

Markovian characterisation of H.264/SVC scalable video

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Abstract. In this paper, a multivariate Markovian traffic model is proposed to characterise H.264/SVC scalable video traces. Parametrisation by a genetic algorithm results in models with a limited state space which accurately capture both the temporal and the inter-layer correlation of the traces. A simulation study further shows that the model is capable of predicting performance of video streaming in various networking scenarios.

1 Introduction

A video stream is called scalable if parts of the stream (layers) can be removed such that the resulting substream forms another valid video stream for some decoder [1]. The benefits of efficient scalable video coding for video transmission over packet-switched networks include, amongst others, support for heterogeneous clients in multicast transmission scenarios and the capability of graceful degradation of the video quality if required by the network conditions. Since a single stream offers the same content in different formats, heterogeneous clients may decode multicast video streams in their preferred format: preferred spatial and temporal resolution and preferred fidelity. Moreover, by service differentiation the network can ensure delivery of some substreams of the video stream while discarding other substreams during network congestion. From the vantage point of the receivers, the perceived video quality then degrades gracefully during congestion by reducing the spatial or temporal resolution or the fidelity.

This contribution addresses the statistical characterisation of H.264/SVC scalable video streams. Sufficiently detailed statistical traffic models are important for network design and performance evaluation [2]. A good statistical model is able to predict performance of the real video source in various networking scenarios. It should lead to comparable performance predictions when used instead of the actual video traces. Furthermore, if the model is to be used as input for various queueing analyses, the mathematical tractability of the associated queueing models is an additional requirement. Obviously, there is a trade-off between the mathematical tractability and the complexity and accuracy of the video models.

Characterisation of variable bit rate video has been an active research area for almost 20 years. See amongst others the survey by Izquierdo and Reeves [5] on statistical traffic models for MPEG-1 encoded video. Proposed statistical models include Markovian processes [6–10], autoregressive processes [11, 12], spatial renewal processes [13] and self-similar processes [14]. Although video coding standards such as MPEG-2, H.263 and MPEG-4 Visual already support various scalability modes, they have been rarely used in practice due to decreased coding efficiency and increased coding complexity [1]. These issues however have recently been addressed in the H.264/SVC standard.

Hence, few statistical traffic models focus on the scalability of the video sources. Existing models describe two layers at most; a base layer and a temporal enhancement layer. However, traffic models for H.264/SVC video need to take into account the correlation between the base and enhancement layers not only in the temporal, but also in the spatial and quality scalable dimensions. Capturing the multi-layered structure of H.264/SVC is the subject of this paper.

In this contribution, we propose a multivariate Markovian model — in particular, a multi-class discrete batch Markovian arrival process (DBMAP) — to characterise H.264/SVC scalable video. This model can capture the temporal correlation as well as the correlation between the different layers of the H.264/SVC source. Moreover, the associated queueing behaviour can be investigated efficiently by means of matrix analytic methods [3, 4].

We use a genetic algorithm to parametrise the Markovian model for a given trace. The genetic approach for video characterisation has recently been proposed by Kempken and Luther [15] in the context of characterising single layer H.264 video sources at the group of pictures (GOP) level. These authors show that a genetic approach yields Markovian models with small state spaces that can capture the time correlation of the trace accurately. We here extend the approach of [15] to Markovian characterisation of multi-layered video at the sub-GOP level. In particular, the different types of slices are grouped into a number of traffic classes and the H.264/SVC source is investigated at the traffic class level. A key notion of the present approach is the matrix-valued covariance function which is used to assess the fitness (see further) of the Markov model. As opposed to the correlation function used in [15], the covariance function depends on the second order moments in each of the Markov states. Hence, inter-layer correlation is taken into account while assessing the fitness of the model.

The remainder of this paper is organised as follows. In the next section, the H.264/SVC traces and their statistical properties are introduced. We then focus on the properties of the multivariate Markovian process in section 3. The genetic algorithm for video characterisation is presented in section 4 and numerically evaluated in section 5. Finally conclusions are drawn in section 6.

2 H.264/SVC Traces

The H.264/SVC traces are encoded with the SVC reference software version JSVM 8.9. We characterise two traces: a trace of the movie “Brotherhood of

the Wolf” consisting of 13447 GOPs and a trace of the movie “Pirates of the Caribbean” consisting of 12770 GOPs. Both traces are encoded into a base layer and a Medium Grain Scalability (MGS) quality enhancement layer. Further, within each of these layers there are 5 temporal layers as depicted in Figure 1. Notice that I, P and B slices refer to intra-picture predictive coded, inter-picture predictive coded and bi-directional predictive coded slices respectively. In total, there are 2×16 slices per GOP. The frame rate is equal to 25 frames per second — hence a GOP corresponds to $0.64s$ — and the spatial dimensions are equal to 720×304 pixels for the base layer as well as for the enhancement layer. Encoder quality parameters (QP, MeQP1 to MeQP5 and MeQPLP) are set to 31 and 25 for the base layer and the enhancement layer respectively. Further information on H.264/SVC encoding can be retrieved from [1].

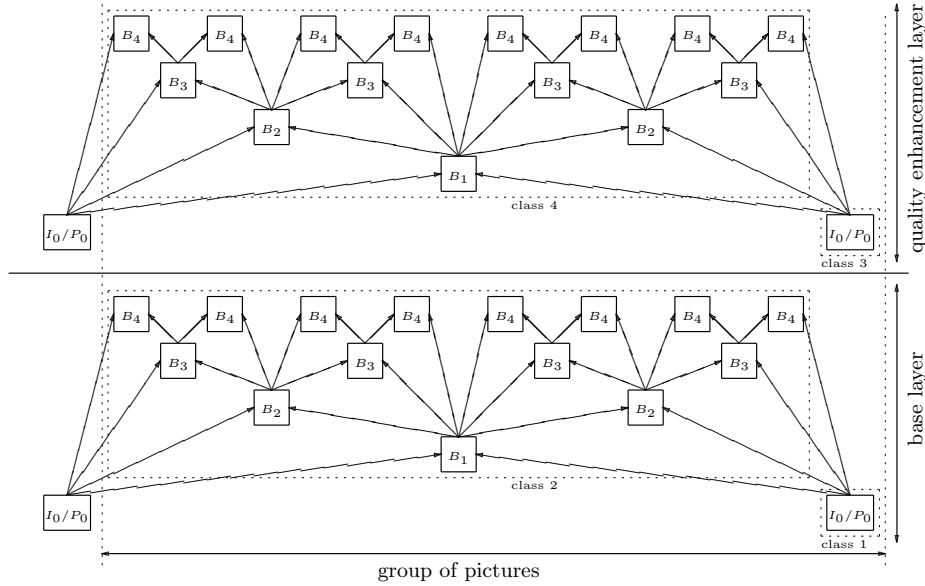


Fig. 1. Group of picture structure of the H.264 traces under consideration.

As already mentioned, we here investigate the H.264/SVC sources at the traffic class level. We define the following 4 traffic classes:

- class 1: I and P slices of the base layer;
- class 2: B slices of the base layer;
- class 3: I and P slices of the quality enhancement layer;
- class 4: B slices of the quality enhancement layer.

The correspondence between these traffic classes and the different slices of the GOP is also illustrated in Figure 1.

Although we focus on the traffic classes defined above in the remainder of this contribution, our approach also works for different sets of traffic classes. From the vantage point of characterising the video source at the traffic class level, a trace is a series of row vectors $X = \{X_k, k = 0, \dots, N-1\}$ where X_k is a row vector of size C whose j th element $X_{k,j}$ equals the number of bytes of class j that are generated during GOP k . Here, N denotes the number of GOPs in the trace and C denotes the number of traffic classes. Given the trace X , we now define some statistics.

The sample mean (row) vector and the $C \times C$ sample covariance matrix of the trace are defined as,

$$\bar{X} = \frac{1}{N} \sum_{n=0}^{N-1} X_n, \quad \text{cov}(X) = \frac{1}{N} \sum_{n=0}^{N-1} X'_n X_n - \bar{X}' \bar{X}, \quad (1)$$

respectively. Here the vector Y' is the transposed of the vector Y . Notice that we use the biased estimator of the covariance matrix. This will hardly influence the results since the numbers of GOPs N in the traces under consideration are sufficiently large.

With the trace X we associate the sum traces $S^{(k)}(X) = \{S_n^{(k)}(X), n = 0, \dots, N-1\}$, with,

$$S_n^{(k)}(X) = \sum_{i=n}^{(n+k) \bmod N} X_i. \quad (2)$$

for $k = 0, 1, 2, \dots$. The (matrix valued) sample covariance function then maps k onto the sample covariance matrix of $S^{(k)}(X)$,

$$\text{cf}(k) = \frac{1}{N} \sum_{n=0}^{N-1} S_n^{(k)}(X)' S_n^{(k)}(X) - (k+1)^2 \bar{X}' \bar{X}, \quad (3)$$

for $k = 0, 1, 2, \dots$.

Of particular interest for the statistical characterisation of the video source at the traffic class level are the scalar valued covariance functions of the aggregated traffic of a subset of the traffic classes. Let \mathcal{C} be any subset of the set of traffic classes $\{1, 2, \dots, C\}$ and let $X_{\mathcal{C}}$ denote the series

$$X_{\mathcal{C}} = \left\{ \sum_{j \in \mathcal{C}} X_{k,j}, k = 0, 1, \dots, N-1 \right\}. \quad (4)$$

The corresponding scalar valued covariance function $\text{cf}_{\mathcal{C}}(k)$ then equals,

$$\text{cf}_{\mathcal{C}}(k) = \epsilon_{\mathcal{C}} \text{cf}(k) \epsilon'_{\mathcal{C}}, \quad (5)$$

with $\epsilon_{\mathcal{C}}$ a row vector of size C whose i th element equals 1 if i is an element of \mathcal{C} and 0 if this is not the case.

3 The Multi-Class DBMAP

Let $q = \{q_i, i = 0, 1, \dots\}$ denote an irreducible Markov chain defined on a finite state space $\mathcal{K} = \{1, \dots, K\}$. Such a Markov chain is completely characterised by the transition probabilities $\gamma_{i,j}, i, j \in \mathcal{K}$. Further, let $\Gamma = [\gamma_{i,j}]_{i,j \in \mathcal{K}}$ denote the $K \times K$ transition matrix of the Markov chain and let $\pi = [\pi_1, \dots, \pi_K]$ denote the row vector of its steady state probabilities. The vector π is the unique normalised solution of $\pi = \pi\Gamma$. The Markov chain q is referred to as the modulating Markov chain of the DBMAP.

A multi-class discrete-time batch Markovian arrival process $x = \{x_k, k = 0, 1, 2, \dots\}$ is a discrete time stochastic process which takes values in \mathbb{R}^C such that the multivariate distribution of x_k only depends on the states q_k and q_{k+1} of the modulating Markov chain (for all k). Hence, this process is completely characterised by the transition matrix Γ of the modulating Markov chain and the doubly indexed set of multivariate distribution functions $\{\Phi_{i,j}(y), i, j \in \mathcal{K}, y \in \mathbb{R}^C\}$. $\Phi_{i,j}(y) = \Pr[x_{k,1} < y_1, \dots, x_{k,C} < y_C | q_k = i, q_{k+1} = j]$ is the multivariate distribution of x_k given $q_k = i$ and $q_{k+1} = j$. Here $x_{k,j}$ and y_j are the j th entries of the vectors x_k and y respectively. Notice that in literature DBMAPs only take values in \mathbb{N}^C . The process described here is somewhat more general but we will also refer to it as a DBMAP. However, one may discretise the traffic model for performance evaluation purposes. The resulting process is then a DBMAP as described in literature.

In the remainder, we will make the additional assumptions that (i) the process x_k at time k only depends on q_k and (ii) that for a given state q_k , the random vector x_k is multivariate normally distributed. Hence, the process (x_k, q_k) is completely characterised by the transition matrix Γ and the following mean vectors and covariance matrices in the different states $i \in \mathcal{K}$,

$$\mu_i = E[x_k | q_k = i], \quad \Omega_i = E[x'_k x_k | q_k = i] - \mu'_i \mu_i. \quad (6)$$

Notice that the normal distribution takes negative values with a positive probability. This probability will however turn out to be negligibly small for the DBMAPs that characterise the video traces.

We now retrieve some characteristics of the process x in terms of the characteristics Γ, π, μ_i and Ω_i of the multi-class DBMAP. The mean vector μ and covariance matrix Ω are given by,

$$\mu = \sum_{i \in \mathcal{K}} \pi_i \mu_i, \quad \Omega = \sum_{i=1}^N \pi_i (\Omega_i + \mu'_i \mu_i) - \mu' \mu. \quad (7)$$

Further, let $s^{(k)} = \{s_n^{(k)}, n = 0, 1, 2, \dots\}$ denote the sum process corresponding to x . Here $s_n^{(k)}$ is defined as,

$$s_n^{(k)} = \sum_{i=n}^{n+k} x_i. \quad (8)$$

The matrix valued covariance function $\Theta(k)$ of the DBMAP then maps k on the covariance matrix of the process $s^{(k)}$,

$$\Theta(k) = \mathbb{E}[(s_n(k) - \mathbb{E}[s_n(k)])(s_n(k) - \mathbb{E}[s_n(k)])']. \quad (9)$$

Since we have $s_n(k) = s_n(k-1) + x_{n+k}$ and by conditioning on the states of the modulating Markov chain, one shows that the covariance function can be obtained recursively by means of the following expressions,

$$\Theta(k) = \Theta(k-1) + \Psi(k) + \Psi(k)', \quad (10)$$

with,

$$\begin{aligned} \Theta(0) &= \Omega, \\ \Psi(k) &= \sum_{i,j \in \mathcal{K}} \psi_i(k-1)' \mu_j \gamma_{i,j}, \\ \psi_l(0) &= \mu_l \pi_l, \\ \psi_l(k) &= \mu_l + \sum_{j \in \mathcal{K}} \psi_j(k-1) \gamma_{j,l}, \end{aligned} \quad (11)$$

for $k = 1, 2, \dots$ and for $l \in \mathcal{K}$.

As for the traces, the scalar valued covariance functions of the aggregated traffic of subsets of the traffic classes can be expressed in terms of the covariance function $\Theta(k)$. For any subset \mathcal{C} of the traffic classes, let $x_{\mathcal{C}}$ denote following scalar valued DBMAP,

$$x_{\mathcal{C}} = \left\{ \sum_{j \in \mathcal{C}} x_{k,j}, k = 0, 1, \dots, N-1 \right\}. \quad (12)$$

The scalar valued covariance function of $x_{\mathcal{C}}$ then equals,

$$\Theta_{\mathcal{C}}(k) = \epsilon_{\mathcal{C}} \Theta(k) \epsilon_{\mathcal{C}}'. \quad (13)$$

Recall that $\epsilon_{\mathcal{C}}$ denotes a row vector of size C whose i th element equals 1 if i is an element of \mathcal{C} and 0 if this is not the case.

4 Genetic Characterisation

The genetic approach under consideration exploits the fact that Markovian characterisation is almost trivial if not only the trace, but also the states of the modulating Markov chain are known. That is, given the trace X and a series of states $Q = \{Q_k, k = 0, \dots, N-1\}$ associated to the consecutive GOPs, one easily constructs a multi-class DBMAP by counting state transitions and by calculating

conditional moments. We find the following DBMAP characteristics,

$$\begin{aligned}
N_i &= \sum_{k=0}^{N-1} 1(Q_k = i), \\
\gamma_{i,j} &= \frac{1}{N_i} \sum_{k=0}^{N-1} 1(Q_k = i, Q_{(k+1) \bmod N} = j), \\
\mu_i &= \frac{1}{N_i} \sum_{k=0}^{N-1} X_k 1(Q_k = i), \\
\Omega_i &= \frac{1}{N_i} \sum_{k=0}^{N-1} X'_k X_k 1(Q_k = i) - \mu'_i \mu_i.
\end{aligned} \tag{14}$$

In the former expressions $1(\cdot)$ denotes the standard indicator function.

Hence, finding a multi-class DBMAP corresponds to finding a series Q such that the statistical properties of the derived DBMAP closely match the statistical properties of the trace. It is easily shown that the mean vector and the covariance matrix of the DBMAP with parameters as given in equation (14) match the sample mean and sample covariance matrix of the trace. To capture temporal correlation, the authors of [15] focus on matching the autocorrelation function of the DBMAP with the autocorrelation function of the trace. However, the autocorrelation of a DBMAP only depends on the covariance matrix Ω of the DBMAP and not on the covariance matrices Ω_i in the different states of the DBMAP. Since it is our objective to accurately capture the correlation between the different traffic classes, we here focus on matching the sample covariance function of the trace with the covariance function of the DBMAP. In accordance with equations (10) and (11), the covariance function does depend on the matrices Ω_i .

Given the length of the trace N and the number of states of the Markov chain K , there are K^N possible series Q of state assignments. For the traces under consideration and for a Markov state space of size $K = 3$ this means that there are more than 10^{6000} possible series Q of state assignments. The size of the set of possible solutions clearly makes it infeasible to find the best solution by testing all possible solutions. We therefore use a genetic algorithm to search the space of all possible state assignments more efficiently.

A genetic algorithm is a search and optimisation procedure, inspired by Darwin's theory of evolution (see e.g. [16] for a survey on genetic algorithms). A genetic algorithm transforms a set or generation of solutions into a new generation of solutions using the Darwinian principle of reproduction and survival of the fittest. That is, given a generation of solutions, a new generation of solutions is created by means of mutation and crossover of solutions of the given generation (reproduction) and only the best solutions are retained (survival of the fittest).

In the present context, a solution is a series Q of state assignments to the consecutive GOPs. Its fitness measures the accuracy of the match of the covari-

ance function of the DBMAP with the sample covariance function of the trace. In particular, the fitness of a solution Q is defined as follows,

$$\frac{1}{\text{fitness}(Q)} = \frac{1}{L} \sum_{k=1}^L |w(\text{cf}(k) - \Theta(k))w'|. \quad (15)$$

Here $\text{cf}(k)$ is the sample covariance function of the trace as given in equation (3), L is the maximal lag for which the covariance function of the DBMAP and the sample covariance function of the trace are compared and $\Theta(k)$ is the covariance function of the DBMAP. The latter can be obtained by means of equations (10) and (11) in terms of the vectors π and μ_i ($i = 1, \dots, K$) and the matrices Γ and Ω_i ($i = 1, \dots, K$) that characterise the multi-class DBMAP. For a given solution Q , these vectors and matrices are given in equation (14). Finally, w is a weight row vector. Notice that a high fitness indicates an accurate match of covariance and sample covariance functions.

The row vector w in equation (15) allows one to assign different weights to the various elements of the covariance matrix. In particular, one can assign weights to the variance functions of aggregated traffic from subsets of the traffic classes as follows. For all i , let α_i denote the weight assigned to the variance function of the aggregated traffic class \mathcal{C}_i (\mathcal{C}_i is a subset of the set of traffic classes). In view of property (5) of sample covariance functions and in view of property (13) of the covariance function of a DBMAP, we obtain the following weight vector,

$$w = \sum_i \sqrt{\alpha_i} \epsilon_{\mathcal{C}_i}. \quad (16)$$

Recall that $\epsilon_{\mathcal{C}_i}$ is a row vector of size C whose i th element equals 1 if i is an element of \mathcal{C} and 0 if this is not the case.

Given the fitness function, the execution of the genetic algorithm operating on the generations of solutions of state assignments can now be summarised as follows.

First, a random generation of solutions is created. Each solution is created by randomly assigning states to the consecutive GOPs. Then, the following substeps are performed until a sufficiently fit solution is found.

1. Calculate the fitness of each solution in the current generation. The fitness of the generation is defined as the fitness of the best solution of the generation.
2. Create a new generation by means of the following operations.
 - (a) Mutation: randomly choose a solution of the current generation with probability inversely proportional to the fitness of the solution. Then either (i) change a continuous block of state assignments to a randomly chosen state or (ii) reverse a continuous block of state assignments. Add this new (mutated) solution to the new generation.
 - (b) Crossover: randomly choose two solutions of the current generation with probability inversely proportional to the fitness of these solutions. Interchange the state assignments of a randomly chosen sub-part of the state assignments. Add these new solutions to the new generation.

3. Copy the fittest solution of the current generation to the new generation.

Notice that step 3 implies that the fitness of consecutive generations never decreases.

5 Numerical Results

We now evaluate the genetic video characterisation approach by means of a numerical example. We here focus on the characterisation of the trace of the movie "Brotherhood of the Wolf". Similar results were obtained for the trace of the movie "Pirates of the Caribbean". The size of the state space of the generated DBMAP is set to $K = 3$ or $K = 5$ and the fitness of a solution is based on the (sample) covariance functions of lag 1 up to lag $L = 10$. The weight vector w equals $[5, 3, 3, 1]$. This choice is motivated by assigning the same weight to all decodable substreams; class 1, class 1 and 2, class 1 and 3, class 1 to 3 and class 1 to 4 constitute decodable substreams.

In Figures 2 and 3 the statistical characteristics of the multi-class DBMAP are compared with the corresponding characteristics of the trace. For all plots, the lines correspond to DBMAP values whereas points correspond to trace values and different values of the state space size are considered as indicated. Figures 2 and 3 show that the distributions and the variance functions of subclasses of the multi-class DBMAP closely match the corresponding trace histograms and sample variance functions respectively. From Figure 2 it is seen that the match between distribution functions and histograms does not improve by increasing the number of states of the DBMAP. This is not unexpected since the genetic algorithm does not take into account how well histogram and distribution match. In fact, it is somewhat surprising that there is such a close match in the first place. In contrast, increasing the size of the state space improves the accuracy of the match of the (sample) variance functions as can be seen in Figure 3.

We now evaluate the Markov model in a networking scenario. For this, we consider a discrete-time finite capacity buffer with partial buffer sharing (PBS) through which the traffic stemming from 4 video sources is routed. The data from the video sources is divided into fixed length packets of 1500 bytes of which the buffer can store up to 200. The bandwidth of the output line of the buffer equals 8 Mbit and the partial buffer sharing thresholds are set to 90%, 80% and 70%. That is, class 2, 3 and 4 packets are accepted as long as the buffer occupancy is less than 90%, 80% and 70% respectively. In Figure 4 the probability mass function (pmf) of the queue content of the different traffic classes is depicted. Both the results from trace based simulations (thick lines) and model based simulations (thin lines) are depicted. The match is already reasonable for the 3 state DBMAP but further improves by adding states. However, one can see that even for the 5 state DBMAP, there is no accurate match for the tails of the distributions of the queue content. Nevertheless, this is crucial since the tail distribution relates to the packet loss ratio which is an important performance measure. That is, a close match is necessary if the model is to be used to assess the packet loss ratio accurately.

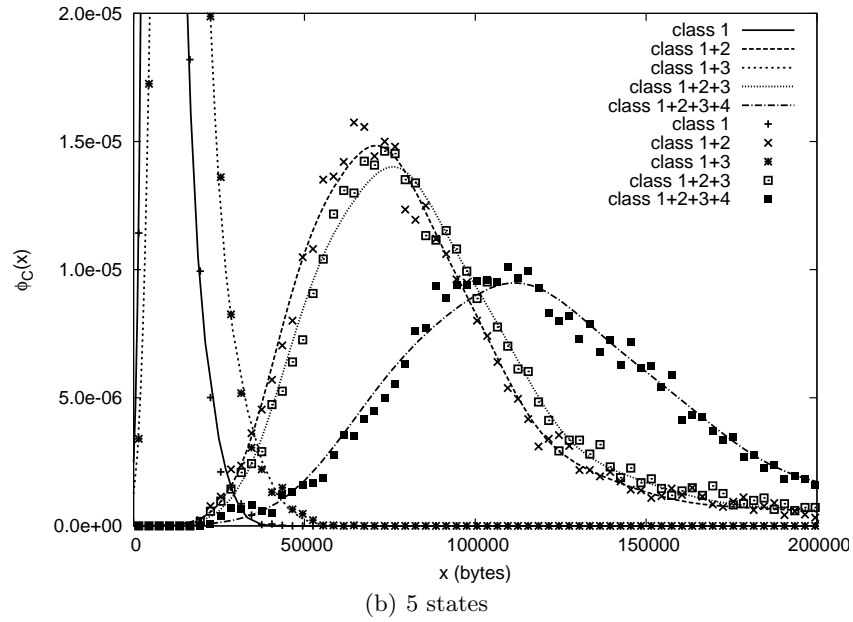
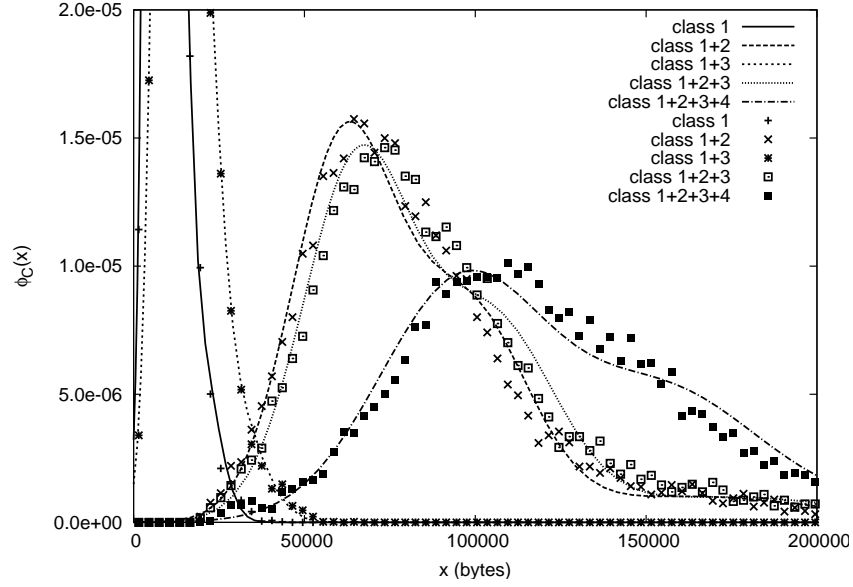


Fig. 2. Histogram of various subtraces and the corresponding density functions of the trace “Brotherhood of the Wolf” for different DBMAP state sizes.

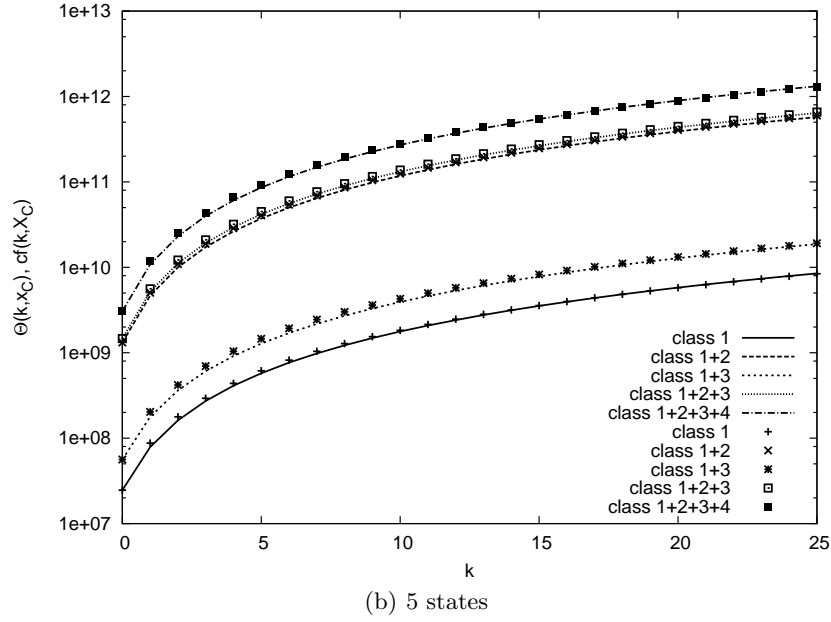
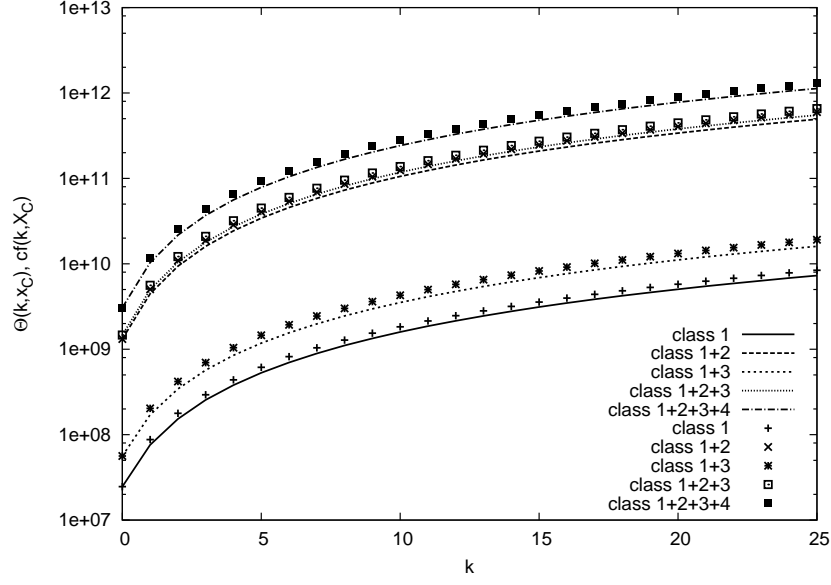


Fig. 3. Sample variance functions of various substraces of the trace “Brotherhood of the Wolf” and the corresponding variance functions for different DBMAP state sizes.

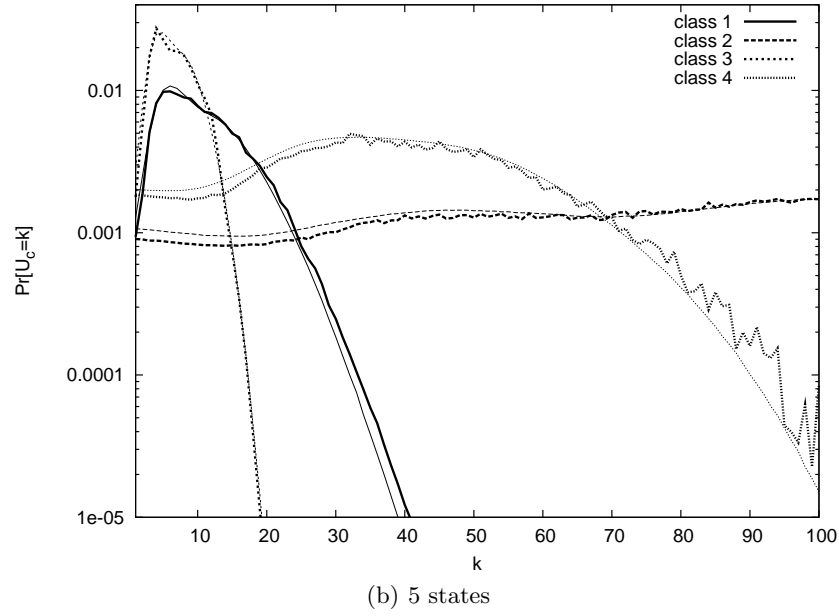
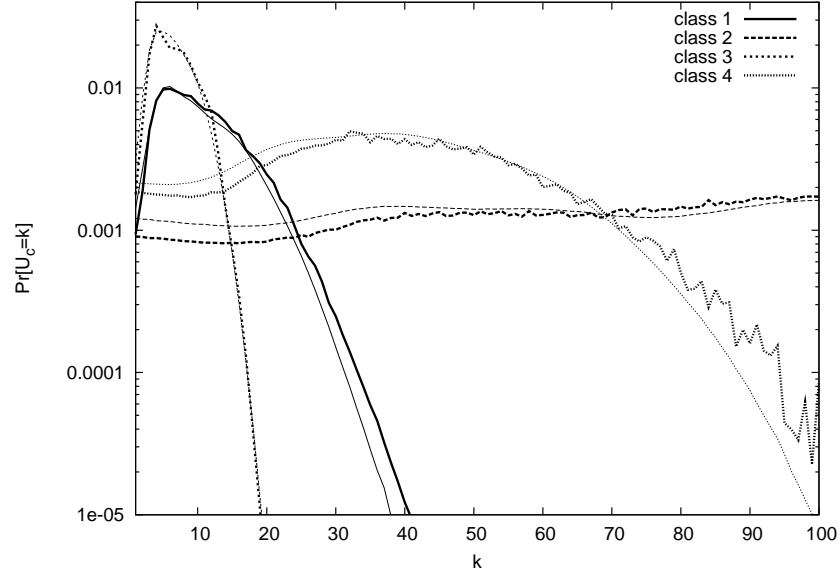


Fig. 4. Probability mass function of the queue content of the different classes for a PBS queue with an 8 Mbit output line and aggregated traffic from 4 times “Brotherhood of the Wolf”.

The former observation suggests that more Markov states are required to accurately assess the packet loss by means of the Markov model. Hence, we investigate performance of the Markov model for DBMAPs with $K = 10$ states: the pmf of the queue content of the different traffic classes is depicted in Figure 5(a) for the network scenario of Figure 4. Now, an accurate match of the tail distributions is obtained. Finally, the packet loss ratio is depicted versus the number of video sources that are routed through a PBS buffer with a 12 Mbit output line in Figure 5(b). Buffer size and thresholds are the same as in Figure 4. Clearly, a good match is obtained between model based and trace based simulations which shows that the DBMAP can be used to accurately assess the packet loss ratio.

6 Conclusions

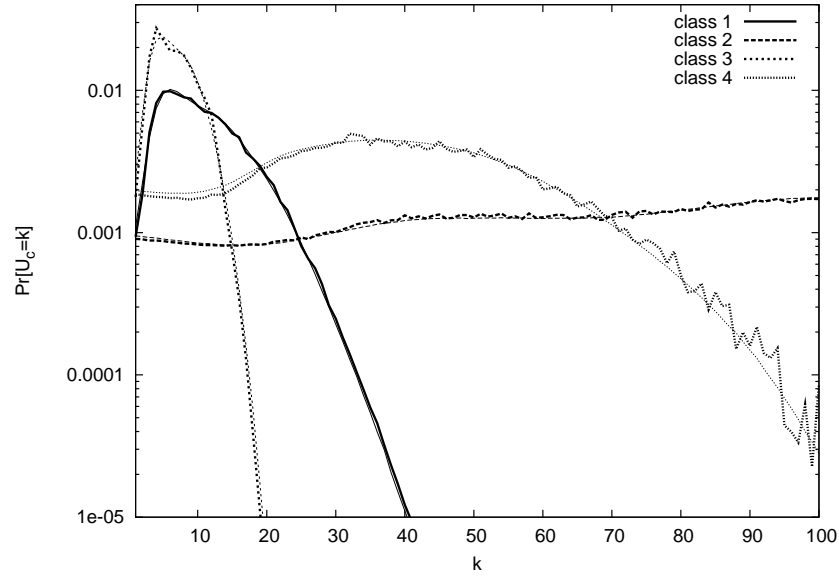
In this contribution we proposed the multi-class DBMAP for the characterisation of H.264/SVC scalable video at the sub-GOP level. We showed that — by means of a genetic algorithm — multi-class DBMAPs with a limited state space can be found that accurately capture the characteristics of the video traces. Finally, a simulation study demonstrated that the Markov model can be used to accurately assess the performance of video streaming in networking scenarios.

Acknowledgement

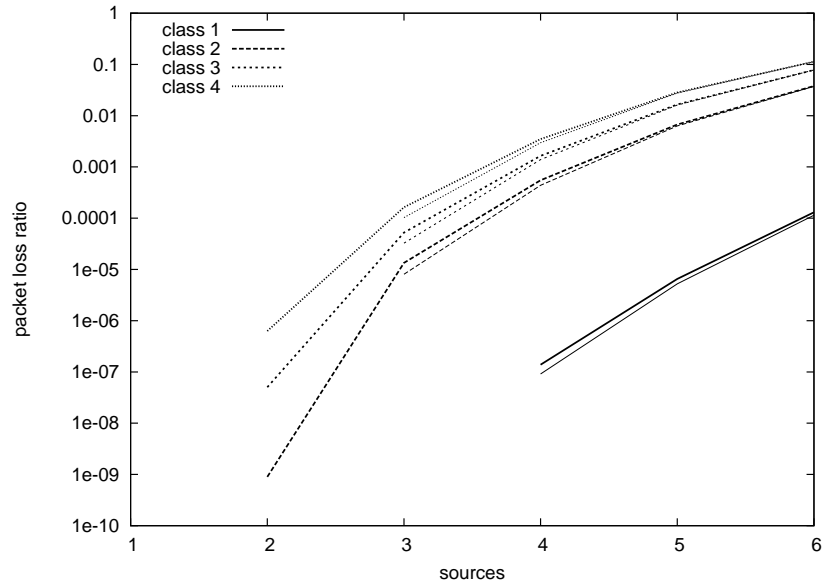
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(a) pmf of the queue content



(b) packet loss ratio

Fig. 5. Probability mass function of the queue content of the different classes for a PBS queue with an 10 Mbit output line and aggregated traffic from 4 times “Brotherhood of the Wolf” (a) and packet loss ratio versus the number of video sources for a PBS queue with a 12 Mbit output line (b).

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