MODELING VBR VIDEO TRAFFIC BY MARKOV-MODULATED SELF-SIMILAR PROCESSES*

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Abstract - It is estimated that video traffic will be increasingly occupying a major portion of future network bandwidth, and thus traffic modeling plays an important role for network design and management. In this paper, we propose Markov modulated self-similar processes to model MPEG video sequences that can capture the LRD (long range dependency) characteristics of video ACF (auto-correlation function). The basic idea behind this modeling is to decompose an MPEG compressed video sequence into three parts according to different motion/change complexity. Each part can individually be described by a self-similar process. In addition, Beta distribution is used to characterize the marginal cumulative distribution (CDF) of the video traffic. To model the whole data set, Markov chain is used as a dominating process to govern the transitions among these three self-similar processes. Initial simulations on a real MPEG compressed movie sequence of *Star Wars* have demonstrated that our new model can capture the LRD of ACF and the marginal CDF very well. Video traffic synthesis using our model is presented. Further research in this direction is discussed.

INTRODUCTION

The trend to transmit video over network, especially over ATM, is emerging. Traffic models are important to network design, performance evaluation, bandwidth allocation algorithm design, and bit-rate control. It was, however, observed that traditional models fall short in describing the video traffic because video traffic is strongly auto-correlated and bursty [1]. To accurately model video traffic, auto-correlations among data should be taken into consideration. A considerable amount of effort on video modeling has been reported. These models can be categorized into two classes: short range dependency

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(SRD) models and long range dependency (LRD) models. They are used to capture two statistical quantities: marginal distribution and auto-correlation function of traffic arrival times.

Most of the work in video source modeling has been largely confined to a short period of video sequences and video conference sequences, where frames with sudden scene change or large motion are rare. That is not the case, however, in full length movies. There has been some effort to model full length movies, such as $M/G/\infty$ [2] and LRD model. These models, however, are based on JPEG compressed video sequences, which are seldom used in practice.

Markov modulated TES (Transform Expand Sample) model was used to model JPEG and MPEG encoded motion pictures [3]. One of the drawbacks of TES is that the ACF of a TES process for lags beyond one cannot be derived analytically. It can only be obtained by searching in the parameter space, and thus good results can hardly be guaranteed. One of the important tasks of traffic modeling is to obtain an analytical model so that the network performance can be evaluated analytically. TES model fails to provide such an analytical model.

In this paper, we propose to model MPEG compressed video sequences by Markov modulated self-similar processes. This model is analytical in nature. The motivation of our proposed model is illustrated in the next section.

MOTIVATION BEHIND THE PROPOSED NEW MODEL

The empirical data used in our work are MPEG-I coded data of *Star Wars*[1], which contains materials ranging from low complexity/motion scenes to those with high and very high actions. The ACF of frame size vs. frame lags of MPEG coded *Star War* is shown in Fig. 1, and it is quite different from that of JPEG coded movies *Star Wars* (see Fig. 2). Specifically, the ACF of MPEG coded data fluctuates around three envelopes, reflecting the fact that, after the use of motion estimation techniques, the dependency between frames is reduced. This characteristic should be taken into consideration in modeling MPEG coded video sequences.

It is known that a self-similar process is a kind of LRD process. Since empirical video traffic exhibits self-similarity and long range dependency, it is natural to use self-similar process to model video traffic [4]. The above-mentioned observation, however, tells us it is not suitable to model the MPEG coded data with a single self-similar process. Several different self-similar processes with different ACFs should be used to model the fluctuation of ACFs. We therefore divide the sequence into three different subsequences, each modeled by a separate self-similar process. The transition among these three processes is governed by a Markov chain, whose transition matrix can

[1]The MPEG-I coded data were the courtesy of M. W. Garrett of Bellcore and M. Vetterli of UC Berkeley

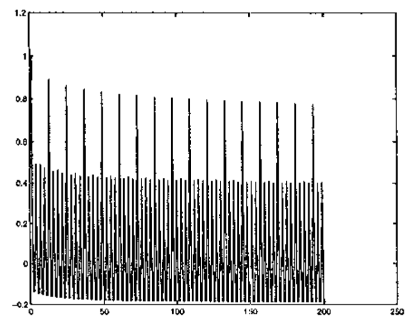

Figure 1: ACF of MPEG video.

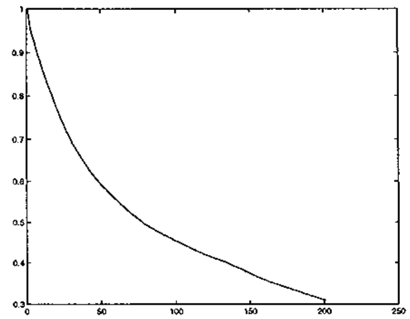

Figure 2: ACF of JPEG video.

be obtained from empirical data.

DECOMPOSITION OF MPEG DATA

From the above analysis, we suggest to divide the traffic data into three different parts – inactive part, active part, and very active part. Suppose $f(i)$ is the number of bits in the ith frame. The video traffic can be classified as follows:

1. If $f(i+1)/f(i) > T$, $i = 2, 3, \cdots$, then $f(i+1)$ belongs to the non-inactive part; otherwise, $f(i+1)$ belongs to the inactive part, where T is a threshold.
2. Similarly, the non-inactive part can be classified into active and very active parts.

Taking these three data sets as three different random processes, we can calculate their ACFs.

MODELING OF DECOMPOSED DATA

The ACF of each sub-process is quite different (as shown in Figs. 3, 4, and 5) from that of the original sequence. The fluctuation is no longer that big. We have used $k^{-\beta}$, $e^{-\beta k}$ and $e^{-\beta\sqrt{k}}$, corresponding to the ACFs of a self-similar process, Markov process, and $M/G/\infty$ input process, respectively, to approximate the ACF of the decomposed empirical data. It is apparent that $k^{-\beta}$ is a better approximation of ACFs of these decomposed data, and we therefore use self-similar processes s_1, s_2, and s_3 to model these processes, respectively.

Using the least squares method, we obtained $\beta = 0.3321$, 0.3069, and 0.4396 for the inactive, active, and very active part, respectively. The corre-

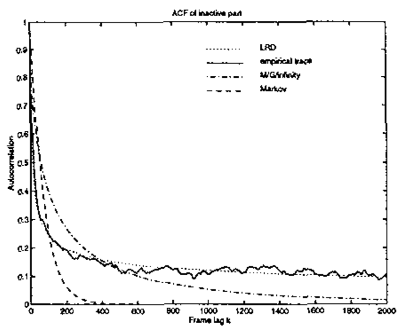

Figure 3: ACF of the inactive part.

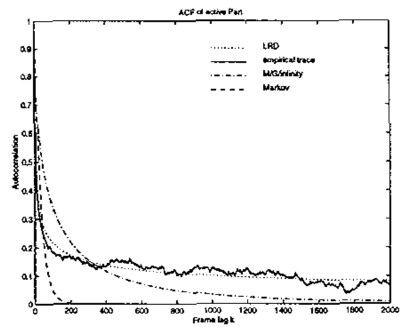

Figure 4: ACF of the active part.

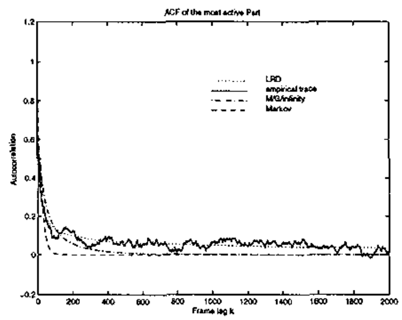

Figure 5: ACF of the most active part.

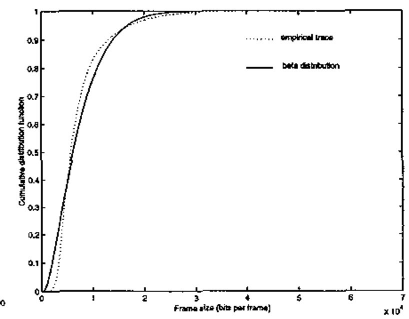

Figure 6: CDFs of the inactive part and its model.

sponding Hurst parameters for these processes are $H = 0.8339$, 0.8465, and 0.7802, respectively.

Beta distribution is proposed to model the marginal distributions of these processes. Owing to its versatility, Beta distribution can model random processes with quite different shapes of marginal distributions. The marginal distribution of a Beta distribution process has the following form

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

where γ and η are the shape parameters.

The marginal distributions of the empirical data and the corresponding Beta distributions are shown in Fig. 6, 7, and 8, respectively.

MODELING OF MPEG DATA

To model the whole data set, we need a process to govern the transition among the processes s_1, s_2, and s_3 obtained above. We choose to use Markov chain as the dominating process because of its simplicity. Our model for MPEG video traffic can thus be described by the state diagram drawn in Fig. 9.

S_1, S_2, and S_3 correspond to the three respective self-similar processes. At state S_i, bit rates are generated by process s_i. The transition probability from S_i to S_j can be estimated from the empirical data as follows:

$$p_{ij} = \frac{N_{ij}}{N_i}. \tag{2}$$

N_i is the total number of times that the system goes through state S_i, and N_{ij} is the number of times that system transits to state S_j from state S_i. For the *Star Wars* video, the following transition matrix

$$\hat{P} = \begin{bmatrix} 0.0002 & 0.9998 & 0 \\ 0.1174 & 0.5232 & 0.3594 \\ 0.0209 & 0.9791 & 0 \end{bmatrix}$$

was obtained. This matrix is useful for the synthesis of video traffic.

VIDEO TRAFFIC SYNTHESIS

To synthesize video traffic using our model requires a self-similar traffic generator. We have used asymptotically self-similar fractional auto-regressive integrated moving-average (F-ARIMA) method to generate three self-similar processes. Since these processes are Gaussian, they can be mapped into Beta distribution by the following formula:

$$Y_k = F_\beta^{-1}\left(F_N(X_k)\right), k > 0, \tag{3}$$

where X_k is a self-similar Gaussian process, F_N is the cumulative probability of the Normal distribution, and F_β^{-1} is the inverse cumulative probability function of Beta model.

After the generation of three self-similar processes, video traffic can be synthesized by combining the three processes via a Markov process, whose transition matrix was given in the previous section.

FUTURE WORK

Network performance issues such as cell loss rates with sources generated by our proposed model and those from empirical data are under investigation. More MPEG compressed video sequences will be applied to our proposed model to test its performance.

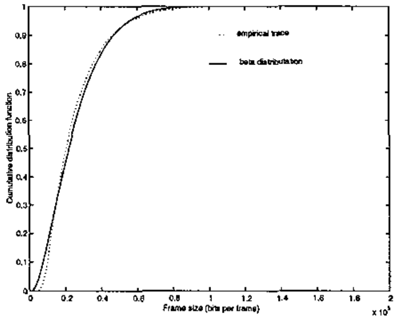

Figure 7: CDFs of the active part and its model.

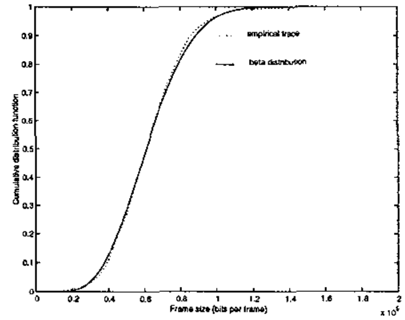

Figure 8: CDFs of the most active part and its model.

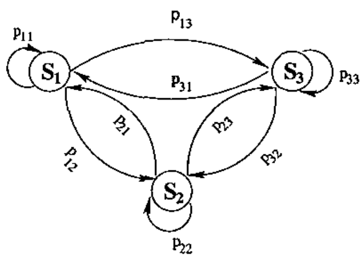

Figure 9: A Markov modulated self-similar process model.

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