# Entropy Coding of Neural Network Latent Space Coefficients for Point Clouds



# Dominik Mehlem, Mirco Dilly

Institut für Nachrichtentechnik, RWTH Aachen University

# **Point Cloud Compression**

### **Point Clouds**

- 3D collection of points representing objects
- Geometry: points in space  $(x, y, z) \in \mathbb{R}^3$
- Attributes: color information, normal vectors, ...

#### **Compression Necessary**

• Raw point cloud with approx.  $0.7 \cdot 10^6$  points per frame and 30 fps

### **Autoencoder-based Geometry Compression** [1]

#### Architechture

- Static geometry compression
- Size of block tensor (input)  $x: 64 \times 64 \times 64$
- Size of LSC tensor (output)  $y: 8 \times 8 \times 8 \times 32$

#### side information



- 10 bit geometry precision, 8 bit attribute precision
- Every point requires  $3 \cdot (10 + 8)$  bit = 54 bit
- Due to data types up to 24 Byte per point:

 $R = 0.7 \cdot 10^6 \frac{\text{points}}{\text{frame}} \cdot 30 \frac{\text{frames}}{\text{s}} \cdot 24 \frac{\text{Byte}}{\text{point}} \approx 500 \frac{\text{MByte}}{\text{s}}$ 

# **Entropy Coding**

- Coding of Geometry LSCs
- Lossless coding
- Input: Quantized latent space coefficients

### **Different Methods tested**

- Huffman Coding (HC)
- Adaptive Huffman Coding (AHC)
- Arithmetic Coding (AC)
- Context-based Adaptive Binary Arithmetic Coding (CABAC)
- Dictionary-based Coding

### Training

• Loss function: Rate and focal loss

 $\mathcal{L} = R + \lambda \sum_{\boldsymbol{z} \in X} \operatorname{FL}(\boldsymbol{z})$ 

 $\begin{array}{l} \textbf{Compression Ratio} \\ C = 1 - \frac{r_{\mathrm{enc}}}{r_{\mathrm{ref}}} \end{array}$ 

# CABAC – Block Diagram and Binarization [3]



- –LZMA2 (7zip)
- Deflate (Gzip)
- $\Rightarrow$  Dictionary-based methods and CABAC show most promising results

# **CABAC – Context Modeling**

### **35 Contexts**

- Sign bit and remainder >10 bypass coded
- Significance bit, Comparison bits with third-order model
- Remainder <10 with zeroth-order model (only marginal probability)

Bins	Binarization	CABAC Engine	Model Order	Context ID	Template
$b_{\neq 0}$	Coding Tree	Adaptive	3rd	0-7	$oldsymbol{T}_3$
$b_{\pm}$	Coding Tree	Bypass	—	—	—
$b_{>1}$	Coding Tree	Adaptive	3rd	8-15	$\boldsymbol{T}_3$
$b_{>2}$	Coding Tree	Adaptive	3rd	16-23	$oldsymbol{T}_3$
$b_{>10}$	Coding Tree	Adaptive	3rd	24-31	$\boldsymbol{T}_3$
$b_{r_{<10},1}$	Fixed-length	Adaptive	Oth	32	_
$b_{r_{<10},2}$	Fixed-length	Adaptive	Oth	33	—
$b_{r_{\leq 10},3}$	Fixed-length	Adaptive	Oth	34	—
$\overline{b_{r_{>10},i}}$	Exp-Golomb	Bypass	_	_	_

### **Results**

- AHC and HC with density estimation show similar results
- CABAC: Conditional dependencies within LSCs can be exploited
- Dictionary-based coding achieves highest compression



### References

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mehlem@ient.rwth-aachen.de

www.ient.rwth-aachen.de

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Institut für Nachrichtentechnik, Melatener Str. 23, 52074 Aachen