

# Scalable Neural Video Representations with Learnable Positional Features

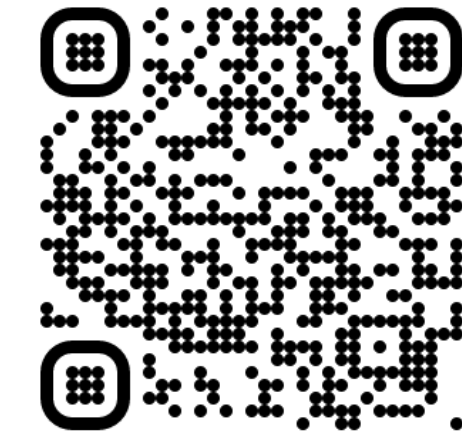
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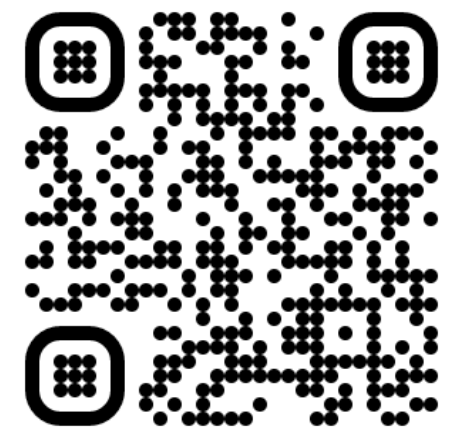
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Project page



Paper



Code



**TL;DR: We propose a compute-/memory-efficient neural representation for videos**

## Summary

NVP can capture the detail of a video containing dynamic motions after training for “**1 minute**”.

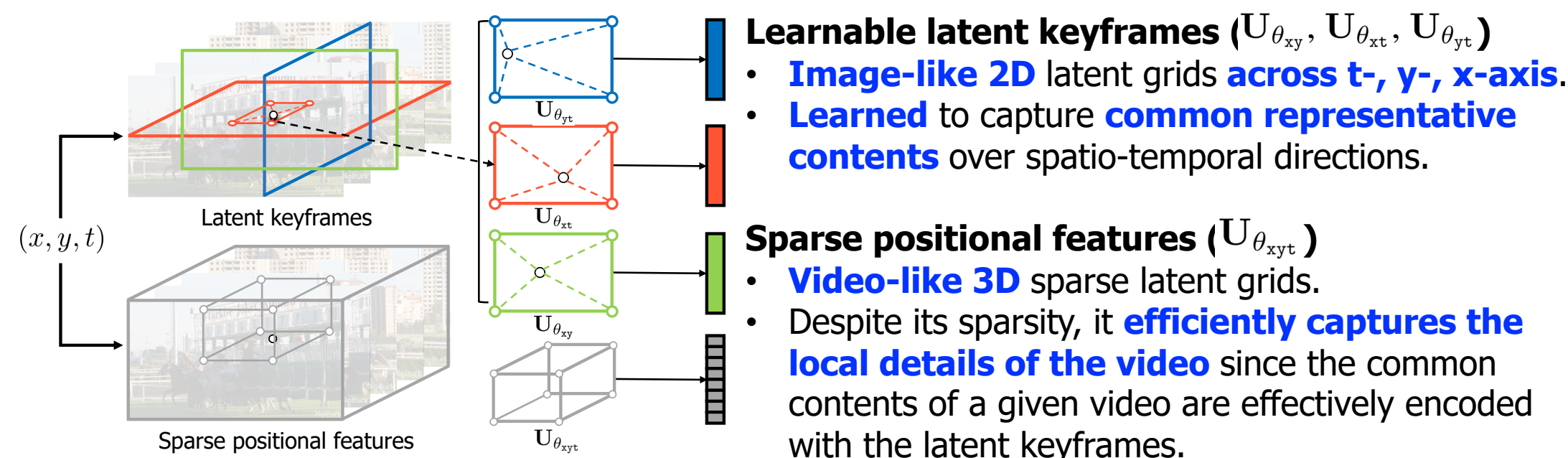


NeRV(BPP: 0.938) Instant-ngp (BPP: 6.489) NVP (ours, BPP: 0.189) Ground Truth

**Motivation:** Recent advances in coordinate-based neural representations (CNRs) have shown great promise in the field as a new paradigm for representing complex signals. However, video CNRs often suffer from two inefficiencies that prevent them from practical usage; (1) severe compute-inefficiency and (2) sacrifice of the parameter-efficiency.

**Contribution:** We introduce a *neural video representation with learnable positional features (NVP)*, a novel CNR for videos that is the best of both worlds, **achieving high-quality encoding** and the **compute-/parameter-efficiency simultaneously**.

## Amortize a Given Video as Succinct Latent Grids



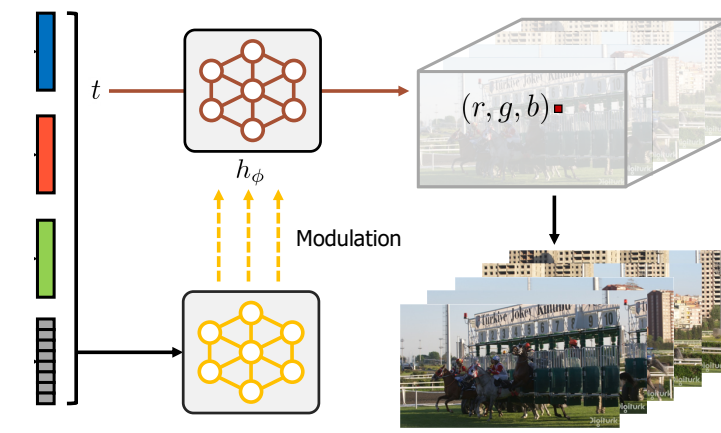
**Learnable latent keyframes ( $U_{\theta_{xy}}, U_{\theta_{xt}}, U_{\theta_{yt}}$ )**

- **Image-like 2D** latent grids **across t-, y-, x-axis**.
- **Learned** to capture **common representative contents** over spatio-temporal directions.

**Sparse positional features ( $U_{\theta_{xyt}}$ )**

- **Video-like 3D** sparse latent grids.
- Despite its sparsity, it **efficiently captures the local details of the video** since the common contents of a given video are effectively encoded with the latent keyframes.

## Modulate the Latent Codes to the RGB Values



**Modulated implicit function ( $h_\phi$ )**

- Maps a latent vector to the corresponding RGB value.
- Design  $h_\phi$  to be a  $K$ -layer Multi-layer perceptron (MLP) modulated by another modulator network, instead of simple MLP (more expressive power).

## Compute-/Memory-efficient Compression Procedure

- Incorporate powerful existing image & video codecs to compress our latent features**
- Quantize latent keyframes and sparse positional features as 2D/3D grids of 8-bit latent codes.
  - Regard the quantized latent codes as image and video pixels and compress them using codecs.
  - Notably **maintaining the video quality without any fine-tuning** (compute-efficient).

## Quantitative Results

**Compute-efficiency;** achieves reasonable encoding quality within a short training cost.

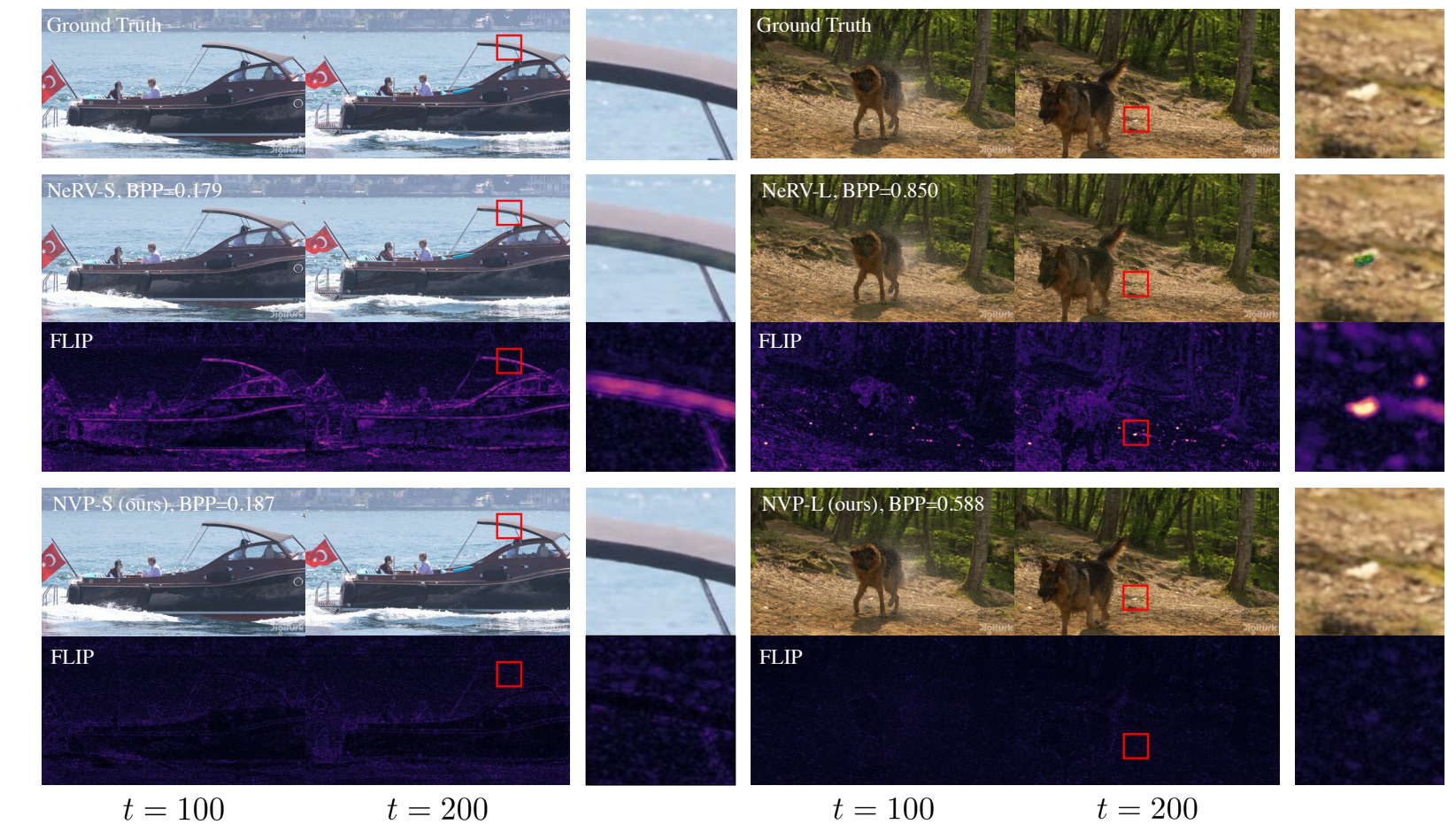
Encoding time	Method	BPP	PSNR ( $\uparrow$ )	FLIP ( $\downarrow$ )	LPIPS ( $\downarrow$ )
~5 minutes	Instant-ngp [34]	7.580	33.15 $\pm$ 3.19	0.090 $\pm$ 0.034	0.226 $\pm$ 0.112
	NeRV-S* [5]	1.072	24.16 $\pm$ 5.17	0.219 $\pm$ 0.097	0.542 $\pm$ 0.180
	<b>NVP-S* (ours)</b>	0.901	<b>34.57<math>\pm</math>2.62</b>	<b>0.075<math>\pm</math>0.021</b>	<b>0.190<math>\pm</math>0.100</b>
~10 minutes	Instant-ngp [34]	7.580	34.07 $\pm$ 3.01	0.082 $\pm$ 0.030	0.204 $\pm$ 0.105
	NeRV-S* [5]	1.072	26.53 $\pm$ 5.92	0.176 $\pm$ 0.088	0.460 $\pm$ 0.184
	<b>NVP-S* (ours)</b>	0.901	<b>35.79<math>\pm</math>2.31</b>	<b>0.065<math>\pm</math>0.016</b>	<b>0.160<math>\pm</math>0.098</b>
~1 hour	Instant-ngp [34]	7.580	35.69 $\pm$ 2.72	0.071 $\pm$ 0.025	0.162 $\pm$ 0.090
	NeRV-S* [5]	1.072	33.26 $\pm$ 4.31	0.094 $\pm$ 0.038	0.240 $\pm$ 0.112
	<b>NVP-S* (ours)</b>	0.901	<b>37.61<math>\pm</math>2.20</b>	<b>0.052<math>\pm</math>0.011</b>	<b>0.145<math>\pm</math>0.106</b>

**Parameter-efficiency;** succinct neural representation with a high-quality encoding.

~15 hours	SIREN [40]	0.284	27.20 $\pm$ 3.77	0.169 $\pm$ 0.059	0.409 $\pm$ 0.124
	FFN [46]	0.284	28.18 $\pm$ 3.62	0.153 $\pm$ 0.055	0.442 $\pm$ 0.126
	Instant-ngp [34]	0.229	28.81 $\pm$ 3.48	0.155 $\pm$ 0.057	0.390 $\pm$ 0.135
	NeRV-S [5]	0.201	36.14 $\pm$ 3.97	<b>0.067<math>\pm</math>0.023</b>	0.163 $\pm$ 0.101
~8 hours	<b>NVP-S (ours)</b>	0.210	<b>36.46<math>\pm</math>2.18</b>	<b>0.067<math>\pm</math>0.017</b>	<b>0.135<math>\pm</math>0.083</b>
	SIREN [40]	0.284	26.09 $\pm$ 3.88	0.175 $\pm$ 0.082	0.486 $\pm$ 0.188
>40 hours	FFN [46]	0.284	29.53 $\pm$ 3.44	0.135 $\pm$ 0.052	0.391 $\pm$ 0.124
	Instant-ngp [34]	0.436	29.98 $\pm$ 3.39	0.138 $\pm$ 0.051	0.358 $\pm$ 0.140
	NeRV-L [5]	0.485	35.00 $\pm$ 3.31	0.079 $\pm$ 0.020	0.145 $\pm$ 0.100
~11 hours	<b>NVP-L (ours)</b>	0.412	<b>37.47<math>\pm</math>2.08</b>	<b>0.062<math>\pm</math>0.017</b>	<b>0.102<math>\pm</math>0.061</b>

## Qualitative Results

NVP does not suffer from undesirable artifacts when compressed.



$t = 100$   $t = 200$   $t = 100$   $t = 200$

## Various Application of NVP as a Video CNR

NVP can show numerous compelling properties as a video CNR.

**Video Frame Interpolation.**



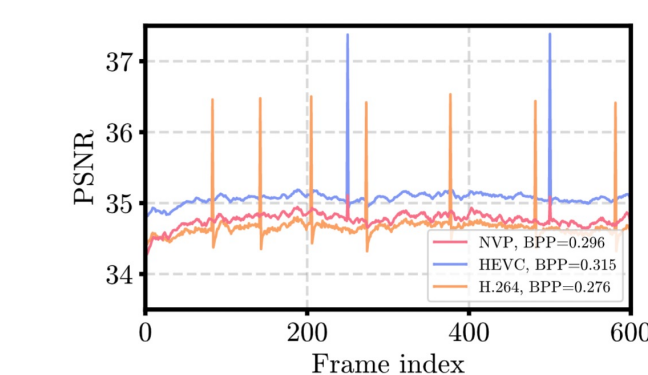
$t = 101$   $t = 101.5$   $t = 102$

**Video Inpainting.**

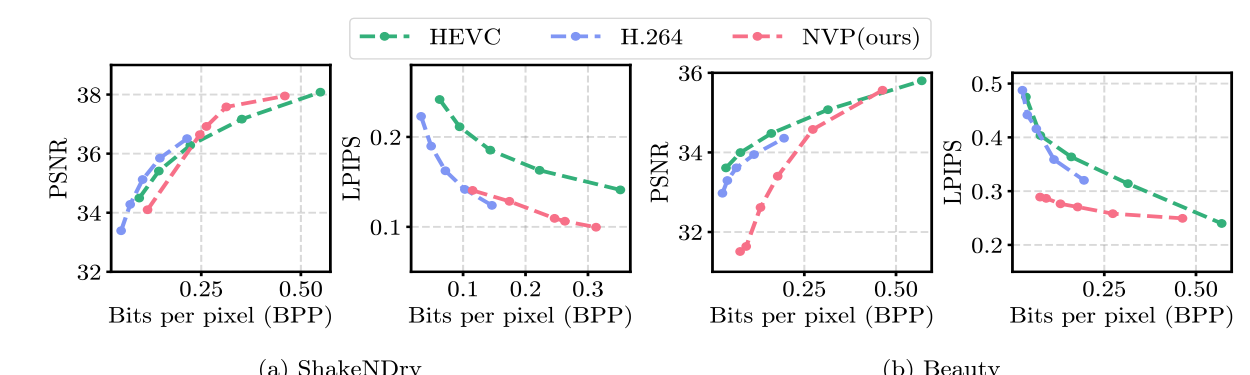


Original Mask Inpainting Result

**Consistent frame-wise encoding.**



**Video Compression.**



See the paper for more experiments, including ablation studies and detailed explanations. For better, playable illustrations and qualitative results, please refer to our project page. ☺