

Adaptive Coded Modulation over Slow Frequency-Selective Fading Channels

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Abstract—We consider adaptive coded modulation for systems using QPSK/8PSK/16QAM constellations with a decision-feedback equalizer for slow frequency-selective fading channels. We investigate several potential channel-quality metrics that could be used to choose the correct coding and modulation scheme. We then present a threshold-adaptive algorithm that is especially useful for channels with a wide range of multipath profiles.

I. INTRODUCTION

It is well known that adaptive-rate transmission can increase the throughput of time-varying channels [1], [2]. While there is a significant amount of literature on adaptive modulation schemes in additive white Gaussian noise (AWGN) and flat fading channels [3], [4], [5], [6], there are few results on adaptive modulation for frequency selective fading channels. Using the techniques for adaptive modulation derived for flat fading or AWGN channels may not be the best for frequency-selective fading channels. We address issues related to adaptive modulation in a frequency-selective fading channel in this paper. Specifically, we consider adaptive modulation for a wide-band fixed-wireless system where the channel undergoes slowly time-varying frequency selective fading. In a fixed-wireless scenario, while the channel may not vary significantly over time, it will be a function of the terminal location. Furthermore, the interference may be a function of both time and location. Hence, adaptive coding and modulation schemes can lead to significant increase in throughput even in a fixed-wireless system.

The adaptation of coded-modulation scheme is usually based on the estimation of channel quality at the receiver. Channel quality estimation has been studied in [9], [10]. The key to correct adaptation is a channel quality metric that accurately captures the channel conditions and hence can be used to predict the packet error rate (PER) of any modulation scheme. The metric is compared with the preset thresholds to determine the appropriate modulation scheme. Intuitively, we can use the PER itself as the metric. However, a good measure-

ment of PER typically requires a long observation window when the PER is small. A desirable metric should allow for fast and fine control, and ideally, be obtained with low implementation complexity. We explore several different metrics for channels with inter symbol interference (ISI) in this paper.

When channels are slowly fading or when the channel variation is primarily due to the location of terminals in a fixed-wireless system it is possible to adapt the thresholds against which the channel quality metric is compared to. We present an algorithm to adapt the thresholds based on packet error statistics observed at the receiver. The threshold adaptation makes the adaptive modulation scheme robust to variations in the delay spread of the channel.

The paper is organized as follows. In Section II we describe our system and channel models. In Section III we present simulation results on the various channel quality metrics that can be used for adaptive modulation. In Section IV we discuss the threshold-adaptive algorithm for channels with slowly varying multipath profile. We present some concluding remarks in Section V.

II. SYSTEM MODEL

The transmitter block diagram is illustrated in Fig. 1. The transmitter consists of the a framing block where training symbols are added to the information symbols, a forward error correction (FEC) encoder with constellation mapping followed by the transmit pulse shaping filter. The standard receiver with separate decision-feedback equalizer (DFE) and FEC decoding is illustrated in Fig. 2. The sampled received signal is filtered using the pulse shaping filter matched to the pulse shaping at the transmitter. The DFE block consists of a tapped-delay line fractionally spaced feedforward and feedback filters [7]. The training symbols are used to train the DFE taps during each packet. A DFE is used because maximum-likelihood sequence estimation becomes prohibitively complex for the larger constellations used. The soft decisions from the DFE are fed to the Viterbi decoding module

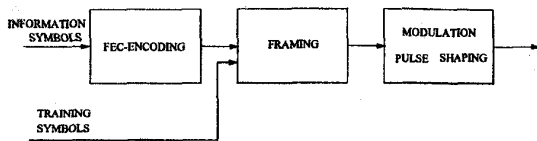


Fig. 1. Transmitter block diagram.

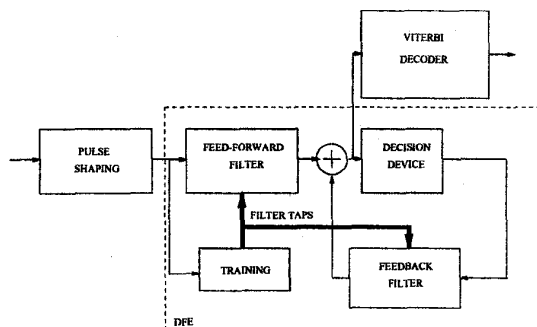


Fig. 2. Receiver block diagram.

for FEC decoding. Depending on the channel and interference conditions, the modulation of the system can be QPSK, 8 PSK, 16 QAM, and even higher-order schemes. We consider three different coded modulation schemes with rates of 4/3, 2, and 3 information bits/symbol corresponding to QPSK, 8 PSK and 16 QAM constellations combined with a rate 2/3 convolutional code, respectively. The same 16 state rate 2/3 convolutional code is used in all three cases [8].

We consider both static and time-varying channel models. The static models are primarily for the purposes of understanding the choice of the metrics. We consider frequency selective Rician fading channels. In the case of the static channel model all the packets are assumed to have the same instance of the channel model. In all our numerical results, we assume an rms delay spread of 1/2 symbol period with an exponential power profile. This typically results in ISI of about 3-4 symbols containing significant power.

III. CHANNEL QUALITY METRICS FOR MODULATION PREDICTION

A channel quality metric is required to determine which modulation scheme should be used. The metric must be capable of accurately predicting the PER for each modulation scheme. A set of target PERs then translates into threshold levels for the metric at which the modulation schemes can be switched. For example, for an AWGN channel the signal-to-noise ratio (SNR) completely determines the PER of each modulation scheme. Hence for

a given set of target PERs one can choose threshold SNRs which determine the switching points between the modulation schemes. We investigate several metrics for the accuracy with which they predict the PER in a frequency selective fading channel.

A. PER-Based Prediction

Cyclic Redundancy Check (CRC) at the receiver allows for detection of packet errors. But an accurate measurement of PER may take a long period, especially when the PER is low. This presents a problem for upward prediction. For example, suppose that the current modulation scheme is QPSK and we want to see if it is possible to switch to 8-PSK on the same channel condition. Our simulation results show that, to ensure a low PER for 8-PSK, e.g., $PER \sim 10^{-1}$, the PER of QPSK should be lower than 10^{-3} . This requires a long observation which prevents a swift adaptation.

PER information is useful for downward prediction, because the PER for the current modulation is high – many packet errors in a short time window indicates that the channel is deteriorating quickly and a downward transition is imminent.

B. BER-Based Prediction

Unlike the PER, the BER of the decoder output can not be measured. As an alternative, we can measure the BER of the hard-decisions at the equalizer output, using the decoder output as the reference. In other words, we use the decision discrepancy between the output of the equalizer and the decoder as an indicator of the channel quality. Our simulation results show that, a $PER \sim 10^{-1}$ for 8PSK requires that the BER of QPSK (before decoding) be less than 10^{-2} . Since there are many bits in a packet, a good measure of BER typically requires less than 100 packets. One problem with BER-based modulation prediction is the sharp drop of the PER-BER curves – it becomes difficult to set the thresholds.

C. MSE-Based Prediction

For channels with ISI, the channel quality can no longer be simply characterized by SNR or SIR. The PER also depends on the ISI profile and the effectiveness of the equalizer. So, a good indication might be the signal distortion at the output of the equalizer, that is, the mean squared error

$$MSE = E|y - x|^2,$$

where y is the equalizer output and x is the transmitted signal. Since the true x is not available at

the receiver, it is replaced with \hat{x} , which can be obtained from the output of the Viterbi decoder for the convolutional code. Also, the expectation is replaced by the time-average over all the symbols of multiple packets. Note that, without ISI and equalization the MSE is precisely the noise power and, for unit signal power, the quantity $10 \log(1/\text{MSE})$ is equivalent to the SNR. This is the fundamental reason that the MSE might be a reasonable metric for modulation prediction. Furthermore, the MSE is easily obtained from the accumulated branch metric of the ending state, a by-product of the Viterbi decoder and therefore requires little extra hardware.

It remains a choice of the algorithm whether to exclude the MSE for those packets which fail the CRC check. Our experiments show that the difference is small. This is because, on one hand, occasional bit errors do not affect the average MSE significantly. On the other hand, the occurrence of many frame errors would already be a clear indication for downward transition, and the accuracy of MSE is no longer very important.

In Fig. 3, we compare the MSE measures for different modulation schemes. We consider Rician channels with $K = 8$ dB and SNR ranging from 5 to 20 dB. For each SNR unit step, we simulate 100 channels, with 1000 packets per channel. The MSE for each channel is obtained through the average of only the first 10 packets, sufficient for good MSE measurement as indicated in our other simulation results. Fig. 3 shows that the MSE measures for different modulation schemes are almost identical for the range of MSE thresholds, which will become clear shortly.

In Fig. 4, we show that there is a reasonably good correspondence between PER and MSE. Based on the results shown in Fig. 3 and Fig. 4, we can set thresholds for modulation predictions according to the PER requirements. Note that we only simulated 1000 packets for each channel. So $\text{PER} = 10^{-4}$ in the figure is just used to indicate no errors were detected in the 1000 packets. The spread of the PER-MSE points is mainly due to the error propagation in the DFE equalizer. The exact relationship between PER and MSE depends on the channel impulse response. In the next section, an adaptive process will be introduced for the fine tuning of the thresholds for different channels.

In Fig. 5, we show the average throughput of all the channels for various threshold settings. The maximum throughput is achieved at $T_1 = 8$ dB and $T_2 = 11$ dB. In an average sense, the MSE-based modulation prediction causes little loss in through-

put, compared with the perfect prediction (PER known *a priori*). Note that throughput is not the only consideration in a real system. The threshold settings will also depend on other specifications such as delay, which can also be derived from the PER depending on the ARQ scheme used. The average throughput shown here depends on the SNR range simulated and is only for illustrative purpose. The actual throughput for each individual channel can be very different. Adding higher-order modulation schemes such as 64QAM may further improve the throughput when high SNR is available. The aggregation of multiple subchannels/slots is certainly another way to increase the throughput.

IV. THRESHOLD ADAPTATION ALGORITHM

The results in the previous section show that the MSE is a good channel quality metric for $K = 8$ dB Rician channel. However, if the channel multipath profile varies significantly (either as a function of time or because it is a function of the terminal location in the case of a fixed-wireless system), the MSE at the equalizer output does not completely characterize the PER. For the same MSE the AWGN channel has a much smaller PER than a strong multipath channel. Furthermore, error propagation in the DFE makes MSE a less reliable metric. Hence it is necessary to adapt the thresholds used dynamically. We present an algorithm for rate adaptation that includes threshold adaptation. For simplicity of presentation we present the algorithm for adaptation between two schemes a, b with $R_a < R_b$.

Algorithm Parameters:

M - channel quality metric obtained by averaging over the last N_a frames

PER - packet error rate estimate

T - metric threshold to switch from scheme a to scheme b

ΔT - metric threshold adaptation step size

$PER_{b,a}$ - PER threshold to scale back from scheme b to a

PER_t - a value much lower than the required PER.

N - window over which PER_t estimation is done

N_e - number of errors required for accurate $PER_{b,a}$ estimate.

The algorithm is illustrated in Fig. 6. The estimation of the $PER_{b,a}$ accurately is done by making sure that at least N_e errors have been accumulated in the last N frames. ($N_e = 10$ for our simulation results.) This is reasonable because $PER_{b,a}$ is typically high. Estimating PER_t is based on counting errors that occur in a window of N frames. ($N = 100$ for all our simulations.)

Essentially for every wrong jump we adapt the

threshold in the direction that makes it harder to jump. On the other hand if the PER is very low in some state we adapt the threshold to make it easier to jump to a higher rate scheme.

The operation of the algorithm is illustrated in Fig. 7 for an adaptive modulation scheme with QPSK, 8-PSK and 16-QAM schemes. The channel was assumed to be an AWGN channel for the first 4500 frames with SNR increasing from 6dB to 14dB in steps of 1dB for every 500 frames. For the next 5500 frames the channel was assumed to be an AWGN channel with ISI with SNR increasing from 7 dB to 17 dB for every 500 frames. The ISI channel was modeled with $T/2$ spaced taps given by $[0.884 + j0.214, -0.101 - j0.352, 0.190 - 0.126, 0.081 - j0.017, 0.034 - j0.049]$. (These channel taps were obtained as an instance of a $K=3$ dB Rician channel with normalized delay spread of $1/2$ symbol.) We see that the thresholds first converge to the optimum thresholds for an AWGN channel and once the channel changes to an ISI channel the thresholds increase again before stabilizing at the new values corresponding to the ISI channel. The speed of convergence depends on the threshold adaptation step size as well as the how soon the channel SNR goes through the different values. Note that the initial adaptation is only used to demonstrate the effectiveness of the algorithm. In practice, the thresholds are preset to the values obtained as shown in the previous section.

V. CONCLUDING REMARKS

We studied efficient adaptive modulation schemes in slow frequency selective fading channels. We investigated several channel quality metrics for choosing the correct modulation scheme. We then proposed an threshold-adaptive algorithm in which the thresholds themselves are adapted according to the channel. The scheme is especially useful for fixed wireless local loop systems where the channel is slowly time varying and the multipath profile is location dependent.

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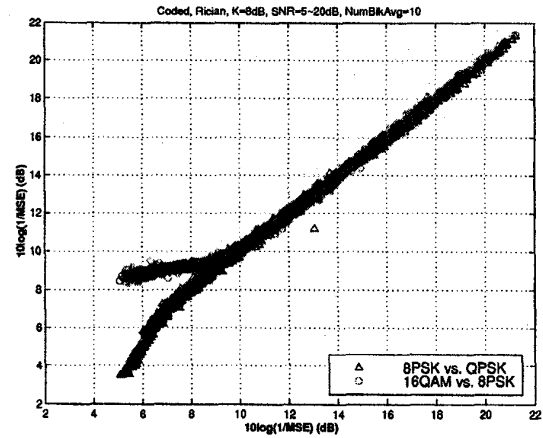


Fig. 3. MSE comparison between different modulation schemes.

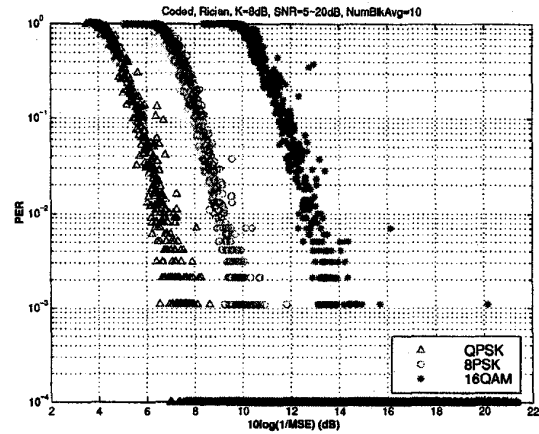


Fig. 4. PER as a function of MSE.

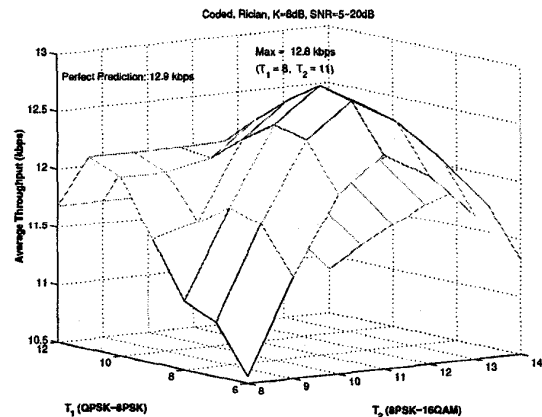


Fig. 5. Average throughput of the channel ensemble for different threshold settings.

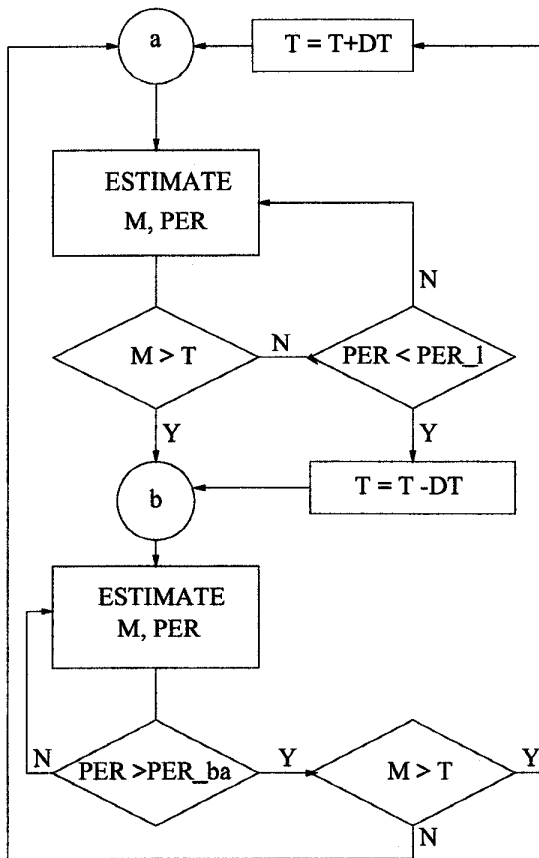


Fig. 6. Flow chart of the threshold adaptation algorithm.

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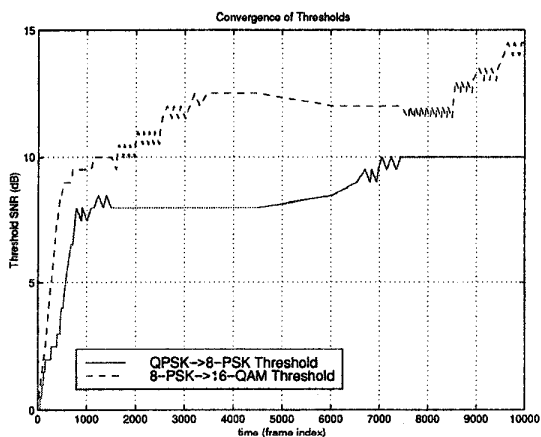


Fig. 7. Threshold adaptation for ISI-free and ISI channels.