Joint Source-Channel Rate Allocation and Unequal Error Protection for Dependent Video Transmission

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***Abstract*— In this paper, based on previously work in [7] and [9], a joint method of optimize source and channel rate allocation is proposed based the dependence and the attenuation of error propagation between video frames. It is assumed that the source coders rely on motion-compensated prediction, and thus error propagation will contribute significantly to the degradation of the reconstructed video. The rate allocation method is based upon generation of operational distortion-rate characteristics. In order to reduce computational complexity, the channel code performance is modeled and the model of the attenuation of intensity of error propagation is employed to generate these rate-distortion surfaces. An analytic method for computing optimal rate allocation both frames in a video sequence is then introduced. Finally, the results of rate allocation and unequal error protection are shown for H.264 compressed video used in convolutional codes.**

***Index Terms*— Joint source/channel coding, rate allocation, video compression, unequal error protection.**

I. Introduction

Shannon's theory allows claiming that source coding and channel coding can be optimized separately. However, this is achievable only for large block sizes from the source and the channel sides. This imposes a high complexity, which is not convenient for real-time video systems. To avoid this drawback, early attempts [1], [2], [3] have been made towards a joint optimization of the source-channel coding. A brief overview of combined source and channel coding methods is provided in [4]. An excellent analytical treatment of the tradeoffs between vector quantization and block channel coding is given in [5] for the binary symmetric channel (BSC). Typically, joint source channel coding has been focused on several broad categories: source-optimized channel coding, channel-optimized source coding, and iterative algorithms, which combine these two code designs.

In the case of source-optimized channel coding, the source coding scheme is fixed. A channel code is then designed for this source code to minimize end-to-end distortion over the given channel. It can be seen that there exists variety of schemes for performing source-optimized channel coding for video transmission. The most of these schemes have been generally developed a method so as to minimize end-to-end distortion through to optimize rate allocation between the source and the channel. Furthermore, previous results in rate allocation for video coding have generally assumed that video frames are independently coded and have neglected error propagation between frames. However, error propagation can be a significant source of degradation in reconstructed video frames. In [6], Ramchandran et al. were the first to introduce bit allocation during source coding assuming dependence between coding units such as image blocks or video frames. They showed that optimal source coding rate allocation is possible in an operational rate-distortion framework, providing motivation for considering the problem of dependent joint source–channel rate allocation. A general joint source–channel rate allocation scheme for a dependent video coding environment is presented in [7]. It is assumed that the source coders rely on motion-compensated prediction, and thus error propagation will contribute significantly to the degradation of the reconstructed video. The rate allocation methodology is based upon generation of operational distortion-rate characteristics. In order to reduce computational complexity, these surfaces and the channel code performance are modeled. An analytic method for computing optimal rate allocation across frames in a video sequence is then introduced. Although the range on temporal and spatial between dependent video frames is expanded with the number of the dependent video frames increasing, however, the intensity of error propagation is gradually attenuation between dependent video frames. The attenuation is due to the half-pixel filter (operating as a low-pass filter over the video frame) used in the motion estimation technique in the video coder. More details on this filter can be found in [8] which explain thoroughly the video encoder/decoder structures and specifications. In [9], the attenuation of propagation over temporal and its effect on the subsequent frame can be approximated by an expression.

In this paper, based on previously work in [7] and [9], a joint method of optimize source and channel rate allocation is proposed based upon the assumption of the dependence and the attenuation between video frames. The use of distortion-rate characteristics is particularly suited to the problem of dependent rate allocation, since the number of parameters in this case is significantly larger than for the independent case. To reduce the complexity of this problem, the proposed method is based on models of the operational distortion-rate characteristics.

This paper is organized as follows: in Section II, an overview of the rate allocation problem is presented. Then, in Section III, the model of Channel Code Performance, the channel distortions model and the attenuation model of intensity of error propagation are presented. In Section IV, generation and modeling of rate-distortion surfaces are discussed. In Section V, a rate allocation method is presented and the results of rate allocation and unequal error protection are shown for H.264 compressed video used convolutional codes. Finally, in Section VI, we conclude the work.

II. Formulation of the Rate Allocation Problem

The general rate allocation problem can be framed in terms of a Lagrangian optimization, with the cost function to be minimized.

Given a L-frame GOP, when $Q=\{q_1,q_2,\ldots,q_L\}$ is the source quantization vector and $r=\{r_1,r_2,\ldots,r_L\}$ is the channel code rate for a L-frame GOP, where q_k is the quantization parameter and r_k is the channel code rate for the kth frame, the Lagrangian optimizing problem is written as

$$J(Q,r,\lambda)=\frac{1}{L}\sum_{k=1}^{L}D_{S+C}^{(k)}(q_1,q_2,\ldots,q_k,r_1,r_2,\ldots,r_k) + \lambda\left(R_{budget}-\sum_{k=1}^{L}\frac{R_S^{(k)}(q_i)}{r_k}\right). \tag{1}$$

In the most general case, the solution is significantly complex because rate allocations in one reference frame affect the following predicted frames. The first term in (1) is the overall L-frame sequence global average distortion for a selected quantization vector Q and a selected channel coding rate vector r. $D_{S+C}^{(k)}(q_1,q_2,\ldots,q_k,r_1,r_2\ldots,r_k)$ is the distortion and $R_S^{(k)}(q_k)$ is the source rate function for kth frame. Computing $D_{S+C}^{(k)}(q_1,q_2,\ldots,q_k,r_1,r_2\ldots,r_k)$ and $R_S^{(k)}(q_k)$, assuming that no errors occur for each frame, would alone require significant storage and computation due to the dependencies. However, with the inclusion of channel errors, the computation becomes infeasible for even small sets of Q and r, since the number of computations for an exhaustive search increases exponentially with the number of frames in a dependency structure. In order to overcome these limitations, in the following sections, a model of the bit-error probability for convolutional codes and a model of rate-distortion surfaces are introduced in [7].

III. Modeling of Channel Code Performance and Channel Distortion

A. Modeling of Channel Code Performance

In order to model the channel codes, assuming an AWGN channel with binary signaling, for a signal-to-noise ratio (SNR) E_s/N_o, Bystrom and Stockhammer[7] have modeled the bit-error probability of the convolutional codes under consideration here as

$$p(r)=10^{-\rho/r_k+\eta} \qquad r_k\in[0.25,1]. \tag{2}$$

where r_k denotes the channel coding rate and ρ and η are parameters depending on channel characteristics. For the AWGN channel, these parameters depend only on the signal-to-noise ratio. Selected parameter values, obtained by regression analysis of simulated curves, for example, ρ and η are 2.5186 and 1.3811 respectively with the E_s/N_o is 1dB.

B. Modeling channel distortion

Given the model of the channel codes, the next step in the rate allocation process is to generate and model rate-distortion formulation that characterize the sensitivity of the video to quantization errors, channel errors, and error propagation. In order to model the rate-distortion formulation, the distortion for overall GOP must be evaluated. The MSE is used to quantify the video degradation, due to video compression and transmission errors.

Generally, to reduce computation complexity for the dependent video sequence, the modeling methods used to formulate rate-distortion characteristic. In [7], a two-dimensional distortion model is here introduced as

$$\begin{aligned} D_{S+C}^{(k)}(p_i) &= D_S^{(k)}(q_k)+D_C^{(K)}(q_k,r_k) \\ &= D_S^{(k)}(q_k)+\sum_{i=1}^{k}\left[\alpha_i^{(k)}\left(log_{10}\frac{1}{p_i}\right)^{-\beta_i^{(k)}}\right] \\ &\qquad \text{for } 1\le i\le k. \end{aligned} \tag{3}$$

where $D_{S+C}^{(k)}(p_i)$ denotes the total distortion in the kth frame, $D_S^{(k)}$ denotes the distortion in the kth frame due to source coding, while the second term of the right side in (3) are the contributions to the kth frame distortion due to channel errors in the first frame, the second frame through the kth frame. α_i^k and β_i^k implicitly depend upon quantization vector Q, they can be obtained by regression analysis of simulated curves. p_i denotes the channel bit-error probability for transferring ith frame.

However, in this method, by using at least $2\cdot i+1$ points in each frame a model of the distortion of the frame can be developed. Furthermore, each a point must be tested in different simulation process due to different channels bit-error probability. So the distortion-rate surfaces generated with error rates becomes difficult with the sequence frames increase.

In this paper, we model the attenuation of intensity of error propagation to solve this difficult. It has been shown [9] that a channel error, with intensity σ^2, occurring on the first

Table 1. Each a Frame Distortions Due to channel errors Distributing Considered Errors Propagation

Frame No.	The currently frame distortions experimental measurements (MSE)	The previous frames errors propagating to the currently frame (MSE)	The currently Frame channel errors resulting distortions (MSE)
I-Frame(1)	$\sigma_{\mathrm{T}}^2(p_1)$	0	$\sigma_{\mathrm{T}}^2(p_1)$
P2-Frame(2)	$\sigma_{\mathrm{T}}^2(p_2)$	$\sigma_{\mathrm{T}}^2(p_1)/(1+\varphi)$	$\sigma_{\mathrm{T}}^2(p_2)-\sigma_{\mathrm{T}}^2(p_1)/(1+\varphi)$
P3-Frame(3)	$\sigma_{\mathrm{T}}^2(p_3)$	$\sigma_{\mathrm{T}}^2(p_2)/(1+\varphi)$	$\sigma_{\mathrm{T}}^2(p_3)-\sigma_{\mathrm{T}}^2(p_2)/(1+\varphi)$
…	…	…	…
Pn-Frame(n)	$\sigma_{\mathrm{T}}^2(p_{\mathrm{n}})$	$\sigma_{\mathrm{T}}^2(p_{n-1})/(1+\varphi)$	$\sigma_{\mathrm{T}}^2(p_{\mathrm{n}})-\sigma_{\mathrm{T}}^2(p_{n-1})/(1+\varphi)$

frame of a GOP, propagates over time and its effect on the *k*th subsequent frame can be approximated by the following expression:

$$D_{\mathrm{C}}^{(k)} = \sigma^2 \frac{1}{1+\varphi k} \quad . \tag{4}$$

where φ is a parameter and can be determined by experimental measurements over the considered video sequence [10]: Considering several measures of $D_C^{(k)}$ for the same video sequence with a large range of signal-to-noise ratio values, we can evaluate this parameter by curve fitting. For the case of the *Missa* sequence, with a GOP length of 30, experimental results yield the following fitting value: φ =0.0082. k is video frames number.

Fig.1 represents our simulated results of MSE as a function of frame number *k*, for the case of a 30-frame video sequence with one channel error occurring on the initiatory each P frame. We also represent the MSE obtained by the analytical

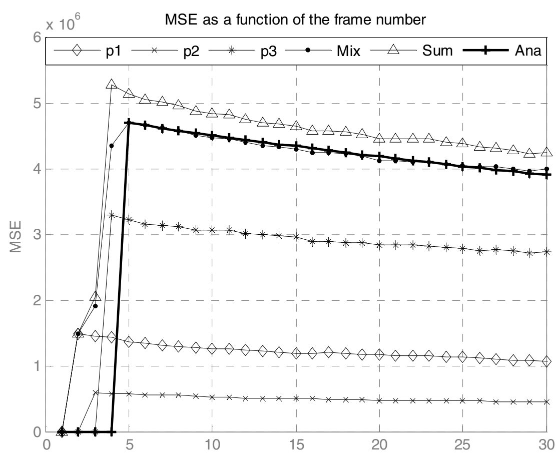

Fig.1. Simulation MSE versus the frame number. *p1*, *p2* and *p3* curves indicate results of MSE as a function of frame number *k*, with one channel error occurring alone on 1st, 2nd and 3rd P-frame. *Mix* curve represents MSE with three channel errors occurring synchronously on three different P frames (p1, p2 and p3). *Sum* curve is sum of p1, p2 and p3 curves. *Ana* is the result of analytical model.

model using the parameter φ =0.0082.

If the *k*th frame is transmitted with channel error probability p_k , the resulting distortion propagating from the first frame on the rest of the GOP will be written as:

$$D_{\mathrm{C}}^{(k)} = \sigma^2(p_k) \frac{1}{1+\varphi k} \,. \tag{5}$$

In [7], σ^2 is considered as a constant. In fact, $\sigma^2(p_k)$ should be a function as channel probability of error p_k . In case of one error at the beginning of the GOP, its effect on the totality of the GOP is estimated as:

$$D_{\mathrm{C}}^{(k)} = \sum_{\mathrm{t}=0}^{\mathrm{L}-1} \sigma^2(p_k) \frac{1}{1+\varphi k} \,. \tag{6}$$

In case of independent error patterns, the overall distortion resulting from all erroneous frames over the totality of the GOP frames is

$$D_{\mathrm{C}}^{(k)} = \sum_{\tau=0}^{\mathrm{L}-1} \sum_{\mathrm{t}=\tau}^{\tau} \sigma^2(p_k) \frac{1}{1+\varphi k} \,. \tag{7}$$

In Fig. 1, Sum curve represents the experimental sum of MSE of p1, p2 and p3 curves, it is not superposition with Mix curve of MSE accumulated through the video sequence with three channel errors occurring one after the other on three different P frames (p1, p2 and p3).

This is due to the fact that, in reality, the errors effects on the transmitted sequence are not truly additive. In practice, the no-truly additive errors effect reflects the dependence or proximity of errors occurring in video frames. Theoretically, therefore, it is very difficult to look for a appropriate expression for $\sigma^2(p_k)$. Therefore, we modify (7) as

$$D_{\mathrm{C}}^{(k)} = \sum_{\mathrm{k}=1}^{\mathrm{L}} \sigma_{\mathrm{T}}^2(p_k) \,. \tag{8}$$

Where $\sigma_{\mathrm{T}}^2(p_k)$ are practical experimental measurements, it reflects the effects with channel errors and errors propagation. Based on (4) ~ (8), we model each a frame distortions distributing considered errors propagation and the attenuation of intensity of error propagation as Table 1.

IV. Generation and Modeling of Rate-Distortion Surfaces

Given the model of the channel codes and the channel distortions, the next step in the rate allocation process is to generate and model rate-distortion surfaces which characterize the sensitivity of the video to channel errors, and error propagation.

As apparent from the complete experimental measurements, calculation of the operational distortion-rate surfaces is extremely computationally intensive due to the large number of iterations required for reasonable confidence in the distortion results [7]. Therefore, we use the models of the attenuation of errors propagation in Table 1 besides employing the same channel distortions model in [7] shown in (3) to reduce the computational complexity of this problem. In (3), the monotonic of $D_{\mathrm{C}}^{(k)}$ with respect to p_I, p_2,…,and p_n are proved in [7,11]. Joint considering the second term in (3) and Table 1, the *I*-Frame of *L*-Frame sequence distortion curve versus the logarithms of the inverse bit-error probabilities p_i ($log_{10}(1/p_i)$) are written as

$$D_C^{(1)}(p_1) = \alpha_1\left(log_{10}\frac{1}{p_1}\right)^{-\beta_1}. \tag{9}$$

The distortion curves of the *I*-Frame are shown as Fig.2. The distortion surface of the second frame of a two-frame sequence coded at two different rates are shown as a function of the logarithm of the inverse bit-error probabilities for the two frames as

$$D_C^{(2)}(p_I,p_{PI}) = \alpha_1\left(log_{10}\frac{1}{p_{\mathrm{I}}}\right)^{-\beta_1}\Big/(1+\varphi) + \alpha_2\left(log_{10}\frac{1}{p_{\mathrm{P1}}}\right)^{-\beta_2} \tag{10}$$

The distortion surfaces are shown as Fig. 3. Where $\alpha_1,\beta_1,\alpha_2$ and β_2 are two parameter sets, they can be obtained by regression analysis of simulated curves by using experimental measurements in Table 1.

The results of modeling the distortion of the p_2 and p_6 frames are shown in Fig. 4 and Fig.5, respectively. Bases (9) and (10), the average transmission distortions with a GOP of *L*-Frames can be written as

$$\overline{D}_{\mathrm{C}} = \frac{1}{L}\sum_{\tau=1}^{\mathrm{L}}\sum_{\mathrm{k}=1}^{\tau}\alpha_\tau\left(log_{10}\frac{1}{p_\tau}\right)^{-\beta_\tau}\Big/(1+\varphi)^{k-1} \tag{11}$$

All transmissions are simulated as described in [7] with the bit-error probabilities $10^{-7} \le P_I$, P_{PI} ;⋯,$P_{Pn} \le 10^{-3.5}$ for the all frames. The upper limit for the range of the bit-error probabilities was determined as the limit of errors above

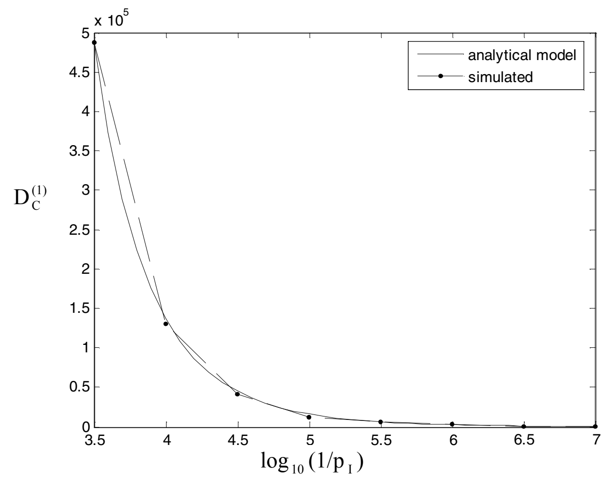

Fig.2 Distortion of the *I* Frame shown as function of BERs. Simulation points are shown by dots and models by solid lines.

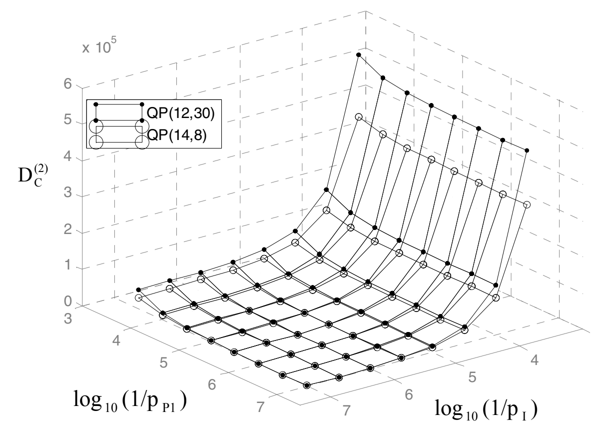

Fig.3 Distortion of the P_1 Frame shown as function of BERs in the *I* frame and P_1 frame for two quantization parameter sets. Simulation points are shown by dots or circles and models by solid lines.

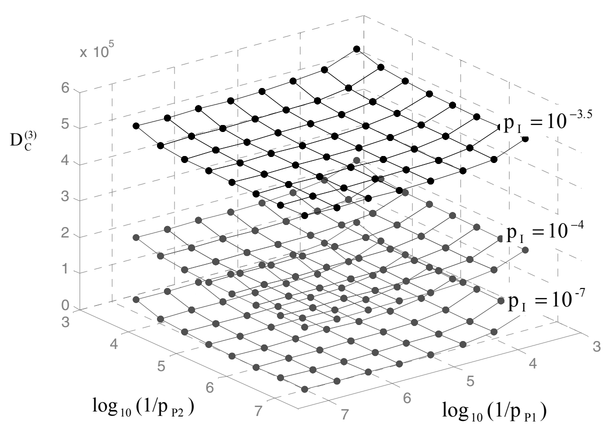

Fig.4 Distortion of the P_2 Frame shown as function of BERs. Simulation points are shown by dots and models by solid lines.

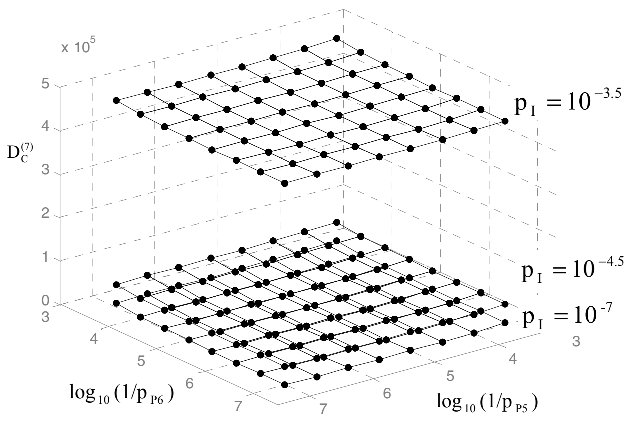

Fig.5 Distortion of the P_6 Frame shown as function of BERs. Simulation points are shown by dots and models by solid lines.

which the decoder would regularly lose synchronization and fail to decode the frames. The lower limit is the error floor at which channel errors are so unlikely that the distortion is due mainly to source coding errors. In all simulations shown, the results of simulations in this paper are similar to the results in [7]. In this example, by using the model of channel distortions and the model of attenuation of errors propagation, the *i*th frame distortion-rate surfaces can be developed only using $i+1$ points. Any surface with error rates in the range $10^{-7} \le P_I$, P_{P1} ;⋯,$P_{Pn} \le 10^{-3.5}$ can be generated with only a linear increase in simulated points per frame.

V. Optimal Rate Allocation and Unequal Error Protection Channel

In the previous two sections, we introduced models for the channel codes and the operational distortion-rate characteristics of a video coder. We now employ these models for rate allocation between frames in a video sequence in a constrained optimization problem.

Consider a transmission system having a channel with varying conditions and rate constraints. This scenario represents any slowly time-varying system with feedback and adaptive resource allocation. Video segments can be precoded, that is, compressed using a selected set of quantization parameters chosen to achieve good reconstructed quality at various source coding rates. The model parameters for each video segment are precomputed and stored. As channel conditions or constraints vary, the optimal channel code vector should be rapidly recomputed into order to deliver the highest quality video. For this optimal allocation, given a set of available Q, (2), (3) and (11) can be used to rewrite the average transmission distortions with a GOP of L-Frames as (12).

The goal of the rate allocation algorithm, as stated in formulation (1), is to find the source and channel coding

$$\overline{D}_{S+C}(Q,r) = \frac{1}{L}\sum D_S^{(k)}(p_k) + \frac{1}{L}\sum_{\tau=1}^{L}\sum_{k=1}^{\tau}\alpha_\tau\left(\frac{\rho}{r_\tau}-\eta\right)^{-\beta_\tau} \Big/ (1+\varphi)^{k-1} \qquad (12)$$

vectors to minimize the average sequence distortion subject to the constraint on overall rate. Despite the decoupling of the effects of source errors and the channel errors, the second term in (12) is a function of both the source and channel coding rates, thus determining the optimum rate allocation is still an intractable problem.

Therefore, we employing the same method as in [7], we divide the optimization problem into two steps. First, for the selected quantization vectors, we determine the corresponding source rates $R_S^{(k)}(q_k)$, $i = 1,2,\cdots,\ N$ and minimize the channel distortion $\overline{D}_C(Q,r)$ subject to the overall bandwidth constraint. We repeat this for each available Q, r and for each desired rate constraint. The optimum rate allocation is then the combination of and which minimizes the overall sequence distortion for the available overall rate.

For a fixed Q, the first step can be performed by a Lagrange multiplier approach with cost function and (1) can be modified as

$$J(r,\lambda) = \frac{1}{L}\sum_{k=1}^{L}\sum_{\tau=k}^{L}\alpha_\tau\left(\frac{\rho}{r_\tau}-\eta\right)^{-\beta_\tau} \Big/ (1+\varphi)^{k-1} + \lambda\left(R_{budget} - \sum_{k=1}^{L}\frac{R_S^{(k)}(q_k)}{r_k}\right). \qquad (13)$$

Taking the partial derivatives of $J(r,\lambda)$ with respect to r and λ yields the following system:

$$\frac{\partial J}{\partial r_l} = \frac{\rho}{L}\sum_{k=l}^{L}\frac{1}{r_l}\alpha_l\beta_l\left(\frac{\rho}{r_l}-1\right)^{-(\beta_l+1)} \Big/ (1+\varphi)^{k-1} + \lambda\frac{R_S^{(l)}(q_l)}{r_l}$$

$$\frac{\partial J}{\partial \lambda} = R_{budget} - \sum_{k=l}^{L}\frac{R_S^{(l)}(q_l)}{r_l}$$

$$l = 1,2,\cdots,N \qquad (14)$$

Using the model parameters found from the methods described in the previous sections, in (14), these equations can then be solved for the optimum for the selected Q with $\partial J/\partial r_l = 0$ and $\partial J/\partial \lambda = 0$. The second step of the optimization problem can be implemented as a simple search over all generated points.

We now present selected results for H.264 video coding with convolutional channel coding and discuss some of the more interesting finding. Table 2 shows the optimal channel rates for the six-frame *Missa* sequence compressed with four different quantization vectors. The selected quantization parameters Q results in a sequence source coding rate R_S of approximately 83000bits.

Table 2. Optimal Channel Rate Distortion and Unequal Error Protection for Fixed Source Rate and Overall Rate R_{budget} =162kbits, and a Channel SNR of 1dB

Q	Rate	I	P1	P2	P3	P4	P5	
Q1 {10,23,24, 25,26,27}	$R_S^{(k)}$	72512	1984	1872	1880	1840	1936	R_S=82024
	r_k	0.5	0.5	0.5	0.56	0.6	0.6	$\overline{D}_{S+C}$=59832
		0.5	0.6	0.6	0.56	0.5	0.5	$\overline{D}_{S+C}$=60003
Q2 {10,27,26, 25,24,23}	$R_S^{(k)}$	72512	1064	1304	2104	2864	4320	R_S=84168
	r_k	0.5	0.5	0.5	0.56	0.6	0.6	$\overline{D}_{S+C}$=56088
		0.5	0.6	0.6	0.56	0.5	0.5	$\overline{D}_{S+C}$=56259
Q3 {10,25,25, 25,25,25}	$R_S^{(k)}$	72512	1536	1648	1960	2512	2880	R_S=83048
	r_k	0.5	0.56	0.56	0.56	0.56	0.56	$\overline{D}_{S+C}$=56740
		0.5	0.5	0.5	0.56	0.6	0.6	$\overline{D}_{S+C}$=56686
Q4 {11,20,21, 22,23,24}	$R_S^{(k)}$	65264	4312	3712	3256	3360	2736	R_S=82640
	r_k	0.5	0.5	0.5	0.56	0.6	0.6	$\overline{D}_{S+C}$=48833
		0.5	0.6	0.6	0.56	0.5	0.5	$\overline{D}_{S+C}$=49003

Firstly, we can observe the differences of average distortions are not distinct for the cases of *Q1, Q2* and *Q3*. In other words, when the quantization parameter and channel coding rate of I-Frame are the same and that subject to the constraint on overall rate R_{budget} , the sequence average distortions are not notable difference whether the subsequent P-Frame are equal error protection (EEP) or unequal error protection (UEP). Specially, in extreme case of no bit error in first frame of the sequence, then the overall quality of the sequence is good. On the other hand, for the same source coding vector, the distortions with the channel UEP are lower than the channel EEP for the *Q3* and all results show also more channel protection should be allocated to frames occurring in earlier in the sequence for the *Q1*, *Q2* and *Q4*. Furthermore, we compare the *Q1* case with the *Q4* case, a conclusion which allocating suitably source coding rate between I-Frame and all P-Frame is more important can be drawn from these results that the average distortions for the *Q4* are obvious lower than the others and the source coding rate and overall rate are consistent with the others. In order to prove this viewpoint is true, we may compare further the *Q1* case with the *Q2* case, for the *Q1* case, more source coding rate are allocated to earlier frames and that channel coding rate are the same with the *Q2* case, reversely, the average distortions are higher than the *Q2* case. Thus, in general, more source and channel coding rate should be allocated to earlier frames in the sequence to prohibit error propagation and that should allocate suitably source coding rate between I-Frame and all P-Frame to reduce the average distortion.

V. CONCLUSION

In this paper, based on previously work in [7] and [9], a joint method of optimize source and channel rate allocation is proposed based the dependence and the attenuation of error propagation between video frames. The rate allocation methodology is based upon generation of operational distortion-rate characteristics. In order to reduce computational complexity, these surfaces and the channel code performance are modeled. Especially, we create a model of the attenuation of error propagation between video frames so as to obtain the multidimensional distortion-rate surfaces for video becoming simpler than the method in [7]. Subsequently, the two-frame sequence distortion-rate surface show that the modeling approach obtained very approximate results as simulated results. An analytic method for computing optimal rate allocation across frames in a video sequence is then introduced. Results are shown for H.264 compressed video used convolutional codes.

Finally, the results of optimal rate allocation show that more rates should be allocated earlier frames in sequence than to later frames and that should allocate suitably source coding rate between I-Frame and all P-Frame to reduce the average distortion.

ACKNOWLEDGMENT

The work is supported by Hubei provincial Department of Education for the excellent youth Science Research Program under Grant No.2004Q001.

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