Qualcomm

CLIC 2022-06-19

Efficient neural codecs

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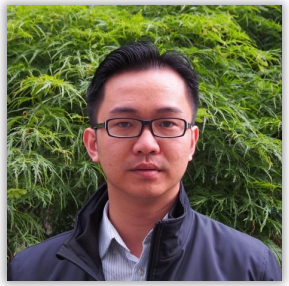
Collaborators


Hoang Le


Reza Pourreza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Yinhao Zhu


Yang Yang


Taco Cohen


Auke Wiggers

Covered in this talk:

- Yinhao Zhu et al., "Transformer-based Transform Coding", ICLR 2022
- Hoang Le et al., "MobileCodec: Neural Inter-frame Video Compression on Mobile Devices", ACM MMSys 2022

At Qualcomm, we are interested in creating efficient neural codecs.

We want neural codecs to be adopted in production-like settings.

If you are working on neural codecs, you should share this interest: real-world deployment often highlights practical constraints and issues.

We believe that adoption will require the codec to…

1. Be efficient: use low-compute transforms and priors
2. Be deployable: run efficiently on-device, not only on desktop GPUs
3. Be performant: outperform existing codecs in metrics that matter

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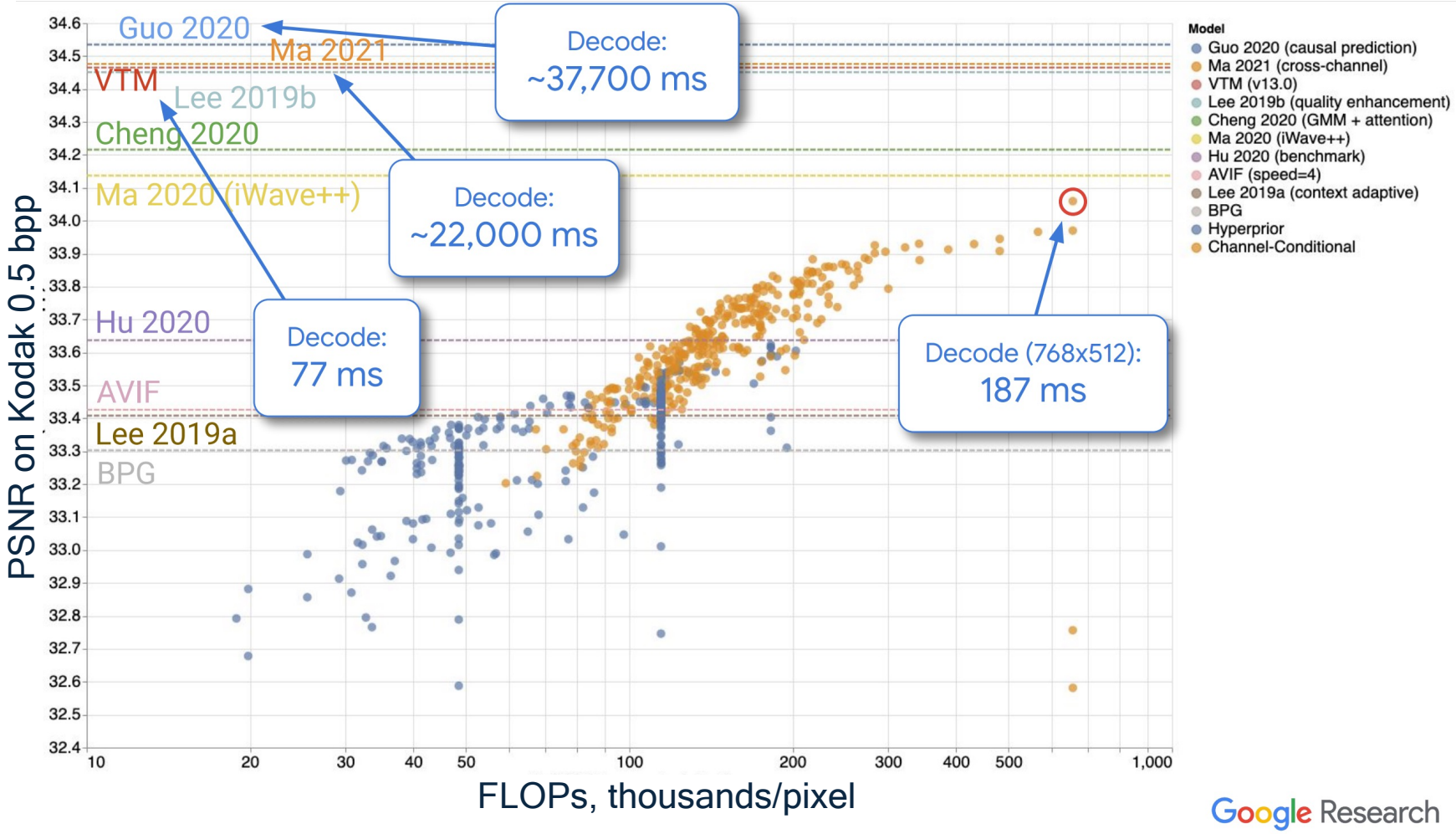
Neural codecs should be efficient

Recent work improves RD performance, but at increasing computational cost.



Google Research

David Minnen, “Curent Frontiers in Neural Image Compression “, ICIP 2021 plenary talk.

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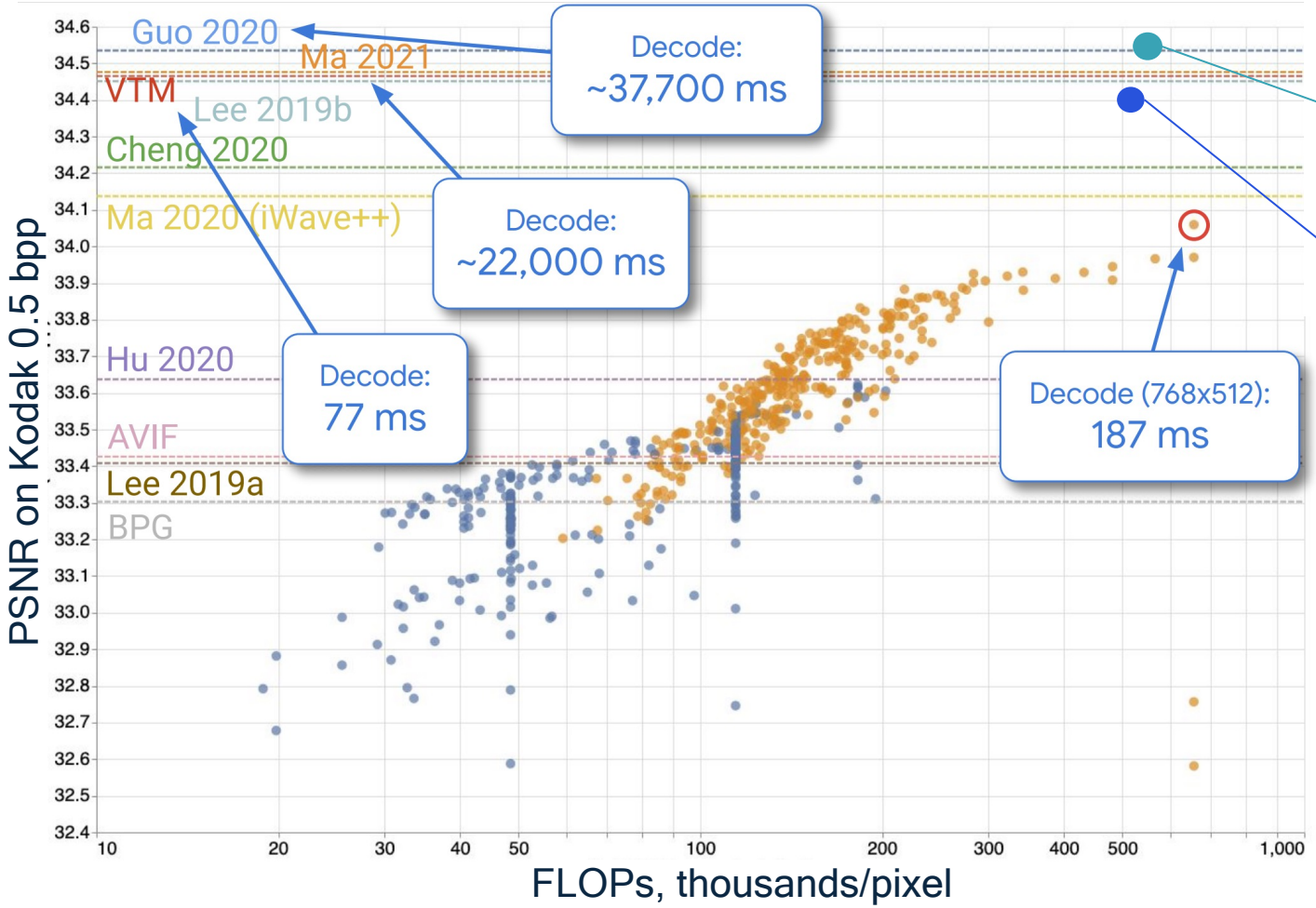

SwinT-ChARM
Decode: 167 ms

SwinT-Hyperprior
Decode: 114 ms

This is where our work comes in!

Small disclaimer

- Our SwinT models benchmarked on 2080 Ti, runtimes for neural baselines taken from papers
- None of the shown methods have been explicitly optimized for runtime

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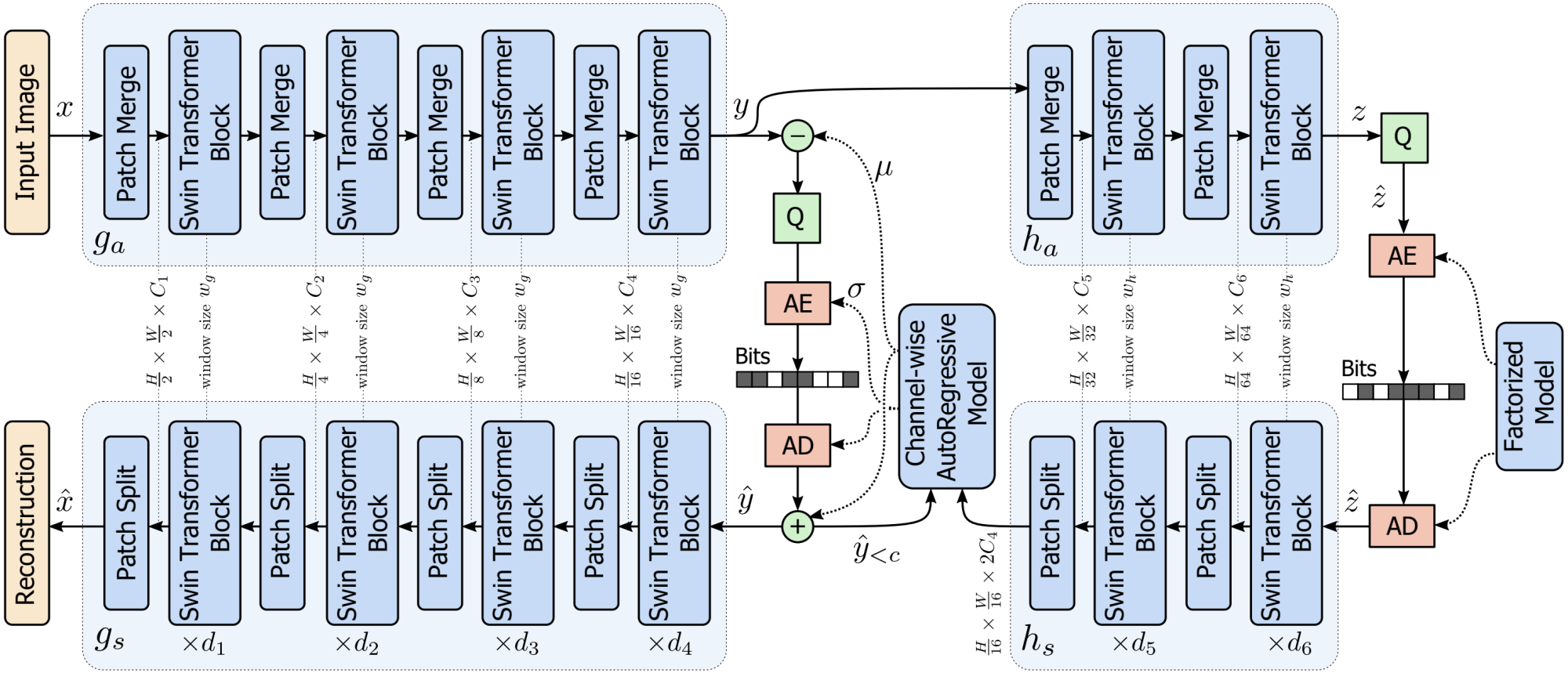
We focus on improving the transform

We replace strided convolutions by swin-transformer blocks [1] and custom up- and downsampling layers.

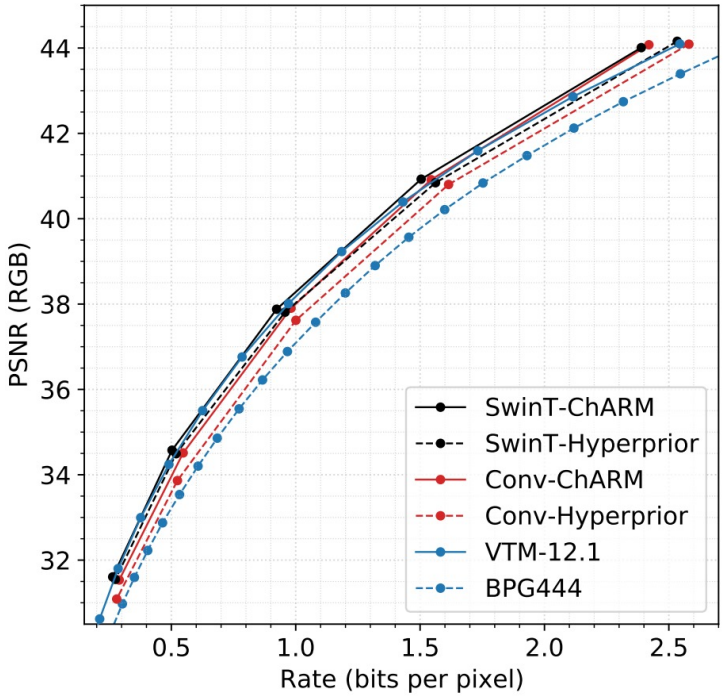


[1] Liu et al, “Swin Transformer: Hierarchical Vision Transformer using Shifted Windows”, CVPR 2021

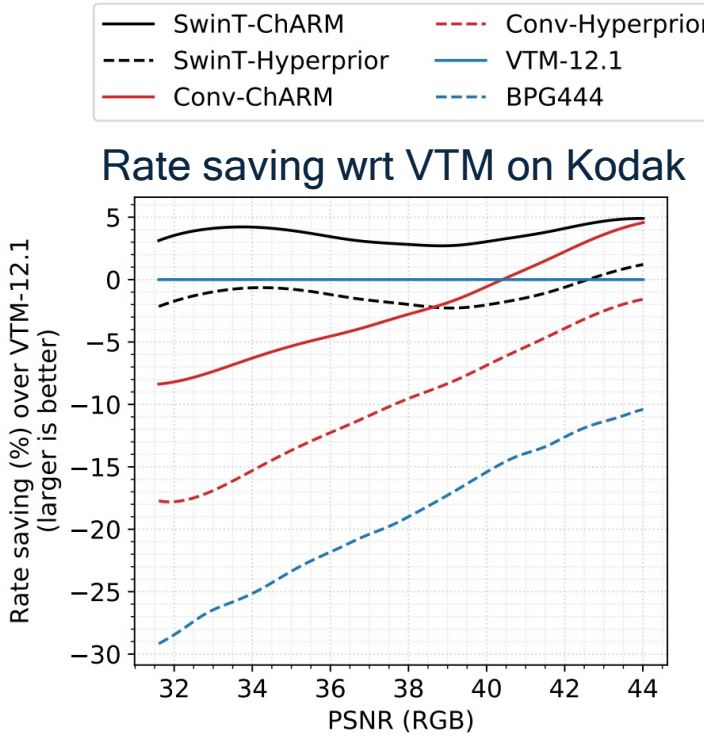
Performance: Image compression

This improves image compression performance, far outperforming convolutional hyperpriors.

Rate-distortion on Kodak (RGB444)



Rate saving wrt VTM on Kodak



BD rate wrt VTM on various image datasets

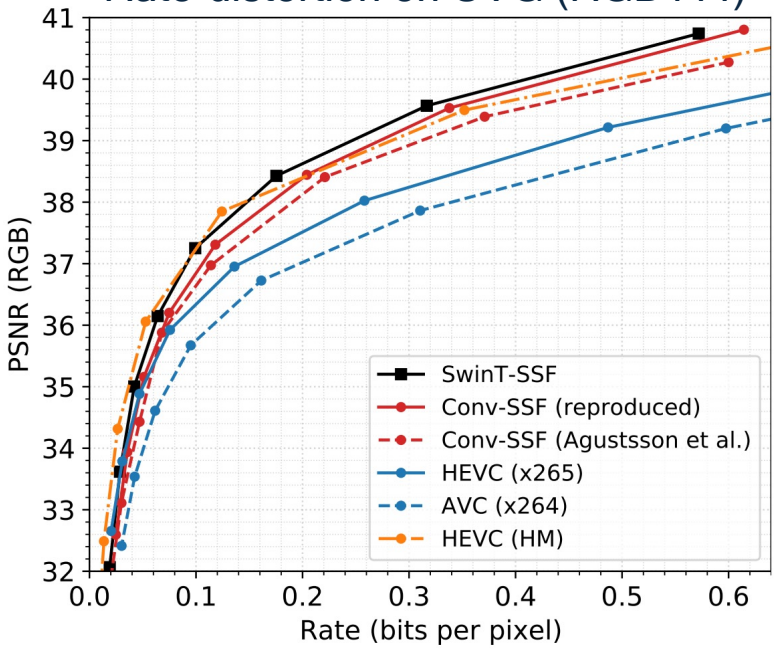
Image Codec	Kodak	CLIC2021	Tecnick	JPEG-AI
BPG444	20.87%	28.45%	27.74%	27.14%
Conv-Hyperprior	11.65%	12.23%	12.49%	20.98%
Conv-ChARM	3.44%	4.14%	3.50%	9.59%
SwinT-Hyperprior	1.69%	0.83%	-0.15%	6.86%
SwinT-ChARM	**-3.68%**	**-5.46%**	**-7.10%**	**0.69%**

Improvement is consistent across datasets, for both factorized and channel-autogressive (ChARM) models.

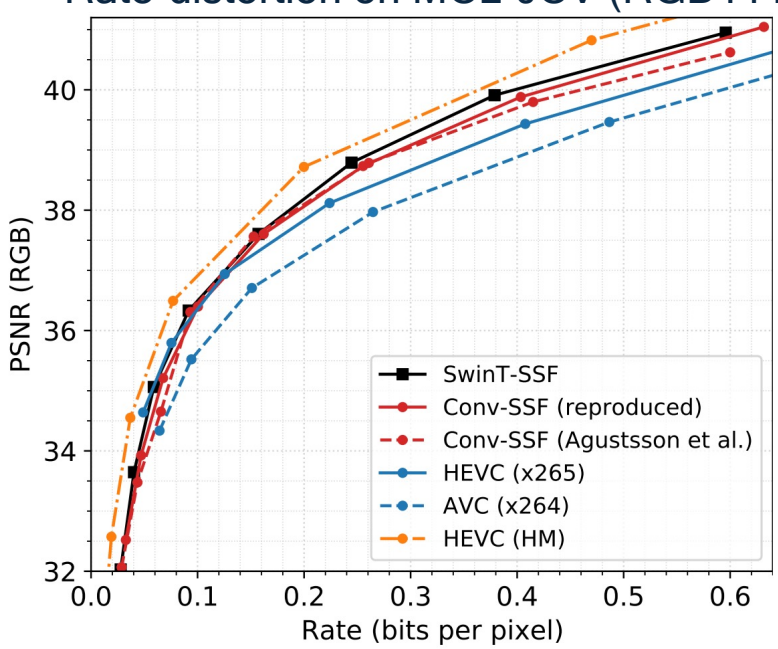
Performance: P-frame video compression

Using SwinT based encoder and decoder in flow+residual hyperpriors of a scale-space flow model [1] improves video compression performance as well.

Rate-distortion on UVG (RGB444)



Rate-distortion on MCL-JCV (RGB444)



BD rate wrt Conv-SSF (reproduced)

Video Codec	UVG	MCL-JCV
HEVC (x265)	25.97%	25.83%
HEVC (HM)	**-15.80%**	**-24.96%**
SwinT-SSF	-12.35%	-10.03%

[1] Agustsson et al. "Scale-space flow for end-to-end optimized video compression.", CVPR 2020

Performance: compute and complexity

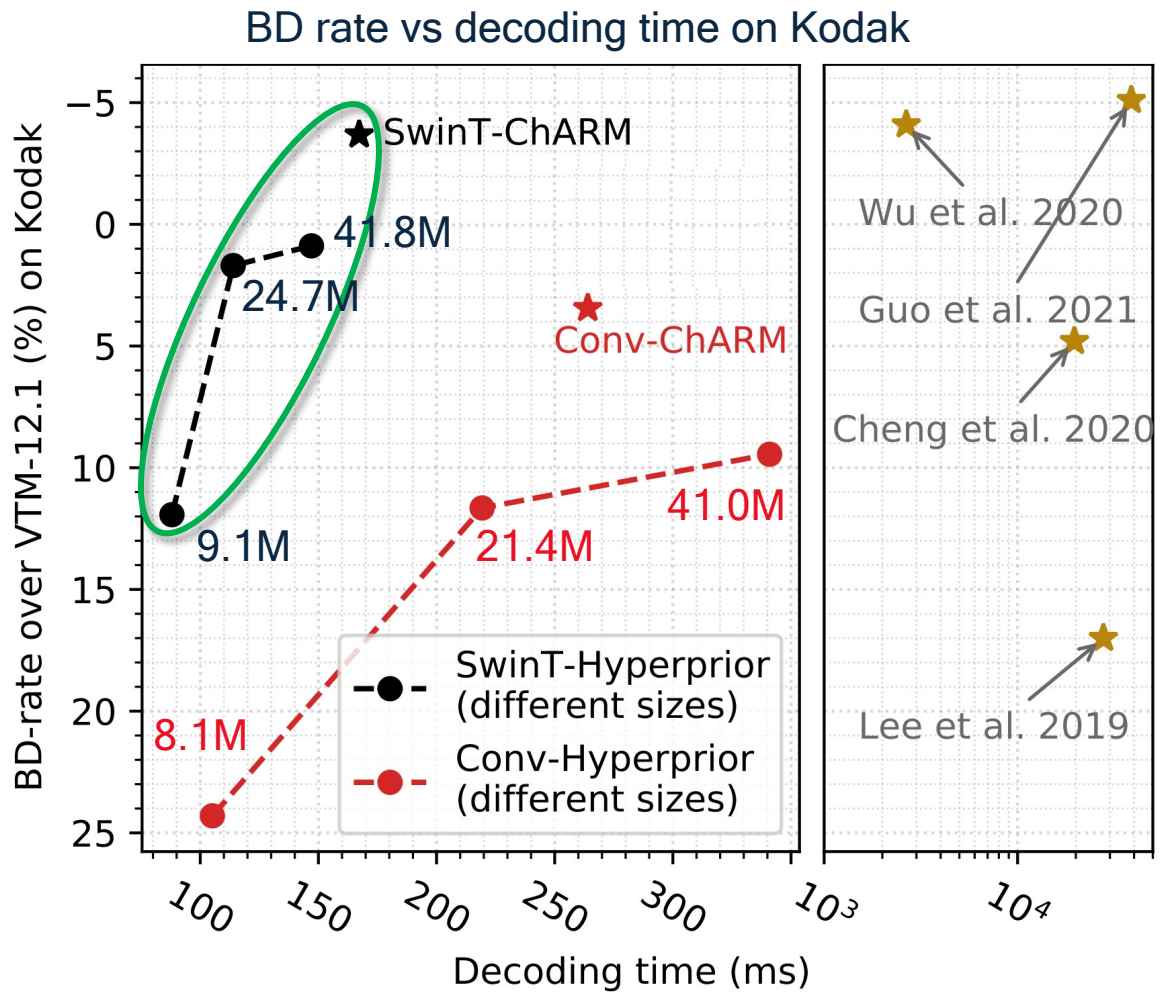
Time-to-decode for decoder g_s and GMACs are much lower for SwinT models than for conv.

Peak memory usage does increase due to the (memory-expensive) linear attention operation.

Codec	Time (ms)					GMACs	Peak memory	Model params
	$\hat{\mathbf{z}}$	h_s	$\hat{\mathbf{y}}$	g_s	total			
Conv-Hyperprior	5.5	4.0	38.2	168.9	219.3	350	0.50GB	21.4M
Conv-ChARM	5.3	4.1	82.9	168.5	264.0	362	0.53GB	29.3M
SwinT-Hyperprior	6.0	4.8	38.1	59.6	114.0	99	1.44GB	24.7M
SwinT-ChARM	5.9	4.8	90.7	60.1	167.3	111	1.47GB	32.6M

Benchmarked 0.7bpp models on Kodak (512x768) on RTX 2080 Ti GPU, deterministic convolution.

Performance: compute and complexity



Our work improves RD performance at much lower computational cost.

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Yinhao Zhu et al., "Transformer-based Transform Coding", ICLR 2022

In conclusion

Vision transformer-based transforms are an **efficient** alternative to convolutional ones.

In the paper, we show that…

- Turning a conv-hyperprior into a SwinT-hyperprior is straightforward
- SwinT models far outperform similar-size convolutional ones in image and video compression
- SwinT models are compute-efficient: lower runtime and MACs for same number of parameters

Consider using these in your encoder / decoder.

Yinhao Zhu et al., "Transformer-based Transform Coding", ICLR 2022

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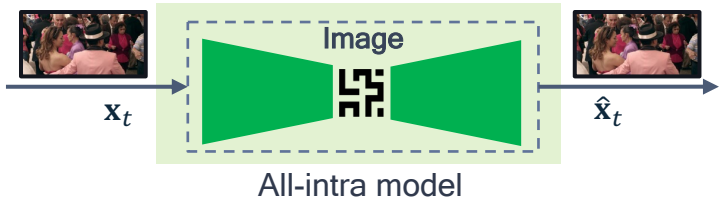
Neural codecs should be deployable

We build prototypes and deploy these to mobile devices.

May 2021

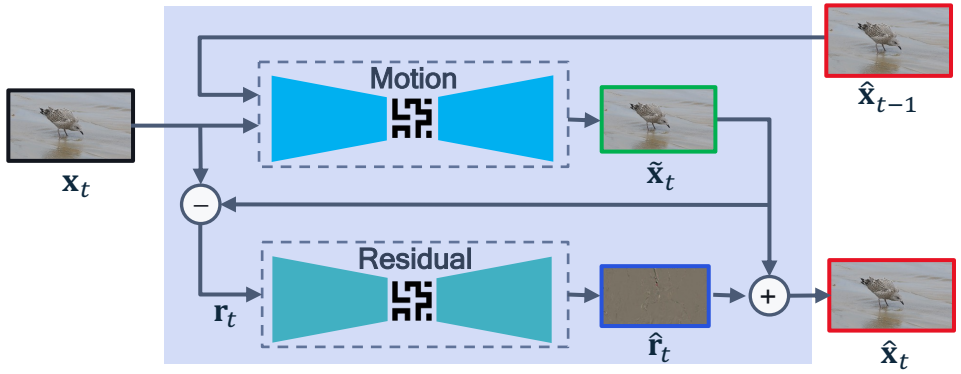
- ✓ All-intra on-device codec
- ✓ 30+ FPS 1280×704 decoding on-device
- ✓ Demo'd at CVPR21, ICML21, and ICIP21



All-intra model

November 2021

- ✓ Low-delay on-device codec
- ✓ 30+ FPS 1280×720 decoding on-device
- ✓ Demo'd at NeurIPS21, ACM MMSys 22

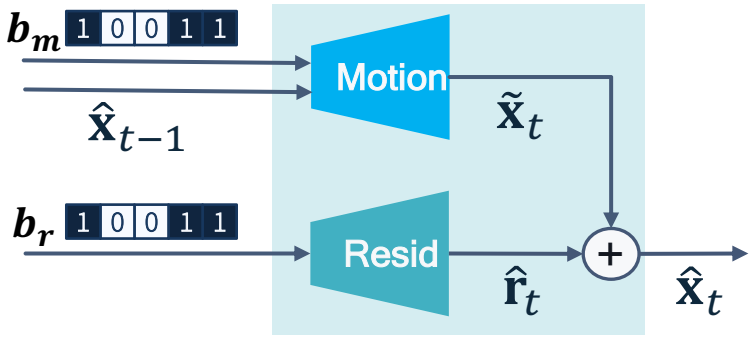


Low-delay model

Hoang Le et al., "MobileCodec: Neural Inter-frame Video Compression on Mobile Devices", ACM MMSys 2022

Solution to practical challenges

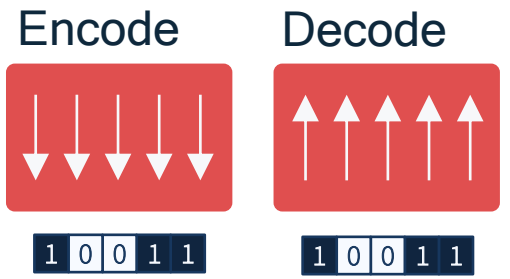
Challenge	High complexity architecture, expensive operators	Inefficient floating-point operations	Slow sequential entropy coding
Solution	Developed warping-free architecture	AIMET channel-wise quantization-aware training	Parallel Entropy Coding (PEC)



P-frame receiver

AI Model Efficiency Toolkit (AIMET)

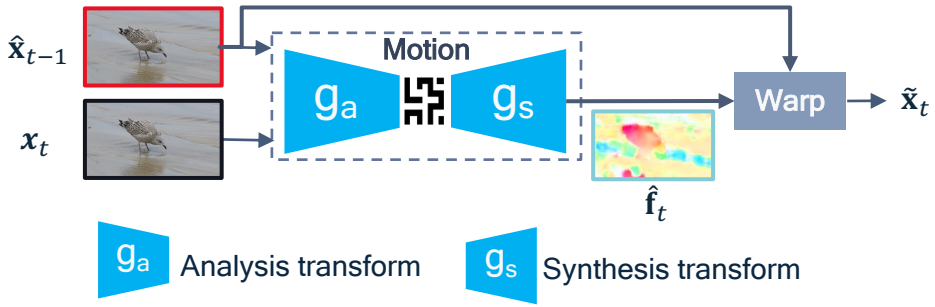
https://github.com/quic/aimet



Warping-free architecture

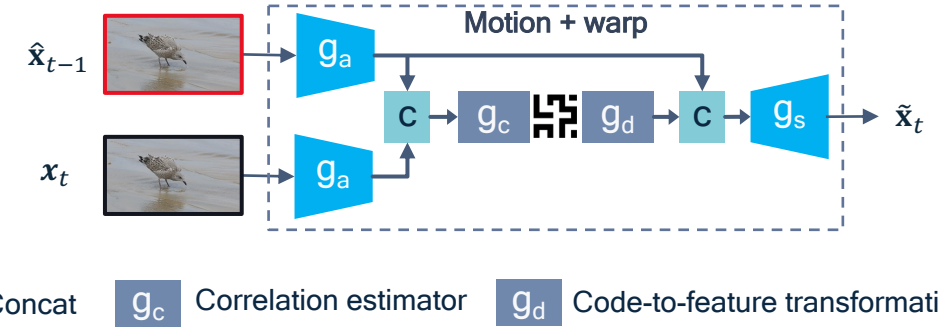
Scale-space flow architecture [1]

First transmit motion information, then perform pixel-level motion compensation (warping).



FLow-AGnostic (FLAG) architecture

Perform motion transmission and compensation jointly in feature-space, using vanilla 3x3 and 5x5 convolutions.

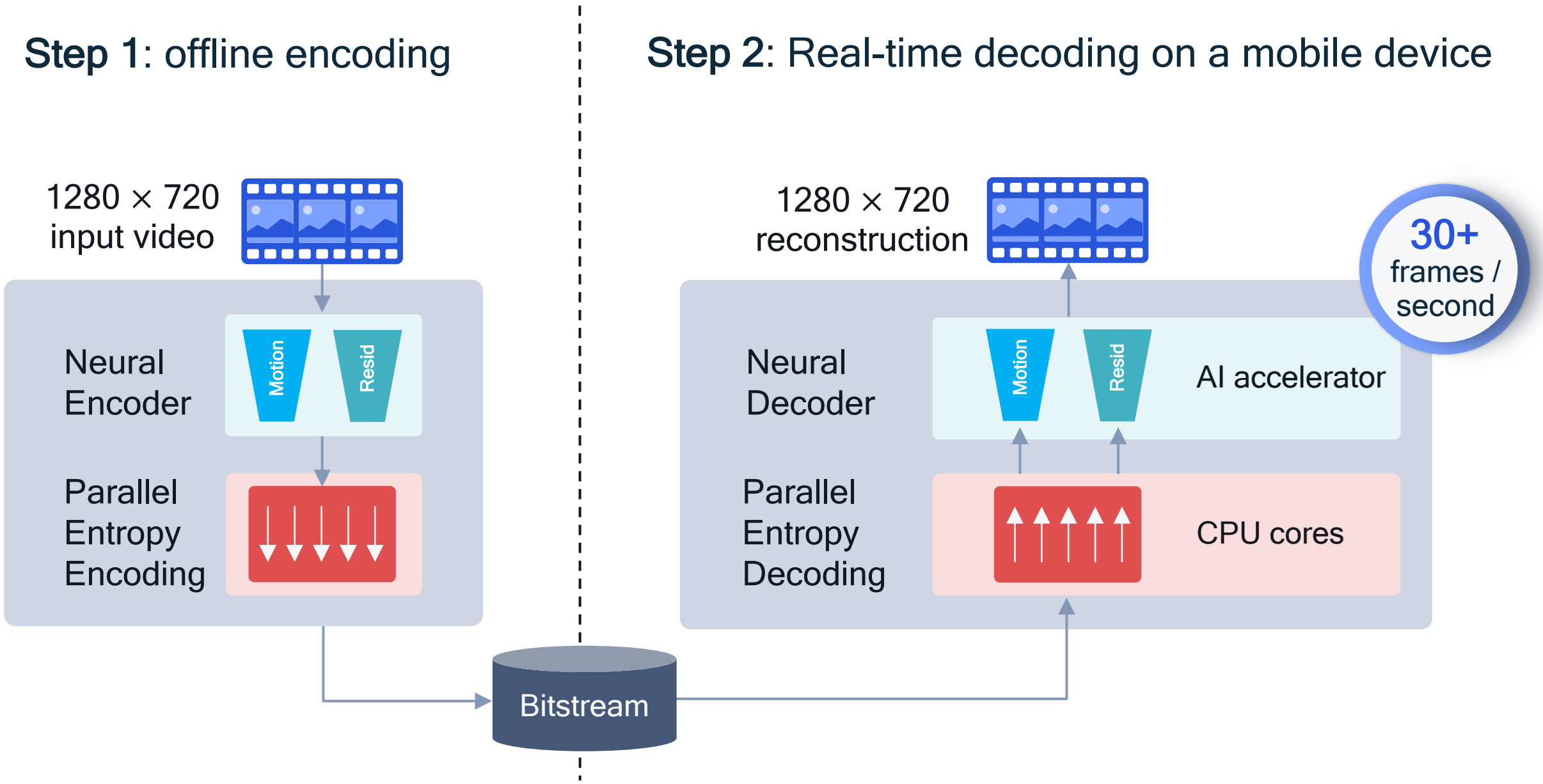


Other steps that improved efficiency:

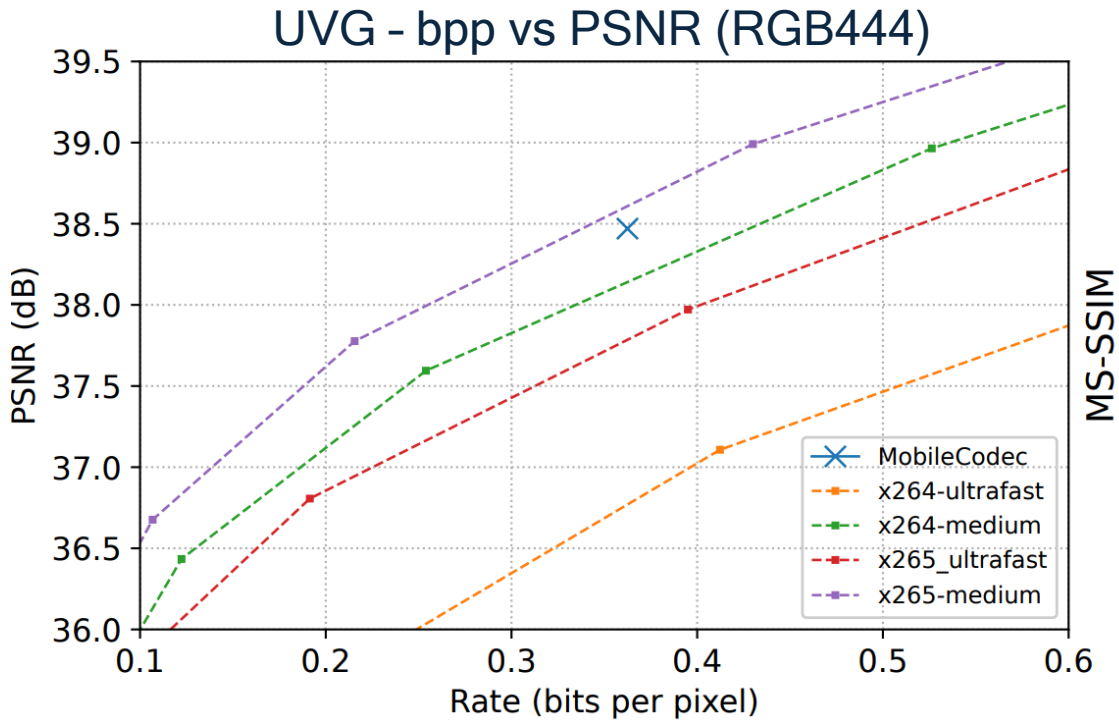
- 3x3 and 5x5 convolutions + ReLU activation throughout
- scale-only hyperpriors
- Gaussian unconditional hyperprior

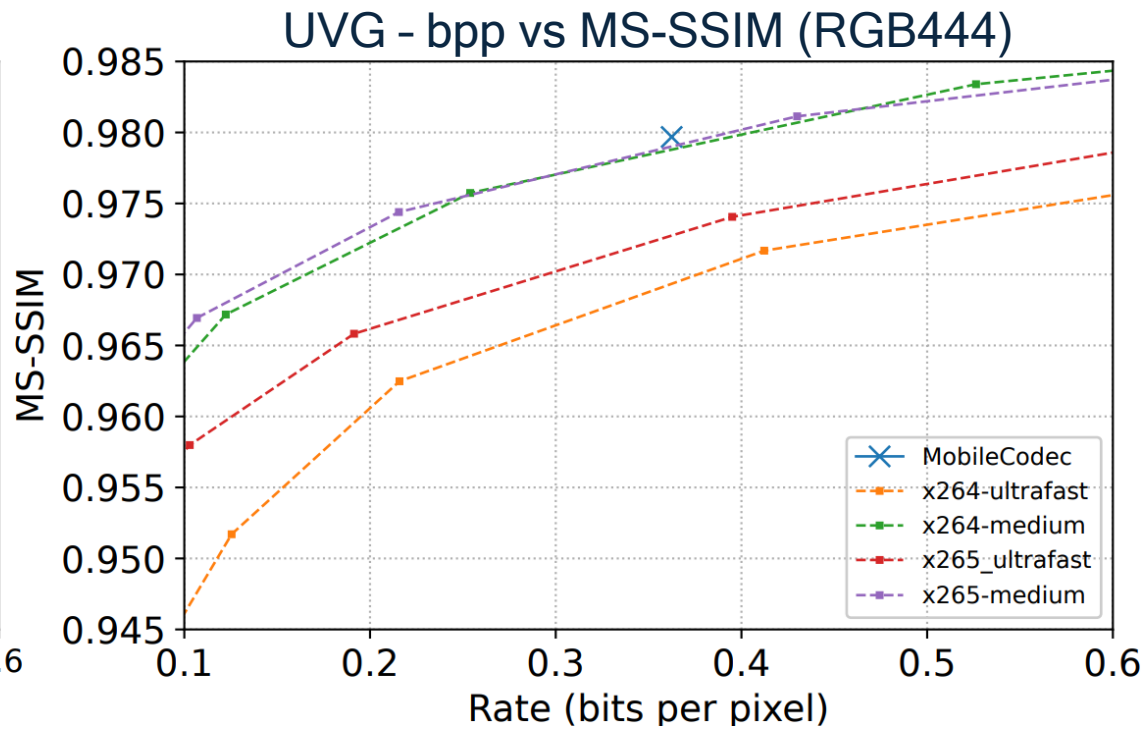
(FVC [2] and C2F [3] warp in feature space using deformable conv)

[1] Agustsson et al. "Scale-space flow for end-to-end optimized video compression.", CVPR 2020
[2] Lu et al., "FVC: A new framework towards Deep Video Compression in Feature Space", CVPR 2021
[3] Hu et al., "Course-to-fine Deep Video Coding with Hyperprior-guided Mode Prediction", CVPR 2022


Step 1: offline encoding
Step 2: Real-time decoding on a mobile device
1280 × 720
input video
Neural
Encoder
Motion
Resid
Parallel
Entropy
Encoding
Bitstream
1280 × 720
reconstruction
30+
frames /
second
Neural
Decoder
Motion
Resid
AI accelerator
Parallel
Entropy
Decoding
CPU cores

Our on-device codec is competitive with ffmpeg x265 (zerolatency) on UVG.





We provide additional results and runtimes for demo videos in the paper.

In conclusion

Neural video codecs can be **deployed** to device, and decode video in real time.

This requires:

- Replacing of expensive or difficult-to-quantize operators (such as dense warping)
- Careful model quantization
- Fast implementation of on-device entropy coding

We will continue to deploy codecs to device to understand the corresponding challenges.

Hoang Le et al., "MobileCodec: Neural Inter-frame Video Compression on Mobile Devices", ACM MMSys 2022

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Neural codecs should be performant (measured in metrics that matter)

Neural codec community mostly evaluates RGB444 PSNR and MS-SSIM. We are guilty of this as well.

This may not convince those working with video codecs ..

- Some favor YUV420 PSNR, which matches human perception more closely than Euclidean RGB
- Some favor learned distortion measures like VMAF
- We've also heard "I only trust my eyes"

For neural codecs to be adopted in realistic settings:

- They need to win in user studies (used in Image and Video compression challenge)
- We need a better metric (Perceptual metric challenge)
- I don't think they need to win on YUV420 PSNR, but I could be wrong

We are working towards a neural video codec that is…

1. Efficient: we’re developing codecs with low complexity
2. Deployable: we’re deploying codecs to identify and solve related challenges
3. Performant: in future work, not just RGB444 metrics

Measure compute in your work, as this will help make the case for adoption!

Thank you

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