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Long Range Prediction Makes Adaptive Modulation Feasible for Realistic Mobile Radio Channels[1]

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Abstract--- ***Adaptive transmission techniques, such as adaptive modulation and coding, adaptive power control, adaptive transmitter diversity, etc., depend on the transmitter's ability to predict future behavior of the channel. Recently, we proposed a reliable long-range prediction algorithm for rapidly time variant fading channels. In this paper, we analyze the statistical behavior of the errors generated by this channel prediction method. We show that our prediction technique makes adaptive modulation feasible for a standard stationary fading channel model (Jakes model), a novel realistic physical channel model and measured data. In addition, we demonstrate that the non-stationarity of the realistic mobile radio channel limits performance of adaptive modulation as the prediction range increases.***

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 [1-6]. These adaptive modulation methods depend on accurate channel state information (CSI) that can be estimated at the receiver and sent to the transmitter via a feedback channel. This information would allow the transmitter to choose the appropriate transmitted signal. The feedback delay and overhead, processing delay and practical constraints on modulation switching rates have to be taken into account in the performance analysis of adaptive modulation methods. For very slowly fading channels (pedestrian or low vehicle speeds), *outdated* CSI is sufficient for reliable adaptive system design. However, for rapidly time variant fading that corresponds to realistic mobile speeds, even small delay will cause significant degradation of performance since channel variation due to large Doppler shifts usually results in a different channel at the time of transmission than at the time of channel estimation [1, 2]. To realize the potential of adaptive transmission methods, these channel variations have to be *reliably predicted* at least several milliseconds ahead.

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 depends 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 the transmitter, and also it was found that even very small delay causes significant loss of bit rate using the 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 was addressed in these investigations.

Recently, we have investigated a *novel adaptive long-range fading channel prediction algorithm* in [7 – 9, 11 - 16]. This algorithm characterizes the fading channel using an autoregressive (AR) model and computes the Minimum Mean Squared Error (MMSE) estimate of a future fading coefficient sample based on a number of past observations. The superior performance of this algorithm relative to conventional methods is due to its *low sampling rate* (on the order of twice the maximum Doppler shift and much lower than the data rate) [8, 9]. Given a *fixed model order*, the lower sampling rate results in *longer memory span*, permitting prediction further into the future. The prediction method is enhanced by an *adaptive tracking* method [8, 9] that increases accuracy, reduces the effect of noise and maintains the robustness of long-range prediction as the physical channel parameters vary. In addition to testing our method on standard stationary fading models [7-9], we utilize a method of images to create a novel physical channel model where fading is viewed as a deterministic process formed by the addition of several scattered components [11, 12]. The amplitude, frequency and phase of each component slowly vary as the vehicle moves through an interference pattern. The variation of these parameters is not captured by the standard Jakes model [10] or a stationary random process description [17]. However, the accuracy of the channel prediction is determined by the rate of change of these parameters. The novel physical model allows us to test the proposed channel prediction algorithm and identify typical and challenging situations encountered in practice. We also use

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field measurements provided by Ericsson, Inc. to validate the performance of our prediction method and the insights of the novel physical model [11 – 13, 16].

In this paper, we concentrate on the study of adaptive modulation in conjunction with the proposed long-range prediction algorithm for realistic mobile radio channels. After a brief description of our long-range prediction algorithm, we develop a statistical model of the CSI error for the MMSE prediction. This model can aid the appropriate modulation level selection. Moreover, the impact of the prediction accuracy on the switching thresholds of an adaptive modulation method can be easily understood from this error model. We examine the bit error rate (BER) gains of adaptive modulation aided by long range prediction, and demonstrate that accurate prediction is required to approach the ideal bit rate. Finally, we compare the BER performance of an adaptive modulation system aided by predicted CSI for the Jakes model, the actual field measured data and a novel non-stationary physical fading model. The effect of the non-stationarity on the prediction accuracy and the performance of adaptive modulation is examined.

2. Adaptive Modulation Using Long Range Channel 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 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: (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) <u>Long Range Prediction Algorithm for Fast Fading Channels</u>

The objective of long-range 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:

$$\hat{c}_n = \sum_{j=1}^{p} d_j c_{n-j} \qquad (1)$$

where the coefficients d_j are determined by the orthogonality principle. The lower sampling rate allows to predict further ahead for the same model order p [9]. 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) <u>Statistical Model of the Prediction Error</u>

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 with the joint probability density function (pdf) [19]:

$$f(\alpha,\hat{\alpha}) = \frac{4\alpha\hat{\alpha}}{(1-\rho)\Omega\hat{\Omega}} I_0\left(\frac{2\sqrt{\rho}\alpha\hat{\alpha}}{(1-\rho)\sqrt{\Omega\hat{\Omega}}}\right) \exp\left(-\frac{1}{1-\rho}\left(\frac{\alpha^2}{\Omega} + \frac{\hat{\alpha}^2}{\hat{\Omega}}\right)\right) \qquad (2)$$

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 I_0 is the 0^{th}-order modified Bessel function. We define the prediction error β as the ratio of the actual fading gain α and the predicted fading gain $\hat{\alpha}$, i.e., $\beta = \frac{\alpha}{\hat{\alpha}}$. From ([20], p. 138), the pdf of β can be calculated based on the equation:

$$p_\beta(x) = \int_0^{+\infty} \hat{\alpha} f(x\hat{\alpha}, \hat{\alpha})\, d\hat{\alpha} \qquad (3)$$

Where $f(\cdot, \cdot)$ is the joint pdf of α and $\hat{\alpha}$ as in (2). From [18]:

$$I_0(x) = \frac{1}{\pi}\int_0^{\pi} e^{-x\cos\theta} d\theta \qquad (4)$$

Substituting (4) into (2) and integrating by parts in (3), we obtain:

$$p_\beta(x) = \frac{2x(\frac{1}{\lambda}x^2 + \lambda)(1-\rho)}{((\frac{1}{\lambda}x^2+\lambda)^2 - 4\rho x^2)^{1.5}} \qquad (5)$$

where $\lambda = \sqrt{\Omega/\hat{\Omega}}$. We plotted both the theoretical pdf curve (3) and the measured pdf of the prediction error β (through simulation) in Figure 1. Parameters $\rho = 0.9965$ and $\lambda = 1.0204$ were estimated through simulation and substituted into (2) to obtain the theoretical pdf.

(3) <u>Design Rule for the Modulation Level Selection</u>

Given fixed transmitter power E_s(or the 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

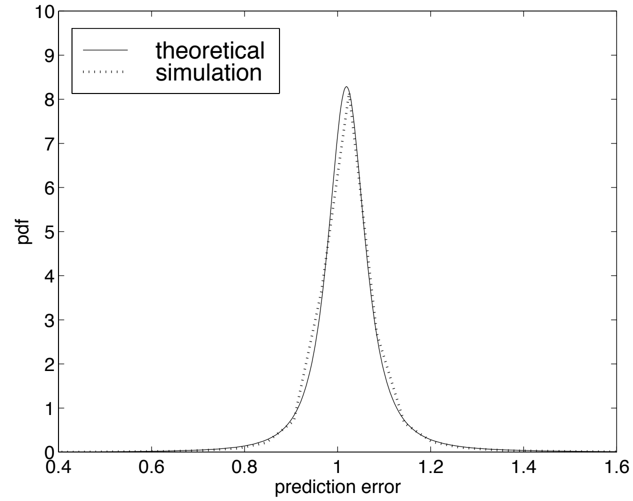

Figure 1. Statistical model of prediction error. (9-oscillator Jakes Model, f_{dm} = 100 Hz, p = 50, 1-step (2ms) ahead prediction, noiseless observations.)

thresholds can be directly calculated from the BER bound of MQAM for an AWGN channel [1]:

$$BER_M \le 0.2 \exp(-1.5\gamma(t)/(M-1)) \text{ for } M>2, \text{ and}$$

$$BER_2 = Q(\sqrt{2\gamma}), \tag{6}$$

where $\gamma(t) = \alpha^2(t)\bar{\gamma}$ is the instantaneous received SNR. However, when the predicted CSI $\hat{\alpha}(t)$ is used, the current channel condition is characterized by the distribution of $p(\alpha|\hat{\alpha})$ which can be calculated as:

$$p_{\alpha|\hat{\alpha}}(x) = \frac{1}{\hat{\alpha}} p_\beta\left(\frac{x}{\hat{\alpha}}\right) \tag{7}$$

Then, the BER bound for predicted CSI $\hat{\alpha}$, say BER^*_M, can be obtained by evaluating the expectation of BER_M over β using $p_\beta(x)$ in (2) as:

$$BER^*_M = \int_0^\infty BER_M(\bar{\gamma}x^2) p_{\alpha|\hat{\alpha}}(x)dx \tag{8}$$

$$= \int_0^\infty BER_M(\bar{\gamma}x^2\hat{\alpha}^2) p_\beta(x)dx \tag{9}$$

This indicates that we need to use BER^*_M rather than BER_M to calculate thresholds when only the predicted CSI is available[2]. (In a related technique in [2], noiseless delayed CSI is assumed available at the transmitter, and the BER^*_M is calculated based on a conditional Rician distribution of the current channel amplitude.)

For flat Rayleigh fading channels, the probability density function of the amplitude $\alpha(t)$ (for perfect CSI) is given by:

$$p_\alpha(x) = \frac{2x}{\Omega} \exp\left(-\frac{x^2}{\Omega}\right), \tag{10}$$

where Ω is the average power of the channel. From [4, 5], the average number of bits per symbol for adaptive modulation with perfect CSI can be expressed as:

$$R_{ada} = \sum_{i=1}^{4} \log_2 M_i \int_{\alpha_i}^{\alpha_{i+1}} p_\alpha(x)dx, \tag{11}$$

where α_i are the threshold values and $\alpha_5 = \infty$. Similarly, when the thresholds $\hat{\alpha}_i$ calculated based on BER^*_M are used, R_{ada} can be computed as:

$$\hat{R}_{ada} = \sum_{i=1}^{4} \log_2 M_i \int_{\hat{\alpha}_i}^{\hat{\alpha}_{i+1}} p_{\hat{\alpha}}(x)dx, \tag{12}$$

where the pdf of predicted amplitude $\hat{\alpha}(t)$ is given by:

$$p_{\hat{\alpha}}(x) = \frac{2x}{\hat{\Omega}} \exp\left(-\frac{x^2}{\hat{\Omega}}\right). \tag{13}$$

The results of this section will be used in the rest of the paper to evaluate performance of adaptive modulation when prediction is used.

3. Performance of Adaptive Modulation Aided by Channel Prediction for Realistic Mobile Radio Channels

Jakes model [10] is often used as a standard simulation model for the Rayleigh fading channel. However, the variation of channel parameters associated with the scatterers (amplitudes, frequencies and phases) is not captured by this *stationary* model or by the *stationary* Rayleigh random process characterization. We addressed realistic physical modeling for flat fading channels in [11, 12] and created *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 to adaptive modulation systems for both typical and challenging cases of channel parameter variation. The actual field measurements were provided by Ericsson, Inc. and were collected in low density urban Stockholm. This dataset contains 100,000 samples of the flat fading signal sampled at the rate of 1562.5Hz. Different portions of the data set have different shapes of the empirical 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. By adjusting the types and positions of the scatterers in our physical model, we were able to match the autocorrelation functions of different data set segments to those produced by the model [12, 15]. These experiments provided us with insights into the nature of flat fading and the impact on the prediction accuracy.

In this paper, we use the Jakes model, the actual measured data and the physical model to validate the adaptive modulation scheme aided by channel prediction. Also, we will show the impact of non-stationarity on the performance of adaptive modulation. For the segment of the actual measured data set used in this paper, the distribution of the amplitude and the empirical autocorrelation function were close to those for the theoretical isotropic Rayleigh fading channel [12, 15]. Physical model data to match this segment was generated by placing several curved randomly distributed scatterers along two sides of the track of the mobile so that the image-sources subtended a large angle from the mobile. In addition, the Jakes model with 9 oscillators was used as the stationary model in the following

[2] Here, we didn't address the threshold optimization. For the method of threshold selection to maximize the average bit rate, refer to [21, 22].

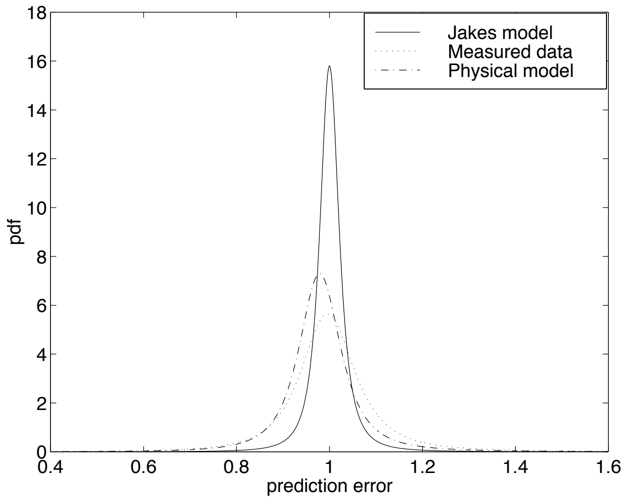

Figure 2. Statistical model of prediction error. (1.92ms ahead prediction, f_{dm} = 46Hz, p=40, noiseless observations)

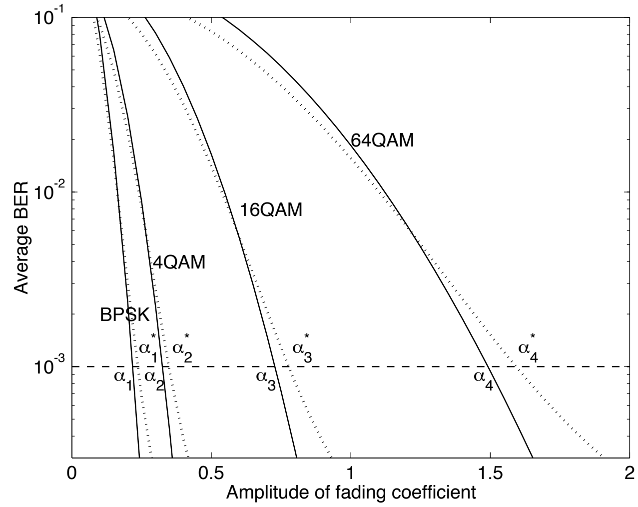

Figure 3. Comparison of threshold α_i calculated based on perfect CSI and thresholds α_i* calculated based on predicted CSI. Solid: BER bound for perfect CSI; Dotted: BER bound for predicted CSI; Dashed: target BER = 10^{-3}. SNR = 20dB per symbol. 3-step (1.92ms) prediction of measured data. ρ = 0.9921 and λ = 0.9985. f_{dm}=46Hz.

performance comparison. The Maximum Doppler shift of 46 Hz was used in both the physical model and the Jakes model. The fading signal was sampled at the rate of 1562.5 Hz. In linear prediction, the model order p = 40 and the observation interval = 100 samples. Finally, the symbol rate was 39 ksymbols/s, and the modulation switching rate was set to the symbol rate. Interpolation and adaptive multi-step prediction were utilized to predict the channel coefficients at the symbol rate as described in [7, 11].

In the following presentation of performance of the adaptive modulation aided by channel prediction, we considered both 3-step (1.92ms ahead) and 5-step (3.2ms ahead) prediction. Here, we employed a pre-training method to obtain accurate initial LP coefficients d_j in (1) [14], and used post-tracking method to track the variation of channel parameters. For the 3-step prediction, the parameters ρ = 0.9990 and λ = 1.0003 in (5) were estimated through simulation for the Jakes model. For the measured data, ρ = 0.9921 and λ = 0.9985, and for the physical model, ρ = 0.9951 and λ = 0.9805. These parameters were substituted into (5) to obtain the theoretical pdf curves shown in Figure 2. We observe that our physical model has almost the same statistical behavior of the prediction error as the actual measured data.

The BER bounds (6, 8) for both perfect and predicted CSI (here we only considered the case of actual measured data since its correlation ρ is the smallest) are shown in Figure 3. We can see that there is small difference between the thresholds calculated using perfect CSI (solid line) and predicted CSI (dotted line). Next, we compare the BER performance of adaptive modulation for the three datasets with and without channel prediction. Here, 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 $BER_{tg} = 10^{-3}$. The results are shown in Figure 4. Note that for all datasets 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. To alleviate this problem, Goeckel

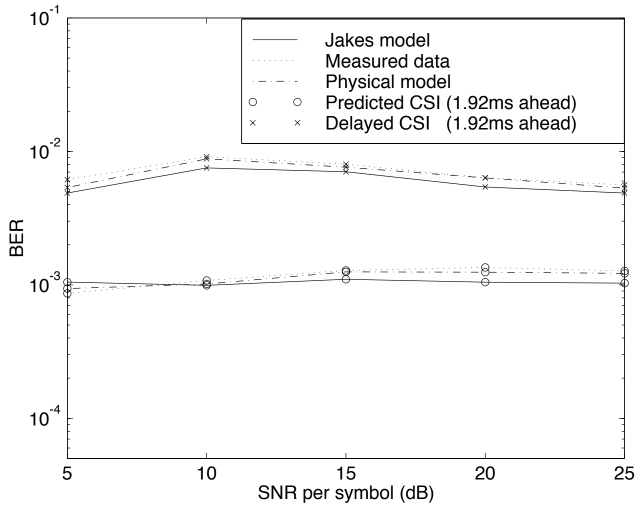

Figure 4. BER performance of adaptive modulation with and without prediction. Thresholds α_i are used. (f_{dm} = 46Hz)

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 bit rate for fast vehicle speeds when the strongly robust signaling design rule is used without long range prediction. E.g., 1.92ms delay for f_{dm}=46Hz corresponds to ρ = 0.92 in [2] which causes at least 1bit/symbol data rate loss relative to the ideal case. As shown in Fig.4, under the same conditions, the long-range prediction preserves the ideal bit rate while maintaining the target BER. Thus, *accurate long-range prediction is required to achieve the bit rate gain of adaptive MQAM for rapid vehicle speeds and realistic delays.*

Comparison of the Jakes model to the physical model and the measured data reveals that the non-stationarity limits performance of adaptive modulation as the prediction range increases. For example, consider 5-step (3.2ms) prediction in Figures 5 ~ 8. The parameters ρ = 0.9948 and λ = 1.0013 for

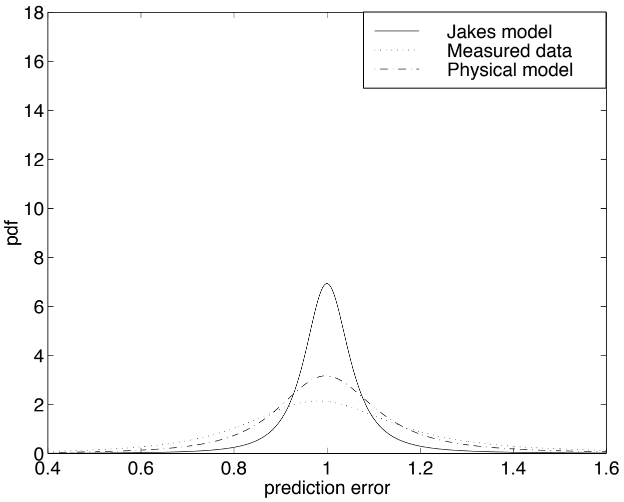

Figure 5. Statistical model of prediction error. (3.2ms ahead prediction) f_{dm}=46Hz, p=40, noiseless observations.

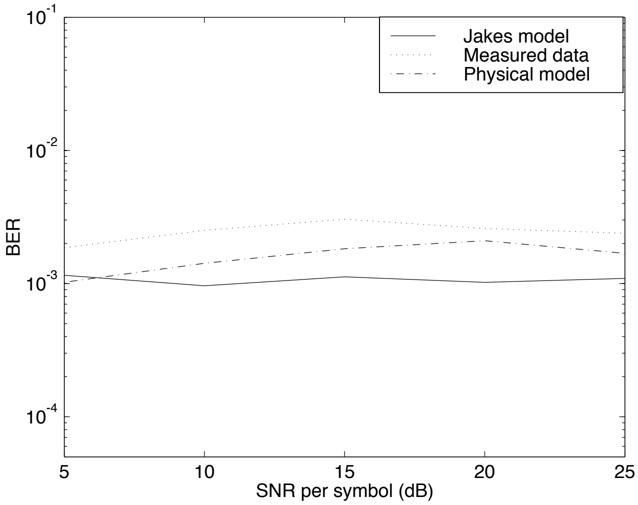

Figure 7. BER performance of adaptive modulation with 5-step (3.2ms ahead) prediction. Thresholds α_i are used. (f_{dm} = 46Hz)

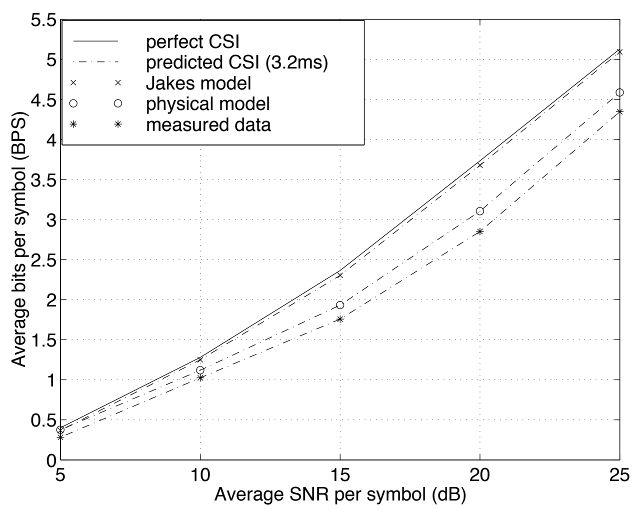

Figure 8. Comparison of average bit rate performance of adaptive modulation for *stationary* data (Jakes model) and *non-stationary* data (physical model and measured data) 3.2ms ahead prediction, target BER = 10^{-3}, f_{dm}=46Hz.

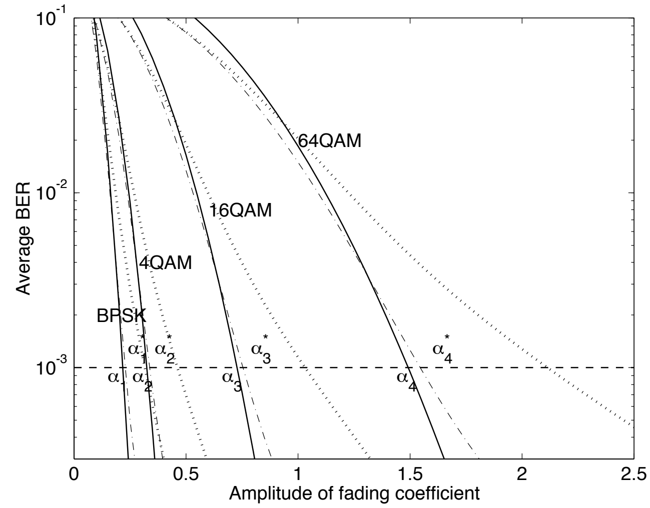

Figure 6. Comparison of thresholds α_i* calculated based on predicted CSI for the Jakes model and measured data. Solid: BER bound for perfect CSI; Dotted: BER bound for predicted CSI (measured data, ρ = 0.9442 and λ = 0.9999.); Dash-Dotted: BER bound for predicted CSI (Jakes model, ρ = 0.9948 and λ = 1.0013); Dashed: target BER = 10^{-3}. SNR per symbol = 20dB. 5-step (3.2ms) prediction. f_{dm}=46Hz.

the Jakes model, ρ = 0.9442 and λ = 0.9999 for the measured data, and ρ = 0.9751 and λ = 1.0055 for the physical model data were estimated through simulations. The theoretical pdf curves of prediction errors (5) for these three datasets are plotted in Figure 5. The statistical behavior of prediction errors as the prediction range increases can be observed by comparing Figures 2 and 5. The BER bounds BER^*_M for the Jakes model and the measured data are plotted in Figure 6. We found that, for the *stationary* Jakes model, even for the 5-step (3.2ms) ahead prediction, the difference between the thresholds calculated based on the perfect and predicted CSI is still small. (This difference remain very small for delays of up to 10 ms, or up to λ/2, where λ is the wavelength.) However, for the *non-stationary* measured data, the differences become nonnegligible. The need to use modified thresholds for non-stationary data when the delay is significant is illustrated in Fig.7. In this figure, the thresholds calculated based on the perfect CSI were used in the simulation. We observe that for the Jakes model, the target BER is still maintained even for 5-step prediction, while for the physical model data and for the measured data, there is some departure from the target BER. Thus, to satisfy the target BER requirement (say, 10^{-3} in this paper), we need recalculate the thresholds for realistic fading channels. This modifications degrades the bit rate performance as illustrated in Figure 8. In this figure, we calculated the thresholds based on BER^*_M for the Jakes model, physical model data and measured data, and plotted the average bit rate per symbol as in equation (12). We found that the bit rate loss is about half a bit for non-stationary data relative to the stationary case. (Although the non-stationarity results in reduction of the bit rate relative to the ideal case when the long range prediction is employed, the bit rate is still significantly larger than when outdated CSI is used to calculate the threshold [2]. For example, the same delay of 3.2ms for f_{dm}=46Hz corresponds to correlation coefficient ρ = 0.8 in [2]. This results in the bit rate of about 0.8 bits/symbol for the target BER = 10^{-3} and the SNR per symbol = 15dB assuming stationary Rayleigh fading model, while the long range prediction allows to achieve the bit rate of about 1.8 bits/symbol for non-stationary measured data, and the near-ideal rate for the stationary model). The limitations of the linear long range prediction method due to parameter variation in realistic fading environments indicate that other techniques need to be explored to increase prediction range further (e.g. see references in [12, 15]).

Another practical consideration in adaptive modulation systems is the rate of change of the constellation size at transmitter. The design rule is determined by the rapidity of channel variations and hardware limitations [1]. The derivation in [1] shows that for the maximum Doppler shift of 100 Hz, and a symbol rate of a 100 ksymbols/s, the signal constellation remains constant on the average over tens to hundreds of symbols (0.1ms to 1ms). In practice, it might be desirable to choose a constant modulation level for a fixed frame of certain duration. We found that it is not sufficient to predict the CSI at the beginning of the frame, so we use the long range prediction to forecast the fading power during the upcoming interval of fixed length, and choose the modulation level by averaging this predicted CSI. In Figure 9, we examined the BER performance of adaptive modulation aided by long range prediction for different modulation switching rates (different frame duration). Observe that modulation size can be held constant for long intervals (up to 2ms) without significant average BER degradation. This result indicates that practical implementation of adaptive modulation is possible for realistic mobile radio systems.

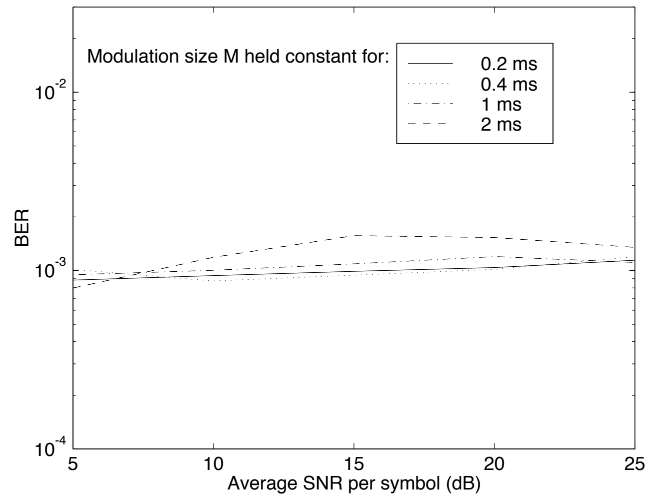

Figure 9. BER performance of adaptive modulation with different modulation switching rates. (Jakes model, f_{dm} = 100Hz)

4. Conclusions And Future Work

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. We also showed that the non-stationarity limits the performance of adaptive modulation aided by long-range prediction as the prediction range increases. 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

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