Extracting Deterministic Parameters from MPEG Video Sources with Quality Adjustment

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Abstract

The most stringent applications in the future will require network services with bounded-delay characteristics. In order to efficiently use the network resources, an accurate deterministic traffic model must be developed. This paper analyses the XGOP-B model proposes an algorithm to extract parameters from MPEG video sources that does not allow unfortunate choices, since it automatically results in an unique set of parameters. The obtained results show that high accuracy with a reasonable number of parameters can be easily achieved.

1 Introduction

The evolution of computer communication together with the development of multimedia techniques have allowed the emergence of applications that require strict quality of service (QoS) guarantees from the networks. Throughput, delay bounds, jitter, and loss rates are the most important parameters to be assured by the communication system.

Guaranteed services can be provided under two basic approaches [1]. In the first one, statistical guarantees are offered to the connections. The second approach considers services with deterministic guarantees, since all packets of a connection are assured to be delivered within the specified delays. While in deterministic services the QoS parameters

are always respected, in the case of statistical guarantees the bandwidth utilization is usually greater. However, these guarantees are not absolute, since they have a probability of being violated.

Three components are directly associated with the quality of the provided service [2, 3, 4]: the traffic model, the packet scheduler and the connection admission control. Among them, a simple and accurate traffic model is mandatory to provide an efficient service. Therefore, the traffic model must capture the traffic characteristics of an application with a minimum set of parameters that the user must send to the network manager for an effective traffic control and for an improved utilization of the network resources.

Several deterministic traffic models have been proposed in the literature [1, 3, 5, 6]. For the most accurate ones, there is a common drawback. For a certain source of traffic, the parameterization of its behavior can not be obtained in an unique way. In other words, given a traffic, the computation of the parameters depends upon some decisions that may result in loss of accuracy.

In this paper, we present the procedures to extract traffic parameters from MPEG video sources using the XGOP-B [7] deterministic traffic model. For this model, for each video traffic it is obtained a single set of parameters whose level of accuracy can be adjusted by a special variable. It will be shown that the presented techniques are very simple and result in an accurate characterization.

This paper is organized as follows. Section 2 introduces the most import concepts for deterministic traffic characterization and presents the XGOP-B model. In section 3, the parameters extractor is detailed and analyzed. Some numerical results concerning the relationship between the adjustment of the model and the level of accuracy are presented in section 4. Finally, some concluding remarks are done in section 5.

2 Deterministic Traffic Characterization and the XGOP-B model

A characterization is said to be deterministic when it is able to represent a traffic for all cases, i.e., when the source transmits at the required rate without buffering or discarding packets. In this paper, to develop a deterministic traffic model, the adopted approach is based on the definition of the traffic constraint function [5]. A function $\mathcal{F}(\cdot)$ is a traffic constraint function if during any interval of length δt the source does not transmit more than $\mathcal{F}(\delta t)$ bits. From another point of view, considering $\mathcal{G}[t, t+\delta t]$ as the actual number of bits transmitted by the source in the interval $[t, t+\delta t]$, the equation

$$\mathcal{G}[t, t+\delta t] \leq \mathcal{F}(\delta t), \qquad t > 0, \tag{1}$$

must be satisfied. In this way, the traffic constraint function $\mathcal{F}(\cdot)$ provides a time-invariant bound on $\mathcal{G}$.

The only restriction on $\mathcal{F}(\cdot)$ is that it must be an upper bound on the behavior of the source. Thus, there is an infinite number of possible solutions to $\mathcal{F}$. A deterministic traffic model selects, among all the possibilities, a group of solutions with specific characteristics.

For a source that transmits according to $\mathcal{G}$, the most accurate traffic constraint function that can be obtained is the empirical envelope [3, 4], defined as $\zeta(\delta t) = \texttt{sup}\ \mathcal{G}[t, t+\delta t]$, $t \geq 0$.

In practice, to represent the behavior of VBR sources by the empirical envelope may be extremely complex, requiring numerous parameters. Thus, the solution is to chose a simple upper approximation to ζ that satisfies

$$\mathcal{F}(\delta t) \geq \zeta(\delta t), \qquad \forall \delta t. \tag{2}$$

Since the traffic constraint function must be an upper approximation to ζ, and the empirical envelope is the most accurate deterministic characterization of a source, the main objective is to find a function $\mathcal{F}$ as close as possible to ζ. Analytically, the expression

$$\mathcal{F}(\delta t) - \zeta(\delta t), \qquad \forall \delta t, \tag{3}$$

must be minimized.

2.1 Deterministic Traffic Models

Several deterministic traffic models have been proposed in the literature. In this work we present four of them: the (σ, ρ) model [5], also known as Fluid model, the $(\vec{\sigma}, \vec{\rho})$ model [3], the $(x_{min}, x_{ave}, I, s_{max})$ [1], also called Discrete model, and the D-BIND model [6, 8].

In the (σ, ρ) model, for an interval of length δt, the source is limited to transmit no more than $\sigma + \rho \times \delta t$ bits. The $(\vec{\sigma}, \vec{\rho})$ model, which is an extension to the (σ, ρ) model, does not define a pair of parameters, but a two-dimensional array of them, resulting in a piece-wise concave function. Thus, this model is able to characterize a source more accurately. The Discrete model uses four parameters to model a traffic, $(x_{min}, x_{ave}, I, s_{max})$, where x_{min} is the minimum interval between two consecutive packet arrivals, x_{ave} is the maximum average interval between two packet arrivals within an interval of length I and s_{max} is the maximum packet size. The D-BIND (*Deterministic Bounding INterval Dependent*) model characterizes a source with a $R(I)$ function, where $R(I)$ is the maximum transmission rate within an interval I. The $R(I)$ function has N pairs $(R_k, I_k)|_{k=1,2,...,N}$ and results in a piece-wise curve which is not necessarily concave.

Table 1 summarizes the traffic constraint functions for each one of the presented models.

Table 1: Traffic constraint function for the models.

Model	**Traffic constraint function**
(σ, ρ)	$\mathcal{F}_{(\sigma,\rho)}(\delta t) = \sigma + \rho \times \delta t$
$(\vec{\sigma}, \vec{\rho})$	$\mathcal{F}_{(\vec{\sigma},\vec{\rho})}(\delta t) = min_i\{\sigma_i + \rho_i \times \delta t\}$
Discrete	$\mathcal{F}_{Discrete}(\delta t) = \lfloor \frac{\delta t}{I} \rfloor \frac{I \times s_{max}}{x_{ave}} + min\{\lceil (\frac{\delta t}{I} - \lfloor \frac{\delta t}{I} \rfloor) \frac{I}{x_{min}} \rceil, \frac{I}{x_{ave}}\} \times s_{max}$
D-BIND	$\mathcal{F}_{D-BIND}(\delta t) = \frac{R_k I_k - R_{k-1} I_{k-1}}{I_k - I_{k-1}} (\delta t - I_k) + R_k I_k, \quad I_{k-1} \leq \delta t \leq I_k$

2.2 The MPEG Standard and the XGOP-B Model

The MPEG (*Moving Picture Expert Group*) coding algorithm [9] was developed for storage of compressed video in digital media. However, recent applications have been using the MPEG standard for a wide variety of services, from multimedia stations to high-definition TV.

A MPEG coder produces three frame types: I frames (intra-pictures), that use intra-picture coding; P frames (predicted-pictures), that use a similar algorithm to I frames, and moving compensation based on previous I and P frames; and B frames (bidirectional-pictures), for bidirectional prediction, that use moving compensation based on previous and future reference frames.

A MPEG video is composed by a cyclic sequence of frames, called GOP (*Group Of Pictures*), which contains an initial I frame and some P and B frames, according to a pre-specified sequence. Figure 1 shows an example of MPEG stream with a IBBPBBPBB sequence of frames.

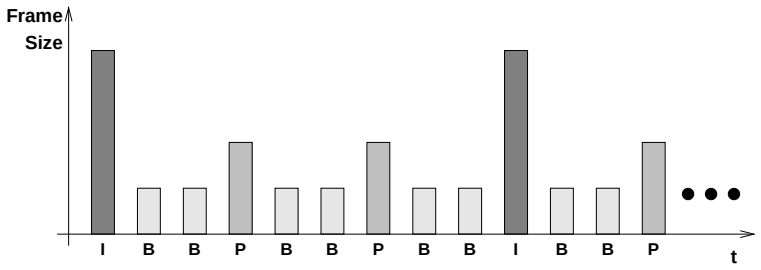


Figure 1: MPEG compressed video sample.

Most of MPEG video streams have I frames much larger than P and B frames. The burstiness characteristic comes from these different sizes of consecutive frames. In terms of transmissions, it means that information bursts occur at the beginning of each GOP. An example of empirical envelope for a MPEG video is shown in figure 2. In the graph, we can note the bursts produced by I frames.

In practice, the compression rates reached by the coder vary a lot. The result may be an irregular sequence of frames. Figure 3 illustrates two video traces[1] with diversified

[1] A video trace is an ordered sequence of frame sizes of a video sample.

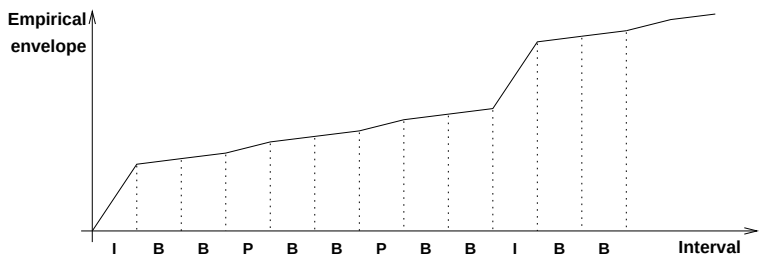


Figure 2: Empirical envelope example.

characteristics, even being captured under the same conditions (GOP pattern, number of elements per frame, sample rate etc).

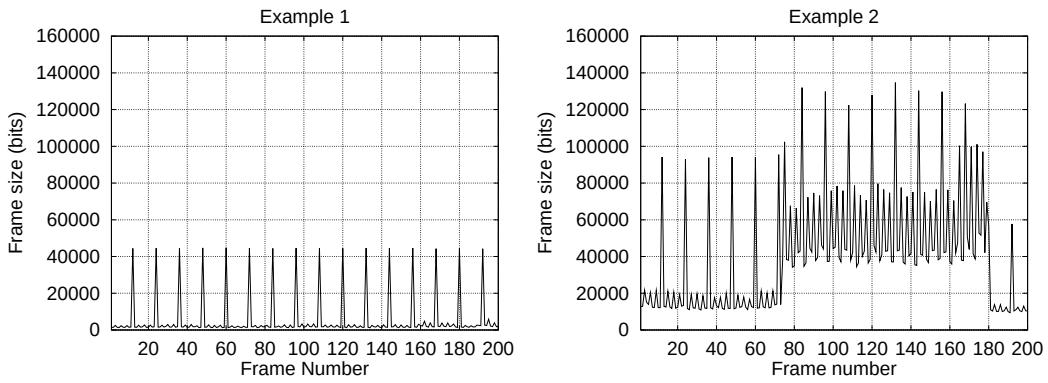


Figure 3: Two examples of video traces.

The property described above is essential, but it is not the only one. As discussed, the compression rate for a MPEG video is not constant. The influence of this observation on the behavior of the empirical envelope is that it suffers from "sudden" deviations in the increase rate of the curve. This effect can be better observed in figure 4. The points where more accentuated variations occur are called **breakpoints** (ξ).

For the (σ, ρ) and Discrete models, the presence of breakpoints is undesired, since these models have the traffic constraint curves with constant increase rates. At a negative breakpoint, i.e., when the average increase rate reduces, the traffic constraint function diverges from the empirical envelope, which may cause imprecision. In the same way, breakpoints are not suitable for the $(\vec{\sigma}, \vec{\rho})$ model when they are positive. The concave characteristic, which is intrinsic to this model, causes a divergence between the traffic constraint function and the empirical envelope at those points.

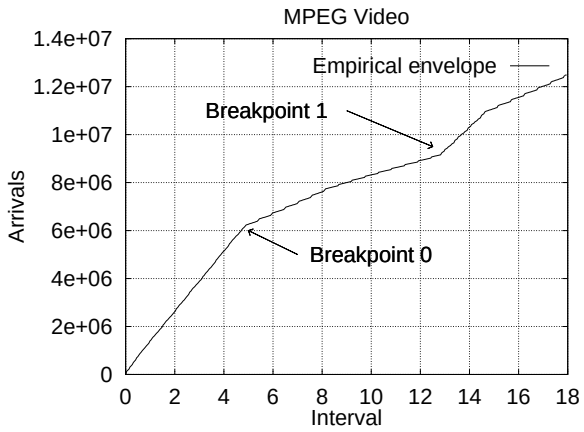


Figure 4: Influence of breakpoints on the empirical envelope.

The XGOP-B is based on the definition of the GOP-B model (*GOP-Based model*) [7]. The GOP-B model is founded on the first analyzed property: the MPEG video sources present information bursts at the beginning of each GOP caused by the transmission of I frames. The GOP-B model defines a pair (η, ν) as traffic parameters. The η factor, called *impulse factor*, models the bursts caused by intra-frames. This factor must be added to the traffic constraint function at intervals proportional to the GOP size. The ν factor, named *average factor*, parameterizes the average increase of the traffic constraint curve.

In this way, the traffic constraint function for the GOP-B model comprises two parts. One directly proportional to all time intervals and other that is added to the traffic constraint function only for time intervals proportional to the GOP size. The GOP-B traffic constraint function is given by

$$\mathcal{F}_{GOP-B}(\delta t) = \lceil \frac{\delta t + T}{T \times D} \rceil \times \eta + \nu \times \delta t, \tag{4}$$

where T is the inverse of the sample rate of the video and D is the GOP size[2].

The GOP-B model is based on group of pictures since the extractor parameters algorithm uses a GOP as the basic computation unit. While the other presented models (excepting the Discrete model) need to know *a priori* the values of the ζ function for all time intervals, the GOP-B model demands the empirical envelope only for one GOP, which significantly decreases the amount of time needed to calculate the parameters.

[2]For instance, if a GOP pattern is IBBPBB its size will be 6.

The GOP-B model incorporates the first property analyzed in this paper. Nevertheless, the breakpoint property is not considered. Thus, it is necessary to develop another traffic model that takes into account this property.

In order to solve the problem introduced by breakpoints, the XGOP-B model adopts a very simple solution. It changes the average inclination of the traffic constraint function at each breakpoint. For that, the traffic constraint function is subdivided in "zones" limited by the breakpoints, as shown in figure 5.

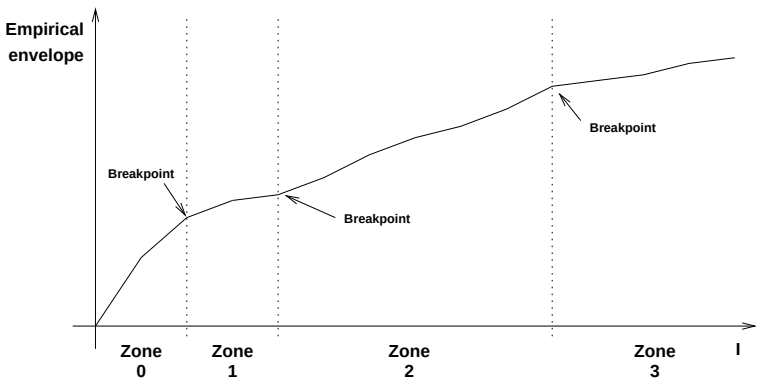


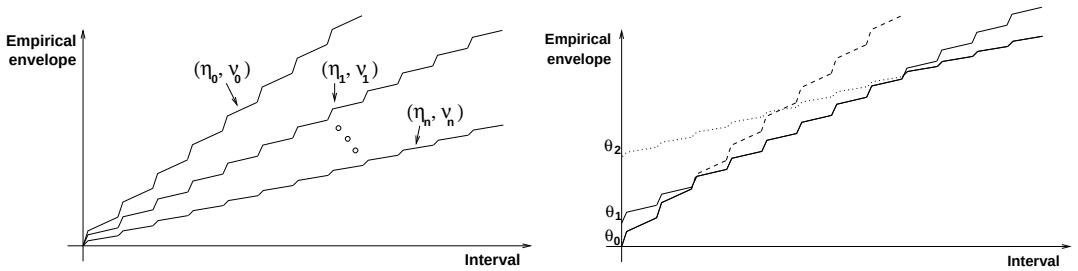
Figure 5: Empirical envelope subdivided in zones.

As for the GOP-B model, the main objective is to still obtain a pair (η, ν) to parameterize the traffic. However, we must now find several pairs (η_0, ν_0), (η_1, ν_1),..., (η_n, ν_n), one for each zone. Yet, if we provide as traffic parameters only the $(\vec{\eta}, \vec{\nu})$ array, the result will be a set of curves without any special characteristics, as we can see in the figure 6(a). Thus, beyond the pairs (η_k, ν_k), we must include another array of offsets $\vec{\theta}$ for the curves and the array of breakpoints $(\vec{\xi})$. The final result is illustrated in figure 6(b).

The traffic constraint function for the XGOP-B model is given by

$$\mathcal{F}_{XGOP-B}(\delta t) = \theta_k + \lceil \frac{\delta t + T}{T \times D} \rceil \times \eta_k + \nu_k \times \delta t, \quad \xi_{k-1} \leq \delta t < \xi_k. \tag{5}$$

We can note that this function is very similar to the traffic constraint function for the GOP-B model. Figure 7 graphically shows the behavior of this function.



(a) (b)

Figure 6: Offsets (θ) included as traffic parameters.

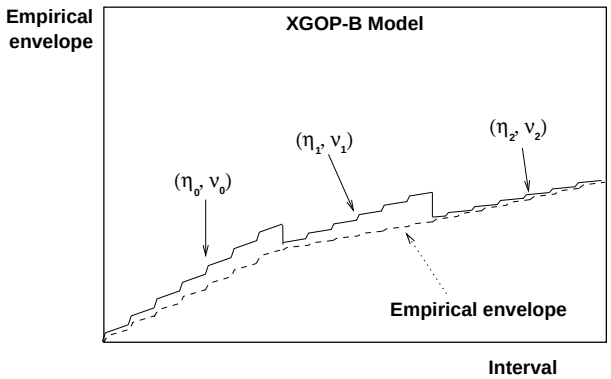


Figure 7: Traffic constraint function for the XGOP-B model.

3 Single-Input Single-Output Parameters Extractor

Except for some of the models proposed in the literature, the computation of the traffic parameters depends on some choices that may result in a non-optimized characterization. For example, in the case of the (σ, ρ) model, given a source of VBR traffic, it is not easy to chose the best values for σ and ρ to obtain a high accurate modeling. Figure 8 shows a number of possible solutions to this problem.

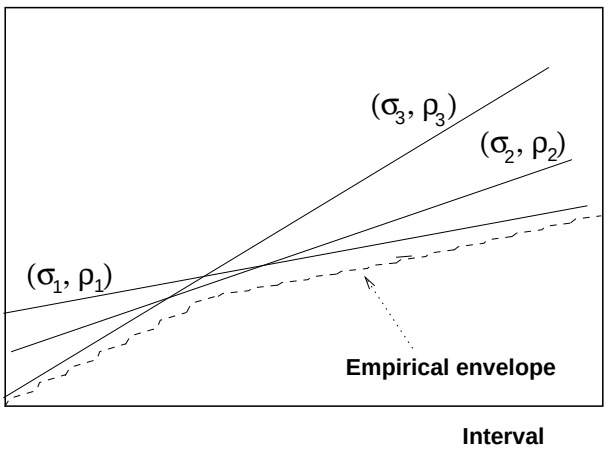


Figure 8: Possible solutions for the σ and ρ parameters.

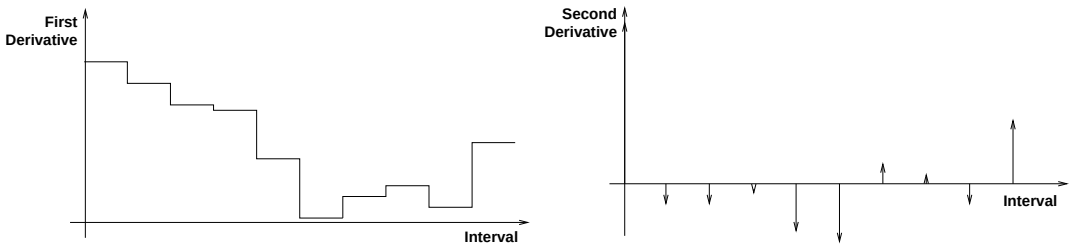
It is clear from this example that different parameters can be obtained for the same traffic source. If the model definition were able to provide a way of limiting to one the number of possible solutions for a certain traffic, the accuracy of the characterization would not be dependent on an appropriate choice of the parameters.

The XGOP-B model defines a structure of parameters that allows a single characterization for each traffic source. As it will be seen, the process of extracting parameters from MPEG video sources is very simple, as desired, and results in a highly accurate solution.

The XGOP-B parameters extractor comprises two principal steps: the search for breakpoints and the computation of the effective parameters.

3.1 Determining the Breakpoints

The first step is to develop a mathematical way of identifying breakpoints. Innitially, we calculate a function that corresponds to the successive inclinations of the empirical envelope. This function stores the transmission rate of the source per time unit. These inclinations are particularly calculated with intervals proportional to the GOP size, and result in the First Derivative Function. In the next step, we obtain, from the First Derivative Function, a discrete function that represents only the variations of the First Derivative. This new function is called Second Derivative Function. The graphs in figure 9 show examples of first and second derivative functions.



(a) (b)

Figure 9: Examples of (a) First and (b) Second Derivatives.

The impulses plotted in figure 9(b) mark the points where the inclinations vary. However, it should be distinguished, among these points, the ones that must be chosen as breakpoints. This choice is performed according to the amount of accuracy demanded by the user. If more points are chosen, more accurate will be the model, since more parameters will be determined. On the other hand, if we select fewer points, the model will be simpler, but will be less accurate. To solve this problem, we adopt the technique of offering to the parameters extractor module a variable β called QoM-rate (Quality of Model rate). The breakpoints are chosen according to the following propositions:

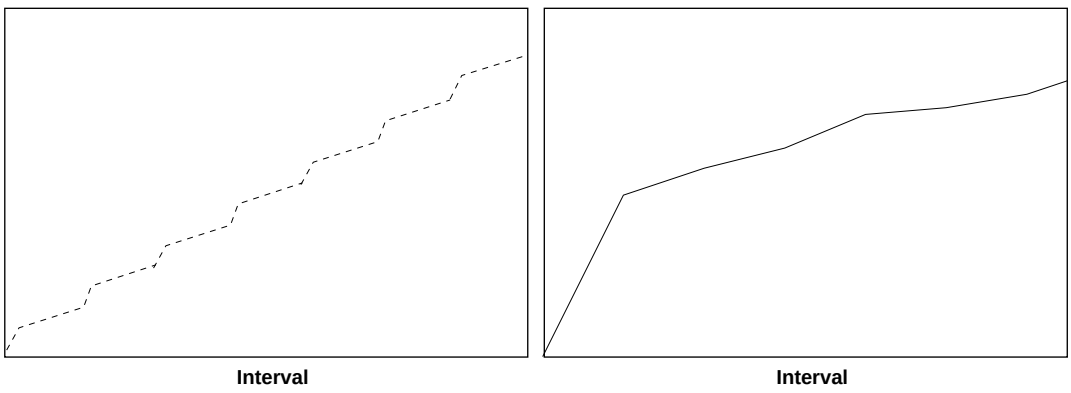
Proposition 1 *Starting with an inclination, a breakpoint will be identified if this inclination varies, negatively or positively, of a factor β, with $\beta > 0$.*

Proposition 2 *Starting with an inclination, a breakpoint will be identified if the sum of an uninterrupted sequence of second derivatives varies, negatively or positively, with regard to the first inclination of this sequence, of a factor β, with $\beta > 0$.*

3.2 Calculating the Parameters

For each zone bounded by the breakpoints, the XGOP-B model defines a set of three parameters: the η parameter, for the impulse information, the ν parameter, for the modeling of the average increase rate, and the θ parameter, which corresponds to the offset of the curve. The method to extract parameters presented in this section will be applied only on the first zone, but can easily extended for other time intervals.

First of all, let's consider the empirical envelope shown in figure 10 as our MPEG video traffic source. Graph 10(a) corresponds to the entire zone, and graph 10(b) represents a zoom of the first GOP. The basic input to the algorithm is the $\zeta[\cdot]$ array, which is a discrete representation of the empirical envelope. In this array, $\zeta[n]|_{n\geq 0}$ is the value of the empirical envelope for a time interval equivalent to $n \times T$, where T is the time duration of a frame.



(a) (b)

Figure 10: Examples of (a) an entire zone and (b) one GOP.

The value of η is given by the worst-case impulse within a zone. The positions of the impulses in the array are given by (considering that the array starts at 0)

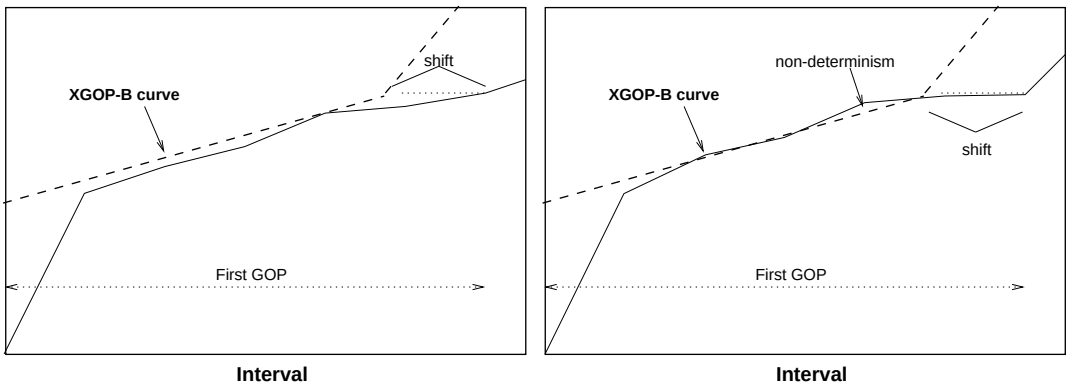
$$n^k_{impulses} = 1 + k \times D, \quad 0 \leq k \leq \lfloor \frac{(M-1)}{D} \rfloor, \tag{6}$$

where M is the last position of the array and D is the GOP size. Thus, the value of η is

$$\eta = max\{n^k_{impulses}\} = max\{1 + k \times D\}\big|_{0 \leq k \leq \lfloor \frac{(M-1)}{D} \rfloor}. \tag{7}$$

The determination of the average increase rate of the empirical envelope comprises a few more steps. As explained in section 2, there is a shift of one frame period in the traffic constraint function for the XGOP-B model. According to some preliminary studies and measurements, this shift leads to an improvement in the accuracy of the model. The parameter ν is initially set to the slope of the straight line between $\mathcal{F}(0)$ and $\zeta[D]$ for an interval of $(GOP - 1)$ frame periods. The correspondent equation is given by

$$\nu = \frac{\zeta[D] - \mathcal{F}(0)}{(D-1)}. \tag{8}$$



(a) (b)

Figure 11: Characterization (a) well done and (b) with non-determinism.

Graphically, the obtained curve is the one shown in figure 11(a). Note that it does not guarantee that this curve is a deterministic characterization of the source. It must be certified that the difference $\mathcal{F}_{XGOP-B}(\delta t) - \zeta(\delta t)$ is *always* positive. The graph of figure 11(b) shows an example where this requisite is not satisfied. To eliminate this problem, the algorithm performs a loop that checks the traffic constraint function for each $\delta t = k \times T$, where $k > 0$ and T is the interval between two consecutive frames. To illustrate this procedure, we will once again consider only the first part of the graph, which is, in this case, the curve between $\zeta[0]$ and $\zeta[D \times T]$, i.e., equivalent to one GOP size. When the

problem of non-determinism shown in figure 11(b) occurs, a new value for ν is computed through

$$\nu = \frac{\zeta[p \times T] - \mathcal{F}(p_0)}{p - p_0}, \tag{9}$$

where p is an integer between two breakpoints and, for the first zone, $p_0 = 0$.

The value of $\mathcal{F}(p_0)$ is obtained as explained in section 2.2. As the adjustment of the slope ν is enough to make the traffic constraint curve totally deterministic, the parameter η is kept unchanged.

The next step is to calculate the proper values of offsets, one for each curve limited by the breakpoints. Considering that η and ν have already been computed, θ can be obtained directly from

$$\theta = \mathcal{F}_{XGOP-B}(\delta t) - \lceil \frac{\delta t + T}{T \times D} \rceil \times \eta_k - \nu_k \times \delta t, \quad \forall \delta t | \xi_{k-1} \leq \delta t < \xi_k. \tag{10}$$

We have described the behavior of the extractor for the first part of the traffic constraint function. For the zones different from the first one, the algorithm remains the same if we shift the x-y axis to the beginning of the new zone.

4 Results

In the first part of this section, the results evaluate the tradeoffs between the adjustment of the β factor and the numbers of breakpoints. This relationship is important in the sense that as the number of breakpoints increases, greater is the number of traffic parameters. Consequently, for a larger amount of parameters, the admission control algorithms and the policing mechanism require more processing.

For the measurements, several MPEG video samples whave been used [10]. These video streams were coded from films, sportive events and TV shows. Figure 12 shows the effec of β on the number of breakpoints. It should be noticed that for some of the videos no breakpoints are identified, even adjusting the β parameter.

Table 2 presents a quantitative comparison between the number of parameters for the XGOP-B and D-BIND models. It should be emphasized that the values for the D-BIND

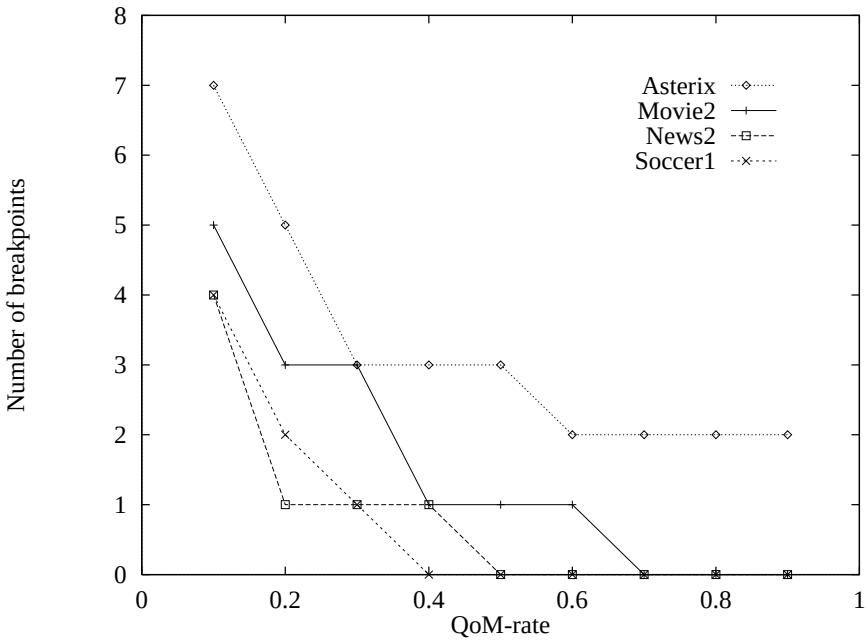


Figure 12: How β affecs on the number of breakpoints.

parameters can be obtained in many ways. Here we present some particular results. In [6], the authors suggest a number of (R, I) duples between 4 and 8. In order to compare the models in a similar basis, we have chosen the number of parameters that lead to the same level of accuracy.

Table 2: Complexity in terms of number of parameters.

	D-BIND	XGOP-B
Asterix	26	28
Movie2	28	20
News2	16	16
Soccer1	26	16

We have performed the comparison among the models through the number of parameters but also through a variable called Modeling Approach Loss (MAL). MAL indicates how much a result is different from the most accurate modeling, the empirical envelope. For each traffic constraint curve, its respective MAL is obtained from the difference of the

areas under the traffic constraint curve and the curve given by the empirical envelope. MAL is calculated according to the following equation

$$PAM = \left(\frac{S_{\mathcal{F}}}{S_{\zeta}} - 1 \right) \times 100\%, \tag{11}$$

where $S_{\mathcal{F}}$ is the area under the traffic constraint curve and S_{ζ} is the area under the empirical envelope. It should be observed that, the smaller is MAL, more accurate is the function. In a particular case, if MAL = 0 %, the two curves meet and the maximum accuracy is obtained, since the empirical envelope is the most precise function.

Table 3 shows the results for the analyzed video traces. For the Discrete model, the calculus were performed with the interval equivalent to one GOP size, i.e., $I = 540ms$. For the XGOP-B model, the QoM-rate is $\beta = 0.03$.

Table 3: Modeling Approach Loss for each model.

	Modeling Approach Loss (%)				
Video	(σ, ρ)	$(\vec{\sigma}, \vec{\rho})$	Discrete	D-BIND	XGOP-B
1. asterix	23.21	3.96	49.21	0.32	1.67
2. atp	9.31	1.02	17.76	1.02	1.96
3. bond	44.02	2.16	31.75	1.48	0.41
4. dino	15.30	2.17	48.78	1.71	1.89
5. lambs	30.56	3.42	20.31	2.23	1.63
6. mbean	17.69	1.26	33.40	1.00	1.48
7. movie2	6.96	1.55	76.96	1.49	1.61
8. mtv1	13.42	1.43	75.44	1.43	1.30
9. mtv2	9.20	1.77	30.14	1.32	1.48
10. news1	23.35	2.43	42.85	1.07	1.37
11. news2	7.44	2.56	33.67	2.47	1.58
12. race	48.95	0.64	24.35	0.60	2.80
13. sbowl	4.51	1.03	19.50	0.96	2.12
14. simpsons	7.91	1.03	55.76	0.95	1.25
15. soccer1	4.62	2.90	28.30	1.10	1.61
16. soccer2	7.21	2.20	39.58	1.53	1.22
17. star	18.19	1.89	22.59	1.88	1.50
18. talk1	14.92	2.99	17.52	1.15	1.57
19. talk2	3.09	2.31	25.28	2.05	1.68
20. terminator	9.26	2.59	41.86	1.17	2.20
21. video	6.79	5.42	13.49	5.18	1.93

Figure 13 shows the traffic constraint curves for a cartoon video trace.

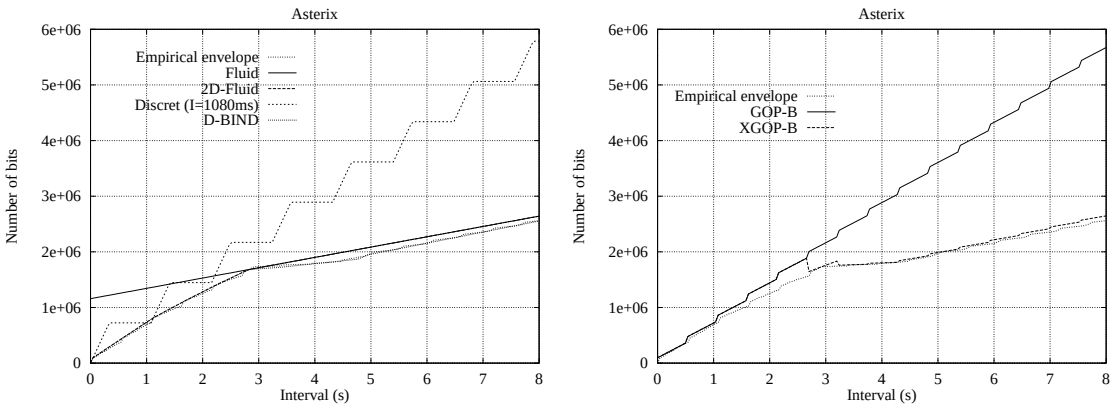


Figure 13: Traffic constraint function for the *Asterix* video trace.

If the obtained results for $\beta = 0.03$ are not suitable, we can adjust β to catch the desired results. But, for smaller values of β, more breakpoints are identified and more traffic parameters are obtained, which results in greater parameterization accuracy. It is clear that if we consider more breakpoints, the number of parameters increases and, consequently, more complex will be the policing mechanism.

5 Conclusions

In this work, we propose an algorithm to extract deterministic parameters from MPEG compressed video sources. This algorithm belongs to the definition of a new deterministic MPEG traffic model, called XGOP-B.

For the majority of the models proposed in the literature, there are not tradeoffs that guarantee that for each traffic source we obtain always the same parameters. For the XGOP-B model, the parameters are obtained with a unique solution, i.e., given a video trace, the parameters extractor algorithm outputs only one set of values. It eliminates inaccuracy introduced by a bad choice. When the user must determine which solution should be chosen, unnecessary inaccuracy may be introduced.

The numerical results show that the XGOP-B model can achieve high modeling accuracy with a number of parameters close to the most accurate traffic model proposed in the literature. The main advantage is the automatic choice of these parameters, what points

out the applicability of the XGOP-B model.

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