

Optimal Deep Rate Control for Intra Coding in High-Efficiency Video Coding Standard

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Article Info	ABSTRACT
<p>Article type: Research Article</p> <p>Article history: Received: 09-December-2024 Received in revised form: 28-January-2025 Accepted: 19-February-2025 Published online: 22-Dec-2024</p> <p>Keywords: Coding Tree Unit (CTU), Convolutional Neural Network (CNN), High-Efficiency Video Coding (HEVC), Rate Control, R-Q Model.</p>	<p>This paper proposes a novel Optimal Deep Rate Controller (ODRC) designed for intra-coding configuration of the High-Efficiency Video Coding standard. The ODRC incorporates a Convolutional Neural Network-based Rate-Quantization Model (CRQM) to effectively predict bits consumption across the entire Quantization Parameter (QP) range at the Coding Tree Unit (CTU) level. The proposed rate controller employs an optimization algorithm to minimize the buffering delay required for video communications. By establishing a specific search space through the CRQM, a greedy search algorithm is utilized to determine the optimal frame-level QP, thereby minimizing discrepancies between buffer occupancy and target occupancy. Unlike CTU-level rate controllers, which can introduce quality variations due to QP fluctuations among CTUs, the frame-level ODRC maintains consistent objective quality across CTUs within a frame. The ODRC is integrated within the standard reference software HM-16.20. Comparative evaluations with the default rate controller, RC-HM, in the same software, demonstrate the superior performance of ODRC in terms of both delay and bit error ratio. Experimental results indicate that ODRC achieves a notably lower average buffering delay of 0.02s and a lower bit error ratio of 11.25%, in contrast to RC-HM's 0.3s and 44.72%, respectively, emphasizing its effectiveness for HEVC low-delay applications.</p>

I. Introduction

High-Efficiency Video Coding (HEVC) [1] has significantly advanced video compression. It offers a 50% bitrate reduction compared to H.264/AVC [2] while maintaining visual quality, especially for high-resolution content. Despite these advancements, transferring high-quality video over networks faces several challenges due to bandwidth, delay, and buffer capacity limitations. To address these challenges, an effective Rate Controller (RC) is crucial for optimizing bit allocation across various coding units, such as Group of Pictures (GOPs), frames, and Coding Tree Units (CTUs). This optimization ensures a high-quality video experience under different network conditions [3-11].

Rate control strategies in HEVC for intra-frames and inter-frames differ significantly due to their inherent coding characteristics. In inter-frame coding, RC can use a Rate-Distortion (R-D) model updated according to previous encoding results. Conversely, in intra-frame coding, RC

relies only on information within the same frame. Consequently, intra-frames require more sophisticated RC approaches to achieve the desired bitrate. Utilizing content-based R-D or Rate-Quantization (R-Q) models can improve the performance of these RC approaches.

II. Related works

So far, various rate control algorithms have been proposed for intra-frame coding within the HEVC standard. The large group of rate control algorithms, commonly called conventional RCs, typically operate in three steps: bit allocation, bitrate control, and parameter updating. During the initial step, a bit budget is allocated to a coding level based on factors such as target bitrate, buffer occupancy, and frame complexity. In the subsequent step, the allocated bitrate and coding complexity are incorporated as inputs for a content-based R-D or R-Q model to determine an appropriate Quantization Parameter (QP) for each coding

level. Finally, the model parameters are updated based on previous encoding results to improve the model accuracy. However, the model can be very inaccurate for the first intra-frame and the intra-frames inserted in scene cuts. Representative examples of conventional frame-level and CTU-level RCs for HEVC can be found in [12-15] and [16-19], respectively.

Conventional rate control algorithms typically employ closed-form analytical models to estimate QPs based on rate, distortion, and hand-engineered content complexity metrics such as mean absolute difference and the sum of absolute Hadamard transformed differences [12-19]. However, these models often struggle to accurately represent the complex relationships between rate, distortion, and video content characteristics, which can result in suboptimal rate-distortion performance. To tackle this issue, some researchers have recently turned to machine learning techniques to extract more relevant features from video content, facilitating the development of more robust and accurate rate control models. Among these techniques, convolutional neural networks (CNNs) have emerged as an effective image and video analysis tool [20-25].

CNNs have emerged as a powerful tool for transforming complex images and videos to the feature space with compressed representations. Within the domain of R-D modeling, CNN-based approaches can be divided into two primary categories. The first category leverages CNNs to estimate parameters for established models such as R-D and R-Q. For instance, [20, 21] proposed a CNN to predict optimal R- λ model parameters, demonstrating the strong dependency of these parameters on both video content and QP. However, the training of these models was limited to a specific QP range. Building upon this, [22] introduced a CNN-based framework to predict parameters for the exponential R-Q model, incorporating multiple CNNs for feature extraction and weight estimation.

The second category of methods focuses on directly estimating rate control parameters, such as bit count, distortion, or QP, using CNNs [23-25]. Early CNN-based models [23-25] were limited in their applicability due to constraints on QP range and input frame size. The model presented in [23] proposes a CNN-based model to predict bit count and Structural Similarity Index Map (SSIM) under constrained conditions of QP range and fixed input frame size. Similarly, [24] employs two CNNs to estimate the rate and Mean Squared Error (MSE) for intra-frames at a limited set of QPs. To address these limitations, our previous work [25] introduced a Convolutional Rate-Quantization Model (CRQM) operating at the CTU level. This model offers significant advancements by enabling simultaneous accurate estimation of bit consumption across all QP values for each CTU and adapting to diverse frame sizes.

The reviewed studies primarily focus on two approaches to predict the rate and distortion of Intra-frames: closed-form

rate-distortion models and CNN-based models. These works do not explicitly address rate control mechanisms [12-24]. Beyond these core approaches, a study in [26] investigates novel NN architectures and optimization strategies for selecting the QP to control the bitrate at the CTU level. However, this model's effectiveness is constrained by its training on a limited QP range, which may hinder its adaptability to diverse rate requirements.

This paper proposes an optimal deep rate controller (ODRC) for intra-frame coding in HEVC. The ODRC aims to achieve precise and optimal rate control. The proposed method leverages our previously developed CRQM [25] to accurately predict the bit consumption of each coding CTU across various QPs. A greedy search algorithm, informed by the CRQM's predictions, determines the optimal frame-level QP, minimizing the discrepancies between buffer occupancy and a target value. This results in efficient operation with low buffering delay, making the ODRC well-suited for low-latency applications.

The key contributions of this paper are as follows:

- This paper proposes an optimal deep rate controller for precise rate control in HEVC intra-frame configuration.
- In contrast to the rate controllers presented in [20-22] that rely on CNNs to update the parameters of conventional RD models, the proposed ODRC provides precise results even at the start of scene cuts.
- Unlike the approach in [23], which employs a CNN-based RD model constrained to fixed video frame size, ODRC is adaptable to varying frame sizes.
- Compared to the rate controller in [24], which uses a CNN-based RD model limited to a narrow QP range, the proposed ODRC can operate on the entire range of QP values.
- While the work in [25] focuses on CTU-level bitrate control using a CNN-based RD model, ODRC operates at the frame level to provide a uniform visual quality for each frame.
- By integrating our CRQM, which estimates bit consumption across the entire QP range, with a low-complexity greedy search algorithm, ODRC efficiently determines the optimal frame-level QP to minimize buffer occupancy discrepancies.

The remainder of the paper is organized as follows: Section 2 outlines the Methodology, Section 3 presents the test results, and Section 4 provides the conclusions.

III. Methodology

The increasing demand for low-delay applications, such as real-time video conferencing, and the growing prevalence of ultra-high-definition (UHD) video content present significant challenges for video transferring systems. The proposed RC in this paper can provide an accurate bitrate close to the target bitrate for the intra-frames. Therefore, it can be used for low-delay UHD applications within the

HEVC standard. The proposed RC can be used for all intra-coding configurations or intra-frames in other coding configurations.

Figure 1 illustrates the block diagram of the proposed rate control algorithm. The core components of the proposed system, including the virtual buffer and proposed RC, are discussed in detail in the sequel.

A. Overview of the CRQM model

The CRQM [25] introduces a novel intra-prediction approach utilizing both Coding Tree Unit (CTU) and reference pixel information. As illustrated in Figure 2, each 64×64 Coding Tree Block (CTB) is extended with reference pixels, creating 66×66 input blocks. Reference pixels extending to the right and bottom are rotated and concatenated to the right and bottom edges of the CTBs, respectively. Three resulting 66×66 blocks are subsequently fed into a CNN to extract features. Figure 3 illustrates the architecture of the CNN-based model. The first convolutional layer employs a kernel size of 9×9 with a stride of 8×8 , while all subsequent convolutional layers utilize 2×2 kernels and strides. ReLU activation is applied across all convolutional layers. The features extracted by the final convolutional layer are combined with the CTB standard deviation (STD) and passed through two fully connected layers, each comprising 40 neurons with ReLU and tanh activation functions, respectively. The output layer, consisting of 51 neurons with a tanh function, generates the estimated bit counts for each QP.

B. Virtual Buffer

The proposed system employs a virtual buffer to simulate the decoder buffer in a constant bandwidth communication channel. The buffer occupancy, O_i , is dynamically updated after encoding each frame as:

$$O_i = O_{i-1} + B_T - B_i \quad (1)$$

where B_i denotes the number of bits consumed to encode i^{th} frame. The initial buffer occupancy, O_0 , is initialized to 60% of the total buffer capacity, simulating the initial buffering delay. The core objective of the proposed control mechanism is to maintain the buffer occupancy close to this initial level, defined as the target buffer occupancy, O_T , throughout the transmission process. The target bits per

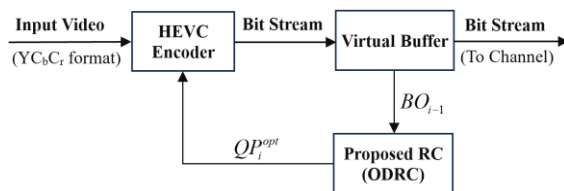


Fig. 1. Block Diagram of the Proposed Rate Control Algorithm

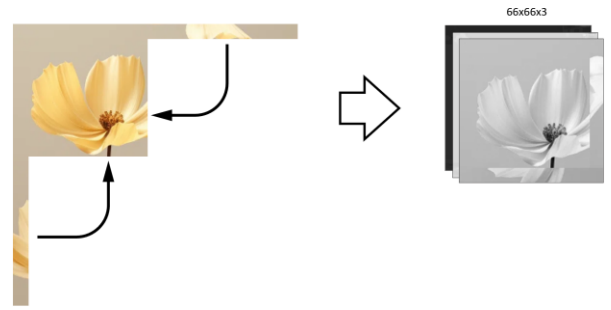


Fig. 2. Preparing Inputs of Convolutional Neural Network-based Rate-Quantization Model (CRQM)

frame, B_T , is calculated as:

$$B_T = \frac{R_T}{f} \quad (2)$$

where R_T denotes the target bitrate and f stands for the frame rate.

C. Content-based Intra Deep Controller

The proposed rate control algorithm aims to maintain the buffer occupancy close to the target level, O_T , by selecting an optimal QP for each frame. The optimal QP for i^{th} frame, QP_i^{opt} , is then determined using a greedy search optimization algorithm to minimize the absolute difference between O_i^{Est} and O_T :

$$QP_i^{opt} = \arg \min_{\forall QP \in \{1, \dots, 51\}} |O_i^{Est} - O_T| \quad (3)$$

where O_i^{Est} denotes the estimated buffer occupancy after encoding i^{th} frame and it is calculated by:

$$O_i^{Est} = O_{i-1} + B_T - B_i^{Est} \quad (4)$$

where B_i^{Est} shows the estimated bits for i^{th} frame that is computed as Eq. (5).

$$B_i^{Est} = \sum_{j=1}^{N_i} b_{i,j}^{Est} \quad (5)$$

N_i denotes the number of CTUs within i^{th} frame, and $b_{i,j}^{Est}$ represents the estimated bit consumption for the j^{th} CTU of the i^{th} frame, determined by the CRQM [25].

IV. Test Results

a) Implementation Details

This subsection presents a comparative performance evaluation of the proposed rate controller (ODRC), implemented in the HEVC reference software HM-16.20 [27], against the default rate controller (RC-HM) included in the same software. RC-HM employs the λ -domain R-D model and considers the standard Hypothetical Reference Decoder buffering model. Given its implementation on HM,

its performance is benchmarked against many RCAs, potentially facilitating cross-verification.

Simulations were conducted using the RAISE dataset [28] at four QP values: 22, 27, 32, and 37. The target bitrate, $R_T = B_T \times f$, derived from CQRM, was used as the anchor target bitrate for both rate control methods. During the experiments, the virtual buffer capacity was set to 60% of the target bitrate. The ODRC initialized its buffer occupancy at 60% of the virtual buffer capacity, while RC-HM used its default 90% initialization as its optimum value.

A subset of 500 frames at a resolution of 4948×3280 pixels was randomly selected from the RAISE dataset to create five 100-frame video sequences with a frame rate of 30 frames

b) Dataset

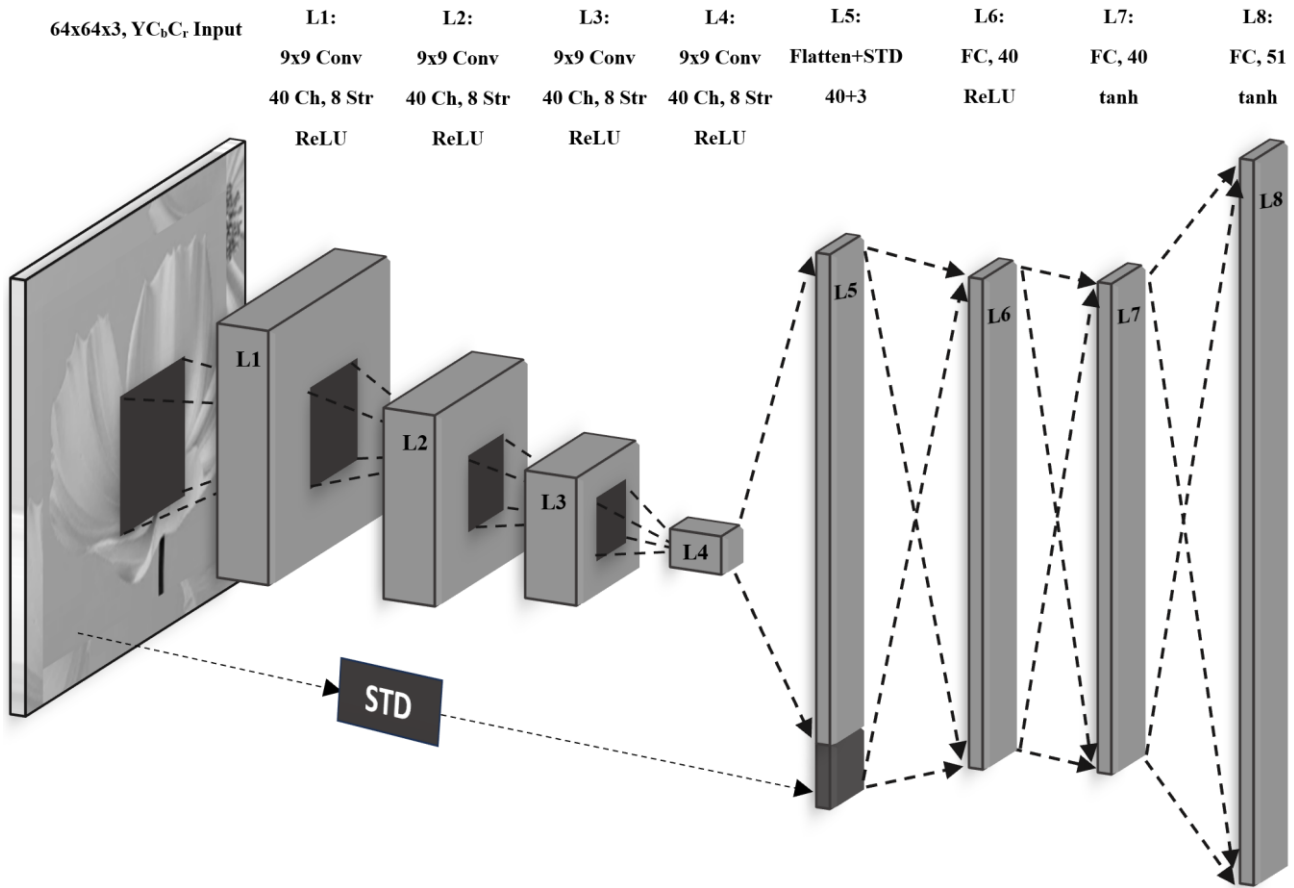


Fig. 3 Convolutional Neural Network-based Rate-Quantization Model (CRQM) architecture to estimate the CTU bit consumption [25].

bitstreams, demonstrating robust bitrate control. For a quantitative comparison of rate control performance, the minimum buffering delay required on the receiver side, proportional to the minimum buffer size, is measured and reported in Table 1. The minimum buffering delay is computed as follows.

per second. Unlike the test video datasets, in which the consequent frames are very similar in each video sequence, the used dataset can simulate about 500 video sequences, which is a large number for test purposes.

c) Quantitative and Qualitative Analysis

Given that the proposed rate controller is tailored for intra-frames, which are encoded independently without reference to other frames, each frame's quality does not influence subsequent frames' quality. Therefore, the performance evaluation of the proposed rate controller emphasizes its effectiveness in controlling bitrate and achieving rate control accuracy.

Table 1 summarizes the comparative results. From the controlling aspect, the proposed controller successfully

prevents both buffer overflow and underflow for all encoded

$$Delay_{\min} = \alpha \frac{O_{\max} - O_{\min}}{R_T}, \tag{6}$$

where O_{\max} and O_{\min} are the maximum and minimum buffer occupancy throughout the encoded video sequence. α for ODRC and HM-RC is set to 0.6 and 0.9, respectively.

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TABLE 1. EXPERIMENT RESULTS OF THE PROPOSED RATE CONTROLLER (ODRC) AND DEFAULT RATE CONTROLLER (HM-RC) ON TEST SEQUENCES IN TERMS OF AVERAGE QP, BITRATE (KBIT/S), DELAY (S), AND BIT ERROR RATIO (%)

Video Seq.	method	Avg. QP	Bitrate (Kbit/s)	Delay (s)	BER%
Video1	ODRC	21.58	274735.7	0.01	9.90
		26.05	131805.1	0.01	6.00
		30.97	61852.2	0.01	8.69
		35.66	30693.0	0.01	7.86
	HM-RC	21.75	276519.8	0.25	38.26
		26.29	127072.7	0.27	38.6
		31.17	62239.1	0.28	45.74
		35.99	31010.7	0.33	48.40
Video2	ODRC	21.69	266452.2	0.02	15.28
		26.61	121270.0	0.02	12.76
		31.38	58626.2	0.02	13.56
		36.00	28756.7	0.02	11.06
	HM-RC	21.88	266584.5	0.29	45.74
		26.67	121456.7	0.31	45.68
		31.46	58670.5	0.34	46.70
		36.28	28835.2	0.33	48.05
Video3	ODRC	21.60	257655.8	0.03	13.89
		26.39	119579.0	0.02	14.24
		30.91	59154.4	0.02	12.06
		35.51	29669.1	0.02	9.73
	HM-RC	21.57	257437.0	0.25	42.14
		26.48	119544.4	0.28	48.10
		31.58	59144.6	0.33	55.82
		36.58	29664.5	0.41	58.75
Video4	ODRC	21.75	287710.8	0.02	12.39
		26.65	133234.5	0.02	13.25
		31.20	65525.3	0.03	10.90
		35.88	32543.9	0.03	11.54
	HM-RC	22.37	287966.1	0.29	46.80
		27.03	133720.5	0.24	45.10
		31.9	66475.7	0.44	53.23
		36.96	32524.0	0.48	57.32
Video5	ODRC	21.89	295528.8	0.01	11.05
		26.76	139093.1	0.02	11.57
		31.29	140149.0	0.01	9.35
		35.92	34219.5	0.01	9.85
	HM-RC	21.75	296576.2	0.15	36.76
		26.40	140149.4	0.19	39.44
		31.34	69255.1	0.26	43.92
		36.42	34291.9	0.27	9.85
Average	ODRC	21.702	276416.7	0.02	12.50
		26.49	128996.3	0.02	11.56
		31.15	77061.4	0.02	10.91
		35.79	31176.4	0.02	10.01
	HM-RC	21.86	277016.7	0.25	41.94
		26.57	128388.7	0.26	43.38
		31.49	63157.0	0.33	49.08
		36.45	31265.3	0.36	44.47

Likewise, to compare the algorithms in terms of rate control accuracy, the bit error ratio is examined as an indicator of deviation between the target and actual bitrates. The bit error ratio is computed as follows:

$$BER\% = 100 \left(\frac{1}{N_F} \sum_{i=1}^{N_F} \frac{|B_T - B_i|}{B_T} \right), \quad (7)$$

where N_F shows the number of frames in each sequence.

Table 1 demonstrates the significant performance advantage of ODRC over RC-HM in terms of both buffering delay and bit error ratio. ODRC achieves an average buffering delay of 0.02s and a bit error ratio of 11.25%, while RC-HM exhibits substantially higher values of 0.30s and 44.72%, respectively. This disparity in performance is directly attributable to the accuracy of the CRQM model employed by the proposed rate control algorithm. The high accuracy of this model enables precise rate control, minimizing deviations from the target buffer occupancy and, consequently, reducing buffering delays.

To further evaluate the proposed RC performance, Figure 4 presents sample results of virtual buffer fullness for the test sequences encoded by ODRC and HM-RC algorithms at the QP of 32. These graphs are plotted according to the frame encoding order. The solid horizontal line represents the buffer size, while the dashed lines indicate the target buffer occupancy for each algorithm. As observed, the buffer occupancy of the HM-RC-encoded bitstream exhibits a more significant deviation from the target than the ODRC-encoded bitstream, which remains closer to its target. Consequently, transmitting the HM-RC-encoded bitstream necessitates a larger buffer size to prevent overflow or underflow, resulting in increased delay compared to ODRC.

Regarding the previous studies reviewed in this paper, the presented works in [12-24] studies focus on rate-distortion modeling without directly addressing a rate control mechanism. Therefore, the proposed RC in this paper cannot be compared with these works. Only the study presented in [26] explores an RC that operates at the CTU level.

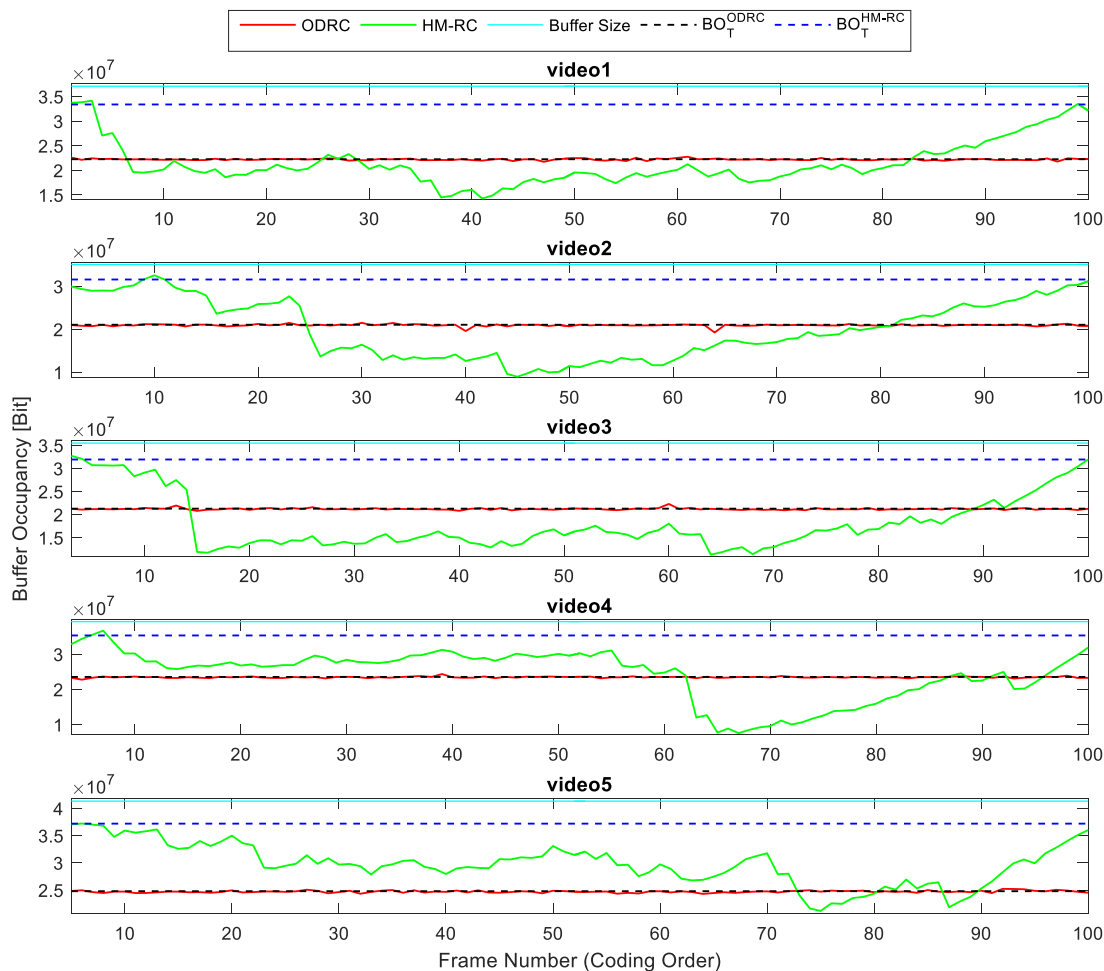


Fig. 4. The buffer occupancy graphs for test sequences encoded by the proposed rate controller (ODRC) and default rate controller (HM-RC) at QP of 32

Consequently, comparing the accuracy of this algorithm with our RC, which operates at the frame level, would be unfair. Furthermore, the work in [26] does not provide frame-level performance metrics such as BER and delay, which are key performance indicators in our study. Notably, the BER metric in [26] is evaluated at the sequence level and, therefore, unreliable for comparison, as it depends on the length of the video sequence and frame size.

V. Conclusions

This paper introduces a novel optimal intra-frame rate control algorithm designed to enhance the performance of low-latency applications in the HEVC standard. The proposed controller utilizes the CRQM to achieve precise bit consumption prediction at the CTU level, enabling frame-level QP determination by a greedy search optimization algorithm. These determinations are based on the deviation between the target and estimated buffer occupancy, ensuring stable and accurate rate control. Integrated into the HEVC reference software HM-16.20, the proposed ODRC algorithm was evaluated against the default rate controller (RC-HM). Experimental results demonstrate that ODRC significantly outperforms RC-HM, achieving notable reductions in both bit error ratio and buffering delay. These results underscore the enhanced performance of ODRC on the aspects of controlling bitrate and rate control accuracy, making it well-suited for real-time video applications requiring high efficiency and accuracy.

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