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Modeling MPEG Coded Video Traffic by Markov-Modulated Self-Similar Processes*

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Abstract. Markov modulated self-similar processes are proposed to model MPEG video sequences that can capture the LRD (Long Range Dependency) characteristics of video ACF (Auto-Correlation Function). The basic idea is to decompose an MPEG compressed video sequence into three parts according to different motion/content complexity such that each part can individually be described by a self-similar process. Beta distribution is used to characterize the marginal cumulative distribution (CDF) of the self-similar processes. To model the whole data set, Markov chain is used to govern the transitions among these three self-similar processes. In addition to the analytical derivation, initial simulations have demonstrated that our new model can capture the LRD of ACF and the marginal CDF very well. Network cell loss rate using our proposed synthesized traffic is found to be comparable with that using empirical data as the source traffic.

Keywords: Markov modulated process, Markov chain, self-similar process, video traffic modeling, MPEG

1. Introduction

The trend to transmit video over networks is emerging. Traffic models are important to network design, performance evaluation, bandwidth allocation, and bit-rate control. To network service providers and users, it is important to describe the video traffic accurately so that charges can be priced based on reasonable parameters, and the parameters for quality of service can be mapped into the parameters that can be used for network administration. It has been observed, however, that traditional models fall short in describing the video traffic because video traffic is strongly autocorrelated and bursty [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 that include:

- Markov Modulated Rate Process (MMRP) [2]
- Discrete Auto-Regressive Process (DAR(1)) [3]
- Fluid Models [4]
- Markov-Renewal-Modulated TES Models [5]
- Long Range Dependency (LRD) models [6] or Self-Similar models [7]
- $M/G/\infty$ input process models [8]
- GBAR Model [9]

The above models can be categorized into two classes:

- Short Range Dependency (SRD) models, and
- Long Range Dependency (LRD) models.

These models are used to capture two statistical factors: marginal distribution (first-order statistics) and auto-correlation function (second-order statistics) of traffic arrival times. The importance of long range dependency is among the most arguable issues in video modeling. Some of the results support the view that LRD has drastic impact on queuing performance [10–13], while

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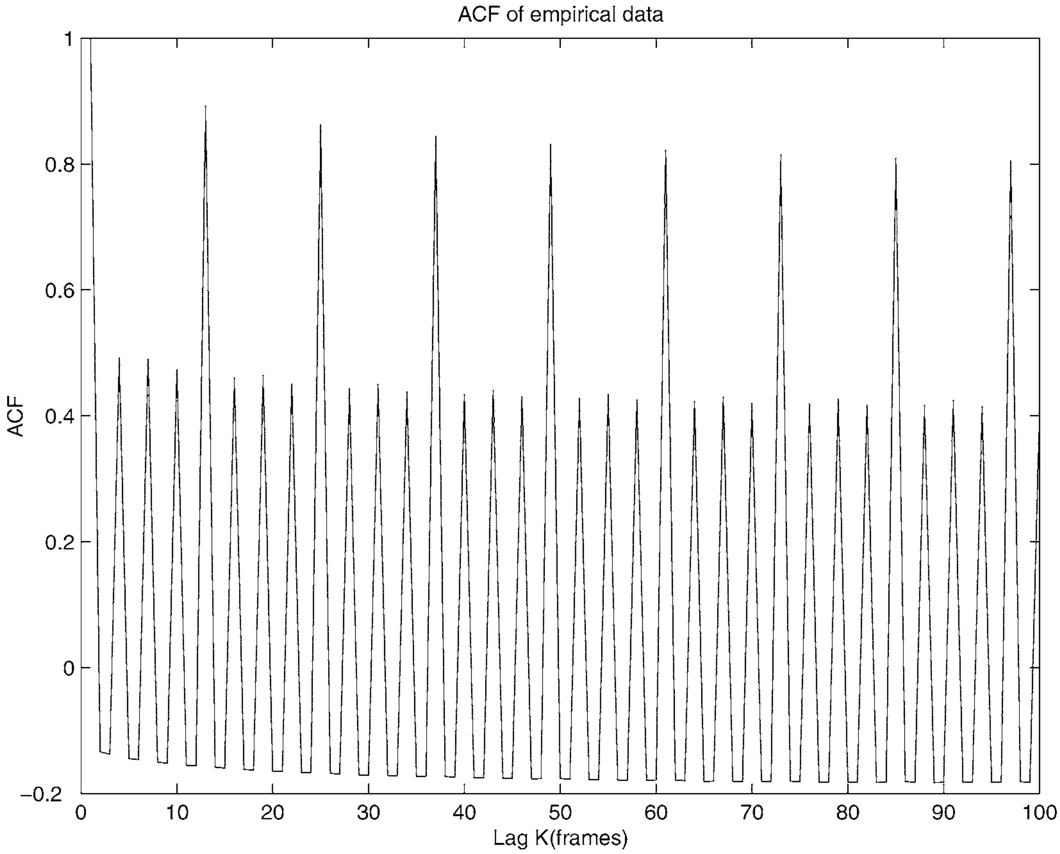

Figure 1. ACF of MPEG compressed video *Star Wars*.

other results support the view that LRD has little impact on queuing performance because of the fact that the buffer capacity is limited in practice [14].

While the importance of long range dependency is arguable, the impact of short term autocorrelation of a traffic process on queuing performance with finite buffer can be very drastic (see [5] and references in it). Simulation results show that network queuing performance with strong and weak autocorrelation traffic may be quite different.

SRD models (such as DAR(1), MMRP, Fluid Flow, and Regression models) can capture short-term autocorrelation, but fail to capture long-term dependency. LRD models, on the other hand, can capture long-term dependency, but underestimate the short term dependency.

The model proposed in [8] (a special $M/G/\infty$ input process model) is a compromise between LRD and SRD models [8]. Simulation results were found to be better than those of a self-similar process when the switch buffer is relatively small. Better results than those of DAR(1) model was found when the buffer size is large. The results were obtained from JPEG and MPEG-2 I sequences. As will be shown later, the ACF of MPEG sequences is quite different from that of JPEG sequences or 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. Markov-Renewal-Modulated TES (transform expand sample) models were used to model JPEG encoded motion pictures. One of the drawbacks of TES approach is that the ACF of a TES process for lags beyond one cannot be derived analytically. The ACF can only be obtained by searching in the parameter space, and thus good results can hardly be guaranteed [8]. One of the important tasks of traffic modeling is to obtain an analytical model so that the network performance can be obtained analytically. TES model fails to

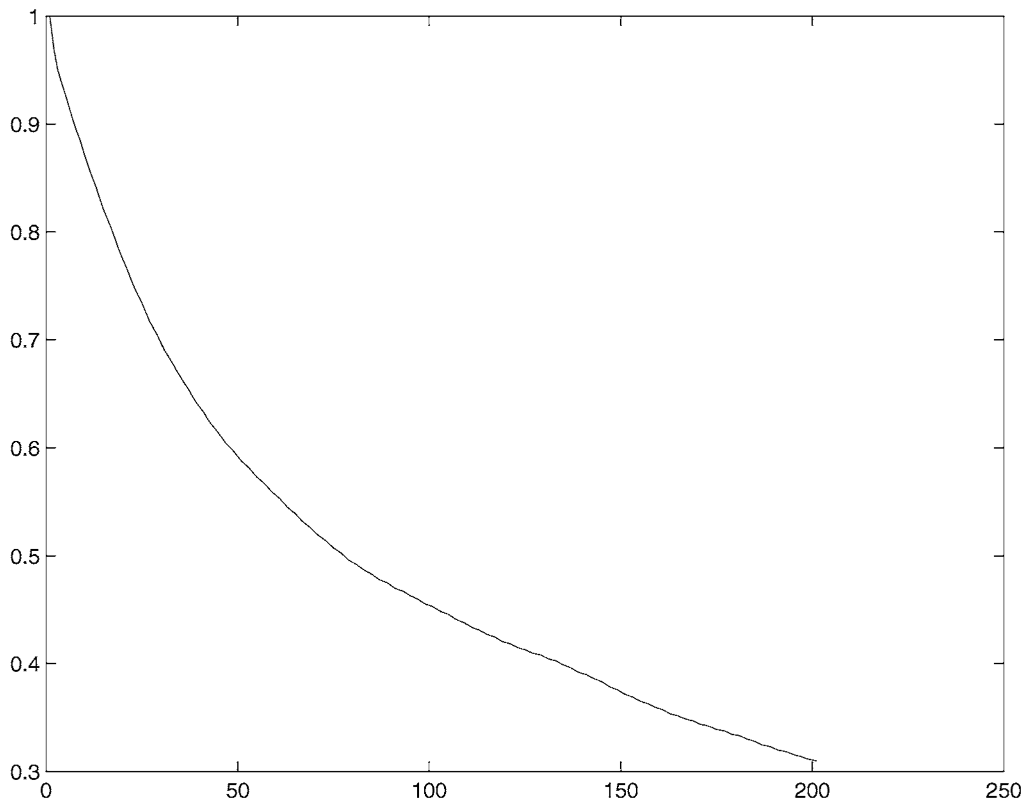

Figure 2. ACF of JPEG compressed video *Star Wars*.

provide such an analytical model. To overcome some shortcomings of video modeling, we propose to model MPEG compressed video sequence by Markov modulated self-similar processes, in which the original sequence is decomposed into several sequences that can be modeled by self-similar processes. A Markov chain is then used to govern the transitions among these self-similar processes. It has been found that video traffic possesses self-similarity, and thus it is natural to model video traffic by self-similar processes. In addition, self-similar processes have simple ACF forms, hence allowing us to readily derive an analytical model for our proposed approach. Our proposed model is shown to be able to capture both the long range dependency and marginal cumulative distribution. This paper is organized as follows. In Section 2, empirical data and ACF are described. Concepts of SRD, LRD and self-similar processes are presented in Section 3. Section 4 discusses the classification of data. Modeling of the classified data is discussed in Section 5. We describe how to model the whole data set as a Markov modulated process in Section 6. Section 7 presents a method to synthesize video traffic. Network performance in terms of cell loss rate based on our proposed synthesized and empirical data as the source traffic is presented in Section 8.

2. Empirical Data and ACF

Most of the work in video source modeling has been largely confined to a short period of video (conference) sequences. The scene change or drastic motion frames are rare in these sequences. As a result, bit rates are relatively low, and bit rate changes are rather small compared with that of full motion movies. Here, we use MPEG-I coded data of *Star Wars*[1] as the empirical data. The source contains motions ranging from low complexity/motion scenes to those with high and very high actions.

The data file consists of 174,136 integers, whose values are frame sizes (bits per frame). The movie length is approximately 2 hours at 24 frames per second. The original video was captured as 408 lines by 508

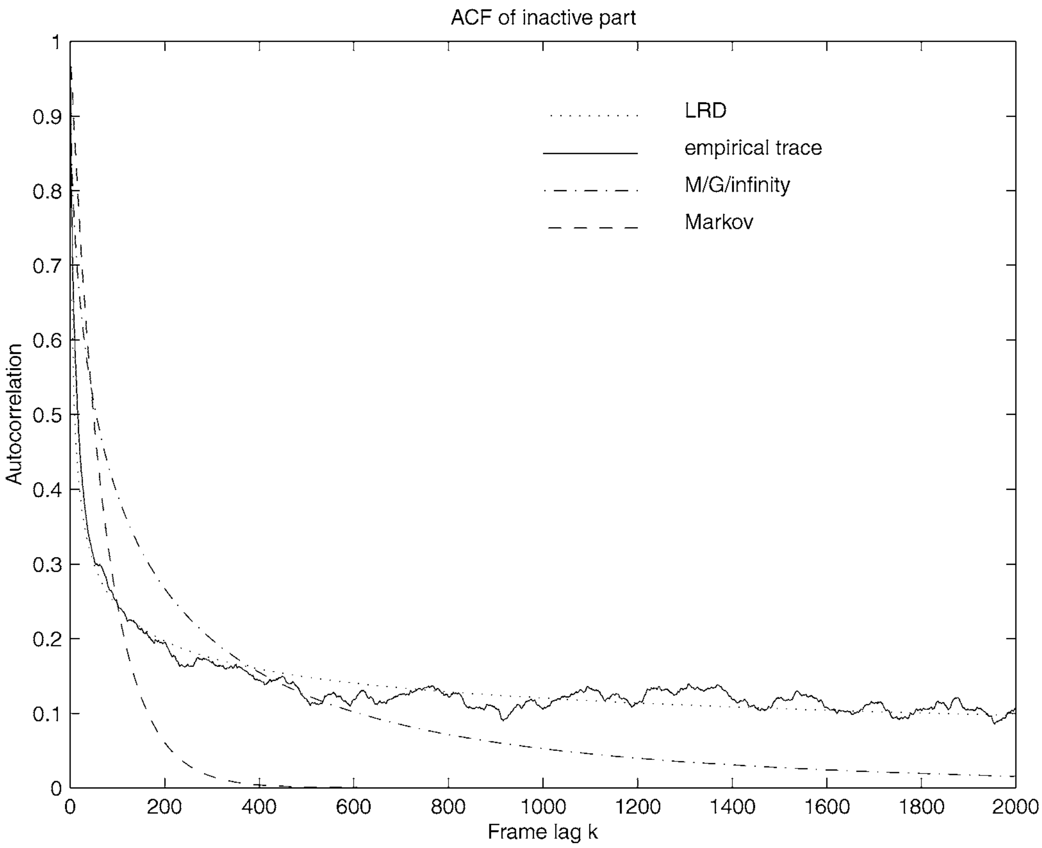

Figure 3. ACF of the inactive part of *Star Wars*.

pels, and then interpolated to 240 × 352 (Luminance—Y), and 120 × 176 (Chrominance—U and V). Every frame was partitioned into blocks of 8 × 8 pixels. These data blocks were transformed using DCT. After DCT transformation, coefficients were quantized and Huffman coded. Run length coding was further used to reduce bit rate. Motion estimation techniques were used to compress data volume. The frames were organized as follows: IBBPBBPBBPBB IBBPBB…, i.e., 12 frames in 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 MPEG coded *Star Wars* is shown in Fig. 1, and it is quite different from the ACF of JPEG coded movies *Star Wars* (see Fig. 2). The ACF of MPEG coded data fluctuate around an envelope, reflecting the fact that, after the use of motion estimation techniques, the dependency between frames is reduced. To capture the ACF accurately, this characteristic should be taken into consideration in modeling MPEG coded video sequences. We propose to use self-similar processes with different ACFs to reflect the fluctuation of ACFs. The basic idea behind this method is to divide the sequence into three different sequences, each modeled by a separate self-similar process. The transition among these processes is governed by a Markov chain, whose transition matrix can be obtained from empirical data.

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:

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

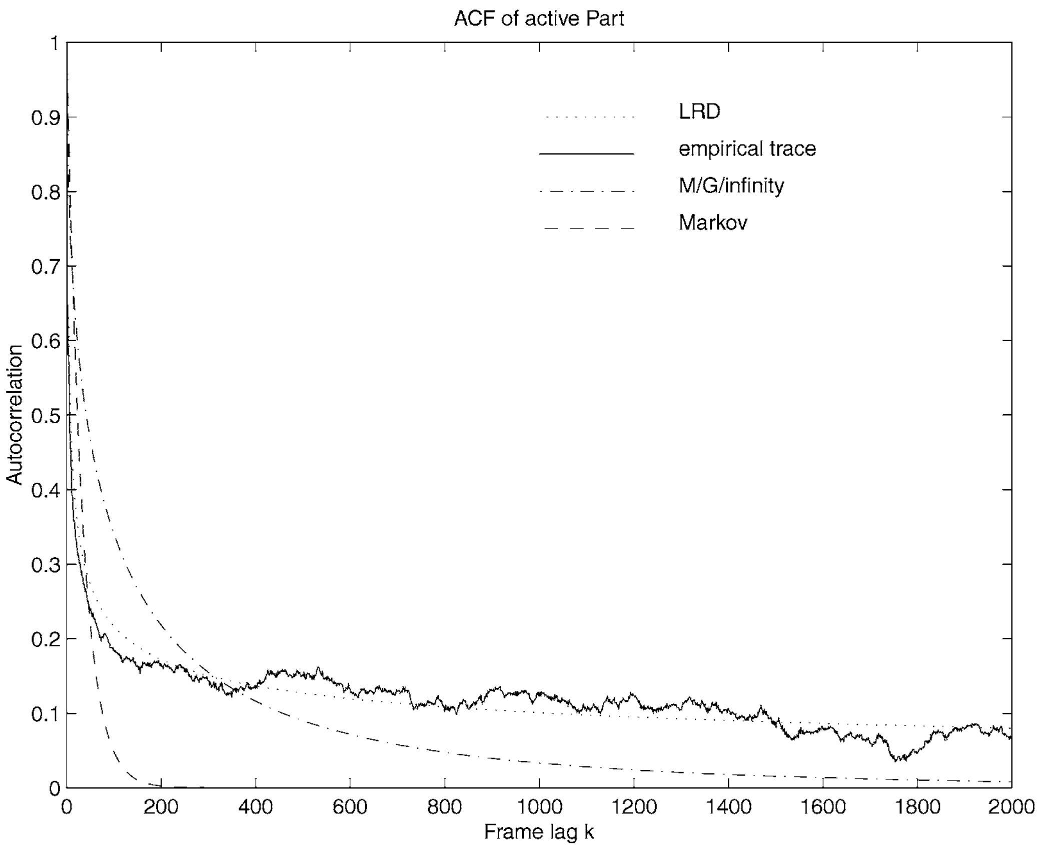

Figure 4. ACF of the active part of *Star Wars*.

and

$$\sigma^2 = E[(X_n - \mu)^2]. \tag{2}$$

X is said to be SRD if $\sum_{k=0}^{K=\infty} r(k)$ is finite; otherwise, the process is said to be LRD [15].

Let X defined above have the following autocorrelation function:

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

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

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

where

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

and P is a positive integer set. X is said to be exactly second-order self-similar [15] if

$$\operatorname{var} X^{(m)} = \sigma^2 m^{-\beta} \tag{5}$$

and

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

for all $m \in \{1, 2, 3, \dots\}$ and $k \in \{0, 1, 2, \dots\}$. Here $r^{(m)}(k)$ is the autocorrelation function of $X^{(m)}$. In fact, Eq. (5) is sufficient to define a self-similar process since Eqs. (3) and (6) can be derived from Eq. (5) [15].

It is apparent that a self-similar process is a kind of LRD process. 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.

The Hurst parameter $H = 1 - \beta/2$ $(0 < \beta < 1)$ is used to measure the similarity of a process. It is

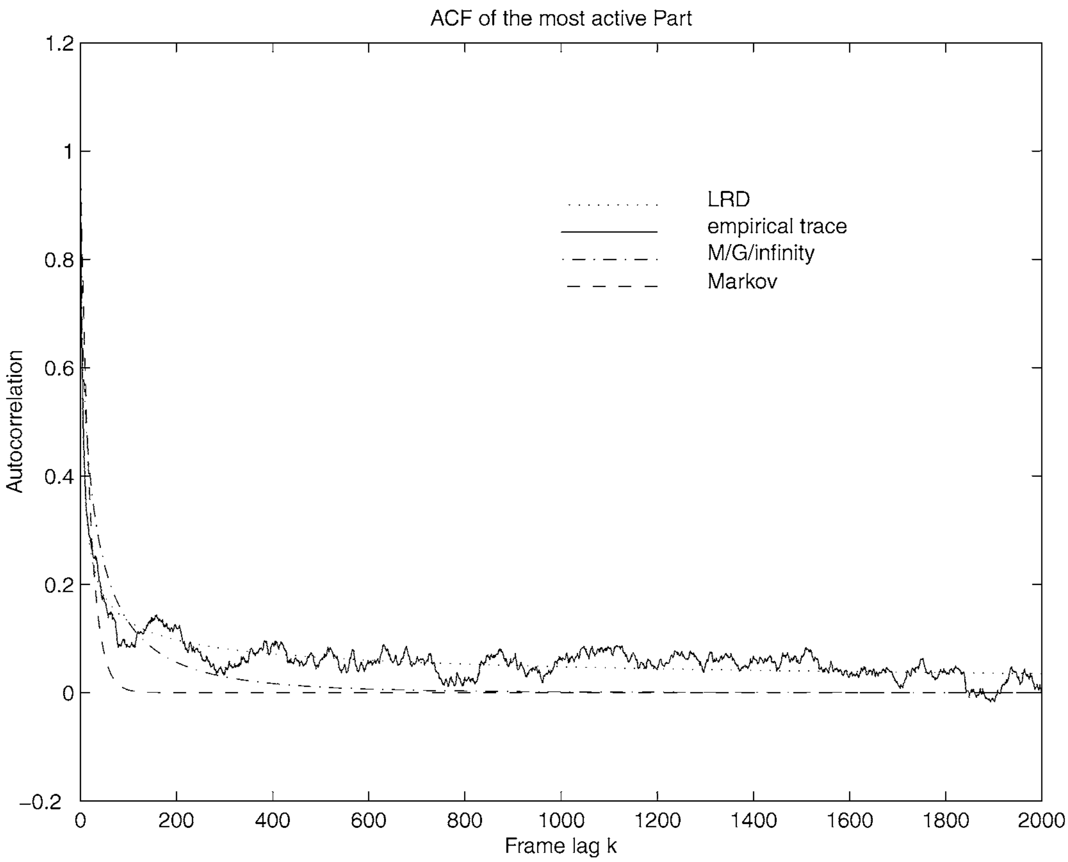

Figure 5. ACF of the most active part of *Star Wars*.

the only parameter needed to describe a second-order self-similar process. For a process with self-similarity, $1/2 < H < 1$.

4. Classification of MPEG Data

It is apparent that ACF of MPEG compressed video traffic cannot be approximated by a single function $r(k) = k^{-\beta}$ because this kind of function decreases monotonically, while ACF of a MPEG compressed video traffic fluctuates dramatically. By comparing JPEG compressed data and MPEG compressed data, we may find that bit rate variation of an MPEG compressed video sequence is larger than that of a JPEG compressed video sequence. We therefore suggest to divide the traffic data into three different parts—inactive part, active part, and the most active part in terms of motion/content complexity similar to the observations made in [2] (i.e., a video bit rate process has three main components: a slowly changing component, a more quickly changing component, and an impulsive component). There are many ways to decompose video data into these three components. One may accomplish the decomposition in the MPEG compressed domain, say, by using readily available motion vectors of blocks. In our simulations, video frames are grouped into three components of different motion/content complexity based on frame size changes using the following heuristics:

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

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

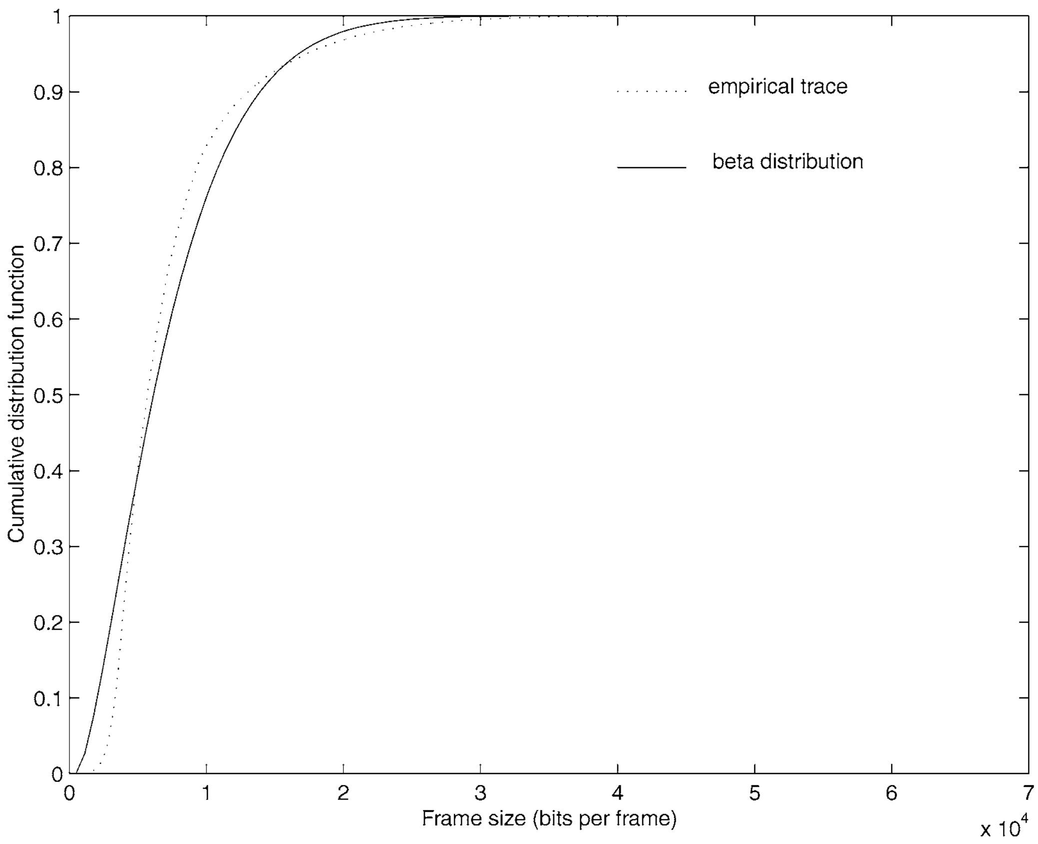

Figure 6. CDF of the inactive part and the corresponding beta distribution.

5. Modeling of Classified Data

The ACF of each process is very different (as shown in Figs. 3–5), from that of the original sequence. The fluctuation is no longer as drastic as that of the original sequence. 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 ACFs of these three processes. It becomes evident that $k^{-\beta}$ is a better approximation of ACFs of these classified data, and we therefore use self-similar processes s_1, s_2, and s_3 to model these processes.

Using the least squares method, we obtained $\beta = 0.3321$, 0.3069, and 0.4396 for the active, inactive, and most active part, respectively. The corresponding Hurst parameters for these processes are $H = 0.8339$, 0.8465, and 0.7802.

Beta distribution [16] was used to model the marginal distributions of these processes. The marginal distribution of a Beta distribution process has the following form

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

where γ and η are shape parameters, and $[\mu_0, \mu_1]$ is the domain where the distribution is defined.

Beta distribution is quite versatile and can be used to model random processes with quite different shapes of marginal distributions. The following formulae are used to derive the parameters of Beta distribution:

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

$$\hat{\gamma} = \frac{\bar{x}\hat{\eta}}{1-\bar{x}} \tag{9}$$

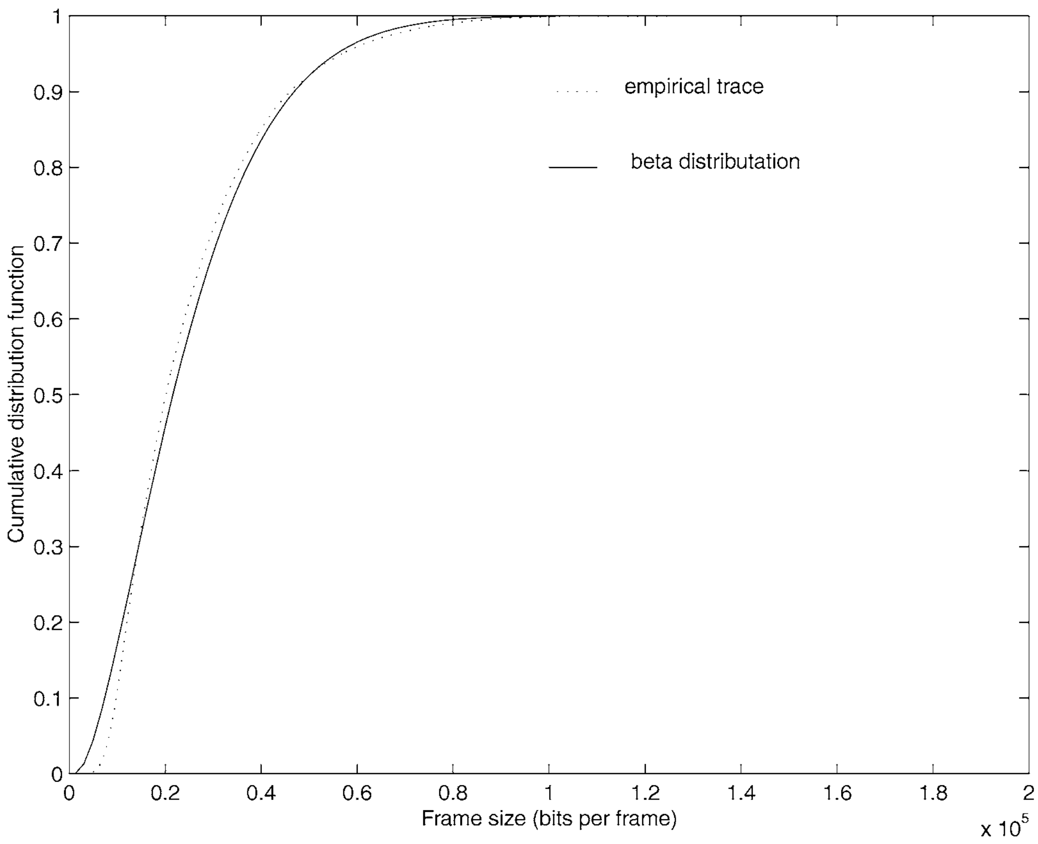

Figure 7. CDF of the active part and the corresponding beta distribution.

where

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

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

and N is the number of data in the data set. Using the classified data sets, $\hat{\gamma} = 1.6179$, $\hat{\eta} = 13.7810$ for the inactive process, $\hat{\gamma} = 1.7977$, $\hat{\eta} = 12.1980$ for the active process, and $\hat{\gamma} = 5.3550$, $\hat{\eta} = 11.4134$ for the most active process. The marginal distributions of the empirical data and the corresponding Beta distributions are shown in Figs. 6–8.

6. Modeling the 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. Markov chain is often used owing to its simplicity.

Using Markov chain as the dominating process, our model for MPEG video traffic can be described by the state diagram shown in Fig. 9, where state 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:

$$p_{ij} = \frac{N_{ij}}{N_i}, \tag{12}$$

where 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 the system make transition to state S_j from state S_i. For the *Star Wars* video, the following transition matrix

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

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

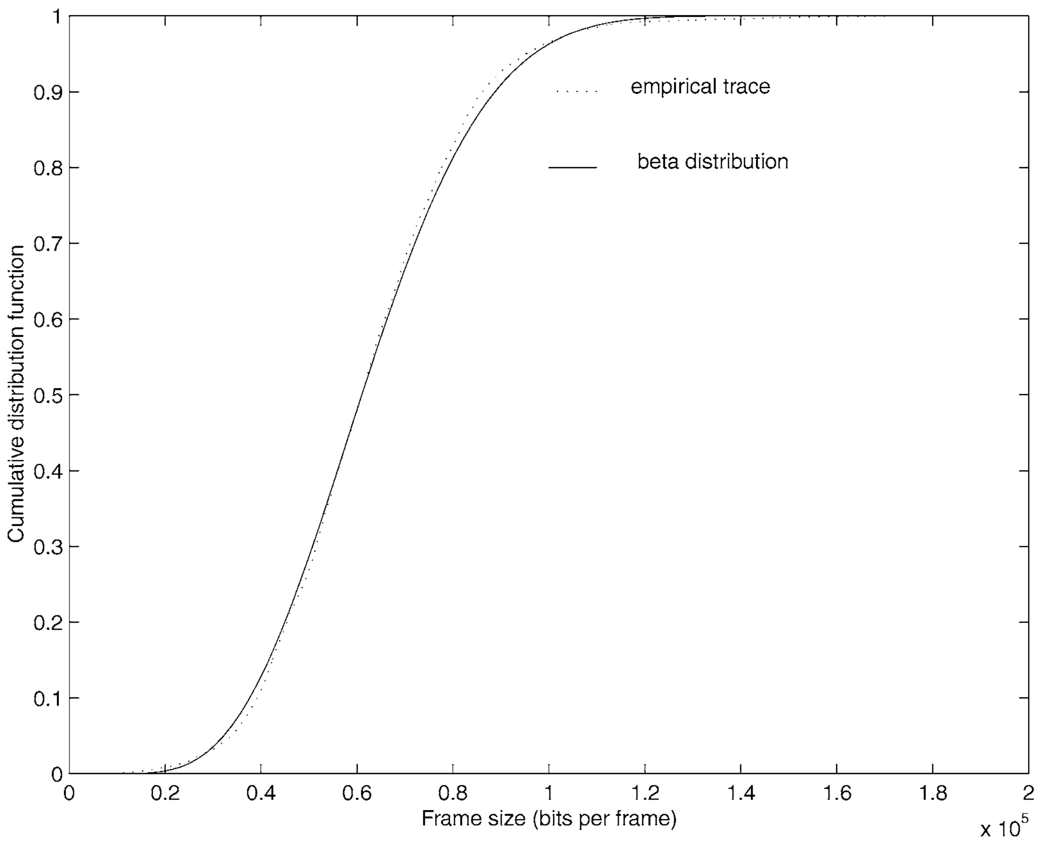

Figure 8. CDF of the most active part and the corresponding beta distribution.

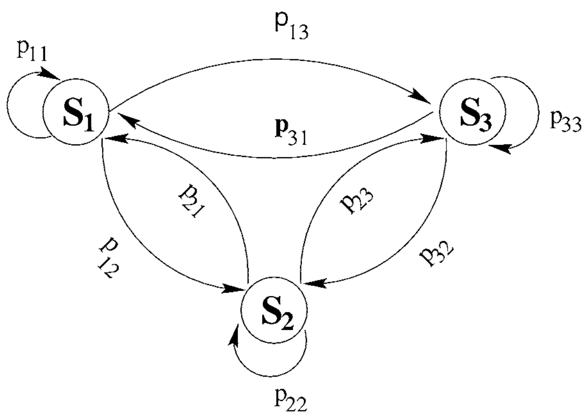

Figure 9. A Markov modulated self-similar process model for MPEG video.

7. Video Traffic Synthesis

To synthesize video traffic using our model requires self-similar traffic generator. Some methods are available to generate approximate self-similar traffic. Two of the most commonly used methods are exactly self-similar fractional Gaussian noise (FGN) [17] and asymptotically self-similar fractional autoregressive integrated moving-average (F-ARIMA) process [17]. F-ARIMA can be used to match any kind of ACF. It takes a long time to generate the video traffic since F-ARIMA is an iterative process. The F-ARIMA process can be generated by the following algorithm [7, 18, 19]:

1. Generate X_0 from a Gaussian distribution $N(0,\ \nu_0)$. Set initial values $N_0 = 0,\ D_0 = 1$
2. For $k = 1, 2, \ldots, N - 1$, calculate ϕ_{kj}, $j = 1, 2, \ldots, k$ iteratively using the following formulae

$$N_k = r(k) - \sum_{j=1}^{k-1} \phi_{k-1,j}\, r(k-j) \tag{13}$$

$$D_k = D_{k-1} - N_{k-1}^2 \big/ D_{k-1} \tag{14}$$

$$\phi_{kk} = N_k / D_k \tag{15}$$

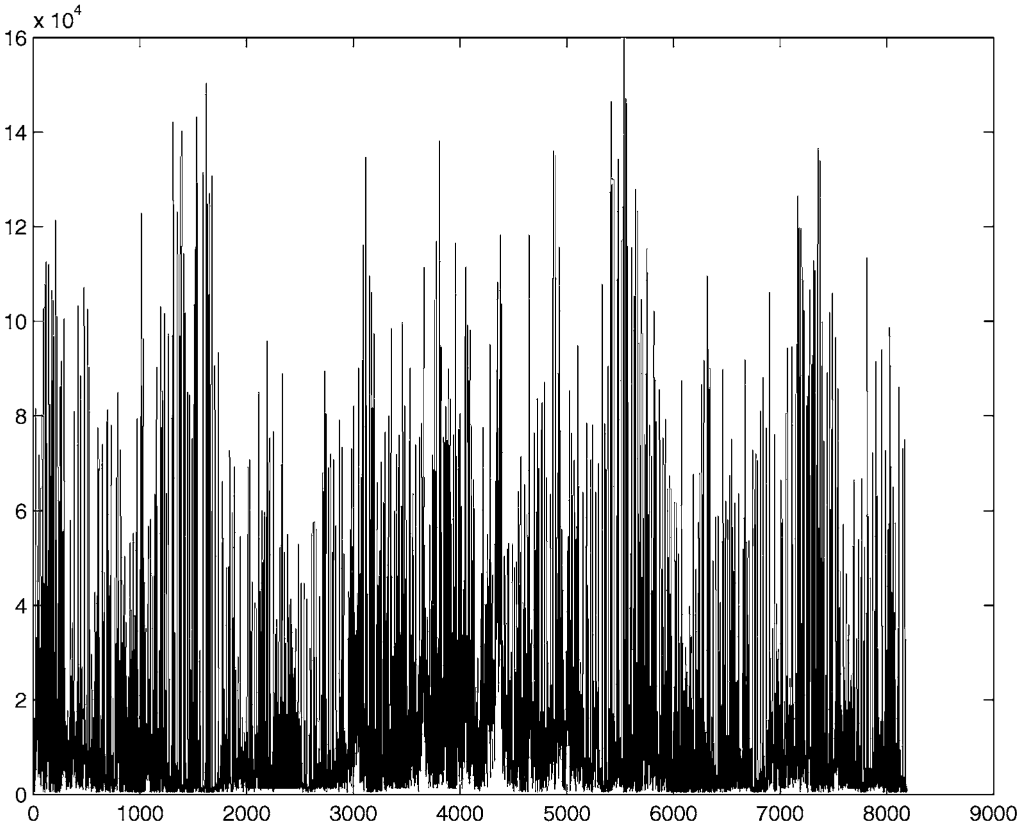

Figure 10. Traffic generated by our proposed model.

$$\phi_{kj} = \phi_{k-1,j} - \phi_{kk}\phi_{k-1,k-j}, \qquad j = 1, \ldots, k-1 \quad (16)$$

$$m_k = \sum_{j=1}^{k} \phi_{kj} X_{kj} \quad (17)$$

$$\nu_k = \left(1 - \phi_{kk}^2\right)\nu_{k-1} \quad (18)$$

Finally, each X_k is chosen from $N(m_k, \nu_k)$. In this way, we obtain a process X with ACF approximating to $r(k)$.

To generate a self-similar process approximately, the autocorrelation function can be calculated in a recursive way as

$$r(0) = 1, \quad r(k+1) = \frac{k+d}{k+1} r(k) \quad (19)$$

where $d = H - 0.5$.

ACFs of F-ARIMA and FGN generated traffic are less than $k^{-\beta}$ for small k. To compensate for the under-estimation of ACFs of a self-similar process, Eq. (19) used to generate F-ARIMA traffic can be enlarged for small k. New self-similar traffic generators need to be devised so that more exact self-similar traffic can be generated.

Distribution of these data is Gaussian. For data to be Beta distributed, the following mapping can be used

$$Y_k = F_\beta^{-1}(F_N(X_k)), \quad k > 0 \quad (20)$$

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 the Beta model.

Video traffic can be synthesized by a combination of the three obtained self-similar processes via a Markov process, whose transition matrix was given in the last section (see Fig. 10 for a traffic example). In the empirical data trace, the size of I frame is often larger than the size of P frame and B frame, implying that a large frame is often followed by several small frames. It is shown in Fig. 10 that the traffic generated by our

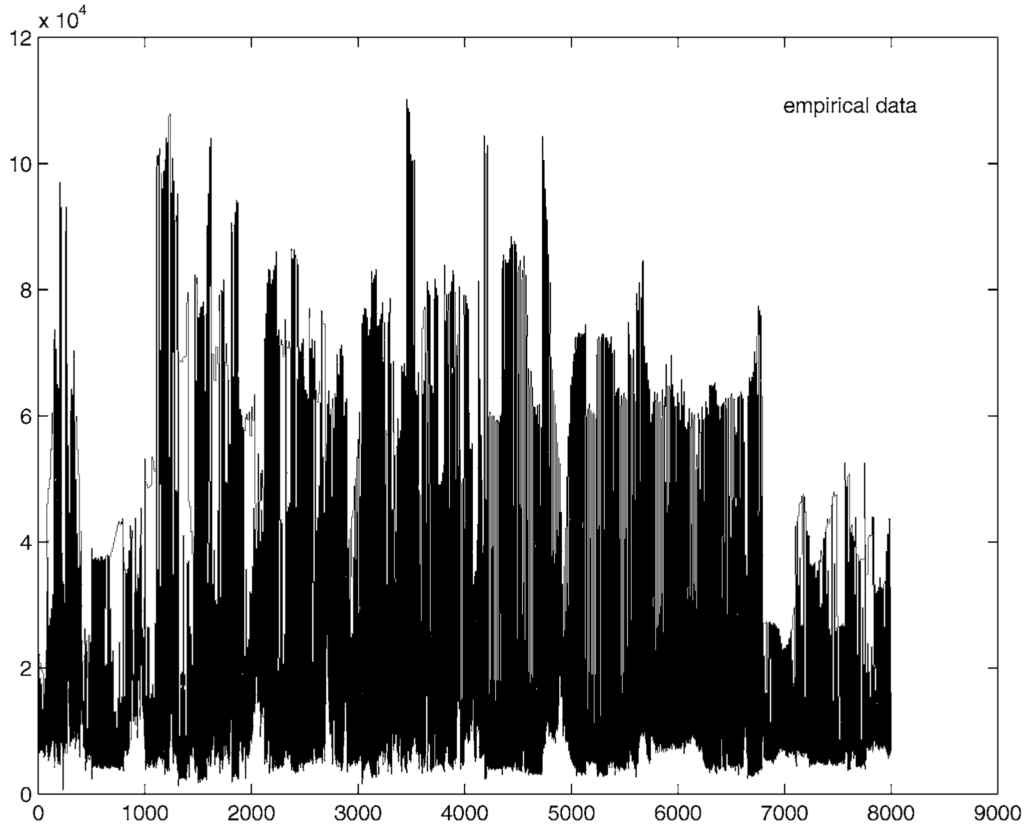

Figure 11. A piece of the empirical traffic trace.

model can capture this kind of characteristic. A piece of the empirical traffic trace is shown in Fig. 11.

8. Network Cell Loss Rate

Cell Loss Rate (CLR) is an important queuing network performance. To justify the queuing performance of our model, our synthetic traffic was used as the source traffic to a single server queue with finite buffer. The performance is compared to the same system using empirical data as the source traffic. A single arrival process is assumed in our simulation, and its service rate is assumed to be constant. To simplify the simulation process, the time is sliced. Every slice is used to transmit one cell (48 bytes of payload per cell). We also assume that cells in a frame must arrive at the switch during the period of this frame. This corresponds to the case that

Table 1. CLRs for different service rate and buffer size.

Buffer size (cells)	4000 cells/s		6000 cells/s		9000 cells/s	
	Trace	Model	Trace	Model	Trace	Model
20	2.24E−2	9.95E−2	2.09E−3	2.30E−2	1.50E−4	4.25E−4
40	1.24E−2	7.43E−2	1.36E−3	1.34E−2	8.07E−5	1.34E−4
60	6.81E−3	5.44E−2	9.72E−4	9.25E−3	7.19E−6	2.28E−5
100	2.30E−3	2.72E−2	4.57E−4	2.91E−3	0	0
200	3.55E−4	4.22E−3	1.00E−5	3.40E−5	0	0
400	6.14E−5	6.40E−4	0	0	0	0

no traffic shaping is applied. Cells are dropped when the switch buffer overflows.

Based on the switch model, performance at different service rates and buffer sizes is examined. Simulation results using empirical data and traffic model are shown in Table 1. The results show that the CLRs obtained using video trace and our proposed model are very close for both high and low service rates.

9. Conclusions

In this paper, we have proposed a Markov-Modulated self-similar process for modeling MPEG compressed video sequence. Compared with other methods, the proposed model is easy to analyze, and it is able to capture the LRD of video ACF. An analytical solution may be obtained for this model because of its simple ACF form. Queuing performance for small and large buffers under different traffic intensity using our proposed model is compatible with that using empirical data.

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Note

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