Characterizing Temporal SNR Variation in 802.11 Networks

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***Abstract*— The analysis and design of wireless MAC protocols, coding schemes and transmission algorithms can significantly benefit from an understanding of the channel quality variation. We attempt to represent channel quality variation using a finite state birth-death markov model. We outline a method to compute the parameters of the model based on measured traces obtained using common wireless chipsets. Using this markov chain, we evaluate the performance statistically based on the channel quality, long term correlations and burst length distributions. Such a model performs significantly better than a traditional two-state markov chain in characterizing 802.11 networks while maintaining the simplicity of a birth-death model. We interpret the variation of the model parameters across different locations and different times. A finite state stationary model is amenable to analysis and can substantially benefit the design of efficient algorithms and make simulations for wireless network protocols faster.**

I. Introduction

Wireless networks are being rapidly deployed all over the world. In the U.S several companies like Boingo, Cometa and T-mobile are deploying nationwide IEEE 802.11b based wireless local area networks. This large scale deployment has motivated the research for design of better wireless systems. An important step in that direction is to characterize the Signal to Noise ratio (SNR) in these networks. SNR determines several important attributes like packet loss that affects network performance and design at all levels of the network stack. The challenge in this characterization is that the SNR process is a result of both interference due to simultaneous transmission of multiple users and vagaries of radio wave propagation.

Significant research has been directed towards modeling fading channels with rayleigh distributed signal to noise ratio [13], [17]. But, it is not clear that the same techniques would apply for modeling IEEE 802.11 channels as these experience both interference and frequency-selective fading. Most of the research for modeling IEEE 802.11 systems have been directed towards modeling protocol behavior [4], [9] or obtaining distributions for error bursts and sequences of error free transmissions using traces of packet losses [1], [12], [15]. These models are non-stationary and as a result are more suitable for trace generation rather than analysis. Furthermore, distribution of error bursts and error-free bursts are not sufficient to characterize the temporal variation of signal to noise ratio of these channels. Several resource allocation policies in wireless local area networks require this characterization in predicting channel qualities. Also, distribution of error bursts and error-free bursts can be obtained from the characterizations for the temporal variations of the SNR as the packet error processes depend on the SNR. Thus, the SNR is a more fundamental attribute of the system.

We characterize the temporal variation of the SNRs of IEEE 802.11 channels and explain several attributes of the wireless systems using the characterization. Note that the variation of the SNR will be a non-stationary process as this is affected by the traffic which is not a stationary process. Hence no stationary model will provide an exact statistical match. However non-stationary models exclude many analytical techniques, and simulations using non-stationary models can take a significant amount of time especially in large-scale systems. Our goal therefore is to approximately characterize the channel behavior with a stationary process that is conducive to analysis and simulation for large systems. Towards this end, we characterize the SNR variations on a packet time-scale rather than bit-time-scale as the latter turns out to be time consuming for simulation. Furthermore, we consider a birth death markov model with finite number of states for characterizing the SNR variations. The advantage of Birth death models is that they are simple and analytically tractable.

Drawing from the literature known for fading channels, we propose a framework for determining the parameters of the birth death markov model for IEEE 802.11 channels (Section II). In Section III we discuss the measurement setup and classify broadly the environments in which we collected the traces. We subsequently validate our model using statistical comparison with SNR traces observed over Wi-Fi channels (Section IV). This validation demonstrates that a simple birth death markov model characterizes the SNR variations in IEEE 802.11 channels reasonable accurately. Finally, using our model we investigate and explain several attributes of the wireless systems like statistics of error bursts. For example, in [1] and [16] the authors conclude that the two state Gilbert-Eliot model is not suitable for characterizing packet losses, whereas the authors in [8] claim that two-state models are sufficient for capturing the packet loss process but not the bit losses. Using our characterization, we explain the difference between these conclusions (Section V). Finally, we provide several general guidelines about the characteristics of IEEE 802.11 channels. We conclude in Section VI.

II. Modeling the 802.11 Channel

We first outline the 802.11 frame format and describe how to evaluate the packet error probabilities based on bit probabilities (Section II-A). The bit error probabilities are functions of the

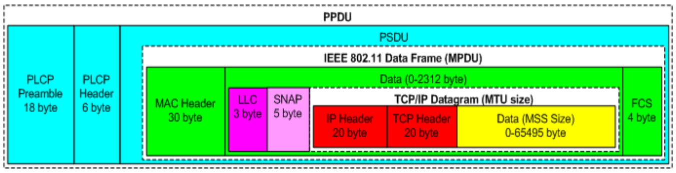


Fig. 1. 802.11 Frame Format

Signal to Interference and Noise ratio. We will then present a framework for modelling the SNR using a finite state markov model and present a methodology for computing the parameters of the model based on measured traces in Section II-B. Henceforth the ratio of signal to the interference and ambient RF energy is referred to as SNR.

A. 802.11 Physical Layer

The IEEE 802.11b physical layer (PHY) is an extension of the original Direct Sequence Spread Spectrum(DSSS) PHY. It operates in the 2.4GHz ISM band and provides PHY data rates of 5.5 and 11Mbps in addition to the 1 and 2Mbps rates supported by the original DSSS. The 1Mbps rate is based on the Binary Phase Shift Keying(BPSK) and the 2Mbps rate is based on the Quadrature Phase Shift Keying(QPSK) modulation. They are encoded using DSSS based on the 11-bit Barker chipping sequence that results in a signal spread over a wider bandwidth at a reduced RF power. For 5.5 and 11Mbps the IEEE 802.11b uses the Complementary Code Keying(CCK) modulation scheme which is a variation of the M-ary Orthogonal Keying Modulation. For each word, the 5.5Mbps rate encodes 4 bits while the 11Mbps encodes 8 bits. The spreading maintains the same chipping rate and spectrum shape as the original 802.11 DSSS and hence occupies the same channel bandwidth. There are 11 channels and each channel occupies 22MHz around the center frequency. This allows for 3 non-overlapping channels(1,6 and 11) in the band.

The IEEE 802.11b frame format is shown in Fig.1. When a higher layer frame also called the Medium Access Control (MAC) Service Data Unit (MSDU) arrives at the MAC layer it is encapsulated in a MAC Protocol Data Unit (MPDU) by adding a MAC header and Frame Control Sequence(FCS). The MAC header is 24 bytes and the FCS is 4 bytes. We now evaluate the packet success probability. The MAC Protocol Data Unit (MPDU) is passed down to the PHY layer which attaches a 6 Byte Physical Layer Convergence Protocol (PLCP) header and a 18 Byte preamble. The PLCP header and preamble is transmitted at 1 Mbps BPSK. Suppose that an L byte MPDU is to be transmitted using Physical layer rate r, where r can be 1, 2, 5.5 and 11 Mbps. A packet is successful if both the PLCP header and the MPDU is received correctly. Hence, the success probability of a packet $P_r(L)$ with an L byte long MPDU can be written as

$$P_r(L) = P_1(24)P_r^{\text{MPDU}}(L). \tag{1}$$

where

$$P_1(24) = \prod_{i=1}^{192} P_1^{b,i} \text{ and } P_r^{\text{MPDU}}(L) = \prod_{i=1}^{8L} P_r^{b,i}. \tag{2}$$

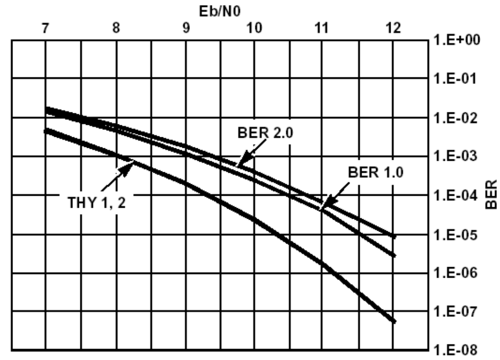


Fig. 2. SNR-BER for PSK Modes

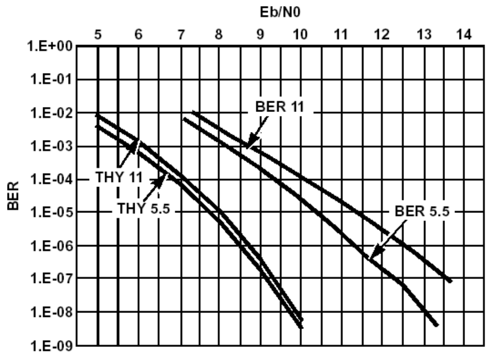


Fig. 3. SNR-BER for CCK Modes

where $P_r^{b,i}$ is the bit-success probability seen by the ith bit when the transmission occurs at rate r. $P_r^{b,i}$ can be obtained from the actual chipset SNR-BER curves in Fig.2 and Fig.3.

Typical off the shelf wireless chipsets [2], [7] report SNR measurements in terms of RSSI value once per packet. Using the available data, we now present the procedure to evaluate the parameters of the markov chain based on measurements that can be obtained from common hardware.

B. Finite State Model for SNR Variation

We next present a methodology to model SNR variations using a finite state markov chain with state space $\mathcal{S} = s_1, s_2 \ldots s_G$. Each of the G states corresponds to a certain channel quality and an associated packet success probability. G is a parameter and needs to be fixed. We will later discuss how to select an appropriate value for G. We will obtain the transition rates and the steady state probabilities for the markov chain. We assume that the transitions happen between the adjacent states. Such a choice is intuitive because normally the channel transitions are not abrupt but continuous and then, if

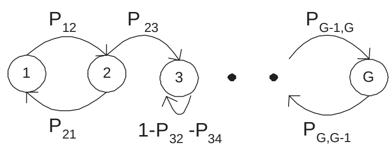


Fig. 4. Channel Model.

the SNR intervals are chosen with a high granularity then transitions between non-adjacent states can be avoided. This allows us to use birth-death models which are amenable to analysis. We adapt the methodology used for fading channels in [13], [17]. We will demonstrate that the framework for fading channels is a good model for Wi-Fi channels. The SNR trace i.e. the SNR recording for every received packet is to be partitioned into G states based on time duration. A received packet is said to face state s_k if the SNR values that the bits comprising the packet face are in the range $[\Gamma_k, \Gamma_{k+1})$. We will compute the SNR thresholds $\vec{\Gamma} = [\Gamma_1, \ldots \Gamma_{G+1}]$, $\Gamma_1 = 0$, $\Gamma_{G+1} = \infty$ and $\Gamma_k < \Gamma_{k+1}$ to partition the SNR process. Let P_{ij} and π_i be the state transition probability and the steady-state probability respectively. Since the transitions happen between the adjacent states, hence $P_{k,i} = 0$ for $|k - i| > 1$.

Let $N(\Gamma)$ be the level crossing rate of the SNR process in the positive direction only (or in the negative direction only). Essentially this is the number of times the SNR crosses a level Γ in a particular direction divided by the total time.

Let $\bar{\tau_k}$ be the average duration of the SNR interval $[\Gamma_k, \Gamma_{k+1})$. This is the average time the SNR process remains continuously between Γ_k and Γ_{k+1} over a measurement interval T. For simplicity of exposition we assume a fixed packet size with transmission time T_p in order to outline the procedure. We require that the average duration of a state is some constant times the packet propagation time T_p, i.e. $\bar{\tau_k} = c_k T_p$. We let $c_k = c \;\forall\; k$. In other words each state has the same average duration. We justify such an assumption. The states in which the system spends more time are more important for characterizing the system. Thus these states should be represented with a higher SNR granularity. This can be achieved by subdividing these states such that the time duration assigned to each substate is reduced, which in turn means that all states have equal duration.

The steady state probability π_i is the total time during which the SNR level is between Γ_i and Γ_{i+1} divided by the total time T i.e. $\pi_i = \text{Prob}(\Gamma_i \leq \Gamma < \Gamma_{i+1})$. Note that π_i can be evaluated from the trace if Γ_i and Γ_{i+1} are known. $\bar{\tau_k}$ is then the ratio of the total time the signal remains between Γ_k and Γ_{k+1} and the number of these signal segments[1].

Hence

$$\bar{\tau_k} = \frac{\pi_k T}{(N(\Gamma_k) + N(\Gamma_{k+1}))T} = \frac{\pi_k}{N(\Gamma_k) + N(\Gamma_{k+1})}.$$

Thus we have

$$cT_p = \frac{\pi_k}{N(\Gamma_k) + N(\Gamma_{k+1})} \text{ for } k \in [1 \ldots G]. \tag{3}$$

We require our solution to satisfy G equations in (3). The variables are c and $\vec{\Gamma} = [\Gamma_1, \ldots \Gamma_{G+1}]$ with $\Gamma_1 = 0$ and $\Gamma_{G+1} = \infty$. Hence there are G variables. One way to solve this system is to take an initial guess for c and then successively obtaining $\Gamma_2, \Gamma_3 \ldots \Gamma_G$ using $k = 1, 2 \ldots G$ respectively in (3). Note that $N(\Gamma)$ can be evaluated from the trace for every Γ.

[1]The number of such signal segments differs from $(N(\Gamma_k) + N(\Gamma_{k+1}))T$ by at most 1 and this error becomes insignificant for large traces.

Once $\vec{\Gamma}$ is determined, the transition probabilities can be computed as the ratio of the level crossing rate and the average number of packets staying in that state, i.e.

$$P_{k,k+1} = \frac{N(\Gamma_{k+1})T_p}{\pi_k}, k = 1, 2, \ldots, G - 1$$

and

$$P_{k,k-1} = \frac{N(\Gamma_k)T_p}{\pi_k}, k = 2, \ldots, G$$

Using the above transition probabilities and (3), the memory of a state i.e. $1 - P_{k,k+1} - P_{k,k-1}$ is $1 - 1/c$.

We describe the method to obtain the average success probabilities for the states. The SNR-BER mappings are obtained from the characteristics in Fig.2 and Fig.3 [7]. Let $P(x)$ be the packet success probability for SNR level x. Also let $n(x)$ be the fraction of time SNR level x is observed in the SNR trace. Then the average probability of success conditioned on state s_k, $\alpha(k) = \frac{\sum_{x=\Gamma_k}^{\Gamma_{k+1}} P(x)n(x)}{\pi_k}$.

Next we present our measurement setup and trace collection scenarios. We will use the data from the trace recordings and evaluate the markov chain based on the preceding discussion.

III. Measurement Setup and Trace Collection

We now describe our measurement setup and the trace collection procedure. Our hardware comprises of two Dell Lattitude X200 laptops with internal Agere cards and a PCMCIA slot. The wireless NICs are Cisco CB21AG-AK9 and the RFgrabber [14] with an Intersil chipset. A host Windows XP workstation running Airopeek NX [14] connects to the RFgrabber to store packets. We use the Airopeek NX [14] packet analyzer for measurement purposes[2]. We capture all IEEE 802.11 management packets (Beacons), data packets (TCP, UDP) and control packets (ACKS) which comprise 98% of the traffic. For each packet from the Access Point (AP), the Airopeek NX trace records the time stamp, the signal strength, the channel number, the noise level, the packet size, the transmission speed, the protocol and the packet error flag. Erroneous Packets are flagged according to radio error, decryption error or a CRC error.

We conduct our measurement in different kinds of Wi-Fi environment and at different time instants to obtain a variety of possible channel characteristics. We broadly describe the different settings that we believe are representative for recording the data.

1) Locations close to the AP with few users e.g. classrooms
2) Locations close to the AP with large number of users e.g. hotspots, conference rooms etc.
3) Locations distant from the AP in relatively less crowded areas e.g. parks
4) Locations distant from the AP in crowded areas.

In the first case the channel is referred to as *good*. Here, the signal strengths are high and the error probabilities are small(<3%) with SNR >25dB. The second and the third cases are what we refer to as *intermediate* channels. In the second case the interference is higher than the first. For the third case

[2]We use Network Stumbler(NS) [11] for cross-verification of signal levels. NS is an active scanner that scans all 11 channels sending probe requests.

the signal strength is lower than the first. As compared to the first case, both the second and the third case experience lower SNR 10-20dB and higher packet error with error rates 5-10%. The fourth case is referred to as a *poor* channel with signal strength lower and the interference higher than the first. Here the packet error rates are as high as 50% with SNR $<$10dB. The first three cases are more likely to arise in practice, but we consider all cases for completeness.

The trace recording is carried out for a duration of 20 minutes at 2 hour interval for a period of seven days. We observe that a majority of the users have short session times that are less than 10 minutes and the duration of portions when the usage pattern remains similar are approximately around 6-7 minutes. This observation is consistent with reports in [3]. We continuously record data for 20 minutes at any given time.

Next we evaluate the effectiveness of the finite state markov model for the temporal SNR variations.

IV. Testing of the Model Based on Traces

We proceed to evaluate the efficacy of the finite state markov model. We first evaluate the performance of the model in terms of tracking the SNR obtained directly from the measurement. We also evaluate the model in terms of capturing statistics relevant from the perspective of higher layer wireless protocols. The statistics of interest typically comprise the moments of the error free and the error burst lengths. Also long term correlation of the packet error process is of interest in predicting the future channel behavior. To test the model, we first examine the SNR values from the trace at equal intervals of time for the purpose of developing the markov chain. The interval corresponds to transmission times of data packets which are longer than the control and management packets. We used the transmission time for a 1000byte packet(0.73ms) as the interval, i.e., the trace is scanned for SNR recordings at intervals of 0.73ms irrespective of the packet type. The time for computing the model parameters depends on the length of the available trace. In our case generating the model from a 20 minutes trace required approximately 25 seconds on a 750Mhz laptop with 256MB RAM. From the markov chain we generate an artificial channel trace for the SNR variation.

We now describe the statistical measure that we use to quantify the performance of the model.

Let $p(x)$ and $q(x)$ be two probability mass functions defined over a common set $\mathcal{X}$. We now describe a commonly used statistical measure that quantifies the 'distance' or the relative entropy between two probability distributions. This comprises a general measure and allows us to compare the statistics of all orders for two distributions.

The *Kullback-Leibler Divergence*(KLD) [5] is defined as

$$D(p(x)||q(x)) = \sum_{x\in\mathcal{X}} p(x)log\frac{p(x)}{q(x)}.$$

The KLD is zero when the distributions are identical and strictly positive otherwise. The KLD is a measure of the 'distance' between two distributions. However the measure is not symmetric and does not satisfy the triangle inequality.

Let $p(x)$ be the probability mass function of random variable X defined over a set $\mathcal{X}$. The entropy $H(p(X))$ of the random variable X with distribution $p(X)$ is the average length of the shortest description of the random variable.

$$H(p(X)) = \sum_{x\in\mathcal{X}} p(x)log\frac{1}{p(x)}.$$

The definition of the divergence measure carries a bias. This discrimination is larger for random variables with higher entropy. Hence to evaluate the model it is important to weigh in the entropy of the source which could be large. Hence we use the normalized Kullback-Leibler divergence NKLD [10].

$$NKLD(p(x)||q(x)) = \frac{D(p(x)||q(x))}{H(p(X))}$$

Since the order of the distributions is important we consider the distributions derived from the measured trace as $p(x)$ and those derived from the markov model as $q(x)$ in the subsequent discussion.

A. SNR Variation

The difference between the SNR values from the actual trace and the trace obtained from the channel model is examined. The difference in the expected values is observed to be less than 4%. The difference arises because the non-stationary traces are represented using a stationary model. We also evaluate the NKLD between the probability mass function of the SNR obtained from the measured trace and the markov model. The probability mass function defines the probability of the SNR belonging to certain intervals. The setup is shown in Fig.5. The NKLD measure is plotted for three kinds of channels in Fig.6 as the number of states increases. The low value of the NKLD measure demonstrates the proximity of the two distributions.

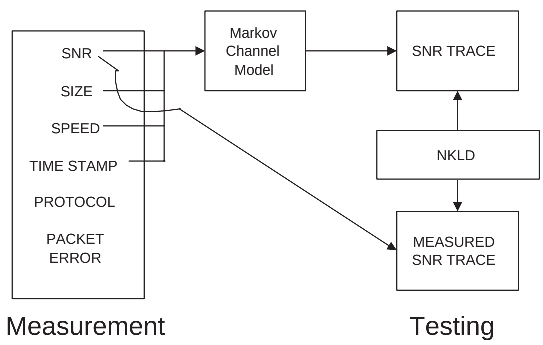


Fig. 5. Measurement and Testing Setup for SNR Trace.

B. Long Term Correlation

We use the trace for the temporal SNR variation as obtained from the channel model. Using (1) and Fig.2 and Fig.3, the SNR values yield the packet success probabilities that results in a packet loss trace which we refer to as the markov generated packet trace. The setup is shown in Fig.7. We study the performance of the markov model in terms of capturing the long term correlation i.e. the conditional probability that packet $n+k$ is in

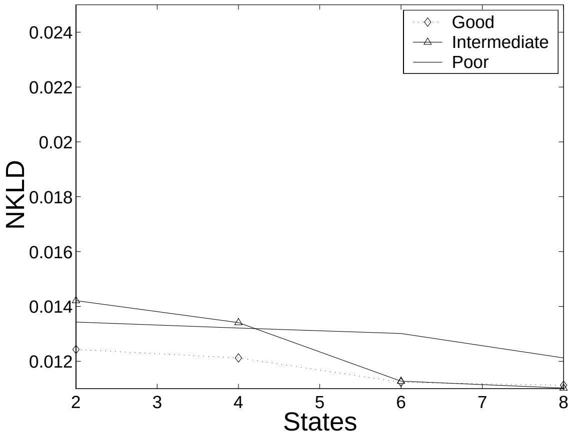


Fig. 6. SNR Distribution.

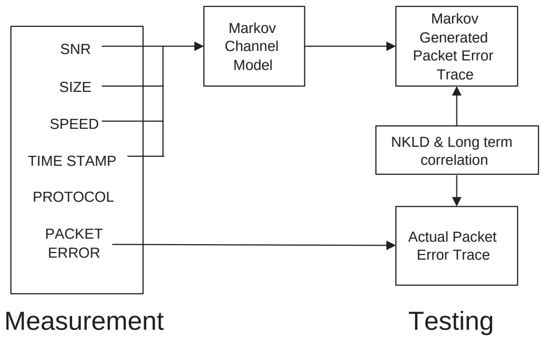


Fig. 7. Measurement and Testing Setup for Packet Loss trace.

error, given that packet n is in error. In Fig.8 we plot the performance of the markov model in tracking long term correlation. As seen in the plot, a markov chain with 8 states performs significantly better than one with 2 states. However both models are not able to capture the long term correlation precisely. This is because the actual trace is non-stationary and no stationary model can capture the variations in a long run.

C. Burst Length Process

Now we study the burst length process that can be derived from the channel model. Specifically we would be focussing on the distributions of the packet error burst lengths and error free lengths. The random variable depicting the error free length I denotes the number of good packets received between error packets. The error burst length B is the length of consecutive packet errors. Packet error bursts are responsible for degrading the throughput in wireless transmission because they are harder to recover from. Isolated packet errors are mostly recovered from, using error correcting and redundancy coding schemes.

We obtain the probability mass function of I and B from the observed packet error trace. Again we compute the probability mass function of I and B from the markov generated packet error trace. The setup is shown in Fig.7.

We compare the NKLD between the actual trace and the markov trace. Specifically, we observe the variation in the NKLD as the number of states in the model is increased. In Fig.9(a), we observe a very slight reduction in the NKLD measure as the number of states is increased. This is because the

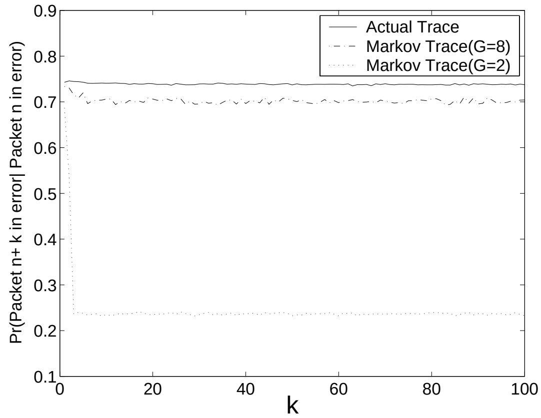


Fig. 8. Conditional probability that packet $n+k$ is in error given that packet n is in error for a poor channel.

actual SNR values are high for all states so that the packet success rate is high. However for intermediate and poor channel the SNR variation is in a range where the packet success probabilities vary. It is in these cases that we need higher granularity to define the state space of the SNR process.

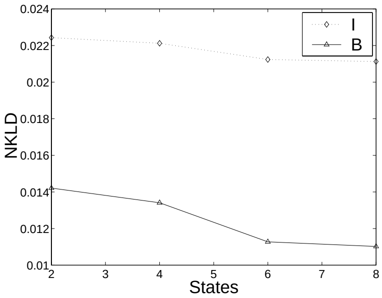
We point out some factors that limit accurate prediction of the packet error process from the SNR. The SNR-BER characteristics as shown in Fig.2 and Fig.3 as reported by card manufacturers are obtained under Additive white gaussian noise(AWGN) environment which might not be the case in practice. Also the RSSI values i.e. the units in which the cards report the signal levels and signal values(dBm) do not have a one-to-one correspondence. Common Wi-Fi hardware record the RSSI and the noise levels once per packet. However any of the intermediate bits of a packet can get corrupted. These factors can result in discrepancies between the calculated packet errors based on SNR measurements and the observed packet error process.

We now discuss some inferences we make from the above measurements.

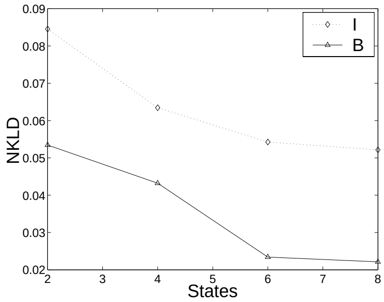
V. INFERENCES FROM THE MODEL

Based on our measurements, we proceed to identify some features of the model that makes it useful for channel representation. Our work is complementary to efforts in [6] who have conducted measurements primarily from an application layer perspective. They study user level characteristics such as application mix, building traffics and mobility patterns while we focus more towards the physical layer aspects and their characterization.

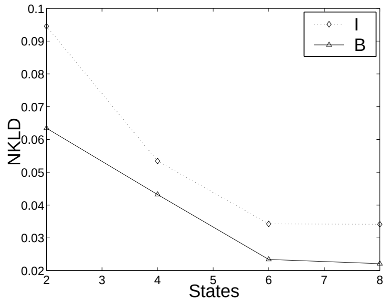
An important difference of our model as compared to the two-state model is the increased number of states to represent the channel. Specifically the value of G i.e. the number of states needs to be high enough and using $G = 8$ resulted in a good match for all the three types of channels we identified in Section III. Based on model generation from traces collected on different days and times, we notice some broad trends in terms of the 802.11 channel behavior. SNR variation is a reasonably good indicator of the channel quality and packet loss in an 802.11b Access point type network. We obtained the following channel state success



(a) Good channel.



(b) Poor Channel.



(c) Intermediate channel.

Fig. 9. NKLD measure for burst lengths from actual and markov generated packet trace for different kinds of channels.

probabilities α. In a crowded park with poor channels (SNR < 10dB), α =[0.0000 0.1057 0.1904 0.3019 0.4297 0.5595 0.6782 1.0000]. For an active hotspot with intermediate channels (SNR 10-20dB), α =[0.0000 0.6785 0.7772 0.8535 0.9083 0.9453 0.9689 1.0000] and for a classroom with good channels (SNR > 25dB) α =[0.0002 0.9980 0.9980 0.9991 0.9996 0.9996 0.9999 1.0000]. Note from α for good channels, that using fewer states (e.g. 2) can result in a close match since most of the packet success levels are high as has been observed independently in [8]. However this is not true for intermediate and poor channels and authors in [16], [1] who have studied channels with higher mean burst lengths and error rates have not observed a good match with a two-state model.

We studied the variation in the model parameters, e.g. memory, at different times of the day and across different days. The memory of the channels, i.e. $1 - P_{k,k+1} - P_{k,k-1}$ (Fig.4) is observed to vary in the range $0.8 - 0.95$. A memory value of 0.8 is seen in locations with high number of users while very high memory is seen in 'good' channels with very low loss rates. Owing to the high memory of the channel, resource allocation algorithms can possibly make decisions less frequently in order to reduce overheads.

In general a strong similarity between parameters (variation $< 2\%$) was observed in terms of same time at different days at a given location. This can be attributed to similar usage patterns. However channel quality is significantly different at different times of the day, e.g. over 3-4 hours on the same day, the channel quality changes from 'good' to 'intermediate' and viceversa as the user loads alter. This indicates that number of users and usage patterns plays a major role in determining channel characteristics. In addition because of recurring user patterns at the same time over different days, models with similar parameters can be utilized again.

Overall, characterizing the SNR gives a good insight of the channel characteristics and helps explain behavior that are not directly answered from packet error traces.

VI. Conclusions

We investigate a model for characterizing SNR variations of a 802.11 channel. The model is simple, analytically tractable and easy to characterize using measured traces. We have discussed an approach to gather the information required to parameterize such a model based on measurements taken from 802.11b access point networks using common hardware. The model is found to represent the packet loss process with reasonable accuracy. The model maintains the birth-death flavor of a two-state model while at the same time improves the performance significantly. Such a model that tracks the temporal variation of SNR can be useful for a variety of resource allocation algorithms and large scale simulations that might require low complexity models.

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