

# Occupancy Map Guided Attributes Deblocking for Video-based Point Cloud Compression

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# Introduction

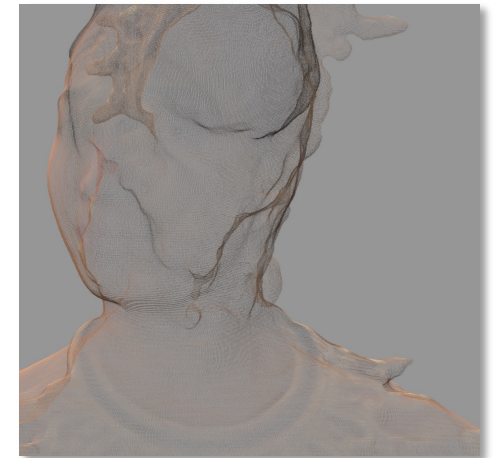
- What is Point Cloud?

- A collection of un-ordered points with
  - Geometry: expressed as  $[x, y, z]$
  - Color Attributes
  - Additional info: normal, timestamp, etc.



- Bringing **immersive** interactions:

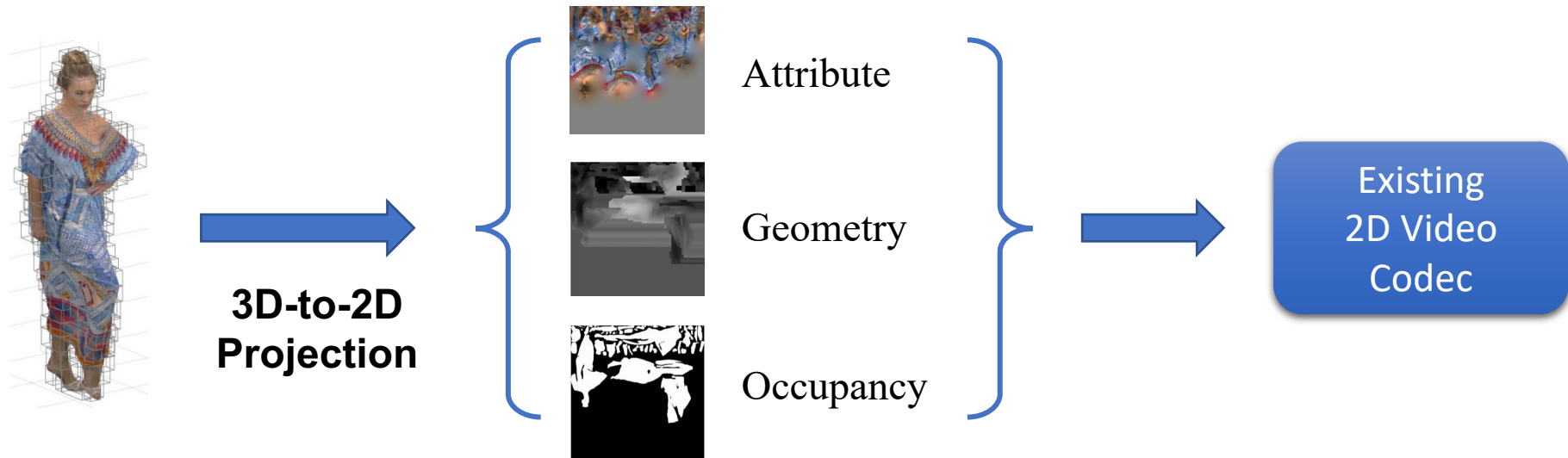
- Augmented reality
- Telepresence conference
- Cultural heritage documentation
- ...



- *But typically require massive storage and bandwidth*  
→ ***Point cloud compression (PCC) is highly demanded***

# Introduction

- Video-based Point Cloud Compression (V-PCC)

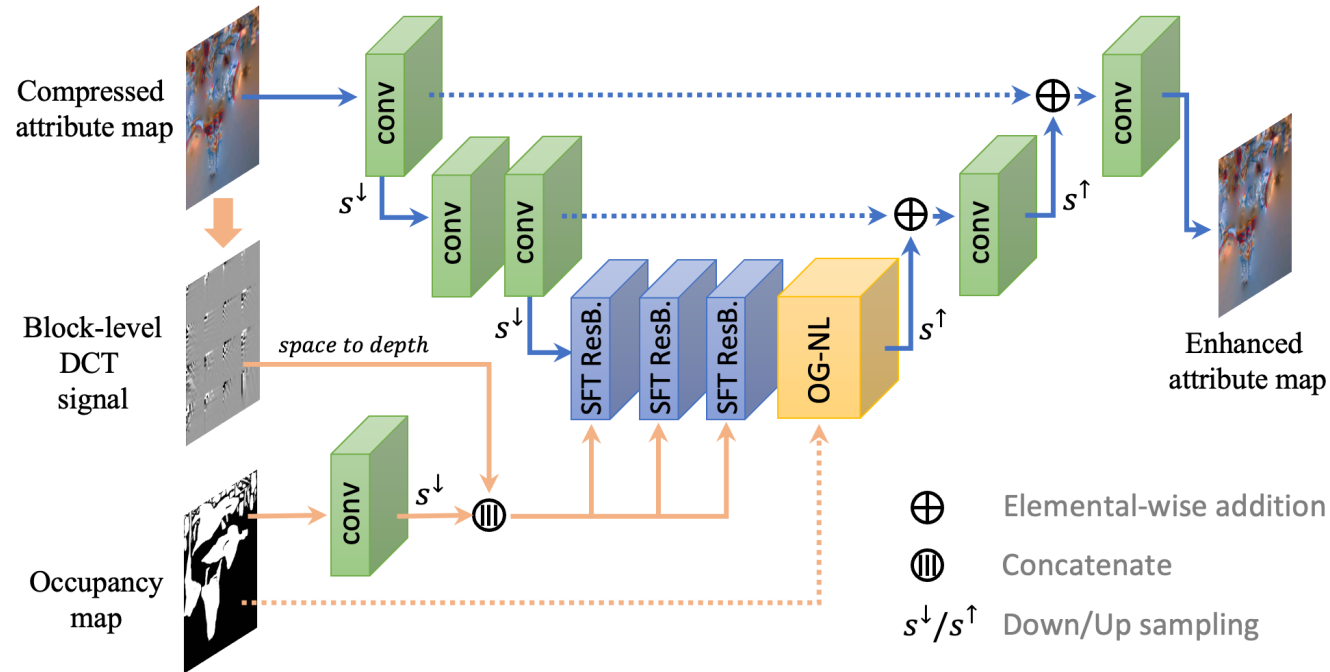


- **Lossy compression** introduce coding artifacts in attributes  
→ *degrade decoded PC quality*

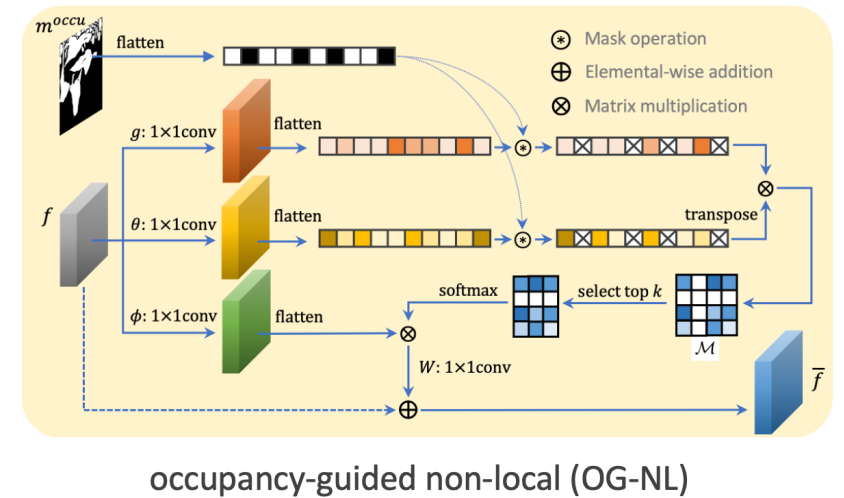
- **\*challenge\***: attributes are irregular mixtures without strong scene priors
- **\*opportunity\***: occupancies are available, which can provide potential clues

**We proposed occupancy map guided attributes deblocking for V-PCC**

# Proposed framework

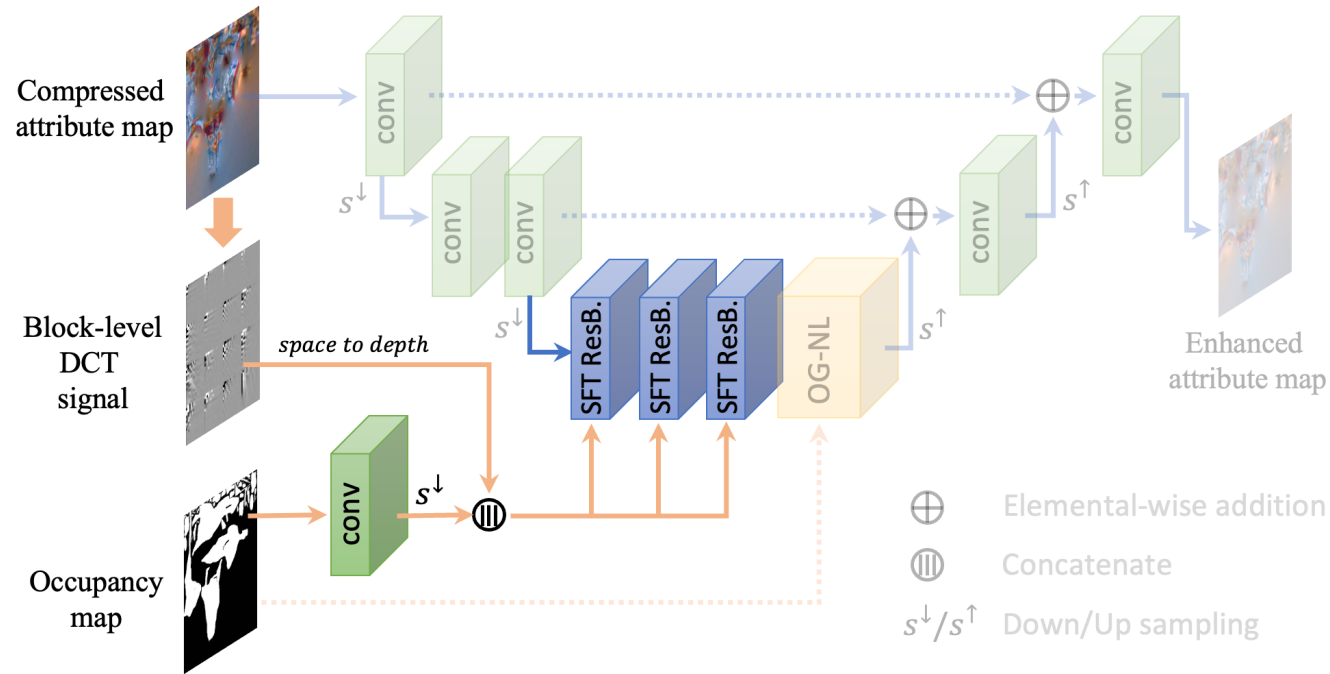


(a) The architecture of the proposed framework.

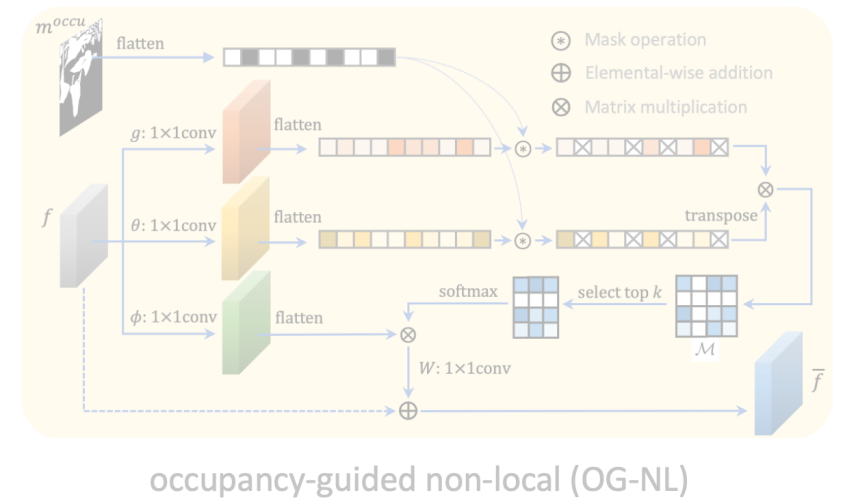


(b) overview of the OG-NL module.

# Proposed framework

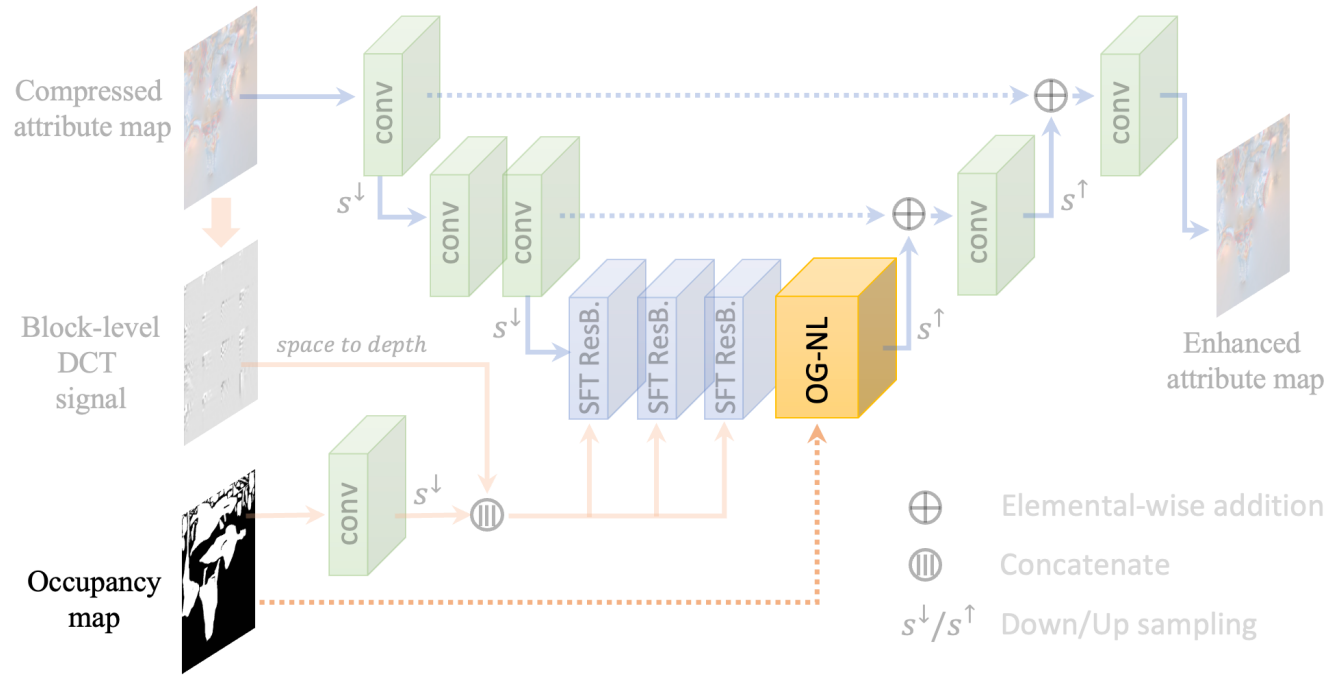


(a) The architecture of the proposed framework.

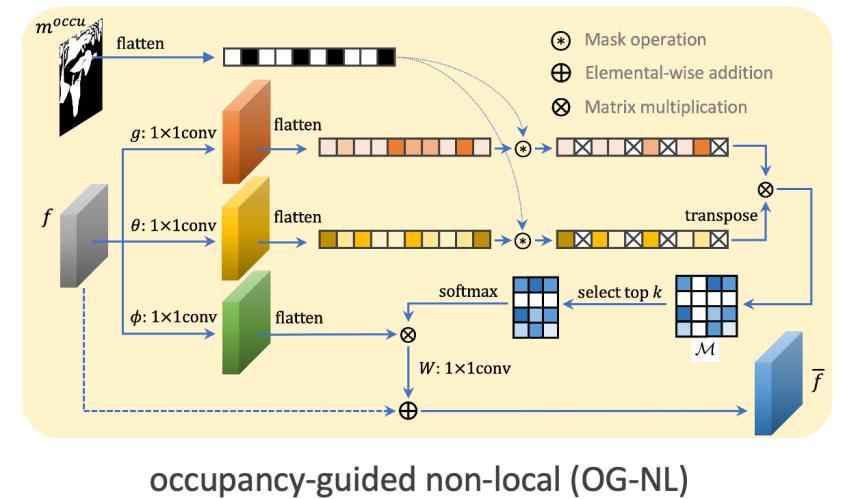


(b) overview of the OG-NL module.

# Proposed framework



(a) The architecture of the proposed framework.



(b) overview of the OG-NL module.

# Experiment settings

- **Codec:** version 18.0 of V-PCC reference software
- **Training:** Eight dynamic point cloud sequences<sup>1</sup> + Thuman2.0<sup>2</sup>
- **Patch size:** 256x256
- **Optimizer:** ADAM (initial lr: 1e-4)
- **Loss:** L1 with occupancy mask: 
$$L(\Theta) = \frac{1}{N} \sum_{i=1}^N \|(m_i^{GT} - F(m_i^{attr}, m_i^{occu} | \Theta)) \odot m_i^{occu}\|_1,$$
- **Test:** Five sequences<sup>3</sup> from the common test condition (CTC)

<sup>1</sup> *soldier, queen, thaidancer, model, exercise, andrew, david and phil.*

<sup>2</sup> *Yu, Tao, et al. "Function4d: Real-time human volumetric capture from very sparse consumer rgbd sensors." CVPR. 2021.*

<sup>3</sup> *loot, redandblack, longdress, basketball player and dancer.*

# Experiment results

Table 1: Overall BD-rate savings of the first 32 frames of each sequence with V-PCC reference software as the anchor under all-intra mode.

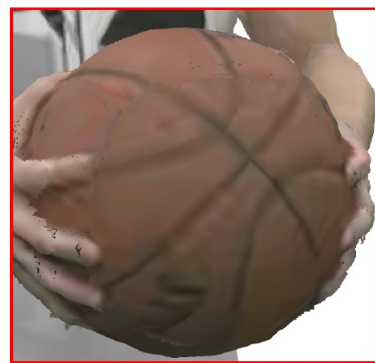
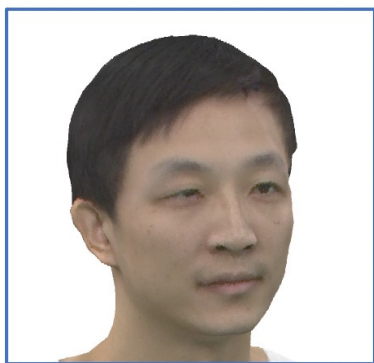
Class	Sequence	BD-AttrRate ↓			BD-TotalRate ↓		
		DCAD [10]	RNAN [16]	Proposed	DCAD [10]	RNAN [16]	Proposed
A	<i>loot</i>	1.7%	-0.9%	<b>-2.0%</b>	1.3%	-0.5%	<b>-1.5%</b>
	<i>redandblack</i>	-1.3%	-3.1%	<b>-3.9%</b>	-0.9%	-2.3%	<b>-3.1%</b>
B	<i>longdress</i>	-1.9%	-3.1%	<b>-3.3%</b>	-1.6%	-2.7%	<b>-2.8%</b>
C	<i>basketball player</i>	-2.6%	-5.5%	<b>-7.5%</b>	-1.6%	-3.6%	<b>-5.3%</b>
	<i>dancer</i>	-3.7%	-6.5%	<b>-8.5%</b>	-2.6%	-4.6%	<b>-6.2%</b>
Average		-1.5%	-3.8%	<b>-5.0%</b>	-1.1%	-2.7%	<b>-3.8%</b>

Table 2: Illustration of model complexities. Results of FLOPs are measured with assumption that the input size is  $128 \times 128$ .

	DCAD [10]	RNAN [16]	Proposed
Parameters (M)	0.296	2.725	0.913
FLOPs (G)	4.851	37.784	1.357



# Experiment results



(a) Original Point Cloud

(b) V-PCC Decoded Point Cloud

(c) Enhanced Result with Our Method



Thank you !