Adaption Overhead in Time-Varying Cognitive Radio Channels

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***Abstract*— The ability to adapt to a changing RF environment is a major feature of cognitive radios. As the interference and noise characteristics change, the radio should be able to select a waveform optimal for a particular scenario. However, more frequent adaptation requires more frequent distribution of radio parameters, increasing the overhead and decreasing available proportion of capacity for transmitting data.**

This paper presents a basic model for analyzing modulation adaption overhead in a point-to-point cognitive radio links, and simulates a few specific cases of interest. We examine how quickly a radio can adapt without that overhead actually causing worse overall performance.

Our major results are as follows: to decrease overhead cognitive engines should be placed at receivers, not transmitters; modulation adaptation in Rayleigh fading environments is only beneficial under high-SNR conditions; the higher the average SNR, the more frequently we can adapt to fading channels and see rate gains; and adaptation to interference channels offers a significant performance gain.

I. Introduction

One major application of cognitive radio is the ability to adapt one's radio physical layer (PHY) properties to optimize overall system performance. This may include changing center frequency, bandwidth, modulation type, coding parameters, or one of many other different components that define how radios communicate. Altering these parameters is often triggered by a changing RF environment that affects the link quality between the cognitive transmitter and cognitive receiver. When a change is observed, the cognitive engine controlling the system executes various adaptation algorithms that evolves the state of the radio to one optimal in the new environment.

In order to perform this adaptation, a cognitive engine needs to be able to control the PHY parameters and both the transmitter and receiver, while also having knowledge of channel statistics measured by the receiver. These receiver statistics are often called Channel State Information (CSI), and must be communicated to the cognitive engine in order for it to make proper decisions. This implies the need for a side channel, either in-band or out-of-band.

In this paper we examine the overhead associated with cognitive radio adaptation. In particular, it is often assumed that the faster we can adapt, the better the system will perform. However, to adapt more quickly, we need to exchange more CSI, and consequently use more of our channel capacity for overhead as opposed to data transmission.

One major application of this work is to examine cognitive radio adaptation in fading channels. Might it be possible for a cognitive radio link to adapt to every channel fade, as it happens?

It's important to distinguish the adaptation capabilities of a cognitive radio from the adaptation supported in many modern, commercial waveforms. For example, IEEE 802.11 supports many different underlying modulation rates, and will change the rate used based on the Receive Signal Strength Indicator (RSSI). This rough metric approximates the Signal to Noise and Interference Ratio (SNIR). An unfortunate side effect of using such a simple sensor is it cannot distinguish between noise and interference. In a dense IEEE 802.11 environment with many active devices, the optimal behavior is to use the fastest modulation rate, thereby reducing the on-air time for each transmitted packet and decreasing the probability of a collision. However IEEE 802.11 devices will instead sense a low RSSI (due to significant interference from other devices) and will lower its transmission rate, only compounding the problem. A cognitive radio, on the other hand, is not bound by a set of prescribed tables defining how it should operate in different scenarios, making it immune to the aforementioned scenario. Thus the types of adaptation available to a cognitive radio, and the resulting performance, can be quite different.

There have been some work investigating overhead in cognitive radio networks [1], [2], [3], [4]. Prior research has focused primarily on dynamic spectrum access applications of cognitive radio, and tradeoffs with spectrum sensing times. This paper instead deals with adaptation to a fading or interference channel. in a communication-

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theoretic context, rather than information-theoretic one. There has also been significant work on CSI in M-QAM fading channels [5], [6], however this work focuses more on the frequency with which CSI should be used, and assumes it must be sent in-band rather than out-of-band. Lastly, we assume fixed transmit power, rather than a fixed *average* transmit power.

The remaining sections of the paper are organized as follows. Section 2 describes the system model used for our analysis. Sections 3 and 4 apply this model to a Rayleigh fading channel with and without a bursty interference source, respectively. Section 5 discusses future work. Section 6 concludes.

II. System Model

In this section we focus on a simplex point-to-point link, and by *simplex* we mean that data is only traveling one direction, though feedback could be traversing the opposite direction. In this scenario, two sub-models are considered.

The first involves cognitive algorithms implemented at the transmitter. This is intuitive, since the cognitive engine is responsible for evolving the transmission parameters of the transmitter/receiver pair. Here CSI is transmitted from the receiver to the transmitter in a feedback channel, the transmitter makes intelligent decisions about how to operate, and then sends its decision to the receiver as overhead in the data channel.

The second sub-model places the cognitive engine at the receiver. In this scenario, the receiver examines its own performance, and selects the optimal communications parameters, which are forwarded to the transmitter in the feedback channel.

Both models are depicted in Figure 1. While it may seem counter-intuitive to place the cognitive engine at the receiver, we can see here that it offers significant performance advantages. In particular, CSI need not be communicated over the channel. Less information traversing the communications link means less overhead, and more capacity available for data transmission. This is our first key result: *cognitive engines should be located at the receiver*[1].

Next we consider our channel model. If our transmitted symbol X traverses the channel and estimate $\hat{X}$ is received:

$$\hat{X}_t = P \cdot H_t \cdot X_t + N_t \tag{1}$$

Here H_t and N_t are the random variables representing multiplicative and additive effects of the channel, respectively, and P represents attenuation due to path loss and

[1]Note that there may be scenarios where we split the cognition capabilities across the transmitter and receiver. The goal is to minimize the amount of data traversing the link while maximizing the amount of information available for making optimal decisions.

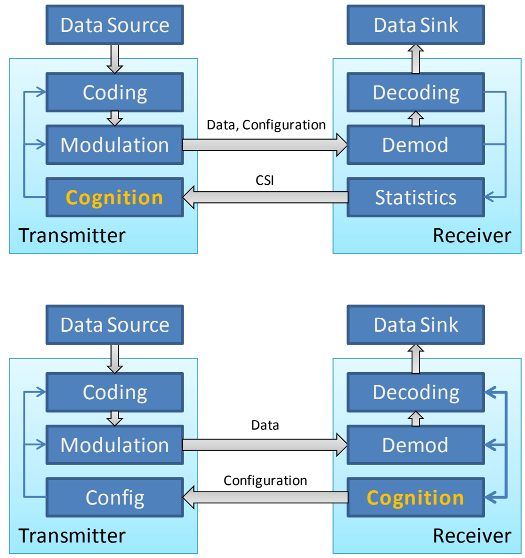

Fig. 1. Above (a): Transmitter-oriented cognitive radio system; Below (b): Receiver-oriented cognitive radio system

shadowing. For non-mobile scenarios, P does not vary as a function of time.

In an AWGN Rayleigh fading channel, N_t and H_t are stationary (i.e. $N_t \stackrel{d}{=} N_{t+\tau}$ and $H_t \stackrel{d}{=} H_{t+\tau}\ \forall\ \tau$). Noise N_t is zero-mean Gaussian random variable with variance σ_N^2, representing the noise power, and H_t has a normalized Rayleigh distribution such that $E[H_t] = 1$.

For an channel with intermittent interference, N_t can be a non-stationary random process with parameters modulated by another random process. This type of model would be appropriate for situations where a cognitive radio was sharing a channel with a bursty interference source. For CDMA systems, N_t can often be modeled as AWGN (with time-varying variance), due to the whitening effects of DSSS.

For fading channels we assume a coherence time T_c such that the value of h at time τ is statistically independent of the value at $\tau + T_c$, for all τ.

Overall, our useful rate R in bits per unit time is

$$R = (1 - 2P_e)(R_M - R_F) \tag{2}$$

where R_M is the total modulated bit rate, R_F is the rate utilized by our feedback messages, and P_e is the probability of a bit error. Note that we assume the presence of an ideal, adaptive error correcting code that can correct these bit errors. Given the presence of our cognitive engine, this assumption is not completely unreasonable.

If every T_a time units an adaptation occurs, and

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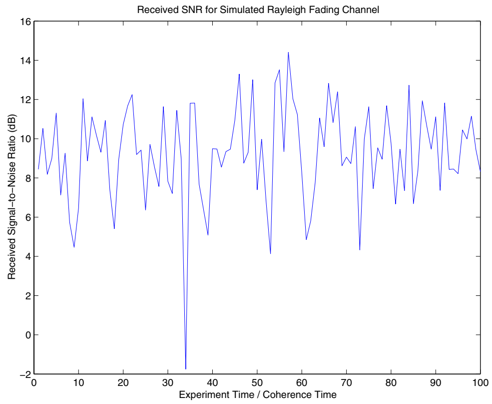

Fig. 2. Received signal to noise ratio for a channel with average SNR of 10 dB, undergoing Rayleigh fading.

requires communication of B_a bits of information,

$$R = (1 - 2P_e)\left(R_M - \frac{B_a}{T_a}\right). \tag{3}$$

If a constellation size of M and symbol time T_s, the resulting rate is

$$R = (1 - 2P_e)\left(\frac{1}{T_s}\log_2 M - \frac{B_a}{T_a}\right) \tag{4}$$

Note that there is an additional, interesting optimization problem not considered here. The more options for M, the more closely we can match the optimal modulation rate. However increasing the number of options also increases the number of bits necessary to uniquely represent them, thereby increasing the overhead B_a.

III. Fading Channels

For fading channels, we assume N is AWGN and H is Rayleigh. Every T_c time units the channel gain changes to a statistically independent value, while every T_a time units our radio system adapts. If $T_a \leq T_c$, then our radio is adapting to small-scale fading. If $T_a > T_c$ then our radio can only adapt to large-scale fading.

This brings up the natural question of adaptation overhead. As T_a increases, our overall rate R decreases, so at what point is it worth our efforts to keep up? Let's consider two specific cases: $T_a = T_c$ and $T_a = \infty$.

To test these different scenarios, a MATLAB simulation was created. The simulation implements an M-QAM modulator and demodulator with adaptive equalization, suitable for fading channels. We simulate a QAM signal with 1 MHz bandwidth and SNR of 10 dB in a Rayleigh fading channel. Figure 2 shows the receive SNR for each fade.

For $T_a = \infty$, we do not modify our transmission parameters throughout the simulation. We obtain the following data rates:

Modulation	Rate
4-QAM	2.0 Mbps
16-QAM	3.7 Mbps
64-QAM	4.3 Mbps
256-QAM	4.1 Mbps

This shows that our cognitive radio should measure the channel gain statistics and select 64-QAM for optimal data transmission.

Next we consider $T_a = T_c$. Our radio will select the optimal transmission parameters based on the receive SNR. Through experimentation, the radio learned the following settings are optimal for our channel:

Instantaneous SNR	Modulation
$SNR < 4$ dB	4-QAM
$4 \leq SNR < 8$ dB	16-QAM
$8 \leq SNR < 12$ dB	64-QAM
12 dB $\leq SNR$	256-QAM

For each coherence time, the cognitive engine will measure the channel properties and select the optimal transmission parameters. We ran a variety of experiments across many different coherence times T_c, and in all cases the above rules had the radio selecting modulation rates that kept P_e negligible and resulted in an average data rate of 5.6 Mbps. Our rate equation is then simplified to

$$R = 5.6 \text{ Mbps} - \frac{B_a}{T_c} \tag{5}$$

Thus in this case if $B_a/T_c < 1.3$ Mbps, the overhead of adaption provides us a net gain in performance.

Next, let us consider B_a. To encode a choice of 4 modulation types, only 2 bits are necessary, however we also need known bits to be transmitted that can be used to measure the receive signal-to-noise ratio. As a result, let $B_a = 5$, and we can compute

$$T_c > 3.8\mu\text{s} = 3.8 \cdot T_s \tag{6}$$

To generalize, we conducted the same experiment over a range of SNRs in an effort to experimentally develop a more universal relation. We had the non-adaptive radio use the optimal modulation rate for the SNR, and then had the adaptive radio compute a new modulation rate for every fade. Figure 3 plots the achieved data rates, assuming $B_a = 0$. It's interesting to notice that the adaptive radio does not offer a significant performance benefit for low SNR, and both appear to be heading toward asymptotes. One important observation is that the adaptive radio's asymptotic data rate is roughly twice that of the non-adaptive radio.

If we look at the performance gap, or difference between the two measured performances, and perform a linear fit, we obtain the approximation for $7 \leq SNR \leq 17$:

$$R_{\text{adaptive}} - R_{\text{static}} \approx \frac{SNR - 6}{3} \text{ Mbps} \tag{7}$$

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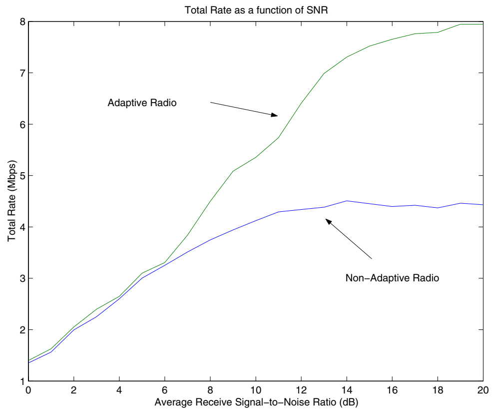

Fig. 3. Rate achieved by the non-adaptive radio and the adaptive radio ($B_a = 0$) over various received SNR.

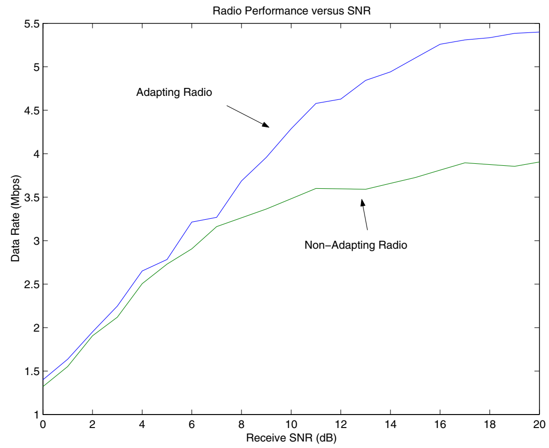

Fig. 5. Rate achieved by the non-adaptive radio and the adaptive radio ($B_a = 0$) over various received SNR, including interference.

This can then be translated into a relation on T_c and B_a:

$$T_c > \frac{3B_a}{SNR - 6} T_s \tag{8}$$

This "rule of thumb" was derived from experimentation, and should only be considered as an order-of-magnitude estimate for QAM-based systems. Certainly specific modems may have better or worse performance, depending on how they operate.

We can, however, draw some interesting conclusions from these results. Adaption is only beneficial in good SNR environments. Otherwise an adaptive radio cannot keep the bit-error-rate low, and consequently must rely heavily on an error-correcting code, just like the non-adaptive radio. Also, in very high SNR environments, an adaptive radio can achieve much higher overall data rates. Lastly, it may be practical to adapt to coherence times on the order of 10s-of-symbols, and achieve a better overall throughput.

IV. Interference Channels

In this section, we consider a different type of time-varying channel. Here, our noise N_t is no longer stationary, but has a variance that is modulated by another random process that takes on discrete values. The transition probabilities between discrete values are a function of the interference environment and transmission parameters of other devices occupying the same frequency range.

Note that if the number of interfering devices in the area is large, the central limit theorem allows us to model the sum of their interference as AWGN with an increased variance. Here we assume there are a n dominant interference sources. The result is a random process M_t that can take on 2^n different output variances for N_t.

For experimentation purposes, we consider $n = 1$ and M_t being a continuous-time Markov process with exponentially-distributed transition probabilities. This is appropriate for simulating interference from a CSMA-based system carrying bursty IP traffic, which is often modeled as Poisson.

Figure 4 shows a time- and frequency-domain representation of a simulation run. Our narrow-band waveform occupies the center frequency and the wide-band interference pulses on and off with exponentially-distributed arrival and service times.

In our first set of experiments, we do not adapt the constellation size, but rather select the size that performs the best given the interference parameters. We run this using the same waveform settings as the previous section, interference duty cycle of 0.5, and vary the average non-interference SNR from 0 to 20.

To this we compare an adapting radio that changes modulation rate on time-scale T_c. This adaptation will also detect changes in the interference environment, and optimize performance to it.

The simulation results are plotted in figure 5. Again we see virtually no performance increase for low SNR, followed by a substantial increase after approximately 7-8 dB. The final performance of the radio systems is lower in the end, due to the additional interference, as expected.

However, if we look at the slope of the difference between the two curves, it's only about half that of the case without interference. The additional interference essentially lowers our *average* SNR, reducing the effectiveness of frequent adaptation. Developing our linear relationship, we obtain

$$T_c > \frac{6B_a}{SNR - 6} T_s \tag{9}$$

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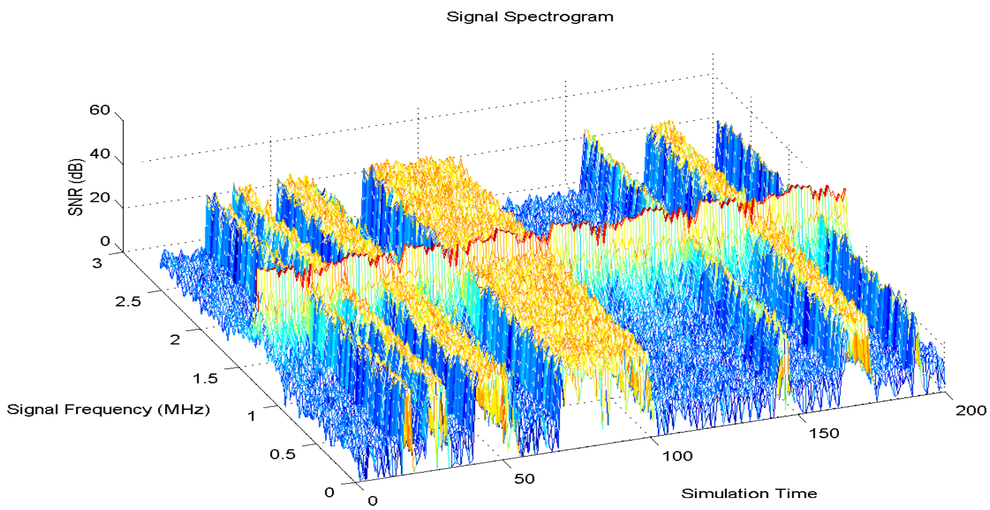

Fig. 4. Signal Spectrogram showing signal and noise power, along with the intermittent power from a wideband interference source.

V. Future Work

This work takes an initial stab at analyzing adaption overhead in cognitive radio networks. It is by no means a complete PHY analysis, or necessarily representative of all waveforms. We examined adaptation overhead for a single class of modulation schemes. Analysis of more advanced PHY layers requires additional work, including how an adapting OFDM waveform would perform in the time-varying channels described in this paper.

Additionally, we assumed an adaptive, ideal code, with block size sufficiently long to span many channel coherence times. Using more realistic error correction would likely widen the performance gap between adaptive and non-adaptive radios, but that gap would likely be consumed by the overhead of conveying additional information bits describing coder adaptation.

In adaption, we did not consider the propagation time necessary to convey updated modulation information to the transmitter. Depending on the duplexing mode, this may or may not be significant. The faster modulation changes can be transmitted to the transmitter, the more accurate our analysis will be.

VI. Conclusion

This paper investigated overhead associated with frequent adaptation of modulation rate in point-to-point cognitive radio links. We presented a few simple scenarios, including multipath fading and multipath fading with a bursty interference source. We examined the performance of a narrowband M-QAM transmitter and receiver pair in these environments.

An initial result of our research was that the decision-making responsibility in a cognitive radio link should be at the receiver. That's where all the channel statistics are, and we only add additional overhead if this data needs to be frequently conveyed to the transmitter.

With respect to a fading channel, we showed that in low-SNR environments, adaption is unlikely to increase overall system performance. Adapting the modulation rate allows us to minimize our BER, and in low SNR environments, it's difficult to maintain a very small BER, and a low-rate coder will likely always be necessary for productive communication. We showed that in high-SNR environments, an adapting radio can perform well. They will offer advantages over non-adapting radios if the coherence time for the channel, and consequently adaptation time, is on the order of several or more symbol times.

In fading channels with a bursty interference source, we showed the tradeoff between adaptation and non-adaptation is similar. In high-SNR scenarios, we can perform better.

References

[1] S. Jafar and S. Srinivasa, "Capacity libits of cognitive radio with distributed and dynamic spectral activity," IEEE ICC 2006.

[2] S. Srinivasa, S. Jafar, and N. Jindal, "On the capacity of the cognitive tracking channel," IEEE ISIT 2006.

[3] N. Devroye, P. Mitran, and V. Tarokh, "Limits on communications in a cognitive radio channel," *IEEE Communications Magazine*, 2006.

[4] Y. Zhao, J. Reed, S. Mao, and K. Bae, "Overhead analysis for radio environment map-enabled cognitive radio networks," IEEE SDR Workshop 2006.

[5] A. Goldsmith and S. Chua, "Variable-rate variable-power mqam for fading channels," *IEEE Transactions on Communications*, October 1997.

[6] A. Goldsmith and P. Varaiya, "Capacity of fading channels with channel side information," *IEEE Transactions on Information Theory*, November 1997.

This full text paper was peer reviewed at the direction of IEEE Communications Society subject matter experts for publication in the IEEE CCNC 2008 proceedings.