Adaptive Prediction, Tracking and Power Adjustment for Frequency Non-Selective Fast Fading Channels[1]

Tugay Eyceoz, Shengquan Hu, Alexandra Duel-Hallen
North Carolina State University
Dept. of Electrical and Computer Engineering
Center for Advanced Computing and Communication
Box 7914, Raleigh, NC 27695-7914
E-mail: {teyceoz, shu, sasha}@eos.ncsu.edu,

Hans Hallen
North Carolina State University
Physics Department
Box 8202, Raleigh, NC 27695-8202
E-mail: Hans_Hallen@ncsu.edu

Abstract -- **Recently, the authors introduced a novel algorithm for long range prediction of fading channels [1-4]. This algorithm finds the linear Minimum Mean Squared Error (MMSE) estimate of the future fading coefficients given a fixed number of previous observations. In this paper, we show that the superior performance of this algorithm is due to its lower sampling rate relative to the conventional (data rate) methods of fading prediction. We also enhance the algorithm by an adaptive prediction and tracking method that increases accuracy and maintains the robustness of long-term prediction as the physical channel parameters vary. Finally, we show that large improvements in the bit error rate (BER) are possible when the proposed prediction method is used. In particular, analysis of the channel inversion with threshold technique is presented to demonstrate that the BER can be reduced to the level of and beyond the additive white Gaussian noise (AWGN) channel.**

1. INTRODUCTION

It is well known that deep fades in signal power due to multipath radio propagation severely degrade the performance of mobile radio systems and impose high power requirements [5-7]. Since the channel changes rapidly, the transmitter and receiver are not generally optimized for current channel conditions, and thus fail to exploit the full potential of the wireless channel. The shorter wavelengths proposed for future mobile radio will only serve to aggravate these problems.

Propagation studies in a variety of environments show that the multipath signal consists primarily of a small number of discrete sinusoidal components (often 10 or fewer) [1, 4, 5]. The superposition of these components changes rapidly as the vehicle moves, producing the familiar fast-fading signal envelope observed in practice. However, the amplitude, frequency and phase of each component change on a much slower time scale, e.g. on the order of 100 times the coherence time of the signal envelope. This variation is slow enough that the fading coefficient can be predicted far beyond the coherence time. In particular, these estimates can be used to *forecast signal fades before they occur*. This prediction capability can provide enabling technology for adaptive coding [8-10], accurate power control, reliable transmitter and/or receiver diversity and many other components of wireless systems.

In [1-3], we described the prediction algorithm which characterizes the channel as an autoregressive model (AR) with slow sampling rate, and computes the 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 for a flat fading channel with an arbitrary number of scatterers. In Section 2, we provide the insight into the performance gains of this prediction technique relative to the traditional approaches [11]. In Section 3, we augment the algorithm in [1-3] with an adaptive method which reduces error propagation and tracks channel parameter variations. Finally, performance gains made possible by channel prediction are illustrated by analyzing the channel inversion with threshold method in Section 4.

2. PREDICTION OF THE FLAT FADING CHANNEL

In this work, we concentrate on flat fading signals which result from interference between several coherent scattered components. The received signal is given by [5]

$$c(t) = \sum_{n=1}^{N} A_n e^{j(2\pi f_n t+\phi_n)}, \qquad (1)$$

where (for the n^{th} scatterer) A_n is the amplitude, f_n is the Doppler frequency, and ϕ_n is the phase. Due to multiple scatterers, the fading signal varies rapidly for large vehicle speeds and undergoes "deep fades". Our approach to prediction of future fading conditions is based on the fact that the parameters A_n, f_n and ϕ_n vary much slower than the actual fading coefficient c(t).

The discrete-time system model at the output of the matched filter and sampler is given by

$$y_k = c_k b_k + z_k, \qquad (2)$$

where c_k is the fading signal c(t) sampled at the symbol rate, b_k is the data sequence, and z_k is the discrete AWGN process. Even for a modest number of scatterers, c(t) and c_k can be accurately modeled as correlated complex Gaussian random processes with Rayleigh distributed amplitudes and uniform phases [5-7], where the accuracy increases as N in (1) grows. In contrast to conventional channel estimation, our objective is to predict the future behavior of the fading coefficient, c_k, rather than to estimate its current value because even with perfect estimation, communication over fading channels is severely limited due to fades. By prediction we imply estimating an *entire* future block of coefficients c_k based on the observation of the received signal during an earlier time interval.

Our linear prediction (LP) method is based on the AR channel modeling [1]. We form the linear MMSE prediction

[1] This research was supported by CACC (NC State University) and NSF grants CCR-9725271 and NCR-9726033

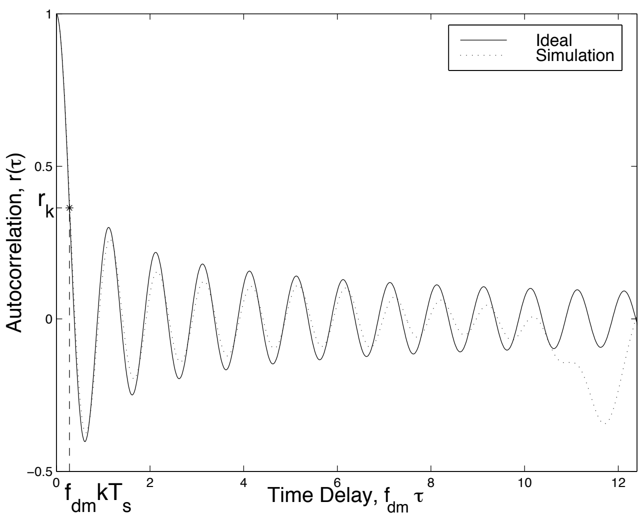


Figure 1. The theoretical autocorrelation function for the Rayleigh fading channel (solid line) and the experimental autocorrelation function for N=16 oscillators (dotted line)

of the future channel sample $\hat{c}_n$ based on p previous channel samples $c_{n-1} \ldots c_{n-p}$:

$$\hat{c}_n = \sum_{j=1}^{p} d_j c_{n-j} \qquad (3)$$

(Actually, the estimates of the past samples c_{n-j} are used beyond the observation interval.) Note that the samples have to be taken at least at the Nyquist rate, which is twice the maximum Doppler frequency, f_{dm} [5,6]. The sampling rate we choose is close to this Nyquist rate and therefore is much lower than the data rate in (2). The predicted samples are interpolated to forecast the fading signal at the data rate [1-3]. To date, most investigations of fading channel modeling and estimation assume sampling at the data rate (e.g., [11]). As a result, even with very accurate coefficient adjustment, it is impossible to specify future channel coefficients from past observations — the filter length is not long enough. This can be illustrated by considering the parameters involved in the MMSE prediction.

We concentrate on the case when N in (1) is infinite (Rayleigh fading), although the discussion below also applies to the more practical case of a modest number of scatterers with the underlying channel parameters varying slowly. The channel is modeled as the complex stationary Gaussian process with the autocorrelation function $r(\tau) = J_0(2\pi f_{dm}\tau)$, where $J_0(.)$ is the zero-order Bessel function of the first kind [5]. The plot of this function and of the experimentally obtained autocorrelation function for N=16 are shown in Figure 1. For illustration, let us fix the data rate at 25Kbps, the maximum Doppler shift at 100Hz, and the sampling rate at 500Hz (2.5 times the Nyquist rate). We consider the LP of order p, where the objective is to find the model coefficients d_j which minimize the MSE, $E[|e|^2]=E[|c_k - \hat{c}_k|^2]$, where c_k is an arbitrary future fading coefficient, and $\hat{c}_k$ is its estimate given by the linear combination of p past samples (0 is the reference time, so the observations are taken prior to $\tau = 0$):

$$\hat{c}_k = \sum_{j=0}^{p-1} d_j c_{-j} \qquad (4)$$

The minimum MSE is given by

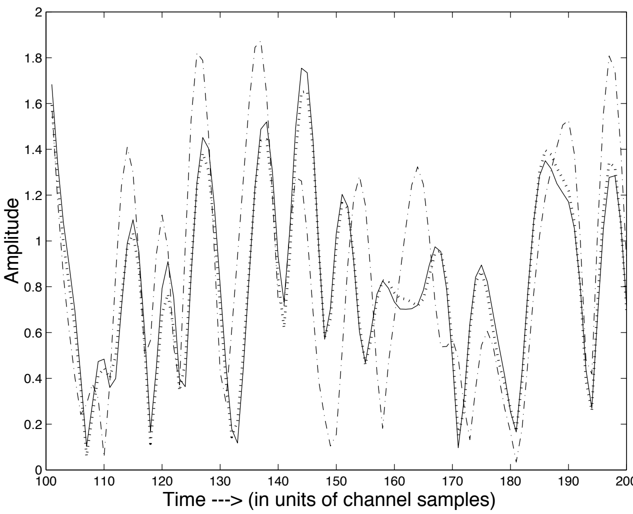
$$E[|e|^2] = 1 - \sum_{j=0}^{p-1} d_j r_{k+j} \qquad (5)$$

where $r_m = E[c_n c^*_{n+m}]$ (see Figure 1).

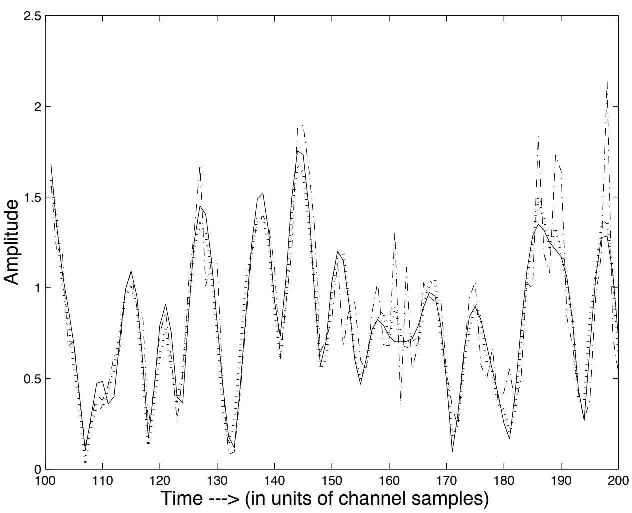
Now, suppose we fix p and assume that the past observations in (4) are taken at the data rate of 25KHz. These observation are spaced at 1/250 of a normalized time (x-axis) unit of Figure 1. Thus, all the observation are very close to each other and the time $\tau = 0$ in Figure 1 (they span only a fraction of a single unit (-1,0]), even if p is reasonably large. Thus, the autocorrelation values, r_{k+j}, used in (5) are all approximately the same and close in value to r_k (Figure 1). When the future sample to be predicted is located further than a few bits from the observations, these autocorrelations become small, and the MSE (5) increases. In particular, if we try to predict the future coefficient about half a unit ahead (this corresponds to the first zero-crossing of the autocorrelation function and is often defined in terms of the coherence time τ_0 as approximately $2\pi\tau_0$ [7]), all these autocorrelations become negligible, and prediction becomes impossible.

Now, let us consider prediction at the lower sampling rate of 500Hz. It is interesting to observe that multiples of half-units of the x-axis in Figure 1 corresponds to spacing between the samples taken at the Nyquist rate. Since we oversample, our observations are spaced at 1/5 of the single time unit - still much further apart than the observations taken at the data rate. Thus, the autocorrelation values used in (5) significantly vary and the samples are sufficiently separated to achieve reliable long term prediction. Even when some autocorrelations are low, the others are large, since they result from sampling large sidelobes of the autocorrelation function (not accessible when the data rate is used). As a result, the MSE (5) is much smaller. Thus, when the sampling rate is reduced greatly relative to the data rate, but the filter length p remains the same, prediction much further ahead becomes feasible [12]. For our method, the future point is just the next sample at the same sampling rate as used for the observations (see (3)). Since it might be desirable to predict further ahead than one sample, we use the sliding window approach (3) to predict c_{n+1}, c_{n+2}, ... , and substitute estimates on the right-hand side of (3) when the observations points are no longer available. Since we often refer to two different rates in this paper, we will use the index k for the data rate, and index n for the lower sampling rate throughout.

By using the proposed prediction algorithm, we can successfully predict future channel parameters [1-3]. In order to access performance advantages of the proposed prediction technique relative to the conventional approach, the following channel inversion with threshold method is investigated [3, 13]. The channel samples taken during the observation interval are sent to the transmitter, which applies the linear prediction, and interpolates to produce predicted fading values at the data rate. The prediction method beyond the observation interval is adaptive and also involves feedback as explained in Section 3. The transmitter interrupts the transmission for the k-th symbol if the power level, $|\hat{c}_k|^2$, is below previously chosen threshold value. Furthermore, if $|\hat{c}_k|^2$ is above the threshold, the transmitter sends the data bits, b_k,



(a) Prediction error for noise-free channel.
dotted: predicted using past actual values;
dash-dotted: using previously predicted values.



(b) Prediction error for the channel inversion method (threshold=0.1, snr=15dB).
dash-dotted: predicted using noisy low rate samples;
dotted: predicted with adaptation of a_k only.

Figure 2. Prediction error reduction using adaptive prediction and tracking. Prediction error for the nine-oscillator model during the prediction interval is shown.

by multiplying them with the inverse of the predicted $\hat{c}_k$ values (3). 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 [8-10]. The bit error rate and the throughput of this method are analyzed in Section 4. First, we discuss in the following section the adaptive channel prediction and tracking method used jointly with the channel inversion technique.

3. ADAPTIVE PREDICTION AND TRACKING

In [1-3], we described how channel parameters d_j and future estimates $\hat{c}_n$ are obtained from the initial observations of the fading channel. We refer to the number of observation samples as the observation interval. The main factors which affect the prediction accuracy of this algorithm can be summarized as: (a) previously predicted values used to predict the future fading coefficients (in (3), $\hat{c}_{n-j}$ is used instead of c_{n-j} later in the prediction); (b) limited number of observations used in initial acquisition of the LP coefficients (short observation interval); (c) limited order p of the AR model; (d) fixed LP coefficients d_j used throughout the entire future prediction block; (e) additive noise and decision-directed tracking.

Factor (a) causes error propagation later in the prediction and often makes prediction accuracy unacceptable as shown in Figure 2a. In practice, it is not necessary to predict ahead further than a few samples (several hundred of data symbols). As new actual observations are collected, they can be used in the LP equation. This significantly reduces error propagation as shown in Figure 2a where the range of prediction is one symbol (50 bits in this case). Larger ranges (several symbols) result in similar performance as can be observed from the initial segment of the dash-dotted curve of Fig. 2a.

Factors (b-d) result in inaccurate channel modeling. In particular, the constant parameter assumption in the deterministic model, e.g. the incident angle of radio wave (and the Doppler shift), are assumed constant during a data block) is not strictly true, and thus (d) causes parameter mismatch [4,15]. For example, as mentioned in [14], for the mobile moving at 30m/s (≈ 67.5 miles/h), the incidence angle changes at the rate of 4.2°/s (with respect to a base station 3km away). Consequently, learning the fast fading channel using just the observation samples is not sufficient.

Finally, the additive noise and decision-directed tracking (e) result in poor prediction accuracy. In this paper, Least Mean Squares (LMS) adaptive tracking method is employed in conjunction with the channel inversion algorithm to mitigate the channel mismatch and to improve prediction accuracy. When channel inversion is employed at transmitter, and the predicted channel power is above the specified threshold, the new modified discrete-time received signal is given by:

$$y_k = a_k b_k + z_k, \tag{6}$$

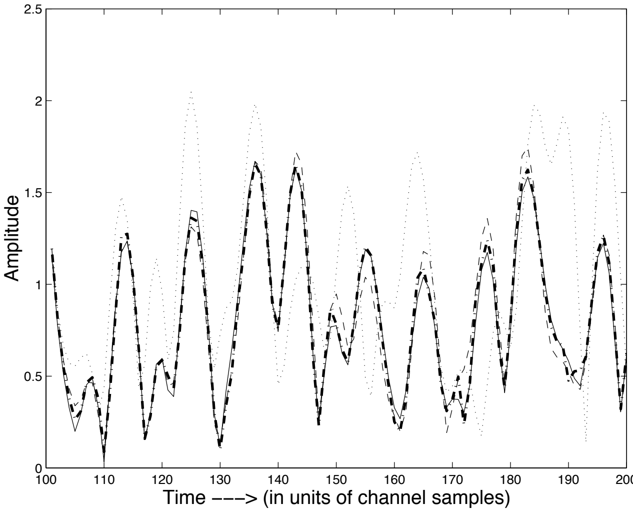
where the prediction accuracy factor $a_k = \frac{c_k}{\hat{c}_k}$. When the prediction gets better, the value of a_k approaches 1. We use the LMS adaptive algorithm to track the variation of the factor a_k at the data rate at the receiver as:

$$\tilde{a}_{k+1} = \tilde{a}_k + \mu e_k \hat{b}_k^*, \tag{7}$$

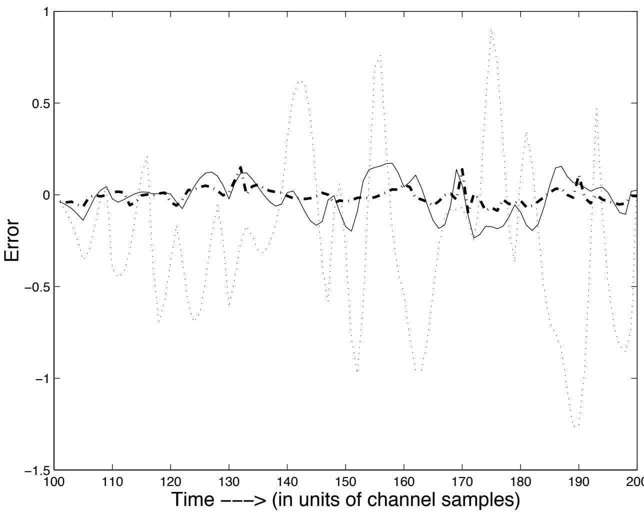
where μ is the step-size controlling the convergence rate, $\hat{b}_k$ is the decision of b_k, and error signal e_k is defined as:

$$e_k = y_k - \tilde{y}_k = y_k - \tilde{a}_k \hat{b}_k \tag{8}$$

Adaptive tracking of a_k is beneficial when noise is non-negligible and/or decision-directed operation is desired. Since variation of a_k is not significant, the convergence is better than for channels without inversion. The estimate $\tilde{a}_k$ is used for coherent detection. In addition, the updated factor $\tilde{a}_n$ is sent back to transmitter at the low sampling rate and used to update previously predicted fading channel coefficient $\hat{c}_n$ as



(a) Solid: actual channel samples; dash-dotted: predicted with adaptive tracking; dashed: predicted using actual past samples with fixed parameters d_j; dotted: no adaptation



(b) Prediction error comparison. Solid: predicted using actual past samples with fixed parameters d_j; dash-dotted: predicted with adaptive tracking; dotted: no adaptation

Figure 3. Comparison of prediction accuracy for the nine-oscillator model with the incidence angle variation of 4.2°/s.

$$\tilde{c}_n = \tilde{a}_n \hat{c}_n, \tag{9}$$

When the estimates $\tilde{c}_{n-j}$ are used in (3) to predict future samples, the prediction accuracy is maintained even in the presence of additive noise as illustrated in Figure 2b, where the performance of this adaptive approach is compared with prediction using the estimates of c_{n-j} obtained from noisy received samples (6) as $y_{n-j}\hat{c}_{n-j}$ at the same low sampling rate (it is assumed that $b_{n-j}=1$). The performance of the adaptive approach is almost the same as using actual noise-free values in the prediction (Fig. 2a). In Fig. 2, the range of prediction is one symbol (50 data bits). In practice, a greater prediction range might be desired, and previously predicted $\hat{c}_{n-j}$ might have to be used in (3) for a few recent samples, but this does not significantly increase the propagation error.

In addition to the error propagation problem, short observation interval and the time-variant channel model also significantly affect the prediction accuracy. These factors are mainly reflected in the LP coefficients d_j in (3). The LMS algorithm for updating model parameters is:

$$\underline{d}(n+1) = \underline{d}(n) + \eta e_n \underline{\tilde{c}}_n^* \tag{10}$$

where η is the step-size, $\underline{d}(n)=(d_1(n), \ldots d_p(n))$ is the time-dependent vector of channel model parameters (see (3)), $\underline{\tilde{c}}(n) = (\tilde{c}_{n-1}, \ldots, \tilde{c}_{n-p})$ is the vector of updated channel estimates, and the error signal,

$$e_n = \tilde{c}_n - \hat{c}_n. \tag{11}$$

The improvement in prediction accuracy using joint adaptive tracking of a_k's and d_j's is illustrated in Figure 3 for the channel with parameter variation and high SNR. Simulation results show that the predicted values using adaptive tracking method follow very closely the actual channel envelope. Again, in practice, the parameters d_j could be updated with a delay of several samples without significantly degrading performance.

In this section, we assumed that the decision $\hat{b}_k$ was given by the actual data b_k, the threshold was chosen as 0.1, and while the power of the predicted coefficient was below the threshold, the parameters d_j were not updated. The observation interval was 100 samples, and the order p=60. We are currently investigating adaptive prediction and tracking for lower SNR values, different thresholds, shorter observation intervals and orders p [12]. Our results suggest that prediction for a wide range of parameters is feasible. We are also able to predict accurately even if the number of scatterers is very large. In addition, we are applying this algorithm to realistic datasets obtained by the method of images [4, 15] and systems with diversity [16].

4. Performance Analysis of the Channel Inversion with Threshold Algorithm

In the bit error rate (BER) simulations, we assumed coherent detection and used Binary Phase Shift Keying (BPSK) modulation scheme. Given binary signal b_k and $E(|c_k|^2) = 1$, the signal-to-noise (SNR) is $\gamma_b = \frac{E(b_k^2)}{N_0}$. The BER for the conventional detector and the channel inversion with threshold method for the nine-oscillator model without channel parameter variation are plotted in Figure 4. The predicted values used for simulation results in this figure correspond to the dotted line in Figure 2a. The theoretical results are obtained as follows. Without transmitter pre-compensation, the channel is closely approximated by the Rayleigh fading channel with the BER $P_e = \frac{1}{2}\left(1-\sqrt{\frac{\gamma_b}{1+\gamma_b}}\right)$ [6]. When channel inversion is applied, the power of the transmitted signal is multiplied by $\frac{1}{|\hat{c}_k|^2}$. In the analysis, we assume perfect prediction, and use Rayleigh distribution to model the predicted amplitudes. When no threshold is used, the infinite power boost is introduced at the transmitter. On the other hand, given the threshold $\rho>0$, the average transmitted power is

$$E\left(\frac{1}{|\hat{c}_k|^2} \,\Big|\, \frac{1}{|\hat{c}_k|^2} < \frac{1}{\rho}\right) = \frac{1}{e^{-\rho}}\Gamma_{inc}(0,\rho),$$

where Γ_{inc} is the incomplete gamma function defined as

$$\Gamma_{inc}(0,\rho) = \int_{0}^{1/\rho} e^{-1/x}/x\,dx.$$

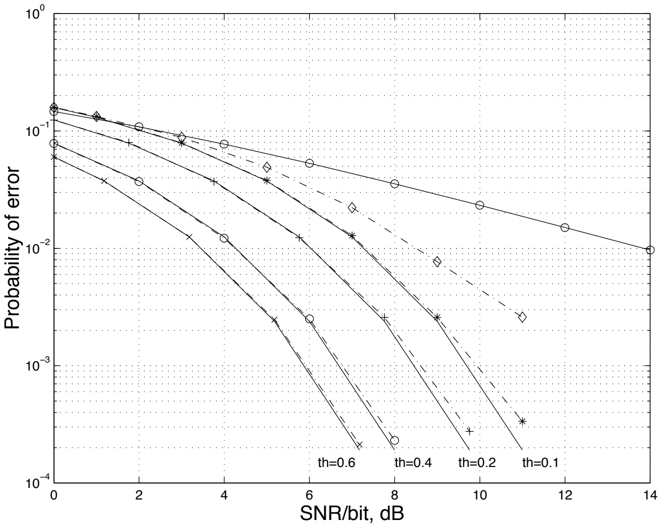


Figure 4. Probability of bit error vs SNR for Rayleigh fading channel with no threshold and no compensation at the transmitter (o—o); channel inversion with prediction for thresholds 0.1 (*- - -*), 0.2 (+- - -+), 0.4 (o- - -o) (also Gaussian channel BER), and 0.6 (x- - -x). Channel inversion (thr. 0.1) for feedback without prediction (◊- - -◊). The dashed lines are the simulations and the solid lines are the theoretical results for the each threshold level.

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 calculated for a given ρ as $\Pr(|\hat{c}_k|^2>\rho) = \int_{\rho}^{\infty} e^{-y}dy = e^{-\rho}$ and confirmed by the simulations. For example, 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. However, the agreement with the theoretical results is very good, despite the fact that Rayleigh fading and perfect prediction is assumed in power calculations, while the actual channel has only 9 oscillators. Since the power of the transmitted signal $\frac{b_k}{\hat{c}_k}$ is greater than $E(b_k^2)$ for thresholds <0.4, the BERs for these threshold values are above the AWGN channel BER. For the threshold=0.4, the transmitted power is equal to $E(b_k^2)$, and the analytical curve in this case is also the BER of the AWGN channel [9]

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

Moreover, for thresholds greater than 0.4, the BER is lower than for the AWGN channel. This is due to the fact that for these thresholds the most favorable channel conditions are chosen for transmission, i.e., the data is sent only when the channel is strong. Thus, by using the proposed prediction method, we were able to reduce the BER to and beyond the level of the AWGN channel.

In Figure 4, performance of the channel inversion algorithm for threshold level 0.1 is also shown for the case when the channel coefficient c_n is fed back to the transmitter as the same sampling rate (500Hz) and used as an estimate of the channel coefficient c_k (at the data rate) between the samples c_n and c_{n+1}. This estimate is used to adjust the power for all data points on the interval [n, n+1]. This method was simulated for other thresholds, and the degradation relative to the results with prediction is similar to the case shown. Note that the performance of the feedback without prediction method is optimistic, since the delay is assumed to be zero. This result illustrates the importance of long range prediction for reliable performance of adaptive modulation and coding techniques.

5. Conclusion and Future Work

We discussed a novel fading prediction method, and the advantages of using low sampling rate to achieve long term prediction. Adaptive prediction and tracking technique is also presented for reducing the error propagation and channel mismatch. The performance of the channel inversion with threshold method that utilizes the proposed prediction algorithm is analyzed. It is shown that the performance for the flat fading channels can be significantly improved when prediction is used. The extension of the proposed method to multipath fading channels, antenna array systems, and adaptive modulation and coding are under investigation.

References

[1] T. Eyceoz, A. Duel-Hallen, and H. Hallen, “Prediction of Fast Fading Parameters by Resolving the Interference Pattern”, *Proceedings of the 31st ASILOMAR Conference on Signals, Systems, and Computers*, pp. 167 - 171 November 2 - 5, 1997.

[2] T. Eyceoz, A. Duel-Hallen, and H. Hallen, “Using the Physics of the Fast Fading to Improve Performance for Mobile Radio Channels”, in *Proc. 1998 IEEE International Symposium on Information Theory*, p.159.

[3] T. Eyceoz, A. Duel-Hallen, and H. Hallen, “Deterministic Channel Modeling and Long Range Prediction of Fast Fading Mobile radio Channels”, *IEEE Communication Letters*, Vol. 2, No. 9, pp. 254 – 256, September 1998.

[4] H. Hallen, S. Hu and A. Duel-Hallen, “Physical Insights into the Nature of the Fast Fading in Wireless Communications”, *to be submitted to JSAC.*

[5] W. C. Jakes, *Microwave Mobile Communications*, IEEE Press, 1993.

[6] J. G. Proakis, *Digital Communications*, McGraw-Hill, New York, 1995.

[7] T. S. Rappaport, *Wireless Communications*, Prentice Hall, NJ, 1996.

[8] A. J. Goldsmith and S. G. Chua, “Adaptive Coded Modulation for Fading Channels”, *IEEE Trans. on Comm.*, vol. 46, No. 5, pp. 595 - 601, May 1998.

[9] D. L. Goeckel, “Adaptive Coding for Fading Channels using Outdated Channel Estimates”, Proceedings of VTC, May 1998.

[10] E. Biglieri, G. Cairo, and G. Taricco, “Coding and Modulation under Power Constraints”, *IEEE Personal Communications*, pp. 32-39, June 1998.

[11] R. Haeb and H. Meyr, "A Systematic Approach to Carrier Recovery and Detection of Digitally Phase Modulated Signals on Fading Channels", *IEEE Transactions on Comm.*, 37(7): 748-754, July 1989.

[12] T. Eyceoz, S. Hu, and A. Duel-Hallen "Performance Analysis of Long Range Prediction for Fast Fading Channels", to appear in *Proc. 33rd Annual Conference on Information Sciences and Systems (CISS'99).*

[13] A. J. Goldsmith and S. G. Chua, “Variable-Rate Variable-power MQAM for Fading Channels”, *IEEE Trans. Commun.* , vol. 45, No. 10, pp. 1218 - 1230, Oct. 1997.

[14] M. C. Vanderveen, A. J. Van der Veen, and A. Paulraj, “Estimation of Multipath Parameters in Wireless Communications”, *IEEE Trans. Signal Processing*, vol. 46, No. 3, pp. 682 - 690, March 1998.

[15] S. Hu, H. Hallen and A. Duel-Hallen, "Physical Channel Modeling, Adaptive Prediction and Transmitter Diversity for Flat Fading Mobile Channels," Proceedings of SPAWC'99.
[16] T. Eyceoz, S. Hu, A. Duel-Hallen, and H. Hallen "Transmitter Antenna Diversity and Adaptive Signaling Using Long Range Prediction for Fast Fading DS/CDMA Mobile Radio Channels", to appear in *Proc. IEEE Wireless Communications and Networking Conference (WCNC'99).*