Learned Video Compression with Feature-level Residuals

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Motivation

Prediction errors of optical flow

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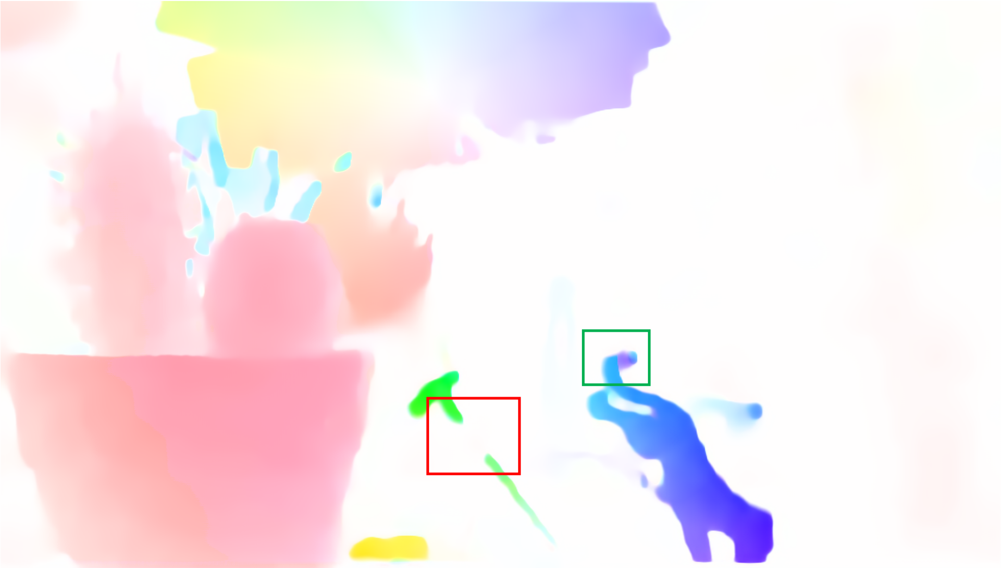
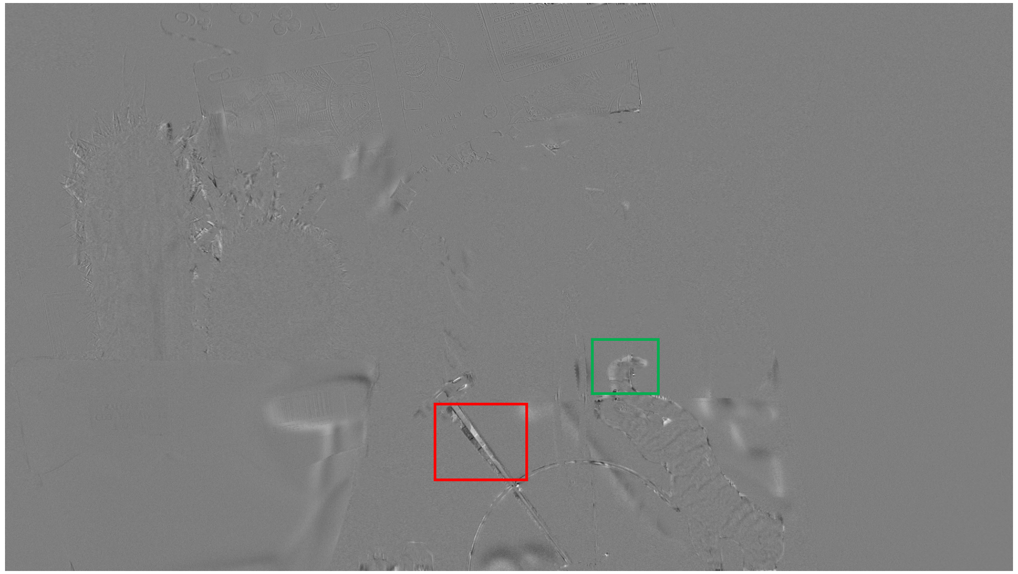
Large pixel space residual

Compensation Frame

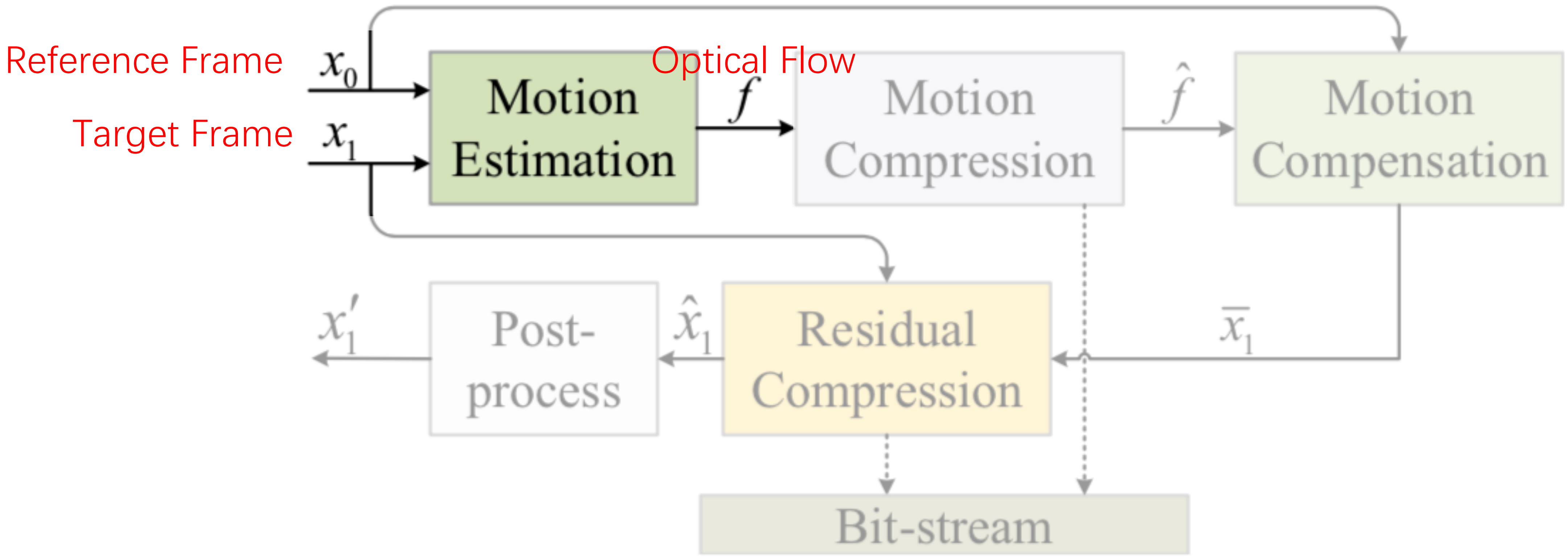
Decoded Optical Flow



Pixel Space Residual



The overall coding pipeline of our P-frame compression framework.



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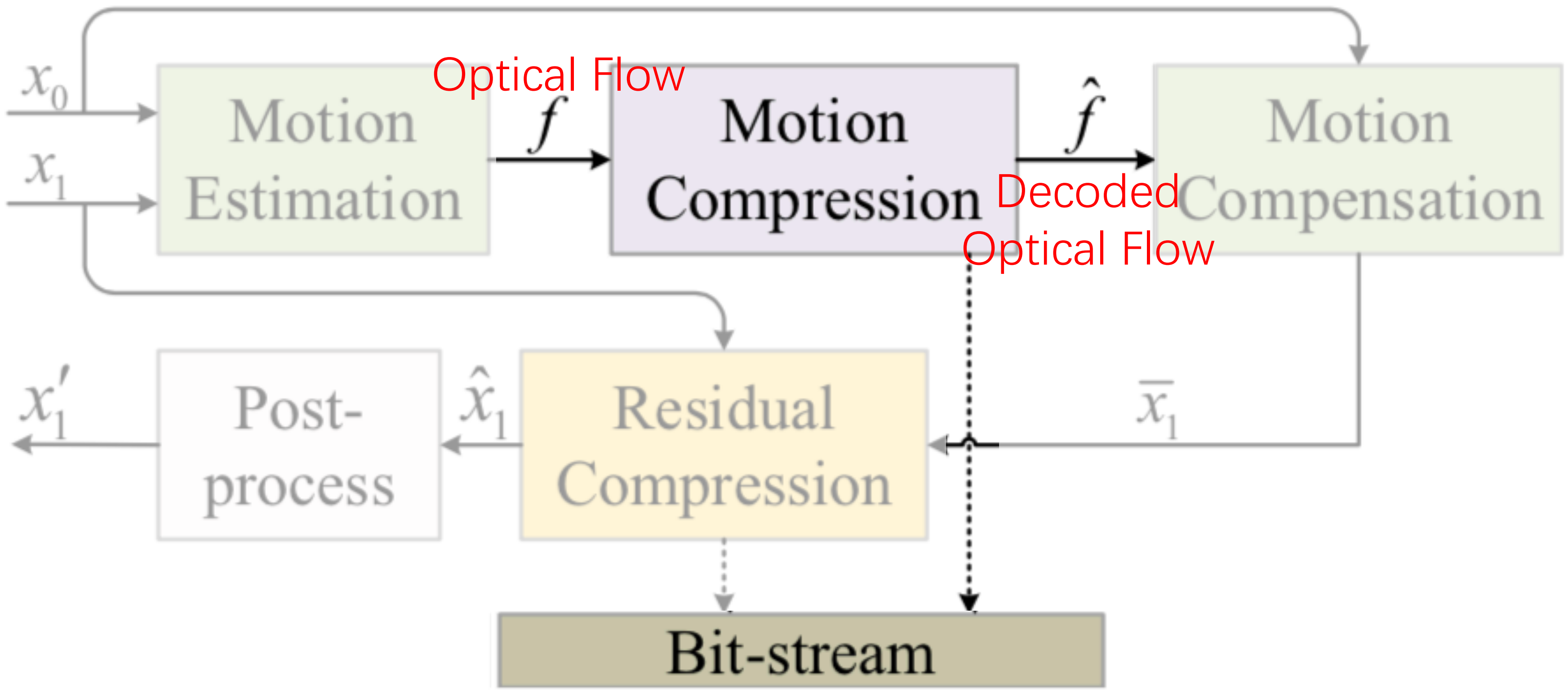

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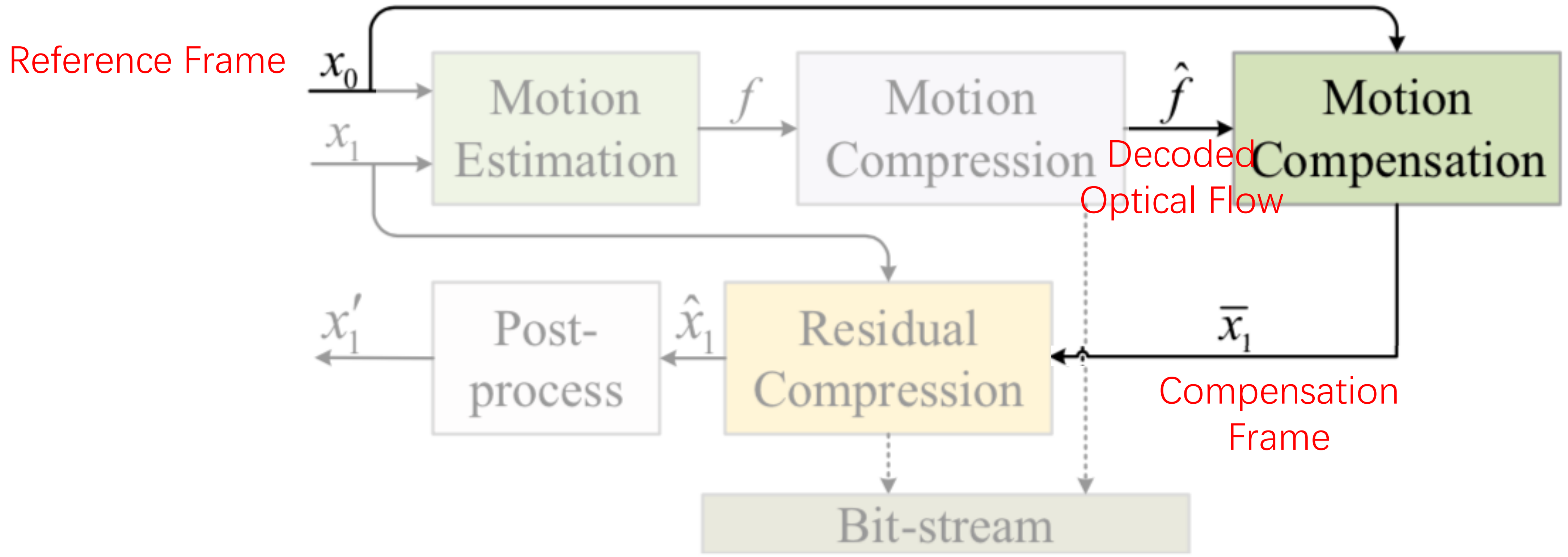

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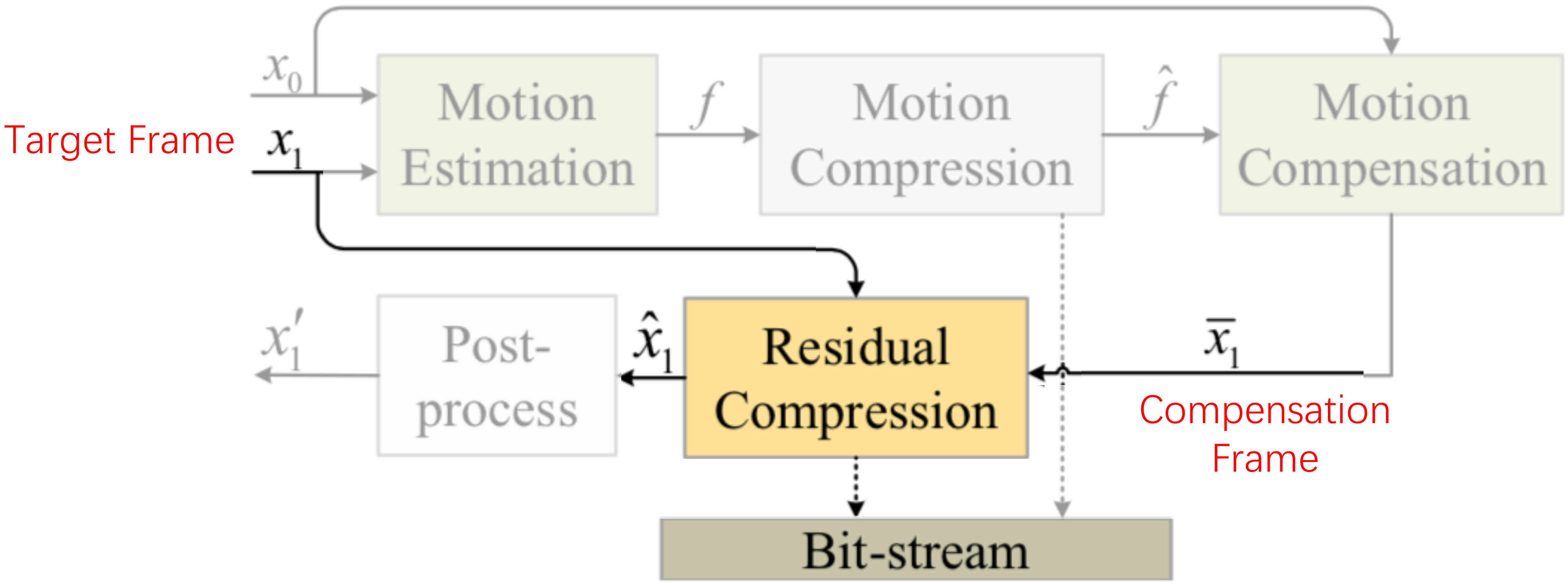

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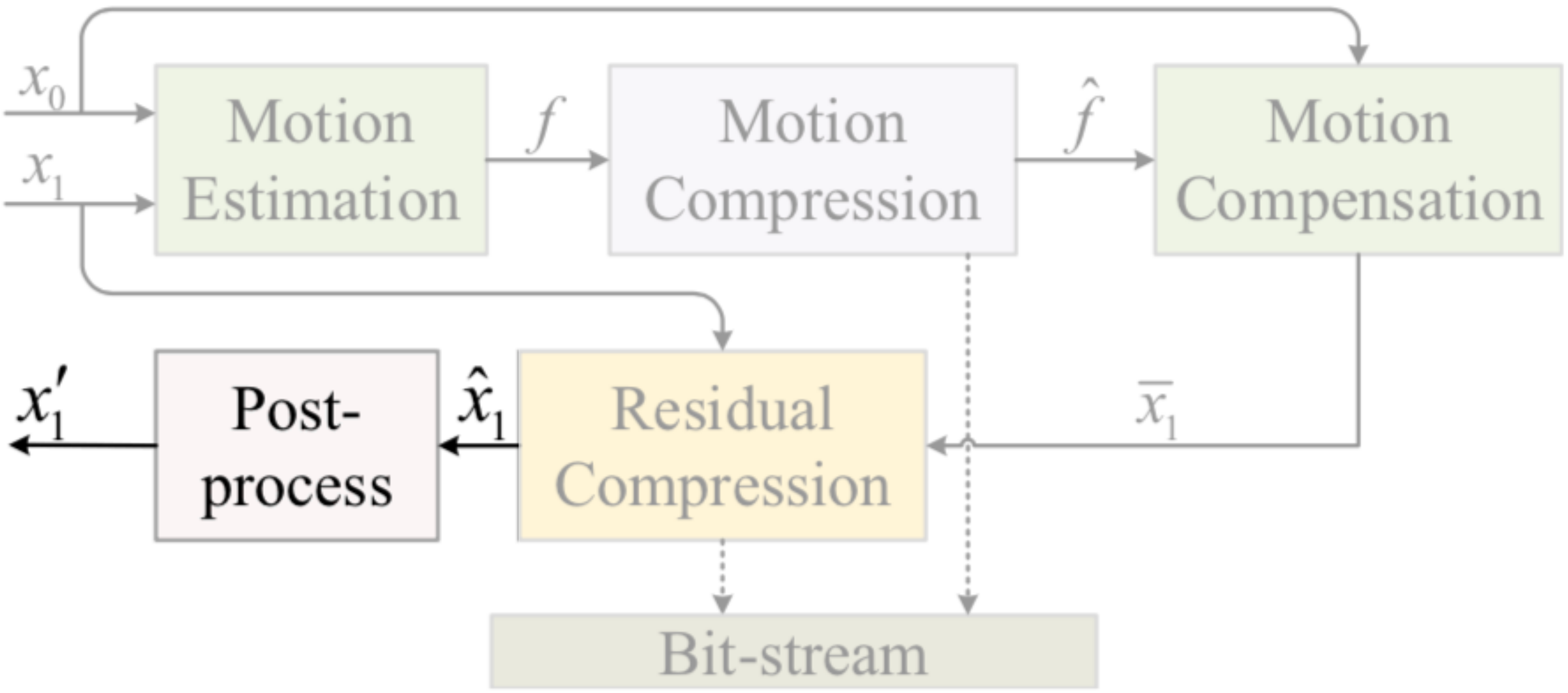
Reconstruction



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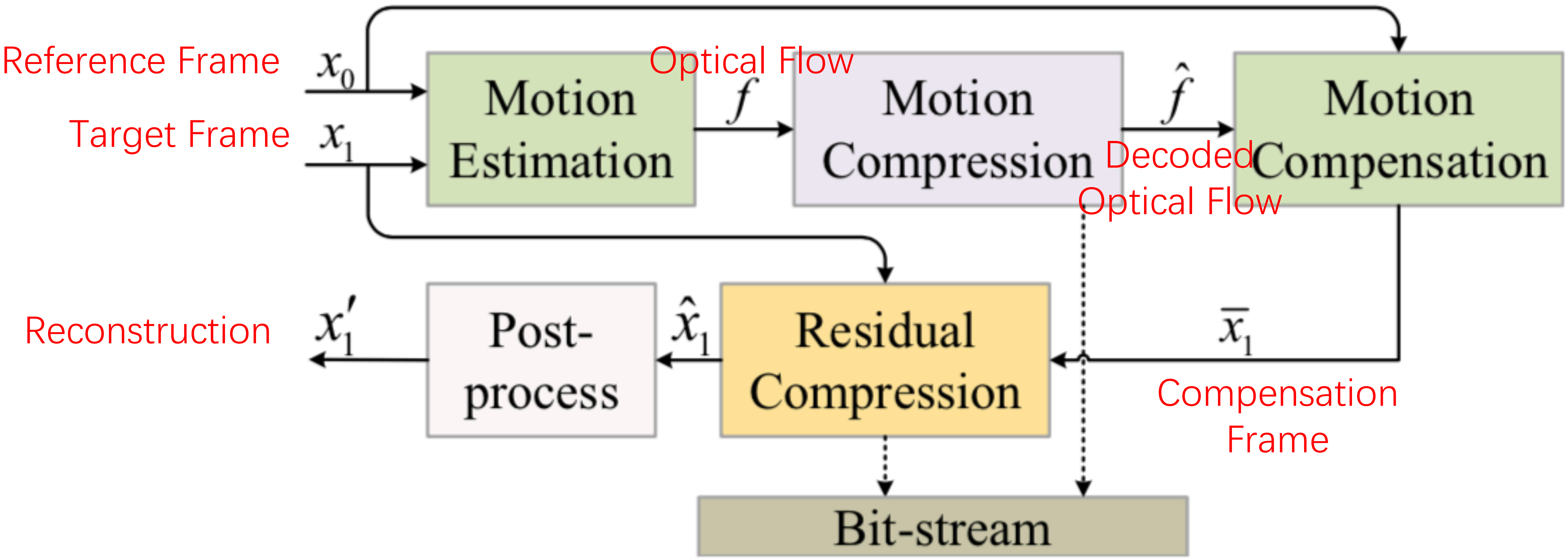
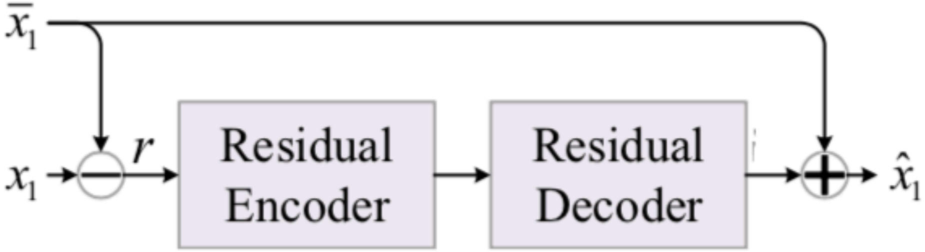
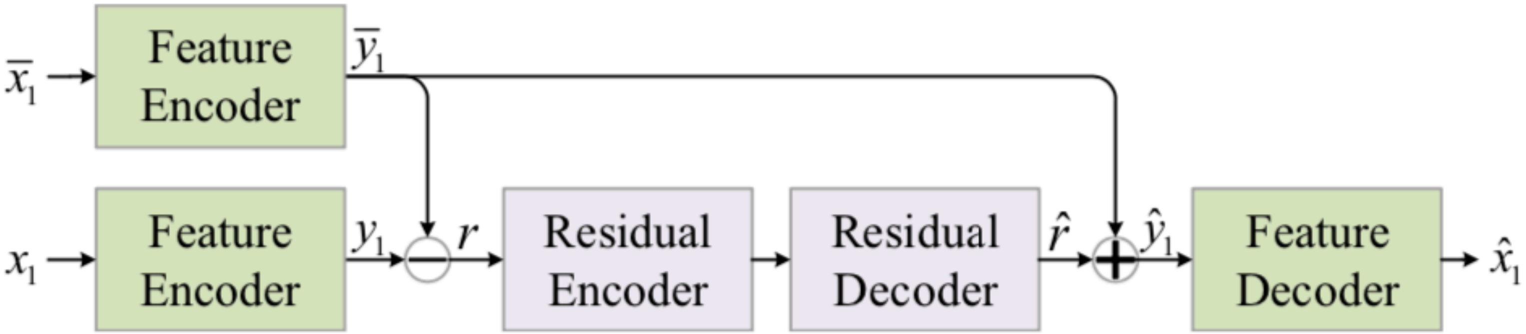


Computing residual in feature space.

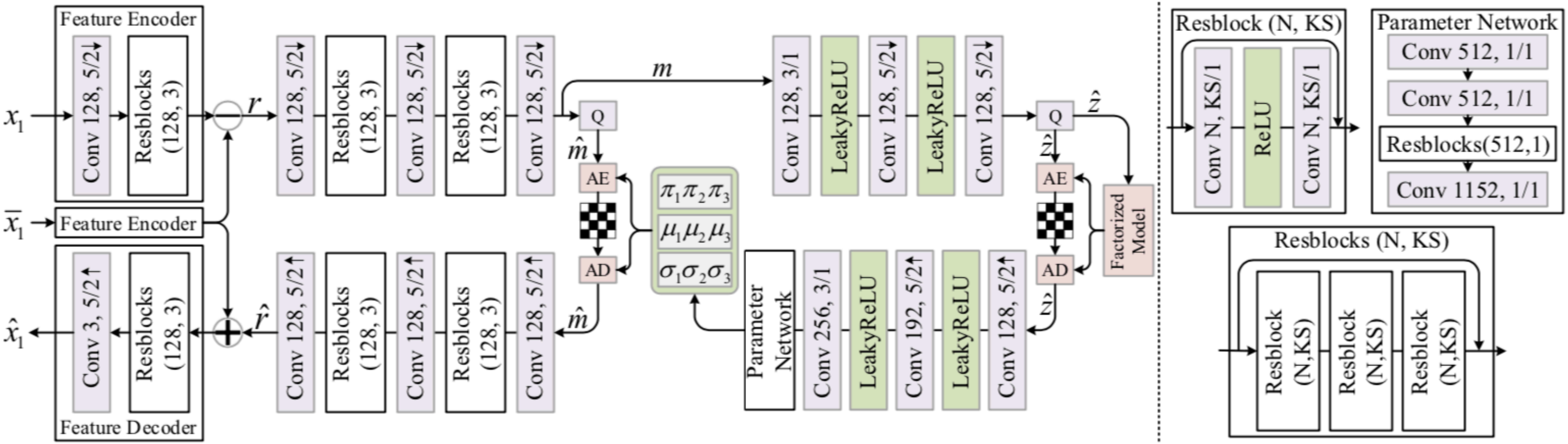


(a) Residual compression on pixel level.



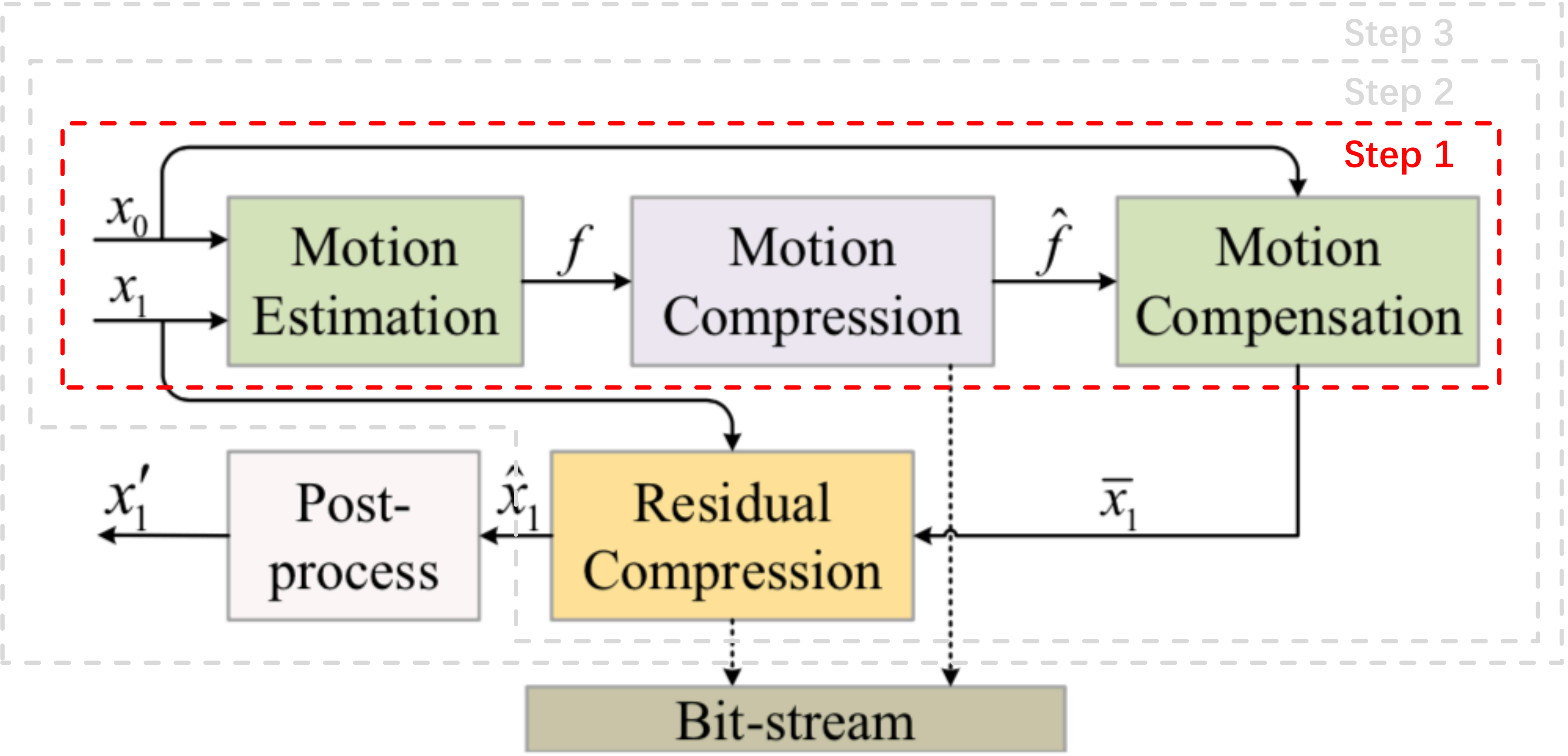
(b) Residual compression on feature level.

Detailed structure of our feature residual compression method.



$$p_{\hat{\boldsymbol{m}}|\hat{\boldsymbol{z}}}(\hat{\boldsymbol{m}} \mid \hat{\boldsymbol{z}}) = \prod_i \left(\sum_{k=1}^{K} \pi_{i,k}\mathcal{N}(\mu_{i,k}, \sigma_{i,k}^2) * \mathcal{U}(-\frac{1}{2}, \frac{1}{2})\right)(\hat{m}_i)$$

Step-by-step training strategy.



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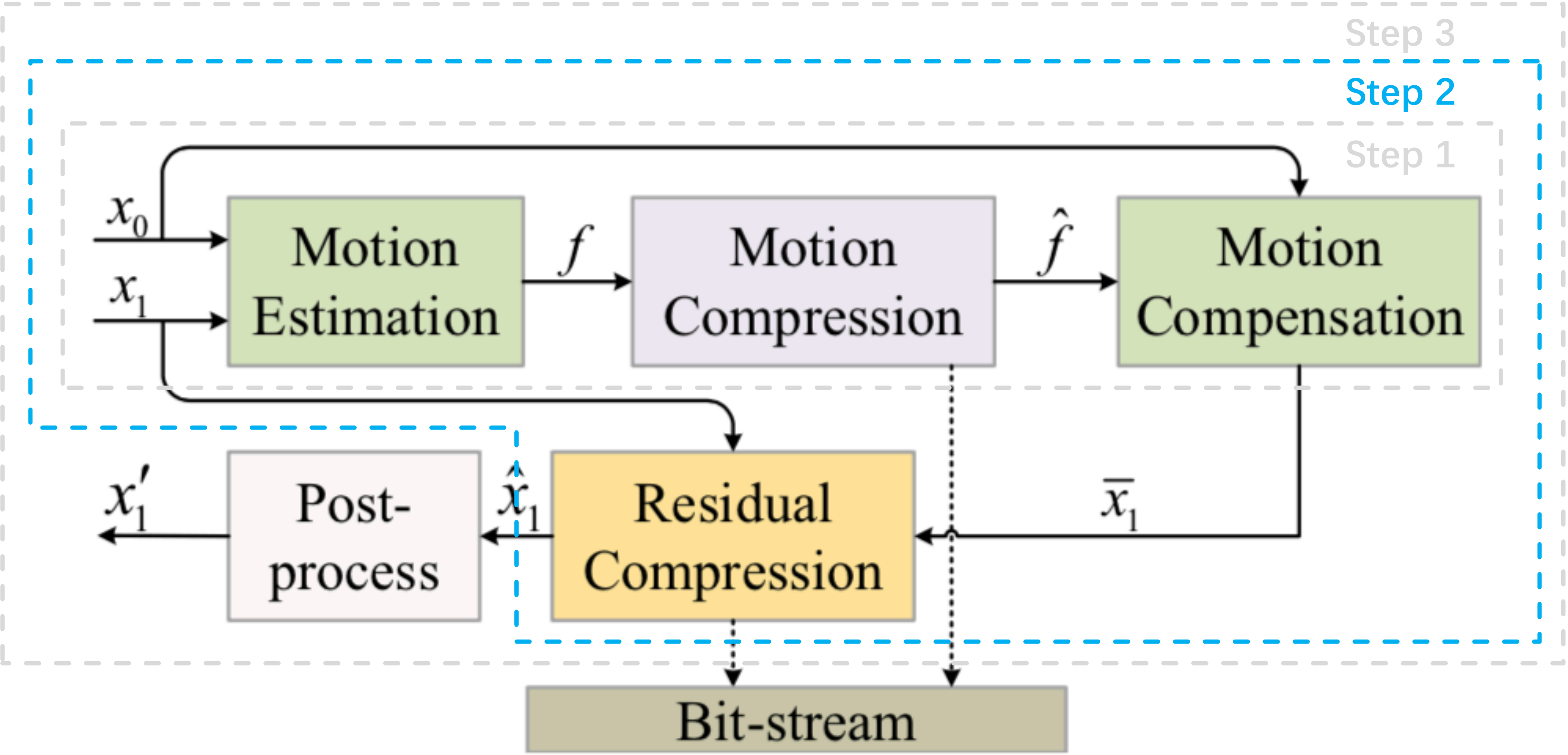

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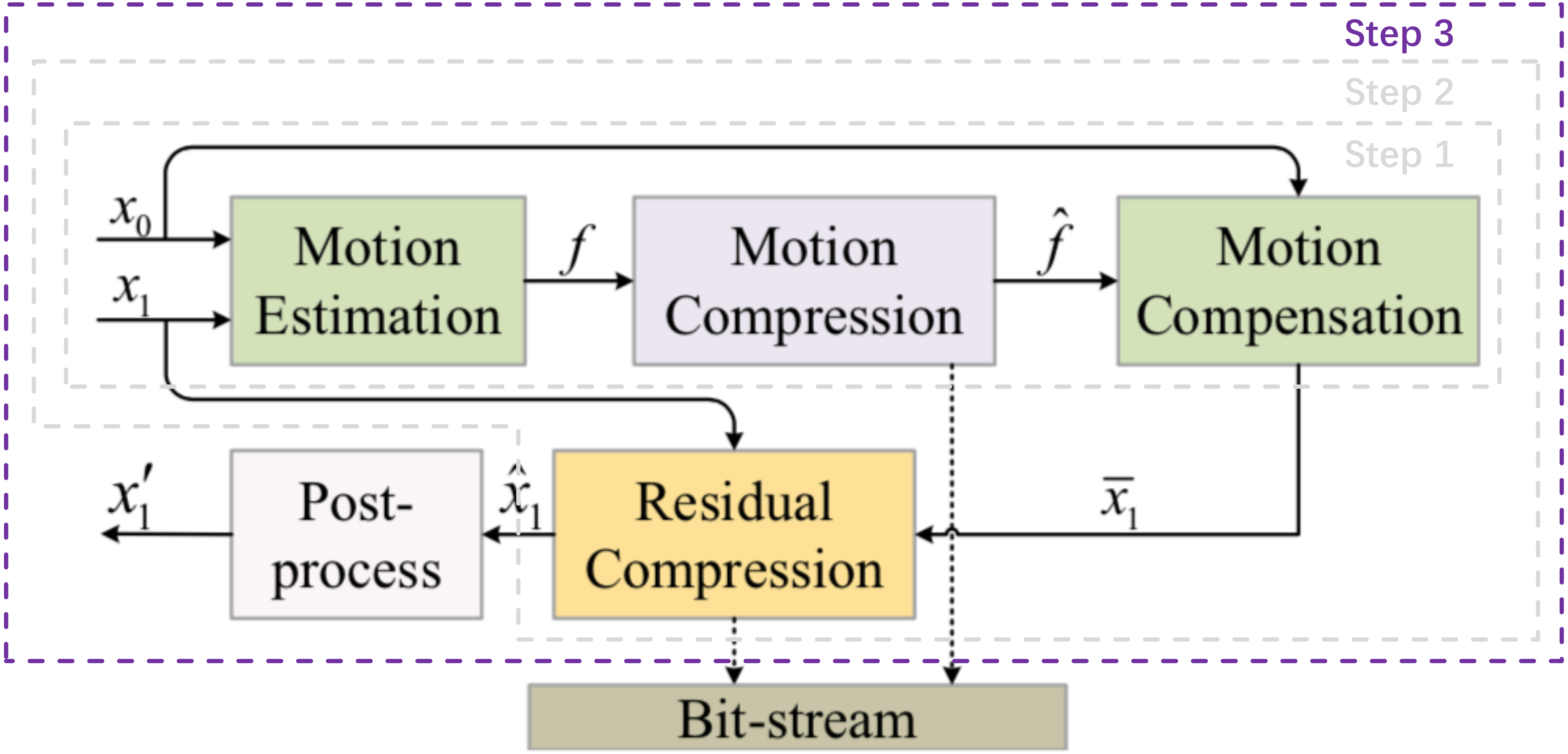

The overall rate-distortion (R-D) loss:

$$\mathcal{L} = R_f + R_r + \lambda d(\boldsymbol{x}_1, \boldsymbol{x}_1')$$

Evaluation results

Table 1: Evaluation results on P-frame validation dataset.

Model #	Pixel-level residuals	Feature-level residuals	GRDN	Ensemble	Data size	Model size	MS-SSIM
# 1	✓				38205911	79114205	0.996302
# 2	✓		✓		37788576	120847836	0.996619
# 3		✓			38133059	86399558	0.996645
# 4		✓	✓		37716003	128105152	0.996700
# 5	✓	✓	✓	# 1, # 4	37960950	103610323	0.996792
# 6	✓	✓	✓	# 2, # 4	37735411	126164272	0.996866

* The unit of data/model size is Byte. For P-frame challenge in CLIC, we limit the total size to 3,900,000,000 bytes, which is calculated as follows: model size + 100 $\times$ data size.

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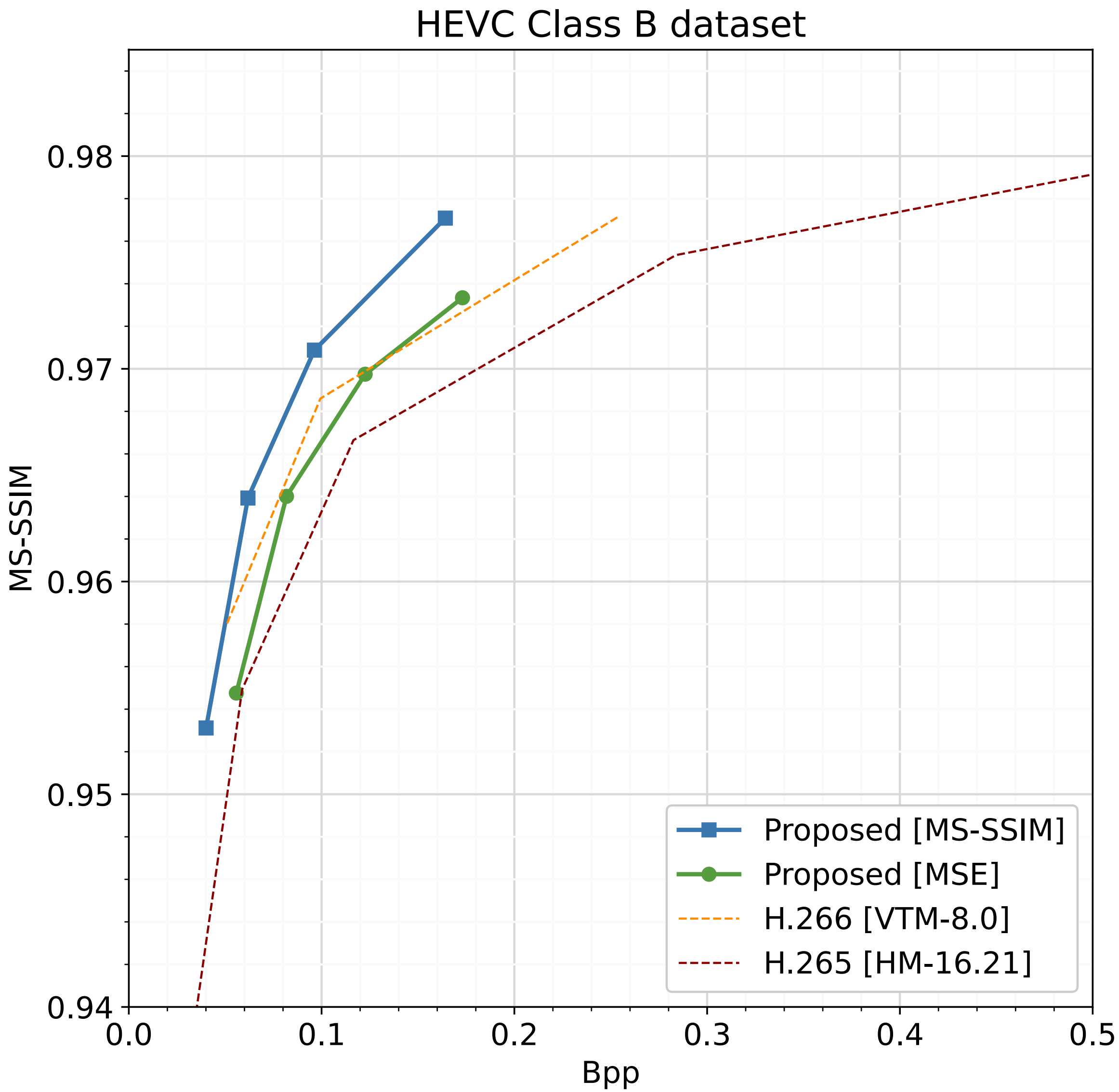
Team name: IMCL_MSSSIM

Workshop poster ID: 5

Our recent work of learned video compression for low-latency scenarios.



Thank you

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