Modeling Video Traffic from Multiplexed H.264 Videoconference Streams

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Abstract—**Due to the burstiness of video traffic, video modeling is very important in order to evaluate the performance of future wired and wireless networks. In this paper, we investigate the possibility of modeling H.264 videoconference traffic with well-known distributions. Our results regarding the behavior of single videoconference traces provide significant insight and help to build a Discrete Autoregressive (DAR(1)) model to capture the behavior of multiplexed H.264 videoconference movies from VBR coders.**

I. INTRODUCTION

As traffic from video services is expected to be a substantial portion of the traffic carried by emerging wired and wireless networks [7][13], statistical source models are needed for Variable Bit Rate (VBR) coded video in order to design networks which are able to guarantee the strict Quality of Service (QoS) requirements of the video traffic. Video packet delay requirements are strict, because delays are annoying to a viewer; whenever the delay experienced by a video packet exceeds the corresponding maximum delay, the packet is dropped and the video packet dropping requirements are equally strict.

Hence, the problem of modeling video traffic, in general, and videoconferencing, in particular, has been extensively studied in the literature. VBR video models which have been proposed in the literature include first-order autoregressive (AR) models [2], discrete AR (DAR) models [1][3], Markov renewal processes (MRP) [4], MRP transform-expand-sample (TES) [5], finite-state Markov chain [6][7], Gamma-beta-auto-regression (GBAR) models [8][9] (which capture data-rate dynamics of VBR video conferences well but was found in [9] to not be suitable for general MPEG video sources), discrete-time Semi-Markov Processes (SMP) [10], wavelets [11], multifractal and fractal methods [12].

In [14][15], different approaches are proposed for MPEG-1 traffic, based on the log-normal, Gamma, and a hybrid Gamma/lognormal distribution model, respectively.

H.264 is the latest video coding standard of the ITU-T Video Coding Experts Group (VCEG) and the ISO/IEC Moving Picture Experts Group (MPEG). It has recently become the most widely accepted video coding standard since the deployment of MPEG2 at the dawn of digital television, and it may soon overtake MPEG2 in common use. It covers all common video applications ranging from mobile services and videoconferencing to IPTV, HDTV, and HD video storage [18].

Standard H.264 encoders generate three types of video frames: I (intracoded), P (predictive) and B (bidirectionally predictive); i.e., while I frames are intra-coded, the generation of P and B frames involves, in addition to intra-coding, the use of motion prediction and interpolation techniques. I frames are, on average, the largest in size, followed by P and then by B frames.

Similarly to our recent work on modeling H.263 videoconference traffic [17], our present work initially focuses on the accurate fitting of the marginal (stationary) distribution of video frame sizes of single H.264 video traces. More specifically, our work follows the steps of the work presented in [3], where Heyman et al. analyzed three videoconference sequences coded with a modified version of the H.261 video coding standard and two other coding schemes, similar to the H.261. The authors in [3] found that the marginal distributions for all the sequences could be described by a gamma (or equivalently negative binomial) distribution and used this result to build a Discrete Autoregressive (DAR) model of order one, which works well when several sources are multiplexed.

An important feature of common H.264 encoders is the manner in which frame types are generated. Typical encoders use a fixed Group-of-Pictures (GOP) pattern when compressing a video sequence; the GOP pattern specifies the number and temporal order of P and B frames between two successive I frames. A GOP pattern is defined by the distance N between I frames and the distance M between P frames.

In this work, we focus on the problem of modeling videoconference traffic from H.264 encoders, which is a relatively new and yet open issue in the relevant literature.

II. SINGLE-SOURCE H.264 TRAFFIC MODELING

A. *Frame-size histograms*

In our work, we have studied two different long sequences of H.264 VBR encoded videos in eighteen formats, from the publicly available Video Trace Library of [19]. The selected videos are of low or moderate motion (i.e., traces with very similar characteristics to the ones of actual videoconference traffic), in order to derive a statistical model which fits well the real data.

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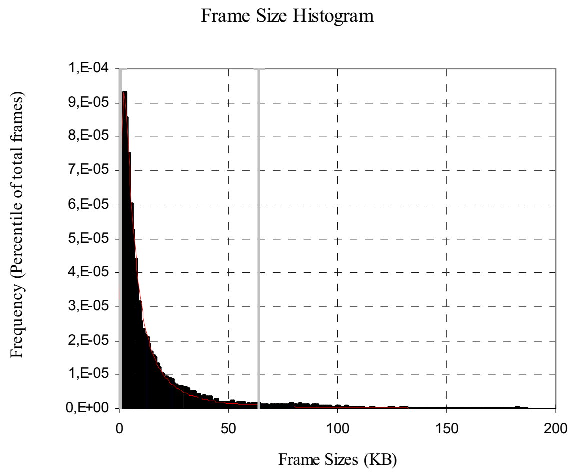

Figure 1. Frame size histogram for the NBC News trace with parameters: [CIF, G16, B7, F28].

The two traces are, respectively:

1) *A demo from the Sony Digital Video Camera*
2) *An excerpt of NBC News*

The length of the videos is 10 and 30 minutes, respectively. The data for each trace consists of a sequence of the number of cells per video frame and the type of video frame, i.e., I, P, or B. Without loss of generality, we use 48-byte packets throughout this work, but our modeling mechanism can be used equally well with packets of other sizes. Table I presents the trace statistics for each trace. The interframe period is 33.3 ms.

We have investigated the possibility of modeling the eighteen traces with quite a few well-known distributions and our results show that the best fit among these distributions is achieved for all the traces studied with the use of the Pearson type V distribution. The Pearson type V distribution (also known as the "inverted Gamma" distribution) is generally used to model the time required to perform some tasks (e.g., customer service time in a bank); other distributions which have the same general use are the exponential, gamma, weibull and lognormal distributions [20]. Since all of these distributions have been often used for video traffic modeling in the literature, they have been included in this work as fitting candidates, in order to compare their modeling results in the case of H.264 videoconferencing.

The frame-size histogram based on the complete VBR streams is shown, for all four sequences, to have the general shape of a Pearson type V distribution. Fig. 1 presents indicatively the histogram for the NBC News ([CIF, G16, B7, F28]) sequence.

B. Statistical Tests and Autocorrelations

Our statistical tests were made with the use of Q-Q plots [3][20], Kolmogorov-Smirnov [20] tests and Kullback-Leibler divergence tests [21]. The Q-Q plot is a powerful goodness-of-fit test, which graphically compares two data sets in order to determine whether the data sets come from populations with a common distribution (if they do, the points of the plot should fall approximately along a 45-degree reference line). More specifically, a Q-Q plot is a plot of the quantiles of the data versus the quantiles of the fitted distribution (a z-quantile of X is any value x such that P ((X ≤ x) = z). The Kolmogorov–Smirnov test (KS-test) tries to determine if two datasets differ significantly. The KS-test has the advantage of making no assumption about the distribution of data, i.e., it is non-parametric and distribution free. The KS-test uses the maximum vertical deviation between the two curves as its statistic D. The Kullback-Leibler divergence test (KL-test) is a measure of the difference between two probability distributions.

TABLE I. TRACE STATISTICS

Video Name	[RES, G, B, F][a]	Mean (bits)	Peak (bits)	Variance (bits^2)
NBC News	[CIF, 16, 1, 28]	15816	181096	471117539
NBC News	[CIF, 16, 1, 48]	1197	28032	4925112
NBC News	[CIF, 16, 3, 28]	14632	182520	467920380
NBC News	[CIF, 16, 3, 48]	1084	28216	5007541
NBC News	[CIF, 16, 7, 28]	15081	186872	467131784
NBC News	[CIF, 16, 7, 48]	1054	29768	5179470
NBC News	[CIF, 16, 15, 28]	16624	192272	456464433
NBC News	[CIF, 16, 15, 48]	1059	31840	5246908
Sony Demo	[CIF, 16, 1, 28]	14067	221664	752947478
Sony Demo	[CIF, 16, 1, 48]	954	23096	4693753
Sony Demo	[CIF, 16, 3, 28]	12801	222888	770225078
Sony Demo	[CIF, 16, 3, 48]	887	23232	4856589
Sony Demo	[CIF, 16, 7, 28]	13129	227680	787021301
Sony Demo	[CIF, 16, 7, 48]	898	25480	5243752
Sony Demo	[CIF, 16, 15[b], 28]	14861	233296	803054805
Sony Demo	[CIF, 16, 15[b], 48]	933	28224	5818976
Sony Demo	[HD, 12, 2, 48]	22513	398544	2684852964
Sony Demo	[HD, 12, 2, 38]	7618	143408	327728805

a. RES: Resolution, G: GoP Size, B: Number of B Frames, F: Quantization Parameters

b. When B=15 and G=16 there are no P frames in the trace sequence

The Pearson V distribution fit was shown to be the best in comparison to the gamma, weibull, lognormal and exponential distributions, which are presented here (comparisons were also made with the negative binomial and Pareto distributions, which were also worse fits than the Pearson V). However, as already mentioned, although the Pearson V was shown to be the better fit among all distributions, the fit is not perfectly accurate. This was expected, as the gross differences in the number of bits required to represent I, P and B frames impose a degree of periodicity on H.264-encoded streams, based on the cyclic GoP formats (therefore, this case is different than the case of H.263 traffic we studied in [17], where the number of I frames was so small in each trace that the trace could be modeled as a whole).

Hence, we proceeded to study the frame size distribution for each of the three different video frame types (I, P, B), in the same way we studied the frame size distribution for the whole trace. This approach was also used in [9][22].

Another approach, similar to the above, was proposed in [14]. This scheme uses again lognormal distributions and assumes that the change of a scene alters the average size of I frames, but not the sizes of P and B frames. However, it is shown in [4][15] that the average sizes of P and B frames can vary by 20% and 30% (often more than that), respectively, in subsequent scenes, therefore the size changes are statistically significant.

The mean, peak and variance of the video frame sizes for each video frame type (I, P and B) of each movie were taken again from [19] and the Pearson type V parameters are calculated based on the following formulas for the mean and variance of Pearson V (the parameters for the other fitting distributions are similarly obtained based on their respective formulas).

The Probability Density Function (PDF) of a Pearson V distribution with parameters (α, β) is $f(x)= [x^{-(\alpha+1)} e^{-\beta/x}]/ [\beta^{-\alpha} \Gamma(\alpha)]$, for all $x>0$, and zero otherwise.

The mean and variance are given by the following equations: $\text{Mean}=\beta/(\alpha-1)$, $\text{Variance}=\beta^2/[(\alpha-1)^2(\alpha-2)]$

The autocorrelation coefficient of lag-1 was also calculated for all types of video frames of the eighteen movies, as it shows the very high degree of correlation between successive frames of the same type. The autocorrelation coefficient of lag-1 will be used in the following Sections of this work, in order to build a Discrete Autoregressive Model for each video frame type.

From the five distributions examined (Pearson V, exponential, gamma, lognormal, weibull) the Pearson V distribution once again provided the best fitting results for the 54 cases (18 movies, 3 types of frames per movie) studied.

In order to further verify the validity of our results, we performed Kolmogorov-Smirnov and Kullback-Leibler tests for all the 54 fitting attempts. The results of our tests confirm our respective conclusions based on the Q-Q plots (i.e., the Pearson V distribution is the best fit). Fig. 2 presents indicative results from the KS-test. Regarding the KL-test, the results for the {I, P, B} frames of the Sony Demo ([CIF, G16, B3, F48]) trace are respectively, for the Pearson V distribution {0.364, 0.721, 0.432), for the Lognormal distribution {0.378, 0.864, 0.479}, for the Gamma distribution {0.387, 1.027, 0.543} and for the Weibull distribution {0.453, 1.024, 0.533}.

Although controversy persists regarding the prevalence of Long Range Dependence (LRD) in VBR video traffic ([25][26][27]), in the specific case of H.264-encoded video, we have found that LRD is important. The autocorrelation function for the NBC News ([CIF, G16, B7, F28]) trace is shown in Fig. 3 (the respective Figures for the other three traces are similar). Three apparent periodic components are observed, one containing lags with low autocorrelation, one with medium autocorrelation and the other lags with high autocorrelation. We observe that autocorrelation remains high even for large numbers of lags and that both components decay very slowly; both these facts are a clear indication of the importance of LRD. The existence of strong autocorrelation coefficients is due to the periodic recurrence of I, B and P frames.

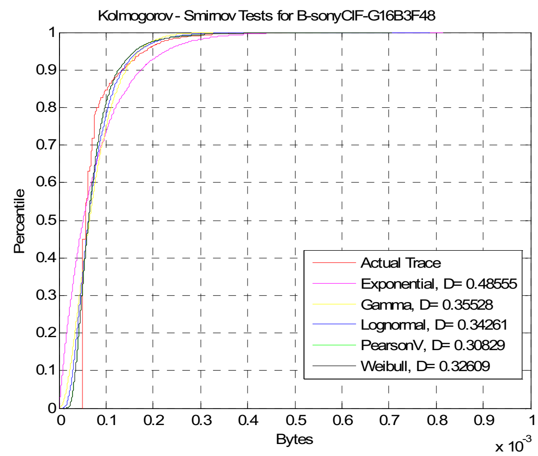

Figure 2. KS-test (Comparison Percentile Plot) for the Sony Demo B frames ([CIF, G16, B3, F48]).

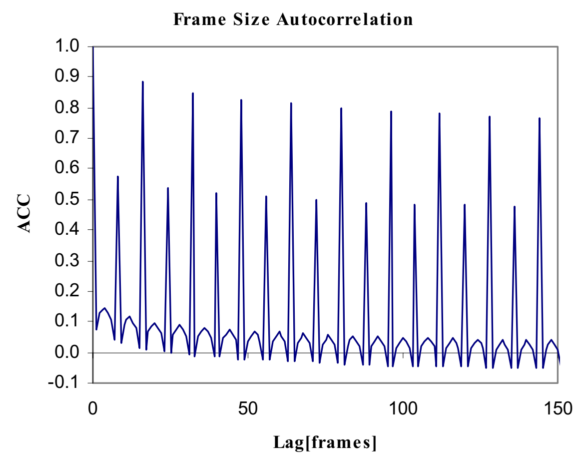

Figure 3. Autocorrelation Coefficients of the NBC News trace ([CIF, G16, B7, F28]).

Although the fitting results when modeling each video frame type separately with the use of the Pearson V distribution are clearly better than the results produced by modeling the whole sequence uniformly, the high autocorrelation shown in the Figure above can never be perfectly "captured" by a distribution generating frame sizes independently, according to a declared mean and standard deviation, and therefore none of the fitting attempts (including the Pearson V), as good as they might be, can achieve perfect accuracy. However, these results lead us to extend our work in order to build a DAR model, which inherently uses the autocorrelation coefficient of lag-1 in its estimation. The model will be shown to accurately capture the behavior of multiplexed H.264 videoconference movies, by generating frame sizes independently for I, P and B frames.

Finally, it should be noted that in [16] we have successfully modeled *High Definition* (HD) H.264 traces as a whole (i.e., with a similar approach to that of [17] for H.263 traces) and used the result to propose an efficient MAC protocol for GEO satellite networks. The Weibull distribution was shown to provide the best results when modeling the traces as a whole, slightly outperforming the Pearson V distribution. However, in the case of the "Main Profile" traces from [19] (which consume significantly smaller amounts of bandwidth than the HD ones) the Pearson V distribution clearly excels as a fit both for the whole trace and for the separate modeling of I, P, B frames.

III. THE DAR (1) MODEL – RESULTS AND DISCUSSION

A Discrete Autoregressive model of order p, denoted as DAR(p) [23], generates a stationary sequence of discrete random variables with an arbitrary probability distribution and with an autocorrelation structure similar to that of an Autoregressive model. DAR(1) is a special case of a DAR(p) process and it is defined as follows: let $\{V_n\}$ and $\{Y_n\}$ be two sequences of independent random variables. The random variable V_n can take two values, 0 and 1, with probabilities 1-ρ and ρ, respectively. The random variable Y_n has a discrete state space S and $P\{Y_n = i\} = \pi(i)$. The sequence of random variables $\{X_n\}$ which is formed according to the linear model:

$$X_n = V_n X_{n-1} + (1- V_n) Y_n \tag{1}$$

is a DAR(1) process.

A DAR(1) process is a Markov chain with discrete state space S and a transition matrix:

$$\mathbf{P} = \rho\mathbf{I} + (1-\rho)\,\mathbf{Q} \tag{2}$$

where ρ is the autocorrelation coefficient, **I** is the identity matrix and **Q** is a matrix with $Q_{ij} = \pi(j)$ for i, j ϵ S.

Autocorrelations are usually plotted for a range W of lags. The autocorrelation can be calculated by the formula:

$$\rho(W)= E[(X_i - \mu)(X_{i+w} - \mu)]/\sigma^2 \tag{3}$$

where μ is the mean and σ^2 the variance of the frame size for a specific video trace.

As in [3], where a DAR(1) model with negative binomial distribution was used to model the number of cells per frame of VBR teleconferencing video, we want to build a model based only on parameters which are either known at call set-up time or can be measured without introducing much complexity in the network. DAR(1) provides an easy and practical method to compute the transition matrix and gives us a model based only on four physically meaningful parameters, i.e., the mean, peak, variance and the lag-1 autocorrelation coefficient ρ of the offered traffic (these correlations, as already explained, are typically very high for videoconference sources). The DAR(1) model can be used with any marginal distribution [24].

As already explained, the lag-1 autocorrelation coefficient for the I, P and B frames of each trace is very high in all the studied cases. Therefore, we proceeded to build a DAR(1) model for each video frame type for each one of the eighteen traces under study. More specifically, in our model the rows of the **Q** matrix consist of the Pearson type V probabilities (f_0, f_1, … f_k, F_K), where $F_K = \Sigma_{k>K} f_k$, and K is the peak rate. Each k, for k<K, corresponds to possible source rates less than the peak rate of K.

From the transition matrix in (2) it is evident that if the current frame has, for example, i cells, then the next frame will have i cells with probability $\rho+(1-\rho)*f_i$, and will have k cells, $k \neq i$, with probability $(1-\rho)*f_k$. Therefore the number of cells per video frame stays constant from one (I, P or B) video frame to the next (I, P or B) video frame, respectively, in our model with a probability slightly larger than ρ. This is evident in Fig. 4, where we compare the actual B frames sequence of the NBC News ([CIF, G16, B15, F28]) trace and their respective DAR(1) model and it is shown that the DAR(1) model's data produce a "pseudo-trace" with a periodically constant number of cells for a number of video frames. This causes a significant difference when comparing a segment of the sequence of I, P, or B frames of the actual NBC News video trace and a sequence of the same length produced by our DAR(1) model. The same vast differences also appeared when we plotted the DAR(1) models versus the actual I, P and B video frames of the other traces under study.

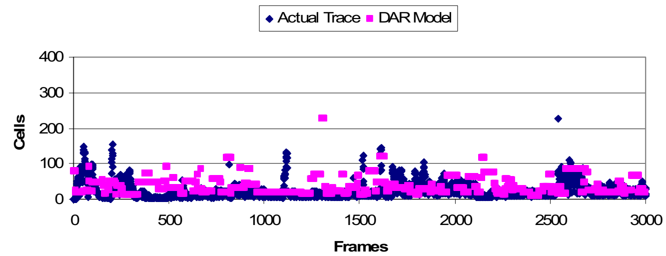

Figure 4. Comparison for a single trace between a 10000 frame sequence of the actual B frames sequence of the NBC News ([CIF, G16, B15, F28]) trace and the respective DAR(1) model in number of cells/frame (Y-axis).

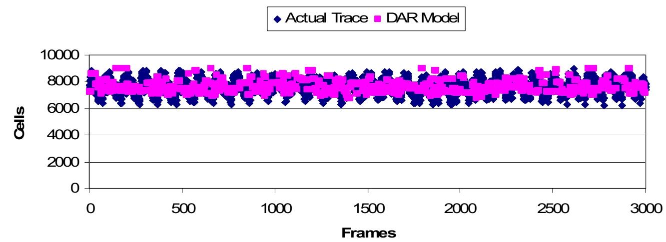

Figure 5. Comparison for 30 superposed sources between a 3000 I frame sequence of the actual NBC News ([CIF, G16, B1, F28)] trace and the respective DAR(1) model in number of cells/frame (Y-axis).

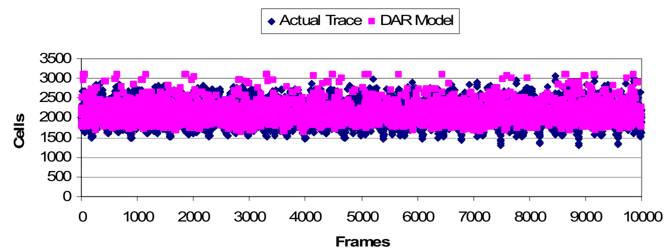

Figure 6. Comparison for 30 superposed sources between a 10000 P frame sequence of the actual NBC News ([CIF, G16, B1, F28)] trace and the respective DAR(1) model in number of cells/frame (Y-axis).

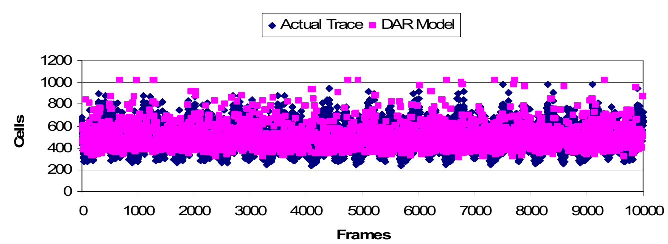

Figure 7. Comparison for 30 superposed sources between a 10000 B frame sequence of the actual NBC News ([CIF, G16, B1, F28)] trace and the respective DAR(1) model in number of cells/frame (Y-axis).

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However, our results have shown that the differences presented above become small for all types of video frames and for all the examined traces for a superposition of 5 or more sources, and are almost completely smoothed out in most cases, as the number of sources increases (the authors in [3] have reached similar conclusions for their own DAR(1) model and they present results for a superposition of 20 traces). This is clear in Figs. 5-7, which present the comparison between our DAR(1) model and the actual I, P, B frames' sequences of the NBC News ([CIF, G16, B1, F28)] , for a superposition of 30 traces (the results were perfectly similar for all video frame types of the other three traces; we have used the initial trace sequences to generate traffic for 30 sources, by using different starting points in the trace). The common property of all these results (derived by using a queue to model multiplexing and processing frames in a FIFO manner) is that the DAR(1) model seems to provide very accurate fitting results for P and B frames, and relatively accurate for I frames.

However, although Figs. 5-7 suggest that the DAR(1) model captures very well the behavior of the multiplexed actual traces, they do not suffice as a result. Therefore, we proceeded again with testing our model statistically in order to study whether it produces a good fit for the I, P, B frames for the trace superposition. For this reason we have used again Q-Q plots, and we present indicatively some of these results in Figs. 8-9, where we have plotted the 0.01-, 0.02-, 0.03-,… quantiles of the actual *B* and *I* video frames' types of the NBC News trace versus the respective quantiles of the respective DAR(1) models, for a superposition of 30 traces.

As shown in Fig. 8, which presents the comparison of actual P frames with the respective DAR(1) models for the NBC News ([CIF, G16, B3, F48]) trace, the points of the Q-Q plot fall almost completely along the 45-degree reference line, with the exception of the first and last 3% quantiles (left- and right-hand tail), for which the DAR(1) model underestimates the probability of frames with a very small and very large, respectively, number of cells. The very good fit shows that the superposition of the P frames of the actual traces can be modeled very well by a respective superposition of data produced by the DAR(1) model (similar results were derived for the superposition of B frames), as it was suggested in Figs. 6, 7. Fig. 9 presents the comparison of actual I frames with the respective DAR(1) model, for the NBC News ([CIF, G16, B7, F48]) trace. Again, the result suggested from Fig. 5, i.e., that our method for modeling I frames of multiplexed H.264 videoconference streams provides only relative accuracy, is shown to be valid with the use of the Q-Q plots. The results for all the other cases which are not presented in Figs. 8-9 are similar in nature to the ones shown in the Figures.

One problem which could arise with the use of DAR(1) models is that such models take into account only short range dependence, while, as shown earlier, H.264 videoconference streams show LRD. This problem is overcome by our choice of modeling I, P and B frames separately. This is shown in Fig. 10. It is clear from the Figure that, even for a small number of lags, (e.g., larger than 10) the autocorrelation of the superposition of frames decreases quickly, for all the traces. Therefore, although in some cases the DAR(1) model exhibits a slower decrease than that of the actual traces' video frames sequence, this has minimal impact on the fitting quality of the DAR(1) model. This result further supports our choice of using a first-order model.

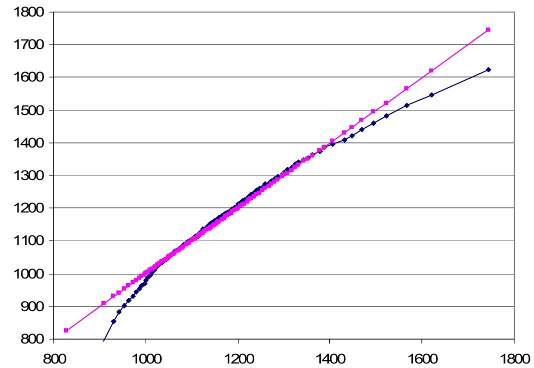

Figure 8. Q-Q plot of the DAR(1) model versus the actual video for the P frames of NBC News ([CIF, G16, B3, F48]), for 30 superposed sources.

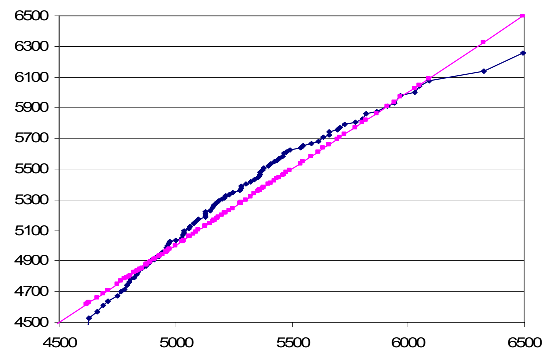

Figure 9. Q-Q plot of the DAR(1) model versus the actual video for the I frames of NBC News ([CIF, G16, B7, F48]), for 30 superposed sources.

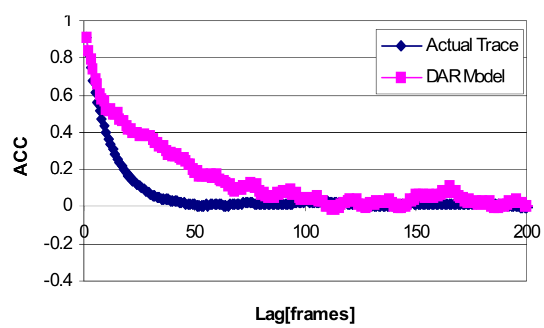

Figure 10. Autocorrelation vs. number of lags for the I frames of the actual NBC News ([CIF, G16, B15, F28]) trace and the DAR(1) model, for 30 superposed sources.

IV. Conclusions

In this paper, we have proposed and tested a new model for traffic originating from VBR H.264 videoconferencing sources. Models of video traffic will prove very important in the immediate future, as networks will need to competently handle video traffic (i.e., to guarantee its strict QoS requirements despite its burstiness). The Discrete Autoregressive model built in this work is shown to be highly accurate and, to the best of our knowledge, is one of the first works in the relevant literature to address the specific problem. Based on the very good results of our study in modeling P- and

B-frames' sizes of multiplexed H.264 videoconference traces, and the low complexity of our first-order model, we believe that our approach is very promising for modeling this type of traffic. However, since our modeling scheme shows relative accuracy in modeling I -frames' sizes, the use of wavelet modeling for the I -frames' size sequence may provide a very competent solution, and our future work will be pointed towards this direction.

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