Mobile Fading

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ABSTRACT

In wireless communication systems, the direct signal and the reflected signals form an interference pattern resulting in a received signal given by the sum of these components. They are distinguished by their Doppler shifts at the mobile. Once the slowly varying parameters associated with these components are determined, the fading coefficients can be accurately predicted *far ahead*. This novel approach to fading channel prediction is combined with transmitter signal optimization to mitigate the effects of "deep fades", which severely limit the performance of mobile radio systems. This capability will potentially help to reduce power requirements for wireless channels and improve the system performance.

The performance of the wireless communication system is limited by intermittent power losses, or "deep fades", associated with the fading channel [1,2]. The transmission path between the transmitter and the receiver can include reflections by terrain configuration and the man-made environment. Therefore, the fading signal results from interference between several scattered signals and perhaps the direct signal [2-5]. Consider a low-pass complex model of the received signal:

r(t) = c(t) s(t) + n(t),

where c(t) is the flat fading coefficient (multiplicative), s(t) is the transmitted signal, and n(t) is additive white Gaussian noise (AWGN). Let the transmitted signal be $s(t) = \sum_k b_k g(t - kT)$ where bk is the data sequence, g(t) is the transmitter pulse shape, and T is the symbol delay. At the output of the matched filter and sampler, the discrete-time system model is given by

rk = ck bk + zk,

where ck is the complex fading signal c(t) sampled at the symbol rate, and zk is a complex discrete AWGN process with variance N0. Usually, c(t) and ck are modeled as correlated complex Gaussian random processes with Rayleigh distributed amplitudes and uniform phases . Several adaptive channel estimation methods

have been developed by using this statistical description to estimate rapidly varying fading coefficients . However, the performance of these methods degrades when the fading rate increases due to a large estimation error. In addition, these algorithms do not address the most serious limiting factor in communication over fading channels. The greatest bit error rate (BER) loss and the associated high power requirements result from "deep fades" in the fading signal. Therefore, it is desirable to predict deep fades, and, in general, fading variations, and compensate for the expected power loss at the transmitter. Therefore, we address *long term* prediction of the variations in ck. By prediction we imply estimating an entire future block of coefficients ck based on the observation of the received signal during an earlier time interval. This task is not feasible with current Kalman filtering and other adaptive channel estimation techniques, which can predict only one coefficient at a time, nd require observation of the received sample to produce this estimate. In this paper, we propose a prediction method which would allow to determine the channel coefficients prior t o transmission. In particular, the timing of future "deep fades" would be revealed and the variations in received signal power could be compensated.

In our simulations, we assumed the maximum Doppler frequency, fdm, is 100 Hz, and the data rate is 25 Kbps. We sample the channel at the rate of 500 Hz. Thus, there are 50 data points between adjacent sampling points. To determine initial observations of the fading coefficients, ck, at the sampling points, one can send training symbols bk at the channel sampling rate of 500 Hz (see (1)). This overhead affects the throughput only by 2%. In Figure 1, we examine the Jakes channel model with nine oscillators (scatterers) [5], i.e., N=9 in (2). The channel is observed for the first 100 samples (0.2 seconds). Here actual channel coefficients are used during observation. As shown in [3], noisy measurements do not significantly increase the prediction error. In this example, we chose p=60 in (4). By employing MEM, the prediction coefficients dj in (4) were determined. Since actual channel coefficients are not available beyond the observation interval, the estimates of previous p fading coefficients are used to form future predicted values,. For example, earlier predicted values c^ n-j can be used instead of the actual values cn-j in (4) to form future estimates c^ n. This approach was taken in [3]. However, it was observed that this method causes error propagation later in the prediction. Therefore, we are investigating adaptive algorithms to update channel estimates during transmission. Using adaptive channel estimation combined with transmitter pre-compensation (see below), more reliable data aided estimates of fading coefficients can be obtained at the receiver, and fed back to the transmitter at the sampling rate. Our results (not shown here due to space constraints) indicate that this technique significantly reduces error propagation, and that the channel can be accurately forecasted for several hundred of future data symbols. Therefore, in our performance analysis below we are assuming that perfect estimates of fading coefficients cn-j are available in (4), and in Figure 1 we use actual fading coefficients for prediction. This assumption is realistic in view of the accuracy of the combined prediction and tracking technique. The future values of the channel coefficients are predicted and plotted in dotted lines for the last 100 samples in the Figure 1. It can be seen that the predicted values follow very closely the actual future envelope shown in solid lines. Therefore, we can determine future channel variations and predict when the channel is going to enter deep fades in the future. Note that Figure 1 shows only sampled points at the rate of 500 Hz. Since this sampling rate is much lower than the data rate, we perform interpolation between predicted channel coefficients to get better resolution. In this interpolation process, four consecutively predicted channel coefficients are interpolated by a Raised Cosine (RC) filter to generate estimates of the fading coefficients, c^ k, between two adjacent predicted samples at the data rate [10]. We found that for the normalized sampling rate fs'=2.5, where fs' is given by fs/2fdm , the optimum rolloff factor is 0.64. Although fs'=2.5 results in oversampling, it produces much more accurate interpolated values than lower values of fs'.

The proposed prediction method can be combined with tracking and transmitter optimization. In our simulations, we assumed coherent detection and used Binary Phase Shift Keying (BPSK) modulation scheme. Given binary signal bk and E(|ck|2) = 1, the signal-to-noise (SNR) is

$$\gamma_b = \frac{E(b_k^2)}{N_0}.$$

The following channel inversion with threshold method is investigated to accomplish reliable communication. The channel samples taken during the observation interval are sent to the transmitter, which applies MEM and adaptive linear prediction, and interpolates to produce predicted fading values at the data rate. Note that this feedback is not going to introduce significant delay since the sampling rate is much lower than the data rate. The transmitter interrupts the transmission for the k-th symbol if the power level, |c^ k|2, is below previously chosen threshold value. Furthermore, if |c^ k|2 is above the threshold, the transmitter sends the data bits, bk, by multiplying them with the inverse of the predicted c^ k values (4). This power adjustment is not proposed as a practical solution, since it will result in large transmitter power fluctuations. It is considered here to access performance advantages of the proposed prediction technique. We are currently investigating efficient adaptive coding and modulation methods for transmitter optimization [11]. The bit error rates (BER) for this channel inversion with threshold method for the nine-oscillator model and the prediction algorithm described earlier in this section are plotted in Figure 2. With no threshold and no compensation, the channel exhibits Rayleigh fading characteristics, and the bit error rate (BER) is .

$$P_e = \frac{1}{2}\left(1 - \sqrt{\frac{\gamma_b}{1+\gamma_b}}\right)$$

By increasing the threshold from 0.1 to 0.6, we observe performance improvement. However, the throughput reduces with the increasing thresholds (or equivalently, the bandwidth increases). The throughputs are 90.5%, 82%, 67%, and 55% for the thresholds 0.1, 0.2, 0.4, and 0.6 respectively. The simulation results slightly deviate from the theoretical values due to the prediction and the interpolation errors. Since the power of the transmitted signal b_k/c_k is greater than E(bk2) for thresholds <0.4, the BER for these threshold values are above the AWGN channel BER. For the threshold=0.4, the transmitted power is equal to E(bk2), and the analytical curve is also the BER of the AWGN channel [1].

$$P_e = Q(\sqrt{2\gamma_b})$$

where the $Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^{\infty} \exp(-t^2/2)dt.$

Thus, by using the proposed prediction method, we were able to reduce the BER to and beyond the level of the AWGN channel.