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Adaptive Modulation Using Long Range Prediction for Flat Rayleigh Fading Channels[1]

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Abstract--- ***Adaptive transmission techniques, such as adaptive modulation and coding, adaptive power control, adaptive transmitter diversity, etc., implicitly depend on the transmitter's ability to predict the future behavior of the channel. Recently, we proposed a reliable long range prediction algorithm for fast fading channels. In this summary, we show that this prediction technique makes adaptive modulation feasible for the standard fading channel model (Jakes model), a novel realistic physical channel model and the actual measured data (provided by Ericsson, Inc.)***

1. Introduction

New adaptive transmission techniques were proposed recently to satisfy the tremendous growth in demand for wireless communications capacity. 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, the knowledge of the channel variations is required several hundreds of symbols into the future. For fast fading conditions, conventional fading estimation techniques cannot predict the channel sufficiently far ahead to aid adaptive modulation and power control. References [1, 2] show that even small estimation errors can severely degrade the performance of existing adaptive modulation systems. To date, most research work on adaptive modulation falls into three categories. The first class includes investigation of adaptive modulation methods under the assumption that the transmitter knows the fading coefficients exactly [1, 3, 4]. In general, this is not true due to the noise and the delay in the feedback path. The second approach is to design adaptive signaling using delayed fading estimates [2]. In [2], the current channel fading amplitude when conditioned on the delayed fading estimates was characterized as a Rician random variable, and the signaling design is highly dependent on the knowledge of correlation coefficient between the current channel state information (CSI) and the outdated fading estimates. However, in practice, the autocorrelation function is generally not known at transmitter, and also it was found that even very small delay causes significant loss of capacity using this design rule in [2]. The third class includes adaptive modulation design aided by the predicted CSI [5, 6]. However, either only short range prediction or a slowly fading channel were addressed in these investigations.

To realize adaptive modulation methods in practice, the fading channel needs to be predicted far ahead for realistic mobile radio conditions. Recently, we proposed an adaptive *long range* prediction algorithms for rapidly varying fading channels [7- 9]. 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 method does not require prior knowledge of the autocorrelation function, the maximum Doppler frequency shift, the number of scatterers, etc. It can reliably predict future fading coefficients *far beyond* the coherence time of the fading channel due to its significant memory span achieved by using sufficiently low sampling rate given a fixed model order [8]. In [8], 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 [9], we theoretically analyzed the MMSE performance of the long range prediction. Also, the performance of the adaptive prediction algorithm for a truncated channel inversion method was studied in [8, 9]. This simple adaptive power control 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 range prediction is employed. When prediction is not used, the delayed CSI becomes unreliable for fast vehicle speeds and truncated channel inversion results in poor performance. In addition to testing our method on standard fading models [10], we introduced novel physical channel models required for validating the proposed prediction algorithm in [11, 12], and used actual field measurements which were provided by Ericsson to validate the performance of our prediction method in [13].

In this paper, we concentrate on the study of adaptive modulation in conjunction with the proposed long range prediction algorithm. The Jakes model and actual field measured data are used to evaluate the Bit Error rate (BER) performance of an adaptive modulation system aided by predicted CSI. A novel non-stationary fading model suitable for testing the long range prediction method is also discussed.

2. Adaptive Modulation Using Long Range Prediction

The basic idea of adaptive modulation methods investigated in e.g. [1, 2, 5] is to vary the constellation size according to the instantaneous channel condition which can be measured as either the signal-to-noise (SNR) ratio or the fading gain. The modulation level selection is generally subject to the average power constraint for the given target BER performance requirement. The number of modulation levels, or the bit rate, is larger when the channel is stronger, whereas during deep

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fades transmission is avoided completely. Thus, the time-variant nature of the channel is exploited, resulting in much faster bit rates relative to non-adaptive techniques. In this paper, we only consider the fixed power and modulation level-controlled scheme using Square MQAM signal constellation for the target $BER_{tg} = 10^{-3}$. We restrict ourselves to MQAM constellations of sizes M = 0, 2, 4, 16, 64. In the development of adaptive modulation systems, three key components need to be considered are: (1) prediction of channel conditions; (2) statistical model of the prediction error; (3) design rule for the modulation level selection. We first discuss (1) ~ (3) for adaptive modulation aided by long range prediction and then present the BER performance results.

(1) *Long Range Prediction Algorithm for Fast Fading Channels.*

The objective of long-term prediction is to forecast future values of the fading coefficient far ahead. To accomplish this task, we use the linear prediction (LP) method based on the AR modeling [7, 8]. Suppose a sequence of p previous samples of the fading signal is observed, where the sampling rate f_s is much lower than the symbol rate (on the order of the Nyquist rate given by twice the maximum Doppler shift). The linear MMSE prediction of the future channel sample $\hat{c}_n$ based on p previous samples $c_{n-1}...c_{n-p}$ is given by:

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

where the coefficients d_j are determined by the orthogonality principle. 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 [8, 11, 13] and also to reduce the effect of noise [9, 14]. Equation (1) results in the 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 (1) using previously predicted fading samples instead of the observations.

(2) *Statistical Model of Prediction Error;*

In this analysis, we assume that channel samples c_n are modeled as zero-mean complex Gaussian random variables, i.e., the channel is Rayleigh fading. From the linear prediction algorithm (1), the estimate $\hat{c}_n$ is a linear combination of c_{n-j}, so it is also a zero-mean complex Gaussian random variable. Thus, the amplitude $\alpha = |c_n|$ and its predicted value $\hat{\alpha} = |\hat{c}_n|$ have a bivariate Rayleigh distribution. We define the prediction error β as the ratio of the actual fading gain α and the predicted fading gain $\hat{\alpha}$, i.e., $\beta = \frac{\alpha}{\hat{\alpha}}$. Then the probability density function (pdf) of β can be derived as:

$$p_\beta(x) = \frac{2x(\frac{1}{\lambda}x^2 + \lambda)(1-\rho)}{((\frac{1}{\lambda}x^2+\lambda)^2-4\rho x^2)^{1.5}}, \tag{2}$$

where the correlation coefficient $\rho = \frac{Cov(\alpha^2,\hat{\alpha}^2)}{\sqrt{Var(\alpha^2)Var(\hat{\alpha}^2)}}$, $0 < \rho < 1$, $\Omega=E\{\alpha^2\}$, $\hat{\Omega} = E\{\hat{\alpha}^2\}$, and $\lambda = \sqrt{\Omega/\hat{\Omega}}$. We plotted both the theoretical curve (2) and the measured pdf of the prediction error β (through simulation) in Figure 1. Parameters ρ = 0.9965 and λ = 1.0204 were estimated through simulation and substituted into (2) to obtain the theoretical pdf. This prediction error will be used in the following sections to compute the BER of the adaptive modulation method.

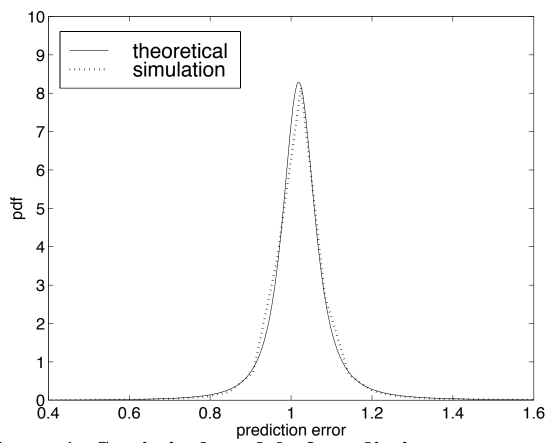

Figure 1. Statistical model of prediction error.

In the numerical and simulation results of this section and throughout the paper, the following parameters were used. The average channel power was normalized to unity. The Jakes model with 9 oscillators [10] can closely approximate the Rayleigh fading channel and was used as a standard fading model in our simulation. We set the maximum Doppler shift f_{dm} = 100 Hz. In linear prediction, the channel sampling rate was 500 Hz, the model order p = 50 and the observation interval = 100 samples. Thus, using one-step prediction, the channel was predicted 2 ms ahead. Finally, the symbol rate was 25 ksymbols/s, and the modulation switching rate was initially set to the symbol rate. Interpolation and multi-step prediction were utilized to predict the channel coefficients at the symbol rate as described in [7, 11].

(3) *Design Rule for the Modulation Level Selection:*

Given fixed transmitter power E_s(or average SNR level $\bar{\gamma} = E_s/N_0$), to maintain a target BER, we need to adjust the modulation size M according to the instantaneous channel gain $\alpha(t)$. In other words, the adaptive modulation scheme can be specified by the threshold values α_i, i = 1, …, 4 defined as: when $\alpha(t) \geq \alpha_i$, M_i-QAM is employed, where $M_1 = 2$, $M_i = 2^{2(i-1)}$, i > 1. When perfect CSI $\alpha(t)$ is available, these thresholds can be directly calculated from the BER bound of MQAM for an AWGN channel [1]: $BER_M \leq 0.2 \exp(-1.5\gamma/(M-1))$ for M>2, and $BER_2 = Q(\sqrt{2\gamma})$,where $\gamma = \alpha^2(t)\bar{\gamma}$ is the instantaneous received SNR. However, when the predicted CSI $\hat{\alpha}$ is used, the BER bound, say BER^*_M, can be obtained by evaluating the expectation of BER_M over β using $p_\beta(x)$ in (2). This indicates that we need to use BER^*_M to calculate thresholds rather than use BER_M when only the predicted CSI is available. (In a related technique in [2], noiseless delayed CSI is assumed available at transmitter, and the BER^*_M is calculated based on a conditional Rician distribution of the current channel amplitude.) However, we found that when long-term prediction is empoyed and the prediction error is obtained as described in Section (2), there is very small difference between the thresholds calculated using perfect CSI and BER^*_M. Thus, when using long range prediction, it is not necessary to compute new threshold values. This simplified approach is utilized in the following section.

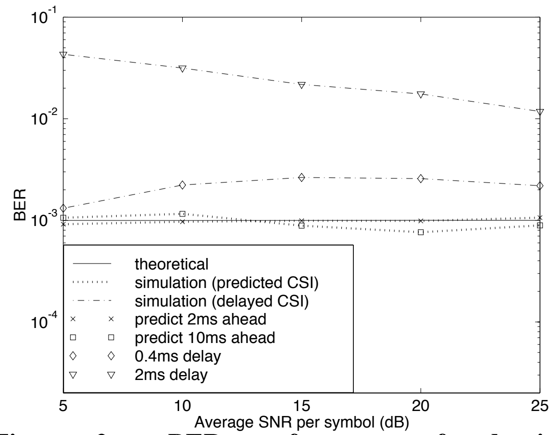

Figure 2. BER performance of adaptive modulation. (Jakes model, f_{dm} = 100 Hz)

(4) BER Performance of Adaptive Modulation Aided by Channel Prediction

We use predicted CSI $\hat{\alpha}$ to select the modulation level, while the thresholds are calculated based on the perfect CSI assumption. We set target $BER_{tg} = 10^{-3}$ and assume the modulation switching rate is 25 kHz. We considered both one-step (2 ms ahead) and five-step (10 ms ahead) prediction. In the five-step prediction, we employed a pre-training method to obtain accurate initial LP coefficients d_j in (1) (for details, refer to [14]). The results are shown in Figure 2. We can see that our long range prediction algorithm provides accurate enough CSI to maintain the target BER using the thresholds which are calculated based on the perfect CSI. However, when delayed CSI is used, and the thresholds are still calculated based on the perfect CSI (this procedure is called '*static design*' in [2]), the BER performance significantly departs from the target BER even for modest delays as can be seen from the dash-dotted lines in Figure 2. To alleviate this problem, Goeckel studied a novel approach (called '*strongly robust signaling design*') to calculate thresholds based on the delayed CSI in [2]. From the results in [2], we found that even very small delay will cause great loss of capacity for fast vehicle speeds when the strongly robust signaling design rule is used without long range prediction. Therefore, accurate channel prediction is necessary in adaptive modulation system. Our long range prediction algorithm satisfies these accuracy criteria, and provides enabling technology for adaptive modulation.

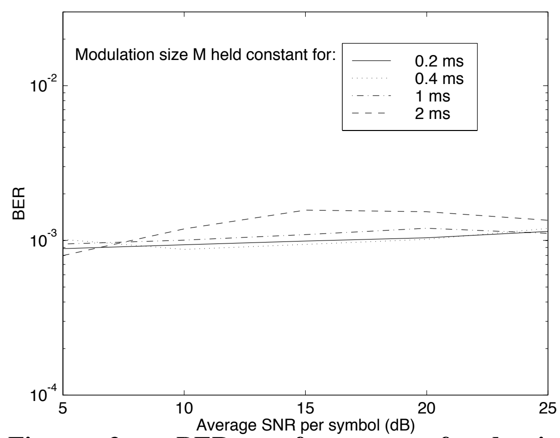

Figure 3. BER performance of adaptive modulation with different modulation switching rates.

Another practical consideration in adaptive modulation systems is how fast the transmitter can change its constellation size. This design rule is determined by two aspects: one is the rapidity of channel variation, and another is hardware limitation [1]. It was shown in [1] that for the maximum channel Doppler shift of 100 Hz, and a symbol rate of a 100 ksymbols/s, the signal constellation remains constant over tens to hundreds of symbols (0.1ms to 1ms). In Figure 3, we examined the BER performance of adaptive modulation aided by long range prediction for different modulation switching rates. The predicted channel powers were averaged over the future modulation switching interval to select the modulation level. This technique greatly improves system performance and makes lower switching rates available without significant average BER degradation.

3. Adaptive Modulation for Realistic Physical Model and Actual Field Measured Data.

Jakes model [10] used above is a stationary model in which the variation of channel parameters is not considered. We addressed realistic physical modeling for flat fading channels in [11, 12] to create non-stationary models to test our adaptive prediction algorithm. By comparing the shape of the autocorrelation function, the pdf of the amplitude and the fading envelope for this physical model and the actual measured data, we found that our physical model closely matches the actual fading channel. Thus, this physical modeling provides a realistic non-stationary fading model to validate our proposed prediction algorithm and its application in the adaptive modulation systems for both typical and worst case variation of channel parameters. In this paper, we further use the actual measured data to validate the adaptive modulation scheme aided by channel prediction. The actual field measurements were provided by Ericsson, Inc. and were collected in low density urban Stockholm. It contains 100,000 samples of the flat fading signal sampled at the rate of 1562.5Hz. Different portions of the data set had different shapes of the autocorrelation function. This indicates that the data was clearly non-stationary with differences in the number and location of the scatterers along the measurement track. For the segment of the data set used in this paper, the distribution of the amplitude and the autocorrelation function were close to those for the theoretical Rayleigh fading channel [13]. By examining the autocorrelation function for this section of the data set, the Maximum Doppler frequency shift was calculated to be 46 Hz which corresponds to the vehicle speed of 26.46 km/hr for the carrier frequency of 1877.5 MHz used in the measurement. We measured the BER performance of adaptive modulation for this data with and without channel prediction. The modulation switching rate is the same as the symbol rate set to 39 ksymbols/s. When prediction is used, the CSI predicted 1 and 3 steps ahead (0.64ms and 1.92ms, respectively) is used to determine the modulation level. Without prediction, we used 0.64ms and 1.92ms delayed CSI in the adaptive modulation scheme. The BER comparison is shown in Figure 4, and is consistent with the results for the stationary model in Figure 2.

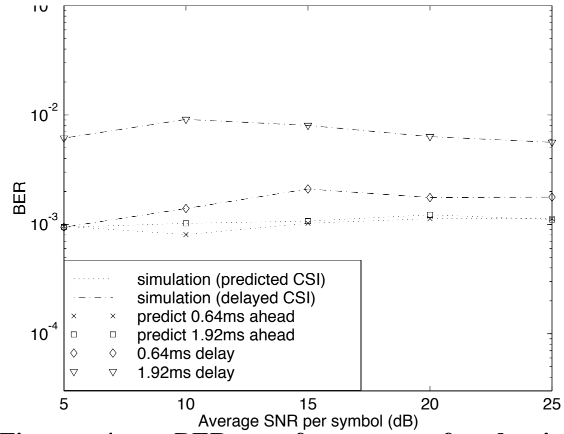

Figure 4. BER performance of adaptive modulation for measured data.

4. Conclusions and Future Works

We analyzed the statistical behavior of the errors generated by our previously proposed long range prediction algorithm, and evaluated performance of adaptive modulation for flat Rayleigh fading channels aided by predicted channel state information. Both theoretical and simulation results show that accurate prediction of the fading channel far ahead makes adaptive transmission feasible for rapidly time-varying mobile radio channels. Current and future work focuses on power adaptation, combined transmitter diversity and adaptive modulation, adaptive coded modulation and adaptive channel coding aided by the proposed prediction algorithm. We are also testing the application of long range prediction to adaptive transmission techniques for realistic channel models and actual measured data.

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