Coded Video Traffic

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Abstract: Self-similar processes, modulated according to the MPEG frame structure, are proposed to capture both the SRD (short range dependency) and LRD (long range dependency) of MPEG video traffic.

Introduction: Traffic generated by video applications is increasingly cramming existing networks, and it is thus essential to accurately characterize video traffic for efficient network management. Traditional models, however, fall short in describing video traffic which is strongly autocorrelated and bursty [1]. Hence, autocorrelations among data should be taken into consideration.

The empirical data used here was MPEG-1 coded data of *Star Wars*[1]. The frames were organized as follows: IBBPBBPBBPBB IBBPBB..., i.e., 12 frames in a Group of Pictures (GOP). I, P, and B frames were compressed by different techniques. It is clear that the autocorrelation function (ACF) of the MPEG coded video, shown in Fig. 1, can hardly be captured by a simple random process.

To Model MPEG Coded Data, we decompose the MPEG traffic into 10 subsequences X_I,X_P,X_{B_1},X_{B_2},$\cdots$, and X_{B_8}. X_I consists of all I frames, X_P all P frames, X_{B_1} the first B frames in all GOPs, X_{B_2} the second B frames in all GOPs, and so on. We have used $k^{-\beta}$, $e^{-\beta k}$ and $e^{-\beta\sqrt{k}}$ (k is the lag between frames, and β is a constant), corresponding to the ACFs of a self-similar process [2], a Markov process, and an $M/G/\infty$ input process [3], respectively, to approximate ACFs of these subsequences. For illustrative purposes, approximations for P and B_1, shown in Fig. 2 and 3, indicates that self-similar processes are better choices, and are thus used to model these subsequences.

Using the least squares method, $\beta = 0.4663$, 0.3546, 0.4468, 0.4779, 0.4294, 0.4656, 0.4380, 0.4682, 0.4465, and 0.4606 for $X_I, X_P, X_{B_1}, X_{B_2}, \cdots$, and X_{B_8}, respectively. The corresponding Hurst parameters (H=1-β/2) for these processes are $H = 0.7668$, 0.8227, 0.7766, 0.7610, 0.7853, 0.7672, 0.7810, 0.7659, 0.7768, 0.7697, respectively.

Marginal distributions of these subsequences are modeled by Beta distributions which have the following form of probability density function:

$$f(x;\gamma,\eta,\mu_0,\mu_1) = \begin{cases} \frac{1}{\mu_1-\mu_0}\frac{\Gamma(\gamma+\eta)}{\Gamma(\gamma)\Gamma(\eta)}\left(\frac{x-\mu_0}{\mu_1-\mu_0}\right)^{\gamma-1}\left(1-\frac{x-\mu_0}{\mu_1-\mu_0}\right)^{\eta-1} & \\ \qquad \mu_0 \le x \le \mu_1, 0 < \gamma, 0 < \eta & \\ 0 \qquad otherwise & \end{cases} \quad (1)$$

where γ and η are the shape parameters, and $[\mu_0, \mu_1]$ is the domain where the distribution is defined. Using the formulae introduced in [4], $\hat{\eta} = 1.5237$, 1.5699, 1.4172, 1.3016, 1.6858, 1.6329, 1.7276, 1.4218, 4.0585, 1.5402, and $\hat{\gamma} = 12.7263$, 11.1939, 8.1089, 8.1604, 11.8499, 13.9278, 12.2180, 8.6536, 10.4233, 11.1768 are obtained for X_I, X_P, X_{B_1}, X_{B_2}, $\cdots$, and X_{B_8}, respectively.

By combining X_I, X_P, X_{B_1}, X_{B_2},$\cdots$, and X_{B_8} in a manner similar to the GOP pattern, a model for MPEG coded traffic is obtained. The ACF of the traffic generated by our model shown in Fig. 4 is very close to that of the empirical data, indicating that our model can capture both SRD and LRD.

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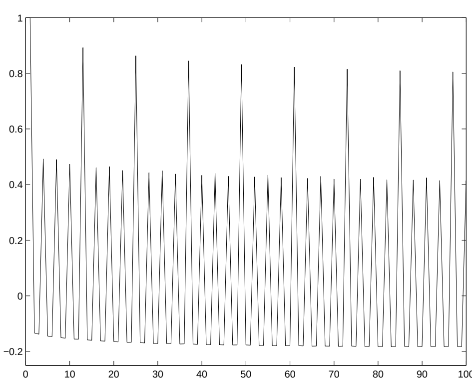

Figure 1: ACF of MPEG compressed video of *Star Wars*

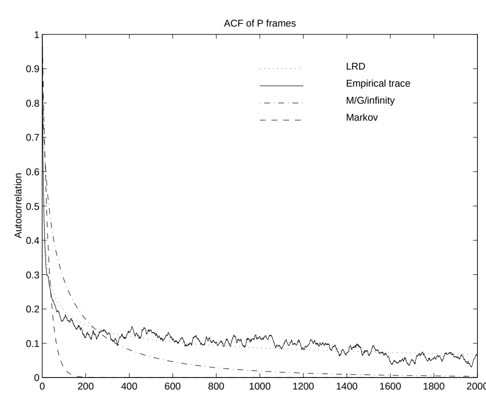

Figure 2: Approximation for ACF of P frames by : self-similar process, $M/G/\infty$, and Markov processes

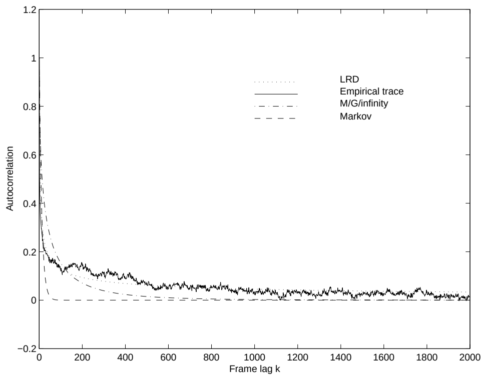

Figure 3: Approximation for ACF of B_1 frames by : self-similar process, $M/G/\infty$, and Markov processes

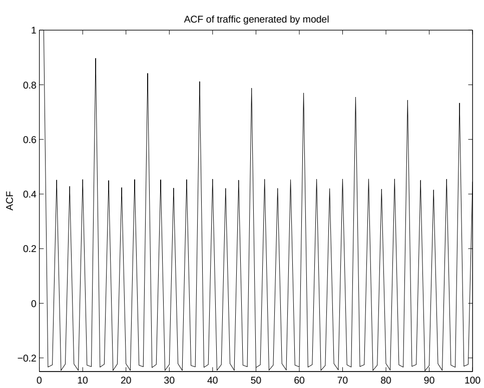

Figure 4: ACF of traffic data generated by our model