CHARACTERISATION AND MODELLING OF H.264 VIDEO TRAFFIC SOURCE

P MALINDI AND MTE KAHN

ABSTRACT

Recent advances in telecommunication and video coding techniques has led to the development of H.264, and since its development, this video coding standard is being adopted in application standards and industry consortia specifications. However, the literature reveals that most of the work that has been done in video traffic characterisation and modelling is based on previous coding standards, which do not include H.264. Therefore, in order to fill this gap this paper presents the characterisation and modelling of H.264 encoded video traffic. Video is encoded using H.264 encoding technique and a trace file is generated. Statistical analysis is performed on the generated traces. Then, based on the statistical analysis, a suitable model is constructed and a synthetic traffic is generated using the proposed model, which in this case is FARIMA. Lastly, the proposed model is validated using the autocorrelation function.

Keywords: H.264 Video Coding, Self-Similar Models, Statistical Analysis, FARIMA model

1. INTRODUCTION

With the growing popularity of multimedia communication, video communication applications such as video-on-demand, video conferencing, and video broadcasting are expected to account for a large portion of traffic in the future networks.

The H.264 encoding standard is also expected to be one of the dominant encoding techniques used due to its advantages, which include error/loss robustness enhancement, flexibility for effective use over a broad variety of network types and application domains, and coding efficiency improvement that is about 50% for equivalent perceptual quality relative to the performance of prior standards [1] - [7] and [12]. However, most of the statistical analysis and models that are reflected in the literature are based on video that was encoded using standards such as H.261, H.263 or MPEG 4, which are prior H.264.

This paper aims at analysing the H.264 encoded video traffic and proposing a model based on the observed statistical characteristics of a full motion video. Since video source modelling depends on the coding technique and the video application itself, two videos are going to be considered: one will be a slow moving picture and the other one an action movie. The characteristics of video traffic that will be considered include distribution of frame size, and the autocorrelation function (ACF) that captures the dependence between the frame sizes.

This paper is organised as follows. In Section 2, we present video trace generation. In Section 3 we present the statistical analysis of the generated video traces. In Section 4 we present a proposed model. In Section 5 a synthetic trace is generated based on the proposed model together with its ACF, and Section 6 concludes this article.

2. VIDEO TRACE GENERATION

Two videos, 'talking head' and 'Mr Bones' were captured as uncompressed YUV information and stored on the disk. 'Talking head', which is a person sitting in front of a webcam, represents the slow moving picture while 'Mr Bones' will represent an action movie. Both videos are captured using Ulead VideoStudeo 8 software and the captured video frames were stored on the disk. 'Talking head' is stored as QCIF with 176 pels in the horizontal direction and 144 pels in the vertical direction (i.e. 176x144) and 'Mr Bones' as SIF with 384 pels in the horizontal direction and 288 pels in the vertical direction (i.e. 384x288 pels). The resulting YUV is grabbed at a frame rate of 25 frames/second. 'Talking head' runs for 300 seconds while 'Mr Bones' runs for 181 seconds. The chrominance sampling used for 'talking head' is 4:2:2 while that of 'Mr Bones' is 4:1:1 and the quantization is 16 bits, thus resulting in 50688 pels/frame for QCIF and 165888 pels/frame for SIF.

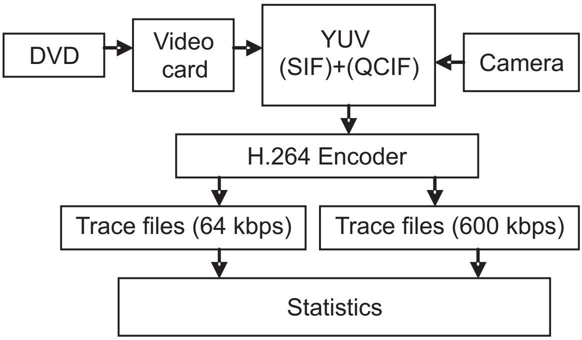


Figure 1: Video capturing and traffic metrics generation

The two YUV sequences are used as inputs for the H.264 encoders: one with an average rate of 64 kbps and another with an average rate of 600 kbps. However, after decoding and replaying the videos it was found that the quality for decoded 'Mr Bones' (which was encoded at 64 kbps) is very poor, hence the low bit rate for 'Mr Bones' was changed from 64 kbps to 150 kbps. For each encoded video output, a corresponding trace file is generated and from these trace files video traffic metrics are retrieved, which are then used for statistical analysis of the recorded videos as shown in Figure 1.

TABLE 1: EXCERPT OF MR BONES AT 600 kbps

Frame num	Frame type	Time	Frame size
0	I	00:00.0	14336
1	P	00:00.0	10240
2	P	00:00.1	4096
3	P	00:00.1	2048
4	P	00:00.2	2048
5	P	00:00.2	4096
6	P	00:00.2	2048
7	P	00:00.3	2048
8	P	00:00.3	4096
9	P	00:00.4	2048
10	P	00:00.4	2048

The observation from all the generated video traces is that the encoded video has two types of frame formats: the intra-coded (I), and the forward motion predicted (P). These I and P frames are arranged in a fixed deterministic pattern IPPPPPPPPPPPP, which is called Group of Pictures (GoP), as shown in the excerpt of 'Mr Bones' in Table 1.

3. STATISTICAL ANALYSIS

After encoding, the size of the QCIF is reduced from 366.656 MB to 6.717 MB at 64 kbps and 47.567 MB at 600kbps, and SIF video is reduced from 754.294 MB to 3.484 MB and 13.824 MB for 150 kbps and 600 kbps, respectively. Therefore the compression ratios (YUV: H.264) are 54.586 and 7.708 for QCIF and 216.502 and 54.564 for SIF at 150 kbps and 600 kbps, respectively. According to [6] and [7], the sample mean of the frame size trace is given by

$$\overline{X} = \frac{1}{N}\sum_{n=0}^{N-1} X_n \qquad (1.1)$$

For QCIF (600 kbps): $\overline{X} = 6340.602 bytes$
For QCIF (64 kbps): $\underline{X} = 895.368 bytes$
For SIF (600 kbps): $\underline{X} = 3049.855 bytes$
For SIF (150 kbps): $X = 768.224 bytes$

The sample variance of the frame size trace is

$$S_X^2 = \frac{1}{N-1}\left[\sum_{n=0}^{N-1} X_n^2 - \frac{1}{N}\left(\sum_{n=0}^{N-1} X_n\right)^2\right] \qquad (1.2)$$

For QCIF (600 kbps): $S_X^2 = 212112.388$
For QCIF (64 kbps): $S_X^2 = 297303.233$
For SIF (600 kbps): $S_X^2 = 6535797.102$
For SIF (150 kbps): $S_X^2 = 1825736.376$

The coefficient of variation CoVX is given by

$$CoV_X = \frac{S_X}{\overline{X}} \tag{1.3}$$

For QCIF (600 kbps $CoV_X = 0.073$
For QCIF (64 kbps): $CoV_X = 0.609$
For SIF (600 kbps): $CoV_X = 0.838$
For SIF (150 kbps): $CoV_X = 1.759$

The maximum frame size Xmax is

$$X_{\max} = \max_{0 \le n \le N-1} X_n \tag{1.4}$$

For QCIF (600 kbps): $X_{\max} = 11.092 kbytes$
For QCIF (64 kbps): $X_{\max} = 4.324 kbytes$
For SIF (600 kbps): $X_{\max} = 43.008 kbytes$
For SIF (150 kbps): $X_{\max} = 14.336 kbytes$

The display time or frame period of a given frame is given by the ratio of the captured video runtime to the number of video frames in a given trace; that is, QCIF with a frame count of 7502 and SIF with a frame count of 4532 will produce frame periods of 39.989 ms for QCIF and 39.938 ms for SIF.

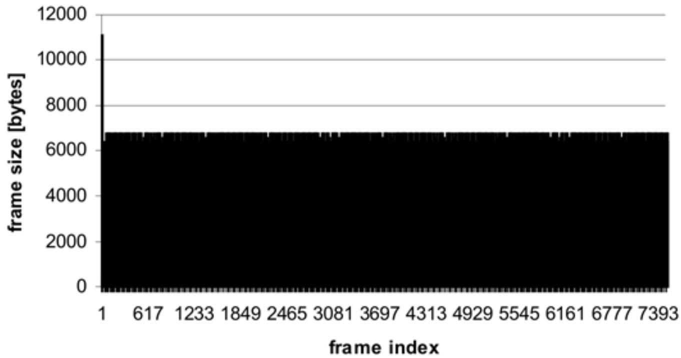
TABLE 2: Overview of the statistical summary of the encoded video frame sizes

Video Format	Mean ($\overline{X}$)	CoVx $S_X / \overline{X}$	Peak / Mean $X_{\max} / \overline{X}$	Mean bit rate $\overline{X} / t$ [kbps]	Peak bit rate $X_{\max} / t$ [kbps]
QCIF (600)	6340.60	0.073	1.749	158.559	277.376
QCIF (64)	895.368	0.609	4.829	22.390	108.130

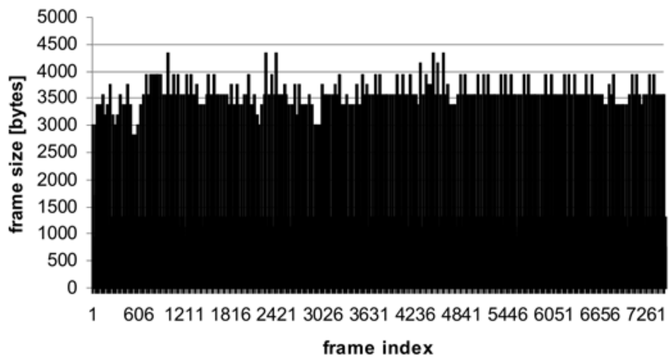
SIF (600)	3049.86	0.838	14.102	76.364	1076.86
SIF (150)	768.224	1.759	18.661	19.235	258.956

It can be observed from Table 2 above that low bit rate encodings have low mean values and low bit rates rather than the high bit encodings. However, it is also observed from the coefficient of variation CoVX values that these low mean and low bit rates values come at the expense of high variability.

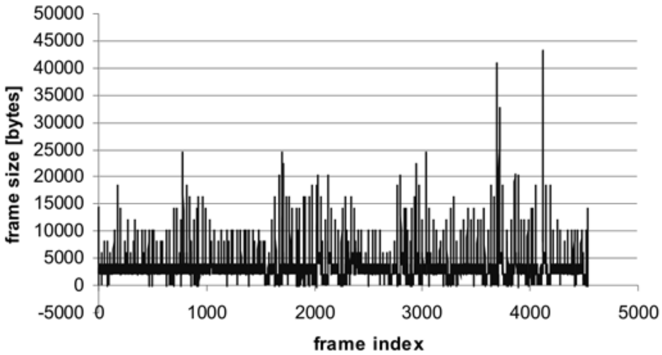
Figure 2 below gives the plots of the frame size Xn (in bytes) as a function of the frame number n for both QCIF ('talking head') and SIF ('Mr Bones').



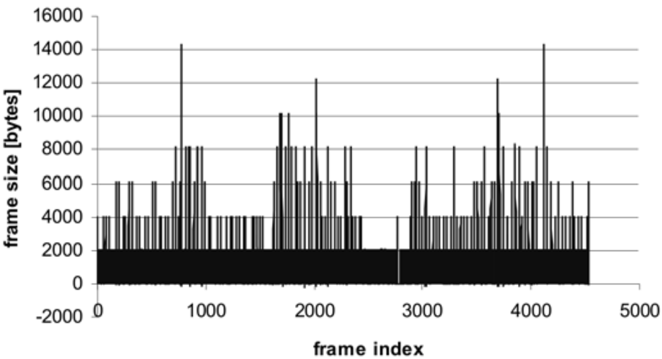
(a) Frame sizes of encoded 'talking head' (QCIF 600 kbps)



(b) Frame sizes of encoded 'talking head' (QCIF 64 kbps)



(c) Frame sizes of encoded 'Mr Bones' (SIF 600 kbps)

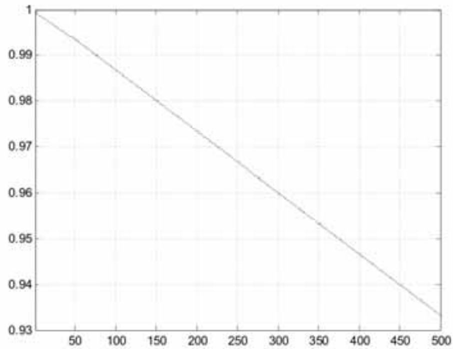


(d) Frame sizes of encoded 'Mr Bones' (SIF 150 kbps)

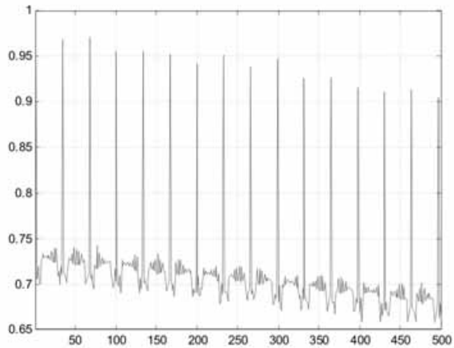
Figure 2: Frame size traces of the encoded videos

It can be observed from the plots that QCIF encoding at high target rate (600 kbps) is relatively smooth for “talking head', while the encoding at low target rate (64 kbps), on the other hand, exhibits extreme changes in the frame sizes.

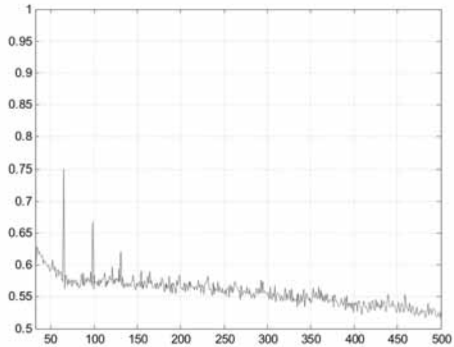
Figure 3 gives the autocorrelation coefficient ρx(k) of the frame size sequence Xn, n = 1, 2, 3, …, N, as a function of the lag k in frames.



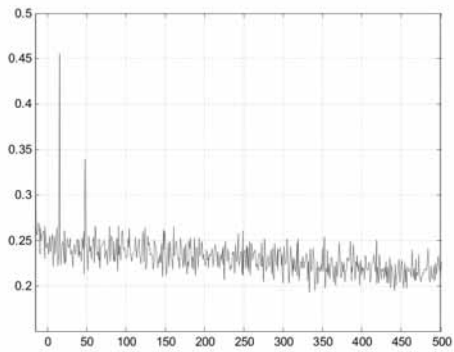
(a) Autocorrelation of frame size trace (QCIF 600 kbps)



b) Autocorrelation of frame size trace (QCIF 64 kbps)



(c) Autocorrelation of frame size trace (SIF 600 kbps)



(d) Auto correlation of frame size trace (SIF 150 kbps)

Figure 3: Autocorrelation of traces of the encoded videos

From the autocorrelation function plots of the frame sizes, in Figure 3 it is observed that the autocorrelation of the frame size series {X0, X1, X2, …, XN-1}consists of a periodic spike pattern, which are superimposed on a decaying curve. The periodic spike pattern reflects the repetitive GoP pattern, where the large spikes represent I frames and the subsequent small spikes represent P frames. The last three plots consist of a fast and a slow decaying slope, which according to [5, 12, 16, 17], is a sign of short and long range dependence. The coexistence of short range dependence (SRD) and long range dependence (LRD) is a sign that variable bit rate (VBR) video traffic is similar to that of a of a SRD at small time lags, and that of LRD at large time lags.

To assess the long-range dependence properties of the encoded video sequences, the Hurst parameter must be determined [12, 18, 19]. There are several methods for determining the Hurst parameter, however, the most commonly used ones includes the R/S statistic plot, Variance-time plot, Periodogram plot, and Whittle estimator [5, 10, 17, 19, 20]. According to [5, 6, 8, 9, 10, 11, 12] and [17] - [21], the Hurst parameters between 0.5 and 1 indicate long-range dependence. This long range dependence is the main feature or characteristic property of self-similar processes; that is, the long range dependence implies that the process is self-similar [13, 33]. The traffic which exhibits this long range dependence or self-similarity also exhibits high variability [33] and is usually referred to as fractal traffic [5, 22, 23, 33].

For this study the variance-time plot method, which is a heuristic graphical method to estimate the Hurst parameter, has been used. This method relies on the fact that a self-similar process has slowly decaying variances. The variance-time plot is obtained by plotting the normalised variance of the aggregated trace $S_X^{2(a)} / S_X^2$ as a function of the aggregated level a in a log-log plot as shown in Figure 4. Where the variance of the aggregated trace is given by

$$S_X^{2(a)} = \frac{1}{(N/a)-1} \sum_{n=0}^{(N/a)-1} \left(X_n^{(a)} - \overline{X}\right)^2 \qquad (1.5)$$

and the aggregated frame size series $X_n^{(a)}$ is derived from the original trace X_n by averaging it over non-overlapping blocks of length a as follows

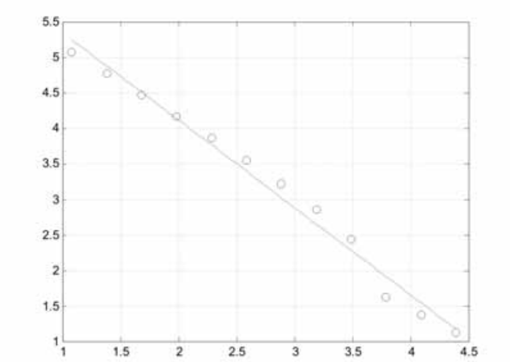
$$X_n^{(a)} = \frac{1}{a} \sum_{j=na}^{(n+1)a-1} X_j \quad \text{for } n = 0, 1, 2, \ldots (N/a)-1 \qquad (1.6)$$

Once the plot is obtained, the slope of the linear part of the variance-time plot is estimated using a least squares fit, and thereafter, the Hurst parameter is then estimated as

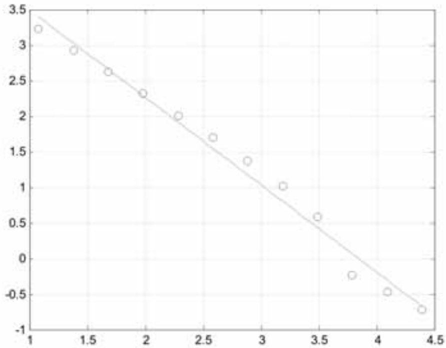
$$H = 1 - \frac{\beta}{2} \quad 0 < \beta < 1 \qquad (1.7)$$

[5, 9, 13, 24, 32] where H is the Hurst parameter and β is the slope.

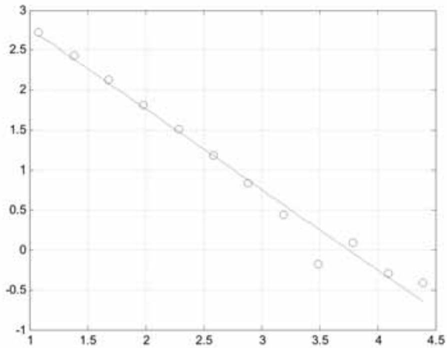
For all of the variance time plots in Figure 4 the initial value of a is 12 and then each iteration is multiplied by 2; that is, a = {12, 24, 48, 96, …, 6144}. The plots are generated using Matlab and they are shown in Figure 4: the straight line is used to estimate the slope of the variance plot, and the values of the Hurst parameter are given in Table 3.



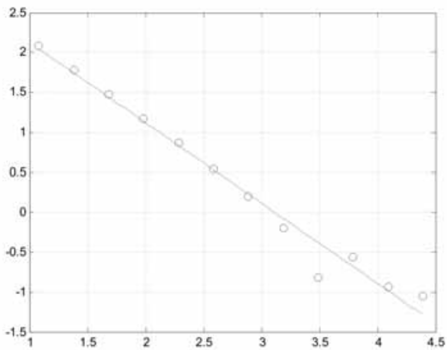
(a) Variance-time plot of 'talking head' (QCIF 600 kbps)



(b) Variance-time plot of 'talking head' (QCIF 64 kbps)



(a) Variance-time plot of 'Mr Bones' (SIF 600 kbps)



(d) Variance-time plot of 'Mr Bones' (SIF 150 kbps)

Figure 4: Aggregated variance-time plots for the videos

TABLE 3: SLOPE AND HURST PARAMETERS

Video format	Average Bit rate	Slope (β)	Hurst parameter (H)
QCIF	600	-0.763	0.619
QCIF	64	-0.763	0.619
SIF	600	-0.841	0.579
SIF	150	-0.841	0.579

All the values of the slope are greater than -1, which according to [21] and [24] indicates self-similarity when using a variance-time plot method. The values of the estimates of Hurst parameter are between 0.5 and 1, which also confirms the self-similarity or 'fractality' of the encoded video sequences.

4. VBR VIDEO MODEL

From the plots in Figures 3 and 4, it can be observed that VBR video traffic streams exhibit the phenomenon referred to as short range dependence as well as long range dependence and self-similarity, which is in agreement with [12, 14, 25, 26, 27, 28, 33, 35]. Furthermore, Figure 2, plots (b) through (d), shows that the video traffic also has another fractal property called 'burstiness' or impulsiveness, especially the action movie, which is in agreement with [4, 6, 7, 8, 12, 15], and this bit variability increases with compression ratios, which is in agreement with [5]. Traffic which behaves in this way is usually referred to as fractal traffic, and according to [5, 16], fractal traffic cannot be sufficiently represented by traditional models, but instead can be more accurately matched by self-similar or fractal models.

Self-similar models include Fractional Gaussian Noise (FGN), Fractional Brownian Motion (FBM), Linear Fractional Stable Motion (LFSM), and asymptotically self-similar Fractional Autoregressive Integrated Moving-Average (FARIMA, sometimes called ARFIMA). While the first three models are used mainly to generate pure self-similar signals [25, 29, 34, 35], FARIMA models are used [13, 14, 15, 32, 34] for video. Their advantage is that, unlike other models which only capture the LRD and not SRD, they can model both long time dependence and short time dependence; that is, LRD and SRD at the same time [16, 23, 30, 31]. Since it was also found from the empirical data that the VBR video also possesses significant SRD, using either an LRD or SRD model alone will not provide satisfactory results [26]. Thus, a more suitable model will be the one that is able to capture both SRD and LRD properties of VBR video such as FARIMA model.

Fractional ARIMA or FARIMA came as a natural extension of the standard Autoregressive Integrated Moving-Average (ARIMA) model [22], which was popularised by Box and Jenkins in 1994. FARIMA is built on a classical ARIMA model by allowing the degree of differencing d in ARIMA (p, d, q) to take non-integer values [12, 23, 30]. According to [12, 23, 30, 31], the FARIMA model is defined by

$$X_t = \Phi(B)^{-1}\Theta(B)\Delta^{-d} \in_t \quad (1.8)$$

Rearranging equation 1.8 we get

$$\Phi(B)X_t = \Theta(B)\Delta^{-d} \in_t \quad (1.9)$$

where d is the fractional difference parameter, which according to [12, 23, 29, 30] can be derived from the Hurst parameter as follows

$$d = H - \frac{1}{2} \quad (1.10)$$

Φ(B) and *Θ(B)* are the p^{th} and q^{th} degree polynomials

$$\Phi(B) = 1 - \sum_{j=1}^{p} \phi_j B^j \quad (1.11)$$

and

$$\Theta(B) = 1 + \sum_{j=1}^{q} \phi_j B^j \quad (1.12)$$

representing Autoregressive (AR) and moving-average (MA) components respectively, ϕ_j are the coefficients of the filter, and *B* is the backward operator defined by

$$BX_t = X_{t-1}, B^2 X_{t-2} = X_{t-2}, \ldots, \quad (1.13)$$

Bj denotes the backward operator iterated *j* times, and *Δ* is the difference operator that is defined by

$$\Delta X_t = X_t - X_{t-1} = (1 - B)X_t \quad (1.14)$$

Δ^d is *Δ* iterated d times, and

$$\Delta^{-d} = (I - B)^{-d} = \sum_{j=0}^{\infty} b_j(-d)B^j \quad (1.15)$$

where b_j are moving average coefficients with b0(-d) = 1 and

$$b_j(-d) = \prod_{k=1}^{j} \frac{k + d - 1}{k}$$

$$= \frac{\Gamma(j+d)}{\Gamma(d)\Gamma(j+1)} \quad j = 1, 2, \ldots, \tag{1.16}$$

Graphically the FARIMA(p, d, q) process is illustrated in Figure 5 below.

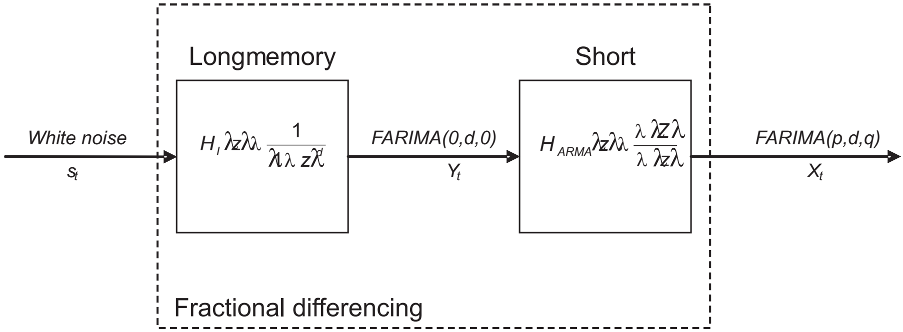


Figure 5: Linear model for the FARIMA(p, d, q) process

5. TRAFFIC GENERATION USING FARIMA

To test the performance of the proposed model, a synthetic traffic is simulated using FARIMA time series with J = 1000, and H = 0.579, which is equal to the Hurst parameter for 'Mr Bones' movie. The generated synthetic video trace is shown in Figure 6 and its autocorrelation function is shown in Figure 7.

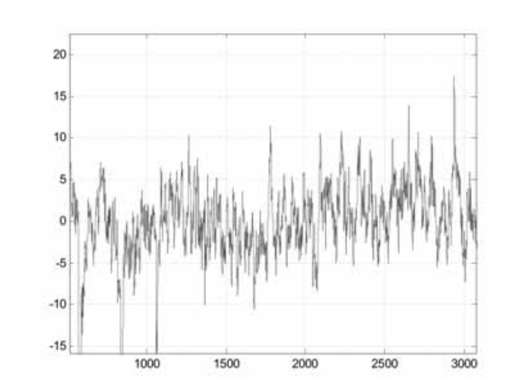


Figure 6: Synthetic video trace based on FARIMA(1,d,1)

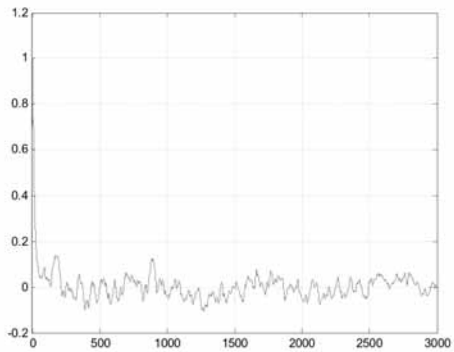


Figure 7: Auto correlation of the synthetic trace

6. CONCLUSION

The statistical analysis of the empirical traces shows that the H.264 encoded video exhibits self-similar characteristics with both short-range and long-range dependency. According to literature, fractional autoregressive moving average (FARIMA) is the best choice to model such traffic hence it is used in this study.

From the generated synthetic trace it can be concluded that FARIMA is able to produce a highly variable signal. The autocorrelation function is used to validate the developed model and the autocorrelation plot reveals that the generated synthetic trace consists of a fast decaying slope at small time lags (i.e. at the beginning) which is a sign of short-range and thereafter a slow decaying slope at large time lags, which is a sign of long-range dependence.

Therefore, the developed model has managed to capture short range dependence as well as all the fractal properties of the video traffic, which include high variability or 'burstiness', long range dependence and self-similarity. Thus, FARIMA is a self-similar model can be implemented as a VBR video traffic source model for H.264 encoded video because it captures almost all the characteristics of the real H.264 video traffic.

7. REFERENCES

[1] Sikora T., “Trends and Perspective in Image and Video Coding”. Proceedings of the IEEE, Vol. 93, No. 1, pp. 6-17, January 2005.
[2] Sullivan G.J. and Wiegand T., “Video Compression From Concepts to H.264/AVC Standard”. Proceedings of the IEEE, Vol. 93, No. 1, pp. 18-31, January 2005.
[3] Etoh M. and Yoshimura T., “Advances in Wireless Video Delivery”. Proceedings of the IEEE, Vol. 93, No. 1, pp. 111-122, January 2005.

[4] Van der Auwera G., David P.T., Reisslein M. and Karam L.J., “Traffic and Quality Characterization of the H.264/AVC Scalable Video Coding Extension,” Advances in Multimedia, Vol. 2008, Article ID 164027, 27 pages, 2008.
[5] Reljin I., Samčović A. and Reljin B., “H.264/AVC Video Compressed Traces: Multifractal and Fractal Analysis.” EURASIP Journal on Applied Signal Processing, Article ID 75217, pp. 1-13, 2006.
[6] Van der Auwera G., David P.T. and Reisslein M., “Traffic Characteristics of H.264/AVC Variable Bit Rate Video”. IEEE Communications Magazine, Vol. 46, No. 11, pp. 164-174, November 2008.
[7] Van der Auwera G., David P.T. and Reisslein M., “Traffic and Quality Characterization of Single-Layer Video Streams Encoded with the H.264/MPEG-4 Advanced Video Coding Standard and Scalable Video Coding Extension”. IEEE Transactions on Broadcasting, Vol. 54, No. 3, part 2, pp. 698-718, September 2008.
[8] Lima A.B. and Amazonas, J.R.A., “State-Space Modeling of Long-Range Dependent Teletraffic”. Proceedings of 20th International Teletraffic Congress, Ottawa, Canada, pp. 260-271, June 17-21, 2007.
[9] Rohani M.F., Maarof M.A., Selamat A. and Kettani H., “Uncovering Among Traffic Based on Loss of Self-Similarity Behavior Using Second Order Statical Model”. International Journal of Computer Science and Network Security (IJCSNS), Vol. 7, No. 9, pp. 116-122, September 2007.
[10] Chen L.-J., Chen Y.-C, Sun T., Sreedevi P., Chen K.-T., Yu C.-H. and Chu H.-H., Finding Self-Similarities in Opportunistic People Networks”. International Conference on Computer Systems and Technologies (CompSysTech'08), Gabrovo, Bulgaria, 12-13 June 2008.
[11] Gospodinova E. and Gospodinov M., “Modeling of network traffic with self-similar process”. International Conference on Computer Systems and Technologies (CompSysTech'08), Gabrovo, Bulgaria, 12-13 June 2008.
[12] Chen T.M. and Bidgoli H. (ed), Network Traffic Modeling, Chapter in Handbook of Computer Networks, Vol. 3, Wiley, 2008.
[13] Rezaei M., Bouazizi I. and Gabbouj M., “Generating Antipersistent VBR Video Traffic”. Proceedings of Picture Coding Symposium 2007, Lisbon, Portugal, 7-9 November 2007.
[14] Tamimi A.K.A, Jain R. and So-In C., "SAM: A Simplified Seasonal ARIMA Model for Mobile Video over Wireless Broadband Networks”. Proceedings of the 2008 Tenth IEEE International Symposium on Multimedia (ISM 2008), pp. 178-183, Berkeley, CA, December 15-17, 2008.
[15] Taute R., “Modeling of Internet Traffic”. Proceedings of Southern African Telecommunications and Applications Conference (SATNAC 2006), Cape Town, 3-6 September 2006.
[16] Huang C., Devetsikiotis M., Lambadaris I. and Kaye A.R., Self-Similar Modeling of Variable Bit Rate Compressed Video: A Unified Approach. Proceedings of ACM SIGCOMM '95. Cambridge, Massachusetts, August 30 - September 1, 1995.
[17] Fitzek F. and Reisslein M., MPEG-4 and H.263 Video Traces for Network Performance Evaluation. IEEE Network, Vol. 15, No. 6, pp.40-54, November/December 2001

[18] Tatipamula M. and Khasnabish B. (editors), Multimedia Communications Networks: Technologies and Services. Artech House, London. 1998.
[19] Seeling P., Reisslein M. and Kulapala B., Network Performance Evaluation Using Frame Size and Quality Traces of Single-Layer and Two-Layer Video: A Tutorial. IEEE Communication Surveys & Tutorials, Third Quarter 2004, Vol. 6, No. 3, pp. 58-78.
[20] Droz P. and Le Boudec J.-Y., A High-Speed self-similar ATM VBR Traffic Generator. Proc. of Globecom96, pp. 586--590, November 1996.
[21] Hlavacs H., Kotsis G. and Steinkellner C., Traffic Source modeling. Technical Report No. TR-99101, Institute of Applied Computer Science and Information Systems, University of Vienna, Austria
[22] Leland W.E., Taqqu M.S., Willinger W. and Wilson D.V., On the Self-Similar Nature of Ethernet Traffic (Extended version). IEEE/ACM Transactions on Networking, Vol. 2, No. 1, pp. 1-15, February 1994.
[23] Harmantzis F. and Hatzinakos D., Heavy Network Traffic Modeling and Simulation using Stable FARIMA Processes. Proceedings of the 19th International Teletraffic Congress (ITC19), Beijing, China, September 2005.
[24] Gospodinov M. and Gospodinova E., The graphical methods for estimating Hurst parameter of self-similarity network traffic. Proceedings of International Conference on computer Systems and technologies CompSysTech'2005, 16 - 17 June 2005, Technical University, Varna, Bulgaria.
[25] Garret M.W. and Willinger W., Analysis, Modeling and Generation of Self-Similar VBR Video Traffic. Proceedings of ACM SIGCOMM, August 1994.
[26] Dai M. and Loguinov D., A Unified Traffic Model for MPEG-4 and H.264 Video Traces. Texas A&M Technical Report, May 2005
[27] Beran J. et al., Variable-Bit Rate Video Traffic and Long Range Dependence. IEEE Trans. Commun., Vol. 43, No.2/3/4, pp. 1566-1579, 1995.
[28] Ma S. and Ji C., Modelling Heterogeneous Network Traffic in Wavelet Domain. IEEE/ACM Trans. On Networking, Vol. 9 October 2001.
[29] Casilari E., Ríos E. and Sandoval F., Characterisation of MPEG Video Traffic Correlation. Proceedings of IEEE Workshop on IP-oriented Operations & Management IPOM'2000, Cracovia (Polonia), pp. 173-180, Septiember 2000.
[30] Stoev S. and Taqqu M.S., Simulation methods for linear fractional stable motion and FARIMA using Fast Fourier Transform. Fracttals, Vol.12, No. 1, pp. 95 121, 2004.
[31] Xue F, Liu J., Shu Y. and Zhang L., "Traffic Modeling Based on FARIMA Models". Proceedings of 1999 IEEE Canadian Conference on Electrical and Computer Engineering, Vol. 1, pp. 162-167, Edmonton, Alta, Canada, 1999.
[32] De la Cruz L.J., Pallarès E., Alins J.J. and Mata J., Self-Similar traffic generation using a fractional ARIMA model. Application to VBR MPEG video traffic. Proceedings of SBT/IEEE International Telecommunications Symposium, 9-13 August 1998.
[33] Millán G. and Lefranc G., Presentation of an Estimator for Hurst Parameter for a Self-Similar Process Representing the Traffic in IEEE 802.3

Networks. International Journal of Computers, Communications and Control, Vol. IV, No. 2, pp. 137-147, 2009.
[34] Zou Q., Feng D., Zhu Y., Jiang H., Ge X. and Zhou Z., A Novel and Generic Model for Synthesizing Disk I/O Traffic Based on The Alpha-stable Process. Proceedings of the IEEE International Symposium on Modeling, Analysis and Simulation of Computers and Telecommunication Systems (MASCOTS 2008), pp. 1-10, 8-10 September 2008.
[35] M. Dai, Y. Zhang and D. Loguinov, A Unified Traffic Model for MPEG-4 and H.264 Video Traces (extended version), Texas A&M Technical Report 2009-4-3, April 2009. [online]. Available from
http://irl.cse.tamu.edu/people/min/papers/tmm2009-tr.pdf