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MPEG-2 Variable Bit Rate Video Traffic Modeling for ATM Networks

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Abstract: This paper proposes a variable bit rate (VBR) video traffic model based on two properties of MPEG-2 video coding: characteristics of GOP and distribution of cell numbers per frame in each picture type. The proposed video model consists of the 3-state MMBP (Markov Modulated Bernoulli Process) and GAR (Gamma Auto Regressive). The 3-state MMBP model considers each picture coding type in MPEG-2 video coding. The GAR model is used for each picture type because cell numbers in each picture frame follows a Gamma distribution. The proposed model demonstrates improved performance. It can be used for theoretical analysis of cell loss probability and engineering design for traffic management.

1. Introduction

We are expecting that variable bit rate (VBR) video services will become a significant portion of traffic load in the future broadband ATM network. Since modeling for VBR video traffic is the basis of video traffic control, it is an important subject for ATM networks.

In VBR video coding, image degradation is determined by the QoS (Quality of Service) of each service. Hence we can obtain constant image quality without respect to the image content and complexity. However, we cannot estimate the bit rate accurately in VBR transmission because the bit rate is changing continuously. Therefore, a video traffic model for VBR transmission is needed.

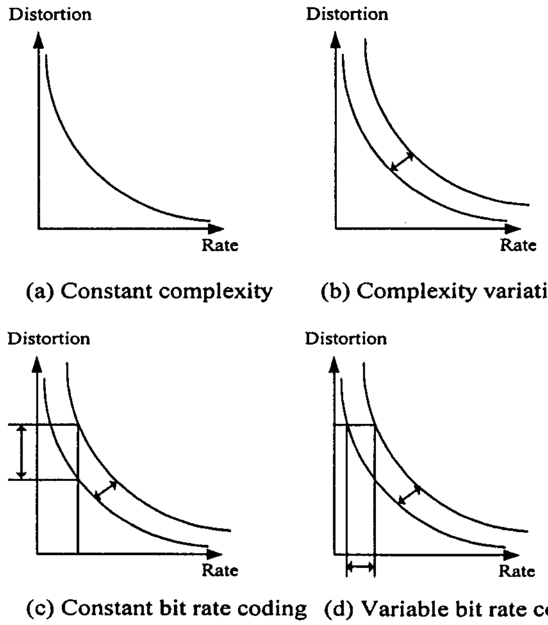
For video traffic modeling, a first-order auto-regressive (AR) process [1,2] and an auto-regressive moving average (ARMA) process [3] are proposed to describe the video source. It is also pointed out that a Markov chain is more suitable for video sequences than AR [4]. Recently, a first-order Gamma auto-regressive process (GAR) is proposed [5].

The conventional video models can characterize video sources with slow or no motion; however, they cannot represent the characteristics of video with fast motion and high complexity properly. Furthermore, the conventional models do not reflect the periodic structure of the group of pictures (GOP) in MPEG-2 video coding.

In this paper, we propose a new traffic model for MPEG-2 video bitstream by combining some features of the conventional video models. The 3-state MMBP (Markov Modulated Bernoulli Process) [6] that considers each picture type in the GOP structure of MPEG provides a good solution, as compared to the conventional models. We also employ the GAR (1) model from the fact that the number of cells per frame in each picture type follows a Gamma distribution approximately.

2. MPEG-2 VBR Video Traffic Model

In video coding, a variable bit rate (VBR) can be achieved by generating the coding bits according to the local and temporal image complexity, while maintaining a constant image quality.



(a) Constant complexity (b) Complexity variations

(c) Constant bit rate coding (d) Variable bit rate codin

Figure 1. Rate distortion functions

Figure 1(a) shows the typical shape of the rate-distortion function of a coding algorithm with a given image complexity. We can make a plot of the function by changing the quantization step size and measuring the generated bit numbers as a function of distortion. Since complexity of the image varies in time, the rate-distortion function can be shifted, as indicated in Figure 1(b).

If a constant bit rate (CBR) is to be achieved, the complexity variations will lead to a varying image quality, as shown in Figure 1(c). Especially at low bit rates, these quality variations may be severe and affect subjective image quality significantly. If VBR is allowed, a nearly constant and subjectively better image quality can be achieved, as indicated in Figure 1(d). Besides providing better subjective image quality, VBR enables to reduce the average bandwidth significantly, depending on the application.

2.1. The 3-State MMBP Model

In MPEG-2 coding, the I-P-B pattern can be specified by two parameters: the distance M between I-picture and P-picture or P-picture and P-picture, and the distance N between I-pictures. For instance, if M=3 and N=15, the sequence of pictures in which a video is displayed is

$I_0\ B_1\ B_2\ \mathbf{P_3}\ B_4\ B_5\ \mathbf{P_6}\ B_7\ B_8\ \mathbf{P_9}\ B_{10}\ B_{11}\ \mathbf{P_{12}}\ B_{13}\ B_{14}\ \mathbf{I_{15}}\ B_{16} \bullet\bullet\bullet\bullet$

In MPEG video coding, the reference picture following a group of B-pictures should be transmitted before the B-picture group. Therefore, we need to reorder the picture frames. The transmission order is as follows.

$I_0\ \mathbf{P_3}\ B_1\ B_2\ \mathbf{P_6}\ B_4\ B_5\ \mathbf{P_9}\ B_7\ B_8\ \mathbf{P_{12}}\ B_{10}\ B_{11}\ \mathbf{I_{15}}\ B_{13}\ B_{14}\ \mathbf{P_{18}} \bullet\bullet\bullet\bullet$

Except for the first I-picture, the transmission sequence consists of successive picture groups, each of them having a reference picture and (M-1) B-pictures. The group led by an I-picture is called "I-GOP" (Group of pictures) and the group led by a P-picture is called "P-GOP". It is clear that I-GOP appears every $L=N/M$ GOP's, and I-GOP appears with the probability 1/L after its preceding GOP. From this assumption, the cell stream of an MPEG video can be modeled by a 3-state MMBP, as shown in Figure 2.

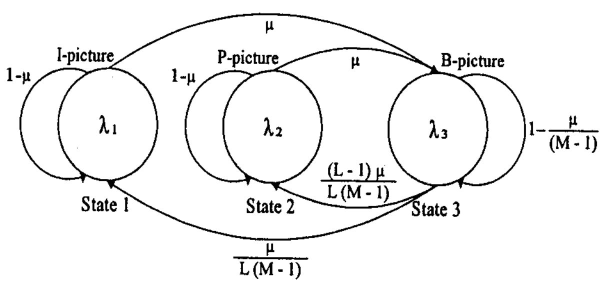


Figure 2. 3-state MMBP for the MPEG-2 video stream

In this model, I-picture, P-picture and B-picture are assumed to be transmitted in each state labeled in the numerical order. For instance, I-picture is labeled 1, P-picture is labeled 2, and B-picture is labeled 3.

In Figure 2, λ_i denotes the mean cell generation rate of the i-th picture, and $\mu_{i,j}$ denotes the transition probability from the i-th picture to the j-th one. The value of $\mu_{i,j}$ is given by

$$\mu_{i,j} = \begin{cases} 1-\mu & :i=1,2\ ,j=1,2 \\ \mu & :i=1,2, j=3 \\ \dfrac{\mu}{L(M-1)} & :i=3, j=1 \\ \dfrac{(L-1)\mu}{L(M-1)} & :i=3, j=2 \\ 1-\dfrac{\mu}{(M-1)} & :i=j=3 \\ 0 & :otherwise \end{cases} \tag{1}$$

where $1/\mu$ denotes the frame duration.

2.2. The Gamma Auto-Regressive Model

Previous research has shown that the number of cells per picture frame of VBR video teleconferences follows a Gamma distribution [5]. In addition, the cell numbers per frame in each picture type of MPEG-2 VBR video are proven to have a Gamma distribution [7]. However, in all the above video source models, it is assumed that the random variable is normally distributed. However, since the number of cells per frame generated by the MPEG-2 encoder is not normally distributed, these models cannot represent characteristics of video sources properly.

In this paper, we employ a novel video model, called the first-order auto-regressive (AR) Gamma sequence, whose variables are marginally Gamma distributed [5].

In general, we can assume X_n is a stationary sequence if $\{\varepsilon_n\}$ is a white noise sequence and

$$X_n = \sum_{i=1}^{p} X_{n-1} + \varepsilon_n \tag{2}$$

Here, $\{X_n\}$ is called as an AR sequence of p-th order. Specifically, if $\{X_n\}$ are marginally distributed as Gamma variables, then it is called a p-th order Gamma auto-regressive (GAR) sequence.

In the following, we consider the first-order GAR sequence, denoted by GAR (1).

$$X_n = \rho \cdot X_{n-1} + \varepsilon_n \tag{3}$$

This sequence can be considered to be asymptotically stationary if $0 \le \rho < 1$. In our video traffic model, this condition is always satisfied.

2.3. Generation of GAR (1) for Video Traffic

Since X_{n-1} is independent of ε_n, the Laplace-Stieltjes transform $\phi_{X_n}(s)$ of the distribution of X_n is

$$\begin{aligned}\phi_{X_n}(s) &= E[\exp(-sX_n)] = E[\exp\{-s(\rho X_{n-1}+\varepsilon_n)\}] \\ &= \phi_{X_{n-1}}(\rho s)\cdot\phi_{\varepsilon_n}(s)\end{aligned} \tag{4}$$

Thus

$$\phi_{\varepsilon_n}(s) = \frac{\phi_{X_n}(s)}{\phi_{X_{n-1}}(\rho s)} \tag{5}$$

As $\{\varepsilon_n\}$ and $\{X_n\}$ sequences are both marginally stationary, we get the following equation

$$\phi_{\varepsilon}(s) = \frac{\phi_X(s)}{\phi_X(\rho s)} \tag{6}$$

Here, X_n is a sequence of i.i.d.(independent, identically distributed) Gamma-distributed random variables with parameter k and λ, and its density satisfies

$$f_X(x) = \frac{\lambda^k x^{k-1} e^{-\lambda x}}{\Gamma(k)} \tag{7}$$

$$where\ \Gamma(k) = \int_0^\infty t^{k-1} e^{-t}\,dt \quad (\lambda \geq 0; k > 0; x \geq 0)$$

Therefore, its Laplace-Stieltjes transform is

$$\phi_X(s) = \left(\frac{\lambda}{\lambda+s}\right)^k \tag{8}$$

From the equation (8), the final solution is

$$\phi_{\varepsilon}(s) = \left(\frac{\lambda+\rho s}{\lambda+s}\right)^k = \left[\rho+(1-\rho)\frac{\lambda}{\lambda+s}\right]^k \tag{9}$$

We can get the distribution of the noise sequence $\{\varepsilon_n\}$ from equation (9) by inverse Laplace-Stieltjes transform.

There are three parameters $(\rho, k, \lambda\}$ in the GAR (1) model. In order to fit the real video traffic source, they should be estimated from the traffic data. Parameter ρ is calculated by

$$\rho = \frac{\sum[X_t - m][X_{t-1} - m]}{\sum[X_{t-1} - m]^2} \quad (t = 2,3,\ldots,N) \tag{10}$$

The other two parameters can be calculated from the moment estimation, because the mean and the variance of the Gamma distribution defined above are k/λ and k/λ^2, respectively. The moment estimation of k and λ should be

$$\lambda = \frac{m}{v} \tag{11}$$

$$k = \frac{m^2}{v} \tag{12}$$

where m and v are the mean and the variance of the traffic data sequence.

3. Simulation Results

We have compared simulation results of the conventional video models and the proposed model. For the test, we have used the "BICYCLE" sequence, which has the 720×480 sized ITU-R 601 format. The test sequence is coded using the MPEG-2 algorithm with N=12 and M=3.

To obtain VBR video traffic, we set the quantization value to 25. Figure 3 shows the number of cells per frame in the case of VBR coding.

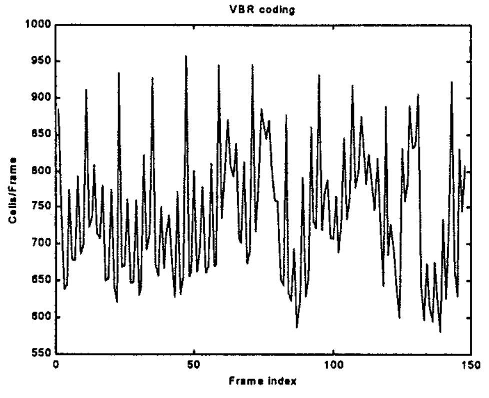


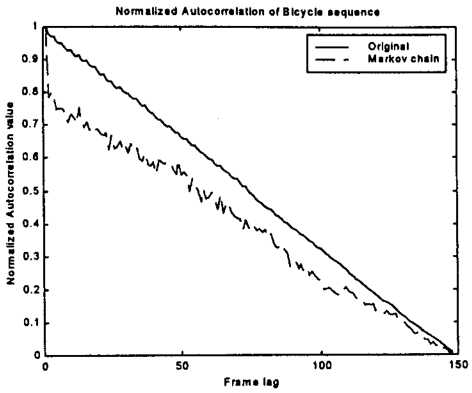
Figure 3. Number of cells per frame

In Figure 4, we compared the result of the autocorrelation of the original sequence, the Markov chain and the proposed model. As you can see, the proposed model represents the characteristic of MPEG-2 video traffic more accurately. Periodicity could be estimated in the autocorrelation function.

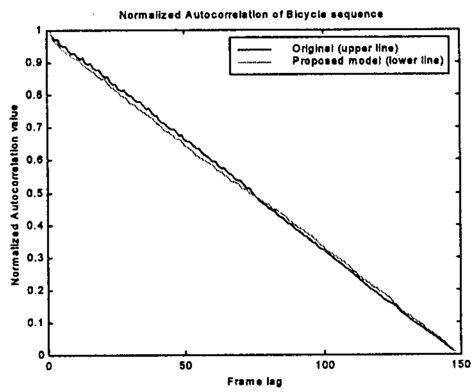
Figure 5 shows the Q-Q(Quantile-Quantile) plot of each picture type. From Figure 5, we can note that the estimated traffic also follows the Gamma distribution.

4. Conclusions

Since conventional video models are not compatible with the video sequences with fast motion, they cannot represent the characteristics of MPEG-2 video traffic properly. In order to overcome this problem, we proposed a new model for the MPEG-2 video traffic using the 3-state MMBP and GAR. In the new model, we consider the periodic GOP structure of MPEG-2 video coding and traffic characteristics of each picture type. With the proposed model, we can obtain improved results and periodicity is represented very exactly.

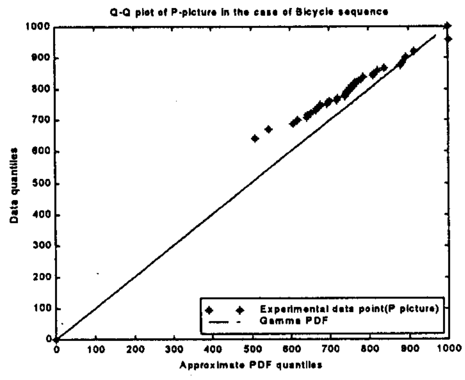


(a) Markov chain process

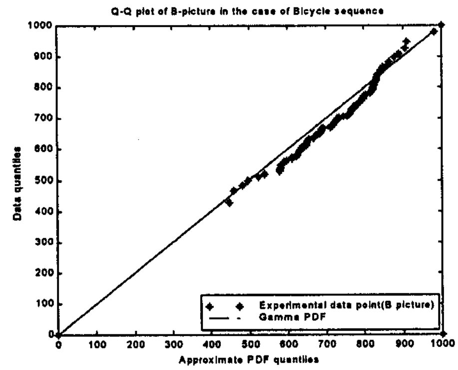


(b) Proposed model

Figure 4. Autocorrelation function



(a) P-picture



(b) B-picture

Figure 5. Quantile-Quantile plot

From the Q-Q plot, we can see that the estimated traffic follows the Gamma distribution approximately. The proposed model can be used for theoretical analysis of cell loss probability and engineering design for traffic management.

Acknowledgments

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