

## Interference Estimation With Noisy Measurements in Broadband Wireless Packet Networks

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It has been shown that link adaptation and power control can improve performance of our future wireless networks. To be concrete, let us consider the Enhanced Data rates for GSM Evolution (EDGE) system, one of the standardized third-generation networks. Using packet-switching technology, and 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 in terms of interference received from neighboring cells and signal-path gain. On power control, due to bursty traffic in the wireless packet networks, results have shown that it is advantageous to monitor the interference level and adjust transmission power accordingly. Thus, 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.

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 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.

To illustrate the impact of bursty transmission, let us consider a cellular network with  $1/3$  frequency reuse. Figure 1 shows the representative autocorrelation coefficient for the downlink interference power when the channel has 30% traffic load with fixed transmission power, no thermal noise and typical radio parameters. As shown in the figure, depending on the average burst length  $L$ , which is defined in terms of the number of time slots, 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.

In devising this new method, we observe that it is possible, e.g., based on training sequences, to fairly accurately identify the number of active co-channels interferers that are transmitting in a given time slot. Since the measured interference power is positively correlated with the number of active interferers, a 2-dimensional Kalman-filter approach can exploit that correlation to enhance prediction accuracy.

Specifically, let  $\mathbf{x}_k = (i_k, n_k)^T$  denotes 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  $\mathbf{x}_{k+1} = \Phi \mathbf{x}_k + \mathbf{w}_k$  where  $\Phi$  is an identity matrix,  $\mathbf{w}_k = (w_k^i, w_k^n)^T$  and  $w_k^i$  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. The observation of the process is  $\mathbf{z}_k = \Phi \mathbf{x}_k + \mathbf{v}_k$  where  $\mathbf{v}_k = (v_k^i, v_k^n)^T$  and  $v_k^i$  and  $v_k^n$  are white Gaussian observation noise for  $i_k$  and  $n_k$ , respectively. We define the covariance matrices:  $\mathbf{Q}_k = E\{\mathbf{w}_k \mathbf{w}_k^T\}$  and  $\mathbf{R}_k = E\{\mathbf{v}_k \mathbf{v}_k^T\}$ . Based on previous interference measurements,  $\mathbf{Q}_k$  and  $\mathbf{R}_k$  can be estimated. As a result, the process state (i.e., the interference power and number of active interferers) for the next time slot can be estimated by a two-dimensional Kalman filter.

Figure 2 compares the 90th percentile of 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 (which itself is assumed to be geometrically distributed). The system parameters correspond to the same network as Figure 1, and the measurement error is due to thermal noise with a normal distribution. The interference-to-noise ratio (INR) is about 13.6 dB. As shown in Figure 2, depending on the burst length and the exponential parameter value, exponential filtering can perform reasonably well or poorly in predicting interference. As a comparison, we also present the performance of the Kalman-filter method without use of the number of active interferers (denoted as "Kalman") in Figure 2. 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 figure) yields the lowest prediction errors for a wide range of parameters, and provides about a 0.5 dB gain 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.

Fig.1. Autocorrelation of Interference Power

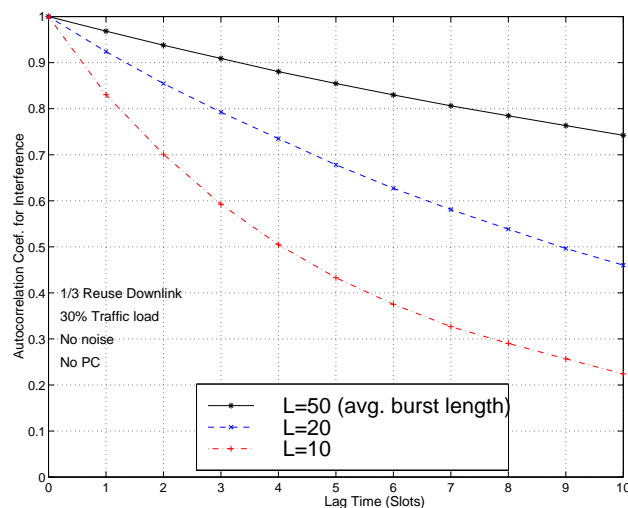


Fig.2. Comparison of Interference Estimation Errors

