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Offline and Online Optical Flow Enhancement for Deep Video Compression

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1. Contributions

- Proposing offline enhancement on the optical flows with the guidance of MV of VTM.
- Enhancing the adaptivity of the optical flows by online optimizing the latent features of the optical flows according to the contents of different coding sequences in the inference stage.
- Superior compression performance on two state-of-the-art schemes DCVC and DCVC-DC without increasing the model or computational complexity of the decoder side.

2. Motivation and Analysis

I. Motivation

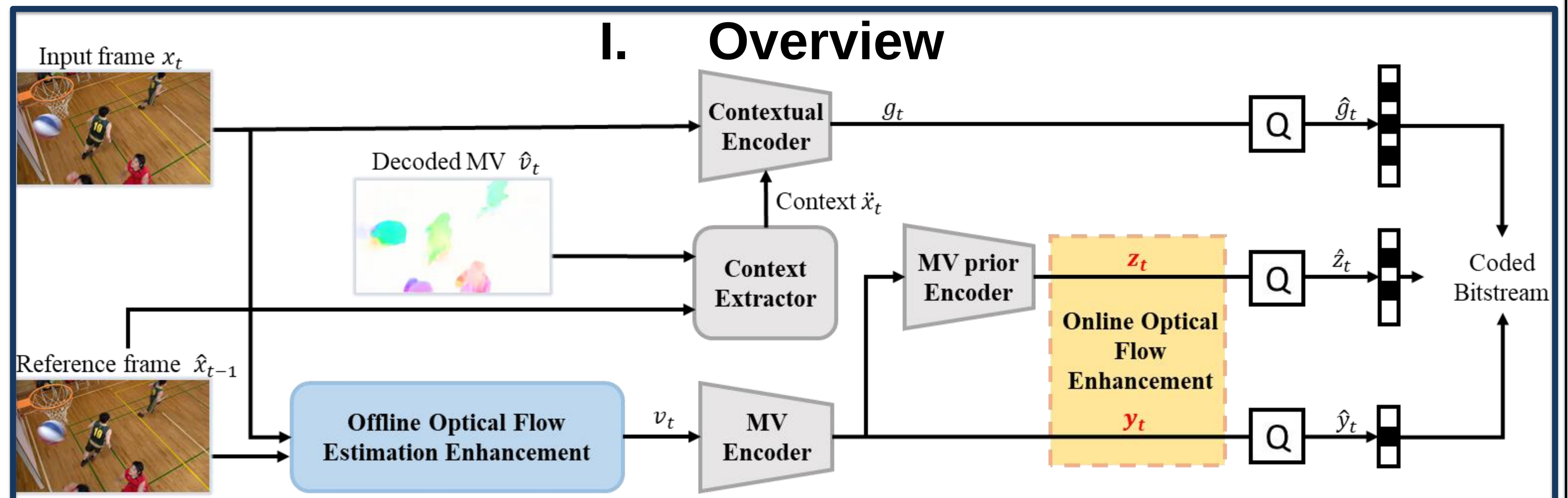
- Mainstream deep video compression networks often adopt pre-trained optical flow estimation networks as motion estimation module, which may be less suitable for video compression.
- The pre-trained optical flow estimation networks are trained to perform inter-frame prediction as accurately as possible, but the optical flows themselves may cost too many bits to encode.
- The optical flow estimation networks are trained on synthetic data, and may not generalize well enough to real-world videos.
- In the inference stage, the motion information is obtained by a simple forward pass through the motion estimation and encoder.

II. Analysis

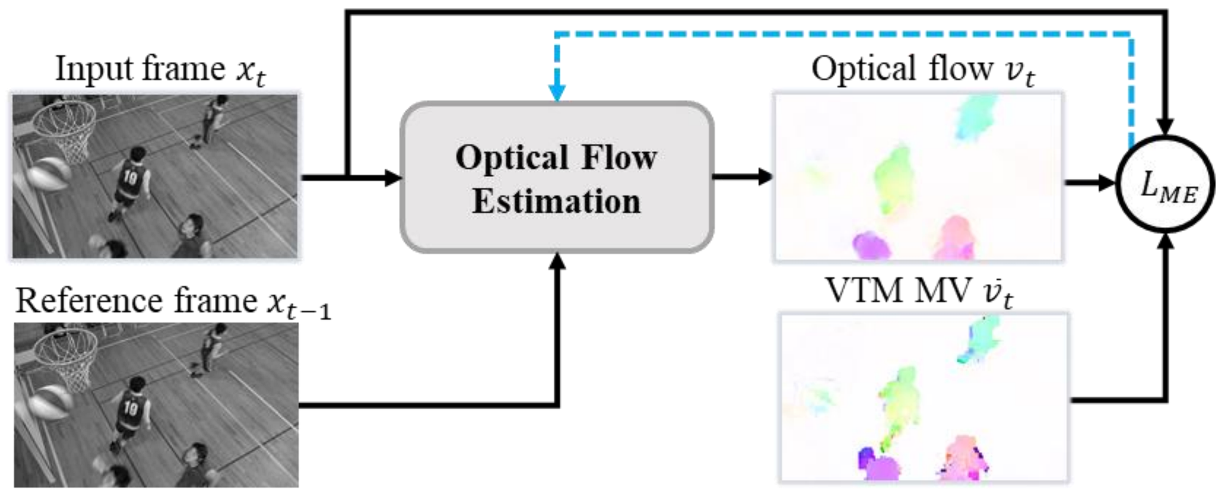
- MV of VTM, searched for the best rate-distortion (RD) performance for each coding sequence, is believed to achieve a better rate-distortion trade-off.
- The online searching strategy in VTM, rate-distortion-optimization (RDO), can achieves content-adaptive video compression.

3. Method

I. Overview



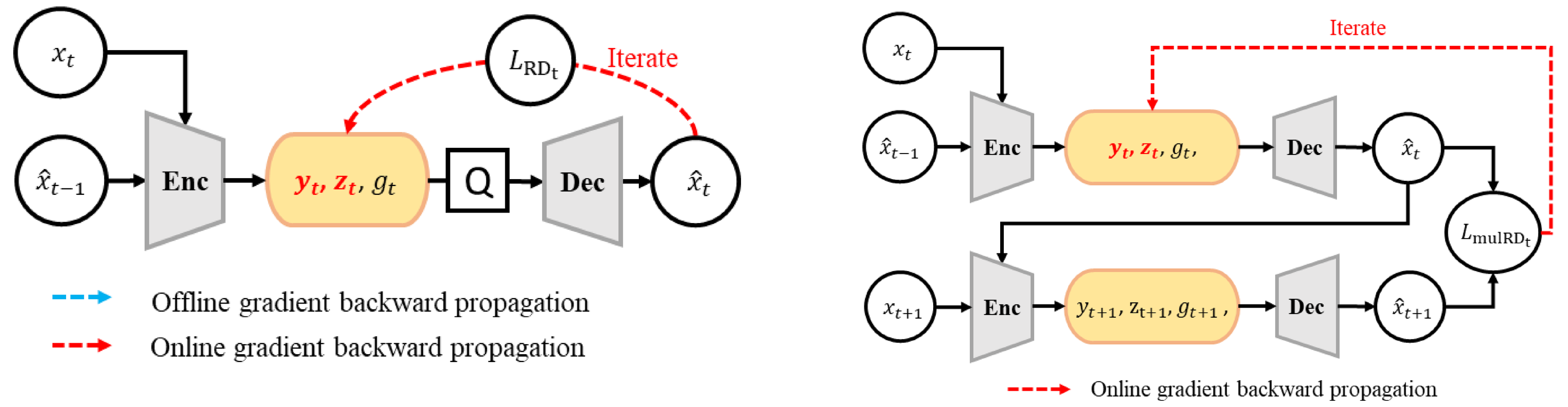
II. Offline Enhancement



- We fine-tune the pre-trained Spynet under the guidance of the extracted MV $\overline{v}_t$. The loss function including the End Point Error (EPE) loss between optical flows and MV and Mean Squared Error (MSE) loss between the input frame and the warp frame $\breve{x}_t$.

$$L_{ME} = \frac{1}{mn}\sum_{i,j}\sqrt{(v_i-\overline{v}_i)^2+(v_j-\overline{v}_j)^2}+\lambda_{ME}*d(x_t,\breve{x}_t)$$

III. Online Enhancement



(a) Single-Frame Online Optimization **(b) Multi-Frame Online Optimization**

- In the inference stage, we online optimize the latent features of the optical flows with a gradient descent-based algorithm minimizing the RD loss in single-frame level and multi-frame level.

$$\tilde{L}^i_{RD_t} = \sum_{j=t}^{W}\alpha_j[\lambda d(x_j,\tilde{x}^i_j)+H(\tilde{y}^i_j)+H(\tilde{z}^i_j)+H(\tilde{g}^i_j)]$$

4. Experiment

I. Comparison with Baseline and SOTA Methods

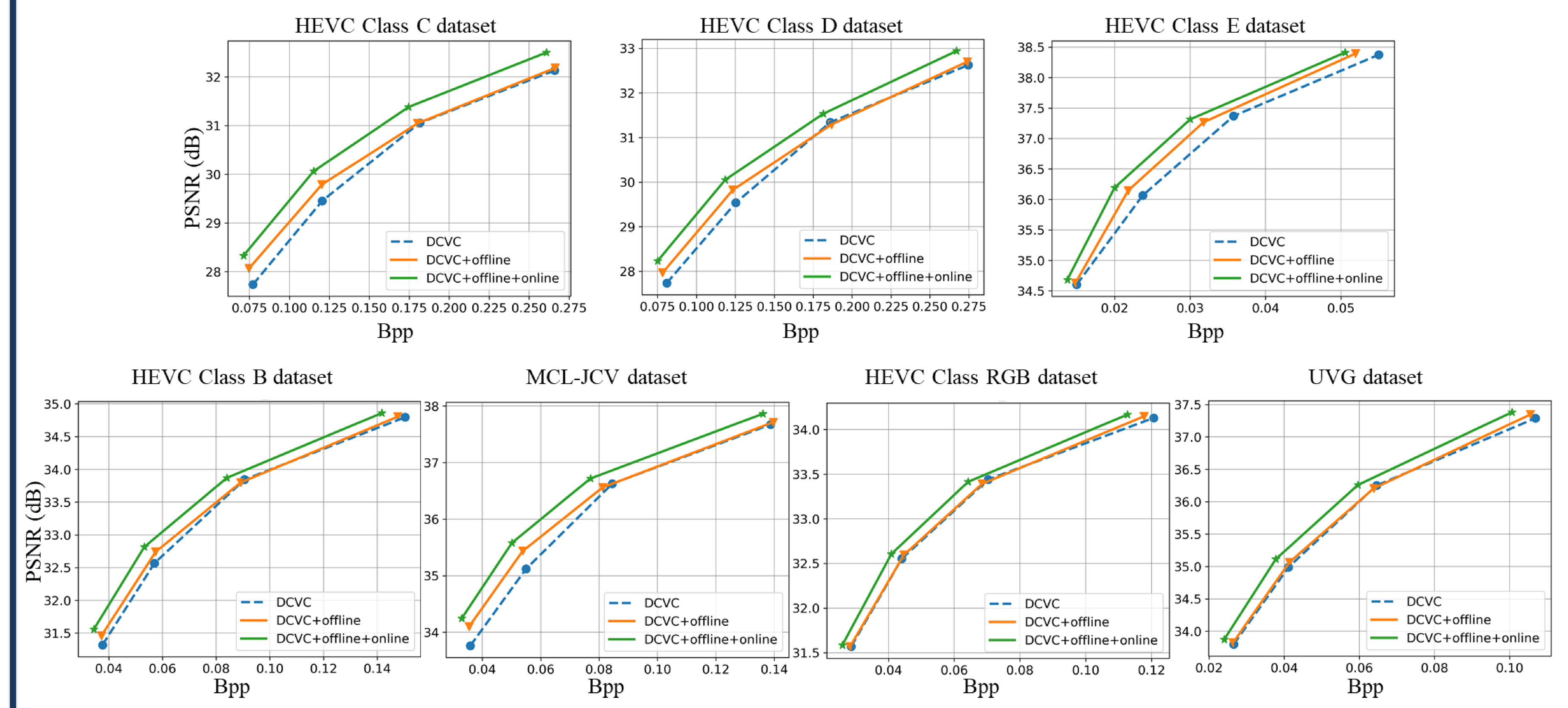
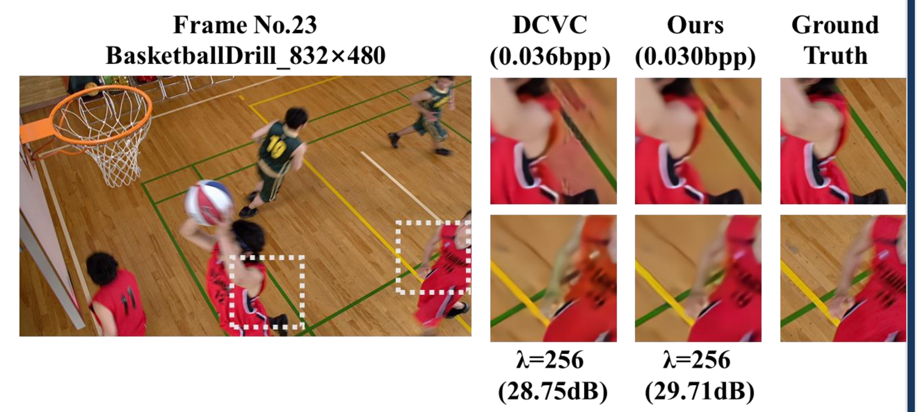


Table 1: Effectiveness of the offline and online enhancement on SOTA method DCVC-DC. BD-Rate(%) comparison for PSNR. Negative values in BDBR represent the bitrate saving.

	B	C	D	UVG	Average
DCVC-DC	0.0	0.0	0.0	0.0	0.0
DCVC	66.6	79.7	76.7	78.7	75.4
DCVC-DC + offline	-0.7	-1.0	-2.1	-0.4	-1.1
DCVC-DC + offline + online	-2.8	-4.9	-4.6	-4.2	-4.1



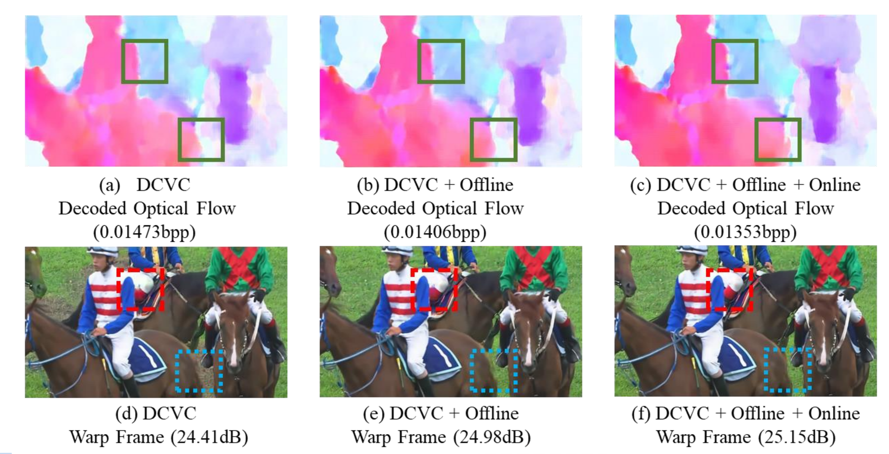
II. Ablation Study

Ablation study of Offline Enhancement and Online Enhancement

Offline	Online	B	C	D	E	RGB	UVG	MCL	Average
✗	✗	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
✓	✗	-3.0	-5.9	-4.4	-7.9	-0.7	-1.3	-6.7	-4.3
✗	✓	-10.7	-14.3	-11.1	-9.0	-8.5	-10.1	-11.3	-10.7
✓	✓	-12.0	-17.1	-13.1	-15.3	-8.8	-10.5	-16.9	-13.4

Ablation Study of Online updating Times

U	C	D	ENC_T C(s)	DEC_T C(s)	ENC_T D(s)	DEC_T D(s)
0	0.0	0.0	2.71	6.94	0.70	1.91
100	-6.1	-5.1	28.15	6.84	10.42	1.90
500	-9.6	-7.9	132.78	6.95	48.99	1.87
1000	-10.8	-8.6	269.20	6.73	92.58	1.89
1500	-11.2	-8.7	388.73	6.86	141.03	1.91
2000	-11.5	-9.1	530.10	6.84	190.64	1.89
2500	-11.6	-9.2	674.54	6.89	239.05	1.88



Ablation Study of Online updating Frames

W	C	D	ENC_T C(s)	DEC_T C(s)	ENC_T D(s)	DEC_T D(s)
2	0.0	0.0	518.25	6.84	187.82	1.89
3	-0.5	-0.4	1631.35	6.84	546.99	1.88
4	-0.7	-0.7	2187.58	6.82	683.04	1.88
5	-0.8	-0.8	2706.39	6.87	874.56	1.86