RATE CONTROL FOR LEARNED VIDEO COMPRESSION

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ABSTRACT

Rate control is a critical part for video compression, especially in bandwidth-limited tasks such as live and broadcast. The newly-rising learned video compression has shown advantageous rate-distortion (RD) performance in previous research, but lack of rate control heavily limits its usage in real coding scenarios. In this work, we present the first rate control scheme tailored for learned video compression. Specifically, we explore the inter-frame dependency of learned video compression and propose a novel R-D-λ model accordingly for efficient rate allocation. Additionally, a staged update algorithm is developed for robust parameter estimation. Experiments on public datasets show that, the proposed rate control scheme achieves low rate error while maintaining equal or even higher RD performance, without introducing coding time overhead.

1. INTRODUCTION

The ability to accurately control the bitrate is crucial for any video codec in real-world applications. Such applications usually impose a limitation on the bandwidth while pursuing a best possible visual quality, which requires video codecs to exploit every bit available.

There has been a a fast rising of learned video compression (LVC) in recent years. End-to-end optimized on large-scale datasets, LVC frameworks achieve impressive RD performance when measured in common metrics such as PNSR and MS-SSIM, proving LVC a promising contestant for the next generation video coding standard.

Despite their outstanding RD performance, LVC approaches suffer from a severe lack of rate control algorithms. Most of current LVC methods need multiple models for different rates. These separate-rate models are trained for a single RD trade-off point, thus only able to output a single fixed bitrate. Every time a new bitrate is requested, a new model has to be trained or fine tuned, which is an unbearable burden for real-world applications. In a recent study [1], Lin *et al.*step forward to variable-rate models by varying the Lagrange multiplier λ. However, when a specific rate is desired, repeated recoding has to be carried out to find the suitable λ. This trial-and-error procedure leads to an extremely inefficient trade-off between coding time and rate error, which is still far from a feasible rate control scheme.

Direct application of conventional rate control approaches on LVC leads to heavy loss of RD performance, which is because conventional rate allocation methods are not suitable to model the inter-frame dependency in LVC. In conventional codecs, inter-frame dependency mostly comes from block-level referencing, therefore conventional methods focus on block-level rate allocation, and use a fixed rate ratio among frames. However, there is no block-level structure in LVC, thus inter-frame dependency only comes from frame-level referencing, which makes inter-frame dependency of LVC much more varied than that of conventional codecs. As a result, fixed rate ratio can no longer adapt to this variation and in turn deteriorates the RD performance.

To address the above problems, in this work, we propose a scheme that brings practical rate control into LVC. To the best of our knowledge, this is the first rate control scheme specially designed for LVC. Our main contributions include:

- a novel R-D-λ model for efficient rate allocation leveraging the inter-frame dependency of LVC
- a staged parameter update algorithm that ensures the robustness of parameter estimation

In our extensive experiments, we show that our proposed rate control scheme achieves low rate error without time overhead, and presents similar or even higher RD performance compared with the separate-rate and variable-rate models.

2. RELATED WORKS

2.1. Learned Video Compression

Equipped with powerful nonlinear representation ability of neural networks, LVC frameworks [2, 3, 4, 5, 6, 7, 8, 9, 10] achieve impressive RD performance and are drawing increasing attention in recent years. Lu *et al.*[2] propose to replace all key components in conventional video compression with neural networks, which is considered to be the first end-to-end optimized video compression framework. Following the

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paradigm of [2], various techniques have been proposed to improve the RD-performance of learned video compression: Lin *et al.*[5] use multiple frames to improve motion estimation; Yang *et al.*[6] introduce the bi-directional frames into learned video compression; Agustsson *et al.*[8] leverage the scale space flow to remove redundancy. Most of studies on LVC require separate-rate models to reach different rates, and are not able to output steady rate.

Some efforts have been made to explore variable-rate models in LVC. Rippel *et al.*[11] propose to adjust rate by changing spatial rate distribution of each frame. Lin *et al.*[1] introduce modulated module to control the rate. Zhu *et al.*[12] design a variable-rate model that can adjust rate through λ. Variable-rate models are solid improvement compared with separate-rate models as they can achieve multiple rates with a single model. However, tedious recoding is still inevitable when searching for the proper mode to attain a target rate, which is too inefficient to be considered as a practical rate control scheme.

2.2. Rate Control for Video Compression

In general, rate control seeks to optimize total distortion given total rate constraint, which is formulated by the method of Lagrange multiplier [13]:

$$\min L = \sum D_i + \Lambda \sum R_i, \text{ and } 0 = \frac{\partial L}{\partial R_i}, \tag{1}$$

where D_i and R_i are the distortion and rate of the i-th frame, and Λ is the *overall* Lagrange multiplier. This is solved by setting $\frac{\partial L}{\partial R_i}$ to zero to calculate for optimal rate for each frame $\hat{R}_i$, and then break the optimization down to frame level:

$$\min L_i = D_i + \lambda_i R_i, \text{ and } 0 = \frac{\partial L_i}{\partial R_i}, \tag{2}$$

where λ_i is the *frame-wise* Lagrange multiplier. Solving for $\hat{R}_i$ is known as *rate allocation* step, and adjusting parameters to achieve $\hat{R}_i$ is known as *rate implementation* step.

For rate allocation, various algorithms have been proposed in conventional video compression. However, many of them are designed on the block-level, which are of little use in LVC as LVC has no blocks. Some methods [14, 15, 16] claim to improve frame-level rate allocation, but they solve $\hat{R}_i$ according to certain fixed ratios, which can hardly adapt to LVC. Other works [17, 18, 19, 20] focus on the spatial rate allocation in learned *image* compression, but the more important across-frame rate allocation remains unexplored.

For rate implementation, a series of models [21, 22, 23] have been developed to estimate and adjust the rate in conventional video compression, among which the R-λ model [23] is widely accepted as the state-of-the-art rate implementation method. There have been few works regarding the rate implementation in LVC.

3. METHODOLOGY

In this section, we describe in detail, the proposed rate control scheme for LVC, including the R-D-λ model for efficient rate allocation and the staged update algorithm for robust parameter estimation.

3.1. R-D-λ model

Directly using state-of-the-art conventional rate control scheme [23] on LVC can achieve low rate error on average, but leads to constant degradation of RD performance in various datasets (detailed in section 4.2). The reason behind is that, R-λ model is capable for rate implementation, but conventional rate allocation methods are not suitable for LVC. To be more specific, conventional rate control approaches can not properly model the inter-frame dependency in LVC.

To address the above problem, we present the R-D-λ model to improve rate allocation for LVC through a concise and efficient modeling of inter-frame dependency. Specifically, taking (2) into (1) yields

$$\Lambda = \lambda_i - \sum_{j \neq i} \frac{\partial D_j}{\partial R_i}, \tag{3}$$

where $\frac{\partial D_j}{\partial R_i}$ measures how frame j is influenced by frame i, i.e. the inter-frame dependency to be modeled. It should not be too simple to describe the characteristics of LVC, and it should not be too complicated to hinder the calculation of $\hat{R}_i$. Knowing these requirements, we model $\frac{\partial D_j}{\partial R_i}$ as a product:

$$\frac{\partial D_j}{\partial R_i} = \frac{\partial D_i}{\partial R_i} \prod_{t=i}^{t<j} \frac{\partial D_{t+1}}{\partial D_t}. \tag{4}$$

The point is, frame i does not influence frame j directly, but in a frame-by-frame manner: change of R_i first causes change of D_i, the latter change then causes change of D_{i+1} as frame $i+1$ references frame i, and finally all the way to change of D_j. In this way, the inter-frame dependency between two arbitrary frames is represented with dependency between frames that have direct referencing relation, which is much simpler to model.

Previous work [24] shows that, the distortion of a frame is linearly related with the distortion of the frame(s) it references, thus we use a single parameter to model $\frac{\partial D_{i+1}}{\partial D_i}$ in (4):

$$\frac{\partial D_{i+1}}{\partial D_i} = p_i. \tag{5}$$

Additionally, $\frac{\partial D_i}{\partial R_i}$ is equal to $-\lambda_i$ according to (2). Taking this relation, along with (4) and (5), into (3) yields

$$\Lambda = \lambda_i \left(1 + \sum_{j>i} \left(\prod_{t=i}^{t<j} p_t \right) \right) \stackrel{\text{def}}{=} \lambda_i \left(1 + \sum_{j>i} p_{i,j} \right), \tag{6}$$

where $p_{i,j}$ represents $\left(\prod_{t=i}^{t<j} p_t\right)$ for clarity. At this point, the inter-frame dependency is totally parametrized by p and is then used for rate allocation.

Taking R-λ model [23] in to (6), we can readily represent the optimal rate allocation $\hat{R}_i$ with the *overall* Lagrange multiplier Λ, and build an equation with the total rate constraint to solve for $\hat{R}_i$. However, there is no analytical solution for this equation, which means time-consuming numerical methods such as binary search have to be used.

To avoid time overhead, we propose to directly solve for $\hat{R}_i$ using an approximated *rate ratio*. Specifically, we represent *rate ratio* with *frame-wise* Lagrange multiplier λ_i

$$\frac{R_i}{R_j} = \frac{(\lambda_i/\alpha_i)^{1/\beta_i}}{(\lambda_j/\alpha_j)^{1/\beta_j}} = (\frac{\lambda_i}{\lambda_j})^{1/\beta_i} \cdot \lambda_j^{1/\beta_i - 1/\beta_j} \cdot \frac{\alpha_j^{1/\beta_j}}{\alpha_i^{1/\beta_i}}, \quad (7)$$

where α_i and β_i are frame-ly varying parameter from R-λ model [23]. The trick is, parameter β does not vary much in the same sequence, thus $\lambda_j^{1/\beta_i - 1/\beta_j}$ in (7) appropriates to 1. Taking this approximation along with (6) into (7) yields

$$\frac{R_i}{R_j} = (\frac{\sum_{t\geq j} p_{j,t}}{\sum_{t\geq i} p_{i,t}})^{1/\beta_i} \cdot \frac{\alpha_j^{1/\beta_j}}{\alpha_i^{1/\beta_i}}. \quad (8)$$

Now, we directly represent *rate ratio* with parameters α, β and p, and is thus able to directly solve for $\hat{R}_i$.

3.2. Staged Parameter Update

Taking the R-λ model [23] into (2), we know that $\frac{\partial D_i}{\partial R_i} = -\lambda_i = -\alpha_i R_i^{\beta_i}$. Further, $\frac{\partial D_{i+1}}{\partial D_i}$ is equal to p_i according to (5). Using these two relations, we represent D_i as a model of R_i and D_{i-1}:

$$\begin{aligned} D_i &= -\frac{\alpha_i}{\beta_i + 1} R_i^{\beta_i+1} + p_{i-1} D_{i-1} + c \\ &\stackrel{\text{def}}{=} f_i(R_i) + p_{i-1} D_{i-1} + c, \end{aligned} \quad (9)$$

where c is a constant. Following [23], we first use a progressive update strategy to update α, β and p simultaneously, which results in an unstable estimation that all parameters experience an abnormal rapid vibration. The problem is, estimation of α β and estimation of p interfere with each other: estimation of α β requires a stable D_{i-1} and a varied R_i, while estimation of p requires varied D_{i-1} and stable R_i. These two requirements can not be met at the same time, thus simultaneous update strategy leads to undesired performance.

To overcome this problem, we propose a staged update algorithm: first update α and β, then update p. Specifically, we first use a gradient-descend-like algorithm to update α and β. We define the loss as

$$l = \frac{1}{2} \ln^2 \frac{R_{i,real}}{\hat{R}_i}, \quad (10)$$

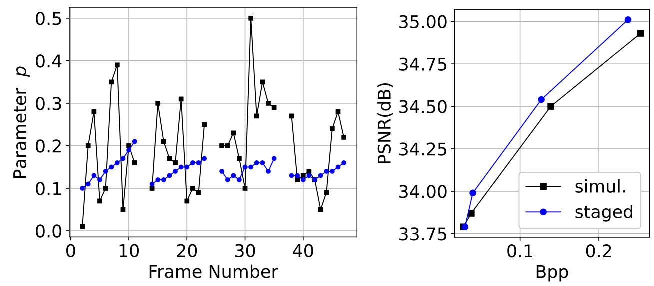

Fig. 1. Simultaneous parameter update and the proposed staged parameter update. Left: change of parameter p along frames. Right: comparison of RD performance.

where $\hat{R}_i = (\lambda_i/\alpha_{i-1})^{(1/\beta_{i-1})}$ as α and β have not been updated for this frame. Using the gradients $\frac{\partial l}{\partial \alpha}$ and $\frac{\partial l}{\partial \beta}$, we build the update rule of α and β:

$$\begin{aligned} \alpha_i &= \alpha_{i-1} - k \times \frac{\alpha_{i-1}\beta_{i-1}}{2} \ln \frac{R_{real}}{\hat{R}_i} \\ \beta_i &= \beta_{i-1} - k \times \frac{\beta_{i-1}}{2 \ln \hat{R}_i} \ln \frac{R_{real}}{\hat{R}_i}, \end{aligned} \quad (11)$$

where k is empirically set to 0.5. After α and β are updated, we update p_i in a delayed manner:

$$p_i = \frac{D_i - f_i(R_i) - D_{i-1} + f_{i-1}(R_{i-1})}{D_{i-1} - D_{i-2}}. \quad (12)$$

This update assumes that p changes slowly between consecutive frames, which is in line with the experiment results.

4. EXPERIMENTS

4.1. Experimental Setup

Datasets: To evaluate the performance of the proposed rate control scheme, we use the sequences in HEVC [25] dataset and UVG [26] dataset. Specifically, we use 16 sequences in Class B, C, D and E from HEVC dataset, whose resolutions vary from 1920×1080 to 416×240, and 7 sequences from UVG dataset, whose resolutions are all 1920×1080.

Metrics: We use bpp (bit per pixel) to measure the rate for fair comparison across different resolutions. Both PSNR and MS-SSIM are tested for distortion metrics, and BDBR [27] is used to compare RD performance. When calculating BDBR, MS-SSIM is transformed to a dB value by $SSIM_{dB} = -10\log_{10}(1 - SSIM)$. Rate error is used to measure the accuracy of achieving target rate as $\Delta R = |R_{out} - R_{target}|/R_{target} \times 100\%$, and coding time is measured by time ratio as TR $= T/T_{anchor}$.

Baselines: We use the DVC [2] framework for separate-rate model baseline and [1] for variable-rate model baseline. For rate control using variable-rate model, we set a rate error threshold (5% in our setting), and use binary search (recoding) to find the proper λ that meets this threshold. Direct application of conventional rate control scheme on LVC is

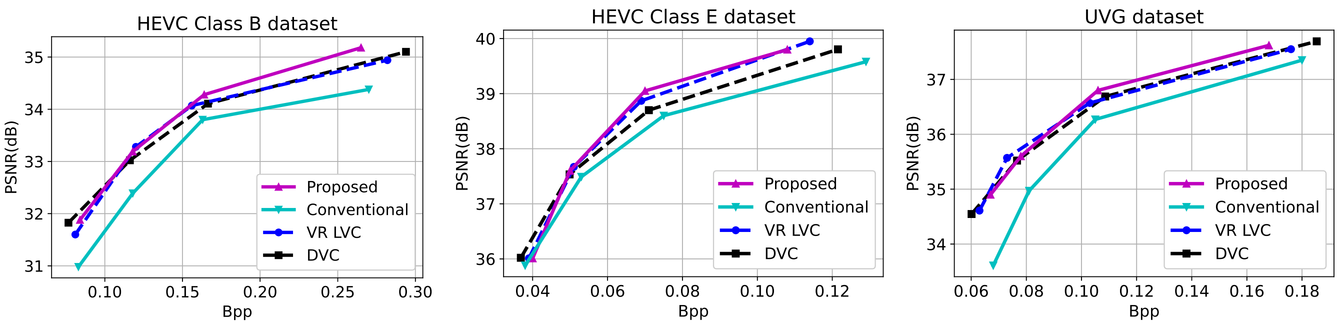

Fig. 2. RD performance of our proposed rate control scheme, separate-rate model (DVC) [2], variable-rate model (VR LVC) [1] and conventional scheme. Our scheme achieves similar or even better results while maintaining a low rate error

Table 1. BDBR, rate error (ΔR) and coding time ratio (TR) on HEVC and UVG datasets. Separate-rate model [2] is used as the anchor. For all metrics, the smaller is the better, and best BDBR of each experiment are highlighted.

	HEVC B			HEVC C			HEVC D			HEVC E			UVG		
	BDBR	ΔR(%)	TR	BDBR	ΔR(%)	TR	BDBR	ΔR(%)	TR	BDBR	ΔR(%)	TR	BDBR	ΔR(%)	TR
(PSNR) VR LVC	-1.22	4.85	3.59	0.30	4.63	3.40	**-0.88**	4.70	2.97	-5.50	4.29	3.09	-1.03	4.92	3.98
(PSNR) Conventional	20.21	5.04	1.01	17.13	6.77	1.00	13.71	5.34	0.99	10.32	5.29	1.02	16.69	6.24	1.00
(PSNR) **Proposed**	**-6.80**	5.64	1.04	**-2.96**	6.92	1.03	-0.48	5.85	1.03	**-6.85**	5.35	1.06	**-4.12**	6.24	0.99
(SSIM) VR LVC	-2.65	4.80	3.79	**1.32**	4.44	3.65	1.89	3.89	3.28	-8.31	4.03	3.66	-0.97	4.62	3.33
(SSIM) Conventional	12.12	8.97	0.99	14.13	7.23	1.00	18.59	5.95	1.01	7.34	6.43	1.02	21.60	6.39	1.02
(SSIM) **Proposed**	**-2.74**	7.47	1.01	1.34	6.78	0.99	**-0.97**	6.09	1.05	**-9.01**	5.95	1.04	**-6.76**	6.42	1.02

implemented by using [23] on [1], which is referred to as `conventional` in the following experiments.

Implementation: The `proposed` rate control scheme is implemented on the basis of [1]. Following most works on LVC, we use the low P delay setting in our experiments. Additional stabilizing skills are included for robustness. Specifically, changes of parameters are empirically limited to a $10\%/30\%$ of their original values, where 30% is for changes that make rate lower and 10% is for changes that make rate higher. To determine the target rate, we first encode the test sequences by [2], then use the output rate as target rate.

4.2. Experimental Results

RD performance: Regarding overall RD performance, our rate control scheme achieves equal or better results with separate-rate model [2] and variable-rate model [1], and outperforms the `conventional` rate control scheme by a large margin (Fig.2). Specifically, `conventional` scheme constantly gives inferior RD performance due to its primitive rate allocation strategy, which is shown by the BDBR in Table 1. On the contrary, the proposed R-D-λ model improves rate allocation by exploiting the characteristics of LVC's inter-frame dependency, which leads to dramatic RD performance gain compared with `conventional` scheme, and can even outperform the variable-rate model [1] and the separate-rate anchor [2] on some datasets. Additionally, similar BDBR gain is also presented by experiments on MS-SSIM, which proves the robustness of our proposed scheme.

Rate error v.s. Coding time: As is shown in Table.1, we achieve a less than 7% overall rate error on all test datasets, without RD performance loss or coding time overhead. In contrast, `conventional` rate control is able to achieve a similar rate error at the cost of heavily degraded RD performance, and variable-rate model takes more than 3 times of recoding on average to achieve a less than 5% rate error.

Influence of staged parameter update: To demonstrate the effectiveness of the proposed staged parameter update, we test both simultaneous and staged parameter update on UVG `Beauty` sequence, and record the value of parameter p for the first 4 GoP (48 frames) as well as the RD performance. As is shown in Fig.1, the proposed staged parameter update provides a much more robust parameter estimation compared with simultaneous parameter update, which in turn boosts the RD performance to achieve a -16.65% BDBR gain.

5. CONCLUSION

In this work, we present the first rate control scheme specially designed for learned video compression. By exploiting the characteristic of inter-frame dependency in learned video compression, we propose a novel R-D-λ model to efficiently solve the rate allocation problem. Additionally, a staged update algorithm is developed for robust parameter estimation. Experiments on public datasets demonstrate that, the proposed rate control scheme achieves equal or even higher RD performance compared with the previous arts, and maintains a low rate error without introducing coding time overhead.

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