Interference Estimation in Presence of Noise for Broadband Wireless Packet Networks*

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Abstract

It has been shown that link adaptation and power control can improve performance of our future wireless packet networks. Realizing the expected performance gain of these techniques requires accurate prediction of future interference power. In this paper, we propose a new method based on Kalman filtering for interference estimation. The new method is devised by observing: a) it is possible to identify fairly accurately the number of active co-channel interferers in the cellular networks and b) interference power is positively correlated with the number of active interferers. The new technique uses a two-dimensional Kalman filter to exploit that correlation to enhance prediction accuracy.

Using a cellular network with 1/3 frequency reuse and partial traffic loading, performance of the new method is compared with a simplified method using a one-dimensional Kalman filter where the number of active interferers is not considered. Further, the new method is compared with the traditional exponential filtering. Since the proposed and simplified methods track interference and measurement errors separately, their predictions represent closely the best estimation by exponential filtering with the optimal parameter. In addition, for a typical network environment, the two-dimensional method yields the lowest prediction errors for a wide range of parameters, and provides a 0.5 dB improvement for the 90th percentile estimation error over the simplified method due to exploitation of the positive correlation between interference and number of active interferers.

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1. Introduction

As Internet access has become so popular, our future wireless networks will be based on packet switching technology to support Internet protocols (IP). As an example, let us consider the Enhanced Data rates for GSM Evolution (EDGE) system [SAEE98, F99], one of the standardized third-generation networks. The EDGE system is designed to support integrated (packetized) voice and data services. Using multiple modulation and coding levels, the EDGE system employs a link-adaptation technique to adapt packet transmission to one of the modulation levels. The main idea of link adaptation is to choose an appropriate modulation level (and associated data rate) for a packet transmission, according to the current link condition. When the radio condition is favorable, a complex modulation is used for transmission to improve network throughput. On the other hand, when the co-channel interference and/or the signal-path gain between the transmitter and receiver are poor, the packet transmission is adapted to a robust modulation as a way to maintain network coverage. The radio link condition can be reflected by the estimated signal-to-interference-plus-noise ratio (SINR), which in turn depends on the interference from neighboring cells, the signal-path gain and the transmission power. Results (e.g., [QC99], [LW00]) have shown that significant performance gain can be achievable by appropriate link adaptation algorithms.

Dynamic transmission power control [Z92, RZ98] has been widely studied and practiced to manage interference in cellular radio networks. To meet the need of bursty traffic characteristics in the wireless packet networks, [L02] proposes a power control to track the (co-channel) interference power and signal-path gain separately. According to the two estimated values, transmission power is then adjusted to yield a given SINR. Results (e.g., [CLQT00], [LDCQ01]) have shown that power control can significantly improve performance of the future wireless packet networks. In order to obtain the expected performance gain by link adaptation and power control, it is important to estimate future interference power accurately and this is the topic of this paper.

The organization of the rest of this paper is as follows. In Section 2, we present the motivation for a new method for estimating co-channel interference power in the wireless packet networks. A new estimation method using a two-dimensional Kalman filter is discussed in Section 3. Section 4 presents numerical results to show the merits of the proposed method over the traditional exponential filtering technique. Finally, Section 5 is our conclusion.

2. Motivation for New Estimation Method

Estimating future interference power with measurement errors in wireless packet networks such as the EDGE system is challenging. The difficulty has two issues. First, interference power is equal to the difference between the total received power and the power of the desired signal, where the latter can be measured by filtering based on the training symbols for the signal. Making such measurements can be very involved, especially when the measurement duration is short, although we assume here that measuring interference power is feasible. The second aspect of the difficulty is that interference measurements typically contain errors (e.g., due to thermal noise). In cellular networks using circuits to support voice service, a transmitter usually remains on for a relatively long period of time. Consequently, interference has a very strong temporal correlation, which enables use of a low-pass filter to remove random measurement errors. For this reason, exponential smoothing techniques are commonly used for that type of environment. However, such simple filtering is no longer adequate for the wireless packet networks under consideration. This is so because the latter networks are based on packet switching and each transmitter uses an assigned channel to transmit for a relatively short time before the channel is re-assigned to another transmitter. As a result, the temporal correlation of interference is weaker in the packet-switching environment than in the circuit-switched networks.

To illustrate the impact of bursty transmission, let us consider downlink transmissions in a TDMA cellular network with 1/3 frequency reuse. Figure 1 shows the representative autocorrelation coefficient for the interference power with fixed transmission power, no thermal noise and typical radio parameters (see Section 4 for details). As shown in the figure, depending on the average burst length L, the autocorrelation decreases quickly as a function of the lag time in slots. Although the burst length depends on the data rates and the traffic characteristics of applications, L reaching as low as 10 is common, especially in high-speed networks. Such reduced autocorrelation reveals rapid changes in interference power. As a result, both the interference power and the measurement error now fluctuate from one time slot to the next. That is, the low-pass filter not only filters out measurement errors, but also smoothes out quick changes in interference power, resulting in erroneous estimation of future interference levels. The main purpose of this work is to propose a method to predict interference power in the presence of measurement errors by tracking interference and noise power separately by Kalman filtering in wireless packet networks.

3. A New Estimation Method by Kalman Filtering

We begin with the operation assumptions for the wireless networks under consideration.

1. Consider a radio channel (frequency) in a TMDA cellular network where time is divided into *slots.* The medium-access control (MAC) protocol in use allows at most one transmitter (either a base station or a terminal) in each sector or cell to send data onto a given channel at a time. That is, no data contention occurs within the same sector or cell. Multiple, contiguous time slots can be used by the same transmitter for sending a data burst. The length of a data message (burst) is random and characterized by a probability distribution.

2. A small number of training sequences are assigned for transmission in various sectors or cells, similar to reuse of radio frequencies. Let all training sequences in the network be known to each receiver (i.e., a base station or a terminal). In addition, a receiver also knows the sequences used for data transmission in its home sector/cell. Interference power in each time slot can be measured quickly, but probably with errors at each receiver. The interference power is equal to the difference between the total received power and the power of the signal sent within the home sector/cell, where the latter can be measured by filtering based on the training sequences for the signal.

3. Based on the knowledge of the training sequences, each receiver can identify fairly accurately the number of active co-channel interferers that are transmitting in a given time slot.

In devising this new method, we observe that interference power is positively correlated with the number of active co-channel interferers. As a result, we propose a two-dimensional Kalman-filter approach to exploit that correlation for enhancing the accuracy of interference power prediction.

Specifically, for a given receiver, let $\mathbf{x}_k = (i_k, n_k)^T$ denote the process state where i_k and n_k are the actual interference power in mW and the number of active co-channel interferers for time slot *k*, respectively. Let us model the process as

$$\mathbf{x}_{k+1} = \begin{bmatrix} i_{k+1} \\ n_{k+1} \end{bmatrix} = \Phi \mathbf{x}_k + \mathbf{w}_k = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} i_k \\ n_k \end{bmatrix} + \begin{bmatrix} w_k^i \\ w_k^n \end{bmatrix} \quad (1)$$

where Φ is an identity matrix and $\mathbf{w}_k = (w_k^i, w_k^n)^T$. Further, w_k^i and w_k^n are white Gaussian sequences, which represent the respective changes of interference power and number of active interferers from one time slot to the next. In essence, both i_k and n_k are modeled as a Brownian-motion process [BH97] in (1). Let the observation state at slot *k* be $\mathbf{z}_k = (j_k, m_k)^T$ and the observation of the process is

$$\mathbf{z}_k = \begin{bmatrix} j_k \\ m_k \end{bmatrix} = \Phi \mathbf{x}_k + \mathbf{v}_k = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} i_k \\ n_k \end{bmatrix} + \begin{bmatrix} v_k^i \\ v_k^n \end{bmatrix} \quad (2)$$

where $\mathbf{v}_k = (v_k^i, v_k^n)^T$ and v_k^i and v_k^n are white Gaussian observation noise (error) for i_k and n_k, respectively. By the Kalman filter theory [BH97], the time and measurement update equations for $\mathbf{x}_k$ are:

$$\tilde{\mathbf{x}}_{k+1} = \hat{\mathbf{x}}_k \quad (3)$$

$$\tilde{\mathbf{P}}_{k+1} = \hat{\mathbf{P}}_k + \mathbf{Q}_k \quad (4)$$

$$\mathbf{K}_k = \tilde{\mathbf{P}}_k [\tilde{\mathbf{P}}_k + \mathbf{R}_k]^{-1} \quad (5)$$

$$\hat{\mathbf{x}}_k = \tilde{\mathbf{x}}_k + \mathbf{K}_k [\mathbf{z}_k - \mathbf{x}_k] \quad (6)$$

$$\hat{\mathbf{P}}_k = [1 - \mathbf{K}_k] \tilde{\mathbf{P}}_k \quad (7)$$

where $\tilde{\mathbf{x}}_k$ $\hat{\mathbf{x}}_k$ are the *a priori* and *a posteriori* estimates of $\mathbf{x}_k$, $\tilde{\mathbf{P}}_k$ $\hat{\mathbf{P}}_k$ are the *a priori* and *a posteriori* estimate-error variances, $\mathbf{K}_k$ is the Kalman gain, and $\mathbf{Q}_k$ and $\mathbf{R}_k$ are the covariance matrices for the process noise $\mathbf{w}_k$ and $\mathbf{v}_k$, respectively. By definition, the covariance matrix $\mathbf{Q}_k$ for $\mathbf{w}_k$:

$$\mathbf{Q}_k = \mathrm{E}[\mathbf{w}_k \mathbf{w}_k^T] = \begin{bmatrix} \rho_k^2 & cov(w_k^i, w_k^n) \\ cov(w_k^i, w_k^n) & \sigma_k^2 \end{bmatrix} \tag{8}$$

where ρ_k^2 and σ_k^2 are the respective variances for the changes of interference power and the number of active interferers in slot *k*, and $cov(w_k^i, w_k^n)$ is the covariance of w_k^i and w_k^n in slot *k*. Similarly, the covariance matrix for $\mathbf{v}_k$ is given by

$$\mathbf{R}_k = \mathrm{E}[\mathbf{v}_k \mathbf{v}_k^T] = \begin{bmatrix} \phi_k^2 & cov(v_k^i, v_k^n) \\ cov(v_k^i, v_k^n) & \pi_k^2 \end{bmatrix} \tag{9}$$

where ϕ_k^2 and π_k^2 are the variance for the interference measurement error and that for the error in estimating the number of active interferers in slot *k*, respectively, and $cov(v_k^i, v_k^n)$ is the covariance of v_k^i and v_k^n in slot *k*. As the number of active interferers in each time slot can be determined fairly accurately, as stated in Assumption 3, $\mathbf{R}_k$ becomes

$$\mathbf{R}_k = \begin{bmatrix} \phi_k^2 & 0 \\ 0 & 0 \end{bmatrix} \tag{10}$$

As our initial approach, elements of $\mathbf{Q}_k$ in (8) are estimated by a windowing scheme as follows. First, using measurements in a sliding window of *W* slots, we obtain the average changes of interference power and the number of active interferers from one time slot to the next by

$$\bar{j}_k = \frac{1}{W} \sum_{l=k-W+1}^{k} j_l - j_{l-1} \tag{11}$$

$$\bar{m}_k = \frac{1}{W} \sum_{l=k-W+1}^{k} m_l - m_{l-1}, \tag{12}$$

respectively. Then, we approximate elements of Q_k as

$$\rho_k^2 \approx \frac{1}{W-1} \sum_{l=k-W+1}^{k} [(j_l - j_{l-1}) - \bar{j}_k]^2, \tag{13}$$

$$\sigma_k^2 \approx \frac{1}{W-1} \sum_{l=k-W+1}^{k} [(m_l - m_{l-1}) - \bar{m}_k]^2 \tag{14}$$

and

$$cov(w_k^i, w_k^n) \approx \frac{1}{W-1} \sum_{l=k-W+1}^{k} (j_l - j_{l-1} - \overline{j}_k)(m_l - m_{l-1} - \overline{m}_k).$$

Note that j_l's in (11) include the interference measurement errors $\{v_k^i\}$, which have a Gaussian distribution with zero mean. Despite this, if W is chosen large enough (e.g., ≥1000), (11) gives an unbiased estimate of average changes of interference power in consecutive time slots. Thus, (13) and (15) provide good approximations of ρ_k^2 and $cov(w_k^i, w_k^n)$. As the number of active interferers can be determined accurately by Assumption 3, v_k^n is zero for all k in (2). As a result, (14) is an appropriate estimate for the variance of w_k^n, σ_k^2.

The variance of the interference measurement error $\{\phi_k^2\}$ in (10) depends on the noise level and the error characteristics of the measurement circuit in use. In practice, ϕ_k^2 can be determined by, for example, measuring the "received" power on a known, idle channel. Thus, the variance of the "received" power over a time window can serve as an estimate of ϕ_k^2.

4. Performance Study

To study the performance of the proposed interference estimation, we simulate a cellular network with 37 cells, each of which has a radius of 1 Km. Every cell is divided into 3 sectors, each of which is served by a sectoral antenna with beamwidth of 60 degrees, antenna gain at the front direction of 7.47 dBi and ratio of front-to-back antenna gain of 25 dB. The radio link is characterized by a path-gain model with an exponential of 3.5 and the median path gain of -73 dB at 100 meters from a base-station transmitter. The standard deviation for shadow fading is 8 dB. Radio frequencies (channels) have a reuse factor of 1/3; that is, all channels are grouped into 3 sets and each of them is assigned to one of the 3 sectors of every cell. Each radio channel is divided into time slots and depending on the burst length, a message (i.e., data burst) is transmitted in consecutive time slots. The length of a data burst has a geometric distribution and an average of L slots. We consider that each channel carries 30% traffic load; that is, after a data burst is sent, the channel in each co-channel sector remains idle for a random number of time slots with a geometric distribution. The transmission (busy) and idle periods yield a channel utilization of 30% in a long run. Only downlink transmissions are considered and transmission power is fixed at 30 dBm in the simulation model.

Interference measurement errors $\{v_k^i\}$ in (2) are due to Gaussian noise where the noise power level is determined based on the actual interference power and a given interference-to-noise ratio (INR). Each cell is populated with 100 terminals at random locations. The time sequences of actual interference power, the number of active interferers, and noise power are collected for a small set of randomly selected terminals in the central cell of the networks. These measurements are fed into (11) to (15) to obtain necessary input parameters $\mathbf{Q}_k$ and $\mathbf{R}_k$. The Kalman filter in (3) to (7) is used to predict the future process state $\tilde{\mathbf{x}}_{k+1} = (\tilde{i}_{k+1}, \tilde{n}_{k+1})^T$ for slot $k+1$ based on the measurements up to slot *k*. Since the actual interference power for slot $k+1$, i_{k+1}, is known from the simulation, a key measure to show the merit of the proposed estimation technique is the absolute estimation error, which is given by $|\tilde{i}_{k+1} - i_{k+1}|$. We consider the average and the 90th percentile of the estimation error below.

Note that the Kalman-filter method in Section 3 makes use of a two-dimensional filter. For comparison, we also consider a simplified version of the method. Specifically, the simplified version does not consider the number of active interferers, resulting in a one-dimensional filtering formulation, as used in [L02] for power control. Furthermore, we also compare the two-dimensional Kalman method with the traditional exponential filtering with various parameter values. For a given parameter *p* between 0 and 1, the predicted interference power for slot $k+1$ by the exponential filtering approach is

$$\tilde{i}_{k+1} = (1-p)\tilde{i}_k + p j_k \tag{16}$$

where j_k is the measured interference power for slot *k* and $\tilde{i}_0$ is assumed to be zero.

Figures 2 and 3 compare the average and 90th percentile of the absolute estimation error (i.e., the absolute difference between the actual interference power and the predicted value) for the new method with that for the traditional exponential filtering with various parameters as a function of average burst length. The INR is about 13.6 dB. As shown in both figures, depending on the burst length and the exponential parameter *p*, exponential filtering can perform reasonably well or poorly in predicting interference. The performance of the simplified Kalman-filter method without use of the number of active interferers (denoted as "Kalman") is also presented in Figures 2 and 3. Since this simplified method tracks the interference and noise separately, its interference prediction represents closely the best estimation by exponential filtering. The proposed method (denoted by "2-dim Kalman" in the figures) yields the lowest prediction errors for a wide range of parameters, and provides a 0.5 dB gain for the 90th percentile error over the simplified method, because the two-dimensional method exploits the positive correlation between interference and the number of active interferers. Since the burst length is unknown in advance, the proposed technique is efficient in estimating interference power for link adaptation and power control in future wireless packet networks.

5. Conclusions

Link adaptation and power control have been shown to be capable of providing significant performance gain in our future wireless packet networks. To realize the expected gain of these techniques, it is essential to estimate future interference power accurately. In this paper, we have proposed a new method based on Kalman filtering for estimating future interference power. The new method is devised by observing two facts: a) it is possible to identify fairly accurately the number of active co-channel interferers in the cellular network environment and b) interference power is positively correlated with the number of active interferers. The new technique uses a two-dimensional Kalman filter to exploit that correlation to enhance accuracy of interference prediction.

For a cellular network with 1/3 frequency reuse and partial traffic loading, the performance of the new method has been compared with a simplified method using a one-dimensional Kalman filter where the number of active interferers is not considered. Further, the new method is compared with the traditional exponential smoothing technique as a function of message burst length. Our performance results reveal that as intuitively expected, depending on the burst length and the exponential parameter, exponential smoothing can perform reasonably well or poorly in predicting interference. Since the proposed Kalman-filter method and the simplified method track interference and measurement errors (due to noise) separately, their predictions represent closely the best estimation by exponential filtering with the optimal parameter. In addition, with 30% traffic load and 13.6 dB INR, the two-dimensional method yields the lowest prediction errors for a wide range of parameters, and provides a 0.5 dB improvement for the 90th percentile estimation error over the simplified method due to exploitation of the positive correlation between interference and the number of active interferers. Since the burst length is typically unknown in advance, the proposed method is efficient in estimating interference for link adaptation, power control and possible other performance enhancement techniques in future wireless packet networks.

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Figure 1. Autocorrelation of Interference Power

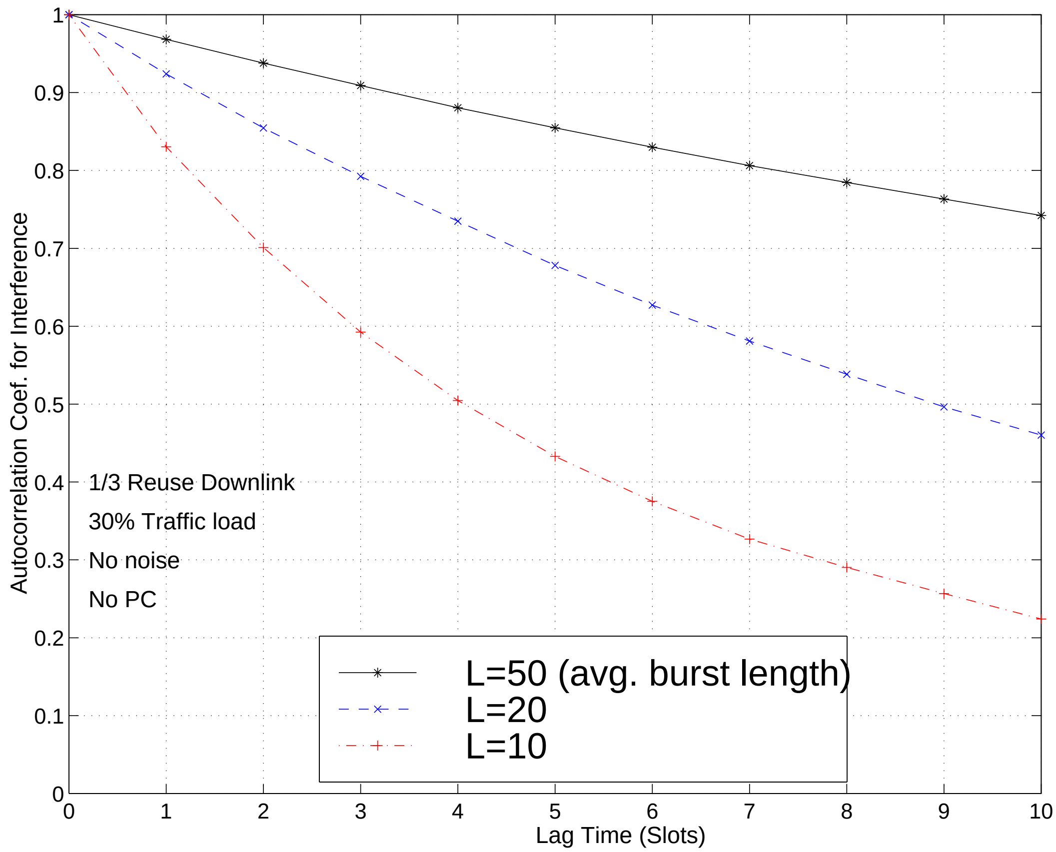

Figure 2. Comparison of Average Estimation Errors

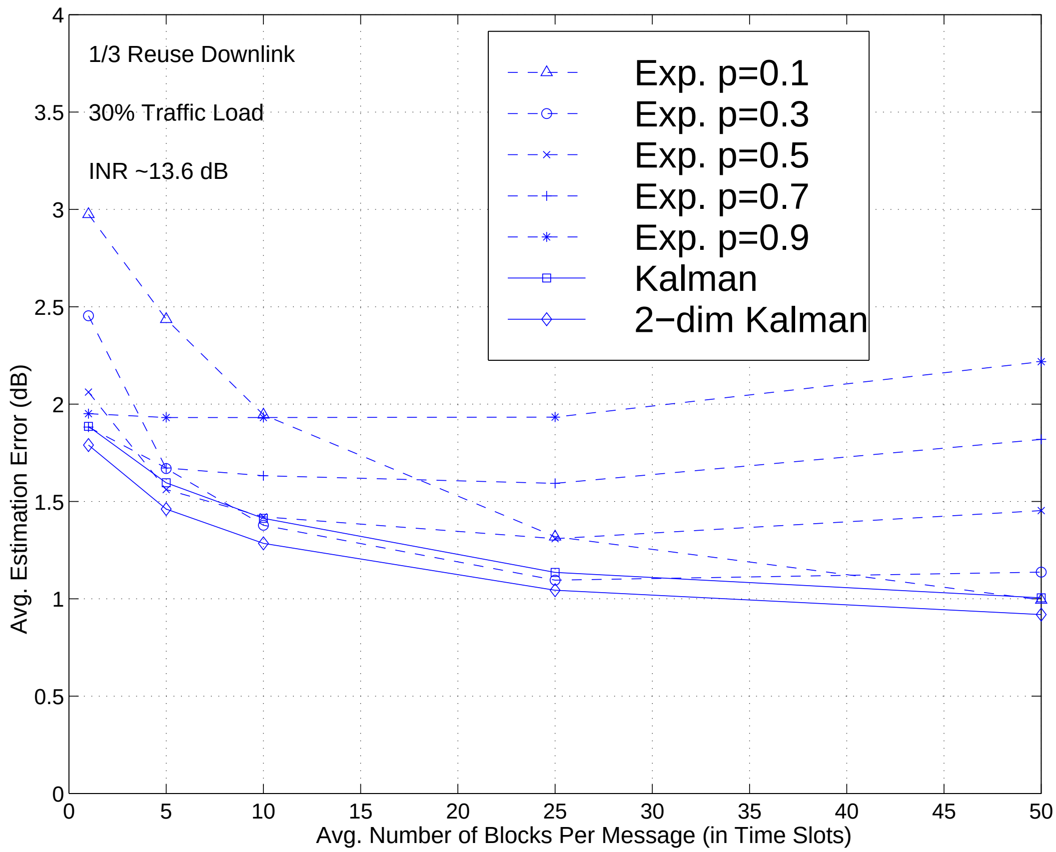

Figure 3. Comparison of 90th Percentile Estimation Errors