Modeling and Generation of AVC and SVC-TS Mobile Video Traces for Broadband Access Networks

Abdel Karim Al Tamimi
Washington University in Saint Louis
Department of CSE,
1 Brookings Dr, St. Louis, MO 63130
+1 314-266-9877
aa7@cse.wustl.edu

Raj Jain
Washington University in Saint Louis
Department of CSE,
1 Brookings Dr, St. Louis, MO 63130
+1 314-322-8092
jain@cse.wustl.edu

Chakchai So-In
Washington University in Saint Louis
Department of CSE,
1 Brookings Dr, St. Louis, MO 63130
+1 314-629-0101
cs5@cse.wustl.edu

ABSTRACT
We propose a simple model that is capable of capturing the statistical characteristics of mobile video traces encoded using MPEG4-Part2, AVC and SVC-TS encoding standards. The model can be adjusted to adapt to diverse workload configurations, which gives fellow researchers a great flexibility to evaluate different network traffic scenarios. We also discuss the model-based trace generator and the challenges of its implementation. Moreover, we present the simulation results validating the model using different encoding settings. In addition to that, we provide several insights about our video modeling approach. This will help in testing, simulating and validating mobile video transmission and resource scheduling strategies over broadband wireless networks such as WiMAX and LTE..

Categories and Subject Descriptors
I.6.4 [**Simulation and Modeling**]: Model Validation and Analysis; C.4 [Performance of Systems]: Modeling Techniques.

General Terms
Algorithms, Measurement, Performance, Design, Experimentation, Verification.

Keywords
Mobile Video, Workload Characterization, Traffic Generation, Video Coding, Broadband Wireless Networks, AVC, SVC, SAM Model, Seasonal ARIMA, .

1. INTRODUCTION
Mobile video traffic is gaining an increased share of access networks and Internet resources. This trend has caused an increased interest in researching the behavior of mobile video communications in order to design better resource management and allocation strategies that can support the needed level of quality of service (QoS) required by the mobile users.

Simulation provides an easy means to analyze different resource allocation strategies. While simulation environments like NS/2 provide the means to create the necessary network topology, there is still a need to provide an accurate workload for the test scenarios. The workload should represent the real world traffic accurately and should be easy to administer and adjust to different simulation conditions.

There are two ways to provide traffic workloads for mobile video simulations: actual video traces used by trace-driven simulations, and statistical models that can be used to generate the required video sequences for the simulations. Fig. 1 illustrates the two approaches. Statistical modeling requires additional step of analyzing the video traces and modeling them in order to generate the sequences that represent the statistical characteristics of real videos.

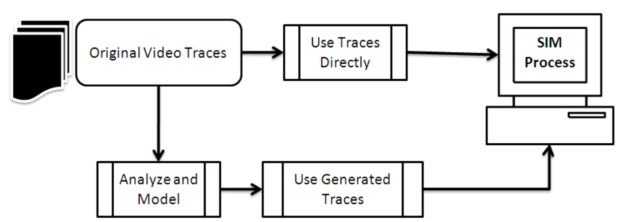


Figure 1. Trace versus statistical model workload

Trace-driven simulations are known for their credibility. It is easy to convince others that the workload is representative and accurate since a real frame trace is used in the analysis. On the other hand, their usefulness and flexibility are questionable. It is hard to adjust any parameter or to extend the trace if there is a need for continuing simulations beyond the frames available in the trace file. Even if a shorter trace is required, it is not easy to determine the starting point in the trace [1, 2].

Statistical traffic models are considered a better workload choice since they provide a better understanding of the tradeoffs of the various traffic characteristics. Once a representative model is obtained, it is easy to change and adapt it to different workload parameters. Most of the statistical models are complex and require a significant amount of time to verify and implement. A simple statistical model is, therefore, preferred as long as it closely represents the real network traffic.

The lack of good and simple video models has deterred researchers from considering statistical models as an option for their simulations. Although, there have been many attempts to provide such models, these attempts have been marked as complex, and hard to implement. In addition to that, many of these approaches were developed by working only on short movie scenes. In order to obtain a reliable and meaningful statistical model, long movie traces with thousands of frames need to be examined [3-9].

In this paper, we propose a statistical model using a seasonal auto regressive integrated moving average (ARIMA) model to represent different video traces encoded with different encoding techniques: MPEG4-Part2, Advanced Video Coding (AVC) and Scalable Video Coding with Temporal Scalability (SVC-TS).

The novelty of our contribution lies in the fact that one model can be used to represent different videos traces that are encoded with different encoding parameters, different encoding standards, and are statistically diverse. The results we are presenting confirm our conclusion that our approach is valid, and thus allows a great flexibility in video modeling.

We also provide the tools that we developed so that fellow researchers can use, extend and improve them. Through this contribution we aims to have a greater impact on other fields of research such as network scheduling optimization, where the knowledge of video traffic characteristics helps to provide a better QoS support.

This paper is organized as follows: Section 2 presents the statistical model and its validation for MPEG4-Part2 encoded videos. Section 3 discusses the modification of the model to represent AVC encoded video traces. Section 4 describes our findings of modeling SVC video traces. Section 5 illustrates the usage of our trace generator to produce the needed video sequences for simulations. Finally, Section 6 concludes our results and explains our future work.

2. MODELING MPEG4-PART2 TRACES

ARIMA is a process in which auto-regression analysis, differencing, and moving average methods are used to fit time series data [10, 11]. ARIMA has three main parts: autoregressive (AR), integrated or differencing (I), and moving average (MA). ARIMA models are usually represented as ARIMA(p, d, q), where p is the order of the autoregressive part, d is the order of differencing part, and q is the order of moving average part. ARIMA models can be implemented using simple equations. For example, ARIMA(1,1, 1) can be described as

$$y(t) = w(t) + y(t-1) + \phi(y(t-1) - y(t-2)) - \theta w(t-1) \quad (1)$$

where $w(t)$ is the error term at time *t*, ϕ is the coefficient of the AR part and θ is the coefficient of the MA part of the ARIMA model.

Seasonal ARIMA (SARIMA) is an extension to ARIMA model to express series that exhibit periodic or seasonal behavior. Seasonal ARIMA is described as ARIMA (p, d, q) × (P, D, Q)s. P, D, and Q represent the order of seasonal AR (SAR) part, the order of seasonal differencing part, and the order of the seasonal MA (SMA) part, respectively. S represents the seasonality of the series (e.g., month seasonality in a year is 12) [11].

A statistical model to represent MPEG4-Part2 video traces using SARIMA model class called Simplified Seasonal ARIMA (SAM) was proposed in [10]. SAM views mobile video traffic as a time-series of frames clustered as group of pictures (GoPs). Using ARIMA representation, the simplified seasonal ARIMA model or SAM can be written as

$$SAM = (1,0,1) \times (1,1,1)^{s} \quad (2)$$

This equation indicates that SAM has one autoregressive (AR) coefficient, no differencing, and one moving average (MA) coefficient (1,0,1). The seasonal behavior includes one seasonal autoregressive coefficient, one seasonal differencing coefficient, and one seasonal moving average coefficient (1,1,1). In MPEG4-Part2, the seasonal period s is equal to the GoP size. In all, there are 5 coefficients for SAM including the modeling error. The modeling error is used in the simulation to perform Monte Carlo random number generation [11-13].

In this section we extend our testing of the model and present the results of our analysis of several full movie traces. The video traces represent the following movies: the Lord of The Rings (LOTR) trilogy, and the Matrix trilogy. These traces have the following common video encoding parameters: MPEG4-Part2 coding using advanced simple profile (ASP), CIF size (352x288), with frame rate of 25fps using a variable bit rate (VBR). The GoP structure used is G12B2 with a quantization level of 10 for I, P, and B frames.

Table 1 lists the SAM model parameters for some of the movies that we analyzed. Notice that the variation in parameter values is small. Not only we can use one model, we can also use one set of parameters to represent a group of movies that belong to the same genre.

Table 1. SAM model parameters values for various movies

	AR	*MA*	*SAR*	*SMA*
LOTR 1	0.9262	-0.6911	0.2411	-0.863
LOTR 2	0.9306	-0.6770	0.2715	-0.861
LOTR 3	0.9322	-0.6818	0.2683	-0.844
Matrix 1	0.9241	-0.6561	0.1602	-0.805
Matrix 2	0.9382	-0.6809	0.2336	-0.876
Matrix 3	0.9327	-0.6372	0.1002	-0.895
Mean	**0.93**	**-0.67**	**0.21**	**-0.86**
[Min, Max]	[0.924, -0.938]	[-0.691, -0.637]	[0.1, 0.271]	[-0.895, -0.805]
Abs ([Max-Min]/Mean)	0.0150	0.0805	0.8142	0.1046

The promising results discussed here and in [10] have encouraged us to pursue the possibility of using the model with other common encoding standards: H.264/AVC and SVC-TS. In the following section, we will discuss our method to adapt SAM model to AVC encoded video traces, and our modeling results.

3. MODELING H.264/AVC TRACES

The H.264 standard has shown significant improvements over its predecessors, like MPEG4-Part2 [14, 15]. AVC encoded movies have lower mean values compared to MPEG4-Part2 videos because AVC compression is more complex, and thus, on the downside, it requires more processing power. Long range dependence (LRD) level between video frames has been recorded to be similar to MPEG4-Part2 videos. Because of the new techniques in AVC compression, the encoded videos have higher variability in their frame sizes. Therefore, an accurate model that can represent the highly variable sizes of the video frames is highly valuable. The reader can refer to [14-16] for more information about AVC codec and the characteristics comparison between AVC and MPEG4-Part2 videos.

One of the main differences between MPEG4-Part2 and AVC encoded videos is the multiple-frame reference feature in AVC. This feature results in the change of the seasonality period from s to 2×s, where s is the GoP size as shown in Figure 2.

.

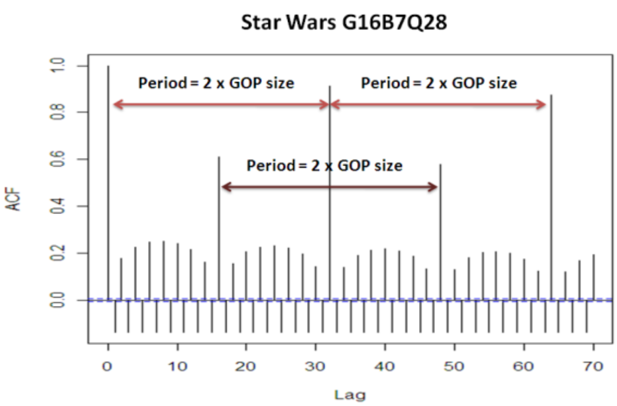


Figure 2. Seasonality in AVC encoded videos

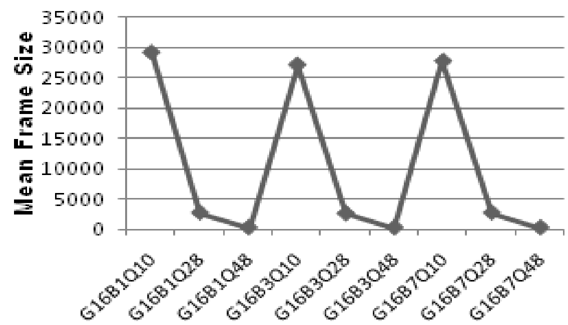
Figure 2 shows the autocorrelation function (ACF) for an AVC coded video. Notice that the repetition period is now equal to 2s, given that the used GoP size is 16 and the observed period is 32. This observation led to the modification of SAM from its previous form to the form shown in equation 3.

$$SAM_{AVC} = (1,0,1)\times(1,1,1)^{2s} \tag{3}$$

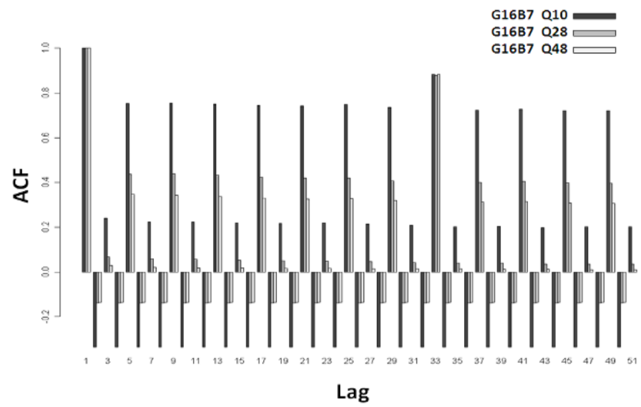
Another way to describe SAM is to represent the seasonality of the model independently of the GoP size. We achieved this by using the interval between the maximum ACF values instead. The interval value can be obtained easily visually or using simple mathematical approaches like comparing the maximum ACF values over a reasonable number of lags.

To further test the applicability of the model, we analyzed several full movie traces encoded with different video encoding settings. Through our analysis, we noticed that different quantization levels will result in scaling the frames sizes up and down without interfering with their autocorrelation, as shown in Figure 3(b). We have chosen GoP structure of G16B7 with a quantization level of 28 (I=28, P=28, B=30) as a good compromise of the quality and the size of video frames.

Increasing the quantization parameter (QP or Q) results in a lower frame sizes, lower quality, and requires more computational power to decode on the receiver side. Q28 is a good choice compared to Q10, and Q48 as shown in Figure 3(a). Our decision is based on the fact that Q28 does not result in large frame sizes, compared to Q10, and does not require extensive computational power, compared to Q48. A quantization level of 28 (Q28) is close to the AVC JM reference software [25] default values (I=24,P=24,B=24) as well.



(a) Quantization effect on mean frame size



(b) Quantization effect on ACF

Figure 3. Quantization level effects on video frames

We have tested our model on the following GoP structures: G16B1, G16B3, and G16B7. We used the following movies : Silence of the Lambs (~30m), Star Wars IV(~30m), the Tokyo Olympics (~74m), a clip of an NBC news broadcast (~30m), and a Sony demo (~10m). We tested several optimized models for AVC encoded traces and compared them against the SAM_{AVC} model. These optimized models are the result of extensive analysis of the video traces to determine the best possible model following the steps in [12]. Our analysis showed that SAM_{AVC} produces Akaike's information criterion (AIC) values that are very close to those for the calculated models. This proves the SAM is capable of producing accurate results without the hassle of performing extensive analysis for each movie trace. We used AIC since it gives a good indication of the goodness-of-fit of statistical models. It describes the tradeoffs between the precision and the complexity of the model. Lower AIC values indicate a better goodness-of-fit for the model. AIC is generally defined as

$$AIC = 2k - 2\ln(L) \tag{4}$$

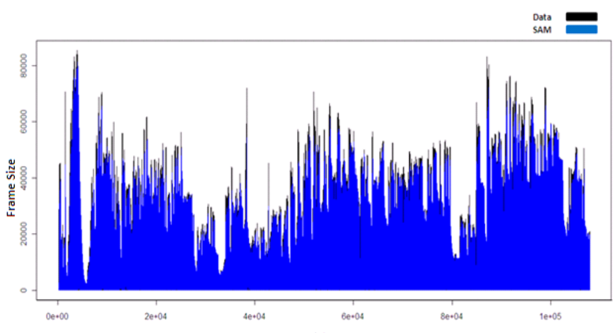
where k is number of the parameters of the statistical model, and L is the maximized value of the likelihood function for the estimated model.

Because SAM_{AVC} is simpler than any of the other calculated models, its AIC results were better than the calculated models. Table 2 shows some of the obtained results.

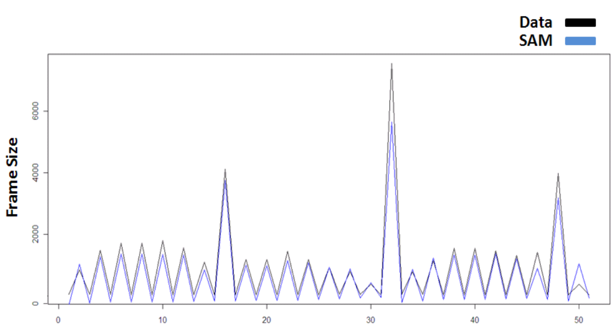
Table 2. Comparison between SAM_{AVC} and calculated models

Movie	Calculated Model	SAM_{AVC} Model
Star Wars IV	$(1,1,1)x(1,1,1)^{32}$	$(1,0,1)x(1,1,1)^{32}$
	AIC = 1045796	AIC = **1040561**
Silence of the Lambs	$(2,2,2)x(1,1,1)^{32}$	$(1,0,1)x(1,1,1)^{32}$
	AIC = 1051632	AIC = **1049195**
Tokyo Olympics	$(2,0,2)x(1,1,1)^{32}$	$(1,0,1)x(1,1,1)^{32}$
	AIC= 2702438	AIC = **2695848**

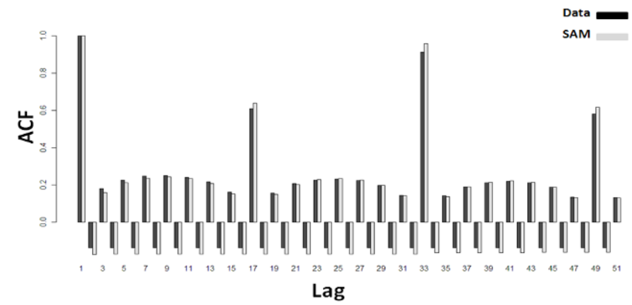
Figure 4 shows some of our results. The figure shows how well the generated trace using SAM_{AVC} for Star Wars IV movie trace compares to the original trace. Notice that the model is capable of representing the modeled traces accurately, which is shown in the full video trace, ACF, and CDF graphs comparisons. Moreover, the results show that SAM_{AVC} is capable of modeling even the sudden transitions of the video frame sizes in the modeled video traces. In our analysis we used both R [21] and SAS softwares [24].



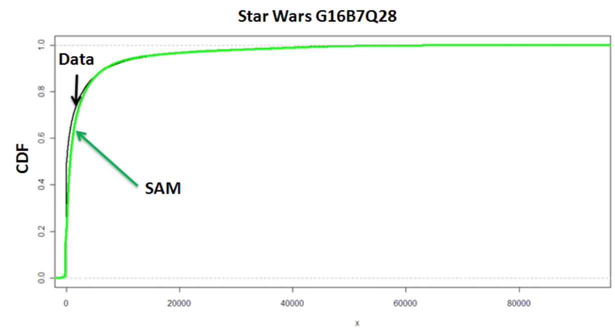
(a) Full trace comparison



(b) Close-up trace comparison



(c) ACF comparison



(d) Cumulative Distribution Function (CDF) Comparison

Figure 4. SAM_{AVC} Comparison Results

We have conducted a similar test on several of the commonly used YUV 4:2:0 reference video sequences available through [26]. To evaluate SAMAVC with different encoding settings, we encoded the video sequences with the following encoding settings, as shown in Table 3.

Table 3. Encoding Parameters for YUV Reference Video Sequences

Parameter	Value
FPS	30
Resolution	CIF (352x288)
Profile	Main & Extended
Decoder Min. Support	CIF and below with 3041280 samples/sec
Number of Reference Frames	3
IDR Period	30
Symbol Mode	CAVLC

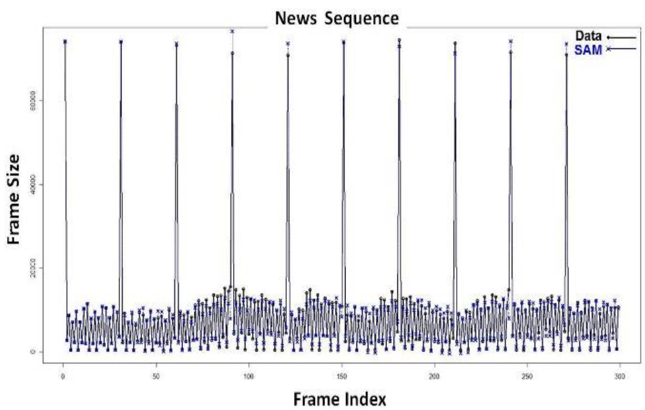
We have encoded the video sequences using Main and Extended profiles with a frame rate of 30fps. We specified the minimum requirement for the decoder to decode CIF resolution videos at 3041280 samples per second. We used instantaneous decoding refresh (IDR) frames with a period of 30, which matches the fps rate. An IDR frame is a special type of I frame that allows better seeking precision and thus enhances the user's experience. We used also Context-Adaptive Variable Length Coding (CAVLC) mode since it is supported by all H.264 profiles, unlike Context-Adaptive Binary Arithmetic Coding (CABAC) mode. We chose these encoding parameters to be close to the suggested settings for HD video in [27].

Table 4 below shows the statistical characteristics of some of the analyzed video sequences, and shows the statistical diversity found in video traces. Hurst index is an indication of the video trace ability to regress to the mean, with higher values indicating a smoother trend, less volatility, and less roughness. Its value varies between 0 and 1.

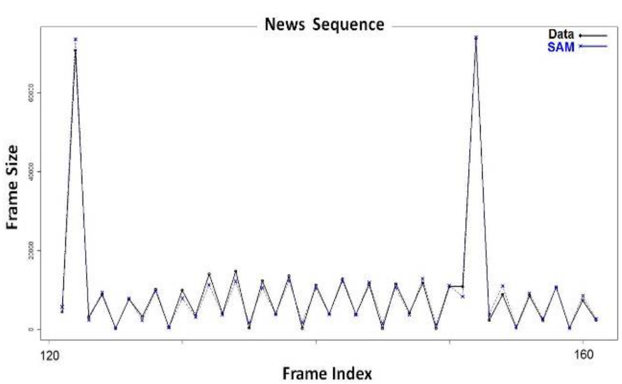
Table 4. Statistical Characteristics of Chosen YUV Video Sequences

Movie	Mean	Max, Min	Hurst Index
Bridge(Close) [1998 frames]	15460	99060,96	0.5491166
News [300 frames]	8602	74490,304	0.4757949
Foreman [300 frames]	15090	137000,264	0.6385751

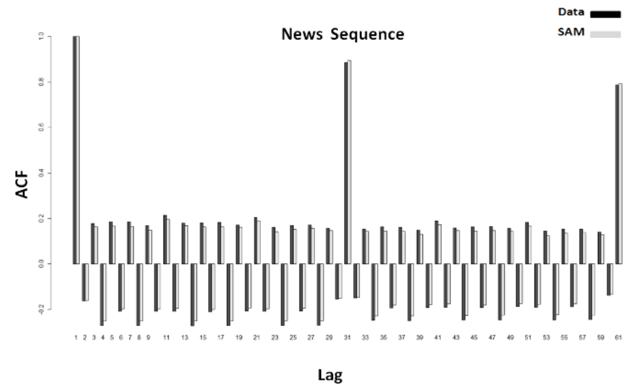
Figure 5 shows a comparison of measured traces and SAM model generated traces for one sample YUV video sequence. Notice that SAM model accurately represents the video sequences.



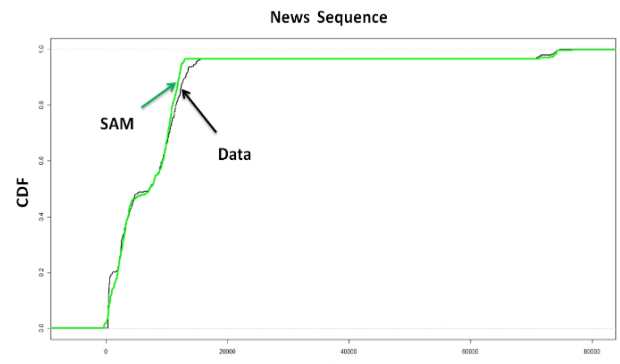
(a) Full comparison [300 frames]



(b) Close-up comparison [frames 120-160]



(c) ACF comparison



(d) CDF comparison

Figure 5. SAM_{AVC} results with YUV reference traces

In this section, we presented our analysis and results of modeling various video traces encoded with different encoding settings using SAM_{AVC} model. In the next section, we will show our analysis and results of modeling SVC-TS encoded video traces.

4. SVC-TS TRACES MODELING

In this section, we discuss our approach to model video traces encoded with the Scalable Video Coding (SVC) extension with emphasis on temporal scalability. SVC provides a better solution to support the wide variety of video quality levels required due to the heterogeneity of hardware and software capabilities of mobile units [15-17]. The two main SVC scalability modes support scalability in two dimensions: spatial and temporal.

Temporal scalability is performed by splitting the frames into a base layer and a hierarchy of enhancement layers. The enhancement layers increase the frame rate of the transmitted video and reference the base layer frames. In spatial scalability, a higher resolution is achieved by assigning a down-sampled resolution to the base layer, then it is combined with one or more enhancement layers.

Temporal scalability, or SVC-TS, is better suited for mobile video devices, since it can meet different bandwidth constraints. It is also better for low power CPU devices [18]. Older video standards encoders support SVC-TS to a certain degree. For instance, AVC encoders did not require any change of the design to support a reasonable number of temporal or enhancement layers [19].

Our analysis of SVC encoded video focused on temporal scalable video. We have tested several movies provided by the same source for MPEG4-Part2 and AVC movie traces [20]. Our analysis has led us to adapt the SAM model to the two different types of layers: base layer, and enhancement layers. We considered in our analysis SVC video traces with base layer (Layer 0) and three enhancement layers. For our analysis, we chose similar encoding parameters to AVC video traces: H.264 SVC single layer, variable bit rate, CIF size, GoP structure of G16B7 with a quantization level of 28 (I=28, P=28, B=30).

SVC encoded video traces are more complex than the traces we previously analyzed. Figure 6 shows the seasonality in SVC coded video traces that led to our formula for SAM_{SVC}. Notice how the enhancement layers correspond to the GoP size s. For example, the seasonality for layer 0, or the base layer, is equal to 2×s, or 32. For enhancement layer 2, the seasonality is equal to s/2, or 8.

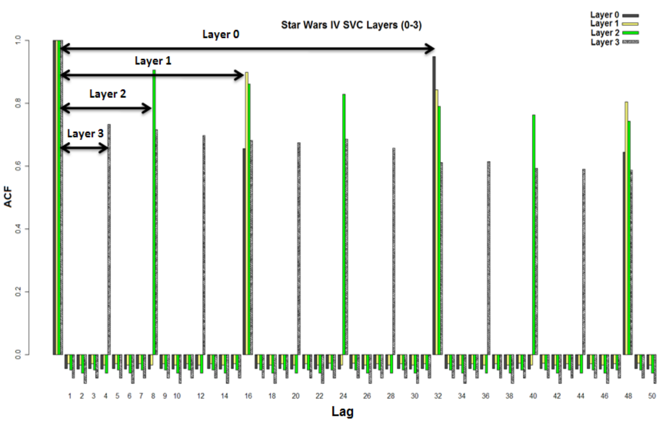


Figure 6. Seasonality in SVC Encoded Video (Star WarsIV)

We have concluded that the following adjustment to the SAM model, as shown in equation 4, is successful in modeling the traces correctly. Here s represents the number of frames between two consecutive I frames, and L represents the layer level. For the base layer, L is zero and SAM_{SVC} will be identical to SAM_{AVC}.

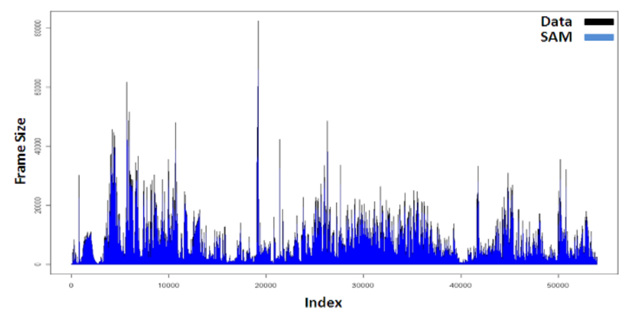
$$SAM_{SVC} = (1,0,1) \times (1,1,1)^{\frac{2 \cdot s}{(2^L)}} \quad (4)$$

Similar to our approach in analyzing AVC video traces, Table 5 shows the difference in AIC values between SAM_{SVC} and calculated models. The AIC values are very close in almost all cases. Again, SAM_{SVC} proves to be a preferred model because of its simplicity and generality.

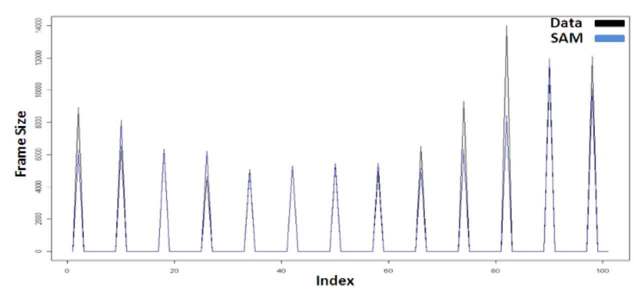
Figure 7 shows some of the results obtained from modeling the Star Wars SVC-TS enhancement layer 1 video trace. Note the ability of SAM_{SVC} to model the layer statistical characteristics correctly as demonstrated by the comparison of the actual trace, ACF, and CDF graphs.

Table 5. Comparison between SAM_{SVC} and the calculated models

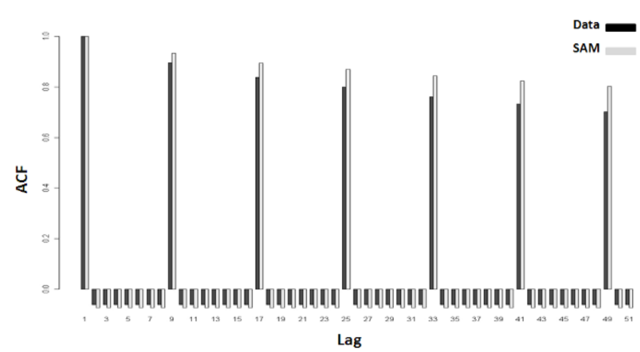
	Layer 0	Layer 1	Layer 2	Layer 3
Movie	**Tokyo Olympics**			
SAM	(1,0,1)x(1,1,1)$^{3}_{2}$	(1,0,1)x(1,1,1)$^{1}_{6}$	(1,0,1)x(1,1,1)$_{8}$	(1,0,1)x (1,1,1)^{4}
AIC	2702089	2434080	2360311	2484516
Cal. Model	$(1,1,1)^{32}$	$(1,1,0)^{16}$	$(1,1,1)^{8}$	$(1,1,1)^{20}$
AIC	2702085	2436772	2361808	2350824
Diff%	~0%	-0.11%	-0.063%	**5.68%**
Movie	**Star Wars IV**			
SAM	(1,0,1)x(1,1,1)$^{3}_{2}$	(1,0,1)x(1,1,1)$^{1}_{6}$	(1,0,1)x(1,1,1)$_{8}$	(1,0,1)x (1,1,1)^{4}
AIC	1071597	947948.2	915773.8	924247.4
Cal. Model	$(1,1,1)^{32}$	$(1,0,1)(1,1,0)^{16}$	$(1,0,1)^{8}$	$(1,1,1)^{4}$
AIC	1071593	952005.8	917630.6	925132.6
Diff%	~0%	-0.43%	-0.2%	-0.1%



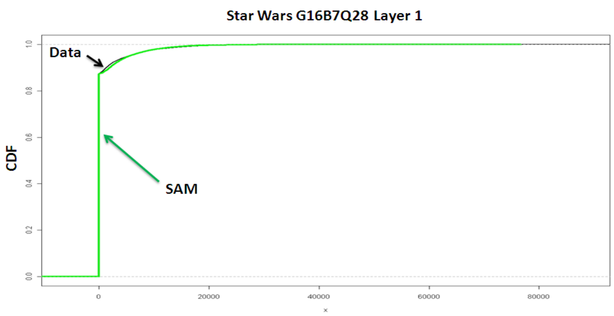
(a) Full simulation comparison



(b) Close-up comparison



(c) ACF comparison



(d) CDF comparison

Figure 7. SAM_{SVC} results

In this section, we demonstrated the validity of SAMSVC and its ability to model several SVC-TS movie traces. In order to facilitate the usage of SAM, we developed a trace generator that is based on the model. The following section will discuss in detail our implementation and our design decisions.

5. SAM-BASED FRAME GENERATOR

In this section we explain the implementation of the SAM frame generator which is capable of generating frames that represent MPEG4-Part2, AVC, and SVC video traces.

As mentioned before, we did our movie trace analysis using the public-domain statistical package R [21]. R provides several tools to model and display the results. In order to generate our video traces, we first tested two mathematical functions provided by R: *arima.sim* and the *gsarima* package's function, called *garsim* [22]. Both functions can simulate ARIMA models but not seasonal ARIMA models. To overcome this obstacle, we had to convert SAM model to an abstracted version as a series of either AR or MA coefficients. This approach is well known to statisticians to simplify model simulations. For more information the readers can refer to [11, 13].

The SAM frame generator incorporates *gsarima* package's *arrep* function as a component of its implementation. *Arrep* is capable of converting ARIMA models to their representations of series of AR coefficients. The SAM traffic generator is capable of generating any specific number of frames, and allows the user either to store the results to a file or to generate a continuous stream to be used with other applications.

One of the challenges in writing the SAM traffic generator is to imitate the sudden transitions and high variations of movies frame sizes. This challenge is due to the fact that the model represents a smoothed version of the modeled traces because of the differencing method used. Therefore, we had to add random shocks in the generated video traces. These random shocks represent the sudden transitions of video frame sizes, and show up as spikes in the video traces. The SAM frame generator includes a simple mechanism that inserts random shocks into the video stream while limiting frame sizes to be within reasonable values (i.e., non-negative frame sizes). Figure 8 shows the measured and generated traces for Matrix 3 movie validating that the random shocks approach works.

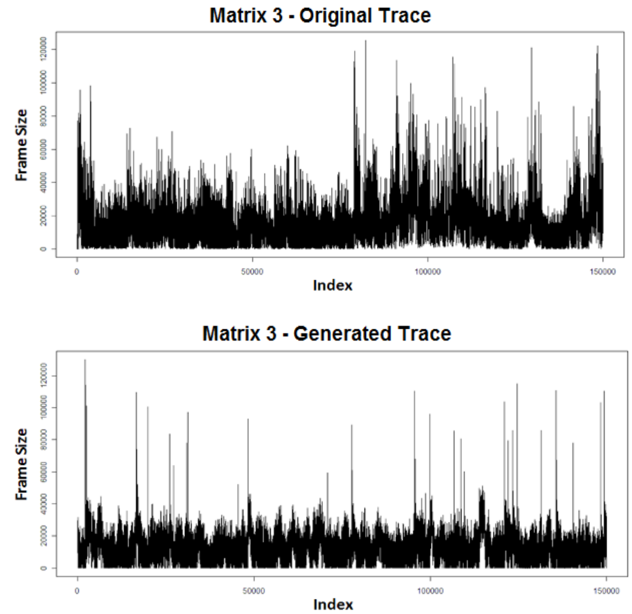
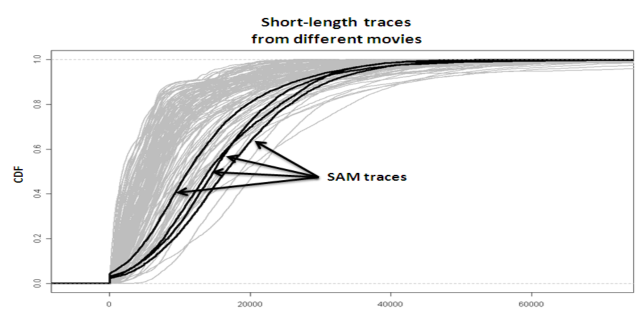


Figure 8. Random shocks implementation in SAM-Sim

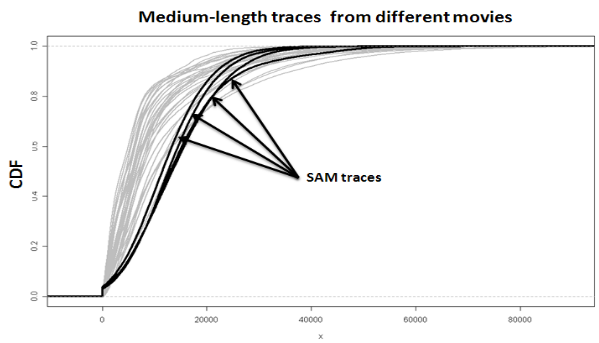
To further test the capabilities of the SAM frame generator to produce valid workloads that closely represent the original traces, we conducted another test. In this test, we generated several traces with different lengths, and compared them to the original movies traces' segments. The traces' lengths were chosen to represent long, medium and short traces as follows:

- Short traces: 5,000 frames
- Medium traces: 30,000 frames
- Long traces: 150,000 frames

Figure 9 shows the comparison between SAM generated traces and the original traces (shown in grey). The original traces represent the six movies traces presented previously in Table I. The generated traces use the mean values of SAM parameters presented in the table. The introduction of random shocks has the side effect of slightly influencing the distribution of frame sizes while the mean frame size is maintained. As a result, the short length traces, presented in 9(a), perform better than medium and long traces presented respectively in 9(b) and 9(c).

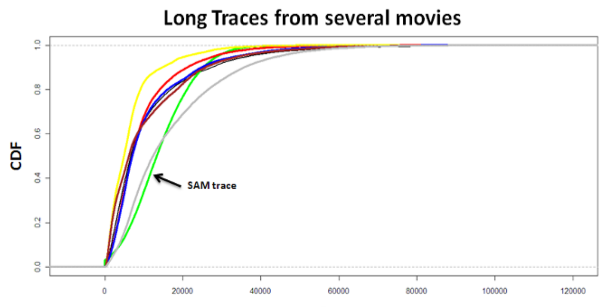


(a) Short length traces comparison



(

b) Medium length traces comparison



(c)Long length traces comparison

Figure 9. CDF comparisons for different traces lengths

Our tools allow further improvements and additions by fellow researchers. For instance, we designed the SAM frame generator to allow additional application protocol layers to be appended easily. As an example, we added seamlessly an additional protocol layer that implements Real-time Transport Protocol (RTP) [23]. Figure 10 shows the GUI interface of the SAM frame generator with RTP add-on implemented using C#.NET. Users can easily specify the SAM model coefficients, encoding method, and the length of the video trace to be generated.

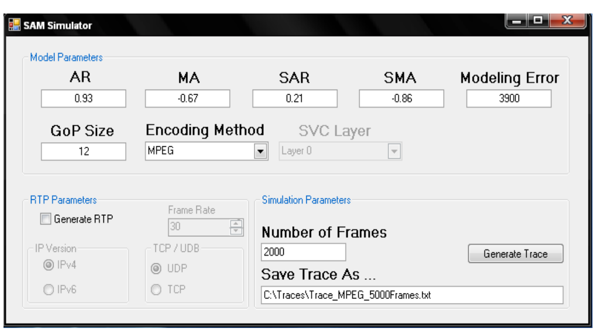


Figure 10. Implementation of SAM frame generator using C#.NET

Figure 11 depicts the design and the addition of the RTP layer, while Figure 12 shows an example of the generated RTP packets compared to an original movie RTP trace, in this case LOTR1. Notice that the generated RTP packets distribution is comparable to the original RTP distribution. In this example, we used a maximum transmission unit (MTU) size of 1500 bytes. Other protocols and packetizing settings can be applied easily.

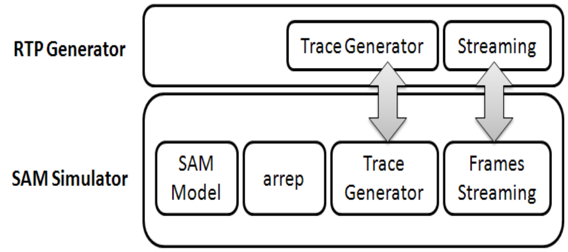


Figure 11. RTP packet generator and SAM frame generator framework

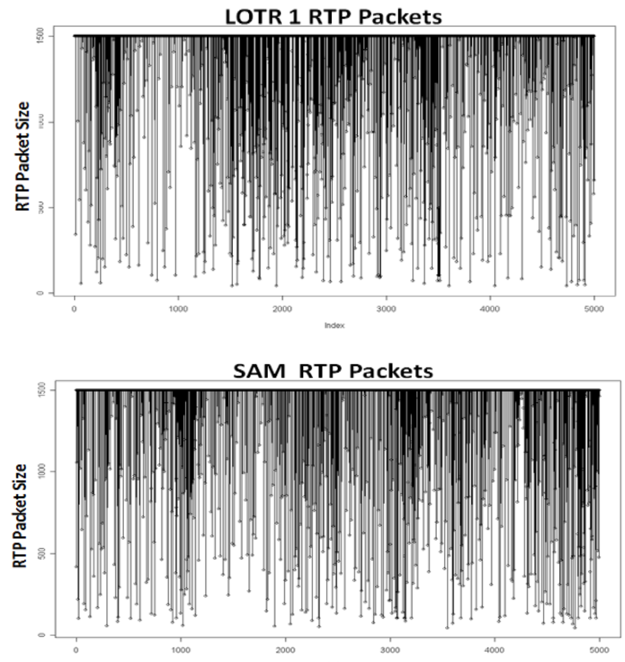


Figure 12. Comparison between the generated and the original RTP packets

In this section we discussed the implementation and the results obtained from the SAM frame generator and the RTP packet generator. The results have shown that the SAM frame generator is capable of generating accurate video workloads that can be used in mobile video simulations. The SAM frame generator implementation allows easy integration of additional protocol layers.

6. CONCLUSIONS AND FUTURE WORK

In this paper, we have provided a simple ARIMA model that is capable of capturing the statistical characteristics of mobile video traces encoded with MPEG4-Part2, AVC, and SVC-TS encoding methods. SAM allows easy adjustments of traffic parameters required for resource allocation studies. SAM has few parameters, and the parameter values for various movies of the same genre may also be similar. This model can be used to generate video sequences that are statistically similar to the original videos.

We have also discussed our implementation of the SAM frame generator and its ability to generate diverse video sequences with various lengths and characteristics. We demonstrated some of the results that we obtained throughout our analysis. Furthermore, we implemented an RTP packet generator to show the ease of adding extra functionalities to the frame generator.

The model helps facilitate the assessment of the QoS strategies for mobile video transmission in upcoming broadband wireless networks, such as those based on WiMAX or LTE. We aim through this contribution to allow better scheduling and admission control mechanisms to maximize the utilization of the scarce bandwidth in these wireless networks.

The tools mentioned in this paper are available at our website [28] and will be available as part of the software archive for the ACM Multimedia Systems Conference.

7. REFERENCES

[1] Raj Jain, "The Art of Computer Systems Performance Analysis: Techniques for Experimental Design, Measurement, Simulation, and Modeling," Wiley 1991. 685 pages

[2] P. Seeking, M. Reisslein, and B. Kulapala, "Network Performance Evaluation with Frame Size and Quality Traces of Single-Layer and Two-Layer Video: A Tutorial", IEEE Communications Surveys and Tutorials, Vol. 6, No. 3, Third Quarter 2004, pp. 58-78.

[3] A. M. Dawood and M. Ghanbari "Content-Based MPEG Video Traffic Modeling," IEEE Transactions on Multimedia, Volume 1, Issue 1, Mar 1999, pp. 77-87.

[4] Yang Sun, and J.N. Daigle, "A Source Model of Video Traffic Based on Full-Length VBR MPEG4 Video Traces," IEEE Global Telecommunications Conference, 2005. GLOBECOM'05, Volume 2, 28 Nov.-2 Dec. 2005, 5 pp.

[5] O. Lazaro, D. Girma, and J. Dunlop "H.263 Video Traffic Modeling for Low Bit Rate Wireless Communication," 15th IEEE International Symposium on Personal, Indoor and Mobile Radio Communications, 2004. PIMRC 2004. Volume 3, Issue, 5-8 Sept. 2004, pp. 2124-2128.

[6] O. Lazaro, D. Girma, J. Dunlop, "Real Time Generation Of Synthetic MPEG-4 Video Traffic Using Wavelets," Proceedings of IEEE VTS 54th Vehicular Technology Conference, Fall 2001 (VTC 2001),Volume 1, pp. 418 - 422.

[7] O. Lazaro, D. Girma, J. Dunlop "A Study of Video Source Modeling for 3G Mobile Communication Systems," Proceedings of First International Conference on 3G Mobile Communication Technologies, 2000, Conf. Publ. No. 471, pp. 461-465

[8] Y. Shu, M. Yu, J. Liu, and O.W.W. Yang "Wireless Traffic Modeling and Prediction Using Seasonal ARIMA Models," Proceedings of ICC'03, Volume 3, 11-15 May 2003, pp. 1675-1679.

[9] Xiao-dong Huang, Yuan-hua Zhou and Rong-fu Zhang, "A Multiscale Model for MPEG-4 Varied Bit Rate Video Traffic," IEEE transactions on broadcasting. Volume:50, Issue: 3, pp. 323- 334.

[10] Abdel-Karim Al Tamimi, Raj Jain, and Chakchai So-In, "SAM: A Simplified Seasonal ARIMA Model for Mobile Video over Wireless Broadband Networks", IEEE International Symposium on Multimedia 2008, pp 178-183, URL=[http://www.cse.wustl.edu/~jain/papers/sam.htm]

[11] Chris Chatfield, "The Analysis of Time Series: An Introduction," Chapman & Hall/CRC, 6th Edition, 2003. 352 pages

[12] Bob Nau, "Duke University, Decision 411 Course," Duke University, URL=[http://www.duke.edu/~rnau/Decision411CoursePage.htm],Feb-28-2009.

[13] D. C. Montgomery, L. A. Johnson, J. S. Gardiner, "Forecasting and Time Series Analysis", Second Edition, McGraw-Hill Companies; 2 Sub edition (July 1990), 381 pages.

[14] G. Van der Auwera, P. David, M. Reisslein, "Traffic characteristics of H.264/AVC variable bit rate video," IEEE Communications Magazine, Volume 46 Issue 11, pp 164-174

[15] G. Van der Auwera, P. David, M. Reisslein, "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, Volume 54, Issue 3, pp 698-718

[16] P. Seeling, F. Fitzek, M. Reisslein, "Video Traces for Network Performance Evaluation: A Comprehensive Overview and Guide on Video Traces and Their Utilization in Networking Research," Springer; 1 edition (December 22, 2006), 274 pages.

[17] T. Schierl, T. Stockhammer, T. Wiegand, "Mobile Video Transmission Using Scalable Video Coding," IEEE Transactions on Circuits and Systems for Video Technology, Volume: 17, Issue: 9
On page(s): 1204-1217.

[18] A. Kouadio, M. Clare, L. Noblet and V. Bottreau, "SVC – a higly scalable version of H.264/AVC," European Broadcasting Union, EBU Technical Review, Edition 2008 Q2.

[19] Fraunhofer HHI, "The scalable Video Coding Amendment of the H.264/AVC Standard," Instititue Nachrichtentechnik Heinrich-Hertz-Institute, 2008.

[20] Mobile video traces, "Mobile Devices: Video Traces, Arizona State University (ASU) and Aalborg University (AAU)," URL = [http://mobiledevices.kom.aau.dk/research/traffic_and_channel_measurements/video_traces/]. Feb-28-2009

[21] R project, "The project R of statstical computing," URL=[http://www.r-project.org/], Feb-28-2009.

[22] Olivier Briet, "gsarima: Two functions for Generalized SARIMA time series simulation," GSARIMA package for R. URL=[http://cran.fyxm.net/web/packages/gsarima/index.html], Feb-28-2009

[23] RFC-3550, "RTP: A Transport Protocol for Real-Time Applications".July 2003

[24] SAS: Business Analytics and Business Intelligence Software, URL=[http://www.sas.com], July 2009.

[25] H.264/AVC JM Reference Software V16.0, URL = [http://iphome.hhi.de/suehring/tml/], July 2009.

[26] YUV Video Sequences, Commonly used video trst sequences in 4:2:0 YUV format for both CIF and QCIF sizes. URL=[http://trace.eas.asu.edu/yuv/index.html].

[27] Jan Ozer, "Producing H.264 Video for Flash: An Overview" ,URL=http://www.streaminglearningcenter.com/articles/41/1/Producing-H264-Video-for-Flash-An-Overview/Page1.html.

[28] Video Modeling and Generation Tools, URL=[http://www.cse.wustl.edu/~jain/sam/index.html]