ANALYSIS AND MODELING OF ERRORS AT THE 802.11b LINK LAYER

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ABSTRACT

In this paper, we analyze the errors observed at the link layer of an 802.11b network. Our analysis at all supported bitrates (i.e., 2, 5.5. and 11 Mbps) establishes that the error patterns are not memoryless, and therefore, they exhibit a certain level of temporal dependencies. Thus, we evaluate the suitability of a two-state Markov model to capture the channel behavior. Non-stationarity of the error patterns renders such a simplistic model inadequate, and hence, we consider higher order models. This formulates a key contribution of this paper, and that is, a hierarchical Markov model, which captures the non-stationarity of the channel while employing real-time application-specific considerations to determine state-transition probabilities.

1. INTRODUCTION

Packet errors and losses can have an adverse affect on the perceived quality of a real-time multimedia transmission. Classical data applications provide reliability by attempting to recover the corrupted/lost packets through retransmissions. Real-time requirements of emerging delay-sensitive multimedia applications (e.g., internet telephony, video conferencing, multicast audio/video etc.) necessitate a retransmission-less infrastructure (to avoid low-latency and/or implosion of feedback messages). Meanwhile, one positive aspect of such applications (especially those delivering streaming media) is their inherent tolerance to a certain level of errors and losses in the multimedia content. Design and implementation of such applications stipulates a thorough understanding of the error and loss patterns encountered over the network.

The reasons stated above motivated studies, such as the ones reported in ([1], [2]), and which analyzed and modeled packet losses over the Internet. Packet corruptions over the wired media are very infrequent and, therefore, packets with errors are dropped without regard to the number and location of such errors. However, the rapidly growing ubiquity of Ethernet-based wireless networks has caused migration of technologies from the current (wired) Internet to the wireless domain. The wireless medium due to its inherent vulnerability is more error-prone than the contemporary wired media. This increased error-rate impedes the ability of wireless networks to support transmission at high-bitrates.

Cross-layer protocol strategies have been suggested in order to mitigate the above drawback of the wireless medium. In particular, schemes tailored for delivery of multimedia content over wireless networks consider the increased error-rate and attempt to improve bandwidth utilization by processing corrupted packets. This allows modern-day multimedia encoders to adjust adaptive parameters based on the number and distribution of corruptions/losses, for example, an audio encoder can adjust its rate [3], and a video encoder can invoke error-resilience features, such as, data partitioning, reversible VLC etc.[4]. Modifications at the link- and transport layer have also been proposed to facilitate such real-time error-resilience features e.g., partial-protection of sensitive headers in UDP Lite [5]. For such technologies, error patterns inside a packet payload are important, since, decision to drop or retain a packet is taken at the application layer. Hence, it is important to investigate how many and what type of errors are introduced in packets transmitted over wireless networks.

In this paper, we analyze and model the error patterns introduced by an 802.11b channel under realistic settings. We performed analysis of errors at the 802.11b link layer, i.e., errors that are not corrected by the physical layer. Hence, our definition of channel encompasses the wireless medium and the 802.11b physical layer (PHY). Our analysis focuses on the byte level since most Forward Error Correction (FEC) schemes employed to combat these errors operate on the byte-level (even if they are across multiple packets), and error resilience schemes in a robust encoder are also byte-aligned. Analysis at higher/lower granularity levels (i.e., packet/bits) is presented in [6].

The remainder of this paper is organized as follows. Section 2 describes the experimental setup for error trace collection. Section 3 analyzes the probability distribution of errors at 2, 5.5 and 11 Mbps, and approximates the main distribution as Gamma and the tail as Pareto. This analysis shows that the channel cannot be classified as memory-less. Section 4 evaluates the suitability of a two-state Markov Model to capture the error patterns. This model fails to capture the non-stationarity of the channel, which necessitates investigation of higher-order Markov models. Therefore, we propose and evaluate the performance of a hierarchical Markov Model (hMM) in Section 5. Finally, Section 6 summarizes some key conclusions of this paper.

2. EXPERIMENTAL SETUP

Our simulation setup employed an 802.11b Access Point (AP) operating in Distributed Coordination Function mode and three wireless stations communicating in the infrastructure network configuration. One of the stations was operating as the server and the remaining two as multicast clients. All wireless stations were Linux boxes using Prism2 chipset device drivers (linux-wlan-ng-0.1.14-pre3). Source code of the device driver at the clients was modified to capture screenshots of MAC data frames.

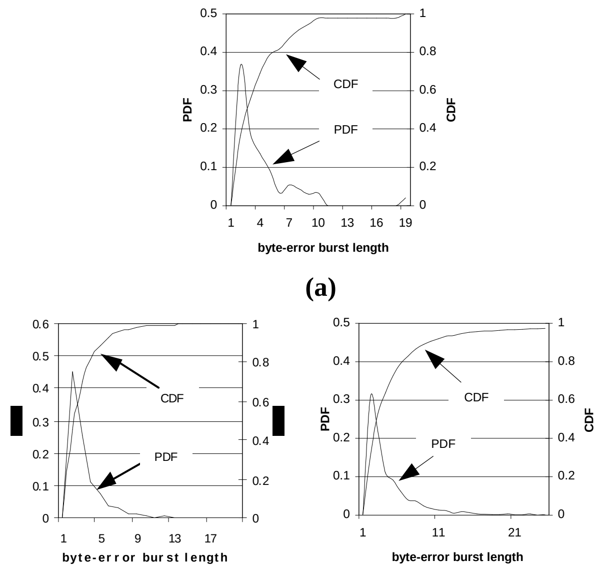
Initially, the server was placed in clear line of sight (LoS) of the AP. The AP was forced to transmit at 2, 5.5 and 11 Mbps for each observation. The server was stationary and transmitted a continuous stream of predetermined patterns to the multicast clients. Traces were generated for each bitrate at different stationary client positions with and without LoS. It was observed that with clear LoS, the error rate, at all bitrates, was extremely low. Such excellent performance deemed further LoS study inconsequential. Hence, both clients were positioned in a separate room across the hallway to simulate a more realistic business/classroom/home-network wireless setup. A total of 3 experiments were conducted for each bitrate. Each experiment involved the transmission of 100,000 packets, and 10 error traces per bitrate were generated as a result. These experiments were performed at different times of day to nullify effects of the environment and unrelated traffic.

3. ANALYSIS

Figure 1 shows the probability and cumulative distribution functions of error-burst lengths at different bitrates. Due to the diversity of the Gamma distribution in capturing the shape and scale of a wide range of statistical data, we employed non-linear regression analysis to generate a best-fit Gamma PDF for the burst length:

$$f(x) = \frac{\lambda e^{-\lambda x} (\lambda x)^{\alpha - 1}}{\Gamma(\alpha)}$$

for $x \geq 0$, $\lambda > 0$, $\alpha > 0$. The shape and scale parameters for the fits are given in Table 1. Overall, the Gamma PDF fits the general shape of the collected-data histograms, but is unable to fit the tails. Our analysis is targeted towards applications, which employ error-resilience/control to combat byte-level packet corruptions. Many error control techniques are not designed for the very worst-case scenario. Hence, distribution of the tail is important for determining an efficient error control scheme.



(a) (b) (c)

Figure 1. CDF and PDF of Error bursts at (a) 2 Mbps, (b) 5.5 Mbps, and (c) 11 Mbps.

Bitrate	α (shape)	λ (scale)
2	4.96682	0.60563
5.5	8.07703	0.31632
11	4.48498	0.726767

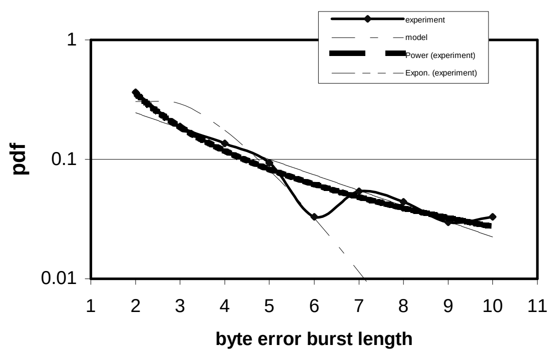
Table 1. Parameters of Gamma Distribution for 2, 5.5 and 11 Mbps

Since the mode of the error-distribution is greater than one, it can be inferred that the observed errors are not isolated (i.e., errors are bursty). This in turn implies that the error patterns do not exhibit memory-less properties. To establish further insight into this property, we fit the tail with an exponential distribution ($\lambda \cdot e^{-\omega \cdot x}$) and a Pareto or power distribution ($\alpha \cdot x^{-\beta}$). These fits are shown in Figure 2. The Pareto distribution provided a good fit as the correlation was greater than 90% for all data rates. The fit provided by the exponential distribution had a lower correlation than the Pareto distribution for all three data rates, but for 5.5 Mbps the fit given by exponential was comparable to the Pareto fit.

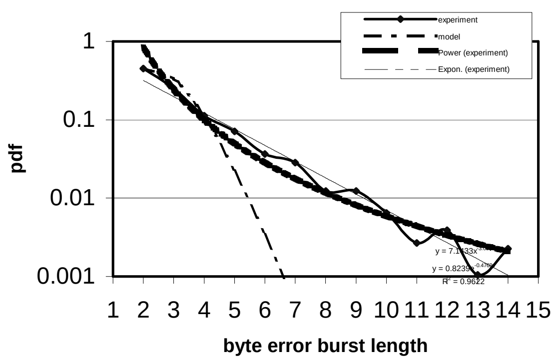
Thus, it can be stated that even though the overall probability distribution looks like Gamma, the tail indeed exhibits a heavy-tail behavior. Therefore, the error distribution is not memory-less. Last column of Table 2 shows the power function parameters obtained by fitting the tail with a Pareto Distribution. The parameter, α, is proportional to the likelihood of the burst length being equal to the mode of the distribution, while the parameter β is inversely proportional to the amount of memory in the channel. In the following section we use this information to develop a model to approximate the channel burstiness.

Bitrate	α	β	chi-square
2	0.4467	0.2994	0.9215
5.5	7.1433	3.0836	0.951
11	1.8613	2.1067	0.8699

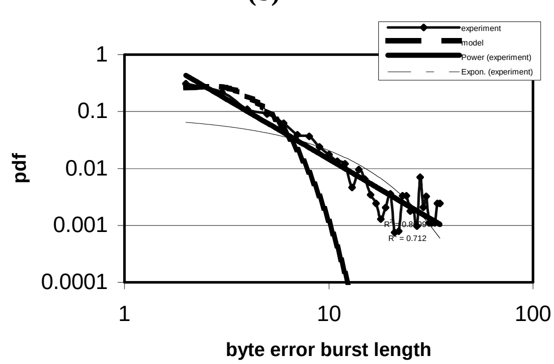
Table 2. Pareto Distribution Parameters



(a)



(b)



(c)

Figure 2. Approximation of PDF tail for (a) 2 Mbps, (b) 5.5Mbps, and (c) 11 Mbps

It should be pointed out that a two-distribution model (Gamma and Pareto) might still not be adequate to capture the highly non-stationary nature of the error data. One potential proof of this inadequacy is the salient anomaly that can be observed in Table 1 and Table 2 by comparing the different parameters of the proposed distributions for the 5.5 Mbps case as compared with the distributions' parameters of the other two bitrates data. Consequently, Markov chain models may be used to characterize these error patterns more adequately.

4. TWO-STATE MARKOV MODEL

Analysis in the previous section shows that the channel is not memory-less. In this section we first model the channel behavior with a simple two-state Markov chain. Table 3 outlines the state transition probabilities and the overall probability that a byte is corrupted. As the bitrate increases, the robustness of the 802.11b PHY decreases. Thus, with increase in bitrate, the overall probability of error should also increase. This intuition is also substantiated by the last column of Table 3 which shows that the probability of byte-error (P_{byte}) is directly proportional to the bitrate. Similarly, channel transitions to the bad state should also increase with an increase in bitrate. Again, the probability of transiting from a good state to a bad state (P_{gb}) in Table 3 increases as the bitrate increases.

Bitrate	P_{gg}	P_{gb}	P_{bg}	P_{bb}	P_{byte}
2	0.999	0.00002	0.327	0.673	0.00006
5.5	0.991	0.00909	0.368	0.632	0.024
11	0.946	0.05419	0.304	0.696	0.15

Table 3. Transition Probabilities of the Two-State Markov Model

However, a potential anomaly can be observed in Table 3, and that is, P_{bb} for 5.5 Mbps is less than the corresponding P_{bb} for 2 Mbps. This outlines the inadequacy of a simplistic 2-state Markov model to capture the non-stationary behavior of the errors.

Furthermore, thorough examination of the error traces revealed two interesting observations that contradict the original assumption (i.e., corruptions are usually bursty): (a) In addition to the consecutive bursts, there existed some small isolated bad bytes; and (b) Bad states had isolated small instances of good bytes amongst a number of corrupted bytes. This motivates the need for a more robust model to capture these observed error patterns.

5. HIERARCHICAL MARKOV MODEL

The two-state Markov model is incapable of handling the abovementioned anomalies. This section addresses this issue by proposing an improved model for the channel. However, it should be noted that the main focus of our paper is to provide a scheme that can be used to model the channel behavior from an application layer perspective.

Most real-time applications can tolerate data corruption/loss below a certain threshold, but are unable to deliver intelligible media beyond that threshold.

In accordance with our previous observations and discussions, we propose a hierarchical Markov model with two high-level states, "severe-burst" and "low-burst". Furthermore, each of the aforementioned states had a two-state Markov model embedded in it as shown in Figure 3.

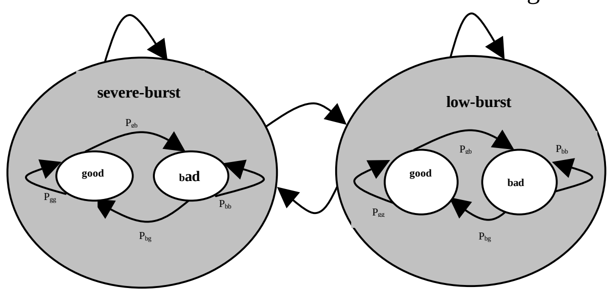


Figure 3. Hierarchical Markov Model

One of the challenges of the proposed hMM model is the delineation of the high-level "severe-burst" and "low-burst" states. Ideally, this delineation should be based on the level of impact that these high-level states have on the application layer. This task, however, becomes very difficult due to the wide range of possible degradations that can result from different patterns of burst and random errors.

5.1.1. State Demarcation Heuristic

We employ the state demarcation heuristic presented in [6] to identify the boundaries of severe-burst and low-burst states. This heuristic exploits error-resilience/tolerance characteristic of the real-time application to cater for small isolated bursts. Transition between the two high-level states is also application-specific i.e., transition is based on two thresholds; 1) error-tolerance characteristics of the application are used in determining transitions from low-burst to severe-burst states; 2) in the severe-burst state, a lower-limit is defined for bursts of good bytes that are used as a criterion to transit to the low-burst state. Further details of the heuristic are skipped for brevity.

The probabilities in Table 4, Table 5 and Table 6 were calculated by employing the aforementioned heuristic using certain threshold values that are suitable for video applications. Clearly, the model addresses the anomalies mentioned before. One testimony of the improved adequacy of the proposed hierarchical model (when compared to the simple traditional two-state Markov chain) is that the P_{bb} is increasing with the increase in bitrate. Also, and as expected, the transition probabilities for the embedded severe- and low-burst states indicate that in a severe-burst state the probability of getting a burst of bad bytes is quite high.

	P_{gg}	P_{gb}	P_{bg}	P_{bb}
Higher states	0.999	0.00001	0.777	0.223
low-burst	0.999	0.0005	0.426	0.574
severe-burst	0.918	0.8168	0.341	0.659

Table 4. hMM Transition Probabilities at 2Mbps

	P_{gg}	P_{gb}	P_{bg}	P_{bb}
Higher states	0.999	0.00008	0.224	0.776
low-burst	0.995	0.00489	0.407	0.593
severe-burst	0.900	0.09958	0.335	0.665

Table 5. hMM Transition Probabilities at 5.5Mbps

	P_{gg}	P_{gb}	P_{bg}	P_{bb}
Higher states	0.999	0.0009	0.013	0.986
low-burst	0.983	0.0168	0.371	0.629
severe-burst	0.895	0.1049	0.292	0.707

Table 6. hMM Transition Probabilities at 11Mbps

6. CONCLUSIONS

In this paper, we analyzed the errors observed at the link layer of an 802.11b network. We performed analysis of the error burst lengths at the three supported bitrates i.e., 2, 5.5 and 11Mbps. Our analysis establishes that the error patterns exhibit highly non-stationary temporal dependencies. This necessitates a Markov-type model to capture the errors patterns. First, we employed a two-state Markov model to track the behavior of the error traces. Non-stationarity of the errors deemed such a simple model inadequate. We, therefore, propose a higher order hierarchical Markov model to provide a better approximate of the channel behavior. The proposed hierarchical approach addresses some common anomalies observed in the traces.

7. REFERENCES

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