Adaptive Transmission Rate Assignment for Fading Wireless Channels with Pursuit Learning Algorithm

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***Abstract*— An adaptive rate assignment technique based on pursuit learning algorithms [7] is presented. For each frame of data, the bit rate is randomly selected according to an assignment probability vector which is iteratively updated so that to achieve the optimal performance. The iterative update of the assignment probability vector is based on finite duration estimates of achieved throughput with each rate during probabilistic assignments. This technique requires no explicit channel estimation phase and uses the single bit ACK/NACK signal feedback from the data link layer. We analyze the operation of algorithm and present the theorems showing successful operation of the technique. We illustrate the usefulness of the method via simulations carried out on a 3G wireless communication system namely High Speed Data Packet Access (HSDPA).**

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

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. The method we present here has been derived from the pursuit learning algorithm [7] and assigns the rates randomly according to an assignment probability vector that evolves with time. In contrast, an ideal rate feedback system requires the estimation of channel parameters at the receiver and transmission of the index corresponding to the best MCS on the reverse link. However, in order to achieve the desired performance with such an approach, channel feedback should take place at a sufficiently high rate (number of feedbacks per second) for the indices to be valid representations of the channel states during each transmission. Delay in feedback results in suboptimal performance. Together with rate feedback based approaches, 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].

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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. The number of rates (MCS) in 3G wireless systems varies and are in the order of ten [4] thus requiring four bits per frame for MCS feedback in addition to the one bit for ACK/NACK. Thus we have a 5 fold reduction in feedback requirements. Unless required for 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* [5] and [6].

In the forgoing we describe the proposed adaptive rate assignment techniques in section II. An analysis on the convergence properties of the method is carried out in section III. Numerical results on the performance are presented in section IV. Conclusions follow in section V.

II. Stochastic Learning and Rate Selection

In the method we consider, the transmitter selects an 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 proposed method 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 and the SINR of the channel during n^{th} TTI is expressed by $\gamma(n)$. The probability of frame error with a given channel SINR, and i^{th} rate (MCS) is expressed as $P_{e,i}(\gamma(n))$. The set of rates available are $\{R_i : i = 1, 2, \cdots, r\}$ (bits/s). Thus the throughput achieved with a rate R_i is given by

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

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

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

Such an approach requires the exact knowledge of channel state. The stochastic learning and rate selection algorithm presented in this paper randomly selects an MCS for each transmission of a frame according to an adaptively evolving selection probability vector, $p(n) = [p_1(n), p_2(n), \cdots, p_r(n)]$. The probabilities of selecting each rate is iteratively updated such that the probability of assigning the best MCS is adaptively maximized. At the bootstrap ($n = 0$), all the rates are assigned an equal probability 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 $p(n)$ toward the optimum. This is done by maintaining a time varying estimate of throughput values, $\hat{D}_i(n)$ for each rate $R_i, i = 1, \cdots, r$. Following each TTI, an update of $\hat{D}_i$ and $p(n)$ are carried out considering the last M ACK/NACK signals of each rate. Thus the length of the "moving window" in terms of number of TTIs may vary. We may write

$$\hat{D}_i(n) = \frac{R_i}{M} \sum_{k=L_i(n)-M+1}^{L_i(n)} J_i(k) \tag{3}$$

where $J_i(k)$ is an indicator function s.t. $J_i(k) = 1$ or 0 depending on whether the feedback following k^{th} use of rate R_i is an ACK or NACK. $L_i(n)$ is the number of TTIs for which the rate R_i is selected during the time from the start till the n^{th} TTI. Following the transmission of each data frame, the index $\hat{m}$ of the best rate is decided by

$$\hat{m}(n) = \arg\max_i \hat{D}_i(n) \tag{4}$$

and the probabilities, $p_i(n),\ i \neq \hat{m}$ are decreased by Δ ($0 < \Delta < 1$) and the probability of the estimated best rate, $p_{\hat{m}}(n)$ is increased by $(r-1) \times \Delta$ where $\Delta = \frac{1}{N}$ 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 $p_{\hat{m}}(n)$ to unity (and set $p_i(n) = 0$ for all $i \neq \hat{m}$). While this could maximize the throughput in a stationary channel, adaptivity to time varying channel requires the avoidance of absorbing states. 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 $i = 1, \cdots, r$.
Initialize $D_i(n)$ for all $i = 1, \cdots, r$ (using (3)) 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 $\hat{D}_i(n)$ accorging to (3).
3) Compute the index $\hat{m}$ of the best rate $R_{\hat{m}}(n)$ with (4).
4) Augment $p(n)$ according to the following equations:

$$p_i(n+1) = \max\{p_i(n) - \Delta, B\}, \forall i \neq \hat{m} \tag{5}$$

$$p_{\hat{m}}(n+1) = 1 - \sum_{i \neq \hat{m}} p_i(n+1). \tag{6}$$

End Repeat

III. Convergence of the stochastic adaptive rate assignment algorithm

We are in need to analyze the behavior of the proposed stochastic iterative technique with respect to the convergence to the optimal solution, and we require to quantify the throughput loss due to delay in tracking the time varying channel. In this section, we establish the theorems related to the convergence of algorithms when the channel variations are slow enough for the convergence to best solution to take place. Define

$$S_i(n) = \sum_{k=L_i(n)-M+1}^{L_i(n)} J_i(k).$$

Since M is a constant not effecting the end result, (4) can be rewritten as,

$$\hat{m}(n) = \arg\max_i \{R_i S_i(n)\} \tag{7}$$

With a decision policy as above, we can compute the probability of making right decision as follows. Let the best rate at time n, $R_m(n)$ is unique. Let $\xi_m(n) = Pr[\hat{m}(n) = m(n)]$ be the probability that the estimated best rate is the actual best rate at time n. This probability is given by

$$\xi_m(n) = Pr\{S_i(n) < \frac{R_m(n)}{R_i} S_m(n) \forall i \neq m(n)\} \tag{8}$$

The above probability is readily obtained by the use of binomial probability distribution. Let $\kappa_i(a)$ be the largest non-negative integer $< a\frac{R_m(n)}{R_i}$ where a is a non-negative integer. Define the indicator function $I(.)$ such that

$$I(.) = \begin{cases} 1, & \text{if condition within parentheses satisfied ;} \\ 0, & \text{else.} \end{cases}$$

thus define the parameter $\zeta_i(a)$ for $i = 1, \cdots, r$ such that

$$\zeta_i(a) = \kappa_i(a) I(\kappa_i(a) \leq M) + M I(\kappa_i(a) > M)$$

Then from (8) we have

$$\xi_m = \sum_{a=1}^{M} [Pr\{S_m = a\} \prod_{\substack{i=1 \\ i \neq m}}^{r} \sum_{b=0}^{\zeta_i(a)} Pr\{S_i = b\}] \tag{9}$$

In (9) and the discussion to follow we omit the time index n for simplicity. Above (9) can be rewritten using binomial distribution as follows.

$$\xi_m = \sum_{a=1}^{M}[\binom{M}{a} q_m^a(1-q_m)^{M-a} \prod_{i\neq m}\sum_{b=0}^{\zeta_i(a)}\binom{M}{b} q_i^b(1-q_i)^{M-b}] \tag{10}$$

In this $q_i, i = 1, \cdots, r$ is the probability of "successful transmission" of a packet using the rate R_i. We consider the case where the time required for the algorithm to converge to the optimal solution is small compared to the time the channel stays in a given state. We are interested in the probability of correct decision given the channel is known to be in a given state. Defining the set (range) of γ for which the rate R_m is the optimum as Γ_m, we can write

$$q_i(\Gamma_m) = \int_{\gamma\in\Gamma_m}(1 - P_{e,i}(\gamma))p^{\Gamma_m}(\gamma)d\gamma,\ i = 1, \cdots, r \tag{11}$$

In this, $p^{\Gamma_m}(\gamma)$ is the probability density function of γ given $\gamma \in \Gamma_m$ and can be written as

$$p^{\Gamma_m}(\gamma) = \begin{cases} \frac{p(\gamma)}{\int_{\gamma\in\Gamma_m} p(\gamma)d\gamma}, & \gamma \in \Gamma_m \\ 0, & \text{else} \end{cases} \tag{12}$$

where $p(\gamma)$ is the unconditional probability density function of SINR, γ.

A. Convergence to optimal solution

Having derived the expression for probability of successful detection, we proceed to explore the conditions to be met for convergence to the optimal solution. At a given time n the update policy as in (5) and (6) will increase the probability $p_m(n)$ of the actual best rate $R_m(n)$ with probability $\xi_m(n)$ and will decrease it with probability $1-\xi_m(n)$. We may write

$$p_m(n+1) = \begin{cases} 1 - \sum_{i\neq m}\max(p_i(n) - \Delta, B), \\ \qquad \text{w.p. } \xi_m(n); \\ \max(p_m(n) - \Delta, B), \\ \qquad \text{w.p. } 1 - \xi_m(n). \end{cases} \tag{13}$$

where w.p. stands for "with probability".

Convergence implies achieving the condition $p_m(n) = 1 - (r-1)B$. Assuming the convergence is not complete, there exists at least one non zero component of $p(n)$ say $p_i(n)$ with $i \neq m$ and hence we assert that

$$\max\{p_i(n) - \Delta, B\} < p_i(n) \tag{14}$$

Since $p(n)$ is a probability vector,

$$p_m(n) = 1 - \sum_{i\neq m} p_i(n) \tag{15}$$

and thus

$$1 - \sum_{i\neq m}\max\{p_i(n) - \Delta, B\} > p_m(n) \tag{16}$$

As long as there is at least one non-zero component $p_i(n)$ where $i \neq m$, it is clear that we can decrement $p_i(n)$ and hence increment $p_m(n)$ by at least min$\{p_i(n) - B, \Delta\}$. Thus we may rewrite (13) as

$$p_m(n+1) = \begin{cases} p_m(n) + c_n\Delta, \\ \qquad \text{w.p. } \xi_m(n); \\ p_m(n) - \Delta, \\ \qquad \text{w.p. } 1 - \xi_m(n). \end{cases} \tag{17}$$

where c_n is bounded by 0 and $r-1$. An expression for the expected value of $p_m(n+1)$ conditioned on the current state of the channel defined by $D(n)$ and the state of algorithm defined by $p(n)$ can be obtained as follows. Define the duplet $Q(n) = \{D(n), p(n)\}$. Then we have

$$E[p_m(n+1)|Q(n)] = \xi_m(p_m(n)+c_n\Delta)+(1-\xi_m)(p_m(n)-\Delta) \tag{18}$$

Since $E[p_m(n+1)|Q(n)]$ is bounded by $1-(r-1)B$ we have,

$$\sup_{n\geq 0} E[p_m(n+1)|Q(n)] < \infty \tag{19}$$

Further we can rewrite (18) as

$$E[p_m(n+1) - p_m(n)|Q(n)] = [\xi_m(n)(c_n + 1) - 1]\Delta \tag{20}$$

Observe that the right hand side of (20) ≥ 0 if and only if

$$\xi_m(n) \geq 1/(c_n + 1) \tag{21}$$

in which case (20) is a sub-martingale. Let the algorithm achieves the condition above at time n_o and continues to hold for all $n > n_o$. Then by sub-martingale convergence theorem, the sequence $\{p_m(n)\}_{n>n_o}$ converges s.t.

$$E[p_m(n+1) - p_m(n)|Q(n)] \to 0 \ \text{ w.p. } 1 \tag{22}$$

as $n \to \infty$ with the limit of $p_m(n)$ in this case being $1-(r-1)B$.

It remains to examine if the requirement in (21) for convergence is satisfied by the system being studied. Given that $p_m(n)$ has not achieved the maximum achievable value we have $p_m(n) < 1-(r-1)B$ and therefore, $c_n > 0$. Furthermore the maximum value of c_n is $r-1$. Therefore we have $\frac{1}{r} \leq \frac{1}{c_n+1} < 1$ and we conclude that $\xi_m(n) > \frac{1}{r}$ for all $n \geqslant n_o$ is a necessary condition for the sequence $\{p_m(n)\}_{n>n_o}$ to achieve convergence. As $p_m(n)$ increases toward the maximum achievable value, c_n decreases and the value of $\xi_m(n)$ required for continued convergence increases. As illustrated in the numerical results presented in section IV, ξ_m rapidly increases as M increases for any typical set of $q_i,\ i = 1, \cdots, r$. We further observe that small values of M in the order of a few are sufficient to achieve sufficiently large ξ_m. This shows the ability of the algorithm to be adaptive when the channel state varies with time.

The resolution parameter N and thus Δ plays a vital role in the performance of the algorithm. When the channel changes states very slowly, larger values of N produce better results. This is verified by observing that in (21) $c_n = 1$ would require

$\xi_m > 0.5$ for (20) to be sub-martingale. This implies that p_m can achieve a value higher than $1-(r-1)B-\Delta$ with ξ_m as low as 0.5. Thus a larger N means smaller Δ that makes p_m be closer to maximum achievable even with ξ_m far less than unity. Nevertheless, when the channel changes rapidly, large value of N are not of much help as there are fever iterations left before a change of state. In such scenarios, smaller values of N produce the best overall throughput. These facts are illustrated via numerical results in section IV.

B. Asymptotic Theorems

In this sub-section, we establish asymptotic theorems reinforcing the analytical results presented above. These theorems follow the line of analysis presented by Oommen and Lanctôt in [7]. Theorem 1 establishes that the proposed algorithm can achieve a required number of trials, M with probability arbitrarily close to unity. Theorem 2 to follow states that there exists an $M < \infty$ s.t. if every rate R_i is selected at least M times, the best rate R_m achieving the best throughput D_m is determined with a probability arbitrarily close to unity. Thus from theorems 1 and 2 we deduce corollary 1 proving that the proposed algorithm can indeed detect the best rate with a probability arbitrarily close to unity.

Theorem 3 establishes a result crucial to the performance of the algorithm. In this it is proven that the time required to achieve the maximum value of p_m, with a probability arbitrarily close to unity is finite and is a function of the resolution parameter N.

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

Proof: Let Y_i^n be the number of times the rate R_i is chosen up to time n. For any iteration of the algorithm

$$Pr\{R_i \text{ is chosen}\} \leqslant 1 \tag{23}$$

The magnitude by which an action probability can decrease in an iteration is bounded by Δ. Thus during first n iterations

$$Pr\{R_i \text{ is not chosen}\} \leqslant 1-\max\{(p_i(0)-n\Delta), B\} \tag{24}$$

With $n \geqslant M$, from (23) and (24)

$$Pr\{Y_i^n \leqslant M\} \leqslant \sum_{k=1}^{M} \binom{n}{k} (1)^k \psi^{n-k} \tag{25}$$

where $\psi = 1-\max\{(p_i(0)-n/N), B\},\ 0<\psi<1$

Since $\binom{n}{k} \leqslant n^k$ we may write

$$Pr\{Y_i^n \leqslant M\} \leqslant \sum_{k=1}^{M} n^k \psi^{n-k} \tag{26}$$

Since $0<\psi<1$ we may write

$$Pr\{Y_i^n \leqslant M\} \leqslant M n^M \psi^{n-M} \tag{27}$$

Consider right hand side of (27).

$$\lim_{n\to\infty} M n^M \psi^{n-M} = M \lim_{n\to\infty} \frac{n^M}{(1/\psi)^{n-M}} \tag{28}$$

Using L'Hopital's rule M times (28) reduces to

$$M \lim_{n\to\infty} \frac{M!}{(\ln(1/\psi))^M (1/\psi)^{n-M}} = 0 \tag{29}$$

Since the limit exists, for every R_i, there exists $n = n(i)$ s.t. the left hand side of (27) is $\leqslant \delta$. Since for any $n > n(i)$, $Y_i^{n(i)} \geqslant M$ implies $Y_i^n \geqslant M$, we have $Pr\{(Y_i^n \geqslant M)\} \geqslant Pr\{(Y_i^{n(i)} \geqslant M)\}$, thus left hand side of (27) $\leqslant \delta$ for all $n > n(i)$. Therefore, for any rate R_i, $Pr\{(Y_i^n \leqslant M)\} \leqslant \delta$ whenever $n \geq n(i)$. Define

$$n_o = \max_{1\leqslant i\leqslant r}\{n(i)\}$$

Then for all $n > n_o$ and for all i we have $Pr\{Y_i^n \leqslant M\} < \delta$ implying

$$Pr\{Y_i^n > M\} \geqslant 1-\delta \tag{30}$$

■

Theorem 2: There exists an M for every $0 < \delta < 1$, if every rate R_i is selected at least M times by the time n, then

$$Pr\{\max_i |\hat{D}_i(n) - D_i| < h/2\} > 1-\delta \tag{31}$$

such that

$$Pr[\hat{m}(n) = \arg\max_i D_i] > 1-\delta \tag{32}$$

Proof: Let $h(>0)$ be the difference between two largest throughput values in the given channel state. Let Y_i^n be the number of times the rate R_i is selected up to time n. If $\hat{D}_i(n)$ is the estimate of the reward probability for rate R_i, then by weak law of large numbers, for a given $\delta > 0$, there exists an $M < \infty$ s.t. if R_i is chosen M times,

$$Pr\{|\hat{D}_i(n) - D_i| < h/2\} > 1-\delta \tag{33}$$

If $\min_{1\leqslant i\leqslant r}\{Y_i^n\} \geqslant M$ then each and every $\hat{D}_i(n)$ will be in an $h/2$ neighborhood of D_i with a probability $> 1-\delta$ thus leading to (31). Let $\hat{D}_m(n)$ be the estimate of best throughput achieved using the rate R_m at time n. By assumption the best throughput D_m is unique and therefore $D_m - h \geq D_i$ for all $i \neq m$. But we know that, if $\hat{D}_i$ is in the $h/2$ neighborhood of D_i for all i,

$$\begin{aligned} \hat{D}_i(n) \ &< \ D_m - h/2 \ < \ \hat{D}_m \ \forall i \neq m \\ &\Rightarrow \hat{D}_m(n) \ > \ \hat{D}_i(n) \ \ \forall i \neq m \end{aligned}$$

Thus we have (32).

■

Corollary 1: Provided the channel remains in a state for sufficient time with a fixed best rate R_m, for any $0 < \delta < 1$ there exists a time n_0 s.t. for all $n \geqslant n_o$,

$$Pr[\hat{m}(n) = \arg\max_i D_i] > 1-\delta \tag{34}$$

Proof: From theorem 1 we know that we can find a n_0 s.t. for all $n > n_0$

$$Pr[\min_{1\leqslant i\leqslant r}\{Y_i^n\} > M] > 1-\delta_1.$$

By theorem 2 we have

$$Pr[\hat{m}(n) = \arg\max_i D_i | Y_i^n > M] > 1-\delta_2$$

Define the events

$$U \equiv \hat{m}(n) = \arg\max_i D_i$$

and

$$V \equiv Y_i^n > M$$

By using the result $Pr\{U\} \geqslant Pr\{U|V\}Pr\{V\}$ we have

$$Pr[\hat{m}(n) = \arg\max_i D_i] \geqslant (1-\delta_1)(1-\delta_2)$$

with $\delta = \delta_1 + \delta_2$ we have (34) for all $n \geqslant n_o$. ■

Theorem 3: In every stationary channel, the adaptive rate selection algorithm is "optimal". More explicitly, given any $\delta > 0$, there exists a $n_0 < \infty$ such that for any resolution parameter $N \geqslant 1$, $Pr[p_m(n) = (1-(r-1)B)] > 1-\delta$ for all $n \geqslant n_0 + N$.

Proof: Let the event $\hat{m}(n) = m = \arg\max_i D_i$ has taken place at time n_o. Then for all $n > n_0$ the probabilities $p_i(n)$ monotonically decrease for all i but $i = m$ in which case the probability monotonically increases according to the update rule,

$$p_m(n+1) = 1 - \sum_{i\neq m} \max\{(p_i(n) - 1/N), B\}$$

Assume that the algorithm has not converged to m^{th} action. Then there exists at least one nonzero component of $p(n)$, say $p_k(n)$ with $k \neq m$, and hence we assert that

$$\max\{(p_k(n) - 1/N), B\} < p_k(n).$$

Since $p(n)$ is a probability vector $p_m(n) = 1 - \sum_{i\neq m} p_i(n)$, and therfore

$$p_m(n+1) = 1 - \sum_{i\neq m} \max\{(p_i(n) - 1/N), B\} > p_m(n).$$

As long as there is at least one nonzero component $p_k(n)$ ($k \neq m$), we can decrement $p_k(n)$ and hence increment $p_m(n)$ by at least $\max\{p_m(n) - B, 1/N\}$. Hence,

$$p_m(n+1) = p_m(n) + c_n/N,$$

where c_n is bounded by 0 and $r-1$. As we know $p_m(n)$ is bounded above by $1-(r-1)B$ implying $c_n \to 0$ and therefore $p_m(n) \to 1-(r-1)B$ within a finite number of iterations. As for the length of time involved, it is maximum for the case with $p_m(n_0) = B$ and only one $k \neq m$ s.t. $p_k(n_0) > B$. For this worst case it requires $\lceil N/(1-(r-1)B)\rceil < N$ more iterations to achieve $p_m(n) = 1-(r-1)B$. Thus in the worst case as $B \to 0$, convergence completes at time $n_0 + N$.

Define the event $W \equiv \{p_m = (1-(r-1)B)\}$. Then we have shown above that for $n \geqslant n_0 + N$

$$Pr\{W|U\} = 1 \tag{35}$$

where U is defined in the proof of corollary 1. By Corollary 1 we have $Pr[U] > 1-\delta$ for all $n \geqslant n_o$. Therefore by using the result $Pr\{W\} \geqslant Pr\{W|U\}Pr\{U\}$ we have for all $n \geqslant n_0 + N$

$$Pr\{p_m = (1-(r-1)B)\} > 1-\delta \tag{36}$$

■

IV. Numerical Results

Numerical computations and simulations were carried out with parameters of a 3G wireless system namely HSDPA operating at 2.0GHz. 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 0.667ms. Instantiations of the fading channel were generated using Jakes' model [8] 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.

Shown in Fig. 1 is the trend of ξ_m, the probability of detecting the best rate as M, the number of ACK/NACK signals used in the estimation. This curve has been derived using (10) with the set of values $q = \{0.999, 0.999, 0.999, 0.999, 0.999, 0.400\}$ corresponding to the set of transmission rates mentioned above at 9dB average SINR. It is observed that the value of ξ_m increases

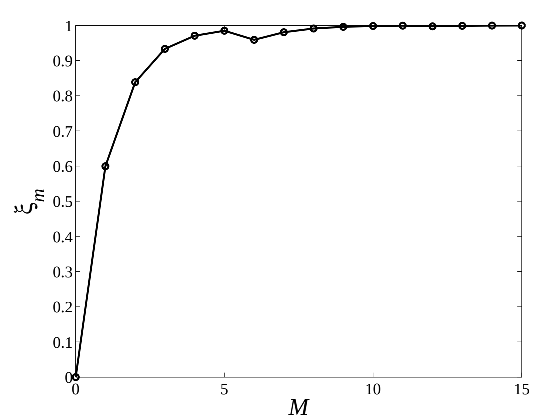

Fig. 1. Probability of correct detection of best rate, ξ_m as M increases as obtained from (10). In this example $m = 5$, or 0.60Mb/s is the optimal rate.

rapidly with M, and $M = 1$ is sufficient to achieve $\xi_m > 0.5$ which guarantees the convergence of p_m such that $p_m(n) > 1 - (r-1)B - \Delta$.

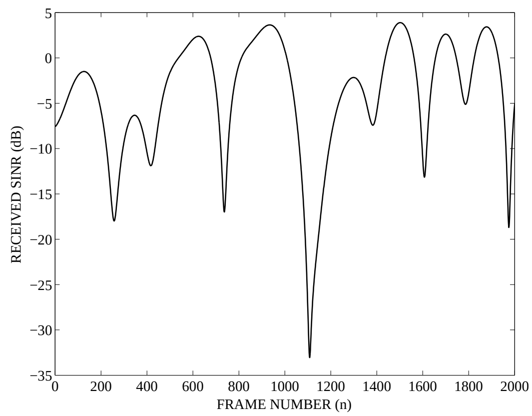

Fig. 2. Simulated SINR variation at a speed of 1 km/h. Average SINR = 0 dB, frame duration = 1 TTI (0.667ms).

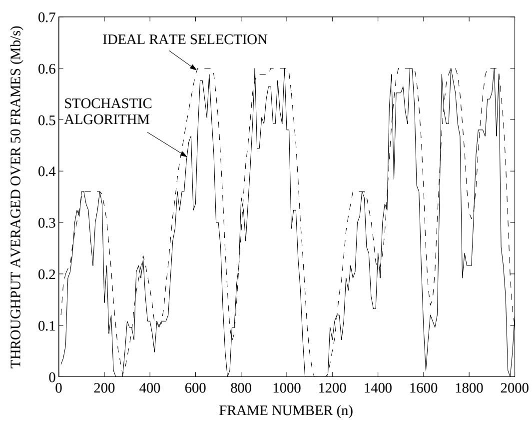

Fig. 3. Throughput (averaged over 10 frames) at 1 km/h with $M = 1, N = 1,$ and$B = 0.028$. Average SINR = 0 dB, frame duration = 1 TTI (0.667ms).

Further it was found from the link level simulations that $M = 1$ results in the best performance except at 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. 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 1km/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 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.

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

TABLE I

Throughput performance of stochastic adaptive algorithm at a set of speeds with best choices of N and B. $M = 1$ and average SINR=0 dB.

Fig. 2 and 3 illustrate the tracking behavior of the stochastic adaptive rate selection at a speed of 1km/h. The simulated time variation of the channel SINR is shown in Fig. 2. 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%.

V. Conclusions

In this paper, 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 excellent adaptivity in low mobility environments with mobile speeds in the order of a few km/h. 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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