Channel-Aware MEC Optimization for Low-Latency Mobile 360 Video Streaming using Reinforcement Learning

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Abstract

Recently, it has been studied to support the streaming of 360-degree mobile virtual reality video (MVRV) by a mobile edge computing (MEC). Live MVRV requires low-latency with high resolution, which is challenging to the conventional server-user communication. Recent works have investigated the method how the MEC enables the ultra-reliable and low-latency communication in the live MRVR streaming. A novel method is to predict the FoV (field-of-view) and cache the corresponding video chunks, while streaming only the video chunk of user's FoV rather than whole video chunks is preferred. In this work, we extend the previous works suggesting to predict the FoV to a channel-aware online MEC optimization for the amount of predicted video and offloading at MEC. Though this work sketches the optimization problem and the solution by reinforcement learning, we will soon present the related numerical results as a future work.

1. Introduction

Recently, discussions regarding virtual reality (VR) have dominated research in recent years. It requires to stream a high resolution video of 360-degree with a harsh constraint of delay. Currently, research in the area of mobile virtual reality video (MVRV) does not include only the traditional approaches such as increasing the transmission rate or deceasing the required bandwidth, but also utilizing the additional caching, computation, and communication (3C) which can be provided by mobile edge computing (MEC).

To reduce the required bandwidth, recent literature focuses on the advanced video coding method, which is field-of-view transmission. It transmits user's current FoV with relative high quality compared to transmitting full-view. Considering the physical characteristic of MVRV, FoV transmission can achieve a better result in a practical situation of insufficient communication resource.

Though FoV transmission enhances the streaming quality, the required bandwidth to support the live MVRV streaming is still overwhelming. To alleviate this issue, the latest literatures have applied the artificial intelligence (AI) to predict the FoV in future based on the FoV history, or route of head motion. Proactive caching is applied with the predicted FoV in order to satisfy the delay limit allowed by users. As a pioneer work, [1] has proposed the FoV prediction for efficient bandwidth usage in 360 video streaming and validated its effectiveness by numerical results showing high accuracy.

As an alternative approach, it has been actively studied to leverage the caching and computing power available at the MEC server, which supports the service at the edge of the network [2,3]. In MVRV streaming, end-to-end (E2E) delay is a strict constraint, which consists of computation delay and communication delay. The image processing requires heavy computation resource which is often insufficient in the user's head-mounted display (HMD). Offloading the computing tasks to MEC server can alleviate the computation burden causing the low quality of service.

Since the head motion prediction is also computation consuming, it has been proposed to offload the prediction to MEC in [4]. In [4], a 360 MVRV streaming scheme jointly considering the video coding, proactive caching, offloading of rendering and head motion prediction is suggested. It derives the probability density function of E2E delay. Numerical result reveals the effect of system parameters to E2E delay.

2. Proposed scheme

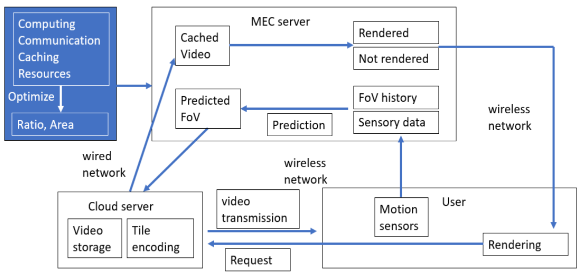

Figure 1. system model

Though the functions and protocols are well defined for the 360 MVRV streaming with the head motion prediction in [4], we observe that the scheme is too straightforward and does not optimize the E2E delay for the given constraints. Optimizing the rendering ratio can improve the quality of service since the rendering ratio has its trade-off between the communication delay and the computation delay. We propose to make the area of FoV prediction variable. Optimizing the area improves the performance since it has clear trade-off between the communication delay and the hit rate in caching. *In this work, we suggest to optimize the rendering ratio and the area of FoV prediction. Additionally, we assume fading channel, storage constraint, and power constraint, considering a practical wireless environment.*

Now, we design the optimization problem when the system model is defined as in Figure 1. MEC server predicts the FoV based on the FoV history and sensory data given from the user's sensor. After the cloud server returns the video tiles of the predicted FoV, MEC server renders the cached videos with a specific ratio. When the actual FoV is determined, user sends a request of missing tiles to the cloud server. Finally, the user combines the video tiles after rendering the not rendered tiles which are from cached video and returned video from the cloud server.

We propose the optimization problem as below. The problem includes controlling the area of FoV prediction, rendering ratio, and power allocation. It aims to minimize the total delay which consists of caching, communication, computation under the constraints of delay, storage, transmission rate, and power constraint.

$$\min_{FoV(t),r_{rend}(t),P_i(t)} D_{caching}(t) + D_m(t) + D_{m,u}(t) + D_{u,0}(t) + D_{c,u}(t) + D_{u,1}(t)$$

$$D_{caching}(t) + D_m(t) + D_{m,u}(t) + D_{u,0}(t) + D_{c,u}(t) + D_{u,1}(t) < D_{th}$$

$$c_{dec} * V(FoV(t)) < S_m$$

$$c_{dec} * c_{rend} * V(FoV(t))) < S_m$$

$$D_{caching} = D_{pred}(FoV(t)) + V(FoV(t))/R_{c,m}(t)$$

$$D_m(t) = Rendering(r_{rend}(t) * V(FoV(t)))/Comp_m,$$

$$D_{m,u}(t) = ((1 - r_{rend}(t)) * V(FoV(t)) + r_{rend}(t) * c_{rend} * V(Fov(t)))/R_{m,u}(t$$

$$D_{u,o}(t) = Rendering((1 - r_{rend}(t)) * V(Fov(t)))/Comp_u$$

$$D_{c,u}(t) = rf(t) * V(Fov(t))/R_{c,u}(t)$$

$$D_{u,1}(t) = Rendering(rf(t) * V(Fov(t)))/Comp_u$$

$$R_{i,j}(t) = log_2(1 + \|h_{i.j}\|^2 * P_i(t))$$

$$\frac{1}{T}\sum_t P_i(t) < \bar{P}$$

The first three constraint correspond to the delay and storage. Following equations define the delay of communication and computing. Remaining equation defines the transmission rate and the final inequality describes the power constraint.

This optimization problem has two significant trade-off relation of communication and hit ratio or computation, which are correlated with the channel gain and power allocation. In our future work, we are planning to provide a closed-form solution for a simplified problem and a reinforcement learning (RL)-based solution for a generalized problem.

3. Conclusion

In this work, we consider a MEC-based low latency 360 MVRV streaming. We establish a generalized optimization problem. It optimizes the area of FoV prediction, offloading ratio, and power allocation under the storage, computing, transmission, and delay constraint. It includes two significant parameter of trade-off between communication and hit ratio or computing. As our future work, we are planning to provide a closed-form solution for a simplified problem and a RL-based solution for the established generalized problem.

4. Acknowledgements

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5. Reference

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