Viewing Impaired Video Transmissions From a Modeling Perspective

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1. INTRODUCTION

The provisioning of broadband access for mass market enables multimedia content to be extensively viewed and exchanged over the Internet. Consequently, Quality of Experience (QoE) aspects, describing the service quality perceived by the user, become vital factors in ensuring customer satisfaction in today's networks.

In the case of streaming video, enforcing QoE is a complex research topic [4] involving various aspects such as the characteristics of network traffic, codec functions, and measures of user perception of video quality. For instance, the impact of packet loss on the user's perception of real-time video can be investigated by using measured packet loss traces or generated by analytical models. These traces are further used to impair video sequences at different packet loss rates, whereas visual quality properties are then derived by decoding the produced sequences.

Both measurement and model based generators for loss traces have advantages and disadvantages. A loss trace obtained from measurements accurately reflects the state of the network. On the other hand, fitting statistical properties observed in measurements to predefined loss models allows producing multiple loss traces with various properties, such as packet loss rates and loss burst length. This flexibility permits studying the behavior of video sequences impaired under different error conditions. A disadvantage of model generated loss traces is that the statistical properties may not adequately replicate those of the measured trace, as they are likely to be biased by model limitations. Consequently, analytical models are needed to closely replicate the loss patterns observed in measurements.

Finite-state Markov chains are a particular class of models for generating packet loss traces. In general, these models are widely used to characterize error processes in telecommunication systems and to evaluate the performance of coding or other measures for error resilience [5, 6, 9]. A large body of work focuses on replicating loss burst and gap length distributions which are relevant for evaluating the performance of FEC algorithms. In the case of encoded video, however, errors over larger time-scales than burst and gaps may cause various visual effects, e.g., distorted areas of an image. Depending on the bitrate, time-scales in video can range over multiple orders of magnitude from microseconds in the case of the transmission of a single macroblock—a small part of a still image—up to seconds for the transmission of an entire group of pictures. Moreover, with the advent of the latest video encoding standard H.264 [3], parameter sets describing a set of pictures with similar decoding properties can introduce even larger time-scales. While losing a single macroblock can have a minor impact by affecting only a small fraction of the image, losing a parameter set can have a severe effect on the decoding process. This consideration suggests to focus on the loss process over multiple time-scales rather than on matching burst and gap length distributions.

To address this observation, this paper uses an M-state Markov chain to generate loss traces for impairing video transmissions. To this end, Section 2 provides a general result for M-state Markov chains to describe the distribution of the packet losses over multiple time-scales using second-order statistics. By using moment matching, 2-state Markov models are fitted to a wireless Digital Video Broadcasting (DVB-H) loss trace. Then Section 3 presents numerical results which illustrate that the visual impairment patterns depend on the chosen modeling technique. For future work we plan to investigate relevant time-scales for the fitting process. Moreover, we plan to evaluate whether increasing the number of states of the underlying Markov chain results in any significant gain. This paper is an extension of [1] where we mainly focused on fitting 2-state Markov models to DVB-H and backbone packet loss traces using second-order statistics.

2. MARKOVIAN LOSS MODELS

A discrete Markov chain with a set of M states $S = \{1, \ldots, M\}$ characterizes the course of the process with regard to the current state, which may change over time at packet arrivals, based on transition probabilities. Each state is associated with different packet loss behavior. Let q_t denote the current state at event time $t \in \mathbb{N}_0$. Then the probabilities a_{ij} to change from state $q_{t-1} = i$ to $q_t = j$, $i, j \in S$, are give in the transition matrix A, with coefficients

$$a_{ij} = P(q_t = j | q_{t-1} = i), \quad i \leq i, j \leq M, a_{ij} \geq 0; \quad \sum_{j=1}^{N} a_{ij} = 1.$$

We restrict our considerations to homogeneous, irreducible and aperiodic Markov chains. The model guarantees the existence of steady state probabilities π_k. Finally, we define packet loss rates in each state $E = (e_1, ..., e_M);\ 0 \leq e_j \leq 1$ as the probability that state i will drop a packet with probability e_i. This Markov process outputs the loss process $O(t)$, where $O(t) = 1$ indicates a lost packet and $O(t) = 0$ stands for error free events, respectively.

2.1 Second-order Statistics of Loss Processes

Second-order statistics in multiple time scales are a standard approach to capture and to describe traffic variability including long-range dependencies and self-similarity [2, 8]. Following this trend, we next derive second-order statistics, in particular the coefficient of variation of the number of packet losses over a range of time frames.

In order to capture a packet loss process generated by an M-state Markov model, we can set up recursive equations for the distribution function of losses in a considered sequence of packets. Let $p_n^{(m)}(k)$ denote the probability of k packets being lost in a sequence of length n generated by a Markov process, which starts in steady state and finally resides at state m ($n \in \mathbb{N}_0$ and $1 \le m \le M$).

The probabilities $p_{n+1}^{(m)}(k)$ for sequences of length $n+1$ can be recursively computed from $p_n^{(m)}(k)$, where steady state starting conditions are expressed as $p_0^{(m)}(0) = \pi_m$:

$$p_{n+1}^{(m)}(k) = \sum_{j=1}^{M} p_n^{(j)}(k)\,(1-e_j)\,a_{jm} + p_n^{(j)}(k-1)\,e_j\,a_{jm}.$$

As a standard approach to obtain the mean and the variance of the distributions of packet losses we introduce corresponding generating functions defined as

$$L_n^{(m)}(z) \stackrel{\text{def}}{=} \sum_{k=0}^{n} p_n^{(m)}(k)\,z^k.$$

A generating function $L_n^{(m)}(z)$ comprises the probabilities $p_n^{(m)}(k)$ for $k = 0, \ldots, n$. The recursive relationship for the probabilities $p_{n+1}^{(m)}(k)$ transfers into the generating function notation as follows:

$$L_{n+1}^{(m)}(z) = \sum_{j=1}^{M} L_n^{(j)}(z)\,(1-e_j+e_j z)\,a_{jm}. \qquad (1)$$

According to steady state starting conditions, we again have $L_0^{(m)}(z) = p_0^{(m)}(0) = \pi_0$. In addition, $L_n^{(m)}(1) = \sum_k p_n^{(m)}(k)$ generally holds for the sum of the probabilities of a distribution by definition of generating functions. Since the considered process stays in steady state, we have $\sum_k p_n^{(m)}(k) = \pi_m$ as the probability to find the process in state m after n packet arrivals. Therefore $L_n^{(m)}(z)$ represent defective distributions with regard to a final state m of the Markov chain, while their sum $L_n(z) = \sum_{m=1}^{M} L_n^{(m)}(z)$ characterizes the complete distribution of packet losses during a sequence of n packet arrivals with $L_n(1) = \sum_{m=1}^{M} L_n^{(m)}(1) = \sum_{m=1}^{M} \pi_m = 1$.

The mean values $\mu_n^{(m)}$ for the distributions $p_n^{(m)}(k)$ can be derived via the first derivative of the generating function using the rule $\mu_n^{(m)} = \frac{d}{dz} L_n^{(m)}(z)|_{z=1}$, resulting in

$$\mu_n^{(m)} = \sum_{j=1}^{M} \pi_j e_j \sum_{k=1}^{n} a_{jm}^{(k)}. \qquad (2)$$

Next we proceed with the second order statistics of the process to calculate the variance of the number of packet losses as our main focus. Therefore the second derivatives of the generating functions are again evaluated at $z = 1$:

$$\frac{d^2}{d^2 z} L_{n+1}^{(m)}(z) =$$
$$\sum_{j=1}^{M} \Big(\big(\frac{d^2}{d^2 z} L_n^{(m)}(z)\big)(1-e_j+e_j z) + 2\big(\frac{d}{dz} L_n^{(m)}(z)\big) e_j \Big) a_{jm}$$
$$\Rightarrow \quad \nu_{n+1}^{(m)} = \sum_{j=1}^{M} (\nu_n^{(j)} + 2\mu_n^{(j)} e_j) a_{jm},$$

where $\nu_n^{(m)} \stackrel{\text{def}}{=} \frac{d^2}{d^2 z} L_n^{(m)}(z)|_{z=1}$. Summing up over the final state m of the Markov process, we approach the result for the complete distribution

$$\sum_{m=1}^{M} \nu_n^{(m)} = 2 \sum_{j=1}^{M} \sum_{r=1}^{M} \pi_j e_j e_r \sum_{k=1}^{n-1} (n-k) a_{jr}^{(k)}.$$

Using $\sum_m \mu_n^{(m)} = \sum_m \pi_m e_m$, i.e., the mean loss rate ne, we obtain the coefficient of variation

$$c_v(n) = \frac{1}{ne} \sqrt{ne - (ne)^2 + \sum_{m=1}^{M} \nu_n^{(m)}} \qquad (3)$$
$$= \frac{1}{ne} \sqrt{ne - (ne)^2 + 2 \sum_{j=1}^{M} \sum_{r=1}^{M} \pi_j e_j e_r \sum_{k=1}^{n-1} (n-k) a_{jr}^{(k)}}.$$

The previous result is generally applicable to compute $c_v(n)$ at a moderate computational complexity, including the determination of the k-step transition matrices for $k = 1, \ldots, n$ as the main step. In addition, it is well known that the coefficients $a_{jr}^{(k)}$ can be expressed in closed form by solving the corresponding eigenvalue problem; numerically this is feasible even for large values of M [7].

2.2 Parameter Estimation

The parameters of the Markov chain can be obtained by fitting the analytical curve $c_v(n)$ from (3) to the empirical curve $c_v^{\text{empirical}}(n)$ of a trace. This can be done using standard methods for numerical optimization of non-linear functions. The quality of the solution can be evaluated using the mean square error function

$$\text{MSE} = \sum_{n=1}^{N} \Big(c_v(n) - c_v^{\text{empirical}}(n) \Big)^2$$

for time scales $1, \ldots, N$, where a smaller MSE for a particular model indicates a better fit.

Using the proposed fitting technique, two versions of a 2-state Markov model have been fitted to a DVB-H error traces on time-scales ranging from 1 to 10^5 packets. A simple version consists only of the two transition probabilities (the loss rate in one of the states is always 1), whereas a more complex version also considers the loss rate for both states. Figure 1 illustrates that the $c_v(n)$ obtained with the latter version closely matches $c_v^{\text{empirical}}(n)$ at all time-scales, whereas the other only matches at short time-scales. The figure also includes the lower bound $c_v(n)$ of a Poisson process with uncorrelated errors.

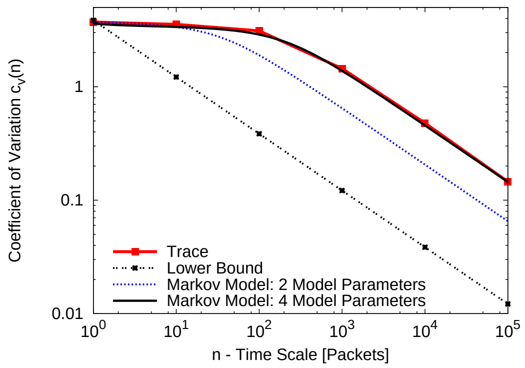
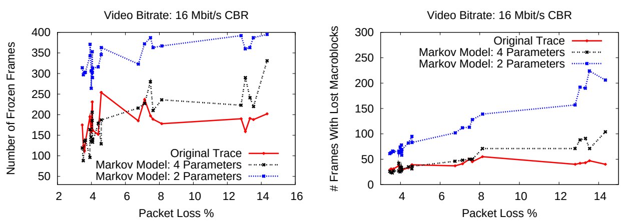


Figure 1: Fit of the estimated Markov models

3. OBJECTIVE EVALUATION OF IMPAIRED VIDEO SEQUENCES

In this section we illustrate visual error characteristics of impaired video sequences. Five H.264 encoded HDTV video sequences have been impaired using different partitions of the original DVB-H packet loss trace to produce different packet loss rates. In addition, loss traces have been generated using the two versions of the Markov chain fitted in the previous section in order to match the mean loss rates for the partitions.

Visual properties of impaired video sequences can be derived at the frame layer by instructing a video decoder. The modified version of the decoder provides statistical information about decoding errors on a picture level, e.g., the amount of lost macroblocks or an indicator for freezing. The observed visual impairments depend on the decoder's error concealment technique, e.g., *freezing* or *slicing*. In the case of freezing, the picture is frozen until the error is completely recovered. Slicing, however, conceals the error on a macroblock level using motion compensation which may result in visual (block) artifacts within the image.



(a) Freezing (b) Slicing

Figure 2: Visual quality properties

Figure 2 shows visual properties of the impaired video sequences for both freezing and slicing. In (a) we plot the number of frozen frames and in (b) we plot the amount of frames in a sequence where at least one macroblock was erroneous, both as functions of the packet loss rate. The figures show that compared to the version of the Markov chain with two parameters, the version with four parameters provides a closer match to the considered visual error characteristics, especially at low loss rates. This indicates that the high variability of video traces require adequate models to generate loss traces with high variability.

It may be thus of interest to consider Markov chain based packet loss generators with a higher state space. A related question of interest is the exact impact of considered time-scales on the fitting process.

Acknowledgements

The authors thank Gerhard Hasslinger for his contribution on the second-order statistics. The video analysis is supported by the T-V-Model project at T-Labs run by Alexander Raake and Marie-Neige Garcia. Many thanks also to Peter List for providing a video decoder and to Jussi Poikonen for providing DVB-H error traces.

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