Adaptive Modulation and Coding in 3G Wireless Systems

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***Abstract*— In this paper, we address the application of Adaptive Modulation and Coding (AMC) for Third-Generation (3G) wireless systems. We propose a new method for selecting the appropriate Modulation and Coding Scheme (MCS) according to the estimated channel condition. In this method, we take a statistical decision making approach to maximize the average throughput while maintaining an acceptable Frame Error Rate (FER). We use a first-order finite-state Markov model to represent the average channel Signal-to-Noise Ratio (SNR) in subsequent frames. The MCS is selected in each state of this Markov model (among the choices proposed in the 3G standards) to maximize the statistical average of the throughput in that state. Using this decision-making approach, we also propose a simplified Markov model with fewer parameters, which is suitable in systems where changes in the fading characteristics need to be accounted for in an adaptive fashion. Numerical results are presented showing that both of our models substantially outperform the conventional techniques that use a "threshold-based" decision making.**

I. Introduction

The use of Adaptive Modulation and Coding (AMC) is one of the key enabling techniques in the standards for Third-Generation (3G) wireless systems that have been developed to achieve high spectral efficiency on fading channels. In particular, the standards support AMC schemes on the forward link that will achieve a peak data rate up to 5 Mbps [1]– [4].

The core idea of AMC is to dynamically change the Modulation and Coding Scheme (MCS) in subsequent frames with the objective of adapting the overall spectral efficiency to the channel condition. The decision about selecting the appropriate MCS is performed at the receiver side according to the observed channel condition with the information fed back to the transmitter in each frame.

Many AMC techniques have been presented in the literature. In [5] and [6], various rate and power adaptation schemes are investigated. The power adaptation policy found is essentially a water-filling formula in time. In [6], a variable-power variable-rate modulation scheme using M-ary Quadrature Amplitude Modulation (MQAM) is proposed. The presented results show that the proposed technique provides a 5–10 dB power gain over variable-rate fixed-power modulation, and up to 20 dB power gain over the nonadaptive modulation.

In [7], the channel capacity of various adaptive transmission techniques is examined. The performance of these techniques employed with space diversity are also investigated. It is shown that the spectral efficiency for a fading channel can be improved by adaptive transmission techniques in conjunction with space diversity. It is also found that when the transmission rate is varied continuously according to the channel condition, varying the transmit power at the same time has minimal impact.

In [8], the adaptation technique from [5] and [6] is modified to take into account the effect of constrained peak power. Simulation results show that with a reasonable peak power constraint, there is a small loss in spectral efficiency as compared to the unconstrained case.

In [9], an AMC scheme is proposed based on the variable-power variable-rate technique from [5] and [6]. This technique superimposes a trellis code on top of the uncoded modulation. Simulation results show that with a simple four-state trellis code, an effective coding gain of 3 dB can be realized.

In [10], a variable rate adaptive trellis-coded QAM is discussed, offering lower average BER and higher average throughput as compared to fixed rate schemes.

In [12], another AMC technique is proposed using M-ary Phase-Shift Keying (MPSK) modulation, which offers 3–20 dB gain in BER performance.

Turbo codes [13], which can achieve near-capacity performance on Additive White Gaussian Noise (AWGN) channels, have also been proposed in adaptive transmission systems to further improve performance [14]. Results show that a gain of about 3 dB can be obtained over an AMC scheme using trellis coded modulation.

The performance of turbo code in AMC systems depends heavily on the accurate prediction of the channel condition, which may be a difficult task given the time-varying nature of the mobile environment. This is due to the fact that turbo codes operate close to the channel capacity and thus have steep performance curves. The sensitivity of turbo codes to prediction errors may cause the system to produce much less favorable results than theoretically predicted. With much of the industry interest in 3G development, it is essential to overcome this shortcoming and find methods for using turbo codes in AMC systems under a more realistic environment, where prediction errors can often occur.

A key factor determining the performance of an AMC scheme is the method used at the receiver to estimate the channel condition and thereby deciding for the appropriate MCS to be used in the next frame. The effect of channel estimation errors is first addressed in [6]. In [10], the proposed scheme uses pilot symbols to estimate channel state at the receiver, and utilizes both an interpolation filter and a linear prediction filter to interpolate and predict channel conditions, respectively. In [11], the design of adaptive trellis-coded modulation schemes using only a single outdated channel estimation is discussed.

In most works, the decision of which MCS to use for the next frame is based on the basic idea of partitioning the estimated channel Signal-to-Noise Ratio (SNR) into regions using a set of "thresholds". Each such region is associated with a particular MCS while the "threshold" values are optimized to maximize the overall throughput. In this paper, we propose a new method for selecting MCS with the objective of maximizing the statistical average of the channel throughput when there may exist an error in predicting the channel SNR. A simplified model with fewer parameters is also proposed, which accounts for the changes in the fading characteristics by updating the model parameters in an adaptive manner. Numerical results show that our method outperforms the conventional "threshold" method.

The remainder of this paper is organized as follows. In the next section, we describe our system setup and channel model. In Section III, we discuss the conventional "threshold" method and its shortcomings. Our proposed method is presented in Section IV. Numerical results are presented in Section V, including throughput comparisons between the "threshold" method and our proposed method. Finally, we conclude in Section VI.

II. System Setup and Channel Model

For our channel model, we consider a fading channel with time-varying lognormal-distributed complex gain, Ω_k, and additive white Gaussian noise. The lognormal complex gain represents the lognormal shadowing effect in the channel and is implemented by the following autoregressive model [15]:

$$A_g(\tau) = e^{-v|\tau|/X_c}, \tag{1}$$

where v is the speed of the vehicle, τ is the sampling period, and X_c is the effective decorrelation distance. This distance is in the order of 10–100 m as reported in [16].

Using (1), the lognormal values can be generated by low-pass filtering of a discrete white Gaussian random process. With this model [15],

$$\Omega_{k+1(dB)} = \xi \Omega_{k(dB)} + (1-\xi) v_k, \tag{2}$$

where $\Omega_{k(dB)}$ is the mean fading level (in dB) that is experienced at location k, ξ is a parameter that controls the spatial correlation of the lognormal shadowing, and v_k is a zero-mean Gaussian random variable, which is independent of $\Omega_{k(dB)}$.

The variance of v_k, σ^2, is related to the variance of the lognormal shadowing, σ_Ω^2, and the parameter, ξ, through [15]

$$\sigma_\Omega^2 = \frac{1-\xi}{1+\xi}\sigma^2. \tag{3}$$

By selecting appropriate values for σ_Ω^2 and ξ such that the correlation between subsequent fading values follow the results reported in [16] for reasonable values of vehicle speed, lognormal shadowing with any desired standard deviation and spatial correlation can be generated.

In our numerical evaluation, we follow the guidelines provided in the 3G standards. The MCS's considered include 16QAM with turbo code rate $R_c = 1/2$, 8PSK with $R_c = 1/2$, and BPSK with $R_c = 1/3$, where all of these MCS's have equal average symbol energy, E_s. Data is transmitted in successive frames. Each frame of bits has a constant duration of 5 ms, and consists of 384 coded symbols. This provides a constant data rate of 76.8 ksymbols/sec regardless of the choice of MCS. Each coded symbol in a frame has a different lognormal gain, $\Omega_{k(dB)}$, generated by (2), and the channel SNR of a coded symbol is defined, in decibel scale, as

$$\gamma_{(dB)} = \Omega_{k(dB)} + 10\log\left(\frac{E_s}{N_o}\right) \tag{4}$$

where N_o is the one-sided noise spectral density. The average channel SNR of a frame of bits, which is the basis of the MCS selection criterion for the subsequent frame, is the average of the SNR of all the coded symbols in the frame.

It is assumed that the channel SNR is accurately estimated at the receiver and that no delay or transmission errors can occur in the feedback channel, so any discrepancy between the predicted and the actual SNR of the next frame can only result from channel SNR prediction errors caused by the time-varying nature of the channel.

The performance criterion used for evaluation of the "threshold" method and our proposed method is the statistical average of throughput per transmitted frame. This is determined by the corresponding probability of Frame Error Rate (FER) and the spectral efficiency of the MCS selected in the frame.

III. Threshold Method

Conventionally, in what we call the "threshold" method, the entire range of channel SNR are partitioned into n regions, denoted by $[\gamma_i, \gamma_{i+1})$ for $i = 0, \ldots, n-1$, using a set of "thresholds". The kth MCS, namely M_k, is assigned to the region $[\gamma_i, \gamma_{i+1})$ if it provides the highest throughput in the region among the set of available MCS's.

With this correspondence between the MCS's and the channel SNR, M_k is selected for the next frame if the average channel SNR in the current frame lies in the region $[\gamma_i, \gamma_{i+1})$.

Since it is assumed in the "threshold" method that the fading is slow enough such that the average channel SNR remains in the same region from the current frame to the next, the estimated channel SNR of the current frame is simply taken as the predicted channel SNR for the next frame. This simplifying assumption, however, is often not true in a mobile environment. In such case, an error in the estimation of average channel SNR can cause inappropriate selection of MCS, resulting in a degradation in FER performance.

For packet data in the 3G standards, turbo codes are specified as the channel coding technique. One of the main characteristics of turbo codes is that they operate close to the channel capacity and the corresponding FER vs. SNR curves have a steep slope. This means that even a small prediction error in channel SNR can result in a large degradation in FER. Therefore, it is essential to take into account the possible prediction errors when designing an AMC system where turbo codes are employed.

IV. Markov Model

We consider a first-order finite-state Markov model to represent the time variations in the average channel SNR. The states in this model represent the average channel SNR of a frame uniformly quantized in dB scale with a given step size Δ, and they form a set $\mathbf{S}=\{S_0, \ldots, S_{m-1}\}$ of m states.

As in the "threshold" method, assume that there are n MCS's. We denote N_i as the number of information bits in a frame of 384 coded symbols that uses ith MCS, namely M_i. Table I shows the values of N_i for the three MCS's used in this paper. We also define F_{ij} as the FER of M_i in state j, and T_{ij} as the expected throughput of M_i in state j.

TABLE I

Values of N_i

Modulation Scheme, M_i	Turbo Code Rate, R_c	N_i (bits)
16QAM	1/2	768
8PSK	1/2	576
BPSK	1/3	128

In the following, we propose a method for selecting the appropriate MCS based on the states of a first-order Markov model, and evaluate its expected throughput. The basic strategy is to assign an MCS to each state such that the expected throughput is maximized in that state.

A. *Full-Scale Model*

We simulate a channel with lognormal shadowing according to (1)–(3) where the average SNR corresponding to each frame is uniformly quantized in dB scale with a given step size Δ. We have selected appropriate values for ξ and σ_Ω^2 in (1)–(3) such that the correlation between subsequent fading values follow the results reported in [16] for reasonable fading characteristics. An appropriate offset is added to the fading values so that they result in an acceptable FER performance.

The calculation of the expected throughput for each MCS in each state of the Markov model requires the knowledge of the corresponding transitional probabilities. For a given number of states, m, and a given Δ, the transitional probabilities can be obtained by simulating the transmissions of a large number (e.g., 100000) of frames of bits. These transitional probabilities form a set $\mathbf{P}=\{p_{ij}, 0<i, j<m-1\}$, where p_{ij} is the transitional probability from state i to state j.

The stationary probabilities of the states, denoted by $\mathbf{\Pi}=\{\pi_j, 0<j<m-1\}$, can be computed using the well-known Markov model equations.

The expected throughput of M_i in state j, T_{ij}, is therefore

$$T_{ij} = \sum_{k=0}^{m-1} N_i p_{jk}(1 - F_{ik}), \tag{5}$$

where N_i is the number of information bits in a frame of 384 coded symbols using ith MCS, p_{jk} is the transitional probability from state i to state j, and $(1-F_{ik})$ is the probability of correct transmission if the ith MCS is selected when the Markov chain is in state k.

Now, for each state, we assign the MCS that has the highest expected throughput in the state according to (5) and select this MCS for the next frame if the estimated channel SNR falls into this state. In other words, M_i is assigned to S_j, if

$$T_{ij} \geq T_{kj}, \quad \forall\, k \neq i. \tag{6}$$

We denote the expected throughput in this state as $\overline{T_j}$. The expected throughput average over all states, $\overline{T}$, is just the sum of the expected throughput associated with each of the states multiplied by the stationary probability of that state,

$$\overline{T} = \sum_{j=0}^{m-1} \pi_j \overline{T_j}. \tag{7}$$

We call this model the *Full-Scale Model* with parameters $\{\mathbf{P}$, $\mathbf{\Pi}$, $\Delta\}$.

B. *Simplified Model*

A drawback in the Full-Scale Model is that it involves many parameters (m^2 transitional probabilities), and consequently, it is difficult to train the model on the fly to adapt to the changes in the fading characteristics (for example, caused by the variations in vehicle speed). To accommodate such an adaptation, we need a simplified Markov model with fewer parameters, which allows us to dynamically recalculate the transitional probabilities over a window of past symbols of a reasonable size.

As in the Full-Scale Model, the set $\mathbf{S}=\{S_0, \ldots, S_{m-1}\}$ represents the m states in the simplified model with a step size Δ between neighbouring states. We assume the connectivities between states are as shown in Figure 1, where

1) $r=2l+1$ determines the maximum number of transitions from a given state. Note that $r \leq m$
2) $\alpha=\min\{m-1, j+l\}$ reflecting the fact that states above S_{m-1} do not exist; transition probabilities to those states are added to the transition probability to S_{m-1}
3) $\beta=\max\{0, j-l\}$ reflecting the fact that states below S_0 do not exist; transition probabilities to those states are added to the transition probability to S_0

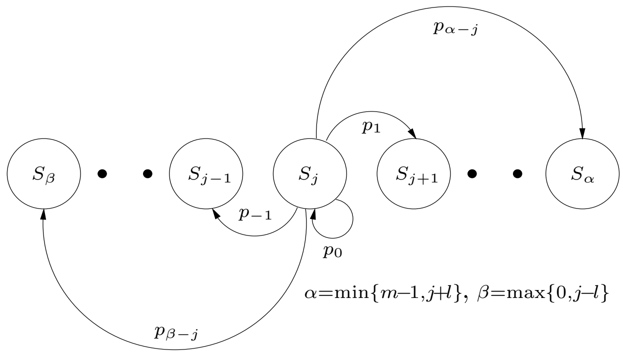

Fig. 1. Simplified Markov Model

4) the transitional probabilities are averaged over all states, and consequently are indenpendent of the state index

The transitional probabilties exist in pairs, and this allows us to set p_a equal to p_{-a}, where $0 \leq a \leq l$, further reducing the number of parameters in the model. We have obeserved that in the Full-Scale Model these probabilities are almost equal.

The calculation of expected throughput in each state follows a relation similar to (5).

Since the average and approximated probabilities are now used instead of the true probabilities, this model is expected to yield smaller throughput than the Full-Scale Model. However, as will be seen, a very good compromise in throughput performance can be achieved (at an appropriate step size) while substantially reducing the number of parameters in the model.

As there are fewer parameters in this simplified model (m transitional probabilities in $\mathbf{P}'$), it requires a window of past symbols of a much smaller size for on-the-fly adaptation to the changes in the fading characteristics.

We call this model the *Simplified Model* with parameters $\{\mathbf{P}'$, r, $\Delta\}$.

C. Algorithm for Implementation of Simplified Model

The goals of using the Simplified Model is to take into account the changes in fading characteristics of the mobile channel. Such a model with parameters $\{\mathbf{P}'$, r, $\Delta\}$ can be implemented using the following algorithm:

1) Throughput versus SNR curves are obtained for each MCS (offline)
2) Enough number of frames are passedd through the channel with the average SNR recorded for each frame
3) The average SNR values are uniformly quantized based on a given step size, Δ, to set up a first-order finite-state Markov model of m states
4) The transitional probability set $\mathbf{P}'$ of the Markov model is computed based on a given r
   a) Set p_a=p_{-a} (optional)
   b) If $r < m$, then the transitions which are not allowed are ignored, and the corresponding p_a's are normalized so that they sum to one
5) The expected throughput in each state of the Markov model for each MCS is calculated using relation similar to (5)
6) MCS's are assigned to each of the states in the Markov model according to (6)

V. Results and Discussions

A. Performance of Full-Scale and Simplified Models

The expected throughput per frame computed using (5) and (7) for both the "threshold" method and our proposed method based on the Full-Scale Model and the Simplified Model are shown in Figures 2–5 for various Δ, r, ξ (corresponding to different fading characteristics), as well as different average received symbol to noise ratio, $\frac{E_s}{N_o}$ as defined in Section II. Note that for all cases, we have used a window size of 100000 frames, and for the case of the Simplified Model, p_a and p_{-a} are not set equal. Numerical results show that for the case of $p_a = p_{-a}$, using a window of 500 – 1000 past frames results in about 0.5% loss in the expected throughput.

From Figures 2–5, it can be seen that both the Full-Scale Model and the Simplified Model outperform the "threshold" method. These results, therefore, prove that our proposed method accomplishes the goal of capturing the transitional behaviour of the average channel SNR that is lacking in the "threshold" method and in doing so it reduces the error rate and increases the average throughput.

For both the Full-Scale Model and the "threshold" method, the expected throughput reaches a saturation point at approximately $\Delta = 0.5$ dB, below which it stays relatively constant. The Simplified Model also reaches this saturation point when $r = m$. When $r < m$, the maximum expected throughput occurs at step size of 1 dB, below which the expected throughput decreases as Δ decreases due to the fact that when $r < m$, using a smaller Δ means a bigger portion of state transitions is ignored, and therefore resulting in lower throughput. In particular, when $r = 3$ and $\Delta < 0.2$ dB, the Simplified Model yields the same throughput as the "threshold" method.

When $\Delta = 1$ dB and $r = 7$, the Simplified model yields the same expected throughput as setting $r = m$ in the Simplified Model. Although the achieved expected throughput is not the maximum for the Simplified Model with $r = m$, it is only at most 8 bits less as shown in Figure 2–5. Thus, we have shown here that with Δ and r set appropriately (i.e., 1 dB and 7, respectively), an expected throughput that is very close to the maximum can be achieved using the Simplified Model.

VI. Conclusion

In this paper, we evaluated the performance of turbo code based Adaptive Modulation and Coding in 3G wireless systems. We proposed a new method for selecting the appropriate Modulation and Coding Scheme according to the estimated channel condition where we use a first-order Markov model to represent the average channel SNR and we take a statistical decision making approach to address the issue caused by the sensitivity of turbo code to the errors in predicting the channel

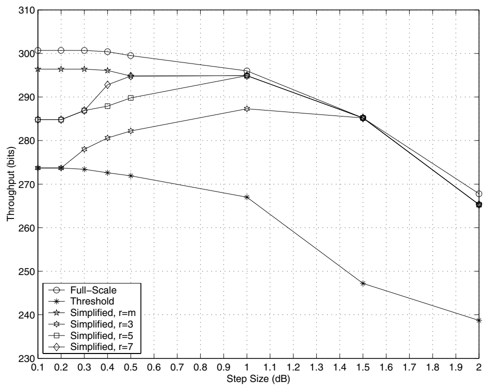

Fig. 2. Throughput vs. Step Size for ξ=0.999 and $\frac{E_s}{N_o}$=4.75 dB

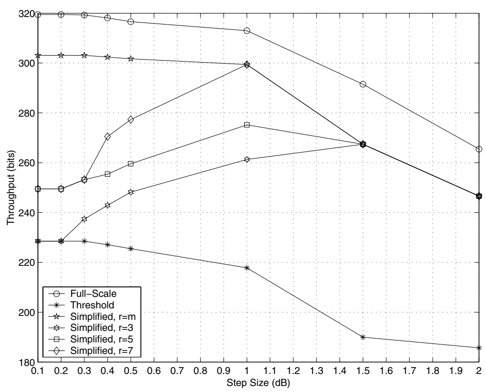

Fig. 3. Throughput vs. Step Size for ξ=0.99 and $\frac{E_s}{N_o}$=4.75 dB

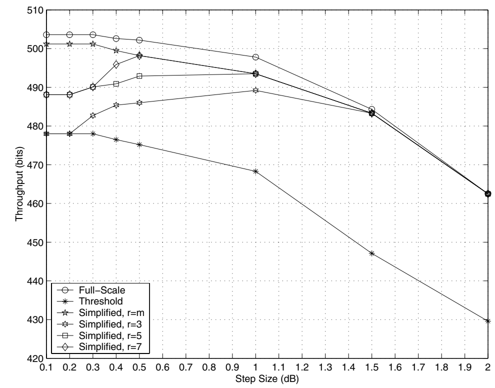

Fig. 4. Throughput vs. Step Size for ξ=0.999 and $\frac{E_s}{N_o}$=6.75 dB

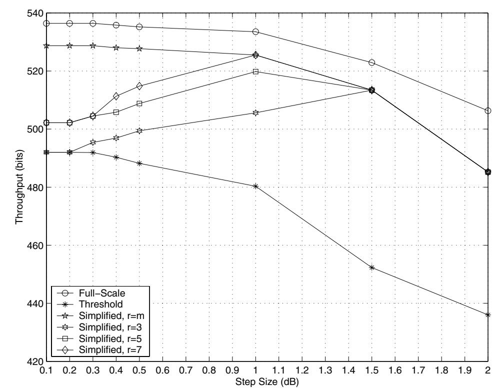

Fig. 5. Throughput vs. Step Size for ξ=0.99 and $\frac{E_s}{N_o}$=6.75 dB

SNR. Numerical results are presented showing that our method substantially outperforms the conventional techniques that use a "threshold-based" decision making approach. We also propose a Simplified Model with fewer parameters which is suitable in systems where changes in the fading characteristics need to be accounted for in an adaptive manner. It is shown that the Simplified Model only results in negligible loss in the expected throughput.

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