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MODELING AND GENERATION OF SELF-SIMILAR BEHAVIOR OF MPEG-4 VIDEO TRAFFIC USING CHAOTIC MAPS METHOD

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Abstract—The rise in popularity of the Internet, and specially the World Web Wide, has resulted in the web browser becoming the most commonly used Internet application. This popularity has driven the increase in multimedia applications with streaming audio and video players becoming almost ubiquitous. These audio and video traffics represent a new class of Internet traffic, which will increase with introduction of various new technologies such as MP3 and MPEG. In order to design networks that can meet the demand of these applications, a solid understanding of video traffic behavior is required. Effective design and performance analysis of such networks thus depends on accurate modeling of video traffic. Modeling of video traffic has always been important research area for design, simulation and performance analysis of packet video networks and Internet streaming. In this paper, we investigate the scaling behavior that is present in MPEG-4 video traffic and to accurately capture the long-range dependent (LRD) properties of the MPEG-4 video traffic, we present a frame-level framework for modeling video traffic, in which the I, B and P frames are modeled using the chaotic maps method. The key findings of our study are that the video encoder output traffic has fractal behavior and this behavior exists regardless of the compression ratio and the simulation results demonstrate that our model not only preserves the temporal burstiness of the empirical traffic traces, but also captures the important statistical features of the original video traces such as the autocorrelation function and the frame-size distribution.

Keywords— Video traffic, Chaotic Maps, Self-Similarity, MPEG4

I. INTRODUCTION

The Internet's impact on daily life is increasing dramatically. Relying on the Internet as a source of information and a means of communication is unmatched in history. This is the reason why some researchers and communication experts believe that sooner or later, all the devices that are parts of our daily life, like home applications, will be connected to the Internet. Connecting those devices and appliances to the Internet will require the transfer of video or at least will include video transfer as an enhancement. This is the one of the motivations behind establishing the ISO Moving-Pictures-Experts-Group (MPEG) family of standards for digital video encoding.

Multimedia applications such as video teleconferencing, video phone and video-on-demand have been predicted to be the major source of traffic for the IP networks. Due to the extremely high bandwidth requirements of uncompressed video streams, many coding algorithms have been developed for video compression. The MPEG standards for video coding have gained world-wide acceptance and they are expected to play a dominant role in the foreseeable future. The MPEG coding utilizes both the spatial and the temporal redundancy of the video stream [5].

Video traffic modeling plays an important role in characterization and analysis of network traffic. Besides providing an insight into the coding process and structure of video sequences, traffic models can be used for many practical purposes including allocation of network resources, design of efficient networks for streaming services and delivery of certain Quality of Service (QoS) guarantees to end users. Although many studies have been conducted in this area, most existing traffic models only apply to a single-layer VBR video and often overlook the multi-layer aspects of streaming video traffic in the current Internet [1, 4]. In addition, traffic modeling research is falling behind the rapid advances in video techniques, which include standards MPEG-4 [6]. Therefore, the goal of this work is to better understand the statistical properties of various video sequences and to develop a model that can generate synthetic traffic with the properties close to those of original MPEG-4 video sequences.

Video traffic modeling has been studied extensively and many results have been reported in [2, 3]. The modeling approach for VBR video traffic can roughly be divided into several main classes, i.e., histogram- based models [8], Markov chain models [7], AR processes [1, 4] self-similar or fractal models [9] and other approaches such as [9, 10, 11].

In this paper, we look at very recent MPEG-4 traces we draw conclusions about the scaling behavior that present on them. We develop a parsimonious, tractable, and accurate model that will capture the important video and data traffic self-similarity characteristics on the IP-based network, we evaluates MPEG VBR traffic model, namely the chaotic map-based model, including it is ability to predict accurately different aspects of network performance. Finally, to justify the validity of this proposed model for video streams we investigate the effect of real and synthetic traces generated using chaotic-based model on the IP-based network performance, as captured by, packet loss rate, and queuing delay.

This paper is organized as follows. In section 2 and section 3, we provide the back ground on chaotic maps and show how to generate synthetic traces. In section 4, we present statistical analysis in terms of Hurst parameter of video traces and we draw conclusions about the scaling behavior that present on them. In section 5, we evaluate the accuracy of our model. Section 6 concludes the paper.

II. CHAOTIC MAP: AN INTRODUCTION

Chaotic maps are low dimensional non-linear systems with a time evolution that can be described by an initial state as well as a set of dynamical laws. The method of using chaotic deterministic maps approach to modeling packet traffic was first suggested by Erramilli and Singh in 1990, when they demonstrated that it is possible to generate complex traffic behavior with low order chaotic systems [2, 3, 8]. Such systems exhibit a chaotic behavior that arises from a property known as Sensitive dependence on Initial Conditions (SIC). If one considers a chaotic map defined as $X_{n+1} = f(X_n)$ and two trajectories with nearly identical initial conditions X_0 and $X_0 + \varepsilon$, then SIC can be stated mathematically

$$\left| f^{N}(X_0+\varepsilon) - f^{N}(X_0) \right| = \varepsilon e^{N\lambda(x_0)} \tag{1}$$

where $f^N(X_0)$ describes the exponential divergence (so-called the Lyapunov exponent). For the map to be chaotic, the parameter $\lambda(x_0)$ should be positive for “almost all” X_0. In other words, the fact that the initial conditions can be specified with only limited accuracy is used in this approach by increasing these uncertainties at an exponential rate, and making so the long term behavior unpredictable.

Some of the best known classes of chaotic maps are the so-called piecewise linear maps (where the map consists of a number of piecewise linear segments, e.g., Bernoulli shift, Liebovitch map) and the non-linear or intermittency maps (where non-linear segments are used, e.g., single intermittency maps, double intermittency maps). Details of these maps as well as of using them as traffic source models are presented in [7].

Traffic Source Models: Consider one-dimensional map in which the state variable x_0 evolves over discrete time $n = 0, 1, 2, \ldots.$ according to the nonlinear map:

$$x_{n+1} = \begin{cases} f_1(x_n) & 0 \le x_n < d \\ f_2(x_n) & d \le x_n \le 1 \end{cases} \tag{2}$$

- For the map to chaotic $f_1(\cdot)$ and $f_2(\cdot)$ should satisfy SIC. We can model a packet generation process by assuming that the source is in a passive state or active state at time n depending on whether x_n is below or above a threshold
- Every iteration of the map in the active state is taken to generate a packet 'or batch of packet". The packet arrival process is then described by the evolution of an associate variable y_n.

$$y_n = \begin{cases} 0 & 0 \le x_n < d \\ 1 & d \le x_n \le 1 \end{cases} \tag{3}$$

III. TRAFFIC MODELING: INTERMITTENCY MAP

A chaotic intermittency map has been studied as a model of ON/OFF behavior of packet traffic streams with long-range dependence (LRD), and is known to be accurate, predictable and computationally efficient

$$f_1(x) = \frac{x}{\left(1 - c_1 x^{m_1-1}\right)^{\frac{1}{m_1-1}}} + \varepsilon_1 \qquad c_1 = \frac{(1-\varepsilon_1)^{m_1-1} - d^{m_1-1}}{(1-\varepsilon_1)^{m_1-1}\, d^{m_1-1}} \tag{4}$$

$$f_2(x) = \frac{x-d}{1-d} \qquad \textit{with } \varepsilon_1 << d, \textit{ and } m_1 \ge 1$$

A chaotic intermittency map can be parameterized to give LRD in either ON/OFF state. Studied conducted in the early 1990's shows that a traffic stream which displays self-similarity when aggregated remains self-similar. This behavior would naturally require models to exhibit this same characteristic. In recent studies on the use of chaotic maps as models a technique has been developed which permits the retention of self-similarity under aggregation. Aggregation as few as 20 sources leads to a good approximation of fractional Brownian motion (fBm). Figure 1 shows the time series obtained by aggregating 50 sources modeled by the Fixed Point Intermittency (FPI) map.

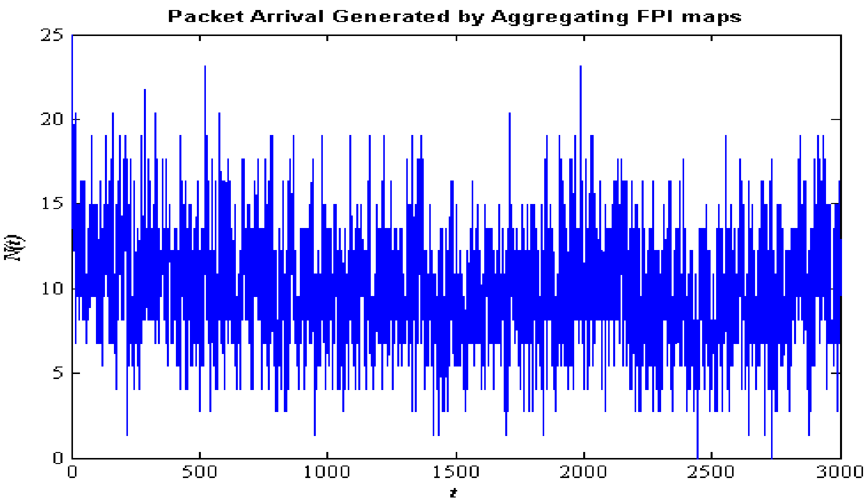

Figure 1. Packet arrival generated by aggregating 50 sources of the FPI map

Accuracy of Generated Sequences: In the section we report on the properties of the chaotic map "Intermittency" generator. The algorithm implemented in MATLAB. We have analyzed the accuracy with which the considered generator generate normal pseudo-random sequences with the required values of . For $H = 0.6, 0.7, 0.8, 0.9$, the generator used to generate a sample sequence of

32768 (2^{15}) records. The self-similarity of the sequences generated was assessed using wavelet-based estimator. As a measure of the generator accuracy we use the relative inaccuracy ΔH , as defined as:

$$\Delta H = \frac{\hat{H} - H}{H} \times 100\% \qquad (5)$$

where H is the exact value and $\hat{H}$ is the estimated value. The estimate of the Hurst parameter inaccuracy is shown in Table 1.

H exact	$\hat{H}$	ΔH %
0.6	0.5980	-0.3333
0.7	0.6948	-0.7428
0.8	0.7964	-0.4500
0.9	0.8952	-0.5333

Table 1. Relative inaccuracy

The wavelet-based estimator clearly confirmed the self-similar nature of the generated traces. Table 1 gives the relative inaccuracy of the estimated Hurst parameters which they are negatively biased. Chaotic-based generator shows quality of output traces in sense of Hurst parameter with relative inaccuracy less than 1%.

IV. ANALYSIS OF VIDEO TRACES

MPEG-4, H.263 and VBR encoded video is expected to account a large portion of the traffic in future networks. In this section we present a publicly available library of frame size traces of long MPEG-4, H.263 and VBR encoded videos, which have generated at the Technical University Berlin. The frame size traces have been generated of over 10 video sequences of 60 minutes length each. In this paper we present three sequences, namely the Die Hard III, Robin Hood and News ARD R&TV video sequences. We also presented a thorough LRD analysis in terms of Hurst parameter of the traces.

Hurst Parameter: We estimate the Hurst parameter of MPEG-4 encoded (high quality), H.263 encoded (16kbits/s target bit rate and 256kbits/s target bit rate) and VBR encoded (unspecified target bit rate) video traces using the wavelet-bases and R/S analysis estimators as shown in Table 2.

Sequence		Estimation Techniques	
		Wavelet	R/S
Die Hard III	MPEG-4 Frame	0.9871	0.9679
	H.263 (16kbs/s)	0.9079	0.8684
	H.263 (256kbs/s)	0.7998	0.8320
	VBR	1.0122	0.8980
Robin Hood	MPEG-4 Frame	0.9248	0.8716
	H.263 (16kbs/s)	0.8350	0.7922
	H.263 (256kbs/s)	0.8580	0.7932
	VBR	0.8984	0.8494
News ARD R&TV	MPEG-4 Frame	0.9893	0.9865
	H.263 (16kbs/s)	0.8044	0.8221
	H.263 (256kbs/s)	0.9593	0.9008
	VBR	1.0924	0.9218

Table 2. Hurst estimate for video traces

For more accurate characterization of the long-range dependence "*H* parameter" in the encoded video sequences we give in Table 3 the Hurst parameter estimates as a function of the aggregation level *m* for our video sequences

Sequence		Aggregation level m			
		50	100	200	500
Die Hard III	MPEG-4	0.9566	0.9838	0.9859	0.8840
	H.263-16	0.9027	0.9249	0.8967	0.8344
	H.263-256	0.8011	0.8010	0.7301	0.8680
	VBR	0.8869	0.9105	0.8377	0.8059
Robin Hood	MPEG-4	0.8840	0.8548	0.8668	0.7564
	H.263-16	0.8847	0.8994	0.9294	0.7280
	H.263-256	0.8210	0.8119	0.8141	0.7427
	VBR	0.8272	0.8057	0.8087	0.7274
News ARD R*TV	MPEG-4	1.1140	1.1361	0.9885	0.6495
	H.263-16	0.8826	0.8094	0.3322	0.7444
	H.263-256	1.2770	0.5536	0.1563	0.4882
	VBR	0.9709	0.8374	0.7911	0.8030

Table 3. Wavelet: Hurst estimate as function of m

Sequence		Aggregation level m			
		50	100	200	500
Die Hard III	MPEG-4	0.8726	0.8792	0.8915	0.7155
	H.263-16	0.8914	0.7601	0.6859	0.3866
	H.263-256	0.7996	0.7912	0.5856	0.8233
	VBR	0.8492	0.8559	0.8773	0.7237
Robin Hood	MPEG-4	0.7405	0.7319	0.7112	0.7332
	H.263-16	0.8204	0.6982	0.7360	0.9493
	H.263-256	0.7987	0.8238	0.6493	0.5784
	VBR	0.7016	0.6879	0.6445	0.6118
News ARD R&TV	MPEG-4	0.7092	0.6201	0.5792	0.2092
	H.263-16	0.5690	0.5858	0.5632	-
	H.263-256	0.4532	0.3753	0.2771	0.2105
	VBR	0.6316	0.3712	0.3415	0.5781

Table 4. R/S: Hurst estimate as function of m

Our results from Table 2, Table 3 and Table 4 show that the video encoder output traffic has fractal behavior and this behavior exists regardless of the compression ratio. In has been suggested that, in case of video traffic, a larger Hurst parameter reflects a large amount of movement. Our results of Hurst parameter estimation show that one cannot necessarily conclude a lot of movement in the video from a high Hurst parameter value. Even news "*News ARD R&TV trace*" can have a Hurst value larger than that of an action movie "*Die Hard III trace*". This lead to the conclusion, that long-range dependence is a property inherent in video traces independently from the content of the video sequences.

V. MPEG-4 VIDEO TRAFFIC: ANALYSIS AND SIMULATION RESULTS

Modeling of MPEG-4 sequences require the frame sizes of the same-type frames "i.e., I, B and P" to be modeled separately. Hence a frame size distribution analysis for the three type of frames I, B and P would provide an understanding of how well the model works for the frames.

The model validation and verification was carried out using 10 empirical MPEG-4 video traces described in the 4th section. Empirical MPEG-4 video traces were used for investigations. The models tested as a predictor (for network management purposes) and a traffic generator (for simulation purposes).

We evaluate the video traffic model in terms of its statistical characteristic and we compared the output of this model with the empirical traces to validate the effectiveness of the model "Hurst parameter, frequency histogram and probability density function PDF".

Statistical analysis of the I, B and P frames, frame-level and GoP-level of the Die Hard III MPEG-4 video real and synthetic traces are shown in Table 5 and Table 6 respectively.

Statistical Features	I-Frame		B-Frame		P-Frame	
	Real	Syn.	Real	Syn.	Real	Syn.
Min Kb	0.516	0	0.071	0	0.120	0
Max Kb	14.464	18.088	14.623	13.211	16.960	13.797
Sum Mb	47.082	47.082	175.83	175.83	90.880	90.880
Mean Kb	6.277	6.277	2.930	2.930	4.039	4.039
Var Mb	5.458	3.321	3.246	2.045	5.248	2.998
Std Kb	2.336	1.822	1.801	1.430	2.290	1.731
CoV	0.372	0.247	0.614	0.487	0.567	0.428
Peak/Mean	2.304	1.964	4.989	4.507	4.198	3.415

Table 5. I, B and P frames statistical features

Statistical Features	Frame-Level		GoP-Level	
	Real	Synth..	Real	Synth.
Min Kb	0.071	0	2.122	15.625
Max Kb	16.960	18.088	165.97	138.63
Sum Mb	313.80	313.80	313.80	313.77
Mean Kb	3.486	3.486	41.844	41.842
Var Mb	4.863	3.468	494.89	74.734
Std Kb	2.205	1.862	22.246	8.644
CoV	0.632	0.534	0.831	0.206
Peak/Mean	4.864	5.188	3.966	3.313

Table 6. Statistical features: Frame-level and GoP-level

Our obtained results were also compared visually by considering the overall shape of the distribution, the histogram plots, CDF plot and Quantile-Quantile QQ plots.

The histogram plots (frame-level and GoP-level) and the CDF and QQ plot (frame-level and GoP-level) of the Die Hard III MPEG-4 video real and synthetic traces are shown in Figure 2 and Figure 3 respectively. The real trace has a frame-level histogram with slightly significant tail on the right. The model is not able to capture the precise shape of the frame distribution for the real trace.

As can be seen from Figure 3, the cumulative distribution function (CDF) of the chaotic-based model has a staircase form "discrete" and it has a best visual match to that of the real trace.

The autocorrelation of I, B and P frames, frame-level and GoP-level of the Die Hard III MPEG-4 video real and synthetic traces are shown in Figure 4 and Figure 5 respectively.

I, B and P frames autocorrelation graphs indicate that the real trace shows positive correlation at short lag, and has both short-range dependence (SRD) and LRD properties. Chaotic-based model frames shows positive correlation, which indicate the presence of the LRD properties. The autocorrelation graph of the real trace "GoP-level" shows strong positive correlation at short lags, and has both SRD and LRD properties. The chaotic-based model trace shows strong positive correlation, which indicates the presence of LRD properties.

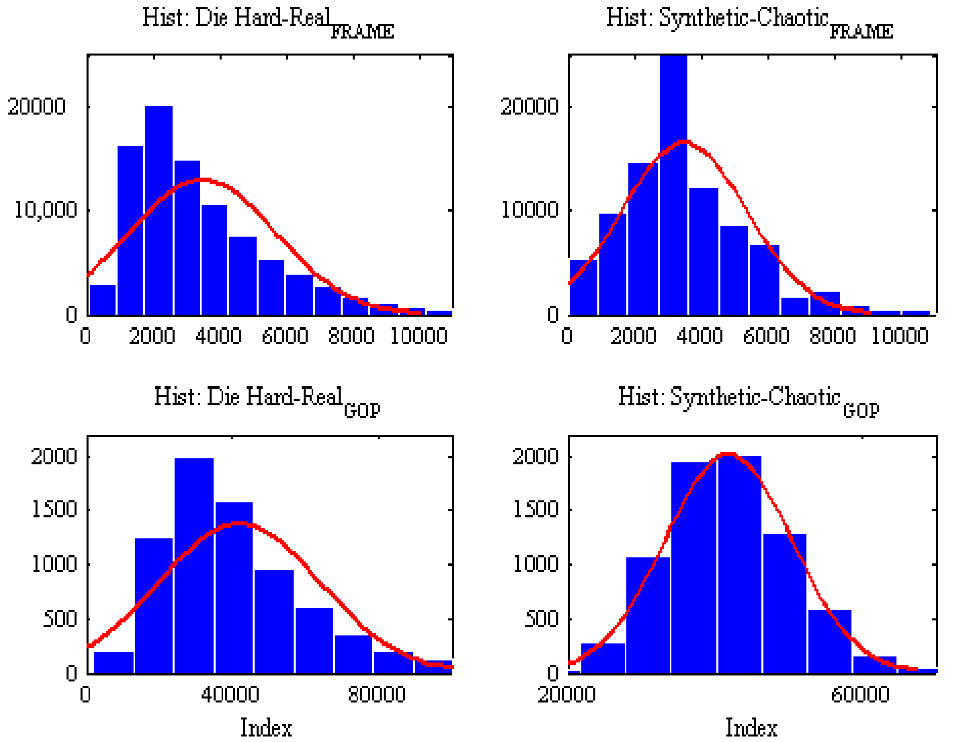

Figure 2. Histogram plots real and synthetic traces

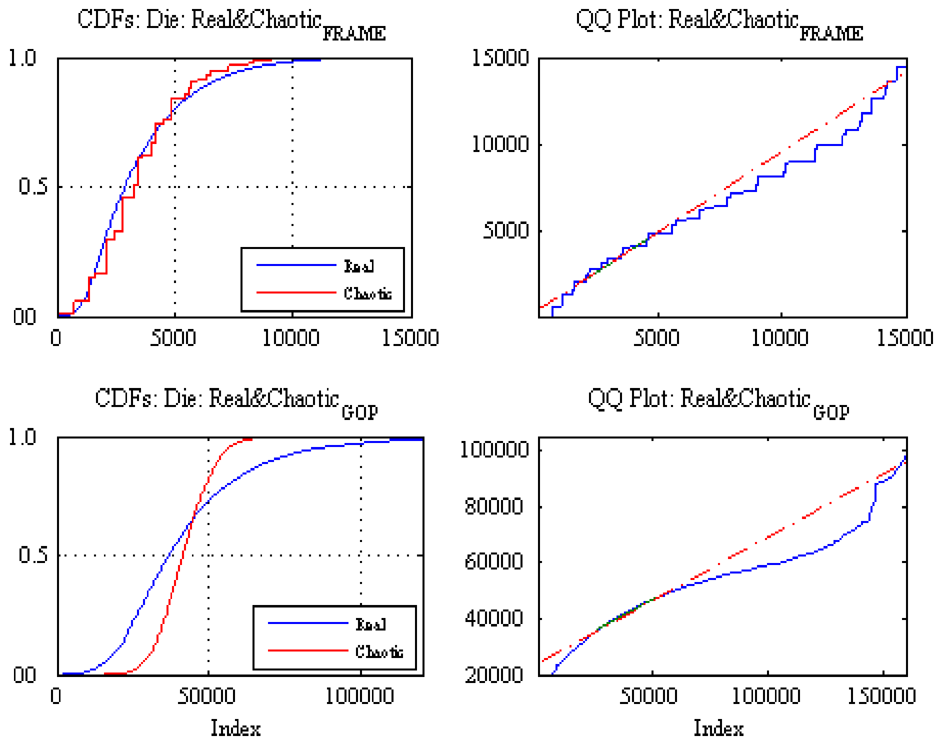

Figure 3. CDF and QQ plots real and synthetic traces

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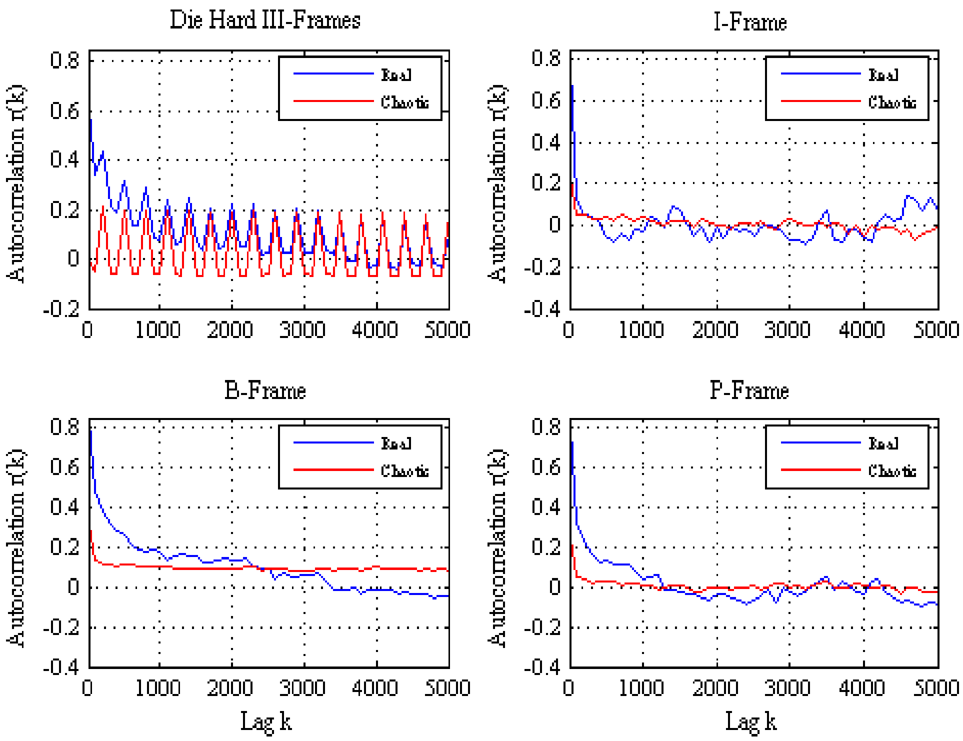

Figure 4. Autocorrelations: Frame-level

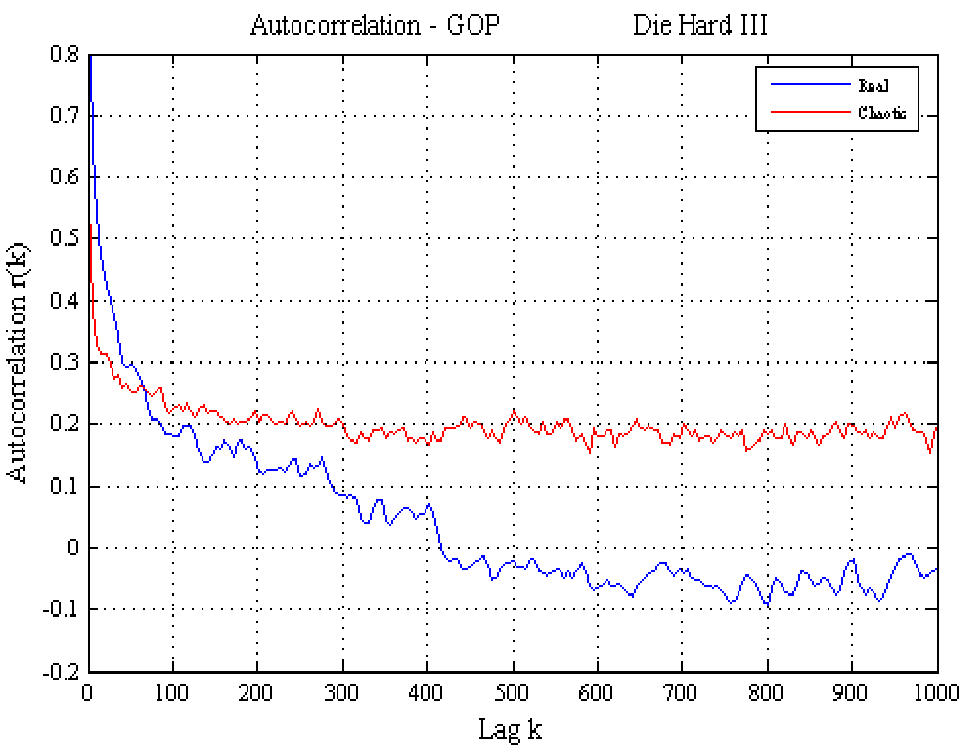

Figure 5. Autocorrelations: GoP-level

Hurst parameter estimation using wavelet-and R/S estimators is carried out to analyze the accuracy of the chaotic-based generator. They clearly confirmed the self-similar nature of the generated traces as shown in Table 7 and Table 8.

sequences		Die Hard III			
		Wavelet		R/S	
		$\hat{H}$	ΔH %	$\hat{H}$	ΔH %
I Frame	Real	0.8890		0.834	
	Chaotic	0.7199	-19.021	0.7444	-10.743
B Frame	Real	1.0702		0.915	
	Chaotic	0.8061	-24.677	0.8126	-11.191
P Frame	Real	0.9769		0.909	
	Chaotic	0.8259	-15.457	0.7855	-13.586

Table 7. Relative inaccuracy: I, B and P frames

sequences	Die Hard III			
	Wavelet		R/S	
	$\hat{H}$	ΔH %	$\hat{H}$	ΔH %
Real	0.9871		0.968	
Chaotic	0.7442	-24.607	0.771	-20.351

Table 8. Relative inaccuracy: Frame-level

In order to determine the accuracy of predictions of network performance provided by a model, it is necessary to make some comparison with results obtained using real data. Such comparisons are vital in the verification of traffic models. In this paper, we presents the results form simulation experiments designed to evaluate the cell loss rate and queuing delay performance for the synthetic video traffic model, compared to those for the empirical trace as shown in Figure 6 and Figure 7 respectively.

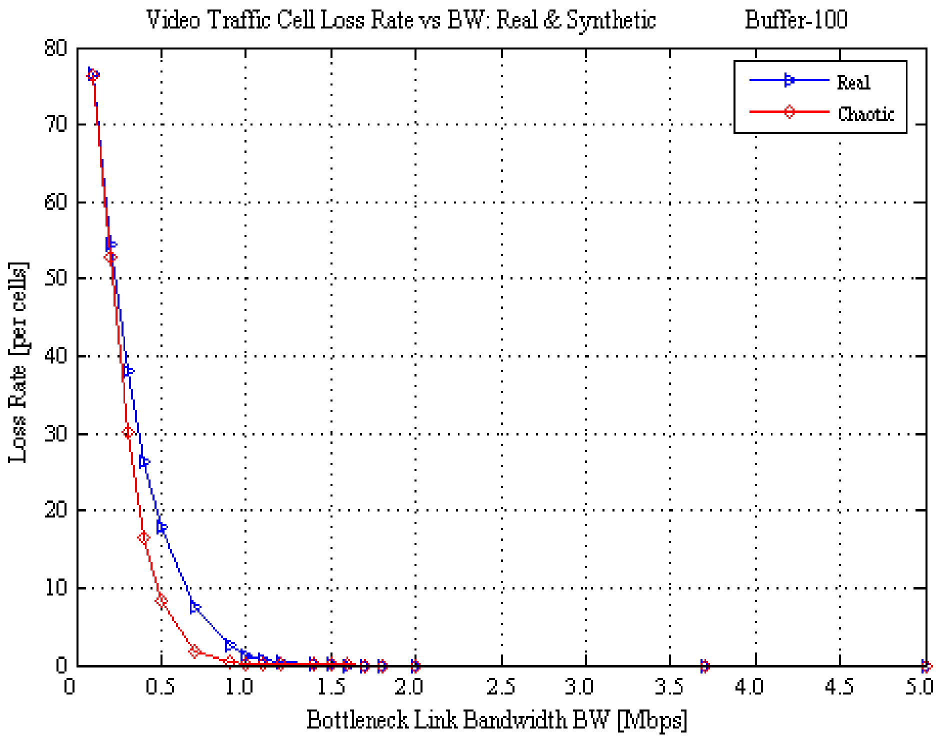

Figure 6. Cell Loss Rate of Die Hard III real & synthetic

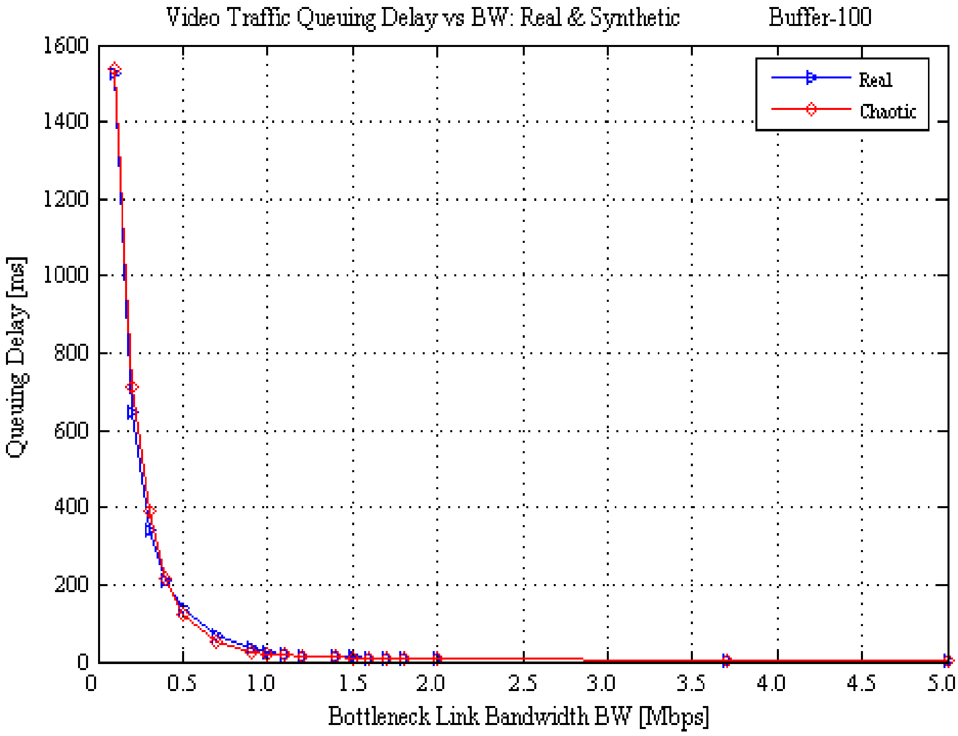

Figure 7. Queuing Delay of Die Hard III real & synthetic

From Figure 6 it is clear that for smaller buffer size from 0.1Mbps up to 1.4Mbps, the chaotic-based model has a lower cell loss rate CLR than that of the real trace. It has a higher CLR compared to that of the real trace for 1.5Mbps and 1.6Mbps bandwidth sizes, and has a CLR that match well to that of the real trace, which equal to zero for bandwidth size of 1.8Mbps and higher.

Figure 7 shows that the queuing cell delay for the real trace decreases as the bandwidth increases from 0.1Mbps up to 5Mbps. The chaotic-based model has higher queuing delay compared to that of the real trace for smaller bandwidth size as it increases form 0.1Mbps up to 0.4Mbps. Chaotic-based model has a lower queuing delay than that of the real trace ones as the bandwidth increases from 0.5Mbps up to 1.7Mbps, and for a higher bandwidth size from 1.8Mbps up to 5Mbps its queuing delay are match to that of the real trace.

VI. CONCLUSION

Understanding the self-similar behavior of video traffic and building models for workload for video servers will undoubtedly help network engineers design better networks and software for video services over Internet. In this paper, we used chaotic maps to generate synthetic MPEG-4 traffic for performance evaluation. To design this model, we proceeded to a detailed statistical analysis which permitted to identify and characterize the major sources of bit rate variations of an MPEG-4 encoded stream. To conclude the paper, a comparative simulation study using synthetic and real traces show this model has a very close statistics and queuing performances to real MPEG-4 streams. This study shows that self-similar scaling is present in video traffic and compression ratio does change this behavior.

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REFERENCES

[1] Min Dai and Dmitri Loguinov, Analysis and Modeling of MPEG-4 and H.264 Multi-Layer Video Traffic. *IEEE INFCOM*, Miami, FL, 2005.

[2] Frank Fitzek, M. Zorzi, P. Seeling & M. Reisslein, Video and Audio Trace Files of Pre-encoded Content for Network Performance Measurements, *Proc. IEEE Consumer Communications and Networking Conference (CCNC2004)*, Las Vegas, Nevada, 2004.

[3] Frank Fitzek and M. Reisslein, MPEG-4 and H.263 Video Traces for Network Performance Evaluation, *IEEE Network*, 15(6), 2001, 40-54.

[4] J.-A. Zhao, B. Li. & I. Ahamad, Traffic Model for Layered Video: An Approach on Markovian Arrival Process, *Packet Video*, April 2003.

[5] Derong Liu, I. Sara & Wei Sun, Nested Auto-Regressive Processes for MPEG-Encoded Video Traffic Modeling, *IEEE Transaction on Circuit and Systems for Video Technology*, 11(2(, 2001, 169-183.

[6] U. K. Sarkar, S. Ramakrishnan & D. Sarkar, Modeling Full-Length Video Using Markov-Modulated Gamma-Based Framework, I*EEE/ACM Trans. On Networking*, 11, 2003.

[7] Pruthi P., An Application of Chaotic Maps to Packet Traffic Modeling, PhD thesis, Royal Institute of Tecnology, Sweden, 1996.

[8] F. H. Fitzek, P. Seeling & M. Reisslein, Using Network Simulators with Video Traces, Arizona State University, Dept. of Elect. Eng., Technical Report, 2003.

[9] F. Fitzek, P. Seeling , M. Reisslein & M. Zorzi, Investigation of the GoP Structure for H.26L Video Streams, acticom-mobile networks, Germany, Tech. Rep., acticom-02-004, 2002.

[10] P. Seeling, F. Fitzek & M. Reisslein, Videometer, *IEEE Network Magazine*, 17(1), 2003.

[11] Dongu Arifler and Brian L. Evans, Modeling the Self-Similar Behavior of Packetized MPEG-4 Video Using Wavelet-Based Methods, *IEEE Conf. on Image Processing*, NY, 2002, 22-25.