Intelligent Connectivity for XR-aided Teleoperation in 6G

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July 15th
2022

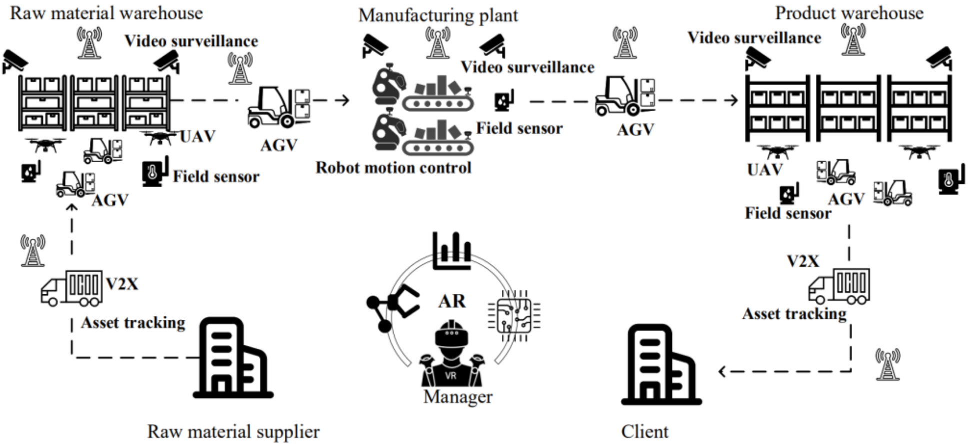
XR-aided Teleoperation

Cellular-Connected XR Networks

Challenges: High transmission bit rate: 35 Mbps – 4.42 Gbps; Low latency: 5 – 10 ms

[1] F. Hu, **Y. Deng***, W. Saad, M. Bennis, A. H. Hamid, "Cellular-Connected Wireless Virtual Reality: Requirements, Challenges, and Solutions", in IEEE Communications Magazine, 2020.
[2] Qualcomm, "VR and AR pushing connectivity limits," Qualcomm Technologies. Inc., Tech. Rep., 2018 (Accessed on 2019-12-19). [Online]. Available: https://www.qualcomm.com/invention/extended-reality/virtual-reality

Cellular-Connected Robotics Networks

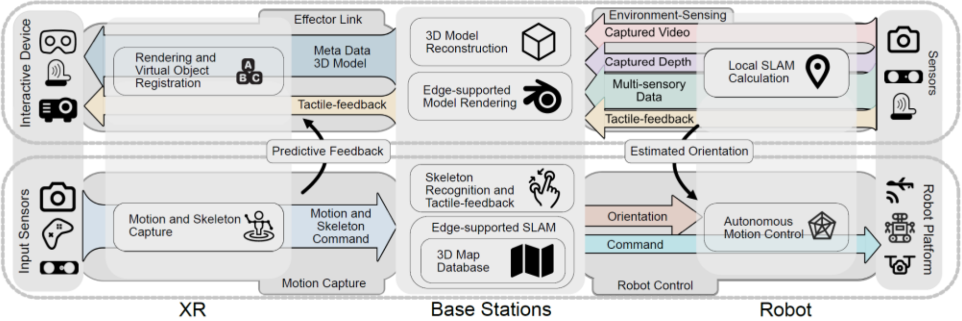


[3] H. Zhou, S. Yang, **Y. Deng***, M. Dohler, A. Nallanathan. "Machine Learning for Massive Industrial Internet of Things" in IEEE Wireless Communications, 2021.

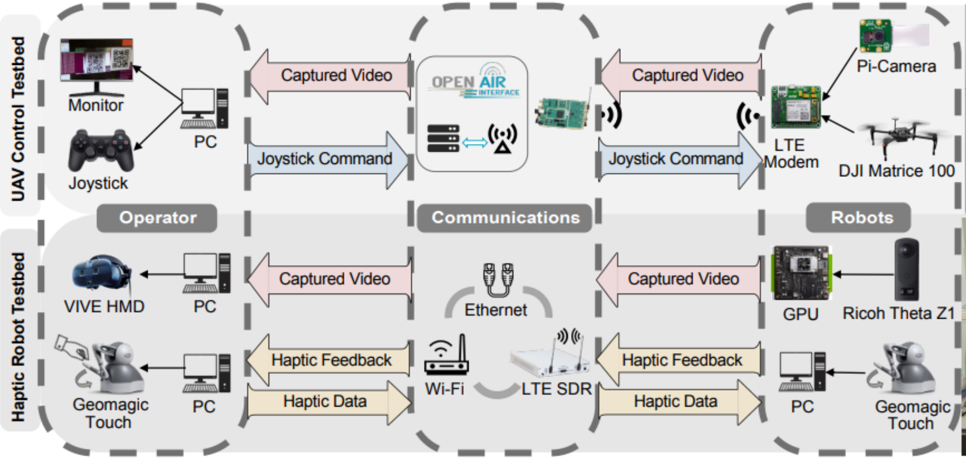
I: Testbeds and Trials

[3] H. Zhou, F. Hu, M. Juras, A. B. Mehta and **Y. Deng***, “Real-time Video Streaming and Control of Cellular-Connected UAV System: Prototype and Performance Evaluation,” in IEEE Wireless Communications Letters, 2021.
[4] F. Hu, **Y. Deng***, H. Zhou, T. H. Jung, C. B. Chae, A. H. Hamid, “A Vision of XR-aided Teleoperation System Towards 5G/B5G”, in IEEE Communications Magazine, 2021.

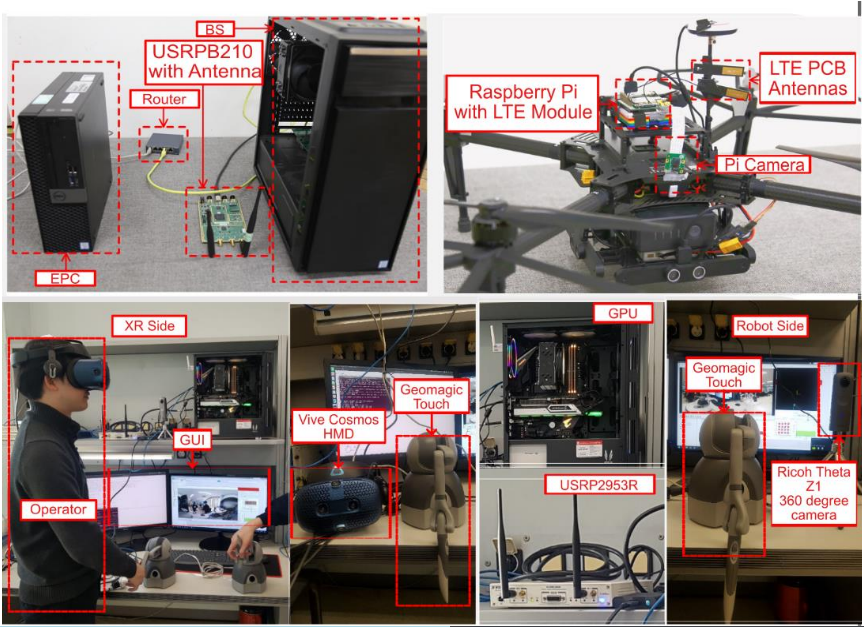
XR-aided Teleoperation



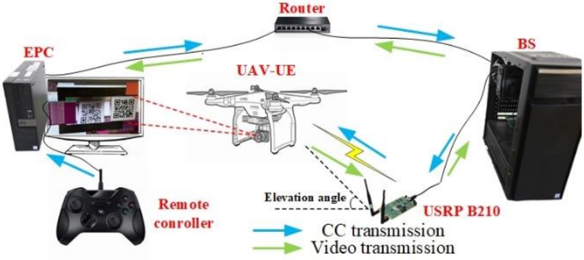
Testbeds and Trials: XR-aided Teleoperation

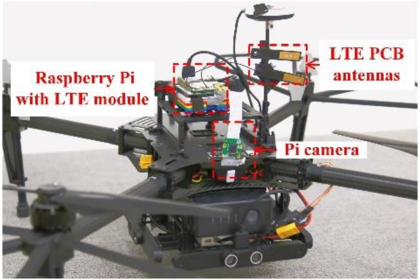


Testbeds and Trials: XR-aided Teleoperation

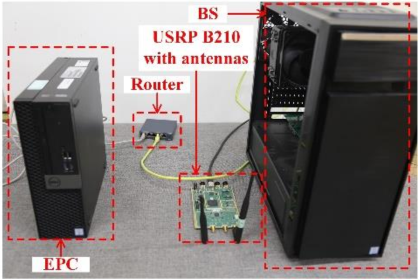


Testbeds and Trials: SDR-based UAV Network





(a) UAV-UE Setup



(b) GCS Setup

Testbeds and Trials: SDR-based UAV Network

Downlink

Algorithm 1 The procedure of sending control signal

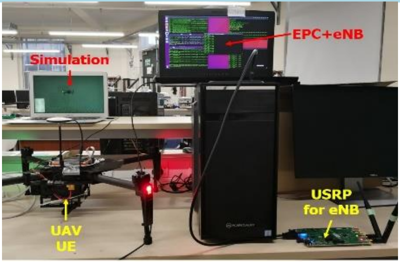
```
procedure CONTROL SIGNAL SENDING
    Initialise UDP socket
    Initialise Joystick
    Setting destination IPV4 address
    loop
        Obtain CC parameters roll, pitch, yaw, thrust
        Normalize CC parameters value
        Encode normalized CC parameters
        Send CC frame to destination
        Record frame ID and transmit time
        Wait for pre-set time
    Close socket
```

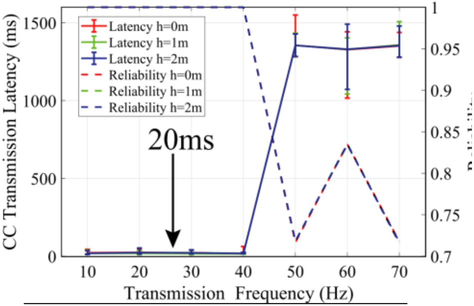
Algorithm 2 The procedure of controlling UAV-UE

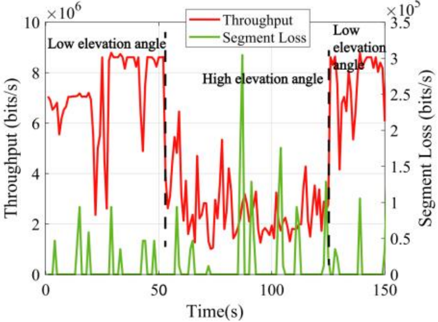
```
procedure CONTROLLING UAV-UE
    Initialize UDP socket
    Initialize UAV control API
    Set the control flag of the UAV
    loop
        Receive the CC frame data
        if data is not NULL then
            Set DJI API parameters to data
        else
            Set DJI API to zeros
        Send parameters and control flag through API
        Record frame ID and received time
        Sleep for 20 ms
    Close socket
```

Uplink - WebRTC: QR code for video transmission delay evaluation

Testbeds and Trials: SDR-based UAV Network







[3] H. Zhou, F. Hu, M. Juras, A. B. Mehta and **Y. Deng***, "Real-time Video Streaming and Control of Cellular-Connected UAV System: Prototype and Performance Evaluation," in IEEE Wireless Communications Letters, 2021.

Trials and Experiments: 5G Drone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Drones to the rescue!

By Mary-Ann Russon
Technology of Business reporter

1 May 2018

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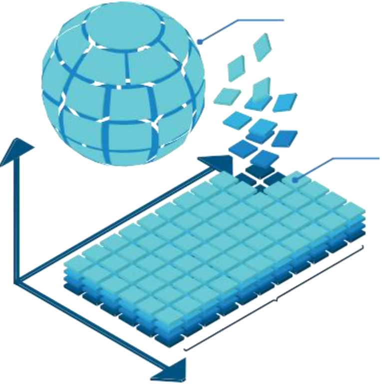
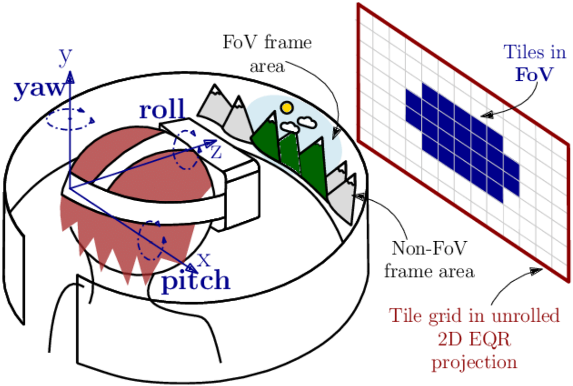
ERICSSON

1st 5G Drone

- World’s first 5G-drone trial where control goes over the Atlantic (22 Feb 2018)
- Trial between Ericsson, Verizon, BT and King’s College London
- http://www.bbc.co.uk/news/business-43906846

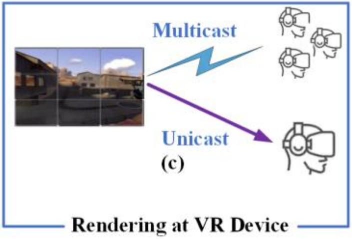
II: Machine Learning for Wireless VR Networks

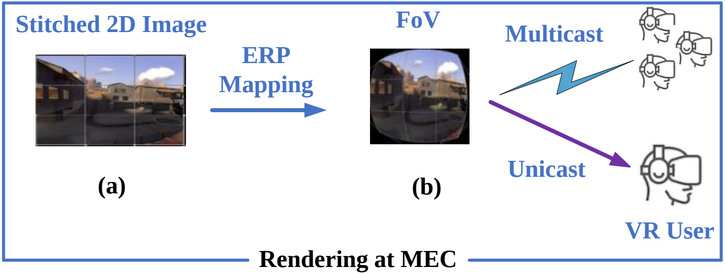




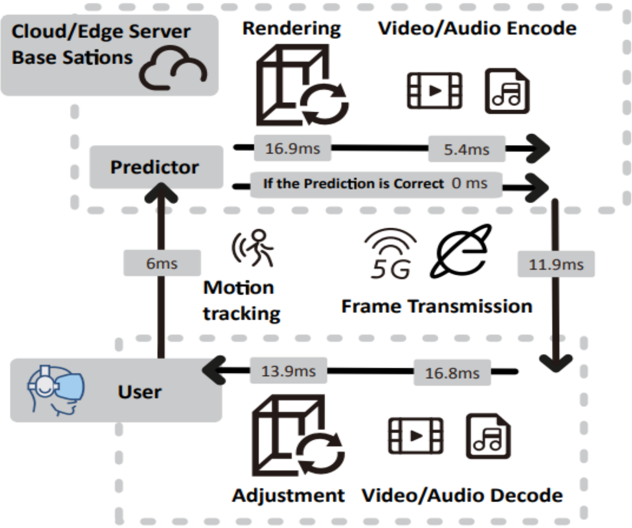
Equirectangular projection (ERP/EQR) and Field of View (FoV)

Wireless VR Rendering: Device or Edge





Wireless VR



Uplink: Head and Eye movements

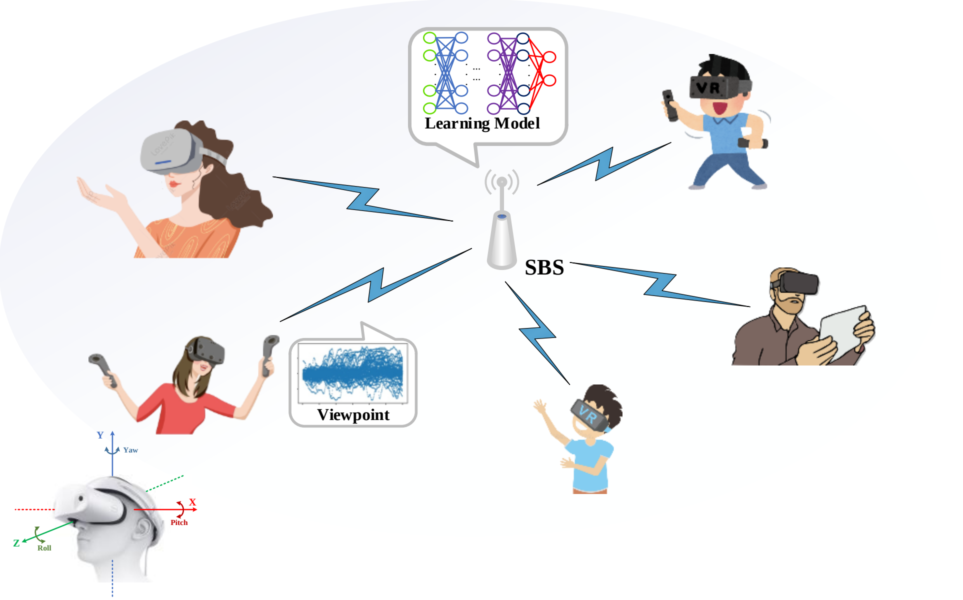
Render: Equirectangular Projection (ERP)

Downlink: FoV/VR video frame

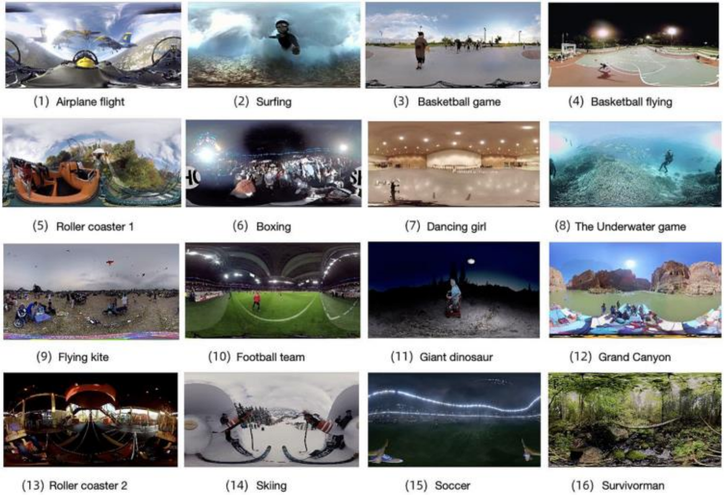
Viewpoint Prediction for Wireless VR Network

[4] X. Liu, X. Li, and **Y. Deng***, Learning-based Prediction and Uplink Retransmission for Wireless Virtual Reality (VR) Network, IEEE Trans. Veh. Technol., Oct. 2021.
[5] X. Liu, X. Li, and **Y. Deng***, Viewpoint Prediction and Uplink Retransmission for Wireless Virtual Reality (VR) Network, IEEE ICC, 2021.

I. Uplink Retransmission for Wireless VR

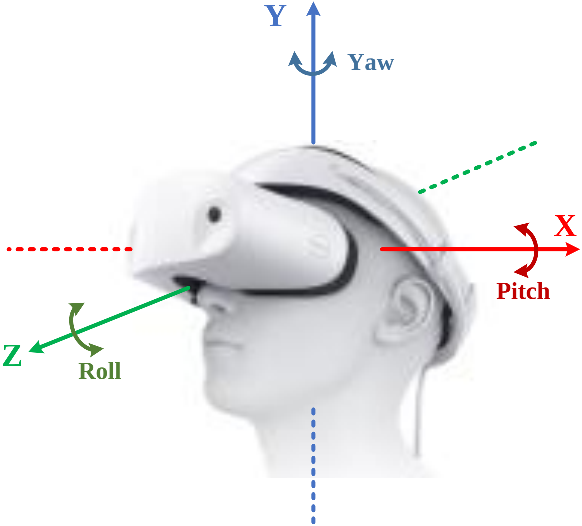


VR Data Description



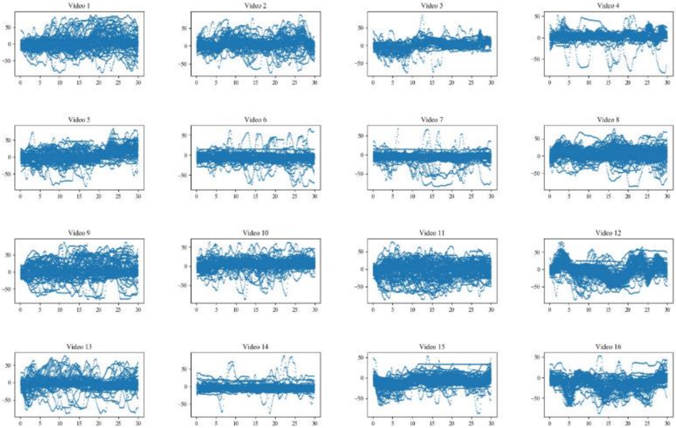
1. Three categories: Sports content, Landscape content, and Entertainment.
2. 16 VR videos, 153 VR users, each VR video has dozens of VR users.
3. Duration of each VR video is 30 seconds, and each VR video is divided into 300 equal parts.

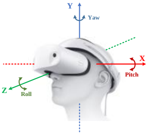
Viewpoint Direction



VR user viewing direction

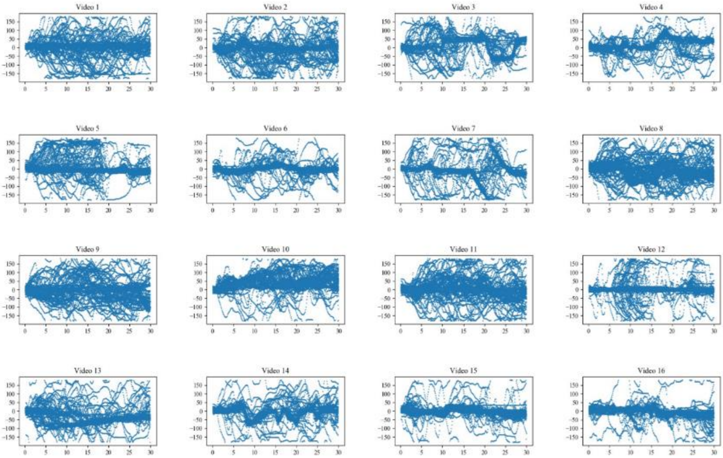
VR Data Description

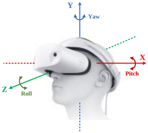




X angle distribution of all VR users

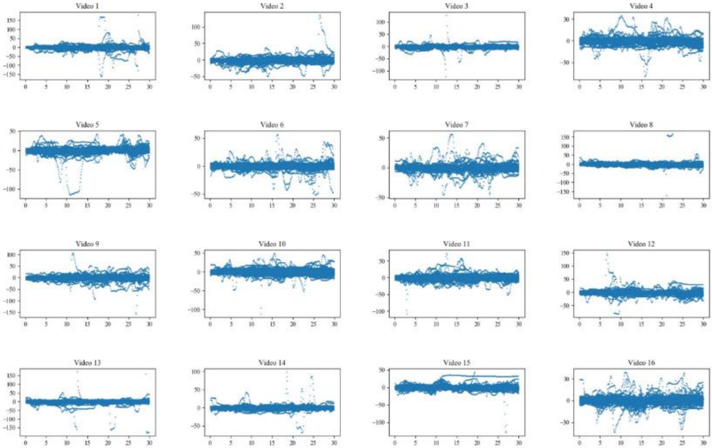
VR Data Description

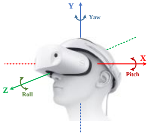




Y angle distribution of all VR users

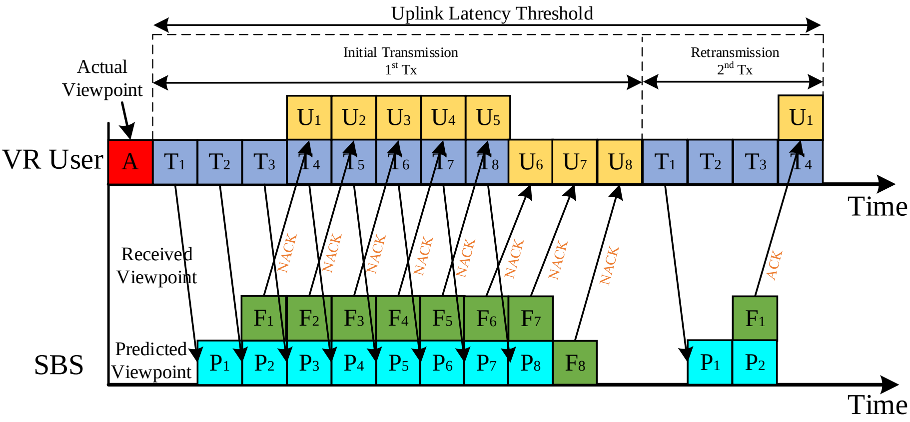
VR Data Description





Z angle distribution of all VR users

Proactive Retransmission Scheme

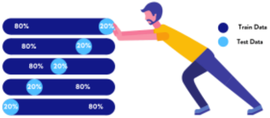


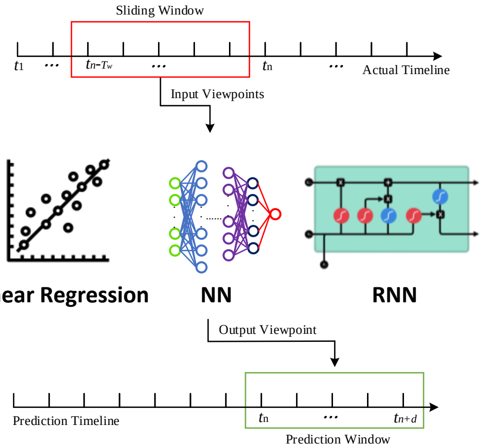
Proactive retransmission scheme

Problem Formulation:

$$\min \frac{1}{T^{tot} N} \sum_{t=1}^{T^{tot}} \sum_{k=1}^{N} (\mathbf{V}_t^k - \mathbf{V}_t^k)^2$$

Cross Validation



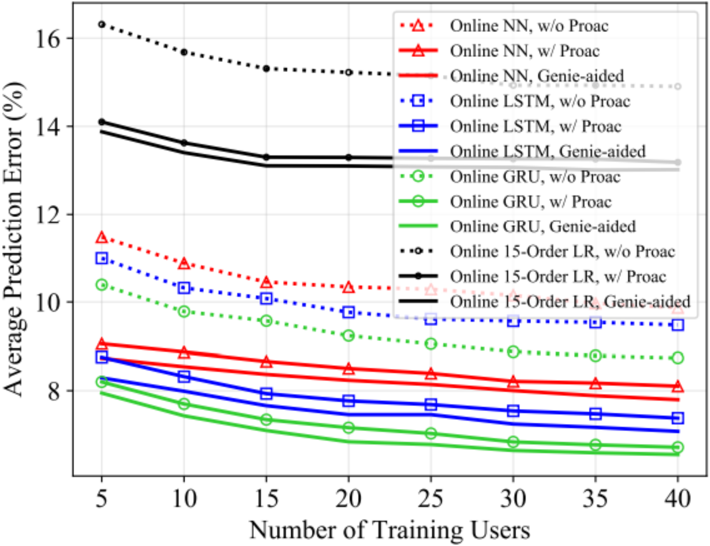


Online Learning Algorithms

Algorithm 1: The Proactive retransmission scheme integrated into Online Learning Algorithms with n-order LR, NN and LSTM/GRU

Initialize the order n of LR, parameters $\boldsymbol{\theta}^{\mathrm{LR}}$ or $\boldsymbol{\theta}^{\mathrm{NN}}$ or $\boldsymbol{\theta}^{\mathrm{RNN}}$, and sliding window size T_w.
Use K Cross Validation to train the parameters of the n-order LR, NN and RNN learning model.
for t = 1,...,T **do**
  Get historical viewpoint from the $(t - T_w)$th time slot to the $(t - 1)$th time slot from the updated sliding window.
  Use the updated online n-order LR, NN, LSTM/GRU to predict the viewpoint of the VR user for the tth time slot.
  The VR user transmits its actual viewpoint of the tth time slot via uplink transmission with the Proactive retransmission scheme.
  if the uplink transmission is successful **then**
    Update parameters $\boldsymbol{\theta}_t^{\mathrm{LR}}$ or $\boldsymbol{\theta}_t^{\mathrm{NN}}$ or $\boldsymbol{\theta}_t^{\mathrm{RNN}}$ of the n-order LR, NN and RNN learning model via (12), (15) and (16).
    Update the sliding window with the actual required viewpoint of the tth time slot.
  else
    $\boldsymbol{\theta}_{t-1}^{\mathrm{LR}} \rightarrow \boldsymbol{\theta}_t^{\mathrm{LR}}$ or $\boldsymbol{\theta}_{t-1}^{\mathrm{NN}} \rightarrow \boldsymbol{\theta}_t^{\mathrm{NN}}$ or $\boldsymbol{\theta}_{t-1}^{\mathrm{RNN}} \rightarrow \boldsymbol{\theta}_t^{\mathrm{RNN}}$.
    Update the sliding window with null of the tth time slot.
  end if
end for

Simulation Results



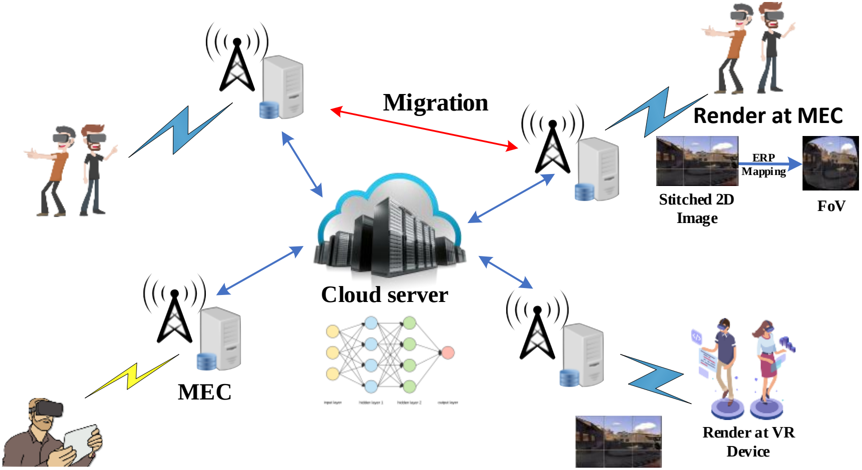
Average prediction error
(Multiple learning models)

MEC-enabled Wireless VR Network

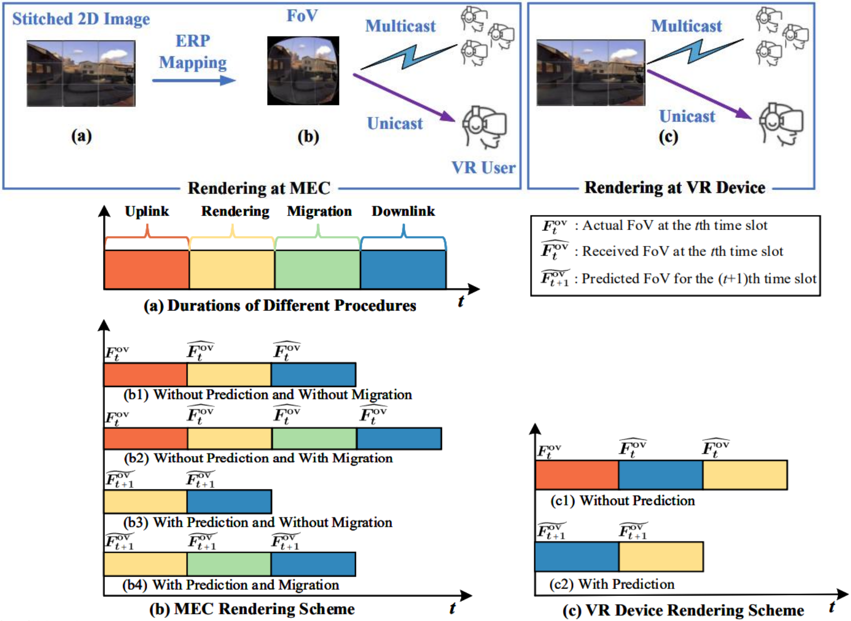
[6] X. Liu and **Y. Deng***, Learning-based Prediction, Rendering and Association Optimization for MEC-enabled Wireless Virtual Reality (VR) Network, IEEE Trans. Wireless Commun., Oct. 2021.

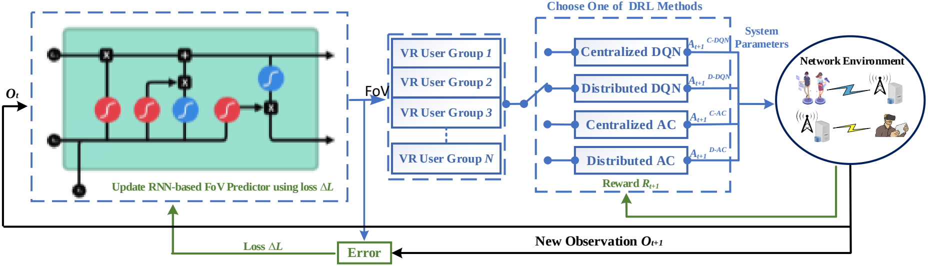
[7] X. Liu and **Y. Deng***, A Decoupled Learning Strategy for MEC-enabled Wireless Virtual Reality (VR) Network, IEEE ICC Workshop, 2021.

II. MEC-enabled Wireless VR



II. MEC-enabled Wireless VR





VR Quality of Experience

$$\mathrm{MSE}_k = (I_k - D_k)^2$$

$$\mathrm{PSNR}_k = 10\log_{10}\frac{1}{\mathrm{MSE}_k}$$

$$\mathrm{PSNR}_k = 10\log_{10}\frac{1+\Delta}{\mathrm{MSE}_k+\Delta}$$

Problem Formulation

$$\max_{\pi(A_t|S_t)} \sum_{i=t}^{\infty}\sum_{k=1}^{K}\gamma^{i-t}\mathrm{PSNR}_k^i$$

$$T_k \le T_k^{\mathrm{th}}$$

Distributed DQN/AC

$$\boldsymbol{\theta}_{\mathrm{DDQN}} = \frac{1}{K_{\mathrm{MEC}}}\sum_{i=1}^{K_{\mathrm{MEC}}}\boldsymbol{\theta}_i$$

$$\boldsymbol{\omega}_{\mathrm{DAC}} = \frac{1}{K_{\mathrm{MEC}}}\sum_{i=1}^{K_{\mathrm{MEC}}}\boldsymbol{\omega}_i$$

Reinforcement Learning

Network state

$$S_t = (\widetilde{\mathcal{F}_t^{\mathrm{oV}}}, \mathcal{L}_{k,i}^t, \mathcal{F}_i^{\mathrm{MEC}}) \in \mathcal{S},$$

$$\text{with } \widetilde{\mathcal{F}_t^{\mathrm{oV}}} = \{\widetilde{F_t^{\mathrm{oV}}}^1, \widetilde{F_t^{\mathrm{oV}}}^2, ..., \widetilde{F_t^{\mathrm{oV}}}^{K_{\mathrm{VR}}}\},$$

$$\mathcal{L}_{k,i}^t = \{l_{k,1}^t, l_{k,2}^t, ..., l_{k,B}^t,\},$$

$$\mathcal{F}_i^{\mathrm{MEC}} = \{F_1^{\mathrm{MEC}}, F_2^{\mathrm{MEC}}, ..., F_B^{\mathrm{MEC}}\},$$

Action space

$$A_t = \{\breve{\mathcal{A}}_{k,q}^t, \acute{\mathcal{A}}_{k,i}^t\} \in \mathcal{A},$$

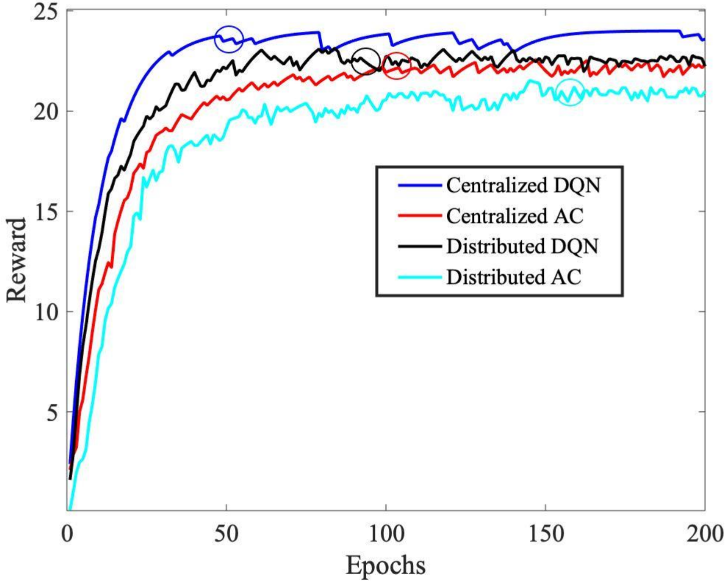
$$\text{with } \breve{\mathcal{A}}_{k,q}^t = \{\breve{A}_{k,1}, \breve{A}_{k,2}, ..., \breve{A}_{k,N_{\mathrm{FoV}}}\},$$

$$\acute{\mathcal{A}}_{k,i}^t = \{\acute{A}_{k,1}, \acute{A}_{k,2}, ..., \acute{A}_{k,K_{\mathrm{VR}}}\},$$

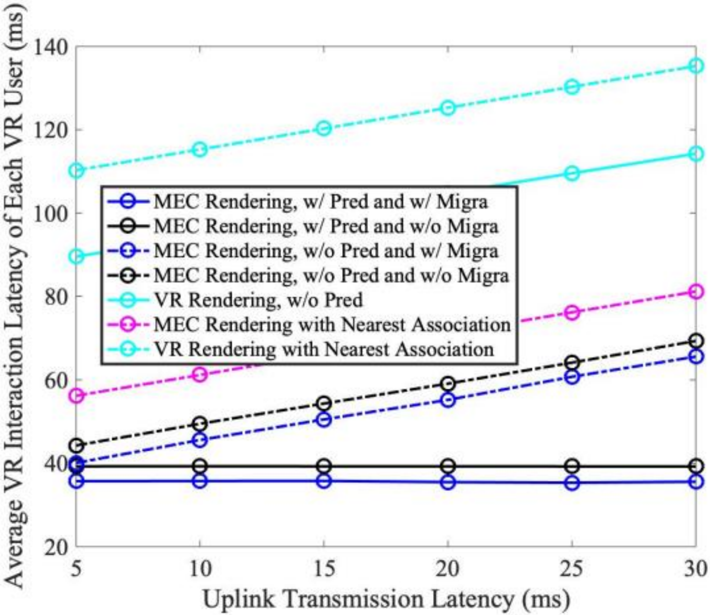
Immediate reward

$$R_t(S_t, A_t) = \sum_{k=1}^{K_{\mathrm{VR}}} \mathrm{PSNR}_k^t.$$

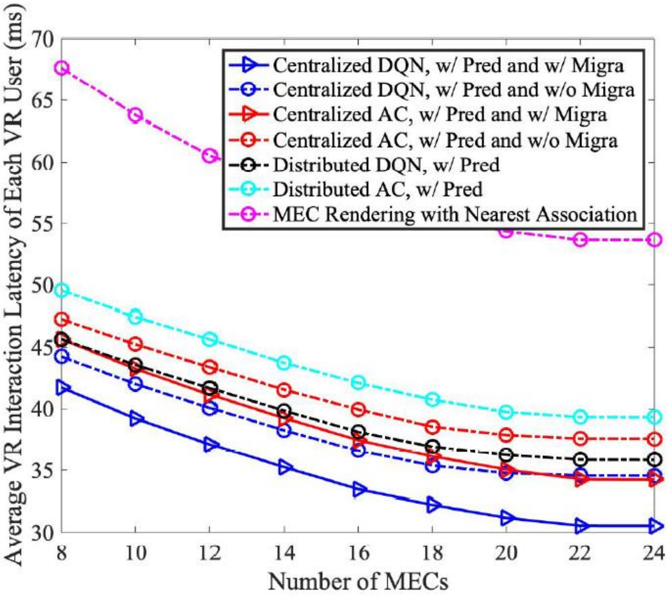
Simulation Results



Simulation Results

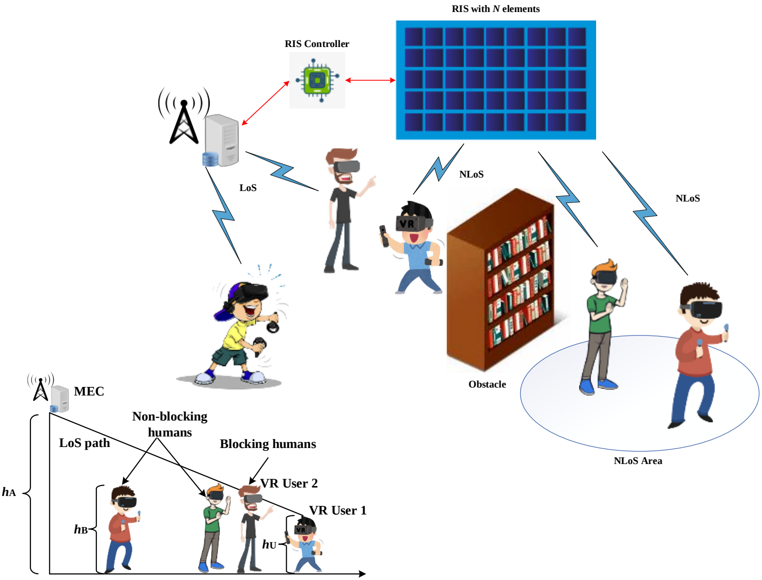


Simulation Results



RIS-assisted Thz Network for Wireless VR

[8] X. Liu, **Y. Deng***, C. Han, and M. Di Renzo, Learning-based Prediction, Rendering and Transmission for Interactive VR in RIS-Assisted THz Networks, IEEE J. Sel. Areas Commun., Feb., 2022.
[9] X. Liu, **Y. Deng***, C. Han, and M. Di Renzo, Ensemble Learning Strategy for RIS-Assisted Terahertz Virtual Reality Networks, IEEE Globecom, 2021.


RIS with N elements
RIS Controller
LoS
NLoS
NLoS
Obstacle
NLoS Area
MEC
Non-blocking
humans
LoS path
Blocking humans
VR User 2
VR User 1
hA
hB
hU

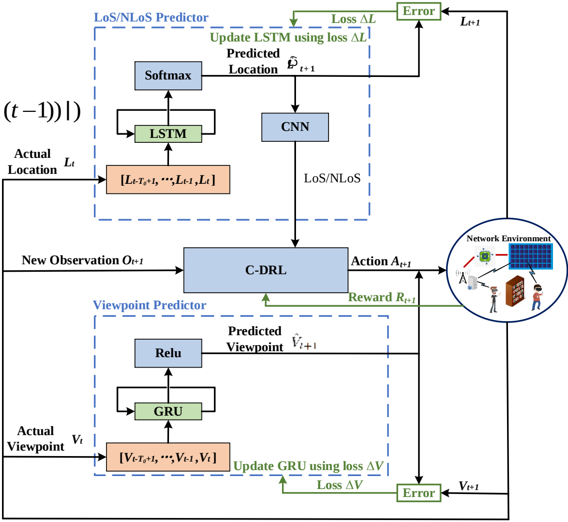
III. Learning Architecture

VR Quality of Experience

$$\delta_k(t) = \begin{cases} 1 & \text{if } \mathbf{V}_t^k = \mathbf{V}_t^k \\ 0 & \text{otherwise} \end{cases}$$

$$\mathrm{QoE}_k(t) = \delta_k(t)(q(R_k(t)) - |q(R_k(t)) - q(R_k(t-1))|)$$

$$q(R_k(\mathrm{t})) = \log\left(\frac{R_k^{\mathrm{down}}(t)}{R_{\mathrm{th}}^{\mathrm{down}}}\right)$$

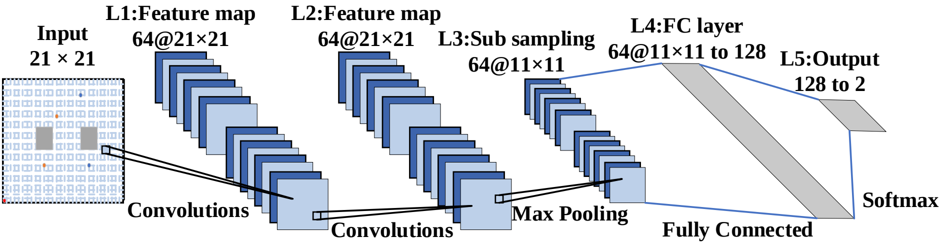


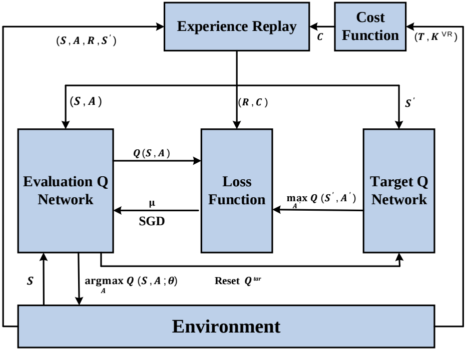
Problem Formulation

$$\max_{\pi(A_t|S_t)} \sum_{i=t}^{\infty} \sum_{k=1}^{K} \gamma^{i-t} \mathrm{QoE}_k(i)$$

$$T_{\mathrm{downlink}}^{k}(i) \le T_{\mathrm{downlink}}^{\mathrm{th}}$$

III. RIS-assisted THz Network for Wireless VR





III. Constrained DRL

- **Network state:**

$$S_t = (\mathcal{L}_t, \mathcal{I}_t, \widehat{\text{QoE}}_{t-1}) \in \mathcal{S},$$

$$\text{with } \mathcal{L}_t = \{L_t^1, L_t^2, ..., L_t^{K^{\text{VR}}}, \}$$

$$\mathcal{I}_t = \{I_t^1, I_t^2, ..., I_t^{K^{\text{VR}}}\}$$

$$\widehat{\text{QoE}}_{t-1} = \{\text{QoE}_{t-1}^1, \text{QoE}_{t-1}^2, ..., \text{QoE}_{t-1}^{K^{\text{VR}}}\}$$

- **Action space:**

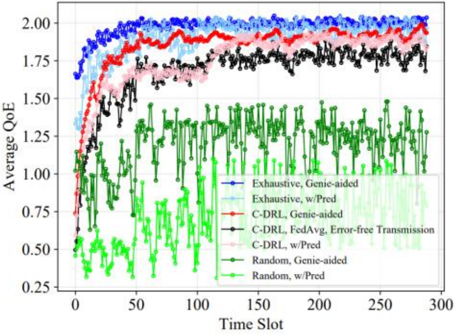
$$A_t = \{\widetilde{\boldsymbol{\Theta}}_t\} \in \mathcal{A}$$

$$\text{with } \widetilde{\boldsymbol{\Theta}}_t = \{\boldsymbol{\Theta}_t^1, \boldsymbol{\Theta}_t^2, ..., \boldsymbol{\Theta}_t^{\hat{L}^N}\}$$

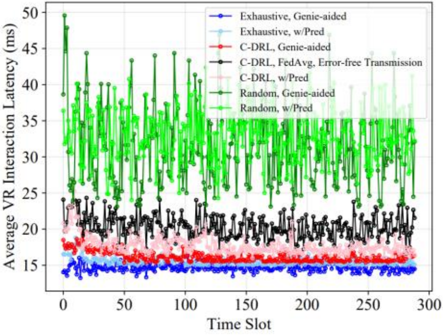
- **Immediate reward:**

$$R_t(S_t, A_t) = \sum_{k=1}^{K_{\text{VR}}} \text{QoE}_t^k$$

Simulation Results



(a)



(b)

VR Interaction Latency Constraint: 20 ms

III: Cooperative 360° Video Delivery Network: A Multi-Agent Reinforcement Learning Approach

[10] F. Hu, **Y. Deng*,** A. H. Hamid, "Correlation-aware Cooperative Multigroup Broadcast 360 Degree Video Delivery Network: A Hierarchical Deep Reinforcement Learning", in IEEE Trans. on Wireless Communications, 2021.
[11] F. Hu, **Y. Deng*,** and A. H. Aghvami, "Cooperative 360° Video Delivery Network: A Multi-Agent Reinforcement Learning Approach,"in Proc. IEEE ICC, 2021.

Cooperative 360° Video Delivery

Figure: Video Capturing from Multiple Viewpoints.

- **Enhance the sport audiences' experience**
- Capture massive amounts of volumetric video (from multiple UAVs).
- Allows audiences to customize the views.
- End-to-end video delivery from remote camera (UAV) to virtual reality (VR) audiences.

Intel, "Intel True View - Intel in Sports", 2020. [Online]. Available: https://www.intel.co.uk/content/www/uk/en/sports/technology/true-view.html

360° Video Sharing in Large Events

- **Challenges:**
- High capacity and uniform VR video service
- Enhanced reception of UAV's signal
- **Potential Solutions:**
- Broadcast the correlated tiles between VR users.
- A cooperative network for VR video reception and transmission.

Discrete Video Resource

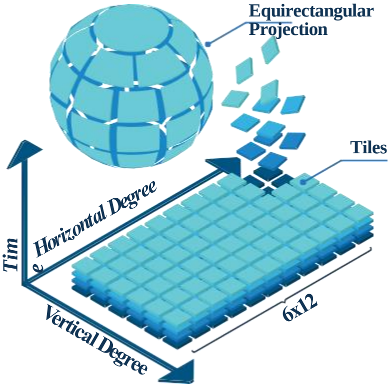


Figure: Tile-based VR Video and 3D-2D mapping.

- **Tile-based DASH VR Video:**
- Video frame is decomposed into tiles.
- Each tile is $30^\circ \times 30^\circ$.
- 6×12 tiles in each 360° video frame.

Dependent Video Codec

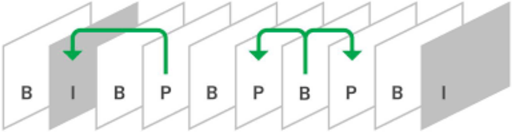
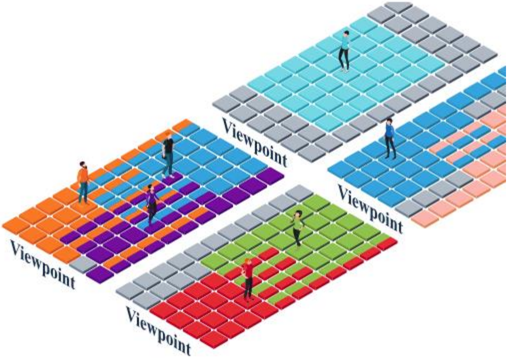


Figure: Tiles are decoded dependently within each GOP.

- Dependent tiles within each group-of-pictures (GOP).
- Intro-frame (I) can be decoded independently.
- Predictive tile (P) requires the previous tile to decode.
- Bi-directional tile (B) is ignored.

360° Video Sharing in Large Events



VR DASH Video Transmission with User Correlation

- Users request titles based on their viewpoints
- Tile requests correlate
- Allows audiences to customize the views.

Cooperative Cell-free Network

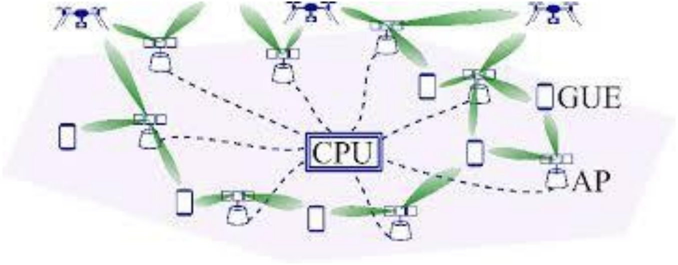


Figure: Cell-free network.

- **Benefits:**
- Ensures the cell-edge performance.
- Enhance the service quality for broadcast.

S. Buzzi and C. D’Andrea, "Cell-free massive MIMO: User-centric approach," IEEE Wireless Commun. Lett., vol. 6, no. 6, pp 706-709, Dec. 2017.

User-centric Cell-free Network

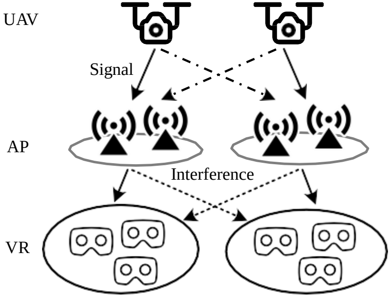


Figure: Access points (AP) are clustered to jointly receive video data from UAV and broadcast to VR users.

- **Basic idea of cell-free network:**
- APs are grouped into multiple virtual-cells.
- Each virtual-cell receive from target UAV and broadcast.

- **The association for APs becomes the major problem.**
- Manage the trade-off between inter-cell interference and transmission efficiency.

S. Buzzi and C. D'Andrea, "Cell-free massive MIMO: User-centric approach," IEEE Wireless Commun. Lett., vol. 6, no. 6, pp. 706-709, Dec. 2017.

Network Transmission Procedures

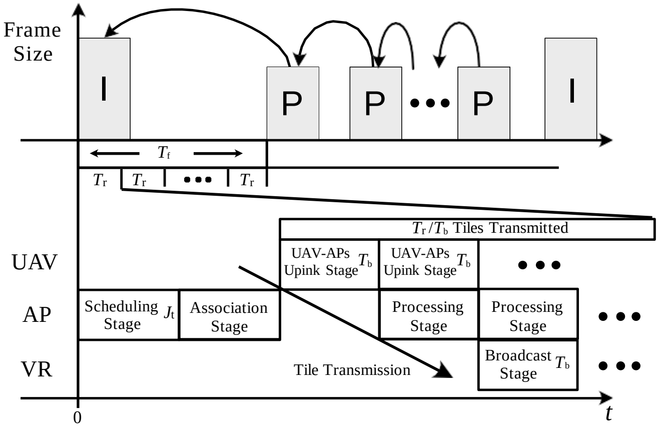


Figure: Tile is received and broadcast from UAV to VR users in three steps.

Channel Model

- **UAV-APs Uplink**

$$y_{u^*,\mathcal{B}_t^u} = \sum_{b\in\mathcal{B}_t^u} w_b \Big[\underbrace{h_{u^*,b} s_{u^*}}_{\text{Signal}} + \underbrace{\sum_{u'\in\mathcal{U}_t\setminus u^*}^{\mathcal{U}} h_{u',b} s_{u'}}_{\text{Interference}} + \underbrace{n_0}_{\text{Noise}} \Big], \quad (1)$$

w_b is a general weighted MRC scheme with weight, $h_{u,b}$ denotes the channel vector from the uth UAV to the bth AP.

- **APs-VR Downlink:**

$$y_{\mathcal{B}_t^u,v^*} = \underbrace{\sum_{b\in\mathcal{B}_t^u} h_{b,v^*} w_b s_b}_{\text{Signal}} + \underbrace{\sum_{b'\in\mathcal{B}\setminus\mathcal{B}_t^u}^{\mathcal{B}} h_{b',v^*} w_{b'} s_{b'}}_{\text{Interference}} + \underbrace{n_{v^*}}_{\text{Noise}} \quad (2)$$

w_b is a general weighted MRT scheme with weight, $h_{b,v}$ denotes the channel vector from the bth AP to vth VR user.

The Successful Decoding of Tile

$$\mathbb{1}[j \in \mathbf{J}_t^v] = \begin{cases} \mathbb{1}[D_{u,v} \geq \mu M_{\mathrm{T}}], & t < T_{\mathrm{f}}, \\ \mathbb{1}[D_{u,v} \geq \mu M_{\mathrm{T}}] \wedge \underbrace{\mathbb{1}[j' \in \mathbf{J}_t^v]}_{\text{Previous Tile Decode State}}, & t \geq T_{\mathrm{f}} \end{cases}$$

- j is required to be decoded with j^I incrementally
- Both UAV-APs uplink and APs-VR broadcast channel need to satisfy the capacity requirement

Quality-of-experience Metric

Peak Signal-to-noise ratio (PSNR) describe the ratio between desired video frame and the information loss in each frame.

$$\text{V-PSNR}_t^v = 10\log_{10}\left(\frac{1}{1+\frac{1}{|\mathcal{J}_t^v|}\left(|\mathcal{J}_t^v| - \sum_{j\in\mathcal{J}_t^v} \mathbb{1}[j \in \mathbf{J}_t^v]\right)}\right),$$

- $\mathbf{J}_t^v$ is the decoded tile set
- The value increase with the number of successfully decoded tiles inside the viewpoint.

Optimization Target

We study how the association algorithm dynamically optimize the overall time-accumulative V-PSNR value within each GOP.

$$\max_{\pi_s, \pi_a} \mathbb{E}[\sum_{t_b=0}^{T_{GOP}} \underbrace{\sum_{j \in J_{t_b}} \sum_{v \in \mathcal{V}_j} \Delta\text{V-PSNR}_{t_b}^{v}]}_{\text{V-PSNR Gain in } T_b \text{ for scheduled tile set } J_{t_b}} ,$$

- The V-PSNR gain is denoted as
  $\Delta\text{V-PSNR}_{t_b}^{v} = \text{V-PSNR}_{t_b}^{v} - \text{V-PSNR}_{t_b-1}^{v}.$
- The problem can be seen as finite Markov Decision Process.

Complex Association Problem

Association for AP and corresponding VR users

APs are dynamically clustered based on association decision

Complexity of dynamic clustering problem increases exponentially with:

- The number of cells
- The size of cluster

↓

Impossible for centralized processor to make decisions

Reinforcement Learning-based Algorithm

The algorithm decides the association decision for all APs dynamically, which introduce **dimensional explosion** problem.

- **Challenges:**
- Action space increase **exponentially** with the number of APs.
- High-dimensional environment.

Distributed Multi-agent System and Mean Field Theorem

Separate the state for each AP as effective/non-effective parts and solve it via mean-field theorem.

- Each AP holds an agent
- Each AP observes surrounding environment (effective state)
- Each AP makes its decision

Grid-based Observation

We design a grid-based observation to capture the complex environment.

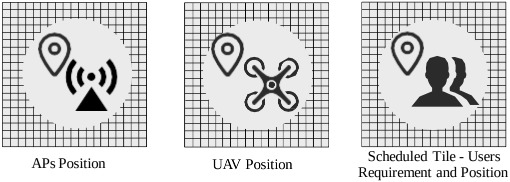


Figure: Grid-based Observation for each AP.

- The first grid-map present the position of UAV (1 if exist, 0 else).
- The second grid-map present the position of AP (1 if exist, 0 else).
- The third grid-map present the overall request in each grid.

Convolutional Neural Network

Convolutional Neural Network (CNN) is shown helpful in capturing the complex spatial information from the environment.

- Convolution operation matches the calculation of gain and interference.
- Estimate the path-loss via geometry distance.

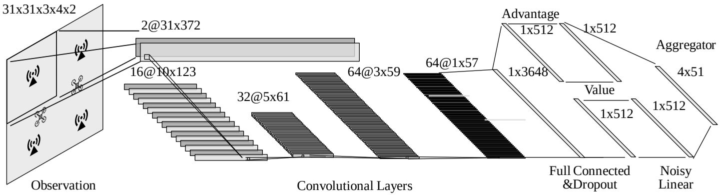


Figure: Network structure for each agent’s neural network.

Rainbow Agent with Distributional RL

The major motivation of applying rainbow is the distributional reinforcement learning approach. The value of state s is

$$v_b(s) = \sum_{a_b \in \mathcal{A}_b} \pi_{\mathrm{a}}^{b}(a_b | s, (\mathbf{a}_{-b})) \mathbb{E}_{a_b, (\mathbf{a}_{-b}) \sim (\pi_{\mathrm{a}}^{-b})} [q_b(s, a_b, (\mathbf{a}_{-b}))].$$

- The random nature of wireless channel and unknown association decision $\mathbf{a}_{-b}$ from other AP.
- Necessary to estimate the distribution of value

Conventional Association Methods

- **Cell-based association:**
  Each AP is associated to the largest VR user group nearby.

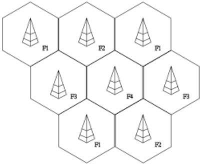


Figure: Cell-based association.

- **Cell-free association:**
  All AP serves one group of UAV and VR user group together.

Performance Problem

Neighboring base stations' actions are unknown

Reward of certain decision is realized with neighboring base stations' cooperation

Base stations have to guess their neighbors' action

Parameter Sharing for Wireless Communication Network

Influence range limited by fading nature of wireless signal

Local problems are similar

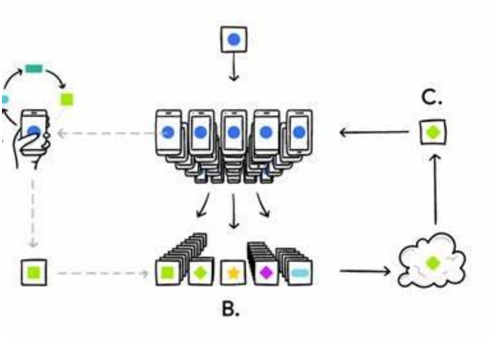
Experience is worth to share among

Federated Approach

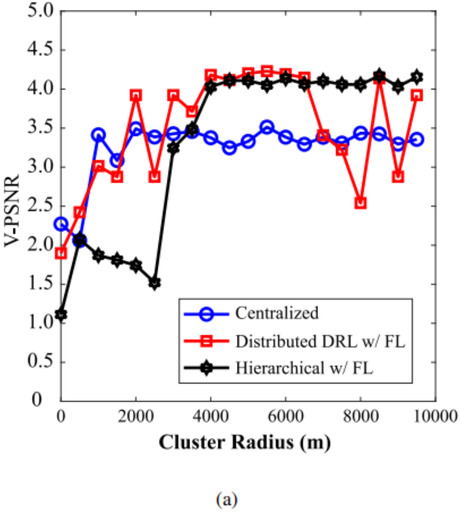
Federated Learning for Parameter Sharing

Average the network parameters from all base stations

Aggregate and share knowledge and accelerate the learning

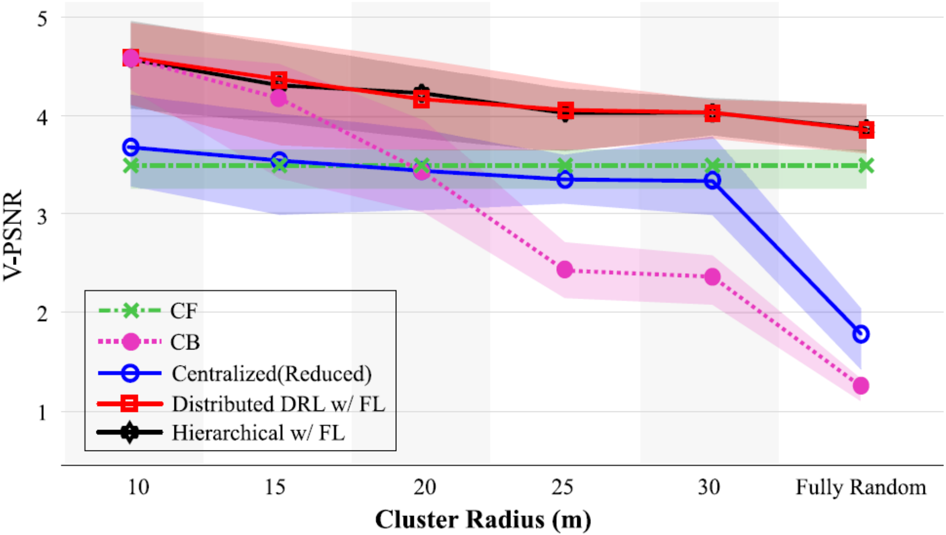


Results



V-PSNR
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0
0
2000
4000
6000
8000
10000
Cluster Radius (m)
Centralized
Distributed DRL w/ FL
Hierarchical w/ FL
(a)
V-PSNR
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0
0
1
2
3
4
5
6
Epochs
×10^4
Distributed DRL w/o FL
Hierarchical w/o FL
(b)

V-PSNR vs the Number of Broadcast Slots



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[13] X. Liu, **Y. Deng** and T. Mahmoodi, "A Novel Hybrid Split and Federated Learning Architecture in Wireless UAV Networks", in Proc. IEEE ICC'22, Korean, Jun. 2021.
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Thank you

Thanks for your attention!
We are recruiting!