# EECE5698 Networked XR Systems

## Lecture Outline for Today

- Quiz
- 360-Degree Video Streaming



3-DoF on angular motion

#### Central to many immersive applications (e.g., VR/AR)



Image credit: Oculus

**Immersive Experience** 



\$ Billion Market

- Motion-to-photon latency a unique metric of importance compared to regular videos
  - "the lag between a user making a movement and the movement being displayed within the display"
  - Should be in the order of a few milliseconds (<20ms)
- Other metrics that we discussed in case of regular videos still apply here (e.g., quality, stalls., etc.)

- How to compress 360-degree videos?
  - Often projected to a 2D equirectangular video and then adopt standard video codecs

• How streaming a 360-degree video is different from regular video?

- How streaming a 360-degree video is different from regular video?
  - Stream it like a regular video problem?

## Streaming Challenge

# How streaming a 360-degree video is different from regular video?



200Mbps

Image from Rollercoaster video

360° videos require more bandwidth compared to regular videos for the same perceived quality

## Streaming Challenge



200Mbps

Image from Rollercoaster video

Can we just stream the viewport?

## Viewport-Adaptive Streaming

- How to stream a viewport?
  - There can be many viewports i.e., different users may look different parts of the scene at different times during the video
  - Viewport is continuous stream of pixels hard to identify viewport pixels and stream viewport directly

#### **Tiled Streaming**

• Divide video into tiles (e.g., 192x192 pixels)



Flare [MobiCom'18], Rubiks [MobiSys'18], MOSAIC [IFIP Networking'19] PANO [SIGCOMM'19], ClusTile [INFOCOM'19]

#### □Tiled streaming

- Divide video into tiles (e.g., 192x192 pixels)
- Predict viewport tiles based on head tracking and video saliency analysis
- Stream only viewport specific tiles





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- Viewport prediction
  - Use video features and users' past history (i.e., head motion data) to predict where the user will look at in the near future
  - Need prediction models



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User head motion ->



# Which tiles and how many tiles to stream?



Figure 3: CDFs of VRH linear and angular speeds for VR applications.

- Viewport prediction
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 Need prediction models

Saliency features ->



- Viewport prediction models
  - Simple ML Models (e.g., SVM)
    - Faster, less accurate
  - Neural Networks
    - Slower, slightly more accurate



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#### Viewport prediction models

- Predicting user head movement is hard
- The accuracy drops significantly as we predict a longer horizon user motion



#### Viewport prediction models

- Predicting user head movement is hard
- Solution:
  - Fetch more tiles to avoid the tile misses
  - Fetching more tiles competes for bandwidth and reduces video quality



• Tile selection strategies



(c) Download predicted viewport only, but prediction inaccurate



(b) Download predicted viewport only



(d) Download rate adapted tiles based on viewport prediction

• Tiles stored at the server in different qualities



• End-to-end streaming pipeline



Equation: Tile Selection Optimization

Let T be the set of all tiles in a video frame, and  $V_p$  be the set of tiles within the predicted viewport. Each tile t has an associated quality level  $q_t$  and required bitrate  $b_t(q_t)$ . The optimization problem aims to maximize the overall quality of the viewport under the total available bandwidth B.

Objective:

$$\max_{\{q_t\}} \sum_{t \in V_p} w(t) \cdot q_t$$

Subject to:

$$\sum_{t\in T} b_t(q_t) \leq B$$

where w(t) is the weight (importance) of tile t based on its position within the predicted viewport  $V_p$ , reflecting the user's likely focus area.

We need throughput estimation similar to the case of regular videos

**Equation: Throughput Estimation** 

Let  $T_i$  be the throughput estimate after downloading the *i*-th video segment,  $S_i$  be the size of the *i*-th segment (in bits), and  $D_i$  be the download duration (in seconds). The throughput estimate can be updated as:

$$T_{i+1} = lpha \cdot T_i + (1-lpha) \cdot \left(rac{S_i}{D_i}
ight)$$

where  $0<\alpha<1$  is a smoothing factor that controls the impact of past throughput measurements on the current estimate.

• Need to adapt spatial quality as well



- Compression overhead with tiling
  - Looses out on exploiting spatio-temporal redundancy that existing across the tiles

• Why?

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  - Tiles need to be encoded independently so that can be streamed independently

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## Summary of the Lecture

- 360-Degree Video Streaming
- Viewport prediction
- Viewport adaptation