Poster: Mobile Volumetric Video Streaming Enhanced by Super Resolution

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Introduction: Volumetric Videos

- 6DoF (degree of freedom) during playback:
 - positions (X, Y, Z) + orientations (yaw, pitch, roll)
 - highly immersive and interactive
- Capture:
 - RGB-D cameras with depth sensors (Figure 1)
- Representation:
 - **Point Cloud (PtCl)**: a collection of points
 - o 3D Mesh
- Enable novel applications
 - Entertainment, health care, education, and etc.

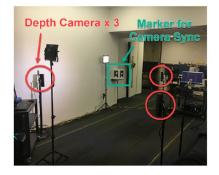
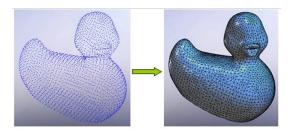


Figure 1: The volumetric video capturing system in our lab.



PtCl to 3D Mesh

Introduction: Motivation

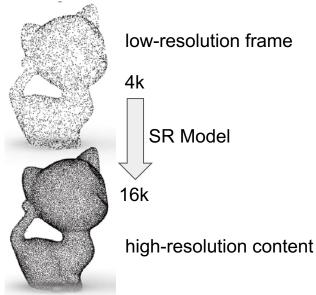
- Streaming PtCl Volumetric Videos
 - Extremely bandwidth demanding, even after compression
 - For a high-resolution PtCl footage, its data rate can be as high as 6Gbps^[1]

Challenge

How to stream high-quality volumetric contents wirelessly to commodity mobile devices in real-time (30FPS) while maintaining a good user's Quality of Experience (QoE)?

VoluSR: Kea Idea

- Apply 3D super-resolution (SR) to enhance volumetric video quality, striking a tradeoff between the network resource and the client-side computation capability.
- SR (or Upsampling) for 3D PtCls
 - A DNN SR model learning: low-resolution content → high-resolution details
 - Online inference stage



Enhancing PtCI Video Quality by 3D SR

- A Benchmark
 - Setup:
 - SR model: PU-GAN^[1]
 - PtCl video: captured in our lab, ~100k points/frame
 - Hardware: A desktop PC with an Nvidia 2080Ti GPU
 - Upsampling Ratio: x4, i.e. ~25k to ~100k
 - Evaluation across 100 frames
 - Pilot Results:
 - Average Chamfer Distance (CD): 0.33 * 10⁻³ m²
 - Video FPS: < 2

$$\mathrm{CD}(S_1, S_2) = \frac{1}{|S_1|} \sum_{x \in S_1} \min_{y \in S_2} ||x - y||_2^2 + \frac{1}{|S_2|} \sum_{y \in S_2} \min_{x \in S_1} ||x - y||_2^2$$

SR model achieves a good accuracy by leveraging overfitting while suffering poor runtime performance

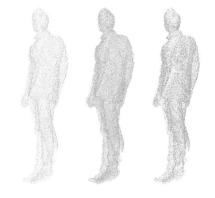
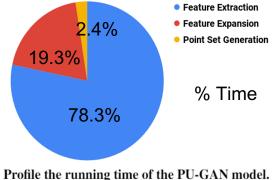


Figure 2: Left: a low-resolution frame (input to PU-GAN), Middle: the high-resolution frame inferred by PU-GAN, Right: the ground truth high-resolution frame.

- Speeding Up Model Inference
 - Observations:
 - Feature Extraction is the bottleneck of Vanilla PUGAN^[1]
 - Strategies:
 - Reducing model complexity
 - Replace feature extraction with a more efficient spherical kernel^[2] for 3D PtCls
 graph convolution
 - General DNN Model Acceleration Methods
 - Pruning & Quantization



- Caching & Reusing Inference Results
 - Observations:
 - Volumetric videos exhibit significant similarities across frames
 - Strategies:
 - Partition each frame into 3D tiles
 - Cache the inference results of the tiles and reuse them aggressively
 - Approximate a tile using a geometrically similar cached tile and a lightweight patch that delta-encodes the difference

- Adapting to User's Perception
 - Observations:
 - Use human users' perception to reduce the computational workload
 - Strategies:
 - Conduct SR for tiles:
 - Fall into the predicted viewport
 - Are not blocked by other tiles
 - Bear a close physical distance to the viewpoint
 - Have sufficiently high brightness

- Adapting to Devices' Computation Capabilities
 - Observations:
 - Heterogeneity of mobile devices
 - Different tiles have different visual importance
 - E.g., a closer tile may take a higher priority than a tile that is far from the viewpoint.
 - Strategies:
 - Dynamically adjusts the upsampling ratio for each tile based on their visual importance

System-level Optimization and Integration

- We are working on developing the holistic VoluSR system:
 - Pipelining
 - Offloading some tasks to the edge/server
 - Will thoroughly evaluate our prototype using real PtCl videos, real users' viewport traces, and off-the-shelf mobile devices.

Thanks for listening!