}(n) - S(n)$ is approximately Gaussian, and the estimation bias can be removed by proper choice of the dc value of the filter's frequency response. The appropriate choice of the dc value depends on the sampling period T_s, the mobile velocity v, the effective correlation distance X_c, and the shadow variance σ_S^2. Even though it is argued in [13] that the standard deviation of the error can be kept within 3 dB over a wide range of mobile velocities and shadow fading characteristics by proper choice of the filter bandwidth,[2] only empirical guidelines were proposed in lieu of an analytical result on the proper choice of filter bandwidth. It should also be mentioned that the worst case investigation in [13] aims to design a filter that minimizes the maximum root mean square (RMS) error over the expected region of (σ_S, X_c). Such a filter does not minimize the RMS error for each possible (σ_S, X_c). In this paper, we adopt the ID approach of [13] as a representative of the conventional linear filtering techniques for local mean power estimation. In discrete time, this corresponds to taking the running average of the received $P(n)$ samples as follows:

$$\hat{S}_{SM}(n) = \frac{1}{N} \sum_{i=n-N+1}^{n} P(i) - \overline{H} \tag{11}$$

where N is the window size, $P(n)$ is the received power measurement, and $\overline{H}$ is given in (5). Under Assumptions A and B, this linear sample mean estimator is unbiased and consistent, but it does not enjoy the minimum variance property [12].

[2]Filter bandwidth is proportional to the reciprocal of the averaging window size.

B. Uniformly Minimum Variance Unbiased (UMVU) Estimator

With Assumptions A and B, the optimum UMVUestimator was derived in [12] as follows:

$$\hat{S}_{UMVU}(n) := 10\left[\log\left(\sum_{i=n-N+1}^{n} |p(nT_s)|\right) - \frac{1}{\ln(10)} \sum_{i=n-N+1}^{n} \frac{1}{n}\right] - \overline{H}. \tag{12}$$

It is shown in [12] that $\hat{S}_{\rm UMVU}(n)$ is consistent and, more importantly, the variance of this estimator is approximately 1.65 times smaller than that of $\hat{S}_{SM}(n)$ for $N \geq 15$. It is also proven in [12] that $\hat{S}_{\rm UMVU}(n)$ is asymptotically efficient, i.e., as $N \to \infty$, it approaches the Cramér–Rao bound (CRB), which is given by $100/[N(\ln 10)^2]$, [12]. It is worth mentioning that this CRB cannot be achieved by any unbiased finite-sample estimators [12].

C. ML Estimator

In [11], the ML estimator $\hat{S}_{\rm ML}(n)$ for local mean power estimation under Assumptions A and B has been derived using the pdf in (4) as

$$\hat{S}_{\rm ML}(n) := 10\left[\log\left(\sum_{i=n-N+1}^{n} |p(nT_s)|\right) - \log(N)\right]. \tag{13}$$

Note that

$$T(N) := \sum_{i=n-N+1}^{n} (|p(nT_s)|)$$

is a minimal sufficient statistic for S [12] under Assumptions A and B.

Both $\hat{S}_{UMVU}$ and $\hat{S}_{ML}$ are nonlinear estimators.

We conclude this section by illustrating the performance of the above-mentioned estimators when Assumption B is satisfied, which in practice can be approximately true if σ_S is small or X_c is large.

Under Assumption B, we show in the Appendix that the variance of $\hat{S}_{\rm SM}(n)$, i.e., the MSE is given by

$$\sigma_{\hat{S}_{\rm SM}}^2 = E\left[\left(\hat{S}_{\rm SM}(n) - S\right)^2\right] = \frac{c_H(0)}{N} + 2\sum_{i=1}^{N-1}\left(\frac{N-i}{N^2}\right) c_H(iT_s) \tag{14}$$

independent of n.

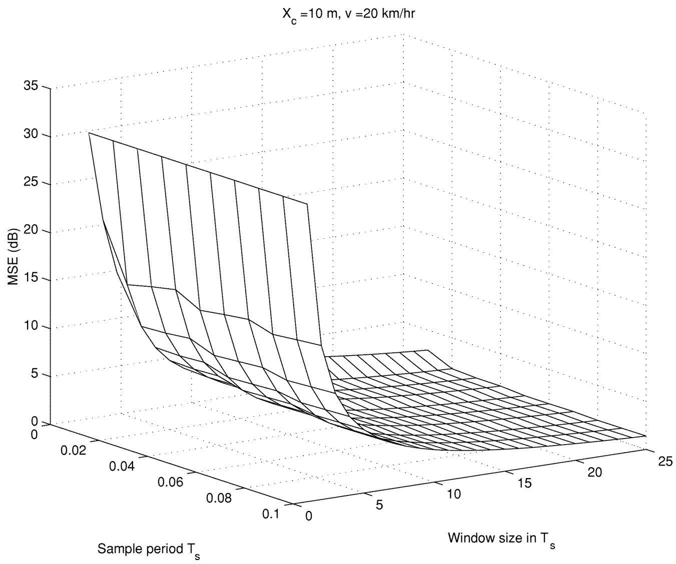


Fig. 1. MSE versus T_s and window size in T_s.

A similar result for the multiplicative model (1) with constant shadow process can be found in [23] and [21], where the variance of $\hat{s} := (1/N)\sum_{n=0}^{N-1} p(nT_s)$ was evaluated. Recall that under Assumptions A and B, $\hat{S}_{\rm SM}$ is unbiased with variance $c_H(0)/N$, which is greater than $100/[N(\ln 10)^2]$, the CRB for this problem. In Fig. 1, it can be seen that, for fixed sample size N, the MSE in (14) is decreasing as T_s increases due to large T_s leading to approximately uncorrelated samples, i.e., $c_H(iT_s) \to 0$, for $i \neq 0$.

In Fig. 2(a), we can see that, under Assumption B, a larger window size improves the MSE performance of all three estimators. As expected, the UMVU has the least mean square error and gets close to the CRB as the window size NT_s increases. The ML estimator provides almost the same performance as UMVU.

Note that independent samples $P(nT_s)$ are assumed in [12]. In practice, we can only choose the sample period T_s large enough to make the successive samples approximately uncorrelated. In general, for non-Gaussian processes, uncorrelatedness does not imply independence, although the latter is often assumed for convenience and mathematical tractability, with acceptable results. When the sampling period T_s is not large enough, the performance of all three estimators deviates significantly from the CRB derived under Assumptions A and B. This is illustrated in Fig. 2(b).

IV. Kalman Filtering for Local Power Estimation

Under Assumptions A and B, the window-based estimators work well, but note that those two assumptions impose conflicting requirements in practice, since making T_s large contradicts the assumption of constant shadow process for a fixed number of samples. When the variation of the shadow process is taken into account, the performance of the window-based estimators deteriorates severely when the window size increases beyond a certain value. The optimal window size is needed for these window-based estimators. To the best of our knowledge, a closed-form expression for the optimal window size is not available in the literature. Our theoretical analysis in Section V will provide the means to compute the optimal size of window-based estimators numerically as a function of the system parameters. Nevertheless, such an approach may not be suitable in practice due to its computational complexity and associated parameter estimation and tracking requirements.

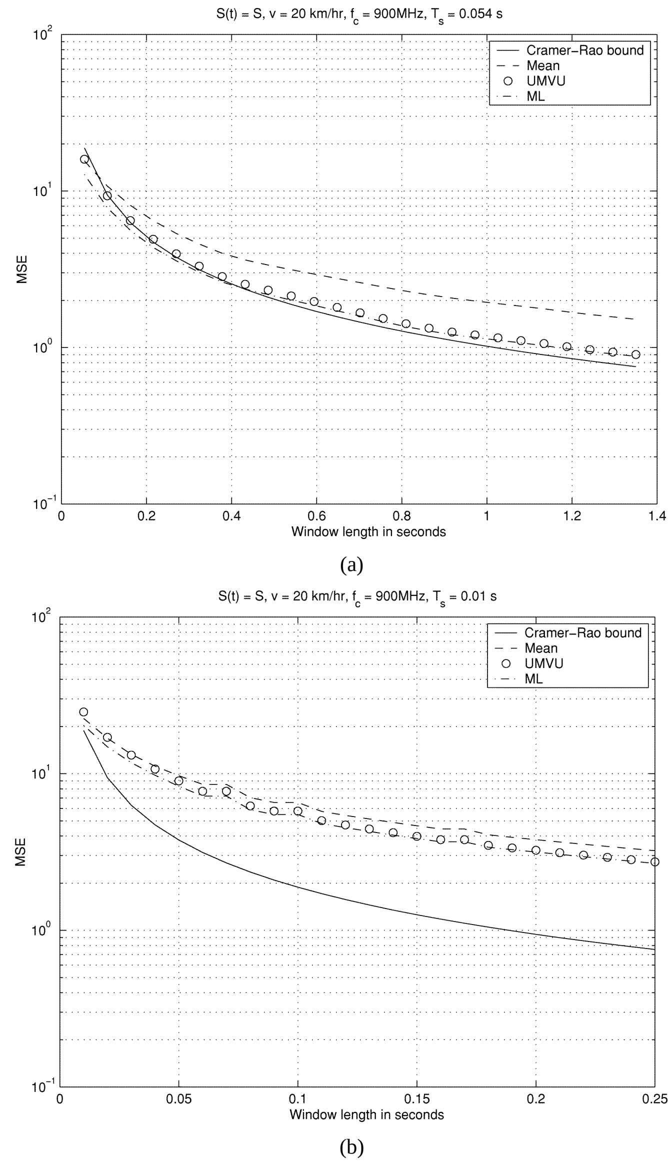


Fig. 2. Comparison of $\hat{S}_{\rm SM}$, $\hat{S}_{\rm UMVU}$, and $\hat{S}_{\rm ML}$ in the idealized case. (a) Large T_s. (b) Small T_s.

Based on the AR(1) model (8) for the shadow process $S(t)$, we propose a scalar Kalman filter (KF)-based approach for local power estimation. The KF can be regarded as a sequential minimum mean square error (MMSE) estimator of a signal corrupted by white Gaussian noise, where the signal is characterized by an AR dynamical model with white Gaussian driving noise. When the Gaussian assumption is not valid, as is the case herein due to the non-Gaussian distribution of multipath, the KF is still the optimal linear MMSE (LMMSE) estimator provided the driving and measurement noises are white [20]. Additionally, when $S(t)$ is stationary and the KF attains its steady state as $n \to \infty$, it reduces to the infinite length Wiener filter. We only invoke whiteness of the multipath component to *motivate* the proposed scalar KF approach as an LMMSE estimator. As we will see, the KF works well in this context, even if this whiteness assumption is violated to a certain degree.

AR *channel* modeling and KF has been extensively studied, e.g., see [24], [25]. However, AR(1) channel modeling is not equivalent to AR(1) shadow modeling. If the channel is AR(1), then so is (total) power; however, the converse is not true, because power is invariant to phase, e.g., channel phase could be piecewise constant, and power could still be AR. The AR(1) model for the shadow component has been empirically derived and shown to fit measurements well [17]–[19]. Furthermore, to track the channel coefficient itself using a KF, one needs pilot (training) symbols [24] or else adopt a decision-directed approach. The latter can only work for very slowly varying channels, and without frequent retraining, it is prone to error propagation. On the other hand, at least for MPSK constellations, total power measurement can be achieved *without* resorting to pilots, because power is invariant to the transmitted symbol phase. Hence, for MPSK, power estimation can be blind, which also allows smaller T_s without a decrease in throughput. Also note that the computational complexity of the extended KF [25] is much higher than that of the scalar KF.

When Assumption C is adopted, the scalar KF offers a promising approach compared with the other window-based estimators for the following reasons.

1) The scalar KF is the natural approach for the problem when the shadow process is characterized by an AR model driven by white Gaussian noise. It implements a window-free approach that is optimal in the LMMSE sense when the multipath is white, with very modest computational complexity (comparable to window-based estimators).
2) Joint parameter estimation and KF is feasible [26]–[28]; KF can be developed into a fully adaptive solution for local power estimation, taking advantage of the slowly changing nature of the shadow component.
3) KF can easily support local power prediction as a direct by-product; this is necessary for adaptive transmission [6]–[8].

Recall that Assumption C subsumes Assumption B. Under Assumption B, and further assuming white Gaussian measurement noise, it can be shown that KF reduces to the sample mean estimator with infinite window size, which is both ML and MMSE optimal. In our problem, the measurement noise $H(n)$ is non-Gaussian. This is exactly the reason why $\hat{S}_{SM}$ does not enjoy the minimum variance property even under Assumption B, since when the measurement noise is non-Gaussian $\hat{S}_{SM}$ cannot be regarded as the approximate ML or MMSE estimator. Meanwhile, KF is still optimal in the LMMSE sense provided the non-Gaussian measurement noise is white.

The scalar KF is summarized in Table I, where the estimator of $S(n)$ based on $\{P(i)\}_{i=0}^{m}$ is denoted as $\hat{S}(n|m)$, $M(n|n-1)$ is the one-step minimum prediction MSE at state n, and $M(n|n)$ is the MMSE at state n. $K(n)$ is the Kalman gain. The parameter σ_H given in Section II can be precomputed, and $\sigma_\phi^2 = (1-a^2)\sigma_S^2$. The Kalman Prediction (KP), and fixed point Kalman Smoothing (KS) algorithm, as it pertains to our specific problem, can be found in the literature (see [20, pp. 436–441] and [29, pp. 397]). We assume that the channel variation is mainly due to the changing mobile velocity v and the correlation distance X_c; hence, only the variation of a is considered.

TABLE I
KALMAN FILTERING

$$\begin{aligned}
&\widehat{S}(n|n-1) = a\widehat{S}(n-1|n-1)\\
&M(n|n-1) = E[(S(n)-\widehat{S}(n|n-1))^2]\\
&\qquad\qquad\quad = a^2M(n-1|n-1)+\sigma_\phi^2\\
&K(n) = \frac{M(n|n-1)}{\sigma_H^2+M(n|n-1)}\\
&\widehat{S}(n|n) = \widehat{S}(n|n-1)+K(n)\ (P(n)-\widehat{S}(n|n-1))\\
&M(n|n) = E[(S(n)-\widehat{S}(n|n))^2] = (1-K(n))M(n|n-1)
\end{aligned}$$

In a suburban scenario, the shadow process coefficient a can be regarded as constant for a wide range of velocities v due to the fairly large X_c. For example, in the case $X_c = 300$ m, when the velocity v is in the range from 5 to 80 km/hr, the sampling period can be chosen as $T_s = 0.216$ s, in which case $a \in [0.9841,\ 0.9990]$. Therefore, in a suburban scenario, a can be assumed known, and only KF is needed. Note that, with this choice of T_s, the sampled multipath process $H(n)$ can be regarded as approximately uncorrelated, even in the slowest case.

In the urban case, the approximate time invariance of the coefficient a may not be realistic due to the relatively small X_c and the wide range of velocity v. For example, in the case $X_c = 10$ m, if the velocity v is in the range from 5 to 80 km/hr, and the sampling period T_s is set to 0.216 s as before, then it follows from the definition of a that $a \in [0.6188,\ 0.9704]$. Smaller T_s can reduce the variation of a significantly, e.g., with $T_s = 0.01$ s, $a \in [0.9780,\ 0.9986]$; however, such small T_s yields highly correlated measurement noise $H(n)$, especially for low mobile velocity v; for example, with $v = 20$ km/hr and $T_s = 0.01$ s, the correlation coefficient a between the successive $H(n)$ can be roughly 0.5. On the other hand, choosing a relatively large sample period T_s in the urban scenario necessitates joint parameter estimation of a and KF.

There are several approaches to estimating a from the received power $P(n)$. One approach is based on second-order statistics of $P(n)$ assuming that the vehicle velocity v has already been accurately estimated [14]. The vehicle velocity v is used to compute $c_H(mT_s)$. The second-order statistics of $P(n)$ are as follows [14]:

$$\begin{aligned}
r_P(mT_s) &:= E[P(nT_s)P(nT_s+mT_s)]\\
&= c_H(mT_s) + \left(\overline{H}+\mu_S\right)^2 + \sigma_S^2\exp(-vmT_s/X_c).
\end{aligned}$$

In practice, however, obtaining an accurate estimate of the velocity v is not trivial; in fact, accurate velocity estimation can be more difficult than estimating the local mean. An alternative method based on second-order statistics of $P(n)$ is to choose the sampling period T_s large so that $c_H(mT_S)$ is approximately zero for $m \neq 0$, in which case the need to estimate v is circumvented. This approach only provides rather coarse estimates of a.

Assuming that a is changing slowly and the initial a is available, joint AR parameter estimation and KF is feasible [26]–[28]. The method in [28] requires neither the transmitted data [26] nor complicated extended KF [27]. The basic idea behind [28] is to use finite sample least squares to update a based on smoothed power estimates.

V. Performance Analysis, Simulation, and Discussion

In this section, the estimation and prediction of local mean power using the approach presented in Section IV are compared with those obtained using the conventional approaches reviewed in Section III, in the practical setting where the shadow process obeys the AR(1) model.

We define the least squares error (LSE) as

$$\text{LSE} = \frac{1}{L}\sum_{n=1}^{L}\left[S(n) - \hat{S}(n)\right]^2$$

as the performance criterion, where $\hat{S}(n)$ is the estimator of $S(n)$ and L is the total sample size ($L \neq$ window size N).

For the KF approach, the MSE

$$E[\text{LSE}] = \frac{1}{L}\,E\left[\sum_{n=1}^{L}\left(S(n) - \hat{S}(n|n)\right)^2\right] = \frac{1}{L}\sum_{n=1}^{L} M(n|n).$$

In a stationary environment, the KF approaches the linear time-invariant Wiener filter, and $M(n|n) \to M(\infty)$ as $L \to \infty$; the closed-form expression for $M(\infty)$ can be found in [20]. For our problem, the specific form of $M(\infty)$ is derived in the Appendix. This yields (15), shown at the bottom of the page.

Equation (15) suggests that smaller σ_S and/or larger a lead to better performance. In fact, (15) goes to zero as a approaches 1 or σ_S goes to 0. In practice, larger a can be obtained for small sample period T_s or large effective correlation distance X_c; however, note that (15) is valid under the assumption that the sampled multipath process $H(n)$ is white. This is approximately true if T_s is relatively large, but small T_s will make the performance of KF deviate from (15).

For the sample mean estimator, it is shown in the Appendix that

$$\begin{aligned}\lim_{L\to\infty} E[LSE] &= \lim_{L\to\infty}\frac{1}{L}\sum_{n=1}^{L} E\left[\left(S(n)-\hat{S}_{SM}(n)\right)^2\right]\\ &= \left[\frac{N-1}{N} - \frac{2}{N^2}\,\frac{a-Na^N+(N-1)a^{N+1}}{(1-a)^2}\right]\sigma_S^2\\ &\quad + \frac{c_H(0)}{N} + 2\sum_{i=1}^{N-1}\frac{N-i}{N^2}\,c_H(iT_s) \qquad (16)\end{aligned}$$

where the N is the window size.

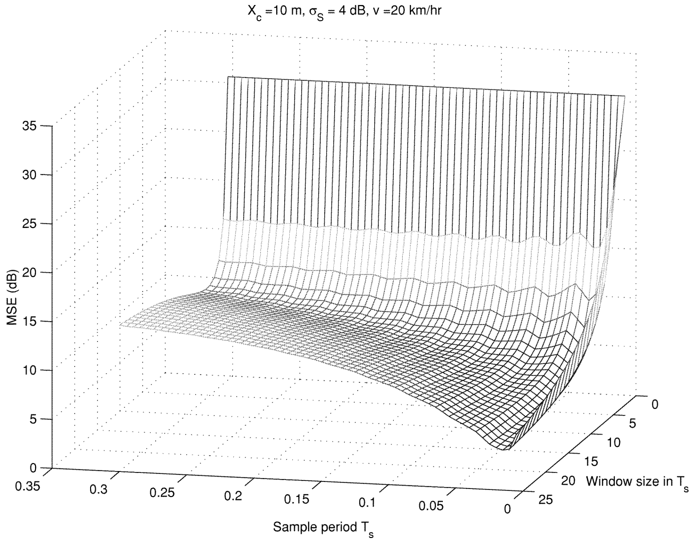


Fig. 3. MSE versus T_s and N.

We note that (16) can be shown to be consistent with (14), either by letting $\sigma_S = 0$ or $a \to 1$

$$\lim_{a\to 1}\left[\frac{N-1}{N} - \frac{2}{N^2}\,\frac{a-Na^N+(N-1)a^{N+1}}{(1-a)^2}\right] = 0.$$

Equation (16) provides an analytical indicator of performance of the sample mean estimator in the varying shadow process scenario without assuming that the multipath process is white. For given parameters T_s, v, σ_S, and X_c, (16) can also be used for computing the optimal window size N for the sample mean estimator numerically.

For fixed N, as $T_s \to \infty$, it can be shown that (16) converges to the limit

$$\frac{N-1}{N}\sigma_S^2 + \frac{c_H(0)}{N}$$

whereas, when $T_s \to 0$, (16) converges to the constant $c_H(0)$, which is roughly 31. In Fig. 3, we plot the MSE in (16) versus T_s and N. We observe that there exists an optimal T_s for each fixed N and an optimal N for each fixed T_s. Based on Fig. 3, for given v, σ_s, and X_c, (16) indicates that there exists an optimal (T_s, N) pair for $\hat{S}_{\text{SM}}$, and the optimal T_s is small. However, it is difficult to compute the optimal (T_s, N) pair analytically due to the following reasons.

1) Equation (16) is discrete in N, and the upper limit of the summation is in terms of N.
2) The derivative of $c_H(i)$ is difficult to compute for $i \neq 0$.
3) Based on Fig. 3, a singularity of the MSE function appears around $T_s = 0$, as we have observed.

We also note that it is very difficult to derive similar formulas for UMVU and ML estimators due to their nonlinearity. However, in all our experiments, we have observed that the optimal

$$\lim_{L\to\infty} E[LSE] = \sqrt{1-a^2}\,\frac{\sqrt{(1-a^2)(\sigma_S^2+\sigma_H^2)^2 + 4a^2\sigma_S^2\sigma_H^2} - \left(\sqrt{1-a^2}\right)\left(\sigma_S^2+\sigma_H^2\right)}{2a^2} \qquad (15)$$

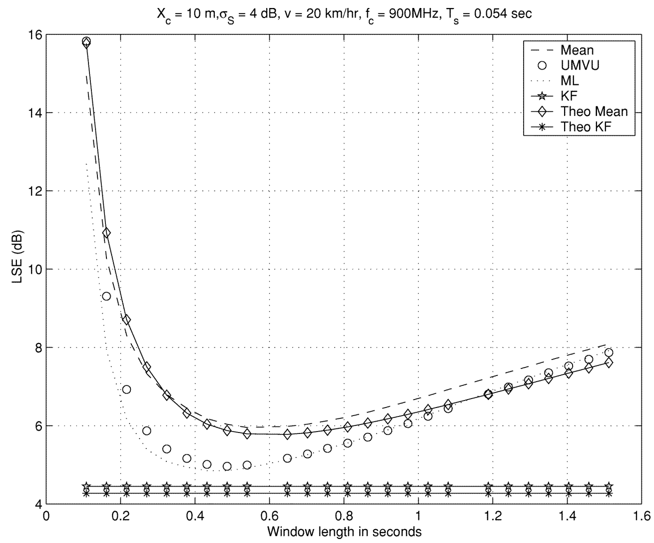


Fig. 4. Comparison in urban areas with large T_s.

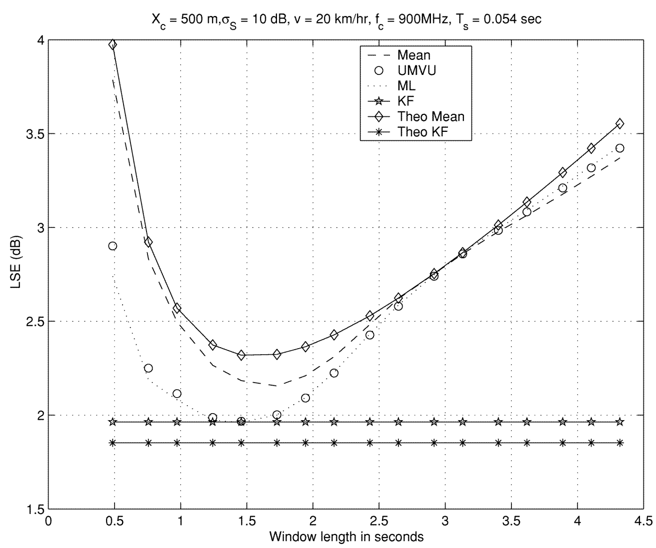


Fig. 5. Comparison in suburban areas with large T_s.

window sizes for UMVU and ML are close to the corresponding optimum for SM.

A. Kalman Filtering Only

In this subsection, the coefficient a is assumed to be available. In Fig. 4, we compare the KF approach with window-based estimators in urban areas, along with the theoretical results in (15) and (16). The theoretical performance of the sample mean and the KF are computed by (15), and (16) accordingly. We observe that the performance of all window-based estimators deteriorates beyond a window size when more samples are used to estimate the local mean. A unique optimal window size for each window-based estimator exists. As expected based on (15) and (16), KF exhibits the least LSE among all estimators, and the large sampling period T_s brings the performance of KF close to its theoretical limit given by (15).

In Fig. 5, the suburban case is considered. In such a scenario, the assumption of almost constant a is acceptable, as we explained in Section IV. Due to the large X_c, the performance

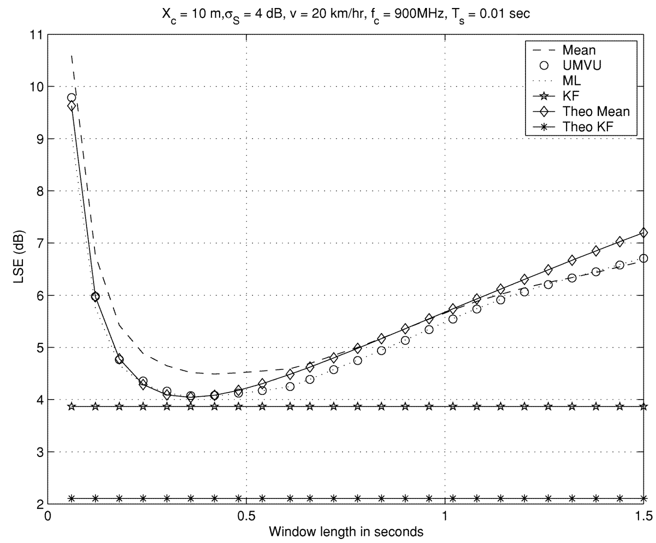


Fig. 6. Comparison in urban areas with small T_s.

of all estimators improves, as expected. The optimal window size for each window-based estimator increases as the effective correlation distance X_c increases, since larger X_c makes the shadow process $S(n)$ more like a constant. Thus, within a certain window size range, the performance of window-based estimators behaves more like in the idealized case, where the performance improves as the window size increases. Due to the varying shadow process, the performance of all window-based estimators will deteriorate eventually when the window size exceeds a certain threshold. In the suburban scenario, the KF still provides the minimum LSE, as it does in the urban case.

The sampling period T_s plays a special role here. For the KF, the smaller the T_s is, the closer a is to 1, and we might expect a better LSE performance according to (15). However, the multipath $H(t)$ sampled at a smaller T_s becomes more correlated, which implies that the KF performance may deviate from what (15) predicts. For example, in Fig. 6, the sampling period T_s is decreased relative to the setup in Fig. 4, and it can be observed that the theoretical performance computed by (15) indeed predicts a better LSE performance than the case where T_s is large. However, the true performance of KF deviates significantly from the theoretical analysis. Although, in the small T_s case, (15) cannot provide an accurate prediction of the MSE performance of KF, the simulations indicate that the KF still almost always provides the minimum LSE compared with all other estimators. The overall performance of all estimators improves slightly as the sample period T_s moderately decreases, before T_s falls below a certain value.

B. AR Parameter Estimation Considerations

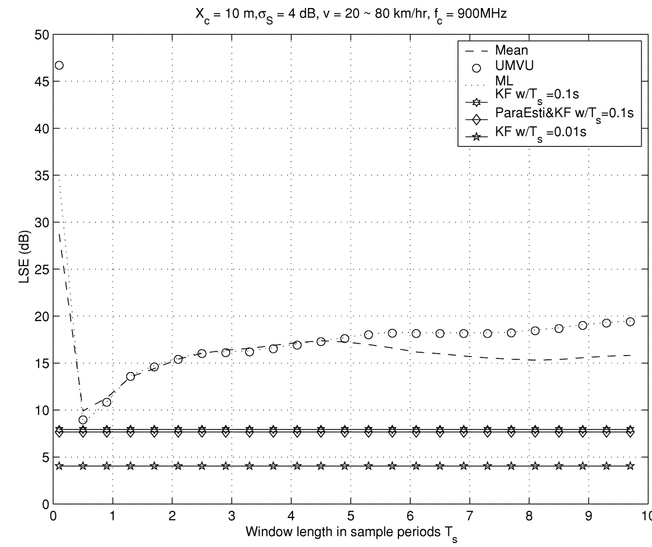
Joint parameter estimation and KF is necessary in urban areas with relatively large sampling period T_s. However, both relatively large and relatively small T_s cases are investigated due to the following two reasons.

1) A large sampling period T_s yields KF performance close to the theoretical analysis. Meanwhile, a large T_s also leads to a large theoretical LSE.

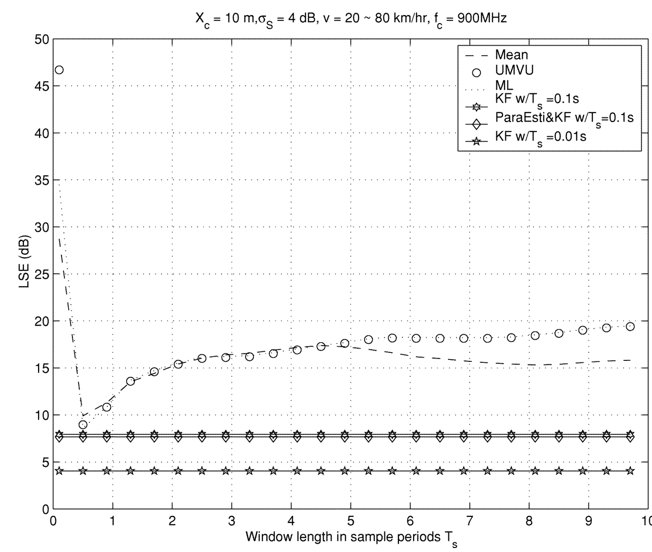
2) A smaller T_s reduces the theoretical MSE, while the LSE performance of KF may not suffer too much by the relatively small T_s, which may lead to better overall performance than the one with larger T_s.

The performance of joint parameter estimation and KF [28] for power estimation will be illustrated as follows. We assume that the coefficient a is initially available, and the mobile velocity v increases slowly from 20 to 80 km/hr over 500 m. Two different sample periods are adopted. With a small $T_s = 0.01$ s, the variation of a can be kept within 2% of the smallest a, and therefore the coefficient a used in KF can be assumed to be constant (taken to be the mean of a). When T_s is chosen as 0.1 s, the largest a can be 18% greater than the smallest one, hence joint parameter estimation and KF [28] is needed. The coefficient a is updated every 500 samples, using a 200-sample LS method on 200 smoothed power estimates (e.g., the 200 estimates $\{\hat{S}(i)\}_{i=251}^{450}$ are smoothed by $\{P(i)\}_{i=1}^{500}$). We observed that the fixed point smoothing converges within less than 50 incoming future received power samples. In Fig. 7(a), we compare the LSE performance of all window-based estimators with large T_s, KF with small T_s, KF with large T_s, and the joint parameter estimation and KF with the same large sampling period T_s. The coefficient a in KF is assumed to be available and given by the mean of the range of a. We first observe that joint parameter estimation and KF reduces the LSE only slightly compared with KF with the same T_s. Second, note that both outperform the best LSE performance achieved by window-based estimators, while KF with the small T_s performs better than all other estimators. Finally, observe that in the varying velocity case KF outperforms the window-based estimators by 1–2 dB, instead of just achieving the best LSE performance attainable by the window-based estimators. Unlike the constant a case, compared with KF, the window-based estimators do not improve much by adopting a smaller T_s. These experiments suggest that, in the urban scenario, parameter estimation can be avoided by choosing a relatively small sampling period (e.g., $T_s = 0.01$ s), and KF with such a sampling period provides the best results.

However, it is not reasonable to expect that the LSE performance of KF gets better and better as T_s becomes smaller and smaller. In fact, we show in Fig. 7(b) that, with a very small sampling period $T_s = 0.001$ s, KF provides slightly worse LSE than the best LSE performance attainable by the window-based estimators. This is not a surprise. As T_s goes down too much, the correlation between the successive multipath samples $H(n)$ comes to play a role. When $T_s = 0.1$ s, the correlation coefficient between successive $H(n)$ samples is less than 0.1, whereas when $T_s = 0.01$ seconds, the coefficient is roughly 0.4, and this number can grow as high as 0.97, when $T_s = 0.001$ s is adopted. KF suffers severely due to the highly correlated $H(n)$. An optimal T_s is desirable for KF. However, (15) neglects multipath correlation; hence, it cannot be used to derive the optimal T_s for KF analytically. It is difficult to calculate asymptotic KF performance under colored measurement noise except if this noise can also be modeled as AR with known parameters [30].



(a)



(b)

Fig. 7. KF without parameter estimation versus KF with parameter estimation. (a) KF with large to moderately small T_s. (b) KF with very small T_s.

C. Kalman Smoothing and Prediction

So far, only causal shadow power estimators have been considered. If future samples are available (equivalently, if one revisits a past shadow estimate with the added knowledge of look-ahead samples), noncausal estimators naturally yield more accurate shadow estimates. However, such delayed estimates may not be very useful for power control, handoff, or adaptive modulation, because noncausal estimates quickly become obsolete, e.g., handoff protocols only allow very limited hysteresis. Note that our use of Kalman smoothing so far has been primarily intended for AR parameter estimation, rather than power estimation. However, it is interesting to compare Kalman-smoothing-based noncausal power estimates versus noncausal (two-sided) SM power estimates. This is illustrated in Fig. 8.

The Kalman algorithm also provides easy prediction of the local mean power. Without undue discussion, we simply

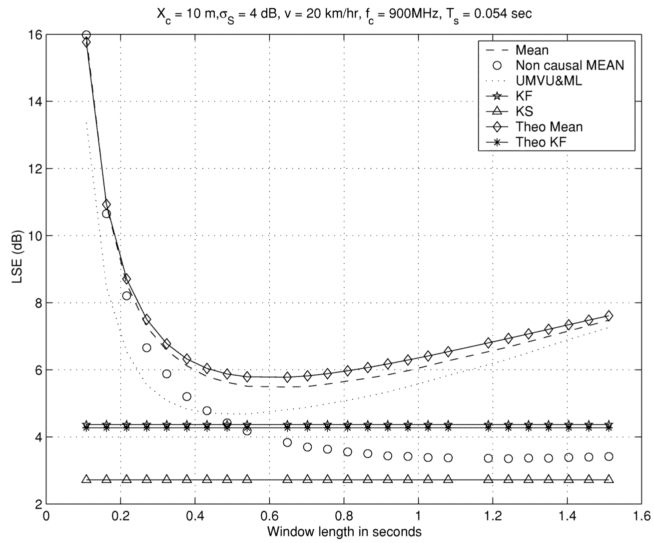
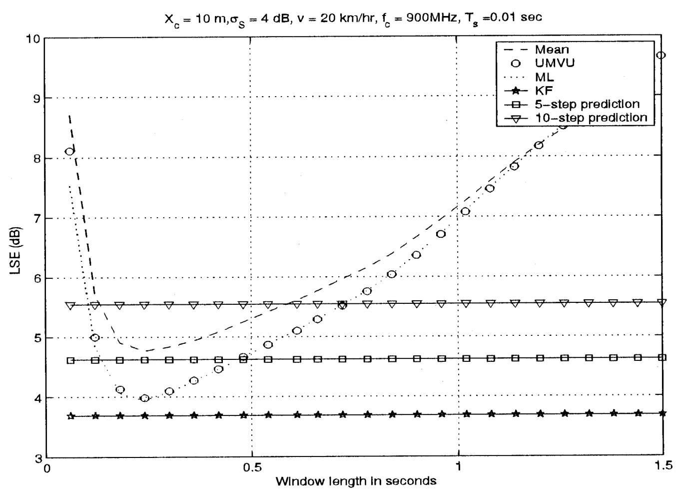
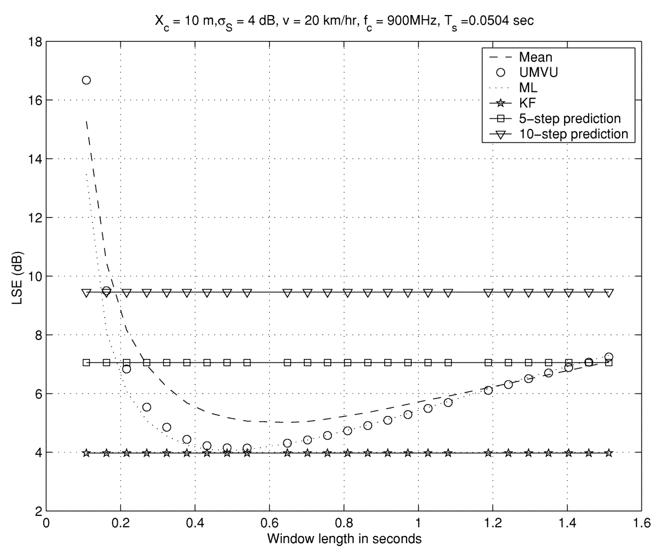


Fig. 8. Comparison of KF and two-sided $\hat{S}_{\rm SM}$.



(a)



(b)

Fig. 9. Kalman prediction. (a) Small T_s. (b) Large T_s.

illustrate performance of Kalman prediction (KP) in Fig. 9(a) and (b).

VI. CONCLUSION

In this paper, based on the widely accepted AR(1) model of the shadow process, we proposed a KF-based approach to estimate the shadow process $S(t)$ corrupted by the multipath $H(t)$ and derived the expected value of LSE achieved asymptotically by the sample mean estimator and KF. Joint parameter estimation and KF was also discussed when the AR parameter varies over a wide range, as is typical in urban areas with small T_s. We showed that window-free KF either meets or exceeds the performance of conventional window-based causal estimators under Assumption C. Our results suggest that a relatively small T_s yields better LSE performance for KF, even though it violates the multipath whiteness assumption. The experiments also suggest that joint parameter estimation and KF can be avoided by choosing a relatively small sampling period T_s. As a side bonus, Kalman prediction for power estimation is also possible. This is important for adaptive transmission. The improvement in performance is partly attributed to the fact that the Kalman filter can be regarded as approximating the sequential LMMSE estimator for the problem at hand (albeit not exactly, due to the mild dependence of multipath samples).

APPENDIX

Derivation of $M(\infty)$: It is shown in [20] that $M(\infty)$ is given by

$$M(\infty) = \frac{\sigma_H^2 \left(a^2 M(\infty) + \sigma_\phi^2\right)}{a^2 M(\infty) + \sigma_\phi^2 + \sigma_H^2}. \tag{17}$$

Recalling that $\sigma_\phi^2 = (1-a^2)\sigma_S^2$, and solving (17) for $M(\infty)$, we find

$$M(\infty) = \frac{-(1-a^2)\left(\sigma_S^2 + \sigma_H^2\right)}{2a^2} + \frac{\sqrt{(1-a^2)^2\left(\sigma_S^2+\sigma_H^2\right)^2 + 4a^2(1-a^2)\sigma_S^2\sigma_H^2}}{2a^2}.$$

□

Derivation of (14) and (16): If $S(n)$ is assumed to be constant, S, then

$$\hat{S}_{SM}(n) = \frac{1}{N}\sum_{i=n-N+1}^{n} P(i) - \overline{H} = S + \frac{1}{N}\sum_{i=n-N+1}^{n} H(i) - \overline{H}. \tag{18}$$

Therefore, (14) is obtained using

$$\begin{aligned} E\left[\left(S - \hat{S}_{SM}(n)\right)^2\right] &= E\left[\left(\frac{1}{N}\sum_{i=n-N+1}^{n} H(i) - \overline{H}\right)^2\right] \\ &= E\left[\left(\frac{1}{N}\sum_{i=n-N+1}^{n} \{H(i) - \overline{H}\}\right)^2\right] \\ &= \frac{c_H(0)}{N} + 2\sum_{k=1}^{N-1}\left(\frac{N-i}{N^2}\right) c_H(kT_s). \end{aligned} \tag{19}$$

When the shadow process follows an AR(1) model, we obtain

$$\begin{aligned} &E\left[\left(\hat{S}_{SM}(n) - S(n)\right)^2\right] \\ &= E\left[\left(\frac{1}{N}\sum_{i=n-N+1}^{n} P(i) - \overline{H} - S(n)\right)^2\right] \\ &= E\left[\left(\frac{1}{N}\sum_{i=n-N+1}^{n} \{S(i) + H(i)\} - \overline{H} - S(n)\right)^2\right] \\ &= E\left[\left\{\frac{1}{N}\sum_{i=n-N+1}^{n} [S(i) - S(n)] \right.\right. \\ &\qquad \left.\left. + \frac{1}{N}\sum_{i=n-N+1}^{n} \left[H(i) - \overline{H}\right]\right\}^2\right]. \end{aligned} \tag{20}$$

Due to the fact that the shadow process and the multipath process are mutually independent, and for fixed N, $E[S(i)] \to 0$, $i = (n-N+1), \ldots, n$, as $n \to \infty$, (20) can be rewritten as

$$\begin{aligned} &E\left[\left(\hat{S}_{SM}(n) - S(n)\right)^2\right] \\ &= E\left[\left\{\frac{1}{N}\sum_{i=n-N+1}^{n} [S(i) - S(n)]\right\}^2\right] \\ &\quad + E\left[\left\{\frac{1}{N}\sum_{i=n-N+1}^{n} \left[H(i) - \overline{H}\right]\right\}^2\right] \end{aligned} \tag{21}$$

when $n \to \infty$.

The second term in (21) has already been obtained in (19). The first term in (21) can be computed from (10) as follows:

$$\begin{aligned} &E\left[\left\{\frac{1}{N}\sum_{i=n-N+1}^{n} [S(i) - S(n)]\right\}^2\right] \\ &= E\left[\left\{\frac{1}{N}\sum_{i=n-N+1}^{n} S(i) - S(n)\right\}^2\right] \\ &= E\left[\left\{\frac{1}{N}\sum_{i=n-N+1}^{n} S(i)\right\}^2\right] \\ &\quad - 2E\left[\frac{1}{N}\sum_{i=n-N+1}^{n} S(i)S(n)\right] + E[S(n)^2] \\ &= \left\{\frac{1}{N^2} N\sigma_S^2 + 2\sum_{k=1}^{N-1} \frac{N-k}{N^2}\, \sigma_S^2 a^k\right\} \\ &\quad - 2\left\{\frac{1}{N}\sum_{k=0}^{N-1} \sigma_S^2 a^k\right\} + \sigma_S^2 \\ &= \frac{N-1}{N}\,\sigma_S^2 - 2\sum_{k=1}^{N-1} \frac{k\,a^k}{N^2}\,\sigma_S^2 \\ &= \sigma_S^2\left[\frac{N-1}{N} - \frac{2}{N^2}\sum_{k=1}^{N-1} ka^k\right] \\ &= \sigma_S^2\left[\frac{N-1}{N} - \frac{2}{N^2}\,\frac{a - Na^N + (N-1)a^{N+1}}{(1-a)^2}\right] \end{aligned} \tag{22}$$

which completes the derivation of (16). □

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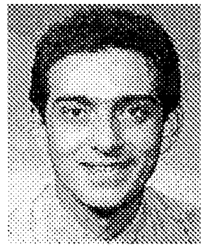

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