Adaptive Power Control Using Long Range Prediction for Realistic Fast Fading Channel Models and Measured Data

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Abstract:-- Recently we proposed the long range prediction algorithm for fast fading channels. This method provides the enabling technology for adaptive transmission techniques such as adaptive coding, adaptive power control, etc. In this paper, we used actual field measurements to validate the long range prediction method and its utilization in adaptive power control.

1. Introduction

The tremendous growth in demand for wireless communications capacity has created a need for new modulation, coding and detection methods that more efficiently use the multipath fading channels encountered in mobile radio. Since the channel changes rapidly, the transmitter and receiver are not usually optimized for current channel conditions, and thus fail to exploit the full potential of the wireless channel. Recently, several adaptive modulation methods were proposed (see, e.g. [1]). In these methods, the transmitted signal varies according to the instantaneous fading channel power. As a result, much higher bit rates relative to the conventional signaling can be achieved. These adaptive modulation methods depend on accurate channel state information, but the rapid variation of the fading channel makes feed back of the current channel estimate insufficient. To design the transmitted signal properly, future knowledge of the channel is required. For fast fading conditions, conventional fading estimation techniques cannot predict the channel sufficiently far ahead to aid adaptive modulation and coding.

This paper focuses on a novel long range prediction algorithm [2, 4-6] suitable for fast fading channels and its utilization in conjunction with adaptive modulation. This prediction algorithm characterizes the channel as an autoregressive model (AR), and computes the Minimum Mean Squared Error (MMSE) estimate of the future fading coefficient sample based on a number of past observations. This algorithm can reliably predict future fading coefficients *far beyond* the coherence time of the fading channel. The superior performance of this algorithm relative to conventional methods is due to its much slower sampling rate (on the order of twice the Doppler shift). For conventional techniques, the sampling rate is usually given by the data rate. Given fixed model order, the lower rate utilizes the large sidelobes of the autocorrelation function of the fading process and results in longer memory span [4], permitting prediction further into the future.

In [4], we introduced an adaptive version of this method, which reduced the propagation error, improved accuracy in the presence of additive noise and decision-directed signaling, and tracked variations in the parameters associated with the scatterers (amplitudes, Doppler shifts and phases). In [6], we theoretically analyzed the MMSE performance of the long range prediction. Also, the performance of this adaptive prediction algorithm for a truncated channel inversion method was studied in [2, 4]. This simple adaptive modulation technique utilizes the a-priori knowledge of the channel at the transmitter and adjusts the transmitted signal according to the predicted fading channel coefficient. We show that a large potential error rate improvement associated with this method can be realized if long term prediction is employed. In [4], we also illustrated the gains of our long term prediction technique relative to conventional channel estimation approaches.

In addition to testing our method on standard fading models [3], we introduced novel physical channel models required for validating the proposed prediction algorithm in [5]. We showed that a more realistic view of the fading signal results from modeling it as a deterministic process formed by the addition of several scattered components, rather than as a stationary random process. The superposition of these *deterministic* sinusoidal components changes rapidly as the vehicle moves, producing the familiar fast-fading signal envelope observed in practice, but the amplitude, frequency and phase of each component change on a much slower time scale. The variation of these parameters is not captured by the standard Jakes model or a stationary random process description. However, the accuracy of the long-term prediction

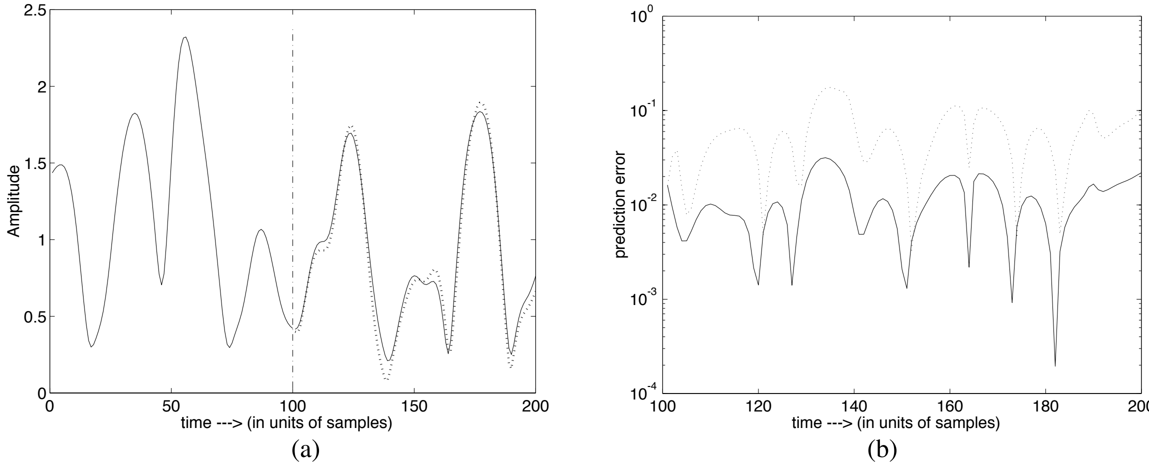

Figure 1. Testing long range prediction algorithm for measured data.
(a) Prediction 3 steps ahead (0.9 ms). First half: the actual fading channel envelope (solid) is observed. Second half: the actual future (solid) and predicted (dotted) fading channel envelopes.
(b) Prediction error comparison for predicting 1 step (solid) and 3 steps (dotted) ahead.

is determined by the rate of change of these parameters. Thus, to test the long-term prediction algorithm, novel channel modeling of the flat fading channel based on the method of images was performed. Using this realistic modeling technique, we created typical and worst case parameter variation scenarios in [5].

In this paper, we use actual field measurements to validate the performance of our prediction method. These narrowband mobile radio channel measurements were provided by Ericsson, Inc. and were collected in urban Stockholm. We show below that joint prediction and power adaptation significantly improves performance on this channel, as expected from our previous theoretical and simulation studies.

2. Numerical Results and Performance Analysis.

Consider the equivalent lowpass discrete-time system model at the output of the matched filter and sampler given by:

$$y_k = c_k\, b_k + z_k, \tag{1}$$

where c_k is the flat fading signal sampled at the symbol rate, b_k is the binary phase shift keying (BPSK) data sequence, and z_k is the discrete AWGN process. The objective of long-term prediction is to forecast future values of the fading coefficient c_k in (1) far ahead. To accomplish this task, we use the linear prediction (LP) method based on the all-pole modeling [2, 4]. To simplify this discussion, suppose a sequence of p previous samples of the fading signal is observed, where the sampling rate f_s is much lower than the data rate in (1). The MMSE prediction of the future channel sample $\hat{c}_n$ based on p previous samples $c_{n-1}...c_{n-p}$ is given by:

$$\hat{c}_n = \sum_{j=1}^{p} d_j c_{n-j} \tag{2}$$

The lower rate allows to predict further ahead for the same model order p. The Least Mean Squares (LMS) adaptive tracking method was further implemented to track channel parameter variation [4,5] and also to reduce the effect of noise [6]. Equation (2) results in prediction one step T_s ahead (e.g. if f_s=1KHz, the prediction range T_s is 1ms). To achieve longer-range prediction (several steps ahead) for the same sampling rate, we iterate (2) using previously predicted fading samples instead of the observations.

In this paper, we use actual field measured data to test this long range prediction algorithm. The data set contains 100,000 samples of the flat fading signal. For the segment of the data set used in this paper, the distribution of amplitude and the autocorrelation function were close to those for the theoretical Rayleigh fading channel [3]. Other portions of the data set had different shapes of the autocorrelation function. By matching these measurements with our realistic channel models [5], we concluded that the measured data was collected from diverse mobile radio environments. The data was clearly non-stationary with differences in the number and location of the scatterers along the measurement track. Based on the estimated autocorrelation function and assuming the Maximum Doppler frequency shift f_{dm}=100 Hz, the channel sampling rate used for this data set was calculated to be 3400 Hz. In Figure 1, we illustrate the long-range prediction algorithm for a segment of the measured data. In this case, f_s=3.4KHz and p=38. Numerous other experiments were performed for various portions of the data and other model parameters (e.g., lower sampling rate, longer prediction range, other values of p, etc). It was concluded that long-range prediction is feasible for this channel.

To demonstrate the application of the proposed prediction method to adaptive power control, we analyzed the truncated channel inversion algorithm (TCI) [1] aided by long-term prediction (see also [2,4]). The basic idea of this scheme is: if the predicted power level is below a previously chosen threshold value during a given time interval, the transmitter interrupts transmission during that time; if the predicted power is above the threshold, the transmitter sends the data symbols scaled by the inverses of the predicted fading coefficients. In the simulation, we assumed the model of eq. (1) and coherent detection. Using measured data described above, we interpolate 25 data rate points between 2 original sample points to obtain fading channel samples corresponding to the data rate of 85 Kbps. Simulation results for the thresholds 0.1 and 0.4 (assume channel power is normalized to 1) and 1-step and 3-step prediction ranges (relative to the beginning of the desired frame of 25 bits) are shown in Figure 2. As described in [2], interpolation is used to predict the channel coefficients at the data rate between two adjacent predicted low-rate samples. In addition, we considered the case when the actual channel coefficient is fed back to the transmitter with 1-step and 3-step delay, and used it to adjust the transmitter power for all 25 data bits between the two lower sampling rate points. The simulation results illustrate the performance gain of long range prediction over the delayed channel estimation for adaptive power adjustment.

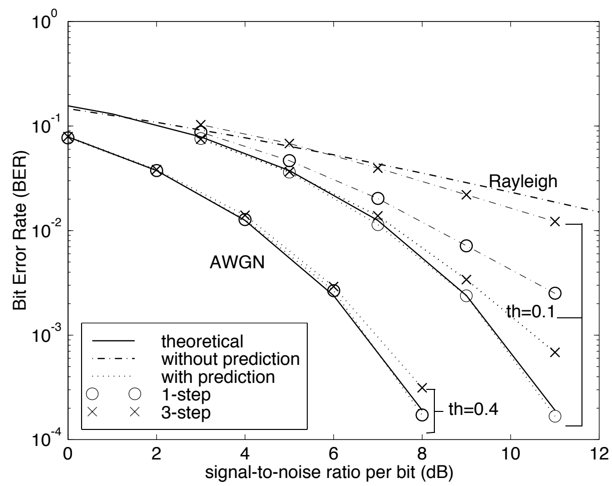

Figure 2. Bit Error Rate vs. Average SNR:
Theoretical: TCI at each threshold (th) level for Rayleigh fading channel.
Without Prediction: TCI using delayed feedback for measured data (th=0.1, 1 and 3 step delay); no adaptation (Rayleigh fading channel).
With Prediction: joint long range prediction (1 and 3 steps, th=0.1 and 0.4) and TCI for measured data.

In summary, we confirm previously introduced theoretical results, simulations and realistic channel models with performance for measured data to show the potential of the proposed long term fading channel prediction method. It is shown that significant performance improvement can be expected when long term prediction is used

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