

EECE5512

Networked XR Systems

# Lecture Outline for Today

- Homework3
- Mesh Streaming

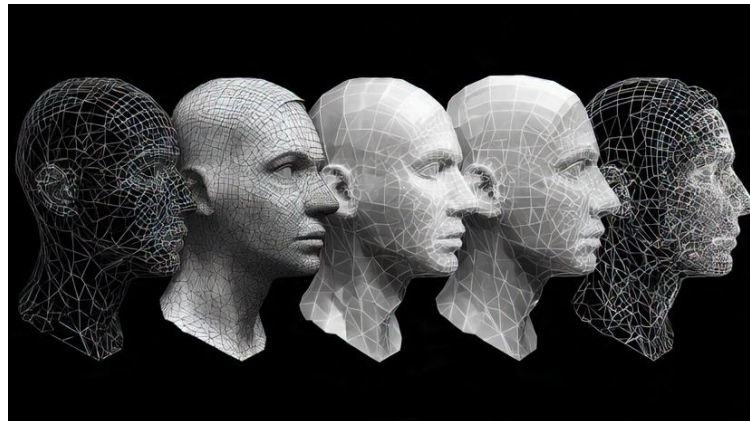
# Recap: Mesh

- Data representation
  - Each frame has vertices and connectivity
  - Color texture is stored independently, so there is also mapping information from texture to polygons



# 4D Mesh Sequence

Think of a 6-DoF, free viewpoint, volumetric video



# 4D Mesh Sequence

Think of a 6-DoF, free viewpoint, volumetric video





# Mesh Streaming

- Bandwidth and latency are a function of the scale of the scene captured.

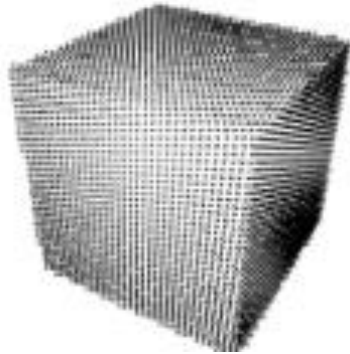


# Requirements in 4D Mesh Streaming

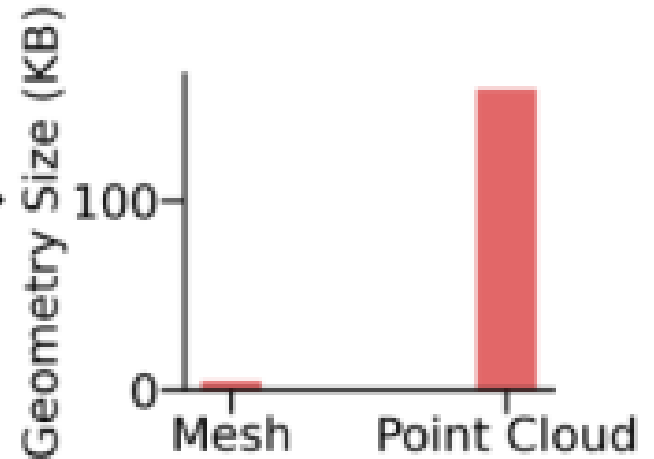
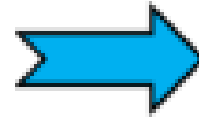
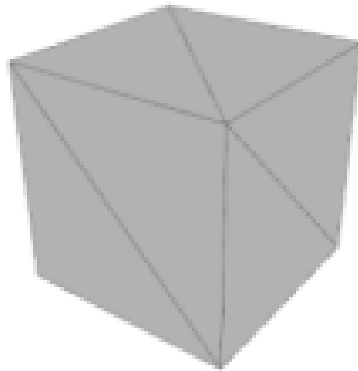
- **Low Latency:** For interactive live streaming, we expect latencies on the order of 2D video conferencing systems ( $<100\text{ms}$ ).
- **Scalable:** 3D video quality is often a function of number of cameras and scene size. An ideal capture solution should support dozens of sensors with commodity hardware.
- **Adaptive Streaming:** The system must operate given practical bitrates for Internet streaming, and the quality of the system should adapt to bandwidth availability.

# Implications of 3D Representations

Point Cloud  
Representation



Mesh Representation

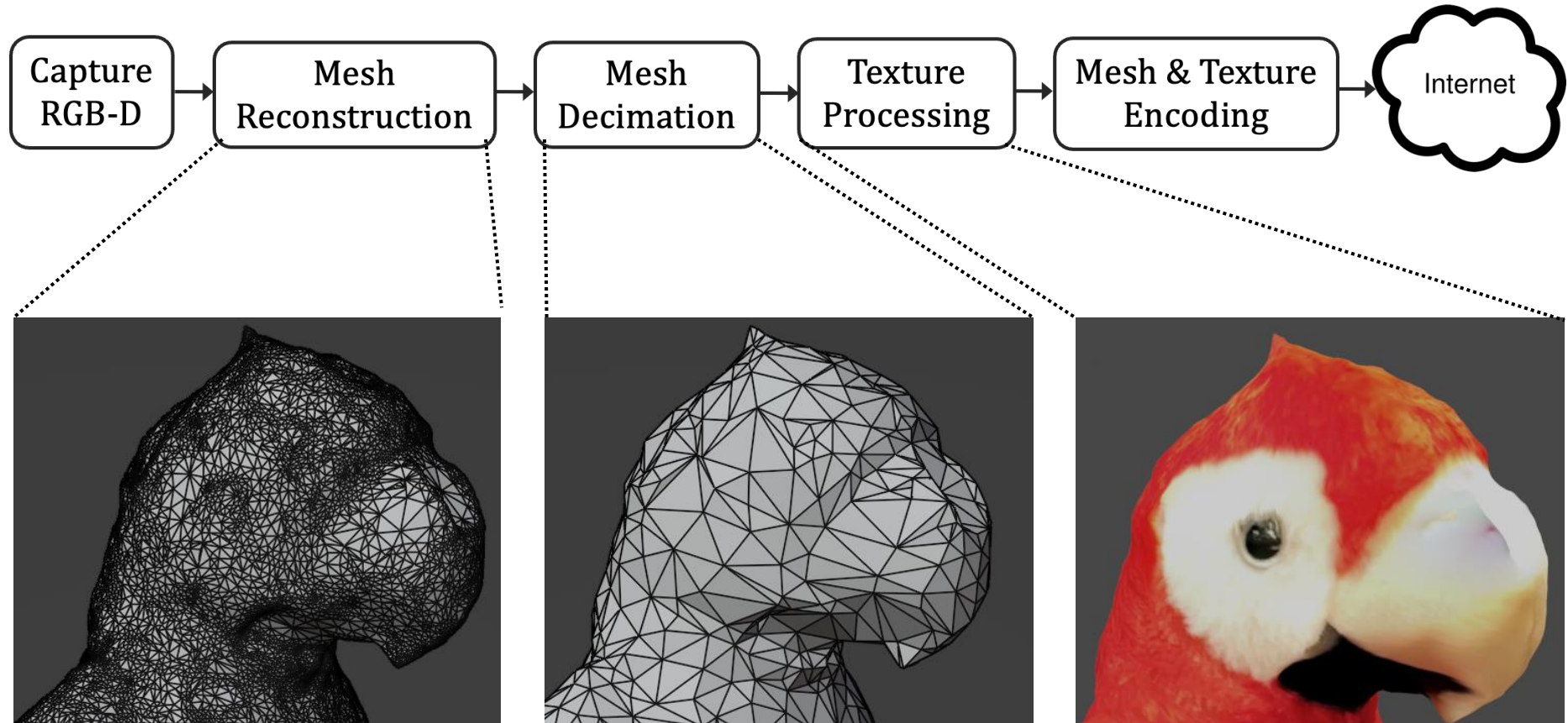


**Mesh is not natively  
available in sensors**

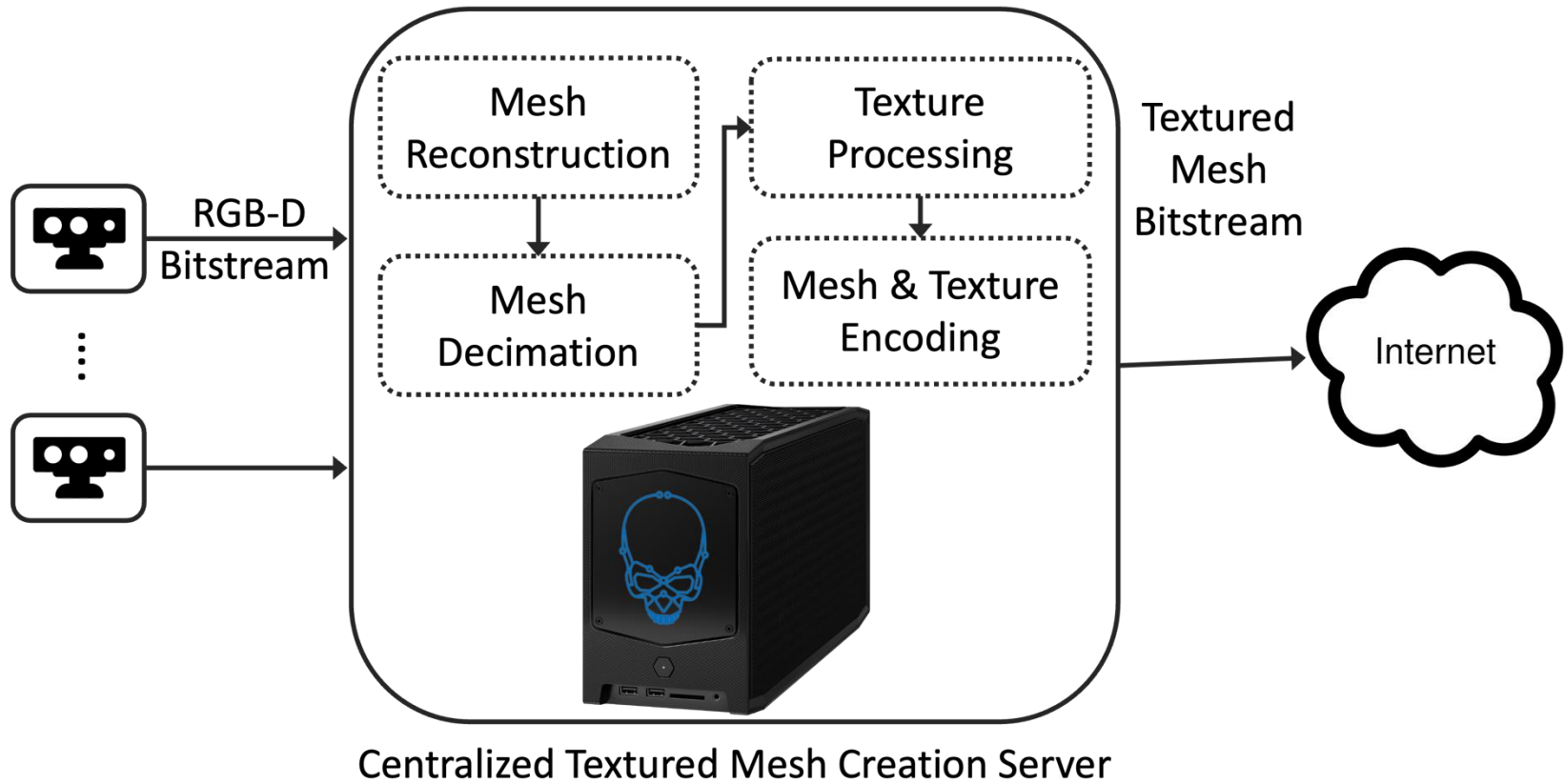
**Mesh requires significantly less data rate but  
poses numerous computational challenges**



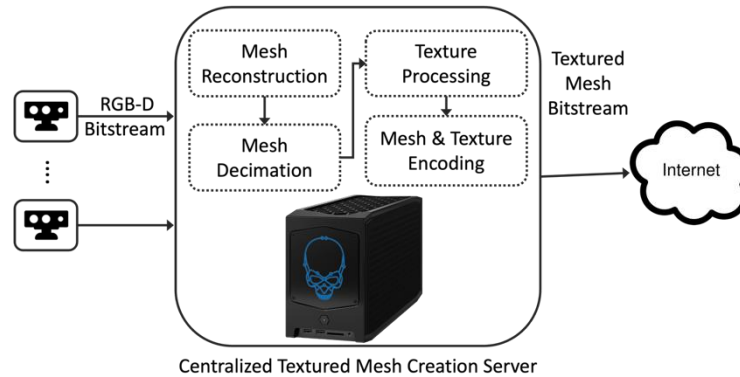
# Mesh Capture



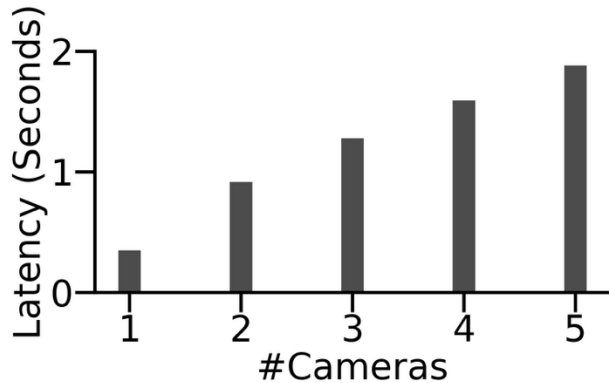
# Mesh Capture



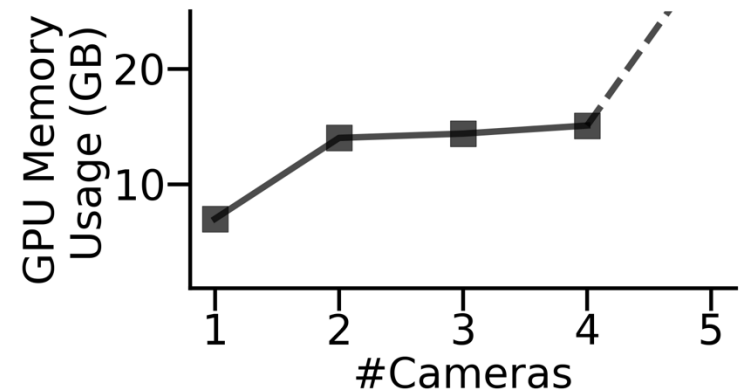
# Mesh Capture



Decimation is computationally expensive task

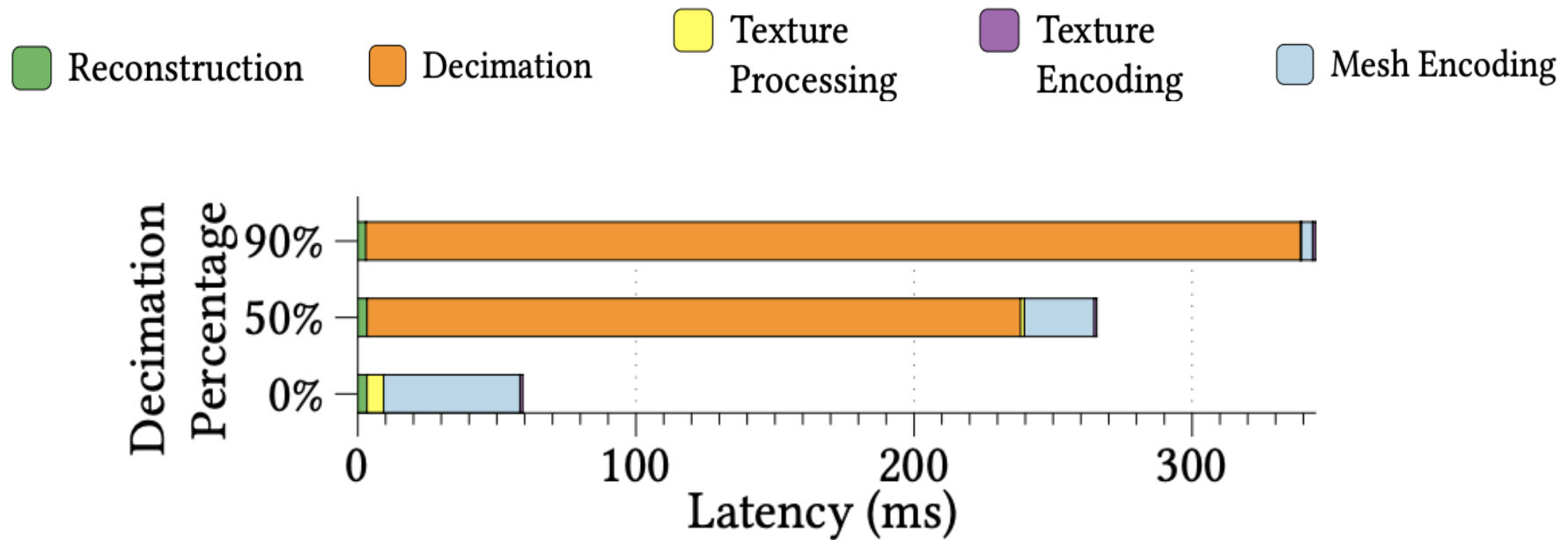


Reconstruction is GPU memory intensive



Not scalable with #cameras, scene size, and high quality

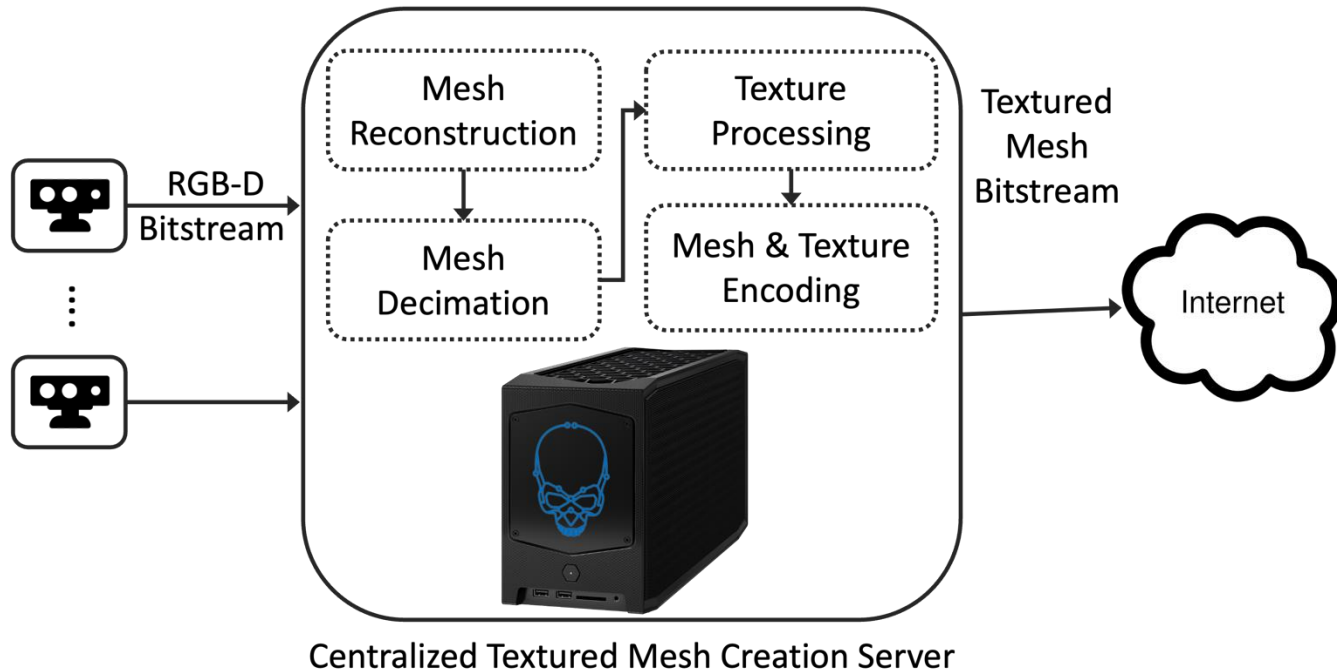
# Root Cause Analysis



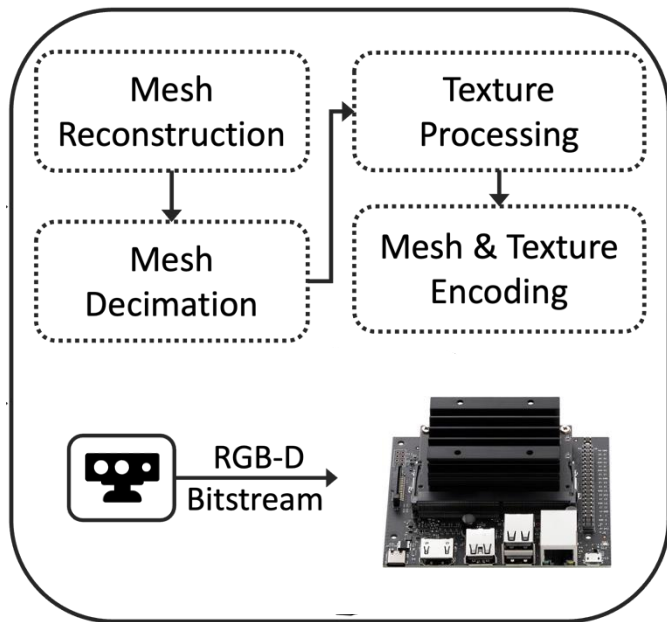
Decimation is computationally expensive task

Reconstruction is fast but GPU memory intensive

# Distributed Capture

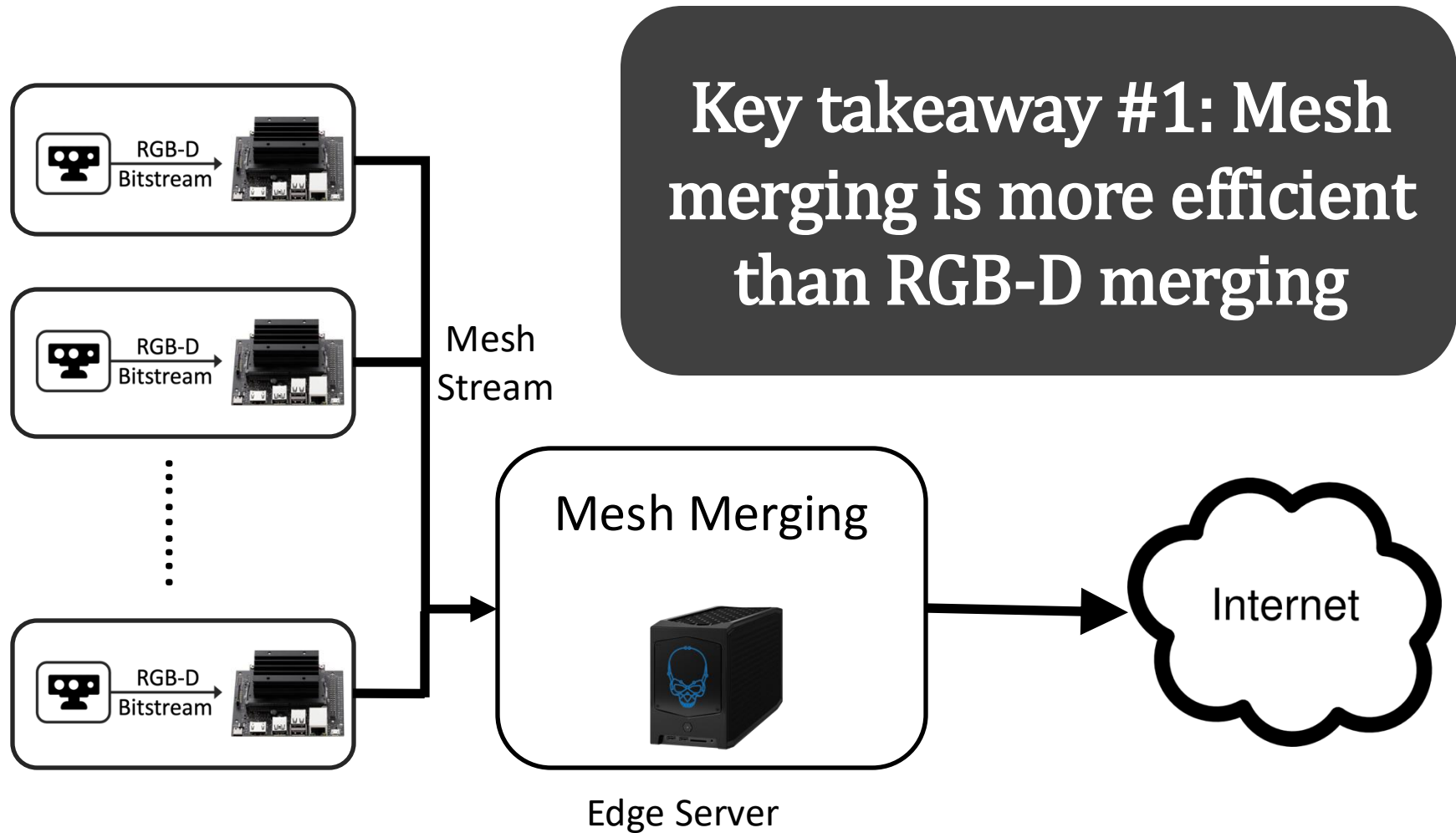


# Distributed Capture

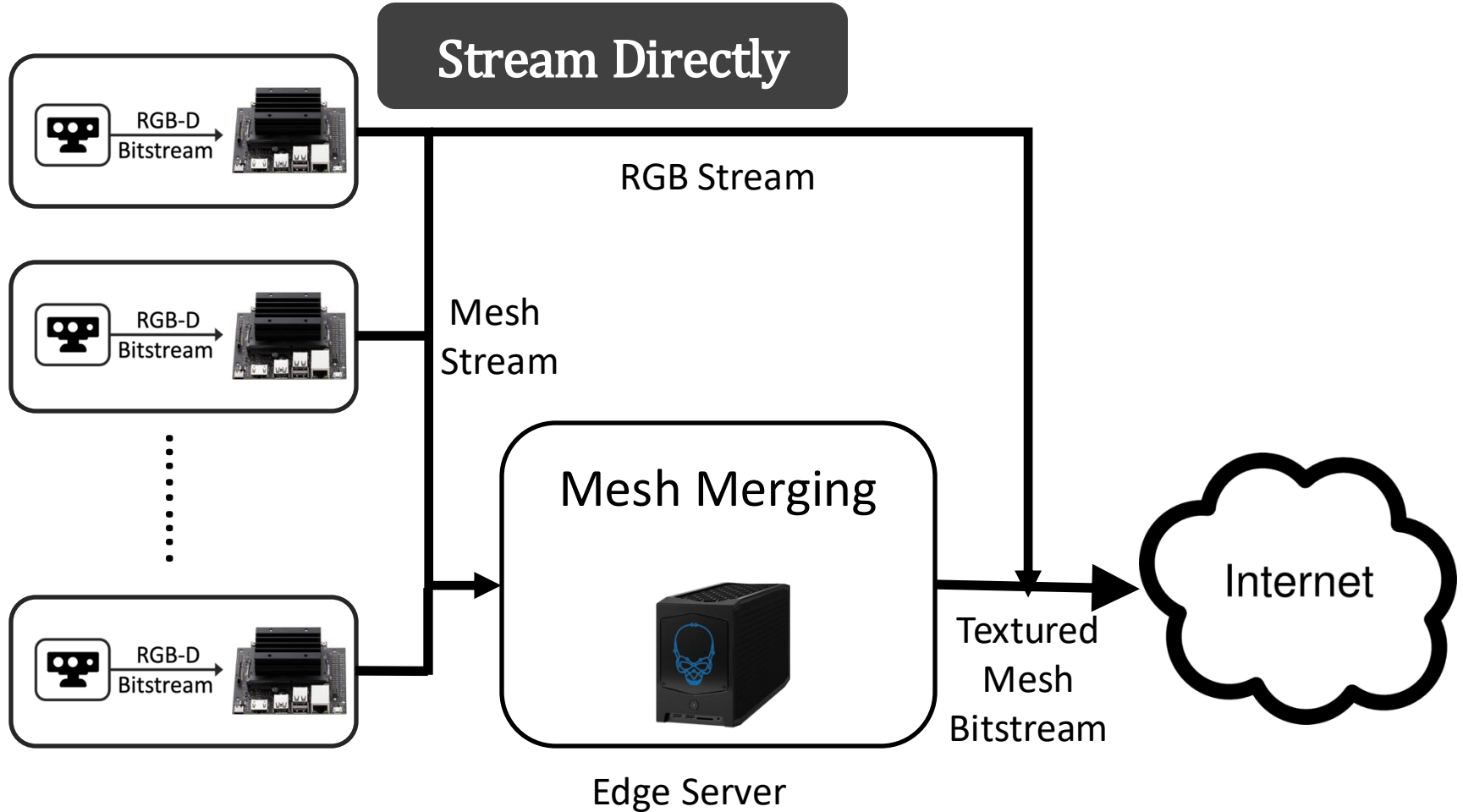




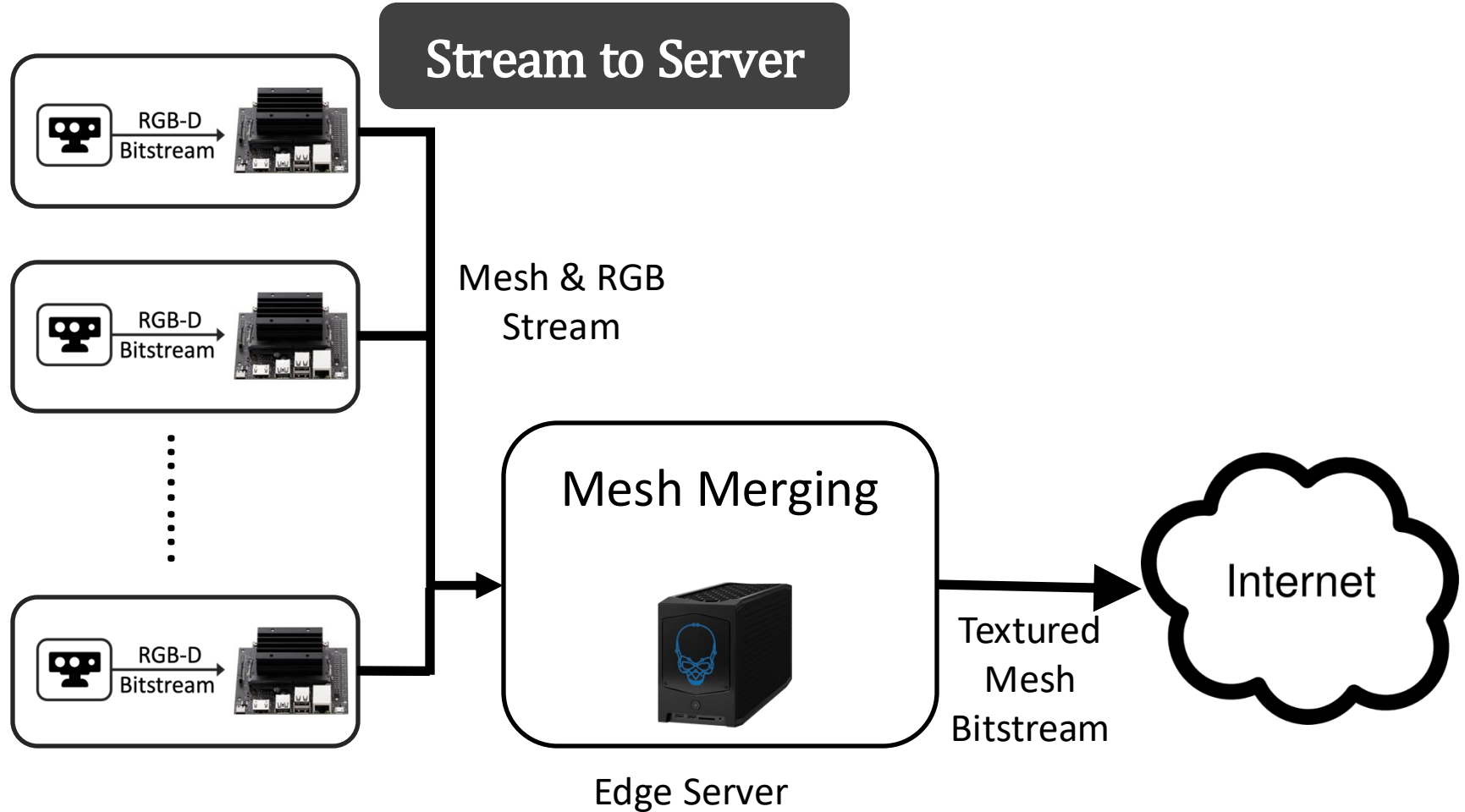
# Distributed Capture



# Distributed Capture



# Distributed Capture



# Texture Processing

NxN



NxN



Compact  
Packing



# Texture Processing

Compact  
Packing

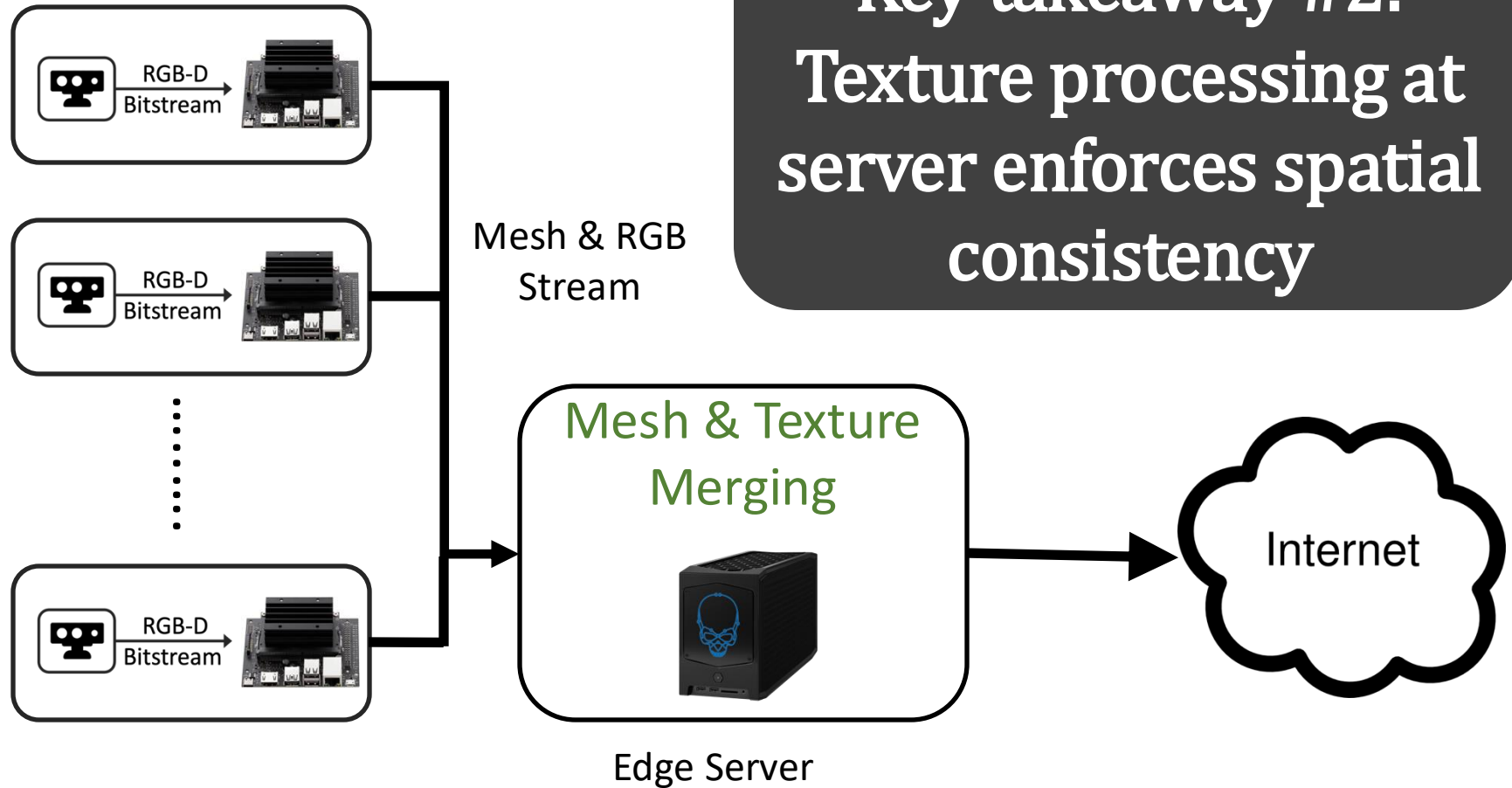
$N \times 2N$



$< N \times 2N$


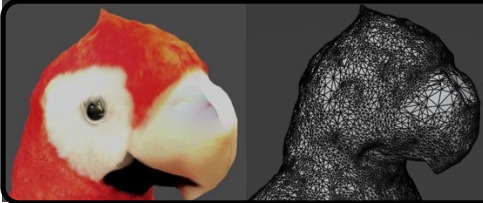
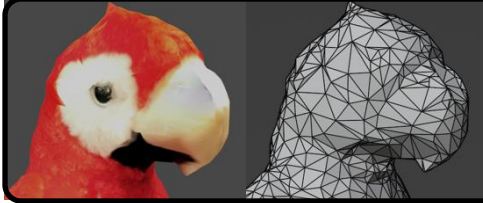
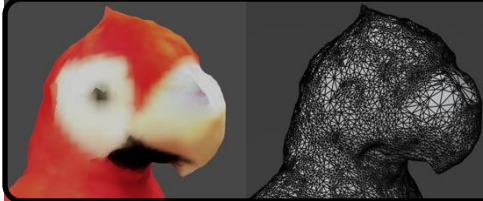
Codec/Bandwidth  
Efficient Packing

# Distributed Capture





# 3D Rate control Problem

		Original texture Original mesh	164MB
		Original texture Low-res mesh	8.2MB
		Low-res texture Original mesh	8.2MB

**Texture has more impact on final rendered quality. It should be allocated more bits.**

# 3D Rate control Problem

# Texture vs. Geometry

$$\mathcal{L} = \mathcal{D} + \lambda_t \mathcal{R}_t + \lambda_g \mathcal{R}_g$$

## Rate distortion Function

## Distortion

## Bitrates for texture and mesh geometry with tuning parameters

# How to split the bandwidth between texture and mesh?

# How to select optimal coding parameters for both texture & mesh?

# 3D Rate control Problem

- Total bitrate:  $R_{\text{total}} = 2000$  kbps
  - Texture constant:  $A_t = 400$
  - Geometry constant:  $A_g = 100$
  - Lagrange multiplier:  $\lambda$  is same for both (so we can equate derivatives)
- 

## Question

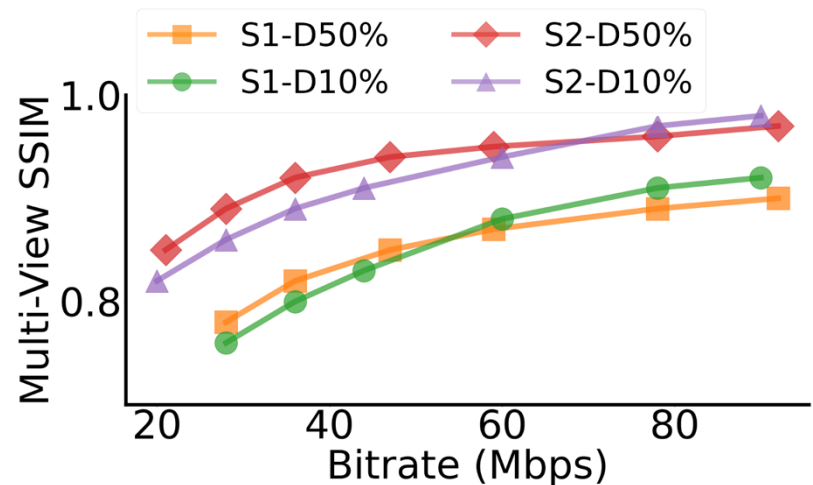
1. Derive the relationship between  $R_t$  and  $R_g$  using:

$$\frac{A_t}{R_t^2} = \frac{A_g}{R_g^2}$$

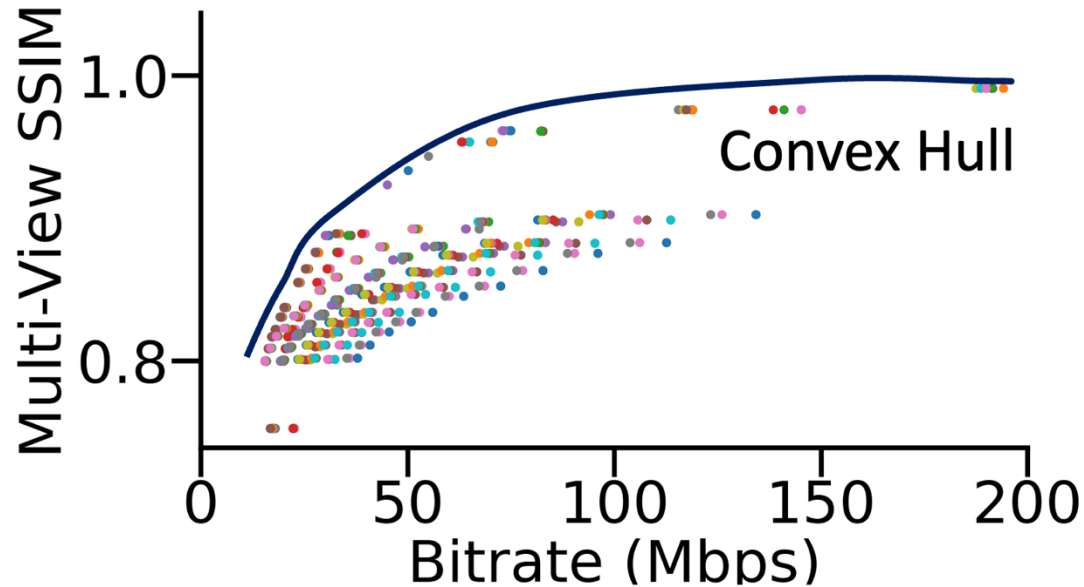
2. Compute the ratio  $R_t/R_g$ .
3. Find the values of  $R_t$  and  $R_g$  given  $R_t + R_g = 2000$ .

# Streaming Texture vs. Mesh Geometry

- Rate distortion with two scenes (S1, S2) with two decimation levels (10%, 50%) encoded at different bitrates.
- For the same bitrates, S1 and S2 produce different qualities, and hence they need different coding parameters to produce same bitrates at same quality.



# Streaming Texture vs. Mesh Geometry



Set of bitrate vs. quality points generated with different coding parameters.

# Streaming Texture vs. Mesh Geometry

How to split the bandwidth between texture and mesh?

How to select optimal coding parameters for both texture & mesh?



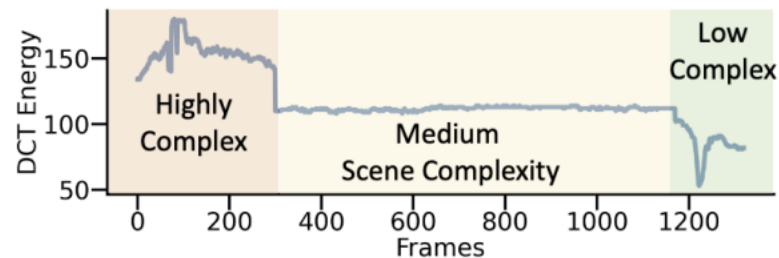


# Scene Complexity Metric

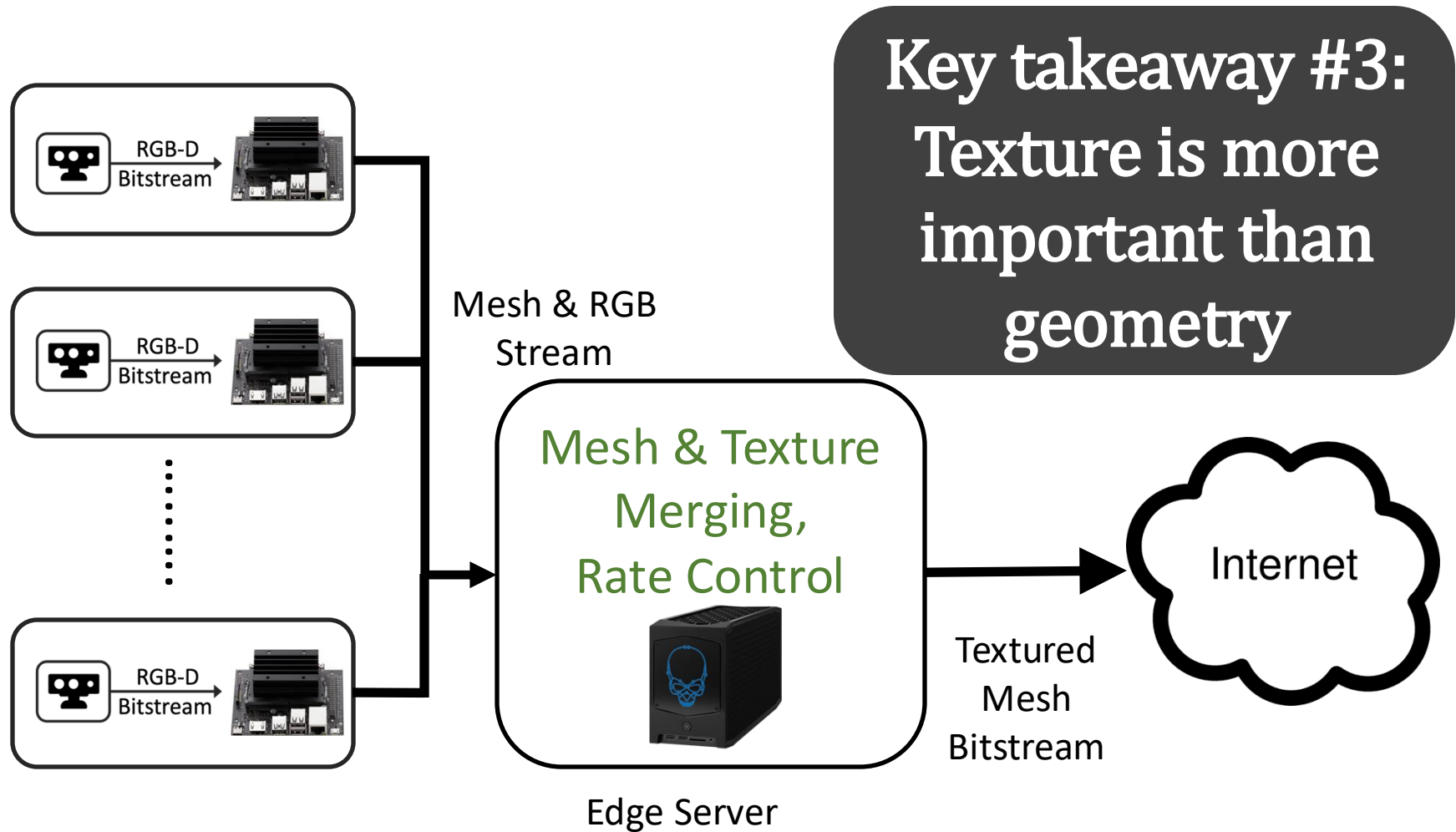
- DCT Energy

$$\mathcal{E}_{dct} = \sum_{i=w}^{j=h} e^{[(\frac{ij}{wh})^2 - 1]} |DCT(i-1, j-1)|$$

where, where  $w$  and  $h$  are the width and height of each block, and  $DCT(i, j)$  is the  $(i, j)^{th}$  DCT component when  $i + j > 2$ , and 0 otherwise



# Distributed Capture



# Adapting Texture and Mesh Streams

The scene is segmented into  $N$  objects:  $1 \dots N$ .

$q_i$  is the perceived quality of the object  $i$ .

the quality  $q$  is a function of the texture video bitrate  $t_r$ , mesh polygon distortion ratio ( $m_r$ ), and the texture mapping distortion ( $t_d$ ).

We can model the function  $q$  in the following way.

$$q = f(t_r \oplus m_r) - t_d$$

where,  $f(t_r \oplus m_r)$  is the perceived quality of rendered quality using the texture quality at  $t_r$  bitrate, and mesh quality at  $m_r$  bitrate.

# Adapting Texture and Mesh Streams

$f(t_r \oplus m_r)$  can be computed in the following ways.

1. A linear function:  $f(t_r \oplus m_r) = t_r + m_r$
2. A ratio:  $f(t_r \oplus m_r) = \frac{t_r + m_r}{\max_{t_r} + \max_{m_r}}$
3. An index into a table of  $t_r + m_r$  estimated through rate distortion curves of  $t_r$  and  $m_r$

# Adapting Texture and Mesh Streams

Given the above quality function for each object in the scene, we can model the overall expected perceptual quality of rendered final scene as

$$E(Q) = \sum_{i=1}^N p_i \times r_{i,d} \times q_i$$

where  $p_i$  is the view probability of object  $i$ , and  $r_{i,d}$  is an integer variable denoting object being downloaded.

If an object is missed i.e., not downloaded, it results in loss of quality. We represent this loss in quality as

$$E(O_m) = \sum_{i=1}^N p_i \times r_{i,m}$$

where  $r_{i,m}$  is an integer variable denoting object being missed.

Thus, the overall QoE can be modeled as

$$\text{QoE} = E(Q) - \sigma E(O_m)$$

Our objective is to maximize the above QoE function subject to the following constraints.

# Adapting Texture and Mesh Streams

## Constraints.

The following constraints ensure the feasibility of the solution. The quality of an object can only be positive if the object is downloaded, i.e.,

$$q_i \geq r_{i,d}$$

also, every object must be either downloaded or missed.

$$r_{i,d} + r_{i,m} = 1, \forall i = 1 \dots N$$

Finally, the downloading must complete before some time  $\delta$  before the playback time  $P_t$ . Let  $d(q_i)$  be the download time of object  $i$  at quality  $q_i$ . Then this constraint can be represented as.

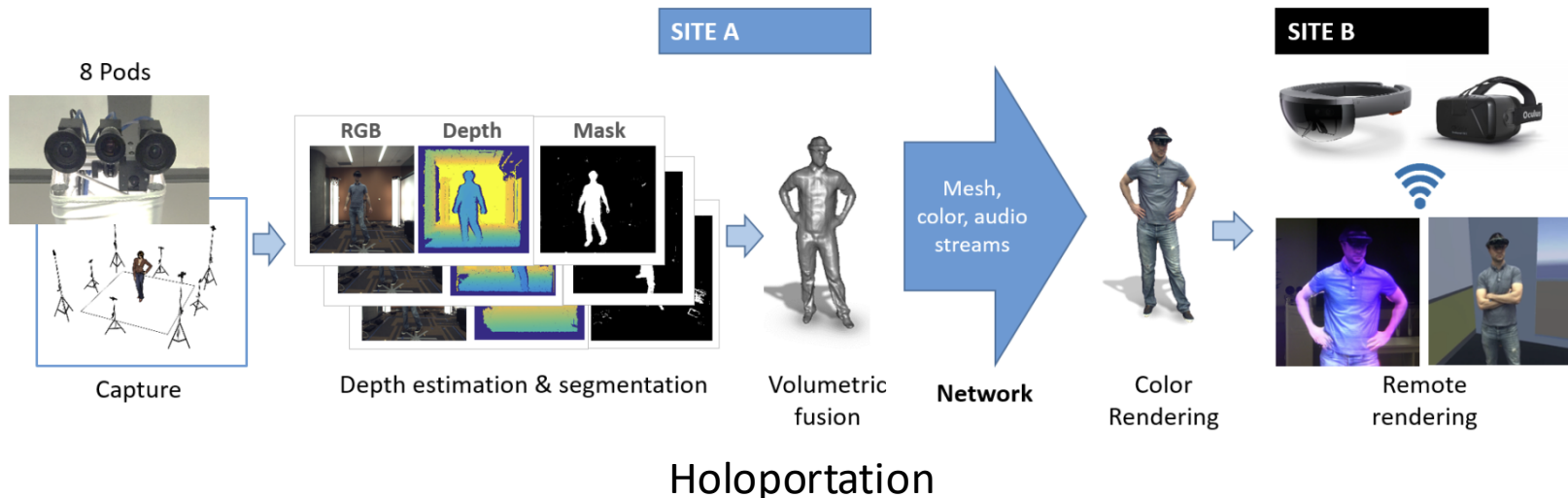
$$\sum_{i=1}^N d(q_i) \times r_{i,d} + \delta \leq P_t$$

This represents the bandwidth constraint, which can also be written as follows,  $t_r + m_r \leq C$ , where  $C$  is the predicted bandwidth.

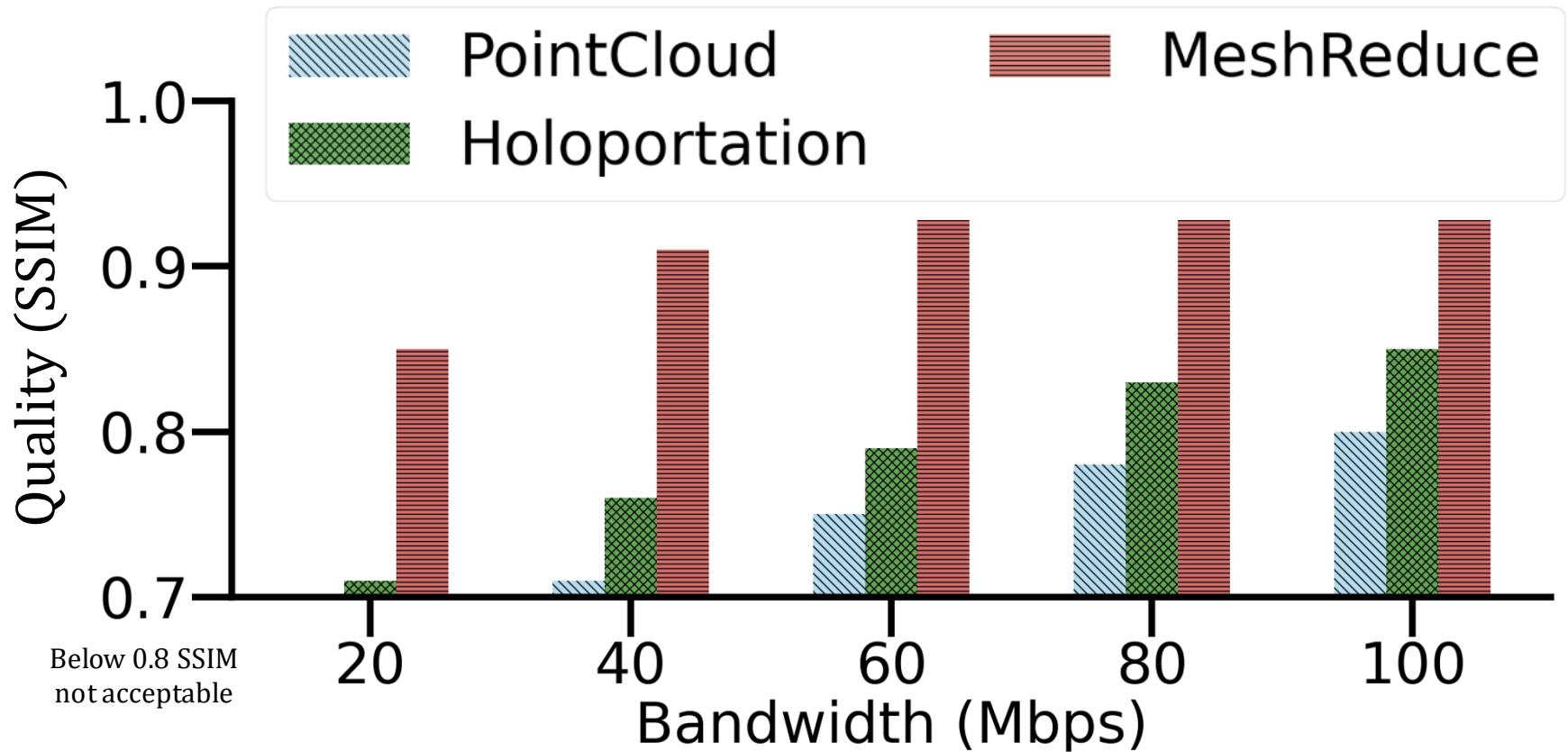


# Distributed Capture Performance

- Comparison
  - MeshReduce
  - Holoportation
  - Point Cloud based streaming

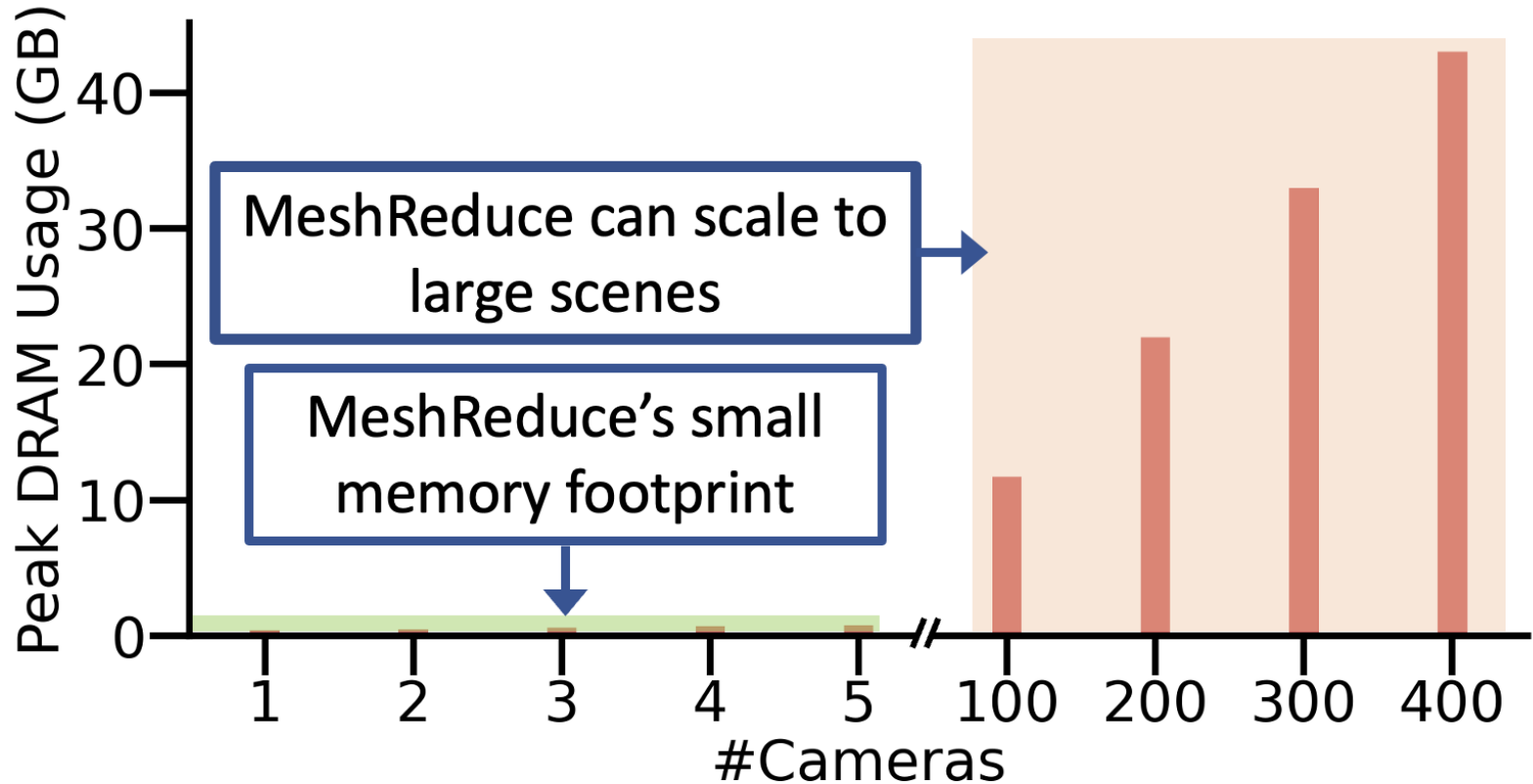


# Distributed Capture Performance



Significantly better quality under lower bitrates

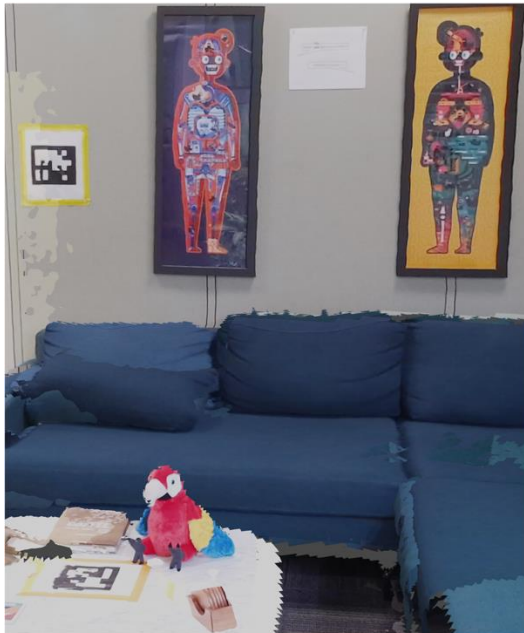
# Scalability of Distributed Capture



Not GPU bottlenecked; DRAM is abundant and scalable

# Visual Quality

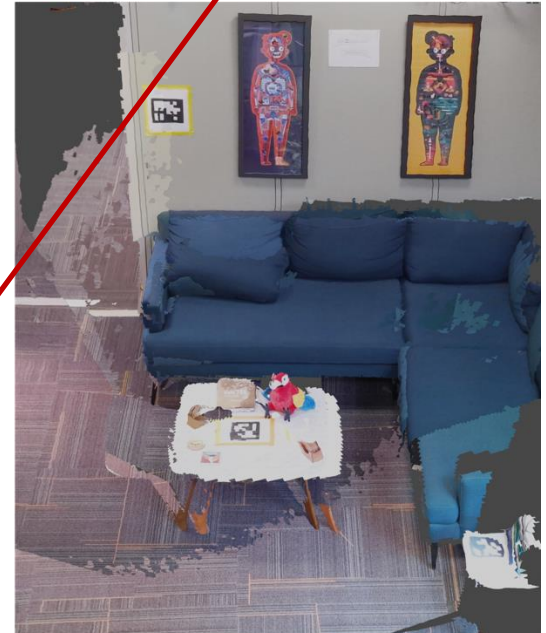
Color inconsistency



Depth holes



Occlusion



# Deep Learning based in-fill



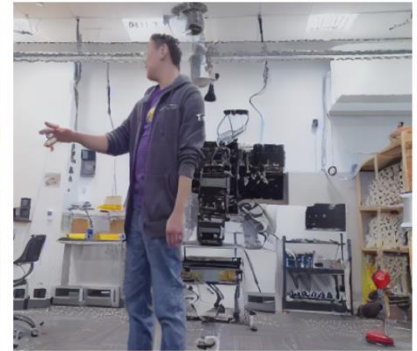
Color Texture



Depth/Geometry



Texture Mapped Mesh



Mesh Diffusion in-Fill

Traditional textured mapped mesh vs. genAI/Diffusion in-filled upsampling.

# Summary of the Lecture

- Mesh streaming
- Distributed Capture
- Adaptation of texture and mesh streams