

APPENDIX A

Source Models for Packet Video

A.1 Two source models

A.2 Discussion

In Chapter 2 it was pointed out that it is necessary to derive reliable models of video sources for, among other things, queueing analysis and network management. This is a difficult task since the output characteristics would depend on both the captured scene and the method used for signal compression. Voice signals have been successfully modeled by a two-state (voice/silence) Markov chain (*e.g.* [DAI86]). However, for video there is no direct analogue such as motion/no motion. The models are therefore expected to be more complex. There have been models suggested for video which we will briefly review in this appendix. To the author's knowledge, only four separate attempts have been reported of models specifically derived for the statistical behavior of video signals. These can be found in [MAG87,* SEN87, MAG88, HUA88, NOM89]. Since all four attempts have a lot in common, we will only describe the models suggested by Maglaris *et alii* [MAG87, MAG88]**. Then, in a discussion, we will relate and contrast the described models with those of Sen *et alii* [SEN87], Huang [HUA88], and Nomura *et alii* [NOM89].

A.1 Two source models

In the sequel two models of the encoded bit rate of a video source are presented, as given by [MAG87, MAG88]. The first model is suitable for queueing simulations,

* *Presented at the First International Packet Video Workshop, Columbia University, New York, NY, May 1987.*

** *The author collaborated on this effort.*

while the second leads to a simple queueing analysis. In both cases, they should be matched to first- and second-order statistical properties of measured data as well as some features of the assumed steady-state distribution of video signals.

The first model of a single source is a continuous-state, discrete-time auto-regressive Markov process. If $\lambda(n)$ represents the average bit rate of the n th frame, it is generated by the recursive relation

$$\lambda(n) = a \lambda(n-1) + b w(n), \quad (\text{A.1})$$

where $w(n)$ is a sequence of independent Gaussian random variables, and a and b are constants. It is assumed that $|a| < 1$ so that the process is stable, *i.e.*, it achieves a steady state as $n \rightarrow \infty$. The discrete auto-covariance $C(n)$ is exponential, and the steady-state distribution of λ is Gaussian with mean $E(\lambda)$ and variance $C(0)$.

The second model attempts to capture the behavior of N statistically multiplexed sources. Their aggregate bit rate is quantized into a finite number of discrete levels and transitions between levels are assumed to occur with exponential transition rates (*i.e.*, a continuous-time discrete-state model). It is concluded in [MAG87, MAG88] that a birth-death Markov chain, with uniform quantization steps, will accurately describe the aggregate bit rate. Furthermore, the probability of a move to a lower state increases linearly from the lowest state to the highest state while, at the same time, the probability of going to a higher state decreases linearly (see Eq. (A.2)). If quantization step is assumed to be A bps, and there are $M + 1$ possible levels, then the exponential transition rates $r_{i,j}$ from state iA to state jA are given

by [MAG87, MAG88]:

$$\begin{aligned}
 r_{i,i+1} &= (M - i)\alpha, \quad i < M \\
 r_{i,i-1} &= i\beta, \quad i > 0 \\
 r_{i,i} &= 0 \\
 r_{i,j} &= 0, \quad |i - j| > 1.
 \end{aligned} \tag{A.2}$$

At steady-state, the rate from the model will have a binomial distribution and an exponential autocovariance function. In this case, the aggregate rate from the N sources can be thought of as the aggregate rate from M independent *on-off*-sources, where each source turns *on* with exponential rate α and *off* with rate β . Note that each *on-off*-source corresponds to the model proposed for analysis of voice sources with speech activity detection (see for example [DAI86]). In that case the *on* state represents a talkspurt and the *off* state a silence interval.

A.2 Discussion

Sen *et alii* extend the second model above to consist of two Markov-chains: one with states iA , as before, and the other with states $iA + \Delta$ ($i \in [0, M]$) [SEN87]. Both chains have the same transition probabilities, given by Eq. (A.2), and the probabilities of going between the states iA and $iA + \Delta$ are ξ and δ , respectively ($\forall i \in [0, M]$). No other transitions between the two Markov-chains are allowed (*i.e.*, $r_{iA, jA+\Delta} = 0$, $i \neq j$). In contrast to the “single chain,” which modeled the aggregate rate of N independent sources, this model is intended to capture the behavior of a single video source. Also, the model can be decomposed into an aggregate of two *on-off*-sources, one with states 0 and A and transition probabilities α and β , and a second type which has states 0 and Δ and probabilities ξ and δ .

Huang proposes a general first-order Markov process as video-source model [HUA88]. Hence, in Eq. (A.1) the Gaussian distributed $w(n)$ is replaced by a

set of random variables $\{w_{\lambda(n)}\}$, whose probability density function depends on the state, $\lambda(n)$. Also, it is required that $E(w_{\lambda_1}) > E(w_{\bar{\lambda}}) > E(w_{\lambda_2})$, $\forall \lambda_1 < \bar{\lambda} < \lambda_2$, where $\bar{\lambda} = E(\lambda(n))$. It is claimed that if the set of random variables, $\{w_{\lambda(n)}\}$, is chosen appropriately, video compressed by various coding schemes may be modeled by the same formula. For the examples, it is assumed that $\{w_{\lambda(n)}\}$ is independent of n and with mean $m(\lambda) = E(w_{\lambda})$. The first example given is the model of Eq. (A.1) and the second is similar but $w(n)$ has a double-exponential distribution. There is also a discussion of non-linear mean-functions, $m(\lambda)$. For statistical multiplexing, Huang also proposes a Markov-chain as discussed above, but with the distinction that it is discrete-time and it contains self-loops (*i.e.*, $r_{i,i} \geq 0$ in Eq. (A.2)).

Nomura *et alii* put forward an auto-regressive model of order M , where, as in Eq. (A.1), $w(n)$ is a Gaussian random process. They also suggest a second model for approximation of multiplexing performance. It does not model the source but gives the expected queue-length (GI/G/1 queue) as a function of the traffic intensity and the deviation-to-average ratio of the sources (given as $D(m) = \sqrt{(m+1)Var(\xi(m,k))}/E(\xi(m,k))$ where $\xi(m,k) = \sum_{n=k}^{k+M} \lambda(n)$). The model assumes that the bit rate from a source is uncorrelated and that all sources are independent.