CHANNEL MODELING AND ITS EFFECT ON THE END-TO-END DISTORTION IN WIRELESS VIDEO COMMUNICATIONS

Eren Soyak[1], Yiftach Eisenberg[2], Fan Zhai[2], Randall Berry[2], Thrasyvoulos N. Pappas[2], and Aggelos K. Katsaggelos[2]

[1] Ingenient Technologies, Rolling Meadows, IL 60008
[2] Department of Electrical and Computer Engineering
Northwestern University
2145 Sheridan Road, Evanston IL 60208

Email: eren.soyak@ingenient.com, {yeisenbe, fzhai, pappas, rberry, aggk}@ece.nwu.edu)

ABSTRACT

A major limitation faced by a mobile user is their dependence on a limited battery supply. For wireless video communications, joint source coding and transmission power management (JSCPM) has recently been considered as a means of efficiently allocating transmission energy. In order to reduce complexity, the design of many of these adaptive resource allocation algorithms utilizes simplified channel models that do not account for the burstiness of the channel. We analyze the effects of such channel model simplifications on the end-to-end distortion. We present a channel model that is based on information theoretic considerations, which captures the bursty nature of wireless channels and accounts for packet lengths when calculating the probability of loss. Given the source coding and transmission parameters derived using a simplified channel model, our goal is to analyze how the end-to-end distortion is affected when a more realistic complex channel model is used to simulate losses. Experimental results suggest that the performance gain predictions for JSCPM using a simpler channel model are also valid when more sophisticated channel simulations are used, provided that a number of additional steps are taken after the optimization to account for the complex characteristics of wireless channels.

1. INTRODUCTION

The development of wireless video communication systems is an active and challenging area of research. Recently, considerable attention has been focused on energy/power efficient wireless video communications. One approach that has been shown to improve video quality by efficiently utilizing transmission energy is joint source coding and transmission power management (JSCPM), e.g., [1], [2], [3]. The motivation behind JSCPM is that energy efficiency is gained by allocating power (protection) to different regions of a sequence based on their relative importance. For example, less power may be used to transmit packets in a static background region in order to allocate more power to regions of the sequence that are more difficult to conceal.

In order to limit computational complexity, adaptive resource allocation algorithms, such as JSCPM, sometimes rely on simplified channel models that, among other simplifications, do not account for the burstiness of the channel. One reason for this is that the complexity required for optimal resource allocation increases dramatically with the complexity of the channel model. The goal of this paper is to analyze the effects of channel model simplifications on the end-to-end distortion. Given the source coding and transmission parameters derived using a simplified channel model, our goal is to analyze how the end-to-end distortion is affected when a more realistic complex channel model is used to simulate losses.

2. MODELING WIRELESS CHANNELS

Channel modeling is an important and well-studied topic in the field of wireless communications. In [1], a channel model based on the concept of outage capacity [4] is used to develop an optimal JSCPM algorithm. One aspect of the channel model used in [1] is that it assumes independent channel fading for each packet. Thus, it does not consider burst errors. In addition, the channel fading varies only between packets and is assumed to be fixed within each packet. Thus, the length of each packet does not affect its probability of loss. We will refer to the channel model used in [1] as "Model A." In this paper, we present a more sophisticated channel model ("Model B") that is also based on the concept of outage capacity, but differs from Model A in two important aspects. First, it uses channel memory to account for burst errors commonly found in wireless channels. Second, the channel fading transitions are assumed to occur at fixed time intervals instead of at packet boundaries. Similar channel models have been considered in [5] and [6]. Next we present the proposed channel model in detail.

2.1. Proposed Channel Model (Model B)

One of the ways in which to study the effects of the wireless channel on the system, hence enabling one to better control for them, is to use an accurate channel simulation. An important aspect of the wireless channel that must be modeled correctly in order to reflect realistic channel characteristics is the channel fading. Typically, the fading in a wireless channel is modeled a Rayleigh random process. The Rayleigh fading process can be generated using two Gaussian processes as

$$f_{Rayleigh}(i) = \sqrt{g_1(i)^2 + g_2(i)^2} \quad (1)$$

where $g_1(i)$ and $g_2(i)$ are independent identically distributed Gaussian random variables with variance σ. In (1), i represents the time increment over which the channel fading is assumed to be fixed[1]. Correlated channel fading is a well known characteristic of wireless channels. In order to simulate correlated fading, memory can be used when generating the Gaussian processes by setting

$$g_n(i) = \alpha g_n(i-1) + \sqrt{1-\alpha^2}\, z(i) \quad (2)$$

where α^2 is the covariance (or autocorrelation) of the channel and $z(i)$ is an independent zero-mean Gaussian process with variance σ. It is important to note that the autocorrelation parameter α must increase appropriately as the time increment size decreases in order to simulate real-world channel phenomena such as deep fades.

Given a model for the channel fading, our next objective is to determine the probability of packet loss. In this work, we model the probability of packet loss in the capacity versus outage framework developed in [4]. We assume that packets are transmitted over a narrow-band slowly-fading channel with additive white Gaussian noise. In this case, the capacity of the channel during time increment i is given by

$$C_i = W_i \log 2\left(1 + \frac{H_i P_i}{N_0 W_i}\right) \quad (3)$$

where W_i is the bandwidth, H_i is the fading level, N_0W is the noise power, and P_i the transmission power. Here, H_i is defined as $H_i = f_{Rayleigh}(i)^2$. The capacity for an individual packet is determined by averaging the capacity over the increments required to send it so that

$$C_p = \sum_{i=1}^{l_p} C_i \quad (4)$$

where l_p is the number of time increments it takes to transmit the p^{th} packet (extra time within the last interval is considered wasted, and the next packet begins at the next incremental boundary). Any packet transmitted at a rate that is less than the average capacity of the channel during transmission is considered "successful." Conversely, if the transmission rate exceeds the capacity offered by the channel, the packet is considered "lost". Hence, the probability of loss for each packet is the probability that the average channel capacity during its transmission is less than the rate at which the packet is being transmitted, which can be expressed as

$$\Pr(loss) = \Pr(C_p < R_p). \quad (5)$$

In order to illustrate the relationship between the channel capacity and the probability of loss, consider the example shown in Fig. 1. Although the capacity of the channel varies significantly over time (due to variations in channel fading), only packet 3 is lost because the average capacity during its transmission is lower than the transmission rate.

[1] Note that the length of the time increment i varies based on the channel conditions and may be on the order of milliseconds or microseconds.

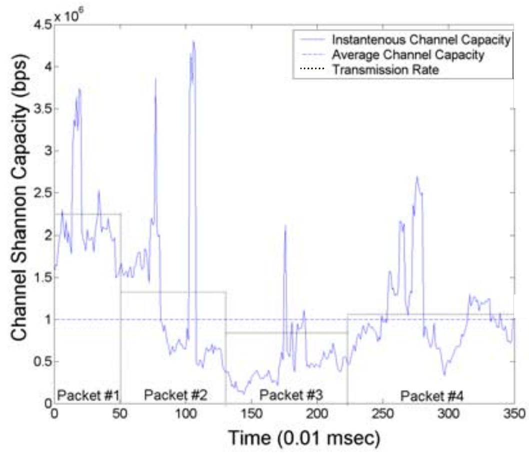

Fig. 1: Data from a sample run of Channel Model B (here packet #3 is lost).

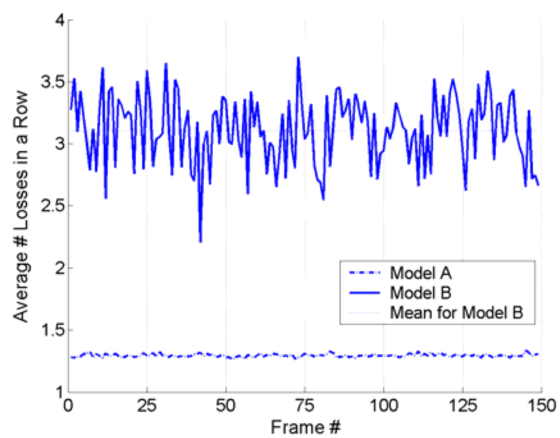

Fig. 2: Avg. Loss run lengths for Model A and Model B.

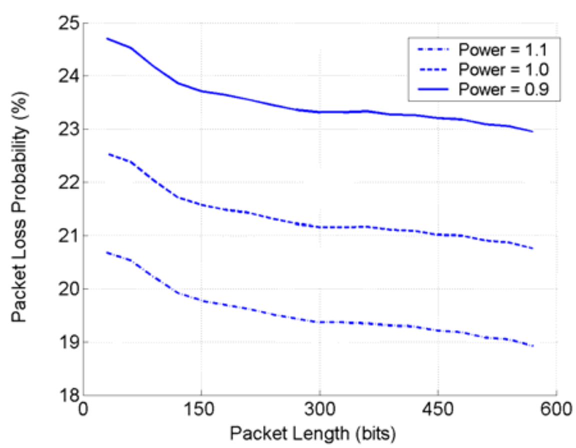

Fig. 3: Packet loss probability as a function of packet length and packet power.

2.2. Comparison of Channel Models

Model B which is used for the experiments in the following sections differs from Model A in that it (a) uses a channel whose state transitions at fixed time intervals and (b) uses channel memory to allow for burst errors. Therefore, packets sent over Model B will be subject to clustered losses. Clustered losses are especially harmful to many error concealment algorithms, where the decoder relies on information from neighboring macro-blocks (MBs) to conceal a lost MB [7], [8]. As shown in Fig. 2, the average number of consecutively lost packets is greater for channel simulations using Model B than those using Model A.

In addition to clustered errors, channel simulations using Model B will result in longer packet having a lower probability of loss than shorter packets. This is because longer packets are less vulnerable to channel fluctuations due to the capacity averaging in (4). As shown in Fig. 3, the probability of loss decreases as the length of packets increases for a given transmission power level. Notice that varying the transmission power appears to have more of an effect on the probability of loss than the packet length. This observation suggests that variations in power may affect the probability of packet loss more than variations in packet length.

3. POWER ALLOCATION ALGORITHMS

In [1], an optimal JSCPM algorithm was presented. In that work, coding parameters, such as the prediction mode and quantization step size, were jointly adapted with the transmission power in order to efficiently utilize the available energy. We will refer to that algorithm as the Varying Power algorithm. As a comparison to the Varying Power algorithm, a Fixed Power algorithm was used in which the source coding parameters were optimally selected for a given fixed power (fixed probability of error). Both approaches use the same amount of transmission energy and delay per packet. As shown in [1], significant gains in end-to-end PSNR may be obtained by using a Varying Power approach in which power is adapted based on the relative importance of video packets. The gains reported in [1] were obtained using Model A channel simulations. In the following section, our goal is to determine if the performance gains of using a Varying versus Fixed Power algorithm also hold under more realistic channel conditions, i.e., channel simulations using Model B.

4. EXPERIMENTS

Using the Model A and Model B channels in conjunction with the Fixed and Varying power allocation algorithms, channel simulations can be run to examine the combined effects of channel fading and power allocation decisions on the end-to-end PSNR.

Since some aspects of our experimental results are content specific, it is important to discuss the characteristics of the video source content. We used the Foreman sequence coded at 15 frames per second. In this sequence there is a relatively static background and dynamic foreground until a scene change occurs around Frame number 80. The nature of the content is relevant in that the number and size of packets transmitted is content-dependent. For example, during a scene change more MBs in a frame are intra-coded than within a scene containing static background and dynamic foreground regions. Due to the bit budget constraint and the increased number of packets, the average packet size sent during the scene change will decrease. Therefore, since the probability of packet loss increases when packet length decreases, this means that during a scene change packets have a higher probability of error when the simulations are based on a Model B channel. In Fig.4, it can be seen that the difference between the curves is greatest around Frame number 100, where the scene change occurs. This is due to the fact that a Model A channel simulation is not sensitive to packet lengths, while in a Model B channel simulation the average probability of loss increases as the average packet length decreases.

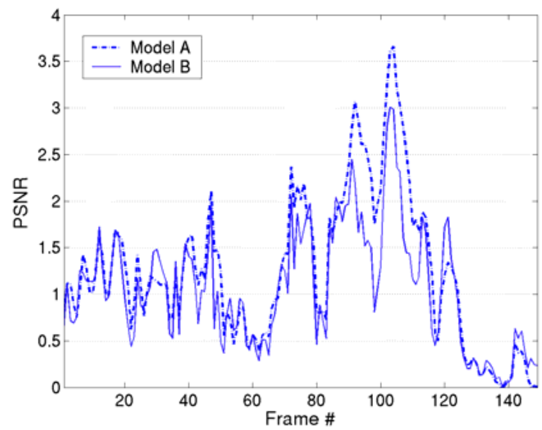

Fig. 4: The PSNR gain from using Varying Power algorithm instead of Fixed Power algorithm when simulated over the Model A Channel vs. the Model B channel. The mean of the Model A curve is 1.24 dB, while the mean of the Model B curve is 1.06 dB.

It is important to note that a Model A channel will lose packets without the clustering one would observe in a bursty Model B channel. For a simulation with equal average fading levels, a Model A channel will spread packet losses across the frame much in the manner aimed for by interleaving algorithms. This will result in a higher PSNR rating when compared to the Model B counterpart due to the fact that error concealment performs worse in the presence of burst errors. Although simulations using Model B suffer from burst errors and increased probability of loss for shorter packet, longer packets have a lower probability of loss than in Model A simulations. Since longer packets typically contain more Intra MBs, they may be more critical to decreasing the end-to-end distortion. Therefore, as shown in Fig. 4, it appears that channel simulations using Model A and Model B return end-to-end PSNR gains that are about 0.2 dB apart on average.

5. PROPOSED ALGORITHM

Using Figs. 2 and 3 we can develop an additional layer of complexity for transmitter resource allocation, which would entail normalizing packet power with respect to packet length while still maintaining the same energy level. Although both empirical and theoretical optimizations may provide operating points that provide superior performance, for the sake of an existence proof we linearly lower packet power as packet length increases while maintaining the energy constraint by increasing the power for shorter packets. However, referring to Figure 3 we can see that a difference in packet length changes the Model B loss probability in the range of a few percentage points. The rest of the difference between the Model A and Model B losses are due to the burstiness of the Model B channel, an effect which can be accounted for during transmission by making use of interleaving within each frame. This will reduce the effect of correlated errors on the concealment algorithm by decreasing the likelihood of clustered losses. The interleaving aims to introduce the most spatial distance between MBs within a frame for purposes of transmission so that burst errors due to a deep channel fade do as little damage as possible to concealment.

Fig. 5 shows the effects of applying the power adjustment based on packet lengths and using interleaving within a frame for the Varying Power Algorithm. As expected, based on the relatively smaller difference in loss probability due to length seen in Fig. 3 the power adjustments made based on the packet lengths yield minimal gain. The interleaving, which is meant to offset the much lengthier burst errors seen in Fig. 2, yields a relatively much higher improvement in PSNR.

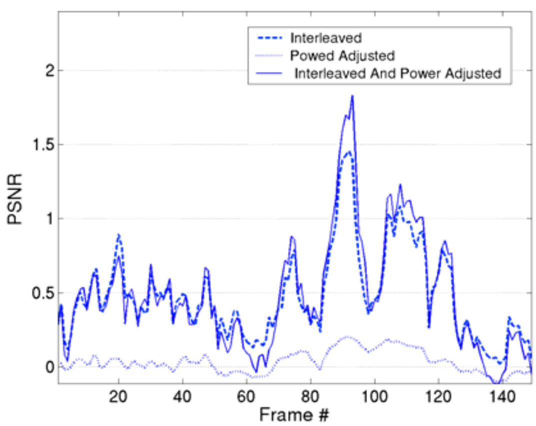

Fig. 5: The gain realized by power adjustments and interleaving when using a Model B channel. The means for the curves are 0.03 dB for the Power Adjusted curve, 0.48 dB for the Interleaved curve and 0.49 dB for the Power Adjusted And Interleaved curve.

6. CONCLUSIONS

We have described a model for simulating realistic wireless channel characteristics. Analysis using this model shows that burst errors have significant impact on the end-to-end distortion of a video sequence transmitted over a wireless channel. Further analysis shows that, although packet length also influences the probability of packet loss, its effect is not as significant as that of clustered losses. We have proposed compensation methods that result in significant PSNR gain by accounting for both packet length and burst channel errors once the optimization in [1] has been completed.

Extensions to the algorithm in [1] that consider burst errors in the optimization stage as an added layer of complexity are currently under consideration.

7. ACKNOWLEDGEMENTS

This work was supported by the National Science Foundation (NSF) under Grant No. CCR-0311838. Any opinions, findings and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the NSF.

8. REFERENCES

[1] Y. Eisenberg, C.E. Luna, T.N. Pappas, R. Berry and A.K. Katsaggelos, "Joint source coding and transmission power management for energy efficient wireless video communications," *IEEE Trans. Circuits Syst. for Video Technol.*, vol. 12, no. 6, pp. 411-424, June 2002.

[2] Q. Zhang, Z. Ji, W. Zhu, and Y.-Q. Zhang, "Power-minimized bit allocation of video communication over wireless channels," *IEEE Trans. Circuits Syst. for Video Technol.*, vol. 12, no. 6, pp. 398-410, June 2002.

[3] X. Lu, E. Erkip, Y. Wang, and D. Goodman, "Power efficient multimedia communications over wireless channels," *IEEE J. Select. Areas Commun.*, vol. 21, no. 10, pp. 1738-1751, December 2003.

[4] L. Ozarow, S. Shamai, A.D. Wyner, "Information theoretic considerations for cellular mobile radio," IEEE Trans. Veh. Technol., vol. 43, pp. 359-378, May 1994.

[5] P. Liu, R. Berry, and M. Honig, "Delay-Sensitive Packet Scheduling in Wireless Networks," *IEEE WCNC*, New Orleans, LA, March 16-20, 2003.

[6] M. Médard, "The effect upon channel capacity in wireless communications of perfect and imperfect knowledge of the channel," *IEEE Trans. Inform. Theory*, vol. 46, no. 3, , pp. 935-946, May 2000.

[7] Y. Wang and Q.-F. Zhu, "Error control and concealment for video communications: A review," *Proc. IEEE*, vol. 86, pp. 974-997, May 1998.

[8] W.M. Lam, A.R. Reibman, and B. Liu, "Recovery of lost or erroneously received motion vectors," *Proc. ICASSP*, vol. 15, pp. 417-420, Minneapolis MN, April 1993.