A Novel Two-Step MPEG Traffic Modeling Algorithm Based on a GBAR Process

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Abstract: In this paper we propose a two-step MPEG video sources modeling algorithm based on three auto- and cross-correlated gamma-beta autoregressive processes of order one GBAR(1). This algorithm is an extension of models originally proposed by Heyman [1] and Lombardo *et al.* [2]. We extend the model proposed by Heyman to the case of periodic frame sequence at the output of the codec. In order to do that we use information about the correlation between frame sizes within the group of pictures. Based on this information we introduce three cross-correlated GBAR(1) processes each of which models a particular type of the frame. The proposed algorithm captures the basic statistical characteristics of the empirical data well: the distribution of frame sizes and the autocorrelation function. Our algorithm is fairly simple computationally efficient and therefore, can be used in simulation studies.

Key words: MPEG, GBAR, traffic modeling

1. INTRODUCTION

Modern broadband telecommunications networks have been intended to deliver traffic generated by multimedia applications. As has been estimated [3], in the near future one of the major parts of the multimedia network load will consists of traffic generated by the video applications. Video-on-Demand (VoD) service is an example of such applications. It is clear that video streams generated by VoD servers and initiated by user request must be delivered to the destinations using a certain network technology; therefore special attention must be paid to how such traffic can be treated carefully by the network. To provide an adequate quality of service (QoS), some means of quality control mechanisms have to be implemented in the network, which in turn provide sufficient amount of bandwidth, buffer space, and also the required end-to-end performance.

It is well known that uncompressed video information can throttle the available bandwidth easily even in the case of broadband networks. In order to achieve an efficient transmission of traffic generated by VoD-type services, video information must be compressed and encoded in accordance with one of the existing compression algorithms. Currently, one of the most frequently used compression algorithms is the MPEG-1 [4].

Recently, special attention has been paid to the videotraffic modeling. Modeling of variable bit rate (VBR) videotraffic became an important issue since it provides the starting point in both theoretical analysis and engineering design. The source models of different types of videotraffic are needed to design and study the performance of the network and also to predict the QoS that a particular video application may experience at different levels of network congestion [5,6].

A number of video source models have been proposed in literature during the past years. The earliest ones were based on several variations of simple autoregressive processes such as autoregressive process of order one AR(1) [7] or autoregressive moving average process ARMA [8]. This is primarily because of their simplicity. These models try to capture the empirical distribution of frame sizes of several simple compression algorithms (H.261, DPCM). Later it was found [3] that they produce unsatisfactory results and cannot be used as a single video source models.

A huge amount of videotraffic models were based on Markov chains which are parameterized by a limited set of parameters [7,9,10]. These models try to capture the empirical distribution of frame sizes and autocorrelation function up to several lags. The main shortcoming of these models comes from the point that in order to define the model a large set of empirical data is needed.

In the middle of past decade special attention was paid to videotraffic modeling using processes with self-similar and long-range dependence properties (LRD) [11,12]. Up to that point many studies on statistical analysis of the frames sequences have noticed that videotraffic exhibits self-similar behaviour [13], and therefore, this property must be taken into account during the design of new videotraffic models. The main drawback of these models is that these models do not allow an analytical analysis of queuing systems.

During the last several years the main attention has again been paid to videotraffic modeling using discrete- and continuous-time Markov chains [6,14]. In contrast to the abovementioned Markov models, they involve an inverse-eigenvalue problem in order to derive the transition probability matrices. Such models produce an excellent approximation of both histogram of frame sizes and autocorrelation function of the empirical data but they are computationally inefficient because of the presence of the inverse eigenvalue problem [14,15]. This drawback restricts their use in simulation studies where the need to produce frame sizes “on the fly” exists.

A survey of the research papers shows that only a small part of the investigations were devoted to the modeling of MPEG sequences at the frame level. Basically, these studies are dedicated to analyze and to model the frame streams of H.261, DPCM, CR compression algorithms, and MPEG traffic at the GoP (Group of Pictures) level [1,8,9,10]. MPEG frames sequences may have sophisticated GoP structure at the output of the codec. Here and further under the sophisticated GoP structure we will imply the case when for the different types of frames the different coding schemes are used.

In this paper we propose a novel frame level two-step MPEG modeling algorithm that emulates the behaviour of single MPEG-1 video elementary stream without considering the underlying transmission technology used in a particular network. The proposed algorithm captures well the basic statistical parameters of empirical data such as distribution of frame sizes and autocorrelation function. It should be noted that in modeling of MPEG video elementary stream we focus on the sequence of frame sizes, ignoring auxiliary MPEG standard information: the sequence header, end-of-sequence code and packet headers.

The rest of the paper is organized as follows. In the next section we briefly outline the basic compression and coding principles of the MPEG standards. Then we consider our modeling methodology. In subsections 3.1, 3.2 and 3.3 we are give more details on the proposed algorithm. Section 4 provides visual and statistical comparison between the modeled data and empirical one. The conclusions are drawn in last section.

2. MPEG CODING AND COMPRESSION

Before we pay attention to the modeling issues, it is necessary to define the basic logical units of the MPEG standard as well as the stream structure at the output of the codec. It is well known that the video sequence has three types of redundancies that a coding scheme needs to exploit in order to achieve good compression: spatial, temporal, and visual. Spatial and temporal redundancies come from the fact that pixel values are not completely independent but are correlated with the values of their neighbouring pixels both in space and time. This means that their values can be predicted to some extent. On the other hand, visual redundancy has to deal with physical limitations of the human eye, which has a limited response to find spatial detail and is less sensitive to details near object edges or around shot-changes. Therefore, controlled impairments introduced into the decoded picture by the bit rate reduction process should not be visible to a human observer.

Based on the types of redundancies three different types of frames have been defined. These are *I*-frames, *P*-frames and *B*-frames.

MPEG-1 standard introduces additional conceptual definition that is called "Group of Pictures" (GoP). GoP is a fixed size sequence of different frame types. The *I*-frame must initiate every GoP. In our study we have used a typical GoP structure for a 25 Hz frame rate in VoD services *IBBPBBPBBPBB* or (12,3,2), where 12 means is the total length of GoP, 3 means the number of *P*-frames within the GoP, and 2 means the number of *B*-frames between two successive *P*-frames. Thus, in our case the stream of the frames at the output of the codec consists of the sequence of GoPs.

In our study we used the MPEG-1 traces archive freely available from the university of Wuerzburg [16]. These traces are well known and were used in several valuable studies [2,14,15]. Traces represent a sequence of the frame sizes where the size of each frame is presented in bits. In order to evaluate the proposed algorithm we used the trace of "Star Wars" movie.

3. TWO-STEP MODELING ALGORITHM

The algorithm proposed in this paper has a two-step structure. Heyman in [1] shows that the model of MPEG traffic at the frame level must incorporate three strongly auto- and cross-correlated processes. These are *I*-frames generation process, *P*-frames generation process and *B*-frames generation process. Therefore, during videotraffic modeling we should take into account the correlation structure of empirical data. At the first step of the proposed algorithm we use the property that *I*-frames are coded autonomously and without references to preceding or following frames, and, therefore we can state that sizes of *I*-frames are independent from the sizes of *P*- and *B*-frames. Based on this property we propose to model *I*-frames generation process as an independent stochastic process. In order to accomplish this we use GBAR(1) process. Then we estimate the intra-GoP correlation structure of the frames stream. The sequence of sizes of *I*-frames that is obtained during the first step together with intra-GoP correlation information is used as initial parameters for the second step of the algorithm.

Before discussing the details of the algorithm we want to point out the necessary prerequisites. As has been shown in [9] the distribution of intra-frame sizes at the output of H.261 codec can be well approximated by negative-binomial distribution or its continuous analogue - gamma distribution. The intra-frame coding scheme utilized by H.261 codecs is almost identical to that one used for *I*-frames coding in MPEG standard. Based on this we can expect that the gamma distribution will provide good approximation of the *I*-frames histogram. In order to prove this we compare empirical *I*-frames distribution and gamma distribution for the pattern "Star Wars" by the quantile-quantile statistical analysis. To obtain the gamma distribution values we used the following parameters' values: shape parameter equals to 3.0 and scale parameter equals to 2.6E-5. These parameters were derived from empirical frame sizes distribution. We can notice from Figure 1 that such approach gives a fairly good approximation of the empirical data.

It is also important to mention that the *I*-frames generation process has both short-range dependence (SRD) and long-range dependence (LRD) correlation properties. Currently, clear results which show how LRD and SRD affects the characteristics of traffic associated with modern broadband telecommunication services are not available yet. But the need to construct models which take the correlation property into account is undoubted. The GBAR(1) process that is considered in this paper is able to capture the behaviour of the autocorrelation function of the empirical data up to lags 50-100.

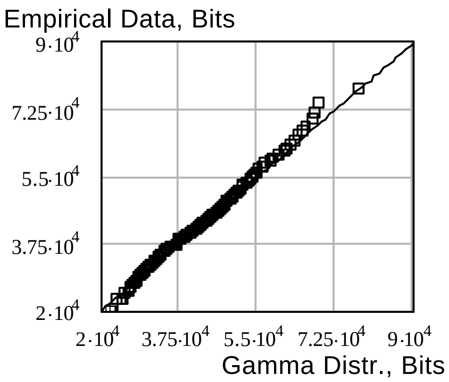

Figure 1. Quantile-quantile statistical analysis performed between empirical and modeled *I*-frame sizes

The property that allows us to proceed from *I*-frames generation process to MPEG aggregate frame generation process is a strong dependence between *I*-frame sizes and *B*- and *P*-frame sizes within the same GoP. This property had been discovered by Lombardo *et al.* [2], clearly explained in [14,15], and later were named “intra-GoP correlation”.

3.1 *I*- frames generation process

In order to represent *I*-frames generation process we select a GBAR(1) process. It was originally presented by Heyman [1], and it has been used as the approximation model of the frame sizes distribution of H.261 codec. The main distinctive feature of the process appears in geometric distribution of its autocorrelation function. This property allows us to model the autocorrelation function of the empirical data that exhibits some sort of LRD behaviour. Moreover, the marginal distribution of frame sizes sequence is a gamma distribution.

Let $G(b, l)$ be a random variable with gamma distribution with shape parameter b and scale parameter l and let $B(p,q)$ be a random variable with beta distribution with parameters p and q.

The GBAR(1) process is based on two well-known results: the sum of independent random variables $G(a, l)$ and $G(b, l)$ is a $G(a+b, l)$ random variable, and the product of independent random variables $B(a, b-a)$ and $G(b, l)$ is a $G(a, l)$ random variable.

Thus, if we denote $G(b, l) = X_{n-1}$ $A_n = B(a, b-a)$ and $B_n = G(b-a, a)$ and if they are mutually independent, then:

$$X_n = A_n X_{n-1} + B_n \tag{1}$$

is a stationary stochastic process $\{X_n\}$ with marginal $G(b, l)$ distribution. Furthermore the autocorrelation function is geometric and is given by:

$$r_k = (a / b)^k . \tag{2}$$

Since the current value of the process is determined only by the one previous value, this is an autoregressive process of order 1. For the sake of simplicity and also because of the processes with higher order will not be mentioned in this paper, the argument 1 will be suppressed below.

The process parameters b and l can be estimated directly from the empirical data set in accordance with formulas for mean and variance of the data:

$$b = M / D^2, \quad l = M / D, \tag{3}$$

where M is the mean of the data and D is the variance.

The parameter a can be defined in accordance with (4). Further, assume that the autocorrelation function is above zero for sufficiently large lag k:

$$r_k = p^k, \tag{4}$$

then the following equation holds:

$$a = pb. \tag{5}$$

The random variables with gamma or beta distributions generate non-integer values because their distributions are continuous. Since the number of bits in the frame is a discrete value we simply round the values obtained from model to the nearest integer.

3.2 Approximation of the correlation structure

In order to approximate the intra-GoP correlation structure and to obtain sizes of the *P*- and *B*-frames, the procedure proposed in [2] has been used. The algorithm is intended to investigate the dependency between the mean value and the standard deviation of the *I*-frames and the sizes of appropriate *P*- or *B*-frames. These dependencies can be determined as follows:

$$M[X] = f^M(K_I), \quad s[X] = f^s(K_I), \quad X \in \{P, B\}, \tag{8}$$

where $M[X]$ is the mean value of the appropriate frame (*P* or *B*), $s[X]$ is the standard deviation of the *P*- or *B*-frames, and K_i is the size of the *I*-frame. Figure 2 and Figure 3 shows results (8) obtained for "Star wars" data.

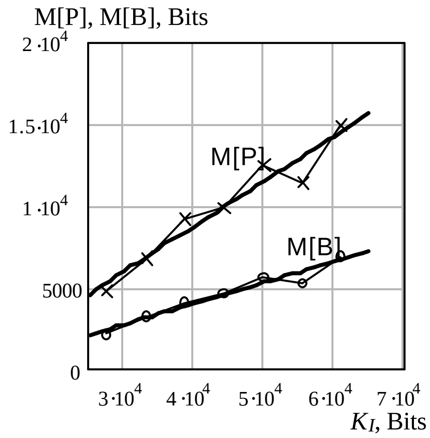

Figure 2. Dependency of the mean value of *B*- and *P*-frame sizes on *I*-frame sizes

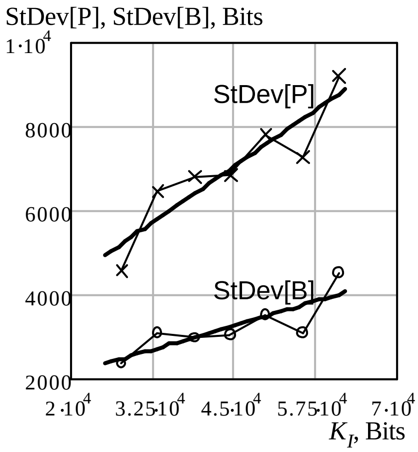

Figure 3. Dependency of the standard deviation of *B*- and *P*-frame sizes on *I*-frame sizes

The mean value and the standard deviation given by (8) serve as initial parameters for certain probability distribution. The probability distribution allows us to obtain *B*- and *P*-frame sizes holding the *I*-frame size constant. Furthermore, the output values will vary even for constant *I*-frame size. This property of the model emulates the behaviour of the real codecs.

3.3 *B*- and *P*-frame sizes approximation

The equations (8) bind together *I*-frame sizes and corresponding mean and standard deviation values of *P*- and *B*-frames. These equations are necessary conditions for the approximation of intra-GoP correlation. At this point we need to define the probability distributions *P*- and *B*-frames.

The histograms of the *B*- and *P*-frame sizes corresponding to a certain *I*-frame size (or, precisely, an interval of *I*-frame sizes) have shown that they follow gamma distribution [2,14,15]. The autocorrelation functions of *P*- and *B*-frame generation processes corresponding to the certain *I*-frame size interval have SRD property only. Since the GBAR process defined above captures well all of the properties mentioned here we can use this process as a model for *P*- and *B*-frames generation processes.

4. MODELING RESULTS

Then we proceed with model analysis and perform the comparison with empirical traces. Our analysis is based on presented later a time-series visual comparison, autocorrelation function comparison and quantile-quantile plots.

Figure 4 shows the comparison of *I*-frame sizes sequence with sequence generated by GBAR process, where K_i denotes *I*-frame size, while i is an index of the frame in the sequence.

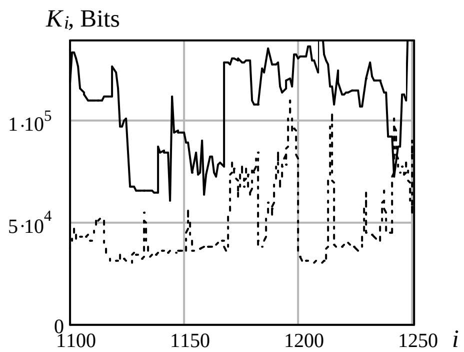

Figure 4. Comparison of the *I*-frame sizes: dotted line is for empirical sequence; solid line is for modeled sequence

It should be noted that GBAR process with p parameter equal to 0.96 produces fairly good approximation of empirical data. We also observe that with the increasing of p parameter the overall structure of generated data has a strong "smoothing" trend. This trend results from strong positive correlation of GBAR process and may offer several potential applications in traffic modeling of multiplexed streams [9].

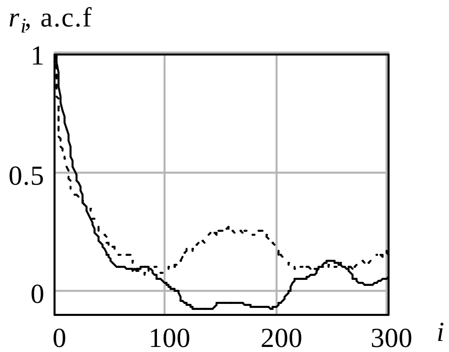

Figure 5. Comparison of the autocorrelation functions: dotted line is for empirical sequence; solid line is for modeled sequence

Further, the autocorrelation function is a subject of our attention. Figure 5 shows an approximation of the empirical autocorrelation function. The p

parameter of GBAR process is set to 0.96. On the plot the dotted line corresponds to empirical autocorrelation function and the solid line represents function of the model. Up to lag 80 the functions are close to each other. Later, the autocorrelation function of the model quickly decays to zero. With the increasing of *p* parameter the correlation has a strong trend to rise for all lags. Thus, the model overestimates the autocorrelation function up to the lag 80 and, consequently, it is not able to give a good approximation for larger lags.

Further, we proceed to short timescale comparison. It is stated that the MPEG traffic model must reflect the frame to frame size variation inside the GoP sequence. In Figure 6 the sequence of the frames in a certain GoP is shown, where K_i is the size of the frame and i is the number of the frame in sequence. It is clear that the modeled data approximates intra-GoP correlations well.

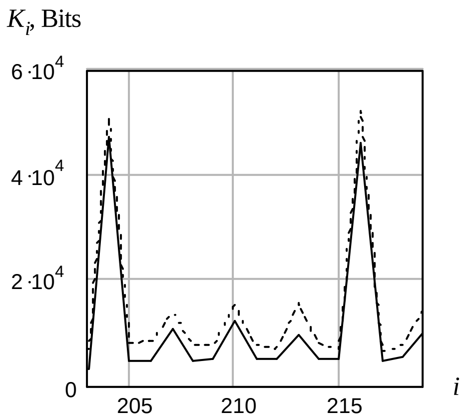

Figure 6. Comparison of the frame sizes: dotted line is for empirical sequence; solid line is for modeled sequence

Figure 7 shows the quantile-quantile statistical analysis for GoP level. Some differences are observed in the area of big frame sizes where the model overestimates the real structure of empirical data.

A one of the major shortcomings of our model stems from the point that the real data trace contains several frames with a very high number of bytes. The model can approximate this property in case of small value of *p* parameter, which will lead to underestimation of the autocorrelation function for large lags. There is a trade-off between two properties of the model: the distribution of frame sizes and the autocorrelation function. One possible solution is the careful choice of *p* values.

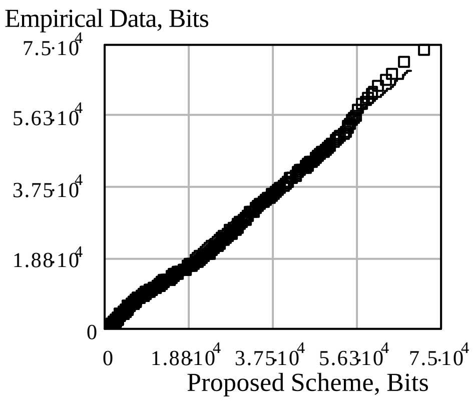

Figure 7. Quantile-quantile statistical analysis performed between empirical data and data modeled by the proposed algorithm for aggregated frame level

5. CONCLUSIONS

In this paper we have considered the modeling of the MPEG-1 video elementary stream at the output of the codec. Our model is fast, computationally efficient [1] and captures the behaviour of autocorrelation function and the distribution of frame sizes well. It can be used in simulation studies where there is a need to generate MPEG traffic "on the fly".

We produced an extension of a modeling methodology originally proposed in [1] and [2]. We have used two-step approach in order to model the video frames sequence. At the first step we approximate the *I*-frames generation process by GBAR process. The second step consists of the approximation of frame sizes based on both the output of the GBAR process and intra-GoP correlations. Proposed algorithm provides a simple model of the MPEG source based on three cross-correlated processes. The algorithm captures both the distribution of frame sizes and autocorrelation function of empirical data well.

GBAR process needs only few parameters which can be estimated directly from the analysis of empirical data. This is a big advantage of GBAR source model compared to other models of video traffic sources.

With the increasing of p parameter, the generated sequence of frames will tend to smooth the sequence behaviour. Previous studies have proved that the multiplexed videotraffic has identical structure. The smoothing property of frame sizes generated by GBAR model can be used to produce GoP size sequences or moving average processes of GoP size sequence.

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