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Offline and Online Optical Flow Enhancement for Deep Video Compression

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1. Contributions

1. Proposing offline enhancement on the optical flows with the guidance of MV of traditional compression framework (***H,266/VVC***).
2. Enhancing the adaptivity of the optical flows by online optimizing the latent features of the optical flows in the inference stage.
3. 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

1. 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.
2. 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.
3. The optical flow estimation networks are trained on synthetic data, and may not generalize well enough to real-world videos.
4. In the inference stage, the motion information is obtained by a simple forward pass through the motion estimation and encoder.

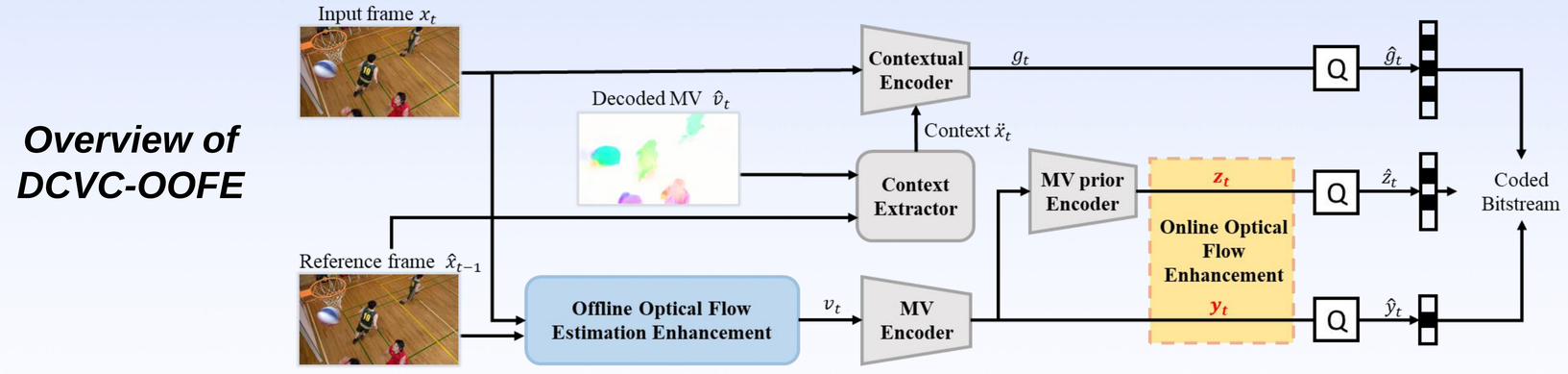
II. Analysis

1. ***MV*** of ***VVC Model***, searched for the best rate-distortion (RD) performance for each coding sequence, is believed to achieves a better rate-distortion trade-off.

2. The online search strategy in ***VVC***, ***rate-distortion-optimization*** (RDO), can achieves content-adaptive video compression.

3. Framework (*Proposed DCVC-OOFE*)

Overview of DCVC-OOFE



Offline Enhancement ***Online Enhancement***

- We fine-tune the pre-trained Spynet under the guidance of the extracted MV $\overline{v}_t$.
- 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.

4. Experiment Results of *Proposed DCVC-OOFE*

Comparison with Baseline and SOTA Methods,
BD-Rate(%) Comparison for PSNR.

	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

DCVC Optical Flow (0.01473bpp)
DCVC + Offline Optical Flow (0.01406bpp)
DCVC + OOFE Optical Flow (0.01353bpp)