Adaptive Stochastic Iterative Rate Selection for Wireless Channels

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***Abstract*—A stochastic algorithm for channel adaptive rate selection (modulation and coding scheme or MCS) is proposed. The algorithm learns the optimal policy by iteratively augmenting a rate selection probability vector. While simple to implement, this technique requires no explicit channel estimation phase. The single bit ACK/NACK signal feedback from the data link layer is used as the input to the stochastic algorithm. As shown in the convergence theorems, the algorithm achieves the optimal rate in "static" channels. A time varying channel is seen as a "quasi-static" channel, and adaptively converged to optimal rates as channel state changes.**

***Index Terms*—3G wireless, adaptive rate assignment, stochastic learning.**

I. Introduction

CHANNEL adaptive rate assignment has been of interest as an efficient way to increase the throughput of 3G wireless communication systems [1]. A channel adaptive transmitter optimizes throughput by selecting among the set of available rates, as given by a set of modulation and coding schemes (MCS), the one that maximizes the throughput in each "short-term" channel state. Here the terms "channel state" refer to a range of signal-to-interference-plus-noise ratio (SINR) for which there is a unique optimal MCS. In an ideal scenario, the receiver estimates the channel parameters with sufficient accuracy to identify the MCS that maximizes the throughput for the given channel state, and feeds back the index representing the selected MCS. The channel feedback should take place at a sufficient rate for the indices to be valid representations of the channel states during each transmission. If the channel state changes fast in comparison to the feed back rate, significant loss of throughput can occur. There have been proposals to use data link layer signaling or cyclic redundancy check (CRC) to improve performance by augmenting the "thresholds" defining the SINR ranges for each MCS [2] and [3].

In this paper we present an alternative approach which uses only the data link layer ACK/NACK signal indicating the success/failure of the transmitted data frame as feedback to adaptively learn and assign the best MCS in each channel state. Since there is no explicit feedback of channel state information, the method has significant savings in uplink capacity otherwise spent on feedback. Note that the number of rates (MCS) discussed in the literature on 3G wireless systems varies and are in the order of 10 [1] thus requiring four bits per frame for MCS feedback in addition to the one bit for ACK/NACK. Thus we have a five-fold reduction in feedback requirements.

Unless required for other purposes such as coherent demodulation, this technique also can save the capacity spent on channel estimation. The new approach is based on stochastic *learning automata* [4] and [5].

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II. Stochastic Learning and Rate Selection

We consider a system in which the transmitter selects the best MCS just before each transmission time interval (TTI). The length of the bit stream is selected such that the data frame can be completely transmitted within a TTI with the selected MCS. In a typical 3G wireless system such as high speed data packet access (HSDPA), a data frame may extend to more than one TTI. The method presented is readily applicable to such scenario as well. In the formulation of the problem and the algorithm to follow, n is the index of the sequence of TTIs. The SINR of the channel during a TTI is expressed by $\gamma(n)$. The probability of frame error with a given channel SINR, and ith rate (MCS) is expressed as $P_{e,i}(\gamma(n))$. The set of rates available are $\{R_i : i = 1, 2, \ldots, r\}$ (bits/s). Thus the throughput achieved with a rate R_i is given by

$$D_i(n) = R_i(1 - P_{e,i}(\gamma(n))), \quad i = 1, \ldots, r. \tag{1}$$

The transmitter is required to find the index of the best transmission rate (MCS) m s.t.

$$m = \arg\max_i D_i(n). \tag{2}$$

The stochastic learning and rate selection algorithm presented in this paper carries out this optimization by probabilistically selecting rates and adaptively increasing the probability of the best rate with an iterative process. It maintains an adaptively changing selection probability vector $p(n) = [p_1(n), p_2(n), \ldots, p_r(n)]'$ to select a rate among the set of r rates at each iteration n. At the bootstrap $(n = 0)$, the probabilities $p_i(n)$, where $i = 1, \ldots, r$, are assigned equal values of $1/r$. Then the rate selection and transmission proceeds with the fixed $p(n)$ until every rate is selected at least M (a tunable parameter) number of times after which $p(n)$ is augmented at each n. Following each transmission, the transmitter receives an ACK/NACK signal indicating the successful reception/failure of the data packet. The current and the past ACK/NACK signals are used in augmenting the probability vector $p(n)$ toward the optimum. This is done by maintaining

[1][Online.] Available: http://www.nokia.com/downloads/aboutnokia/research/library/mobile_networks/MNW23.pdf

a time varying estimate of probability of frame error, $\hat{P}_{e,i}(n)$ for each rate R_i, $i = 1, \ldots, r$. Each $\hat{P}_{e,i}(n)$ is computed to be the ratio of the count of NACK signals corresponding to the transmissions using rate R_i, to the count of instances the rate R_i is selected, within the moving "window". We may write

$$\hat{P}_{e,i}(n) = \frac{1}{M} \sum_{k=L_i(n)-M+1}^{L_i(n)} I_i(k) \quad (3)$$

where $I_i(k)$ is an indicator function s.t. $I_i(k) = 0$ or 1 depending on whether the feedback following kth use of rate R_i is an ACK or NACK. $L_i(n)$ is the number of TTI's for which the rate R_i is selected during the time from the start till the nth TTI. Following the transmission of each data frame, the probabilities $p_i(n), i \neq m$ are decreased by Δ $(0 < \Delta < 1)$ and the probability of the best rate, $p_m(n)$ is increased by $(r-1) \times \Delta$ where $\Delta = 1/N$ is the smallest step size. N here is a "tunable" resolution parameter. If the channel state remains fixed for sufficiently long time, the algorithm is able to increase the probability $p_m(n)$ to unity (and set $p_i(n) = 0$ for all $i \neq m$). While this could maximize the throughput in a stationary channel, adaptivity to time varying channel requires us to maintain nonzero values of $p_i(n)$ for all i and for all n. Therefore we maintain a minimum probability of B called "bias" for all rates. The proposed rate selection algorithm can be summarized as follows.

A. Pseudocodes of the Algorithm

Set $p_i(n) = 1/r$, for $i = 1, \ldots, r$.

Initialize $\hat{P}_{e,i}(n)$ and hence $D_i(n)$ for all $i = 1, \ldots, r$ (using **(3)** and **(1)**) by selecting rates with fixed $p(n)$ until every rate R_i is selected at least M times.

Repeat

1) At time n pick a rate $R_i(n)$ according to the probability distribution $p(n)$.
2) On receiving ACK/NACK feedback, update $\hat{P}_{e,i}(n)$ using **(3)** and $D_i(n)$ using **(1)**
3) Compute the index m of the best rate $R_m(n)$ as in **(2)**.
4) Augment $p(n)$ according to the following equations:

$$p_i(n+1) = \max\{p_i(n) - \Delta, B\} \ \forall\, i \neq m \quad (4)$$

$$p_m(n+1) = 1 - \sum_{i \neq m} p_i(n+1). \quad (5)$$

End Repeat

B. Convergence of the Algorithm

The proposed stochastic rate selection technique is based on the *discrete pursuite reward inaction* (DPRI) learning automata, analyzed in [6]. We state the relevant convergence theorems without proof. These theorems are applicable to a "static" channel i.e., one in which the SINR is bounded within a range s.t. the optimum rate, R_m is fixed. In the sections to follow, we present simulation results showing the adaptivity of the technique in time varying channels.

Theorem 1: Suppose there exists an index m and a time instance $n_0 < \infty$ such that $\hat{D}_m(n) > \hat{D}_i(n)$, for all $i \neq m$ and for all $n \geq n_0$. Then for all resolution parameters $N > 0$ and for all bias parameters $0 < B < 1$, $p_m(n) \to 1$ with probability one as $n \to \infty$.

Theorem 2: For each rate R_i, assume $p_i(0) \neq 0$. Then for any given constants $1 > \delta > 0, M < \infty$, and $N > 0$ there exists $n_0 < \infty$ such that under the DPRI algorithm, for all time $n > n_0$: $P\{$every rate chosen more than M times at time $n\} \geqslant 1 - \delta$.

Theorem 3: In every static channel, the DPRI is optimal. More explicitly, given any $1 > \delta > 0$, $N > 0$, and $0 < B < 1$ there exists $n_0 < \infty$ such that for all $n \geqslant n_0$: $P[p_m(n) = 1 - (r-1)B] > 1 - \delta$.

Theorem 2 above guarantees the ability of the algorithm to select each rate a sufficient number of times to obtain fair estimates of frame error rates with a probability arbitrarily close to unity, within a finite time. This theorem follows the line of analysis as in [6]. Theorem 1 establishes the ability of the algorithm to converge to the best rate. Theorem 3 confirms that the probability of selecting the best rate increases monotonically and can be arbitrarily close to the maximum within finite time. Theorems 1 and 3 were derived with an approach similar to that of [6] and with the inclusion of bias parameter, B.

III. Simulation Results

The simulation was carried out with parameters of a 3G wireless system namely HSDPA operating at 2.0 GHz. A frequency flat fading radio link was assumed. The transmitter and the receiver were assumed to have single antennas. The set of six transmission rates, $\{0.12, 0.24, 0.36, 0.48, 0.60, 0.72\}$ (Mb/s) corresponding to a range of MCS is used in our illustrations. The ACK/NACK signal to follow the transmission of each data frame were simulated using a set of pre-derived frame error probability versus SINR curves. These curves have been derived for the performance in additive white Gaussian (AWGN) channel with an interleaver/deinterleaver and turbo-coder/decoder in the system. The set includes one curve for each MCS for the range of SINR of interest. The frame duration was taken to be one TTI which is 0.667 ms. Instantiations of the fading channel were generated using Jakes' model [7] with an average SINR setting of 0 dB. With each set of parameters, the simulation was performed for a sufficient length of time (in the order of 60 000 frames) and the average throughput values were computed for each such parameter setting. The optimum values of parameters M, N, and B maximizing the average throughput at each speed were found by repeating the simulation for a range of values of these parameters.

It was found from experimentation that $M = 1$ results in the best performance except for very low speeds. This observation is consistent with the intuitive fact that when the channel variations take place at time scales comparable to the TTI, the estimate $\hat{P}_{e,i}(n)$ would not improve by increasing M. Thus the best estimate is achieved with minimum M. We compare the performance of the proposed method to that of an ideal scheme where the channel state in each TTI is known to the transmitter. Shown in Table I are the average throughput of the proposed algorithm as a%ge of the throughput of ideal scheme, at a set of speeds. At zero speed (stationary channel), the proposed method achieves 100% of the throughput of ideal scheme. A 71.6% throughput is achieved at a speed of 3 km/h. As speed increases, the value of N achieving best throughput decreases and becomes $N = 1$ around 1 km/h. Further, it is seen that as speed increases, the optimum bias B increases. Note that timely detection of state changes requires testing of every rate at sufficiently small time

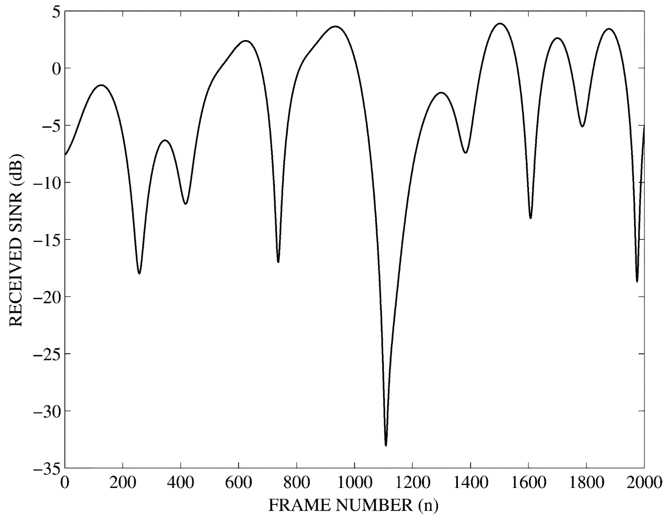

Fig. 1. Simulated SINR variation at a speed of 1 km/h with average $\mathrm{SINR} = 0$ dB. Frame duration = 1 TTI (0.667 ms).

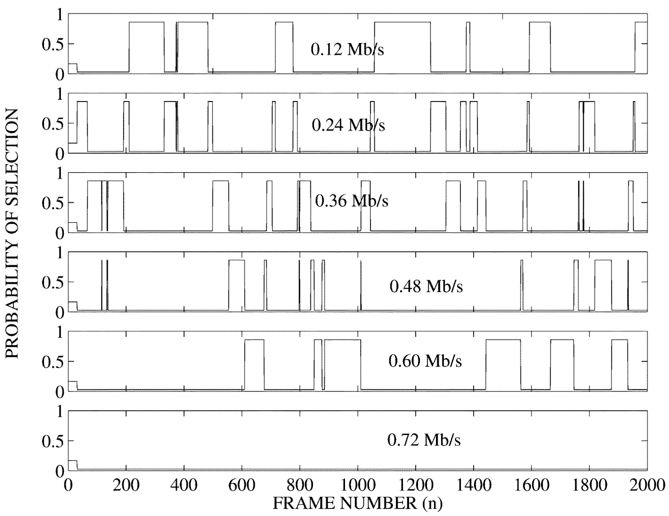

Fig. 2. Rate selection probabilities, $p_i(n)$ at 1 km/h with $M = 1, N = 1$, and $B = 0.028$. Average $\mathrm{SINR} = 0$ dB, frame duration = 1 TTI (0.667 ms).

intervals, which in turn requires sufficiently large probabilities of selection for every rate. An increase in the value of B fulfils this. With smaller than optimum values of B, the penalty arising out of delayed detections becomes more severe than the loss due to the drop in the maximum probability of selecting the best rate.

Figs. 1–3 illustrate the tracking behavior of the stochastic adaptive rate selection at a speed of 1 km/h. The simulated time variation of the channel SINR is shown in Fig. 1. Fig. 2 shows the evolution of selection probabilities as the channel state changes. Fig. 3 compares the short term average (over 10 frames) throughput of stochastic technique to that of the ideal scheme. As shown in Table I, the mismatch in tracking for this case results in a throughput loss of 19.1%.

IV. Conclusions

In this letter, we presented a stochastic learning and rate selection algorithm based on discrete pursuit reward inaction scheme found in learning automata theory. Theorems on the convergence in static channel were given. Simulation results show

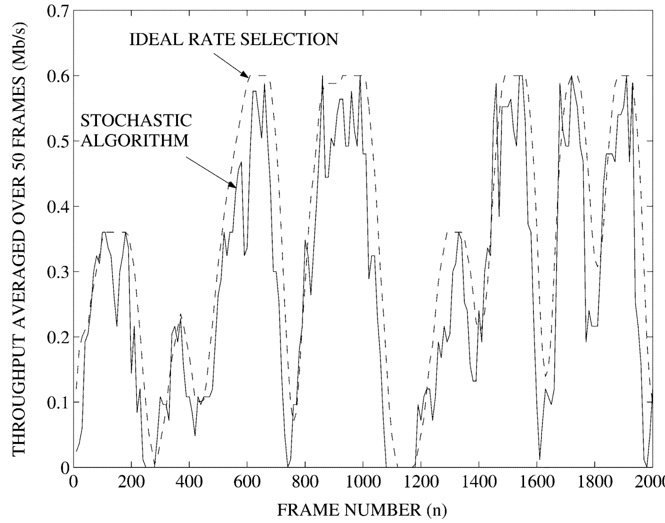

Fig. 3. Throughput (averaged over 10 frames) at 1 km/h with $M = 1, N = 1$, and $B = 0.028$. Average $\mathrm{SINR} = 0$ dB, frame duration = 1 TTI(0.667 ms).

TABLE I
THROUGHPUT PERFORMANCE OF STOCHASTIC ADAPTIVE ALGORITHM AT A SET OF SPEEDS WITH BEST CHOICES OF N AND B. $M = 1$ AND AVERAGE $\mathrm{SINR} = 0$ dB

speed (km/h)	throughput (%ge of ideal)	N	B
0	100.0	$\geqslant 10$	0
0.2	89.8	5	0.017
0.5	85.2	5	0.022
1	80.9	1	0.028
3	71.6	1	0.048

excellent adaptivity in low mobility environments with mobile speeds in the order of a few kilometers per hour. The approach can save the bits needed for feed back of indices of optimal rates by the mobile receivers for adaptive rate selection. With a set of rates in the order of ten, this saves four bits per frame. This is achieved by using the data link layer ACK/NACK signal as the only input to the adaptive algorithm. Unless required for other purposes such as coherent demodulation, it also can save the capacity spent on channel estimation.

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