RR-DnCNN v2.0: Enhanced Restoration-Reconstruction Deep Neural Network for Down-Sampling Based Video Coding

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Abstract—Integrating deep learning techniques into the video coding framework gains significant improvement compared to the standard compression techniques, especially, applying super-resolution (up-sampling) in down-sampling based video coding as post-processing. However, different from the conventional super-resolution works, the output can be distorted by the various compression artifacts in the decoded frames. The straightforward solution is to integrate the artifacts removing techniques before super-resolution. But some helpful features may be removed together with the artifacts, which will degrade the performance of super-resolution. To address this problem, we proposed a restoration-reconstruction deep neural network (RR-DnCNN) using the degradation-aware techniques. Moreover, to prevent the loss of essential features in the very deep network from restoration to super-resolution, we leverage up-sampling skip connections to compensate for the lost information from restoration layers. It is called restoration-reconstruction u-shaped deep neural network (RR-DnCNN v2.0). As a result, our RR-DnCNN v2.0 can achieve 17.02% BD-rate reduction on UHD resolution compared to the standard H.265/HEVC. The source code is available at https://minhmanho.github.io/rrdncnn/.

Index Terms—Super-resolution, Video Compression, Deep Learning

I. INTRODUCTION

Video media has become one of the widest applications in the digital era, depending on the development and popularization of video coding technology. Video coding technology has been iteratively developed for nearly 30 years and has continued the hybrid coding architecture of transform coding and predictive coding. Nowadays, video playback devices are increasingly diversified; however, network bandwidth and storage size are limited under many usage scenarios. Even with the popular advanced coding standard H.265/HEVC, the quality of the reconstructed video is still poor under extreme bandwidth conditions because the quality is sacrificed for a higher compression ratio. Therefore, a more efficient framework is required to reduce the bit-rate and keep high video quality. There are two significant challenges: reducing the various distortions which brought from video compression, and increasing the compression ratio. As many achievements of deep learning techniques, de-noising, and super-resolution works thus are reasonable to address them respectively.

A. Down-sampling based coding (DBC)

Shen et al. [1] propose the seminal work of down-sampling based coding framework, where a super-resolution technique is employed to restore the down-sampled frames to their original resolutions. Recently, deep-learning-based super-resolution techniques outperform traditional methods and inspire researchers to improve the DBC framework. Li et al. [2] propose the CNN-based block up-Sampling for intraframe coding. Lin et al. [3] improve [2]’s work by leveraging information between frames as block-level down- and up-sampling into inter-frame coding. However, these block-based DBC methods ignore the useful information of the whole frame. Furthermore, compression artifacts are roughly learned and inferred. Feng et al. [18] apply a frame-based DBC system with an extra enhancement network to remove the compression artifacts before super-resolution. However, some useful features may be removed together with the artifacts, which will degrade the performance of super-resolution. We thus propose an end-to-end deep neural network to fully address compression degradation and learn super-resolution.

B. Deep-learning approach for reducing the compression artifacts

Images/video resolution rapidly increases from 480p and 720p, to 1080p, 4K, and 8K. The frame rate also increases from 30fps to 60fps and 120fps. Under limited bandwidth, videos are encoded with a high compression ratio by sacrificing quality. According to recent deep-learning super-resolution achievements, transferring the low-size bit-stream for high-resolution images/videos is possible. Similar to the related concept [13], we down-sample the source video before encoding, then up-sample, and reconstruct images/videos after decoding. The bit-stream capacity thus is much lower. Furthermore, the images/videos still meet quality requirements compared to the standard H.265/HEVC.

C. Single Image Super-Resolution (SISR)

SISR, based on deep learning, recently achieves outstanding performance in multiple scales. SISR aims to generate high-resolution (HR) images from a given low-resolution (LR)
images. As the promotion of deep-learning techniques, Dong et al. [10] proposed a CNN based SRCNN network structure to learn an end-to-end mapping from low-resolution to high-resolution. The network includes three layers: patch extraction, non-linear mapping, and reconstruction. This work opened the door to the application of deep learning to image super-resolution. Dong et al. [11] continuously proposed a network named FSRCNN, which can super-resolution in real-time. Kim et al. [12] showed a VDSR network, which can effectively improve image performance by learning residuals and increasing network depth to 20 layers; furthermore, Adjustable Gradient Clipping is used to solve their convergence problem. Zhang et al. [13] propose the DnCNN network for residual learning in a super-resolution task. Kim et al. [14] propose the Deeply-Recursive Convolutional Network (DRCN) introduces a very deep recursive layer via a chain structure with up to 16 recursions. Lai et al. [15] studied a Laplacian pyramid based LapSRN image super-resolution network. Shi et al. [16] provided an ESPCN network to meet real-time deadlines in a single image and video super-resolution. Zhang et al. [17] propose the very deep Residual Channel Attention Networks (RCAN) and channel attention mechanism to exploit the abundant low-frequency information. However, these works perform only on bicubic degradation, forgo or naively train their models on other distortions, which usually happens in daily multimedia such as noise, video compression artifact, JPEG compression; therefore, the existing super-resolution works have poor performance on the unseen distortion.

D. Recent super-resolution works in handling degradation

To address the various degradation in super-resolution, Zhang et al. [18] synthesize bicubic degradation and Gaussian Noise maps and feed them to train together with LR. Zhao et al. [19] propose an unsupervised learning network to learn unseen degradation and reconstruct the output. Bulat et al. [20] use Generative Adversarial Network (GAN) to learn how to degrade and down-sample high-resolution images; from that point, they can achieve the degradation as their super-resolution network expectation. Chen et al. [21] directly train their models on JPEG degradation using an end-to-end deep convolution neural network. In the video coding field, we deal with various degradation, such as blocking artifacts, ringing artifacts, which usually occurs in video compression techniques. The most similar work [18] uses a refinement network before super-resolution to reduce compression artifacts, the bicubic degradation of decoded images/videos thus are more precise. However, they still suffer from distortion due to imperfect refinement. To address the problem, we proposed an end-to-end restoration-reconstruction deep neural network (RR-DnCNN) [20] using the degradation-aware technique as a two-loss function: restoration and reconstruction. Our network thus is capable of effectively dealing with video compression distortion and bicubic degradation.

E. Skip connections

Skip connections are widely used in the modern deep network architecture. The well-know works U-Net [22], ResNet [23] priorly exploit the proficiency of skip connections (or shortcut connections) to learn identical functions as the shallower layers. Consequently, in training, the very deep neural network can avoid vanishing gradient by learning residual [24], [25], [26], [27], [28], [29], [30], [31], [32] using pixel-wise summation. Furthermore, the connections are also used to leverage features from shallower layers and enhance the high-level features as many creative variations in many fields. For example, the works [23], [27], [28], [29] leverages skip connections to transfer shallow features to high-level layers using concatenation. The networks [33], [34] learn residual-attentional information to enhance their feature maps. The AvatarNet [35] leverages skip connections to stylize the high-level features by the shallow features in image style transfer. Iizuka et al. [37] fuse the well-trained features on image classification to consolidate the colorization task. Subjectively, Ho et al. [31] add hyperparameters for skip connections to visualize how the shallow feature’s effects on the stylized result, creating an adjustable image style transfer.

In our case, although our prior work RR-DnCNN [20] shows the proficiency in super-resolution for video compression, its architecture as the long inference from restoration to reconstruction causes the lost of useful information, the super-resolution performance is thus limited and easily saturated. Therefore, we re-design the network architecture as a u-shaped form and propose upsampling skip connections to compensate for the missing information from restoration for reconstruction. The novel network is a so-called restoration-reconstruction u-shaped deep neural network (RR-DnCNN v2.0).

F. Contributions

The main contributions of this paper include the following aspects.

- We improve our previous work RR-DnCNN [20] to enhance the features of reconstruction layers as the degradation-aware restoration-reconstruction u-shaped...
deep neural network (RR-DnCNN v2.0) using up-sampling skip connections.
• Our novel down-sampling based video coding system outperforms previous works [2], [3], [4] and attains 17.02\% bit-rate reduction at the low bit-rate range, compared to the standard H.265/HEVC.

II. PROPOSED VIDEO CODING SYSTEM

A. System overview

In our study, we leverage the superior of deep-learning super-resolution techniques to reduce bit-rate and enhance the video quality for our down-sampling based video coding system. The video coding framework consists of down-sampling, HEVC codec, and a super-resolution network. We first perform bicubic down-sampling of High-Resolution (HR) as its Low-Resolution (LR) for HEVC codec. After decoding bit-stream, the super-resolution network removes compression artifacts and maps the Decoded Low-Resolution (DLR) to its HR at the decoding end, as shown in Figure 1. Due to video compression degradation in lossy coding, in previous work [20], we design an end-to-end restoration-reconstruction deep neural network (RR-DnCNN) using the proposed degradation-aware technique for our loss function. However, the reconstruction leverages only the last feature map from the restoration. That architecture limits useful information for reconstruction. To enhance the learning capability, we propose to use up-sampling skip connections to compensate for the missing features from restoration for reconstruction. Our novel network architecture is a so-called restoration-reconstruction u-shaped deep neural network (RR-DnCNN v2.0).

The advantages of our degradation-aware technique are as follows: 1) Breaking minimizing error from DLR → HR to DLR → LR → HR defines the targets for each part inside the network. The LR is treated as transitional ground-truth. 2) Our up-sampled low-resolution inside the network is refined and adaptive for the reconstruction part. The super-resolution result is thus precise.

In super-resolution, the luminance component in YUV format is crucial for humans to see the objects in detail; therefore, our network takes Y component as $X \in \mathbb{R}^{H \times W \times 1}$ from the HEVC decoder as DLR. $X$ is restored and exaggerated to have $\hat{Y}$ using our RR-DnCNN v2.0 as $h$. Our target is to minimize the error between $\hat{Y}$ and the ground-truth HR. Instead of fully inference from $X$ to $\hat{Y}$, we present the degradation-aware technique to treat the LR as our transitional ground-truth. Additionally, residual learning is applied to learn texture features of the image and speed up the network convergence, defined as:

$$\hat{X}, R_{res}, R_{rec} = h(X) \tag{1}$$

where $R_{res}$ represents the inferred residual between LR and DLR for restoration; meanwhile, $R_{rec}$ represents the inferred residual between refined $X$ as $\hat{X}$ and HR. Inside our network, $X$ is refined to have $\hat{X}$ as:

$$\hat{X} = X + R_{res} \tag{2}$$

then up-sampled by deconvolution, combined to reconstruction residual $R_{rec}$ to have the final $\hat{Y}$ as:

$$\hat{Y} = \text{Deconvolution}(\hat{X}) + R_{rec} \tag{3}$$

B. Restoration-reconstruction u-shaped deep neural network (RR-DnCNN v2.0)

Our previous proposed RR-DnCNN [20] treats the uncompressed low-resolution video as a transitional ground-truth to clarify learning architectures as two parts: restoration and reconstruction. Consequently, the restoration part can compensate for the lossy information from video coding for decoded low-resolution, also restore feature-based information for reconstruction. However, the too-deep inference causes
lossy useful information in shallow layers. We thus propose upsampling skip connections and modify the network as a restoration-reconstruction u-shaped deep neural network (RR-DnCNN v2.0), which can recover the missing information for reconstruction from the restoration.

More details in our RR-DnCNN v2.0 architecture, the restoration part takes the decoded low-resolution (DLR) to remove the compression artifacts and enhance features under residual between DLR and low-resolution (LR). It ends up with two directions: up-sampling features for reconstruction part by a deconvolution, and synthesizing residual map to refine DLR by a convolution. Meanwhile, the reconstruction part continuously leverages up-sampled features to converts from refined DLR into the high-resolution (HR), as illustrated in Figure 2.

Technical details. Our RR-DnCNN v2.0 consists of a convolution module together with 10 convolution layers for repairing compressed video (restoration), and 10 convolution layers for super-resolution (reconstruction). Each convolution layer includes 2 convolution modules using a kernel size of $3 \times 3$, a stride of 1, padding of 1. Each convolution module is followed by a Leaky Rectified Linear Units (Leaky ReLU) with a negative slope of 0.01. Regarding transferring features of each layer from restoration to reconstruction, we utilize up-sampling skip connections using a deconvolution module with a kernel size of $3 \times 3$, a stride of 2, padding of 1 and output padding of 1. Each layer of reconstruction receives the upscaled features at its middle as a summation, as illustrated in Figure 3. Different from other layers, the first convolution module of restoration uses 64 filters of size $5 \times 5 \times 1$ to generate 64 feature maps and cover useful information by a higher receptive field. The depth channel of 64 is maintained in the network. At the end of each part, we use a convolution module that uses one filter of size $3 \times 3 \times 64$ to generate residual maps, as described in Figure 2.

C. Loss function

As previous work [20], our losses computed using Mean Square Error as:

$$MSE = \frac{1}{N} \sum_{i=1}^{N} \| R_i - R_i^* \|^2 \quad (4)$$

where $N$ is number of elements in a batch, $R_i$ represents the ground-truth residuals, while $R_i^*$ can be the $i^{th}$ $R_{res}$ or $i^{th}$ $R_{rec}$. As our degradation-aware technique, the true LR is treated as our transitional ground-truth in the middle of the overall network. We thus add loss weights of $\alpha$ and $\beta$ to balance learning. The total loss function is defined as:

$$L = \alpha \ast L_{\text{restoration}} + \beta \ast L_{\text{reconstruction}} \quad (5)$$

where $L_{\text{restoration}}$ minimizes loss of (LR - $X$) and $R_{res}$, while $L_{\text{reconstruction}}$ minimizes loss of (HR - Deconvolution($X$)) and $R_{rec}$. Different from RR-DnCNN [20], RR-DnCNN v2.0 shows the faster convergence and stable learning; therefore, we empirically set the loss weights in the equation 5 as $\alpha = 0.5, \beta = 0.05$. 

![Diagram of convolution layers and upsampling skip connection.](image)

![Architecture of the proposed restoration-reconstruction u-shaped deep neural network (RR-DnCNN v2.0).](image)
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Fig. 4. Training processes of 3 domains RA, Low Delay P, and LDP at QP=37 in Mean Square Error. Left: restoration loss, right: reconstruction loss.

| TABLE II | ABLATION STUDIES ON COMPRESSION CONFIGURATIONS | W | E TRAIN OUR MODELS USING CONFIGURATION RA, LDP, AI, AND TEST ON DECODED LOW-RESOLUTION VIDEO BasketballDrive 960 × 576, WHICH IS COMPRESSED IN RA, LDP, AI, RESPECTIVELY. THE BOLD/UNDERLINE VALUES SHOW THE BEST/WORST PSNR FOR THE TEST ON EACH CONFIGURATION. THE MODEL TRAINED ON RA GIVES THE BEST PERFORMANCE ON AVERAGE. |
| --- | --- | --- | --- | --- | --- |
| Training on | Test on | RA | LDP | AI | Average |
| RA | 31.99 | 31.83 | 33.21 | 32.34 |
| LDP | 31.92 | 31.84 | 33.06 | 32.27 |
| AI | 31.95 | 31.82 | 33.2 | 32.32 |

D. Training configuration

In previous work [20], we explored the characteristic of compression degradation, which is brought from three default configurations such as RA, LDP, and AI, which leverage neighboring frames, previous frames, and neighboring pixels within frame respectively. Furthermore, we also observe and validate the models on the video BasketballDrive. As shown in Figure 4 training on compressed videos in AI outperforms others in convergence, while the LDP is the most difficult to be converged. In the validation, the model trained on LDP works well on only its domain; meanwhile, the model trained on RA has the best performance on RA, AI and outperform others on average, as shown in Table II. We conclude that the information of degradation brought from RA is rich enough to generalize other degradation cases. Therefore, RA is utilized for training our primary model.

III. EXPERIMENTS, COMPARISON AND RESULTS

A. Experiments

1) Data preparation: Uncompressed videos are significant to provide reliable analysis and understand video compression behavior for training and testing our models. Therefore, we choose training and testing sequences are uncompressed. Our previous work [20] trained on small-scale data with the small resolution CIF 352 × 288, which will limit the performance on larger resolution. In this work, we thus have 2 stages of training:

Firstly training on large-scale uncompressed videos in CIF. Besides 34 uncompressed videos as 18, 478 frames from Xiph Video Test Media in CIF 352 × 288 we mentioned in [20], we add more 1, 912 resized frames from class D including the sequences Blowing Bubbles, Race Horses, BQSqaure, Basketball Pass. The ground-truth HR 352 × 288 is downsampled at scale × 2 to have LR 176 × 144.

Secondly fine-tuning on uncompressed video in larger resolution. We utilize the 11 uncompressed videos as 3, 300 frames from SJTU HDR Video Sequence Dataset [22] (excluding the UHD test sequences in Table VI). The videos are scaled to 1920 × 1152 as HR, 960 × 576 as LR to fine-tune our well-trained model.

For the evaluation, besides the test sequences from class A, B, C, E, we also conduct comparisons on UHD sequences from [22], such as Campfire Party, Fountains, Runners, Rush Hour, Traffic Flow.

HEVC Test Model version 16.20 is used to synthesize the decoded low-resolution. However, our scheme tends to encode the down-sampled videos at scale × 2. We thus resize 1080p to 1920 × 1152 to satisfy the coding unit (CU) requirement. Since our work is super-resolution, all experiments are conducted on only the Y component, which reflects the details of content to the human eye’s experience.

2) Data augmentation: To vary our training data, we step-by-step apply random crop as 120 × 120 for training on CIF resolution and 512 × 512 for fine-tuning on UHD sequences. Afterward, we utilize random flip in horizontal and vertical dimensions, and random rotation in 0, 90, 180, 270 degrees. Finally, Y values are normalized in the range [0, 1].

3) Training details: We change Adam Optimizer [19] to Rectified Adam Optimizer [21], which helps the model con-
TABLE III
ARCHITECTURE COMPARISON BETWEEN BICUBIC, DnCNN, AND OUR RR-DnCNN IN PSNR ON BASKETBALLDRIVE SEQUENCE COMPRESSED AT QP=37 USING RA, LDP, AND AI. OUR NETWORK OUTPERFORMS OTHERS AS **BOLD** VALUES.

| Method            | PSNR on |
|-------------------|---------|
|                   | RA      | LDP    | AI      | Avg     |
| Bicubic           | 31.48   | 31.37  | 32.63   | 31.83   |
| DnCNN             | 31.6    | 31.46  | 32.64   | 31.9    |
| RR-DnCNN [20]     | 31.99   | 31.85  | 33.21   | 32.54   |
| RR-DnCNN v2.0 (Ours) | 32.12   | 31.94  | 33.36   | 32.47   |

verged deeper, with initial learning rate of 0.0001, coefficients $\beta_1 = 0.9, \beta_2 = 0.999$, batch size of 16. Every 100 epochs cost approximately 43 hours on Tesla V100.

B. Comparison between our novel network and its old version RR-DnCNN [27] in learning capability

This work is based on our previous work RR-DnCNN [20]. Besides improving the training strategy such as increasing training data, using RAadam [21], adding 2-stage training process and fine-tuning-trained models, we also enhance the learning capability of our deep neural network as a restoration reconstruction u-shaped deep neural network (RR-DnCNN v2.0) using up-sampling skip connections, as described in Section II-B. To prove the efficiency of our novel architecture, we train RR-DnCNN and RR-DnCNN v2.0 in the same condition and validate them on sequences in 1920×1152 such as Blue Sky, Pedestrian, Rush Hour, BQTerrace, Basketball Drive, Cactus, Kimono, Park Scene. As a result, our RR-DnCNN v2.0 shows the efficient convergence in restoration and reconstruction. Furthermore, the validation error of RR-DnCNN v2.0 is lower than its old version every trained model on the test sequences averagely, as shown in Figure 5. Our novel network RR-DnCNN v2.0 thus outperforms the RR-DnCNN [20] in learning capability.

C. Results

We compare our work to DnCNN [13], our previous RR-DnCNN [20], which are our baseline, in PSNR. Furthermore, we compare our work to the standard H.265/HEVC in compression proficiency using BD-rate, BD-psnr measurement as an objective comparison. Furthermore, we visualize results as a subjective comparison in the same bit-rate with H.265/HEVC. As conducted in Section II-D we train the models on RA configuration at QP=37 in among the QPs={32,37,42,47}, which is considered as having enough useful information to cover other QPs.

1) Compare to the baseline architecture DnCNN [13] and our previous work RR-DnCNN [20]: We continue to conduct comparison from our previous experiment, which evaluates on the test sequence BasketballDrive compressed in 3 configurations RA, LDP, and AI. Although the previous work RR-DnCNN [20] shows its proficiency in reducing artifacts, and super-resolution, its network architecture is still limited by the poor connection between restoration and reconstruction. As a consequence, the performance is easily saturated. To enhance our previous work, we add up-sampling skip connections to leverage the features from restoration (shallower features) for reconstruction. Our RR-DnCNN v2.0 thus shows the more effectiveness of learning capability. As described in Table III our RR-DnCNN v2.0 quantitatively outperforms others in three domains. Furthermore, we also compare in two test sequences People on the street and Traffic with resolution 2160×1600 in both objective (PSNR/SSIM) and subjective ways. As an experimental result, our RR-DnCNN v2.0 shows clearer edges, shapes such as folds and pattern on the shirts, the texts and lines, compared to bicubic and RR-DnCNN [20], as illustrated in Figure 6.

2) Compare to related works on down-sampling based video coding: As our furthest knowledge of down-sampling based video coding to improve the standard HEVC codec, we objectively compare our work to the work(s) [20], [3] on RA, LDP and [20], [2], [4] on AI configuration. Regarding the measurement, we calculate the bit-rate savings (BD-rate) for the QPs={32, 37, 42, 47} anchored by the standard HEVC. The experimental results of related works are provided in their materials [2], [3], [4]. Since we use HEVC Test Model version 16.20 being different from previous works using version 12.1, we thus experiment on both versions to ensure that the performance gap does not prioritize our method.

Our result on HEVC Test Model (HM) both versions 16.20 and 12.1. The experimental results of previous works in this paper are copied from their materials. However, our HM version is different from them. We thus conduct a comparison between both versions in BD-rate for QPs={32,37,42,47} on the video Park Scene to ensure that the performance gap between two versions does not prioritize our method. As a result, our performance on HM version 12.1 is even better than on our current version 16.20 as outperforming $\Delta 0.35\%$ bit-rate reduction, as shown in Table IV. Therefore, the gap does not prioritize our work.

Comparing to [20], [3] on RA, LDP in BD-rate. In the standard HEVC, RA and LDP configurations leverage the information of neighboring frames, showing the more effective compression. However, they give more lossy information of the current frame, which should be effectively compensated by neighboring frames. Therefore, it’s challenging for our approach, which is based on SISR, to deal with degradation brought from RA, LDP. In previous work [20], we design a degradation-aware technique inside our network; plus, we deal with missing information through frames by training on the degradation brought from RA configuration and successfully cover the degradation brought from other configurations, as proved in Section II-D. Additionally, in this work, we improve the network architecture and have 2-stage training/fine-tuning, so-called RR-DnCNN v2.0. As a result, the BD-rate of this work is decreased by 114\%. 17\% on RA, LDP, respectively, compared to our previous work RR-DnCNN [20]. Comparing to the work [3] adopting Multiple-Image Super-Resolution (MISR) technique at block-based level, our work achieves the more efficient BD-rate as outperforming $\Delta 2.51\%$, $\Delta 4.55\%$ on RA, LDP correspondingly, as shown in Table V.

Comparing to [20], [2], [4] on AI in BD-rate. In the standard HEVC, AI configuration purely leverages the information between neighboring pixels within the frame. Therefore, SISR-based method ideally solves the problem, and training model
Fig. 5. Ablation study on learning capability of the network architecture compared to RR-DnCNN \cite{20}. We train two networks in the same condition and visualize its restoration loss (left), reconstruction loss (middle), validation error (right). Our novel RR-DnCNN v2.0 outperforms its old version in learning capability.

Fig. 6. Subjective comparison between bicubic, the previous work RR-DnCNN \cite{20}, and our RR-DnCNN v2.0 in PSNR/SSIM. The **bold** values represent the best performance.
on AI shows the most convergence compared to others. Understandably, the model trained on a specific degradation can achieve the best performance on that degradation, as well as on AI configuration. However, the degradation brought from RA gives the rich information to train and is enough to cover the degradation brought from AI, as proved in Section [ID].

We thus train our model on RA configuration and conduct an objective comparison between our work and the works [2], [4], which are based on SISR for pure intra coding. Besides, we also show the improved performance compared to our previous work RR-DnCNN [20] on the AI domain. As a result, our BD-rate is decreased by 24.28% on average compared to RR-DnCNN [20]. Regarding related works, our method outperforms the works [2], [4] as $\Delta$ -3.95%, $\Delta$ -4.2% respectively on average. Furthermore, our work shows the most proficiency on UHD sequences and attains the average BD-rate -17.02%, anchored by the standard HEVC.

3) Compare to the standard HEVC: In previous Section [II-C2], our method outperforms others, also the standard HEVC, quantitatively as -7.16%, -8.27%, -11.26% BD-rate on RA, LDP, AI respectively and attains 17.02% bit-rate reduction on the UHD. For the more evidence and clarifying our performance, we show the Rate-Distortion curves (R-D curves) between our RR-DnCNN v2.0 and HEVC on People on the street (People), Blue sky, Kimono, Campfire party, Rush hour compressed by the configurations LDP, AI. The R-D curves prove the capability of our work in reducing bit-rate with the same quality PSNR, as shown in Figure 7. Furthermore, we conduct a subjective comparison between our method and the standard HEVC in approximate bit-rate condition on Kimono (RA), Pedestrian (LDP), and Rush hour (AI). Additionally, we provide bit-rate/PSNR/SSIM for each method every sequence. As a result, our work has the higher PSNR $\Delta$0.54 dB, $\Delta$0.88 dB, $\Delta$1 dB and SSIM $\Delta$0.0085, $\Delta$0.0202, $\Delta$0.0096 on RA, LDP, AI respectively. In subjective comparison, our results show less artifacts, more refined edges and surfaces as the highlighted regions shown in Figure 8. For the better experience, please check our supplemental video of comparison in approximate bit-rate.

### IV. Conclusion

We improve our previous work [20] to have an end-to-end restoration-reconstruction u-shaped deep neural network (RR-DnCNN v2.0) using the degradation-aware technique to address various compression distortion from video coding at low bit-rates. The network outperforms our previous work in learning capability as well as performance in both objective and subjective ways. Especially in objective comparison, our work improves the previous work as outperforming $\Delta$0.13 dB in PSNR, decreasing by 114%, 17%, 24% BD-rate on RA, LDP, AI respectively. Furthermore, this work outperforms the
standard HEVC quantitatively as -7.16%, -8.27%, -11.26% BD-rate on RA, LDP, AI correspondingly and can attain 17.02% BD-rate reduction on UHD sequences. Additionally, also in BD-rate, we outperform the previous work [3] as \( \Delta -2.51\% \), \( \Delta -4.55\% \) on RA, LDP correspondingly and the works [2], [4] as \( \Delta -3.95\% \), \( \Delta -4.2\% \) respectively on AI. Outperforming on three main configurations RA, LDP, AI in all comparisons proves the proficiency of our work in dealing with various degradation brought from video compression. Regarding our future work, we tend to leverage neighboring frames as MISR-based instead of this SISR-based work.

V. DISCUSSION

A. Run on smaller resolution gives an unstable performance

Our scheme down-samples spatial dimensions of a video to reduce the compression bit-rate, then up-samples the reconstructed video at the end of the decoder. However, down-sampling smaller spatial size causes losing more useful information on the LR video for SR. Moreover, video compression causes additional lossy information. Therefore, this scheme can work more stably and efficiently on a larger size. As shown in Table VI, our method on sequences from class A,B, UHD [22] outperforms HEVC stably, especially on UHD. However, the results on the sequences from Class C are different and unstable. For example, on RA domain in Table VI, our method achieves -6.10% and -10.72% on Basketball Drill and Race Horses. However, in contrast to BQMall and PartyScene, the performance is dramatically worse than the standard HEVC as 1.02%, 18.03% BD-rate.

B. Uncompensable sequences

Our network learns how to compensate for the missing information from down-sampled videos from the training data. However, the over-fitting problem may happen in a few cases, especially on the video BQTerrace. In the training process, the validation errors on most of the test sequences are converged stably. However, the validation error on BQTerrace becomes larger after several epochs and unstable. Meanwhile, the validation error on Park Scene has decreased epoch by epoch, then converged. Although our RR-DnCNN v2.0 can improve the performance on BQTerrace compared to its old version, the over-fitting still happens, as shown in Figure 9. In three main configurations, RA leverages neighboring frames, LDP leverages previous frames, and AI leverages neighboring pixels within a frame. Therefore, it is easier to compensate for missing information on AI configuration. In this SISR-based work, we successfully outperform the standard HEVC on AI as -1.36% BD-rate compared to our previous work [20], as shown in Table VII. However, the missing information gap on RA, LDP is currently not compensated enough. Therefore, our future work leverages neighboring frames and increase training data, which can cover more types of degradation, especially BQTerrace’s one.

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Fig. 7. Rate-distortion curves of our method compared to the standard HEVC on test sequences People on the street, Blue sky, Kimono, Campfire party, Rush Hour. Our method apparently outperforms HEVC. For each chart, the x-axis (horizontal) represents bit-rate; meanwhile, y-axis (vertical) represents PSNR.

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| Video Type        | HEVC         | RR-DnCNN v2.0 | HR  |
|-------------------|--------------|---------------|-----|
| Kimono (Random Access) | 119.42/31.94/0.8604 | 118.58/32.48/0.8725 | ∞   |
| Pedestrian (Low Delay P) | 156.83/32.20/0.8657 | 157.68/33.08/0.8859 | ∞   |
| Rush Hour (All Intra) | 702.38/35.84/0.9313 | 710.06/36.84/0.9409 | ∞   |

Fig. 8. Subjective comparison between our RR-DnCNN v2.0 and the standard HEVC in the approximate bit-rate condition. Our method outperforms in providing less video compression distortion as finer edges and surfaces in higher PSNR and SSIM (bold values). The measurement information is included for each method on each video as Bit-rate/PSNR/SSIM. For easier concentration, we also highlight and zoom out several places corresponding to red rectangles.
Fig. 9. Validation error on BQTerrace and Park Scene. The performance on Park Scene is converged stably epoch by epoch; meanwhile, BQTerrace's validation error shows the over-fitting problem.

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