A SIMPLE MODEL FOR MPEG VIDEO TRAFFIC

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ABSTRACT

A simple approach to model MPEG coded video traffic is proposed. The idea is to first decompose the MPEG video traffic into three components, corresponding to I, P, and B frames, each modeled by a self-similar process. These processes are then structurally modulated in a manner similar to how the frames are grouped into the GOP (Group of Pictures) pattern. The new model is shown to be able to capture the statistical properties (both LRD and SRD) of the MPEG video traffic.

1. INTRODUCTION

As video is increasingly transmitted over emerging high speed networks, accurate traffic models are called for to facilitate the design of effective admission and flow control algorithms, and network performance evaluation in accommodating video traffic. It was, however, observed that traditional models fall short in describing video traffic because they cannot capture the burstiness and strong autocorrelation of video traffic [1]. To accurately model video traffic, autocorrelations among data should be taken into consideration. A considerable amount of effort on video modeling has been reported. These models are used to capture two statistical factors: marginal distribution and autocorrelation function of traffic data.

While the importance of long range dependency is arguable [2] [3], the impact of short term autocorrelation in traffic processes on queuing performance with a finite buffer can be very drastic (see [4]). Simulation results show that the network queuing performance with strong and weak autocorrelation traffic may be quite different. Thus, a model should capture not only the first-order statistics, but also the second-order statistics. Short range dependency (SRD) models can capture short-term autocorrelation, but fail to capture long range dependency (LRD). LRD models, on the other hand, can capture long-term dependency, but underestimate the short term dependency.

The $M/G/\infty$ input process model is a compromise between LRD and SRD models [4]. The results were derived for JPEG and the I frames of MPEG sequences. As will be shown below, ACF of MPEG sequences is quite different from that of JPEG sequences and that of I sequences. In our opinion, it is almost impossible to accurately capture the ACF of MPEG compressed data by a simple function such as the exponential function, and thus this method fails to capture the second-order statistics of MPEG sequences.

In [5], we proposed a Markov modulated model for MPEG coded video sequence. It cannot track the oscillation nature of the ACF of MPEG video sequences, which are the characteristics of MPEG coded video data. In [6], we proposed a sequentially modulated self-similar process to model MPEG video according to the GOP structure. The MPEG coded video traffic is decomposed into I, P, B_1, B_2, ..., B_8 frames. Through careful analysis we found that the first I and B frames were absent, i.e., the first GOP was corrupted (not complete) in the the original data file of *Star wars* [1]. Thus this corrupted GOP of the sequence has been discarded for our subsequent experimentation. This discovery has led us to an even simpler model proposed here, in which the original sequences are decomposed into three parts, each of which can be modeled by a self-similar process.

2. EMPIRICAL DATA AND ACF

The *Star Wars* is an approximately two hour movie. The source is very representive, containing materials ranging from low complexity/motion scenes to those with high and very high actions. The data file consists of 174,126 frames. The frames were organized as follows: IBBPBBPBBPBB IBBPBB..., i.e., 12 frames in

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a Group of Pictures (GOP). I frames are those which use intra frame coding method (without motion estimation), P frames are those which use inter frame coding technique (with motion estimation), and B frames can be predicted using forward and backward prediction.

The ACF of the MPEG coded *Star War* is shown in Fig 1. It fluctuates around three envelopes, reflecting the fact that, after the use of motion estimation and forward/backward prediction techniques, the dependency between frames is reduced. This characteristic should be taken into consideration in modeling MPEG coded video sequences.

3. SRD, LRD, AND SELF SIMILARITY

Consider a stationary process $X = \{X_n : n = 1, 2, \ldots\}$ with mean μ and variance σ^2. The autocorrelation function and the variance of X are denoted as:

$$r(k) = \frac{E[(X_n - \mu)(X_{n+k} - \mu)]}{\sigma^2} \quad (1)$$

and

$$\sigma^2 = E[(X_n - \mu)^2]. \quad (2)$$

X is said to be SRD if $\sum_{k=0}^{\infty} r(k)$ is finite; otherwise, the process is said to be LRD [7].

Let X defined above have the following autocorrelation function:

$$r(k) \rightsquigarrow k^{-\beta} L(k), k \to \infty \quad (3)$$

where $0 < \beta < 1$, and L is a slowly varying function as $k \to \infty$, i.e., $\lim_{t\to\infty} L(tx)/L(t) = 1$ for all $x > 0$. Consider the aggregated process

$$X^{(m)} = \{X_t^{(m)}\} = \{X_1^{(m)}, X_2^{(m)}, \ldots\},$$

where

$$X_t^{(m)} = \frac{1}{m}(X_{tm-m+1} + \cdots + X_{tm}), t \in Q, m \in Q, \quad (4)$$

and Q is a positive integer set. X is said to be exactly second-order self-similar [7] if

$$varX^{(m)} = \sigma^2 m^{-\beta} \quad (5)$$

and

$$r^{(m)}(k) = r(k) \quad (6)$$

for all $m \in \{1, 2, 3, \cdots\}$ and $k \in \{0, 1, 2, \cdots\}$. Here $r^{(m)}(k)$ is the autocorrelation function of $X^{(m)}$. In fact, Eq. (5) is sufficient to define a self-similar process since Eq. (3) and (6) can be derived from Eq. (5) [7].

Since empirical video traffic exhibits self-similarity and long range dependency, it is intuitive to use self-similar processes to model video traffic. It is one of the most often used processes to capture LRD of video traffic. Often times, a self-similar process is simply referred to as a LRD process.

Hurst parameter $H = 1 - \beta/2 (0 < \beta < 1)$ is used to measure the self-similarity of a process. It is the only parameter needed to describe a second-order self-similar process. For a process with self-similarity, $1/2 < H < 1$.

Table 1: Least square errors obtained by self-similar process, Markov and $M/G/\infty$ method

	I	P	B
LRD	1.5820	0.6630	0.5987
$M/G/\infty$	5.0527	12.8669	13.7523
Markov	7.2517	25.4433	32.0705

4. MODELING MPEG TRAFFIC

In order to model MPEG coded data, we decompose the MPEG traffic into three sub-sequences, X_I, X_P, X_B. X_I consists of all I frames, X_P consists of all P frames, and X_B consists of all B frames. We have used $k^{-\beta}$, $e^{-\beta k}$, and $e^{-\beta\sqrt{k}}$, corresponding to the ACFs of a self-similar process, a Markov process, and an $M/G/\infty$ input process, respectively, to approximate the ACFs of these processes. The ACF of each sub-process and its approximation by Markov process, $M/G/\infty$ process, and self-similar process are shown in Fig. 2 - 4. The sums of squares of errors obtained by the three kinds of methods are tabulated in Table 1. It is quite obvious that self-similar processes are better choices. We therefore use self-similar processes to model these data.

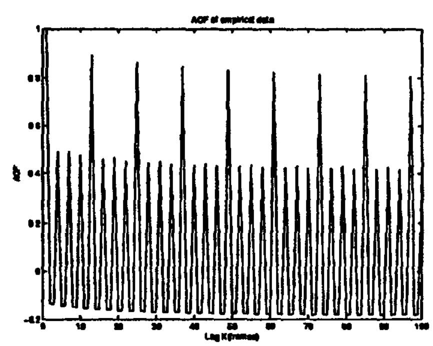

Figure 1: ACF of the MPEG video.

Using the least squares method, $\beta = 0.4662, 0.3404, 0.3040$, are derived for X_I, X_P, X_B, respectively. The

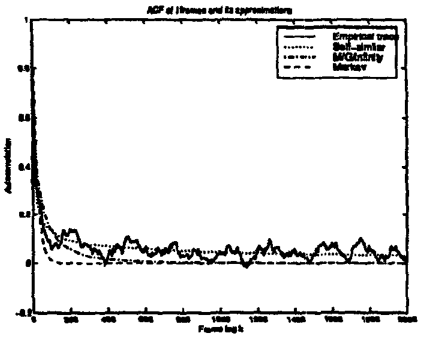

Figure 2: Approximation for ACF of I frames by : LRD, M/G/∞, and Markov processes.

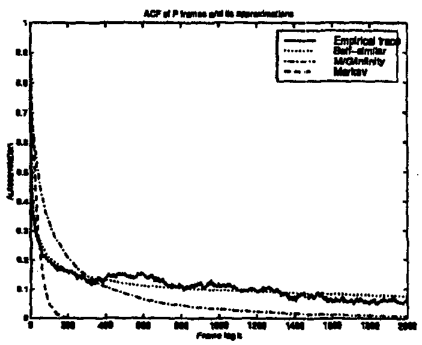

Figure 3: Approximation for ACF of P frames by : LRD, M/G/∞, and Markov processes.

corresponding Hurst parameters for these processes are $H = 0.7669, 0.8296, 0.8480$, respectively.

To model marginal distributions of these processes, we use Beta distributions which have the following form of probability density function:

$$f(x;\gamma,\eta,\mu_0,\mu_1) = \begin{cases} \frac{1}{\mu_1-\mu_0}\frac{\Gamma(\gamma+\eta)}{\Gamma(\gamma)\Gamma(\eta)}\left(\frac{x-\mu_0}{\mu_1-\mu_0}\right)^{\gamma-1}\left(1-\frac{x-\mu_0}{\mu_1-\mu_0}\right)^{\eta-1} & \mu_0 \le x \le \mu_1, 0<\gamma, 0<\eta \\ 0 & \text{otherwise,} \end{cases} \quad (7)$$

where γ and η are shape parameters, and $[\mu_0, \mu_1]$ is the domain where the distribution is defined. They can be estimated by the following formulae [8]:

$$\hat{\eta} = \frac{1-\bar{x}}{s^2}[\bar{x}(1-\bar{x}) - s^2] \quad (8)$$

$$\hat{\gamma} = \frac{\bar{x}\hat{\eta}}{1-\bar{x}} \quad (9)$$

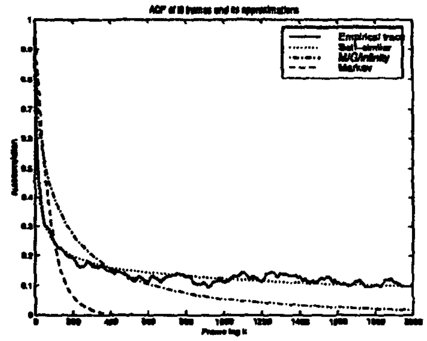

Figure 4: Approximation for ACF of B frames by : LRD, M/G/∞, and Markov processes.

where

$$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i, \quad (10)$$

$$s^2 = \frac{N\sum_{i=1}^{N} x_i^2 - \left(\sum_{i=1}^{N} x_i\right)^2}{N(N-1)}, \quad (11)$$

and N is the number of data in the data set. Using these formulae, $\hat{\gamma} = 4.0605, 1.6605, 1.6431$, and $\hat{\eta} = 10.4273, 12.0277, 14.0742$, are derived for X_I, X_P, X_B, respectively. Owing to limited space, only CDF of I frames and its approximation by Beta distribution are shown in figure 5.

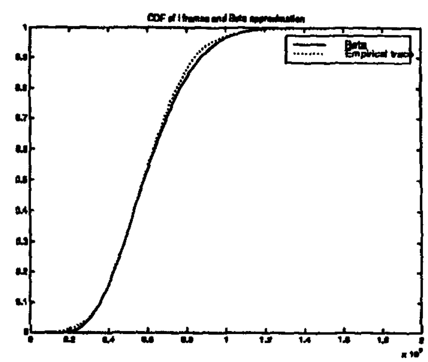

Figure 5: CDF of I frames and its approximation by Beta distribution.

By combining X_I, X_P, X_B in a manner similar to the GOP pattern, a model for MPEG coded traffic is obtained. This model can be used to generate traffic data.

Fig. 6 shows a trace of traffic generated by our proposed model. In general, for the real MPEG sequence, sizes of I frames are larger than those of P frames, while sizes of P frames are larger than those of B frames. This pattern is demonstrated by the traffic generated by our proposed model, and therefore, our model can capture this feature accurately. Since traffic is random, the appropriateness of a traffic model should be judged by its statistical properties rather than the mere similarity of the empirical trace and the trace generated by model. This can be demonstrated by the ACF of the generated traffic shown in Fig. 7.

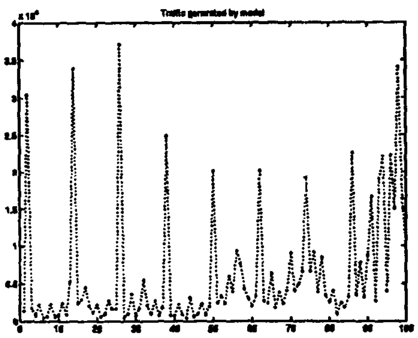

Figure 6: Traffic data generated by our model

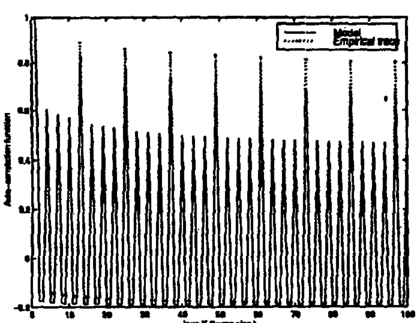

Figure 7: ACFs of empirical trace and our traffic model

5. CONCLUSIONS

We have proposed a new traffic model, structurally modulated self-similar processes, to model MPEG compressed video sequence. It is simpler than our previously proposed models [6], [5] and can match the ACFs of the P, I, and B frame sequences very well. It can capture both the LRD and SRD. In addition, the traffic data generated by our model reflects the GOP structure of MPEG coded video sequences quite well. This model will play an important role in future network design and performance evaluation.

6. REFERENCES

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