

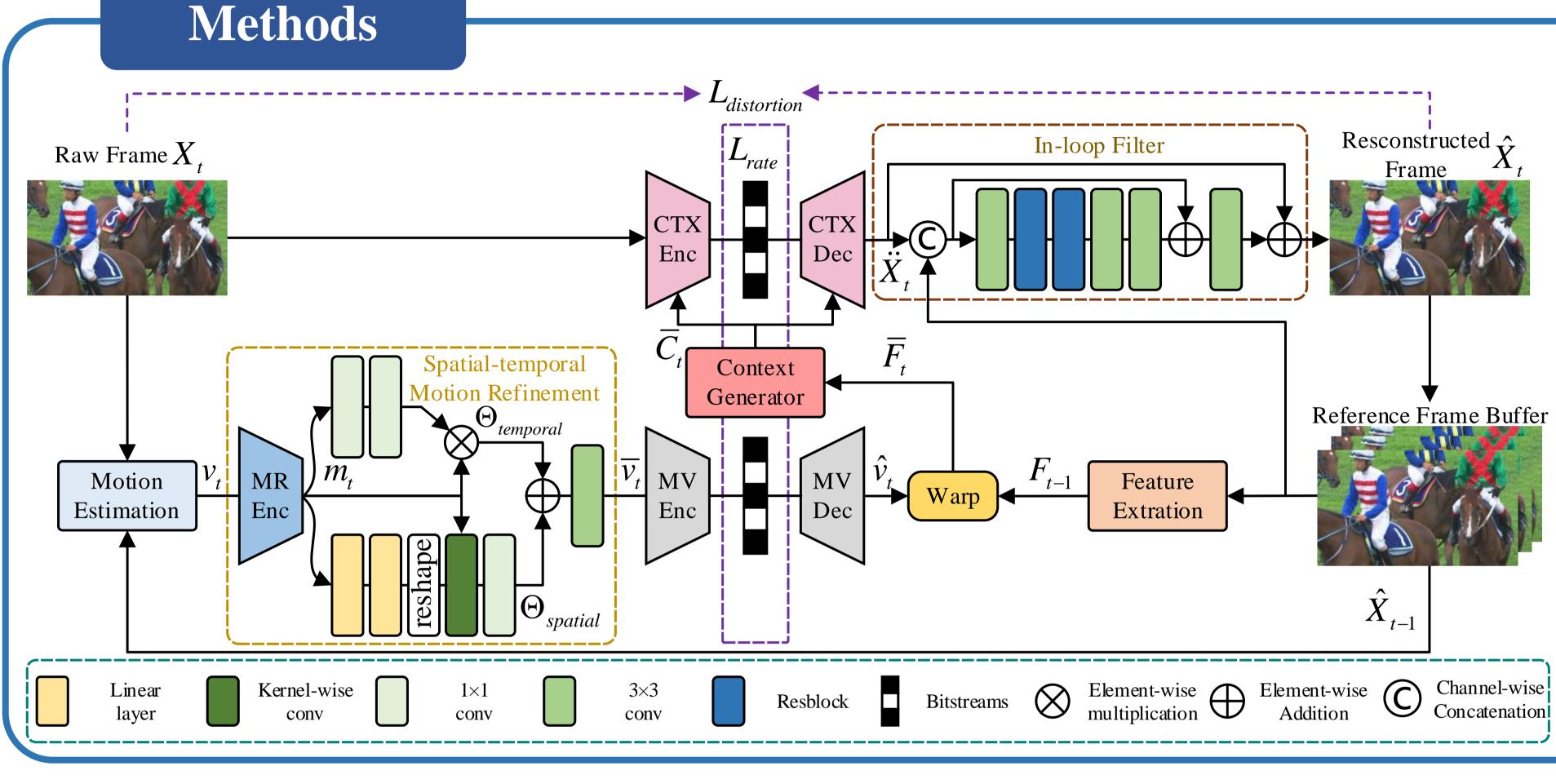
# Learned Video Compression with **Spatial-Temporal Optimization**

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Background

**Motivation:** optical flow network is not accurate and may introduce extra artifacts.

- Pixel-level optical flow based schemes: it replaces the block motion estimation in traditional video coding with pre-trained optical flow model to estimate motion information. Inaccurate optical flow estimation may introduce the reconstructed artifacts.
- Feature-level DCN based schemes: it utilizes the DCN to extract motion information by performing feature alignment in an unsupervised manner. It is difficult to train in practice and results in offset maps overflow for lack of explicit guidance.



We first propose a spatial-temporal motion refinement (STMR) module to extract spatial and temporal components to enhance the original MV for prediction.

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- We adopt the popular context coding scheme instead of the residual coding scheme, mainly because  $H(X_t - \overline{X}_t) \ge H(X_t | \overline{X}_t)$ , H denotes the Shannon entropy,  $X_t$  and  $\overline{X}_t$  denote the current and predicted frame, respectively.
- We propose an in-loop filter (ILF) module, which removes compression artifacts.
  - experiments demonstrate the The coding performance of our proposed method.

Results														
Carriera	PSNR						MS-SSIM							
Sequences	HM-16.20	VTM-13.2	SPME (DCVC)	CANF-VC	DMVC	HDCVC	Ours	HM-16.20	VTM-13.2	SPME (DCVC)	CANF-VC	DMVC	HDCVC	Ours
HEVC Class B	-30.53	-53.23	-35.56	-33.15	-32.12	-27.59	-40.23	-14.21	-41.24	-47.60	-48.02	-51.12	-48.24	-63.79
HEVC Class C	-18.59	-42.39	-10.72	-13.24	-11.34	-10.47	-18.41	-7.93	-34.18	-38.99	-44.76	-43.52	-43.07	-52.81
HEVC Class D	-17.50	-40.34	-15.48	-15.68	-18.51	-9.48	-25.41	-5.86	-31.82	-48.75	-50.64	-54.57	-49.70	-56.63
UVG	-30.26	-53.17	-48.75	-48.35	-36.68	-32.79	-49.80	-14.10	-41.80	-49.26	-50.64	-49.28	-45.98	-58.45
MCL-JCV	-17.57	-40.44	-30.30	-27.02	-14.81	-26.63	-30.85	-2.39	-32.36	-45.03	-47.26	-45.56	-49.77	-57.16
Average	-22.89	-45.91	-28.16	-27.49	-22.69	-21.39	-32.94	-8.90	-36.28	-45.93	-48.26	-48.81	-47.35	-57.77

• HM-16.20, VTM-13.2 — official reference software of H.265/HEVC, H.266/VVC.

• The best result of learned method is highlighted.

In terms of **PSNR** metrics, our proposed method achieves comparable results with VTM-13.2 and even exceed it on 1080p dataset.

GT patch (Bpp/PSNR)

In terms of MS-SSIM metrics, our method is superior to previous SOTA methods (SPME<sup>[1]</sup>, CANF-VC<sup>[2]</sup>, DMVC<sup>[3]</sup>, HDCVC<sup>[4]</sup>) by a larger margin.

STMR	ILF	В	С	D				Scheme	Enc speed	Dec Speed
✓	✓	0.0	0.0	0.0		and the second	and a set of the set of the	x265(veryslow)	0.25	19.2
×	✓	8.75	9.23	7.40				HM-16.20	0.02	9.9
~	×	9.81	13.00	13.46				VTM-13.2	0.001	1.1
×	×	12.45	18.89	18.68	Ground Truth	Coarse MV	Refined MV	CANF-VC	0.6	0.9
			- <b>11</b>	11				DMVC	1.8	_
• Our proposed modules all save								HDCVC	2.4	1.78
BD-rates to varying degrees.								Ours	2.08	2.56
• Right figure shows that refined MV										

- has a richer structural texture.
- One patch after using our method is visually more like the ground truth (GT) patch while consuming

fewer bits.

#### X265(veryslow) (0.16/37.23) VTM-13.2 (0.11/37.62) HM-16.20 (0.14/37.44)

w/o ILF (0.12/37.80)

### frame enhancement module in the test.

Our method achieve the faster speed

we are slower than HDCVC<sup>[4]</sup> because

it removes the time-consuming multi-

(2.56 FPS) than other methods.

# Conclusion

- $\succ$  We propose the learned video compression with spatialtemporal optimization. In particular, spatial-temporal motion refinement module is proposed to refine the MV.
- $\succ$  In-loop filter module is proposed to remove compression artifacts and finally enhance the reconstruction quality.
- > Qualitative and quantitative experiments have shown that our method outperforms the recent learned methods in terms of both PSNR and MS-SSIM metrics.

## Reference

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Ours (0.11/38.01)

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[3] Kai Lin, Chuanmin Jia, Xinfeng Zhang, Shanshe Wang, Siwei Ma, and Wen Gao, "DMVC: Decomposed motion modeling for learned video compression," IEEE TCSVT, pp. 3502–3515, 2023. [4] HuairuiWang, Zhenzhong Chen, and ChangWen Chen, "Learned video compression via heterogeneous deformable compensation network," IEEE TMM, pp. 1–12, 2023.

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