PREDICTIVE CONTROL FOR EFFICIENT STATISTICAL MULTIPLEXING OF DIGITAL VIDEO PROGRAMS

N. Changuel, B. Sayadi

Alcatel-Lucent Bell-Labs France
Centre de Villarceaux
Route de Villejust 91620 Nozay

M. Kieffer

L2S – CNRS - SUPELEC - Univ Paris-Sud
3 rue Joliot-Curie
91192 Gif-sur-Yvette, France

ABSTRACT

In broadcast and multicast systems, Video programs are transmitted over a constant bit rate channel. Apart from bandwidth constraints, the control of each encoder involved in the statistical multiplexing has to satisfy several other constraints: minimum quality, fairness, and smoothness constraints. This paper proposes an improved control scheme for multiplexing H.264/AVC encoded video programs considering all the mentioned constraints. This process is based on grouping pictures of each program into Set Of Pictures (SOP) whose control parameters are determined from parameters of both past and future SOP. This process leads to smoothed multiplexed program and bounded quality differences between programs. Previous results using only past regulation process showed an increase of the multiplexing efficiency compared to the CBR allocation. Using the proposed regulation process, higher multiplexing efficiency is achieved allowing a potential increase of the number of multiplexed programs.

***Index Terms*—** Statistical multiplexing, video broadcasting

1. INTRODUCTION

In broadcast systems such as Digital Video Broadcasting (DVB) or Satellite Digital Multimedia Broadcasting (S-DMB), several programs are transmitted simultaneously over the same bandwidth-constrained communication channel. In such systems, one aims at maximizing the number of programs sharing the bandwidth, while satisfying some quality constraints [1].

To reduce the required bit rate, programs are compressed using efficient video encoders such as MPEG 2, MPEG 4, or H.264/AVC [2]. They are then multiplexed with the other contents. Two encoding modes may be considered, which lead to two types of multiplexing. If each program is encoded at a Constant Bit Rate (CBR), its bandwidth consumption is constant with time. The available bandwidth is then equally distributed among the programs, without any consideration about their respective complexity. This scheme is simple, but the quality may vary significantly with time within a single program and between programs. Encoding with Variable Bit Rate (VBR) allows a simpler program to be encoded with low rate. This leaves additional bandwidth to other programs with more complex scenes, *e.g.*, action motion pictures. This mechanism, called *statistical multiplexing*, [3], allows not to waste bandwidth with programs compressed with an unnecessary quality, while others suffer from bandwidth constraints.

Performing a satisfying statistical multiplexing requires an efficient control of the video encoders producing the compressed programs. The estimation or observation of Rate-Distortion (RD) or complexity models for each program is a prerequisite for an efficient control. In the *feedback* approach [4, 1], parameters of RD or complexity models are estimated *after* the encoding of one or several frames of each program. In the *look-ahead* approach, the complexity of each program is evaluated *prior* to encoding. Both approaches may be combined, as in [5] to allow a quicker reaction to scene changes.

Apart from bandwidth constraints, the control of each encoder involved in the statistical multiplexing has to insure that:

- all programs are encoded by satisfying a minimum quality constraint (*minimum quality* constraint),
- programs are compressed with more or less the same quality (*fairness* constraint) [6],
- for each program, the quality of the reconstructed video has to vary smoothly with time (*smoothness* constraint [7, 8, 9]).

At some time instants, it may be difficult to satisfy all constraints simultaneously. This is mainly due to the non-stationary content of each program. Variations may be due, *e.g.*, to scene changes or to high activity within a scene. Among all constraints, the smoothness one is the most difficult to satisfy. In [7], the quality of past encoded frames is taken into account to determine the appropriate encoding parameters for the current frame in order to simplify the rate control scheme. Other works presented in [9] show that in order to enable transmission across a channel characterized by a limited bandwidth it is possible to obtain better smoothness quality while keeping a small penalty in average distortion. Nevertheless, these control techniques, which account only for the past, may lead to situations where the smoothness and bandwidth constraints cannot be satisfied simultaneously.

The characteristics of the frames next to the one which has to be encoded are exploited in [10] by using the look-ahead approach, but the smoothness criteria was not considered in the optimization problem. In [11], the frames of a program are grouped into sets within which the quality variation between adjacent frames is minimized. Nevertheless, the smoothness between sets is not considered.

This work proposes an improved control scheme for multiplexing H.264/AVC encoded video programs, taking all previously mentioned constraints into account. In each program, pictures are grouped into sets of consecutive pictures (SOP) on which the control is performed. SOP may size from one picture to a whole H.264/AVC group of pictures (GOP). The aim is to ensure a quality smoothed between the SOP of a given program, and bounded quality differences between SOP of the multiplexed programs at any time instant, while satisfying the bandwidth constraint. For the control of a given SOP, an observation window contains the previous, current, and $W-2$ future SOP is considered. The RD characteristics of the current and future SOP have then to be estimated. Adjusting the size of a SOP and the size W of the control window allows to reach a compromise for the control between complexity and efficiency.

The paper is organized as follows. Section 2 introduces the statistical multiplexing problem and defines some notations. Section 3 presents the way all constraints involved to reach high statistical multiplexing performance in terms of inter-program fairness, intra-program smoothness, and statistical multiplexing efficiency [12] translate into a constrained multidimensional optimization problem. Several state-of-art RD models are presented in Section 4 before presenting the RD model used in the proposed control scheme. Section 5 presents the performance of the proposed statistical multiplexing system when the bandwidth is constant with time. Finally, Section 6 concludes this work and provides some perspectives.

2. NOTATIONS AND ASSUMPTIONS

Consider a typical broadcast system in which N video programs have to be encoded in parallel, the compressed bitstreams have to be multiplexed, and finally transmitted over a channel allowing a constant transmission rate R_{c}, see Figure 1.

Any video program, is divided into Groups Of Pictures (GOP) of N_{G} pictures. Each GOP is encoded independently from the previous GOP as it starts by an INTRA picture, *i.e.*, a picture encoded without reference to previous pictures. To facilitate bit rate and quality control, in this paper, each GOP is assumed to be partitioned into several Set Of Pictures (SOP).

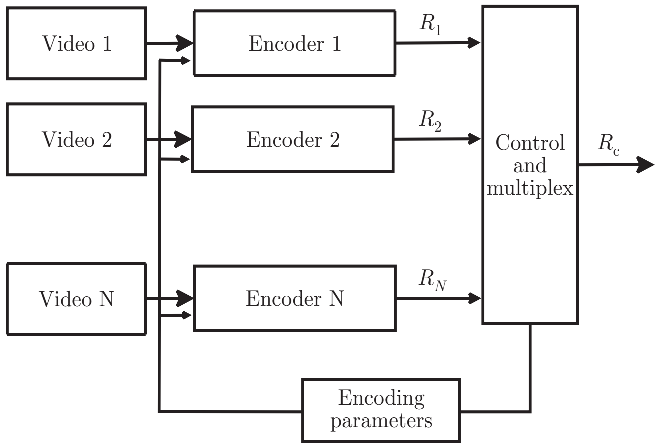

Fig. 1. Structure of a statistical multiplexer

The number of pictures N_{S} of a SOP and N_{G} are assumed to be constant with time and to be the same for all programs. N_{S} ranges from 1 to N_{G}. The beginning of each SOP is assumed to be synchronized for the N programs; this is not necessarily the case for the beginning of the GOP. The encoding rate for the j-th SOP of the i-th program is denoted by R_{ij}.

Using SOP makes it possible to adjust the granularity at which rate and quality control is performed during multiplexing. Moreover, considering SOP of more than one picture smoothes the rapid variations of rate between consecutive pictures and thus facilitates control.

The rate control has to be performed so that the quality of each program is maximized and some additional constraints, detailed in Section 3, are satisfied. Several quality measurement techniques are available, see, *e.g.*, [13, 14] or [15] and the references therein. Here, the average distortion D_{ij} (based on a quadratic distortion measure) of the j-th picture in the i-th program and the corresponding Peak Signal-to-Noise Ratio (PSNR)

$$P_{ij} = 10\log_{10}\left(\frac{255^2}{D_{ij}}\right) \tag{1}$$

are be considered.

For each SOP, D_{ij} and R_{ij} are tuned by several encoding parameters (size of blocks, accuracy of the motion compensation), among which the average quantization parameter Q_{ij} is the most important (Q_{ij} is usually denoted QP in the standards, see, *e.g.*, [2]). Assuming that a rate-distortion optimization is performed for the encoding of each GOP, for each SOP D_{ij} and R_{ij} may be represented as two functions of Q_{ij} only. Thus one has

$$D_{ij} = h_{ij}(Q_{ij}) \tag{2}$$

and

$$R_{ij} = g_{ij}(Q_{ij}), \tag{3}$$

for which a model have to be obtained, see Section 4. In fact, the assumption considered to get (2) and (3) is only valid for the first SOP of a GOP. In general, D_{ij} and R_{ij} depend also on the previous quantization parameters of the GOP the SOP belongs to.

3. OPTIMIZATION PROBLEM

Statistical multiplexing aims at maximizing the quality of each program while satisfying the rate constraint provided by the communication channel. Additional minimum quality, fairness, and smoothness constraints are also taken into account to limit the variations with time and between programs of the perceived video quality.

3.1. Cost function

Ideally, one would search for a constrained Pareto-optimal solution [16], in which any quality increase for a given program would lead to a quality decrease for at least another program. Here, as in [8], one tries to minimize the average distortion for each SOP

$$D_j\left(Q_{1j}, Q_{2j}, \ldots, Q_{Nj}\right) = \frac{1}{N}\sum_{i=1}^{N} D_{ij}\left(Q_{ij}\right), \quad (4)$$

which optimization is tractable.

3.2. Rate and maximum distortion constraints

The constraint on the total rate on the channel is assumed to apply SOP by SOP. Thus, one has to satisfy

$$\sum_{i=1}^{N} R_{ij}\left(Q_{ij}\right) \leqslant R_{\mathrm{c}}, j = 1, 2, \ldots \quad (5)$$

Output buffers are assumed to be large enough to tolerate temporary rate increase above R_{c} within a SOP.

To keep an acceptable visual quality, the distortion within a SOP has to be upper-bounded by a maximum tolerated distortion denoted by $D_{\max}$. Thus, for all programs, one should satisfy

$$D_{ij}\left(Q_{ij}\right) \leqslant D_{\max}, i = 1 \ldots N. \quad (6)$$

Minimizing (4) subject to (5) and (6) provides a first control scheme for the encoders involved in the statistical multiplexer. It also gives some indications on the maximum number of channels which may be simultaneously multiplexed: no solution may exist for too large values of N. Nevertheless, with this approach the quality may vary significantly from one program to the other and within one program.

3.3. Fairness constraint

Inter-program fairness means that all transmitted programs have approximatively the same quality level. This quality is evaluated at a SOP level using the PSNR. The fairness constraint may be translated into the following inequality

$$|P_{ij}(Q_{ij}) - P_j(Q_j)| \leqslant \Delta P_{\mathrm{p}}, i = 1, \ldots, N \quad (7)$$

where

$$P_j(Q_j) = \frac{1}{N}\sum_{i=1}^{N} P_{ij}(Q_{ij}) \quad (8)$$

is the average PSNR of the j-th SOP. Thus, (7) allows a PSNR difference for a given program with the average PSNR of at most ΔP_{p}. As an alternative, not considered here, one may also bound the PSNR difference between any pair of programs, leading to $N\left(N-1\right)/2$ inequality constraints involving less variables.

3.4. Smoothness constraint

Each program should present smooth quality variations: large PSNR variations between pictures may be visually annoying. Smoothness issues have been taken into account by considering previous pictures only, as in [12], or future pictures, as in [10]. Considering only past SOP may lead to situations in which smoothness and total rate constraints become incompatible. Performing predictive control, *i.e.*, taking future SOP into account facilitates the anticipation of future variations of the PSNR, due, *e.g.*, to scene change.

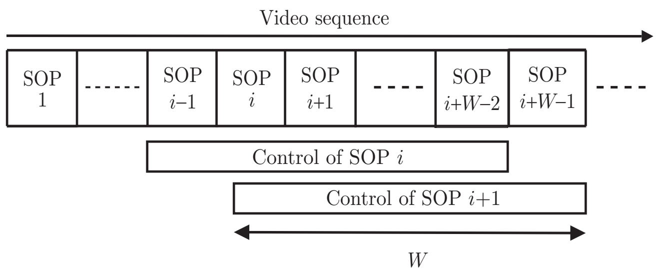

Fig. 2. Regulation accounting for past and future SOP

Control is thus performed at a SOP level, taking into account the PSNR of the past SOP and that of $W-2$ future SOP, as illustrated by Figure 2. A maximum variation ΔP_{S} of the PSNR between two consecutive SOP is tolerated. Taking W SOP for every program into account, the smoothness constraint when evaluating $\mathbf{Q}_j = (Q_{1j}, Q_{2j}, \ldots, Q_{Nj})$ may be formulated as

$$|P_{ij}(Q_{ij}) - P_{i(j-1)}(\widehat{Q}_{i(j-1)})| \leqslant \Delta P_{\mathrm{S}}, \quad (9)$$

and

$$|P_{i(j+k)}(Q_{i(j+k)}) - P_{i(j+k-1)}(Q_{i(j+k-1)})| \leqslant \Delta P_{\mathrm{S}}, \quad (10)$$

for $k = 1, \ldots, W-1$ and $i = 1, \ldots, N$. In (9), $\widehat{Q}_{i(j-1)}$, $i = 1, \ldots, N$ has been obtained during the control of the $j-1$-th SOP. Nevertheless, (10) introduces many new variables $Q_{i(j+k)}$, $k = 1, \ldots, W-1$ and $i = 1, \ldots, N$ to the first optimization problem shortly described in Section 3.2. These variables are useful to ensure that the choice made for $\mathbf{Q}_j$ will be compatible with a satisfaction of the smoothness constraints for at least $W-2$ future SOP.

3.5. Constrained optimization problem

Taking the initial cost function and all constraints into account leads to the following constrained optimization problem for the quality control of the j-th SOP

$$\widehat{\mathbf{Q}}_j(\widehat{Q}_j .., \widehat{Q}_{j+W-2}) = \arg \min_{Q_j .., Q_{j+W-2}} \sum_{i=1}^{N} D_{ij}\left(Q_{ij}\right) \quad (11)$$

subject to

$$\begin{cases} \sum_{i=1}^{N} R_{ij}(Q_{ij}) \leqslant R_{\mathrm{c}} \\ D_{ij}(Q_{ij}) \leqslant D_{\max} \\ |P_{ij}(Q_{ij}) - P_j| \leqslant \Delta P_{\mathrm{p}} \\ |P_{ij}(Q_{ij}) - P_{i(j-1)}(\widehat{Q}_{i(j-1)})| \leqslant \Delta P_{\mathrm{S}}, \\ |P_{i(j+k)}(Q_{i(j+k)}) - P_{i(j+k-1)}(Q_{i(j+k-1)})| \leqslant \Delta P_{\mathrm{S}} \end{cases}$$

for $k = 1, \ldots, W-1$ and $i = 1, \ldots, N$. The control input $\widehat{\mathbf{Q}}_j$ for the j-th SOP is then applied to the video coders.

This optimization problem involves $N(W-1)$ optimization variables to ensure the smoothness of the video quality on each program over a window of length W.

4. RATE AND DISTORTION MODELS

This section reviews briefly rate and distortion models as a function of the quantization parameter Q of the video encoder. Then a model describing $g_{ij}\left(Q_{ij}\right)$ and $h_{ij}\left(Q_{ij}\right)$ defined in (2) and (3) is introduced.

4.1. Some previous results

Most standardized video coders involve uniform fixed-step scalar quantization in the transformed domain. For gaussian sources with zero mean and variance σ^2, the performance of such quantizers is lower-bounded by the rate-distortion function

$$D(R) = \sigma^2 2^{-2R}, \quad (12)$$

see [17]. Nevertheless, this simple model may only be used to estimate the rate-distortion performance of the texture quantization process. Video codes involve other operations such as motion compensation or packetization of data, which contribution to the total rate is much more difficult to evaluate.

Thus, several parametric models have been proposed to represent the rate-distortion behavior of video coders. For example, [18] introduces a *quadratic* model

$$R = K\sqrt{D}, \quad (13)$$

used to solve the rate control problem for constant quality video, but in this model, the control inputs are not apparent. A three-parameter distortion-rate model is considered in [19]

$$D(R) = D_0 + \frac{\theta}{R - R_0}, \quad (14)$$

where again, the values of the parameters depend on the coding scheme and the content of the video. In [20] and [21], a ρ-domain model is proposed, where ρ indicates the proportion of null coefficients of a block in the transform domain after quantification. This rate model

$$R(\rho) = \theta(1 - \rho) \quad (15)$$

is a *linear* function of the number of non-zero coefficients. Since ρ depends on Q, a relation between R and the Q may be deduced.

In [22], the rate and distortion are expressed as functions of the Q as

$$R\left(Q\right) = aQ^{-\alpha} \quad (16)$$

$$D\left(Q\right) = bQ^{\beta}. \quad (17)$$

To be adjusted, all these models (and the one considered in this paper) need at least as many encoding trials at different values of Q as parameter to identify. Parameters may also be recursively updated with less encoding trials.

4.2. Distorsion model

A model of the distortion as a function of the quantization parameter Q of the H.264/AVC encoder may be deduced from the fact that the quantization is mainly scalar, with uniform step-size Δ in the transformed domain. A first step consists in recalling the link between Δ and Q as provided in the H.264/AVC standard [2, 23]

$$\Delta\left(Q\right) = q_{Q\%6} 2^{\lfloor Q/6 \rfloor} / PF \quad (18)$$

where $Q\%6$ is the remainder of the division of Q by 6, $\lfloor \cdot \rfloor$ corresponds to downwards rounding, PF is a constant which value depends of the sub-band (the location in the bloc of the quantized coefficient), and

$$q = [0.625, 0.6875, 0.8125, 0.875, 1, 1.125].$$

In fact, as pointed out by [24], (18) is only a possible implementation of

$$\Delta\left(Q\right) = 2^{\frac{Q-4}{6}} / PF. \quad (19)$$

At high rate, the distortion introduced by a uniform scalar quantizer is

$$D\left(\Delta\right) = \frac{\Delta^2}{12}, \quad (20)$$

see [25]. Thus, for a given sub band in the transform domain, one gets from (19) and (20)

$$D\left(Q\right) = \frac{1}{12PF^2} 2^{\frac{Q-4}{3}}. \quad (21)$$

The dependency with PF (and thus with the sub-band) of the distortion in the transform domain makes it difficult to get a closed-form expression of the distortion in the pixel domain. Nevertheless, one may deduce from (21) the following exponential model

$$D(Q) = a_{\mathrm{D}} \exp(b_{\mathrm{D}} Q), \tag{22}$$

which will be used in the experimental part of this paper. As it involves two parameters, at least two encoding trials per SOP or per GOP are necessary to estimate a_{D} and b_{D}.

4.3. Rate model

As mentioned earlier, obtaining a good rate model from interpretations of the H.264/AVC standard is far from being trivial. In [24] the following simple model

$$R(\Delta) = \frac{a}{\Delta} \tag{23}$$

linking R and Δ has been introduced from experimentations. Combining (23) and (19) , one may obtain the following exponential model

$$R(Q) = a_{\mathrm{R}} \exp(-b_{\mathrm{R}} Q). \tag{24}$$

As for (22), two encoding trials are necessary to estimate the two parameters $(a_{\mathrm{R}}, b_{\mathrm{R}})$ of this model

4.4. Tests for the considered models

Tests have been performed on some video sequences with different characteristics and contents. Figure 3 shows the $R(Q)$ and $D(Q)$ functions for the first GOP of 15 pictures of *Foreman.cif* and for an excerpt of an action motion picture, called *Film* in what follows. Parameters were estimated with 3 and 7 measurements obtained from encoding with different values of Q. Results obtained with 3 measurements are satisfying, thus all parameters estimations are done in what follow with 3 encoding trials.

The rate and distortion models for different GOP of the Film sequence are estimated and represented in Figure 4 for GOP indexes 1, 2, 3, and 11. $D_j(Q_j)$ does not vary significantly with the GOP index j, confirming the fact that the distortion is mainly determined by the size of the quantization step. More significant variations are observed for $R_j(Q_j)$.

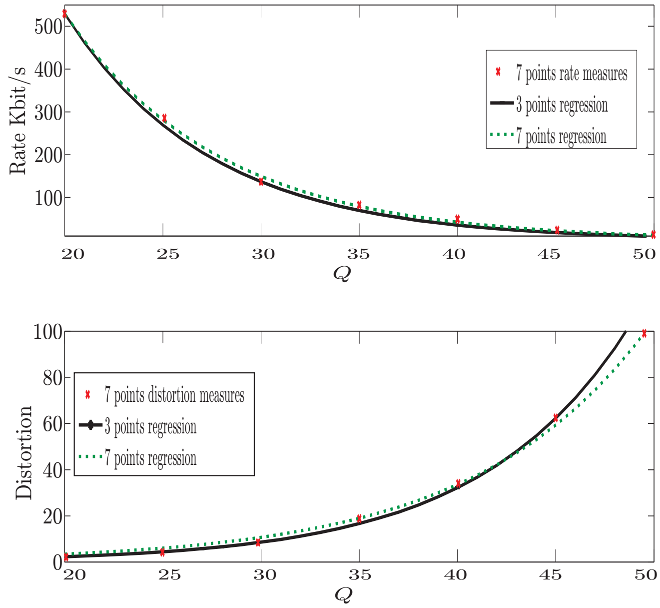

Fig. 3. Rate and distortion model fitting when 3 and 7 experimental values are taken into account (Foreman)

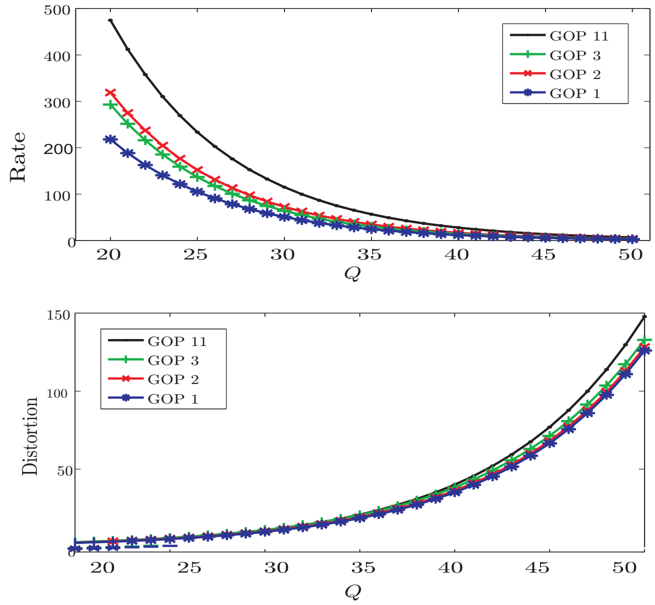

Fig. 4. Rate and distortion models for several GOP of the Film video sequence

5. EXPERIMENTAL RESULTS

This section evaluates the performance of a statistical multiplexer for which the control inputs of video coders are obtained from (11). Various video sequences are considered in CIF format: standard videos such as Foreman, Container, Coastguard, Hall, and excerpts of action motion pictures from a video sequence called Film. All these materials are encoded with H.264/AVC in baseline profile at 16 fps and by considering GOP, whose size $N_G = 16$ pictures. The first picture in the GOP is encoded in Intra mode and the remaining pictures are encoded as P-pictures. In the first set of experiments, we focus on the analysis of the impact of prediction proposed in Section 3 on the smoothness and fairness criterion using a SOP size, denoted by N_S, equal to the GOP size ($N_S = N_G$). To perform the optimization with a smoothness constraint spanning over a window of W SOPs, the rate and distortion models have to be evaluated in advance for at least $W-1$ SOPs. Thus, buffers have to be considered in the control loop. In all simulations, the channel rate $R_c = 1$ Mb/s. The average distortion within a SOP has to be below $D_{\max} = 55$, which corresponds to a PSNR above 30 dB.

5.1. Influence of the smoothness and fairness constraints

First, Film is encoded alone at a constant target bit rate of 200 kbit/s. Figure 5 represents the variation of the PSNR as a function of the SOP index. Constant bit rate encoding results in high PSNR variations reaching 15 dB between SOP 13 and 14.

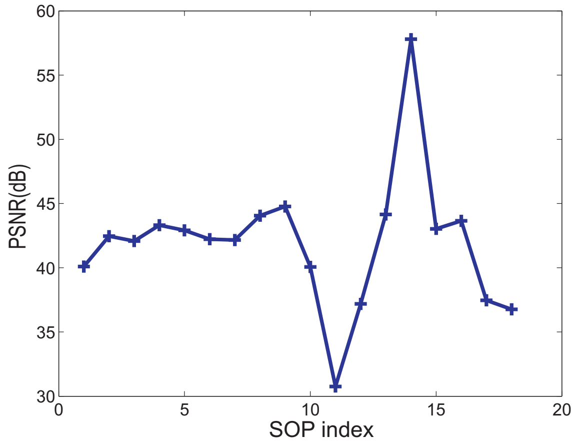

Fig. 5. Variation of the PSNR as a function of the GOP index for Film encoded at a CBR of 200 kbit/s in the $N_S = N_G$ case

Now, Film is multiplexed with Foreman, the fairness constraint being tuned at $\Delta P_{\mathrm{p}} = 4$ dB. Figure 6 illustrates the PSNR differences between successive SOPs of Film when $W = 2$, 3, and 4, corresponding to smoothness constraints with respect to the past, present, and no, one, and two future SOP respectively. In the experiment, the minimum value of ΔP_{S} is searched such that all constraints remain satisfied.

For $W = 2$, ΔP_{S} has to be larger than 5.4 dB, whereas with $W = 3$ and $W = 4$, it may be reduced to 2.2 dB and 1.8 dB respectively. The price to be paid for these encoded video sequences with smooth quality is a less efficient use of the available bit rate, having some space for new programs. Figure 7 focuses on the fairness criterion, representing the evolution of the PSNR for the two previously multiplexed sequences (Film and Foreman), with the parameters defined above, for $W = 2$ and $W = 4$ and ΔP_{S} at its limit in both cases.

Statistical multiplexing and efficient control allows the smoothness and fairness criteria to be satisfied simultaneously. Increasing W allows to anticipate the PSNR variations, and to reduce or increase in advance the PSNR to better account for a large PSNR variation which would occur when encoding a program with CBR. This is evidenced in Figure 7 around SOP 11 and 14 of Film, which were the SOP with the largest PSNR variation when encoded with CBR, see Figure 5.

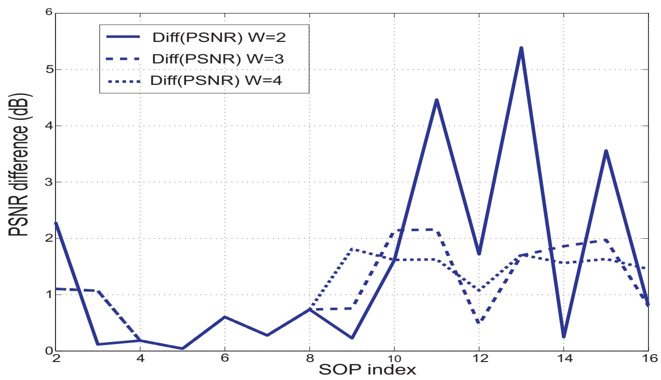

Fig. 6. Variation of the PSNR as a function of the GOP index for Film (multiplexed with the Foreman in the case $N_S = N_G$

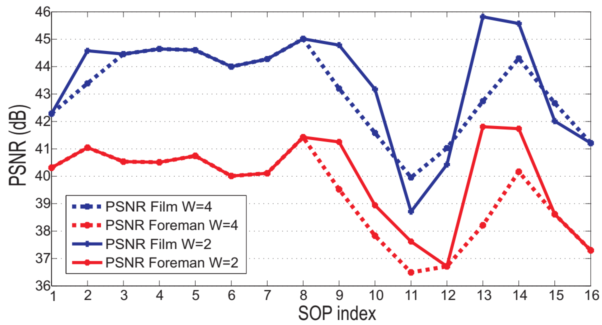

Fig. 7. PSNR as a function of the SOP index for the multiplexed sequences Foreman and Film in the case $N_s = N_G$

5.2. Multiplexing efficiency

In this section, we study the multiplexing efficiency by considering two size of the SOP in order to highlight the feasibility of our approach at different multiplexing granularity level.

5.2.1. $N_S = N_G$

Four video sequences (Foreman, Container, Coastguard, Hall) are multiplexed by considering a SOP size equal to the GOP size ($N_S = N_G$). The channel rate is $R_c = 1$ Mb/s. The fairness and smoothness constraints are such that $\Delta P_{\mathrm{p}} = 4$ dB and $\Delta P_{\mathrm{S}} = 1$ dB.

Figure 8 represents the evolution of the total rate. When all constraints may not be satisfied, the rate constraint is re-

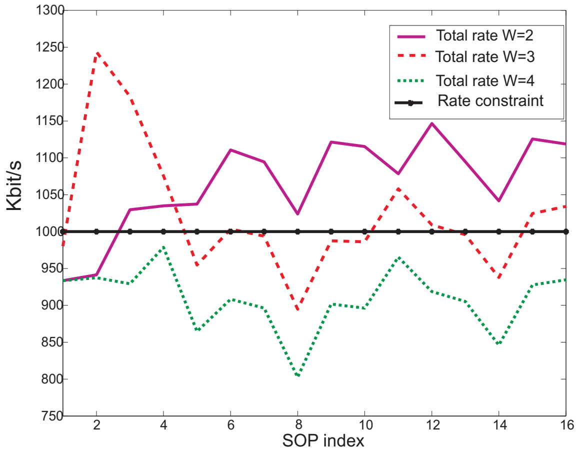

Fig. 8. Evolution of the total rate when multiplexing four sequences with various sizes of the control window W in the case $N_S = N_G$

laxed and one tries to minimize the rate such that all other constraints are satisfied. Again, control is performed over a window characterized by $W = 2$, 3, and 4. Only $W = 4$ allows to satisfy all constraints simultaneously. This shows that increasing the size of the control windows improves the efficiency of the statistical multiplexing. Multiplexing the four test sequences and satisfying all constraints is impossible by performing a regulation accounting only for the past.

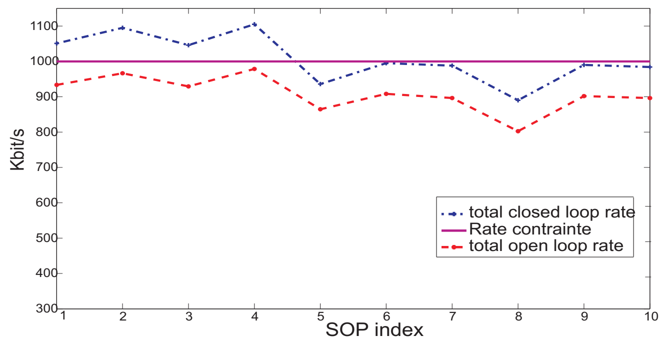

Fig. 9. Comparison between total closed and open loop rate in the case $N_S = N_G$

Curves represented in Figure 9 correspond to the total rate generated from both open and closed loop control using the SOP structure corresponding to $N_S = N_G$ compared to the rate constraint. In the open loop mode, we use the rate and PSNR values resulting from the models presented in Section 4. In the closed loop mode, the rate values are obtained after the quantization parameters being delivered by the statistical multiplexing process to the encoders. A 100 kbit/s difference between the total rate at the output of the encoders and the rate predicted by the models. This difference induces a bandwidth overflow which is small enough to be easily compensated by buffers at outputs of th the encoders. We notice also the same behavior for the PSNR evolution of the multiplexed programs. Using the same values of ΔP_{p} and ΔP_{S} chosen in this experiment, no significant improvement has been noticed in the case $W = 5$.

5.2.2. $N_S = N_G/2$

In a second set of experiments, we use a SOP size equal to half of that of a GOP. In this part, we multiplex the four video sequences mentioned above (Foreman, Container, Coastguard, Hall), using the same optimization parameters as those used in Section 5.2.1. We distinguish two SOPs structures: SOPs containing one I-picture and $(N_S - 1)$ P-pictures (IPP...): I-SOP, and SOPs containing N_S P-pictures (PP...): P-SOP. The SOP transmission is represented in Figure 10.

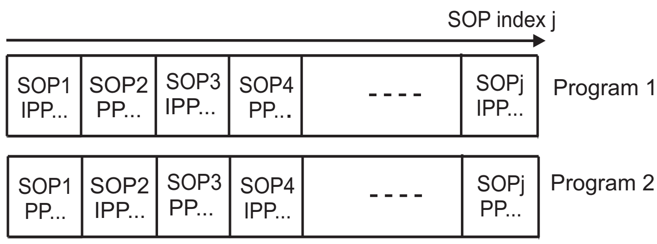

Fig. 10. SOP ordering scheme

Due to its specific structure, SOP can be transmitted in synchronized or unsynchronized way. In the first case, SOPs containing I-pictures are transmitted at the same time for all the multiplexed programs. In the second case, SOPs containing I-pictures are randomly transmitted to fulfill the requirements of the real transmission system where there is no control of the I-picture position.

The four I-SOPs of the multiplexed video used in this experiment are unsynchronized in such a way that the same number of I-pictures at each SOP unit, where SOP unit denotes the set of transmitted SOPs from all the multiplexed programs at the same index j. Such transmission is depicted for the that of two programs in Figure 10. In the sequel, we evaluated the fairness, smoothness and multiplexing efficiency using this organization of SOP.

Figure 11 represents the total rate corresponding to the sum of rate for the four multiplexed program with a bandwidth constraint $R_c = 1Mbit/s$, a window size $W = 4$ and by considering an open and a closed loop control. We notice that in both cases, $N_s = N_G$ (Figure 9) and $N_S = N_G/2$ (Figure 11), we have the same difference (about 100kbit/s) between rate of the output of the encoders and the rate predicted by the models. The smoothness and fairness constraints are also verified even for such specific SOP size.

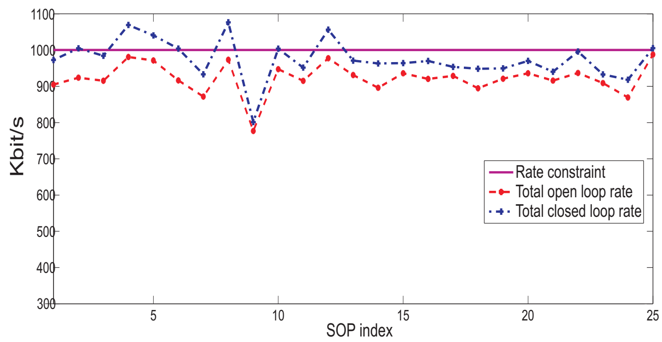

Fig. 11. Comparison between total closed and open loop rate in the case $N_S = N_G/2$

6. CONCLUSION

In this work, we propose a new control process for the statistical multiplexing system using H.264/AVC video encoders. This joint control system is designed to provide high smoothness and fairness performance for the transmission of several video program in parallel. This process distributes the available channel bandwidth among the encoders on the basis of ensuring a comparable quality level for all multiplexed program and minimizing the quality variations within each program.

The proposed control process uses a regulation on different SOP size, so that rapid changes in the rate due to scene changes are smoothed, and to reach a complexity-efficiency tradeoff by adjusting the number of pictures within a SOP. The optimal coding parameters to apply for each SOP in each multiplexed program are evaluated using encoding parameters of both past and future SOPs. This mechanism needs to estimate the parameters of both rate and distortion models in order to have more efficient rate and distortion prediction.

The performance of the proposed system has been evaluated via simulation and compared with a reference control scheme where only regulation with respect to past SOP is performed. Experimental results show that this system introduces a notable decrease in the intra-program quality variation, which leads to an improved multiplexing efficiency. Using both past and future SOP characteristics, it is possible to increase the number of multiplexed programs at a target channel rate and quality level. Further work, will be dedicated to the study of solutions to maximize the use of bandwidth, since imposing a smoothness constraint makes it difficult to fully use the available bitrate.

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