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Hierarchical B-Frame Video Coding Using Two-Layer CANF Without Motion Coding

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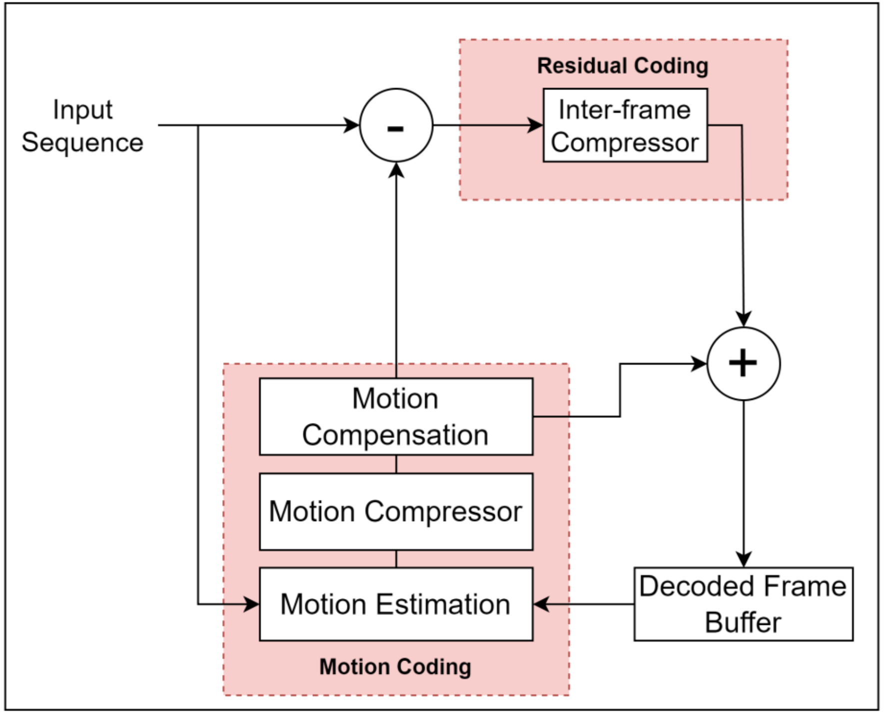
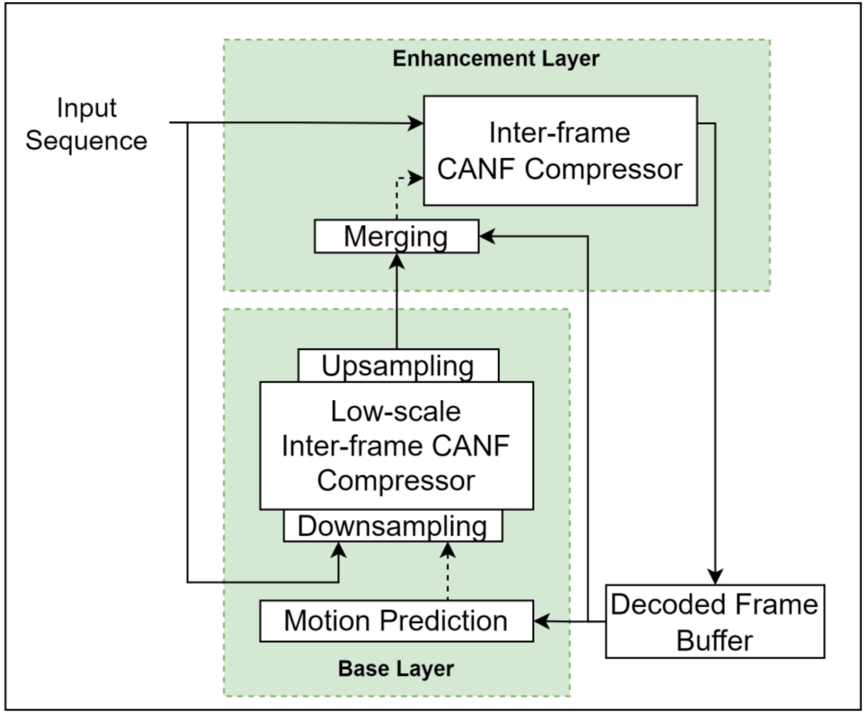
Hybrid Coding vs. This Work

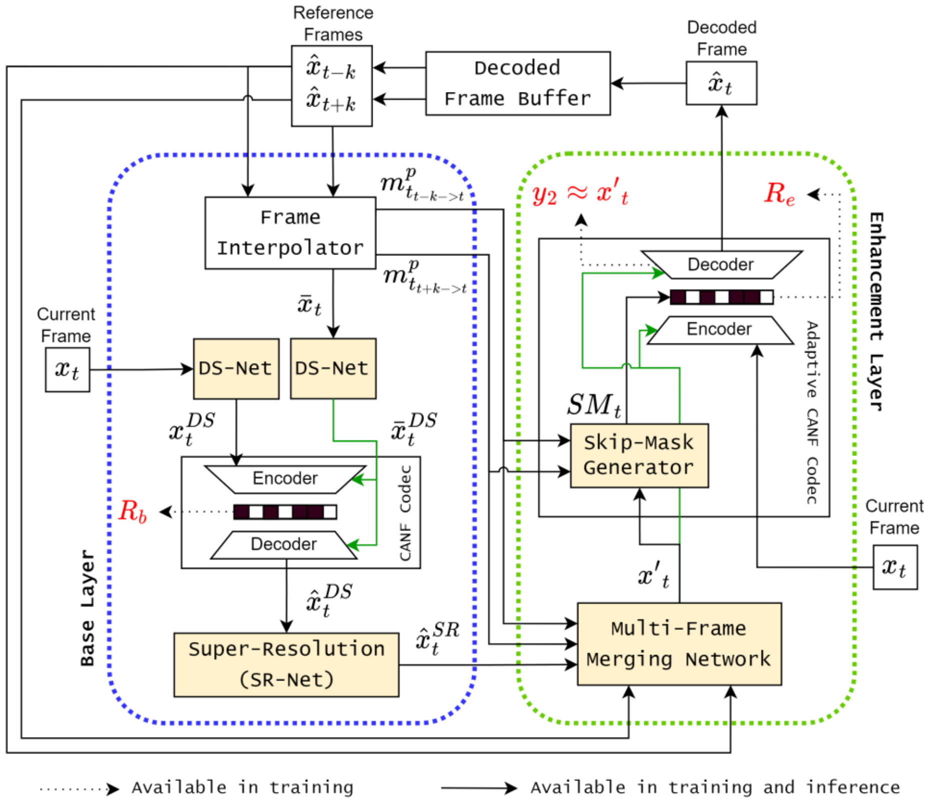


Common Generic Hybrid Video Coding System



Proposed Video Coding System
(Two-Layer without Motion Coding)

TLZMC Framework



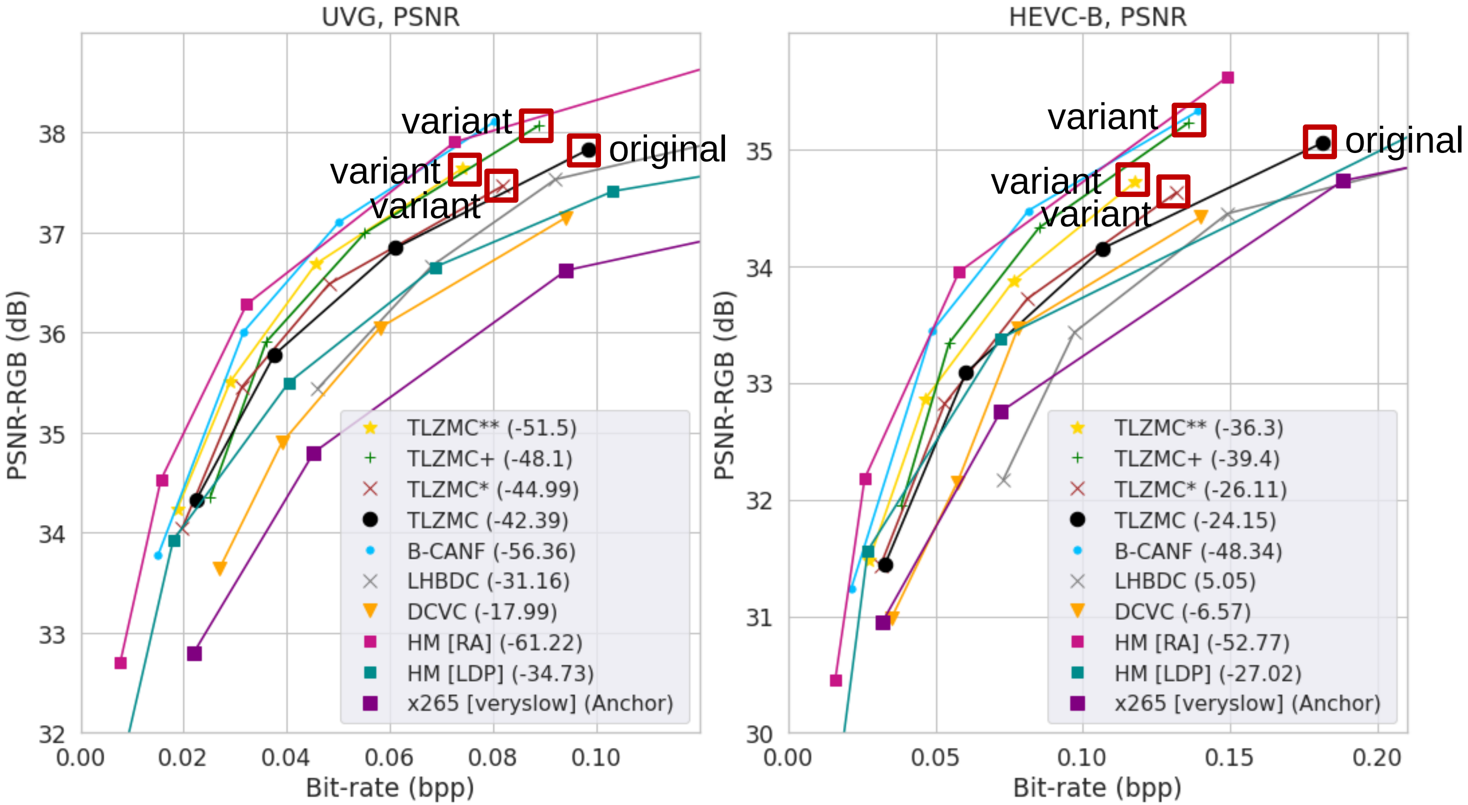
Base-Layer

- Frame Interpolator
- Downsampler (DS-Net)
- CANF Codec
- Super-Resolution (SR-Net)

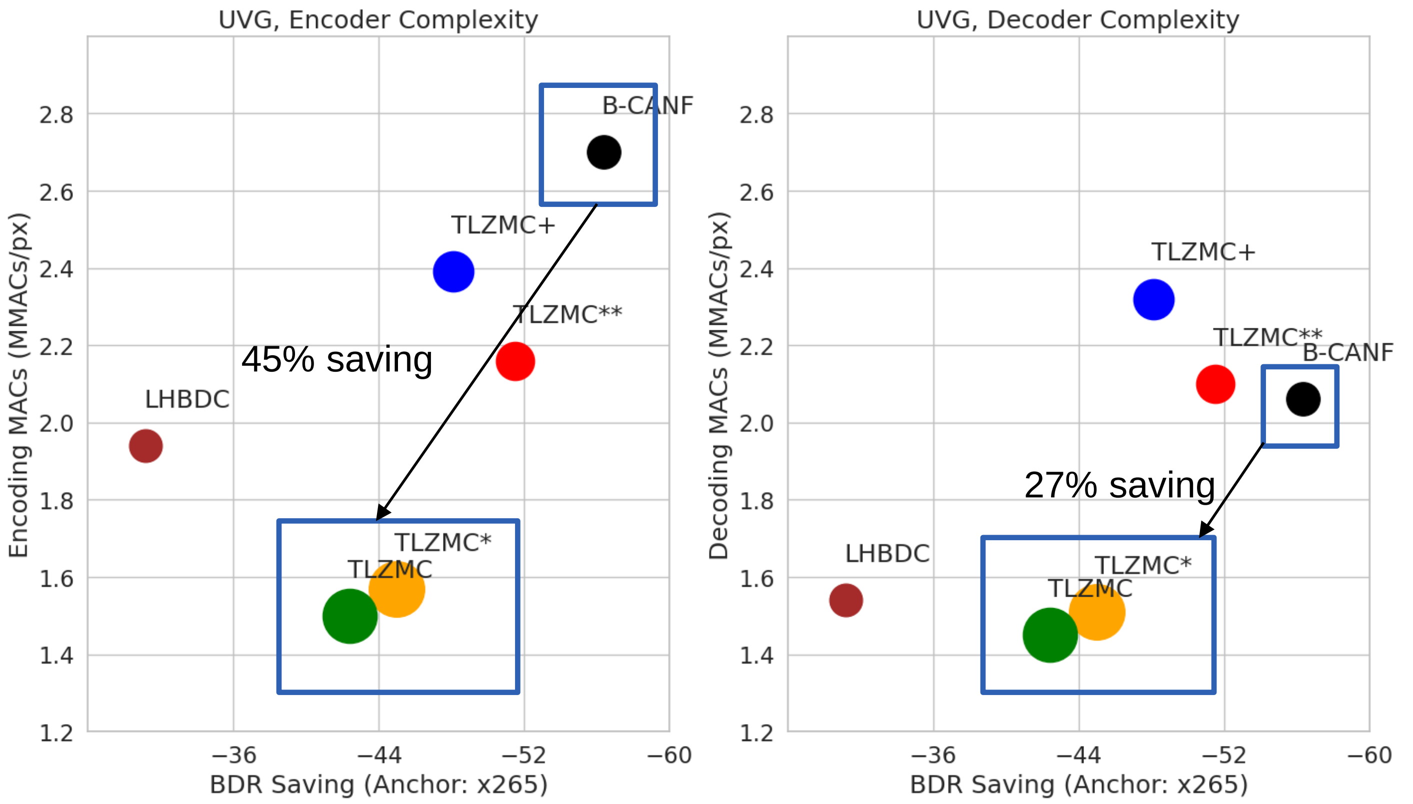
Enhancement Layer

- Multi-Frame Merging Network
- Skip-Mask Generator
- Adaptive CANF Codec

RD-Curve and BD-Rate (UVG, HEVC-B)



Complexity Comparison



Contributions

01 **THE FIRST ATTEMPT**

The first attempt at two-layer coding structure without motion coding

02 **COMPLEXITY REDUCTION**

Shows complexity reduction over the state-of-the-art methods

03 **CONTEXT ADAPTIVE FRAMEWORK**

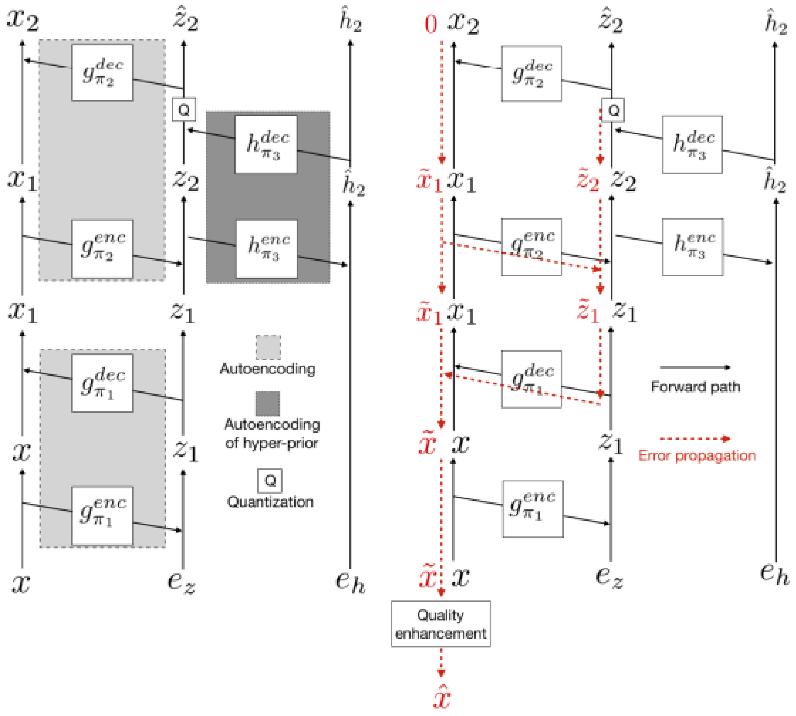
Demonstrates context adaptive framework via rate control

04 **GOOD RD PERFORMANCE**

Comparable RD performance to SOTA for certain video scenes

ANFIC

ANFIC: Image Compression Using Augmented Normalizing Flows

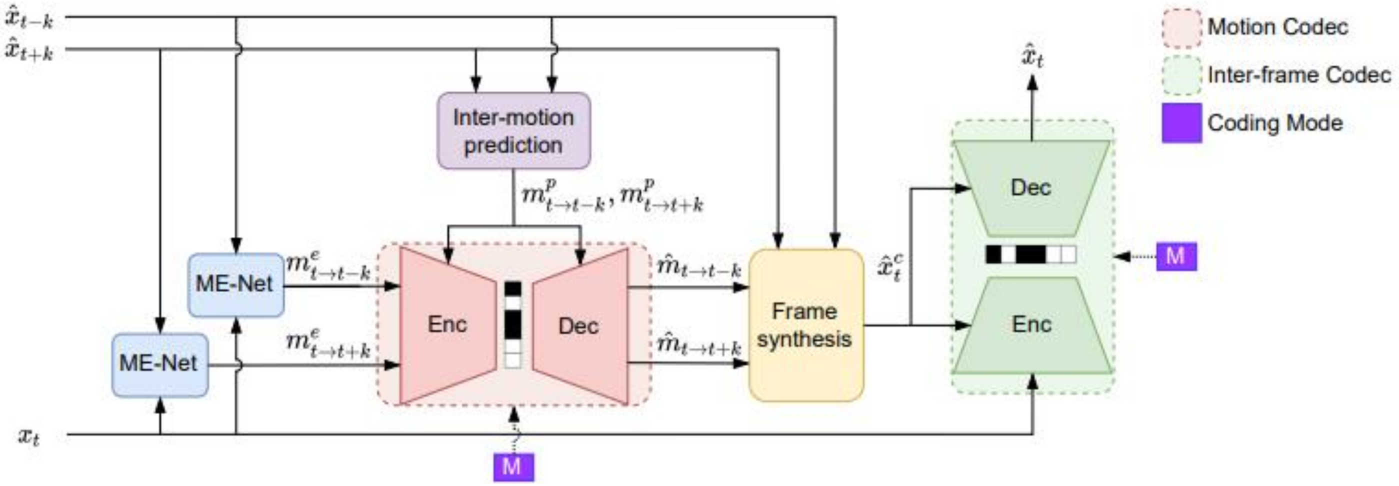


- Based on Augmented Normalizing Flows (ANF)
- Uses a flow-based framework that hierarchically stacks and extends multiple VAEs
- Achieves state-of-the-art coding performance in terms of PSNR-RGB

*Figure from ANFIC: Image Compression Using Augmented Normalizing Flows, (Ho, et al. 2021)

B-CANF: Deep B-frame Coding

B-CANF: Adaptive B-frame Coding with Conditional Augmented Normalizing Flows (Chen, et al. 2022)



- Utilizes conditional augmented normalizing flows
- Incorporates frame-type adaptive coding

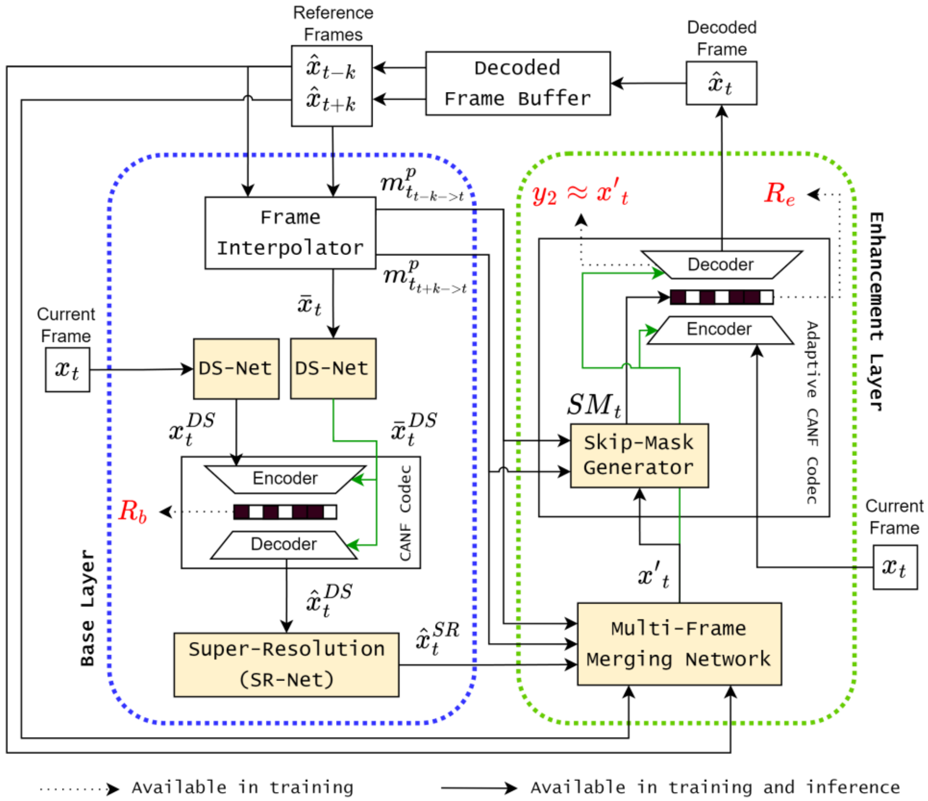
TLZMC

Two-**L**ayer **Z**ero **M**otion **C**oding for Hierarchical B-frames

Key features:

- Lower complexity than the state-of-the-art, B-CANF
- Comparable results to B-CANF in some scenarios
- Outperform other deep hierarchical B-frame coding
- Context adaptive coding and bit rate control

TLZMC Framework



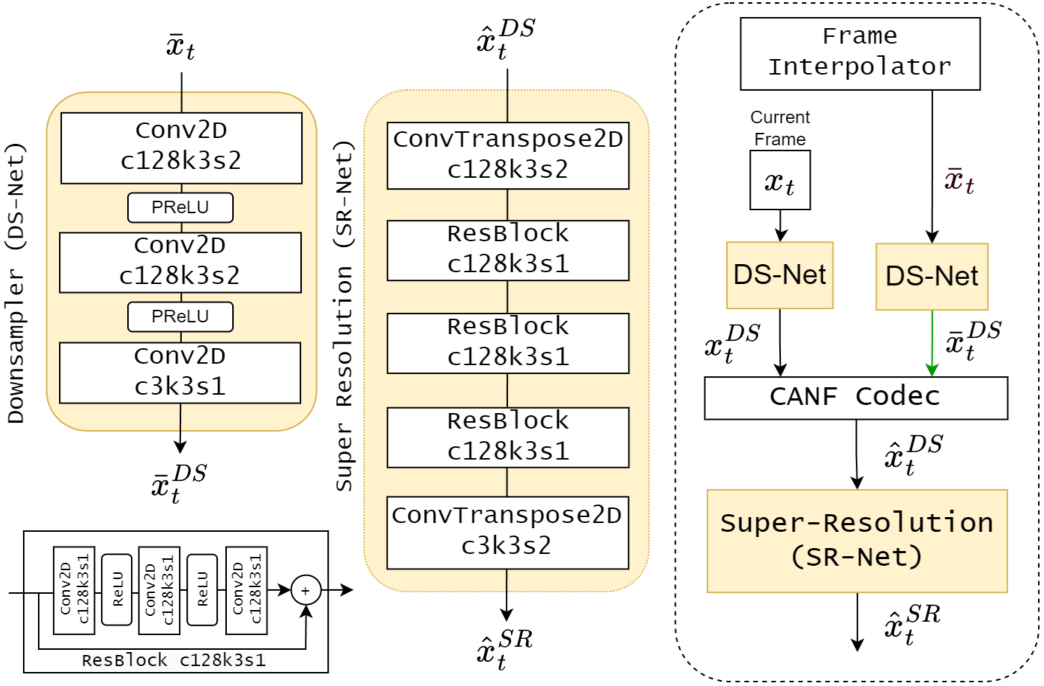
Base Layer

- Frame Interpolator
- Downsampler (DS-Net)
- CANF Codec
- Super-Resolution (SR-Net)

Enhancement Layer

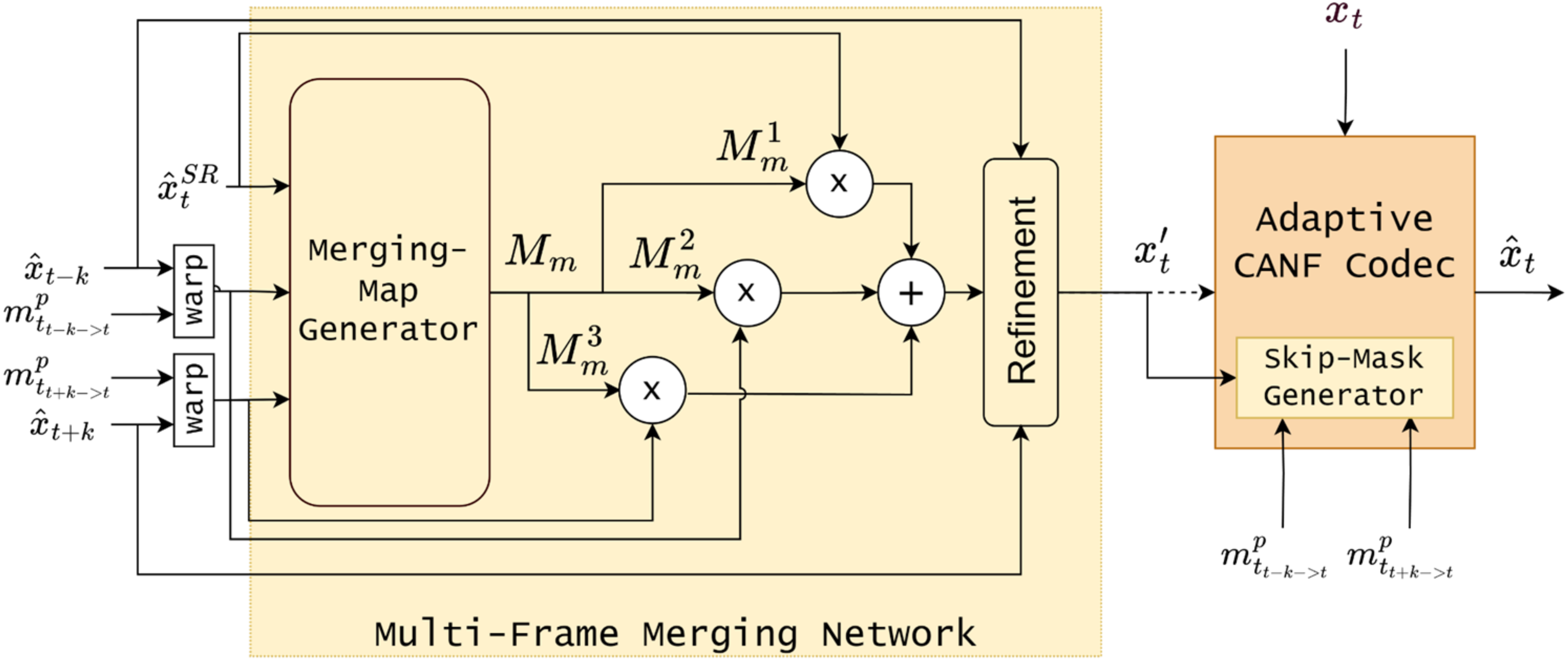
- Multi-Frame Merging Net
- Skip-Mask Generator
- Adaptive CANF Codec

DS-Net and SR-Net



- Uses simple neural networks to perform downsampling (1/4x) and super-resolution
- Supports end-to-end training

Enhancement Layer (EL)



Merging Maps Examples (UVG ShakeNDry)

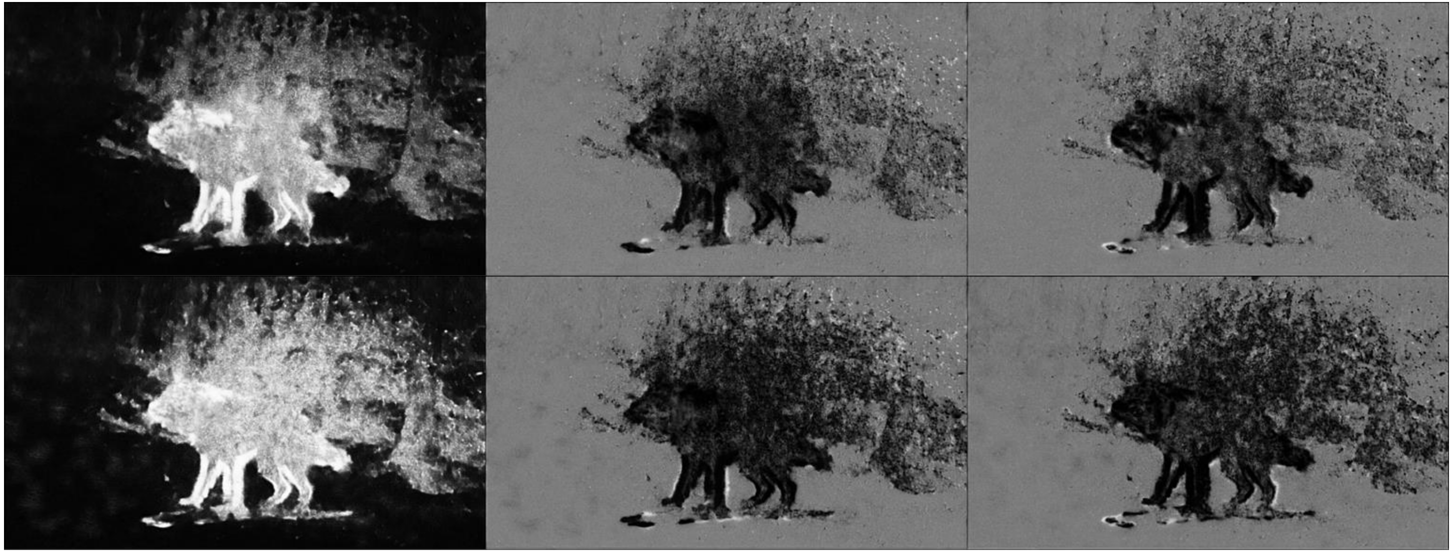
M_m^1
$(*\hat{x}_t^{SR})$

M_m^2
$(*warp(\hat{x}_{t-k}, m^p_{t_{t-k->t}}))$

M_m^3
$(*warp(\hat{x}_{t+k}, m^p_{t_{t+k->t}}))$

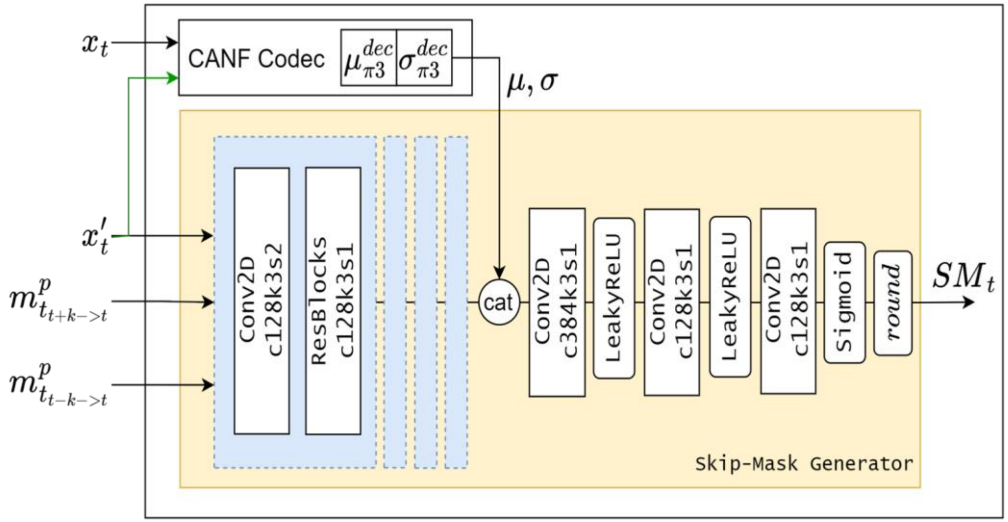
$\lambda = 256$

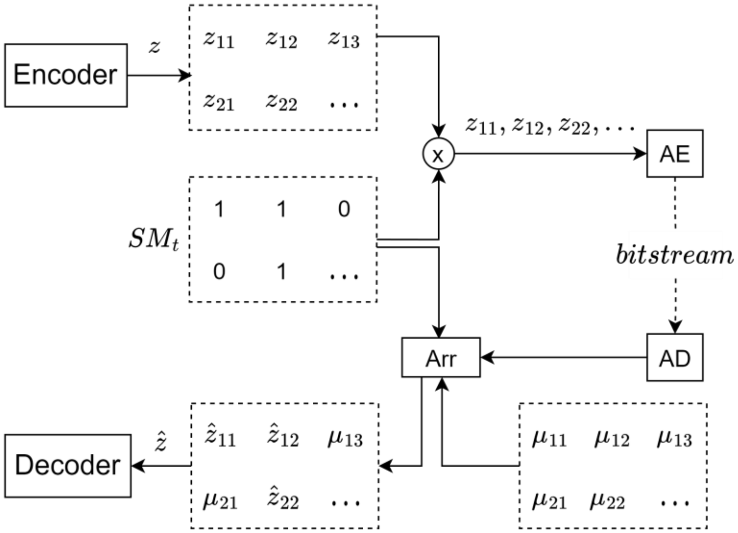
$\lambda = 2048$



Adaptive CANF Codec

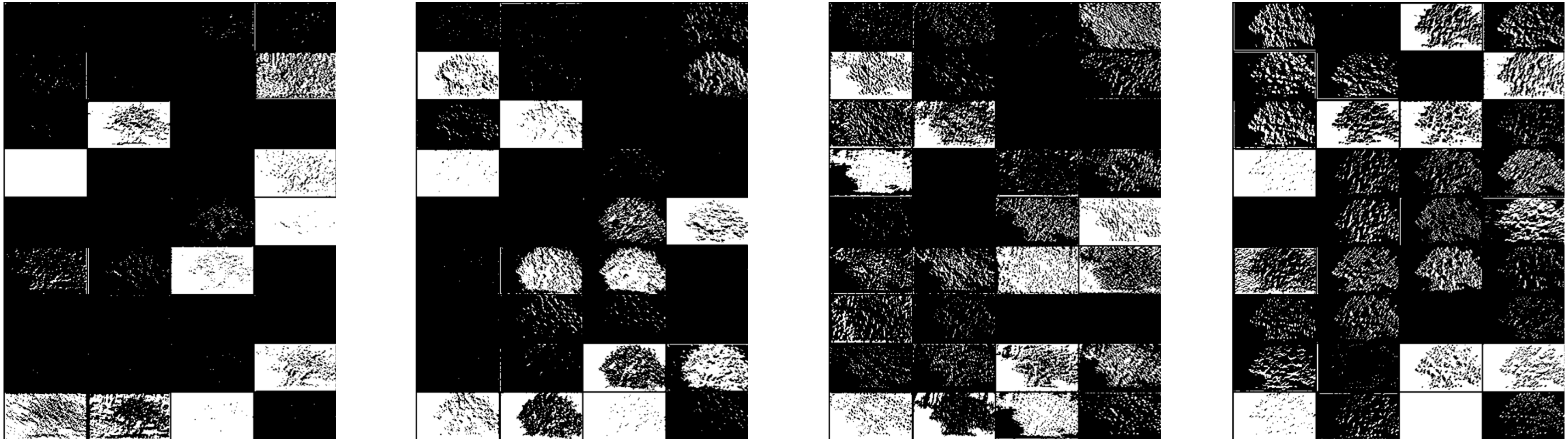
- Skips latent samples by using their mean values for reconstruction
- Predicts a “skip mask” on both the encoder and decoder sides





Skip Mask Examples (UVG ShakeNDry)

Black = skipped



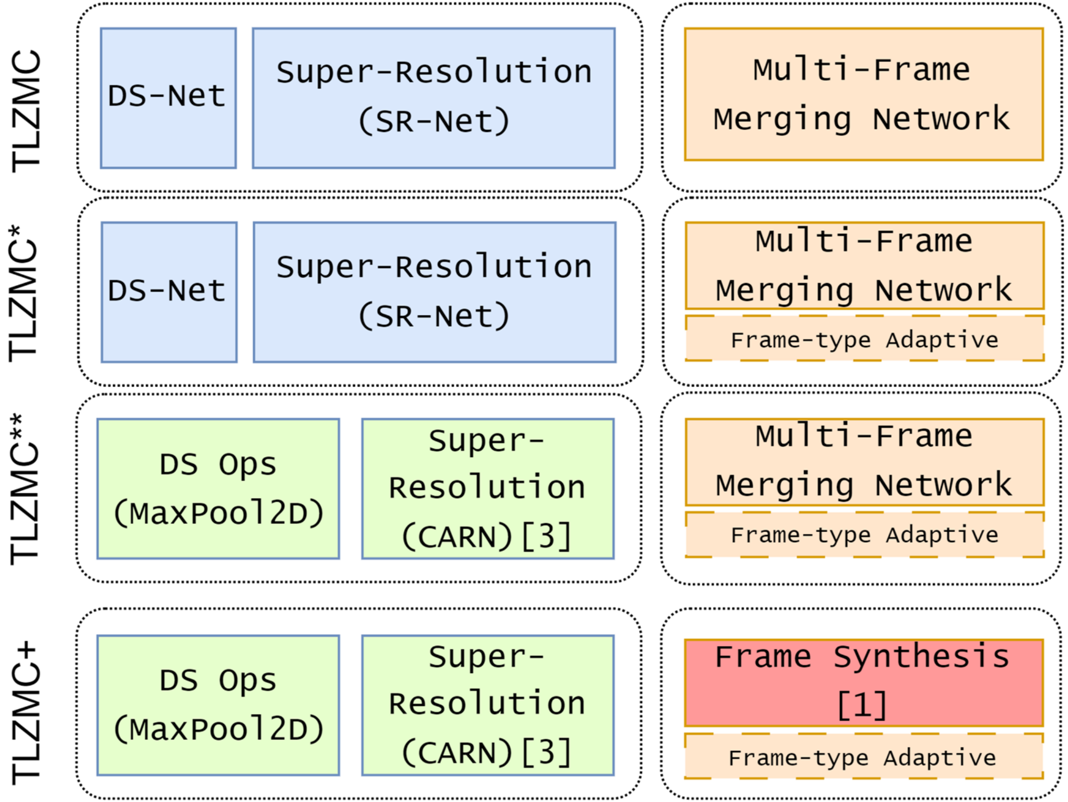
λ=256

λ=512

λ=1024

λ=2048

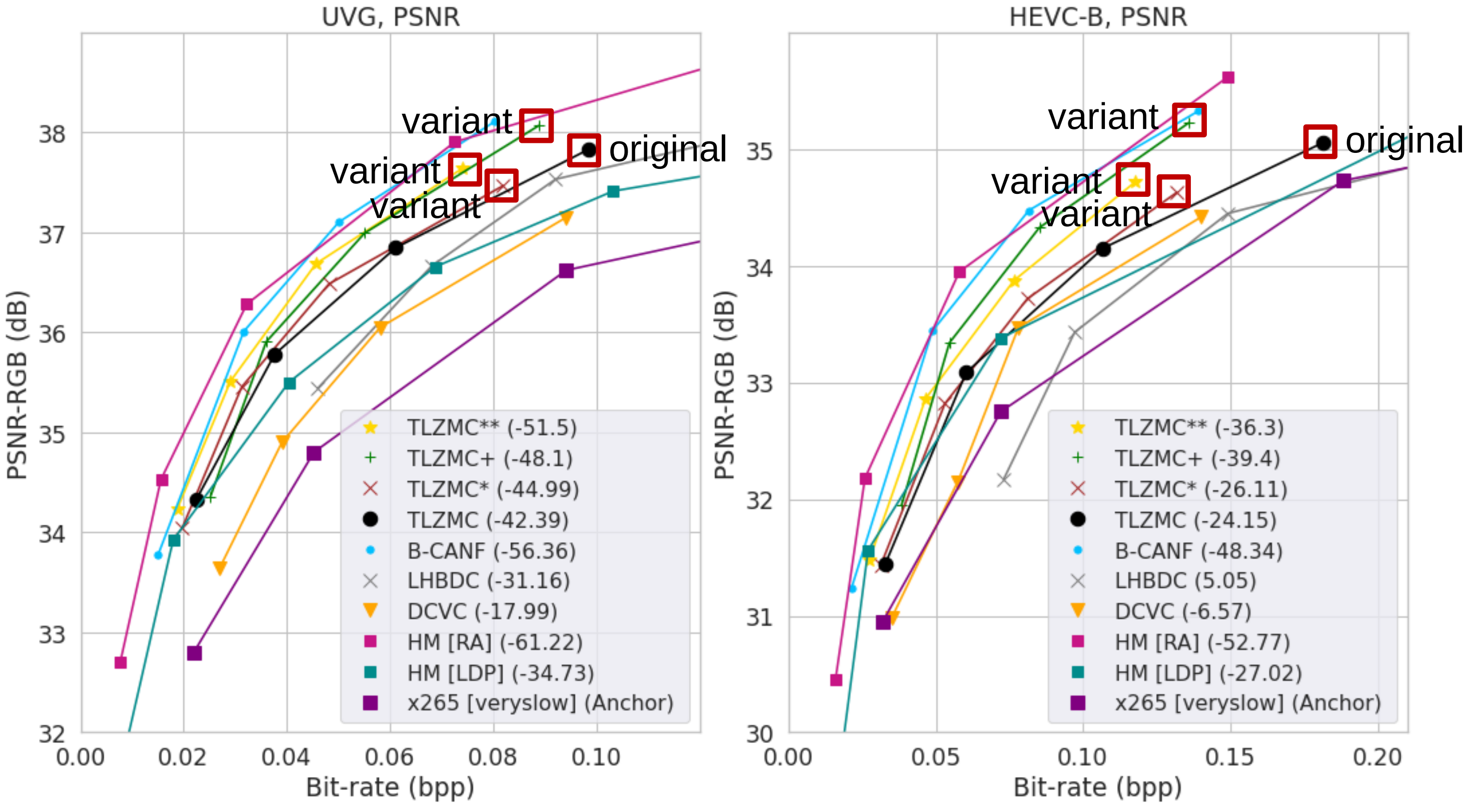
TLZMC Variants



[1] B-CANF (Chen, et al. 2022)

[3] CARN (Ahn, 2018)

RD-Curve and BD-Rate (UVG, HEVC-B) Results



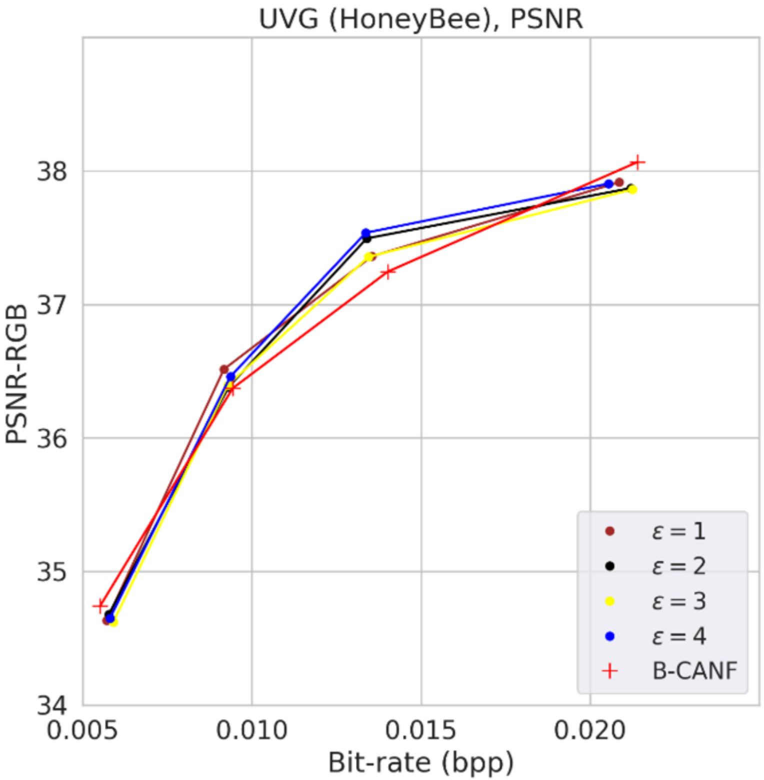
Training Procedure

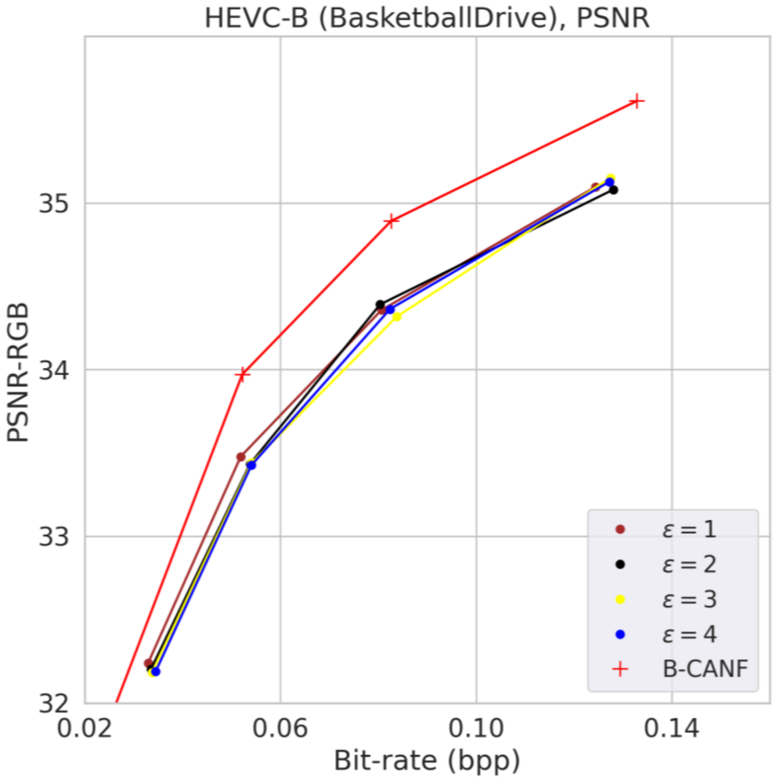
Training Sequence

	TLZMC	Loss Function
1	Frame Interpolator	$D(\bar{x}_t, x_t)$
2	DS + CANF Compressor	$D(\hat{x}_t^{DS}, x_t^{DS}) + R_b$
3	Super Resolution	$D(\hat{x}_t^{SR}, x_t) + R_b$
4	Multi-Frame Merging Network	$D(x'_t, x_t)$
5	Adaptive CANF Compressor	$D(\hat{x}_t, x_t) * \lambda + R_b + R_e$
6	End-to-end	$D(\hat{x}_t, x_t) * \lambda + \varepsilon * R_b + R_e + Aux$

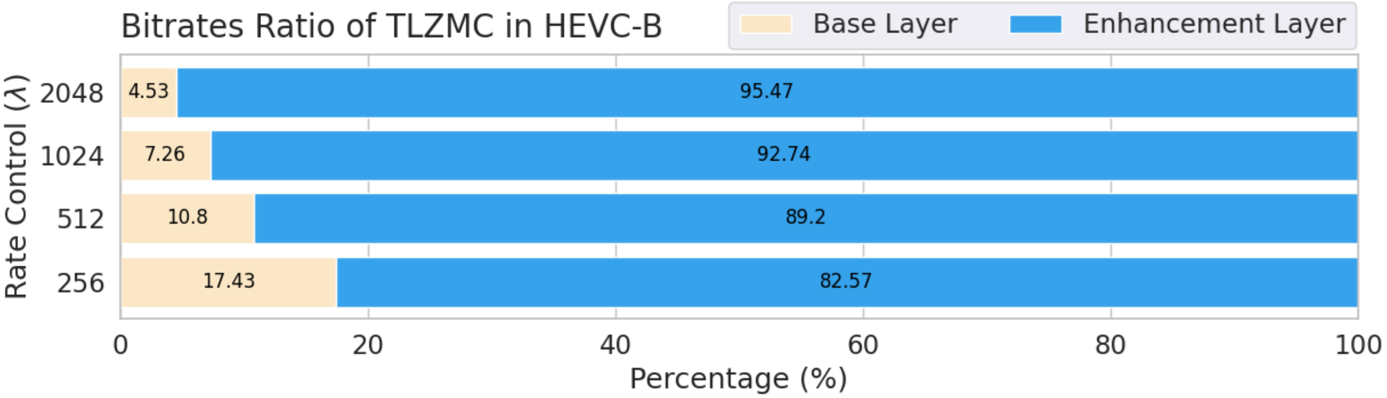
$$Aux = (D(y_2, x'_t) + D(x'_t, x_t) + D(\hat{x}_t^{SR}, x_t)) * 0.01 * \lambda$$

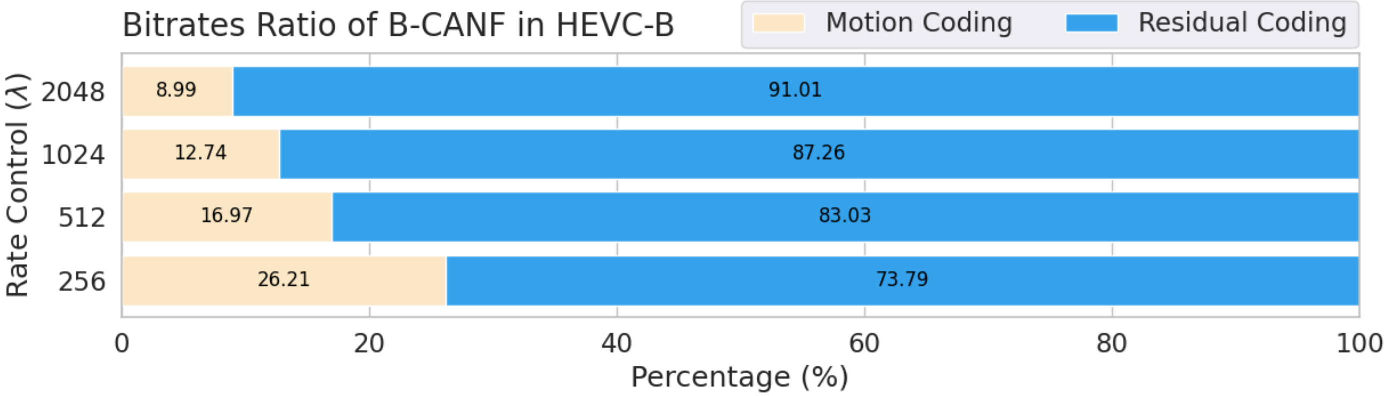
Bit Allocation for BL and EL



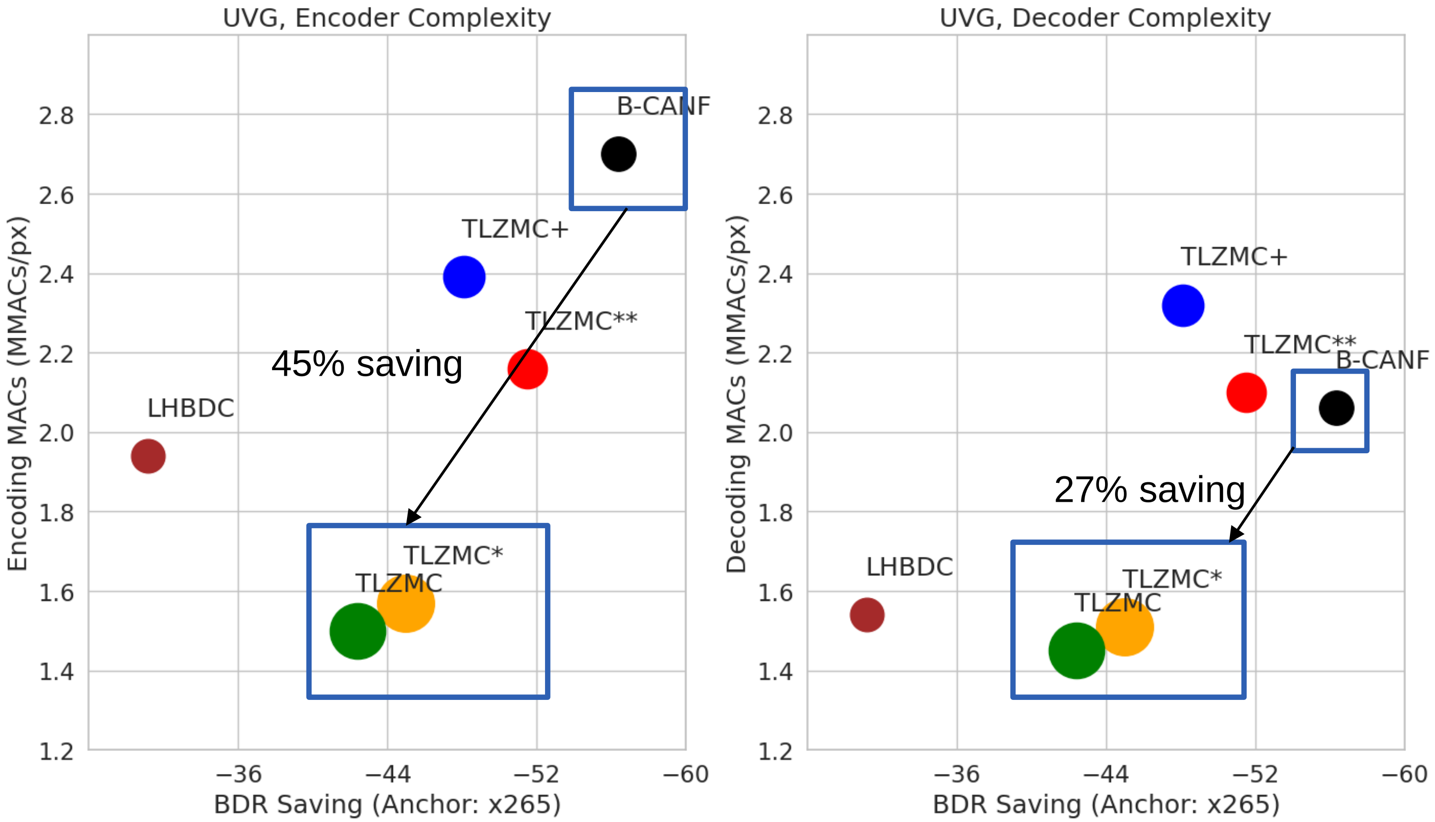


Bit Rate Ratio of BL to EL





Complexity Comparison



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Conclusions

- Motion coding replaced by “neural prediction + base-layer coding”
- Less computational complexity
- RD performance close to the SOTA
- Content adaptivity is crucial to coding gain

Thank you for your attention