

Measuring Millimeter Wave based Link Bandwidth Fluctuations during Indoor Immersive Experience

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Abstract—This letter presents the results of motion-tracking synchronized millimeter wave (mmWave) link bandwidth fluctuations while a user is engaged in immersive augmented/virtual reality applications. Our system, called MITRAS, supports extensive exploration of human-induced impacts on mmWave link bandwidth during immersive experience. MITRAS adopts the packet train measurement application to track link bandwidth fluctuations. Meanwhile, the user movements are tracked using an Oculus Quest 2 headset. Through investigating the impacts of human movements on link bandwidth fluctuations, we further propose a link state prediction model to shed light on higher layer protocol design for immersive applications over mmWave links.

Index Terms—motion-tracking, immersive application, augmented/virtual reality, mmWave, packet train, prediction.

I. INTRODUCTION

Immersive augmented/virtual reality (AR/VR) applications require high-throughput (Gbps level) and low-latency connectivity for real-time delivery of rich interactive content. Meanwhile, untethered (wireless) access between the AR/VR device and the access point (AP) is essential for better user experience.

Unlike the sub-6 GHz band, the millimeter wave (mmWave) spectrum is highly directional. As a result, they require stricter alignments of the transmitter and the receiver beams. Furthermore, the signal attenuates up to 20 dB at 60 GHz band over non-line of sight (NLOS) path, causing severe link bandwidth degradation. The deterioration in mmWave link bandwidth is usually alleviated, after some delay, by adaptive beam management. Therefore, the mmWave link is in poor condition until the new optimal beam is built, which in turn increases higher layer latency and reduces higher layer throughput. A user's immersive AR/VR experience contains frequent interactions between the user and contents. These interactions incurs movements, such as walking and rotation, which impact on mmWave link bandwidth. This frequent impact together with the latency in beam management, in turn, adversely affects the quality of immersive AR/VR experience.

One can alleviate the degradation in user experience by modifying the behavior of higher layer network protocols. Such modifications, however, require knowledge of the link behavior. In particular, the higher layers can take advantage of predictions of the short-term future link conditions based

on knowledge of the user movements in the immersive experience. In this paper, we present results of network layer measurements of link bandwidth fluctuations along with measurements of the user movements. From these measurements, we show that one can build a learning model to help predict link conditions in the near future. The learning model is fairly simple and highly adaptive. Moreover, these measurements and the learning model can be easily integrated into both WiFi and 5G networks.

Studies of mmWave channels is not new [1]–[4]. Over the past decade, mmWave channels have been studied particularly as part of the development of standards such as IEEE 802.11ad [5], IEEE 802.11ay [6], and 5G New Radio (NR) [7]. These studies are mainly designed for developing physical and link layer solutions. In this paper, we focus on measurements targeted on the impact of mmWave links on network layer and above, especially in the context of indoor, immersive AR/VR applications. Note that, network layer bandwidth fluctuations are “aggregate” impacts of channel quality fluctuations and physical and link layer solutions to mitigate deleterious effects of channel quality fluctuations. For example, the data rate observed at network layer is impacted by channel quality, physical layer coding, physical layer modulation, link layer adaptive repeat requests (ARQ) strategies, beamforming solutions, etc. Although, there are many papers on channel characteristics, there are not many papers that measure network layer bandwidth fluctuations along with user movements, and develop a simple learning model to predict near future network layer conditions.

Similarly, there is a large body of literature focused on dealing with the characteristics of mmWave channels at different layers of the protocol stack. For instance, Sur *et al.* propose MUST to predict the best beam and to redirect user traffic over conventional WiFi when there is blockage in the mmWave link [1]. Although MUST provides the solution at the physical layer, higher layer performance enhancement in mmWave accessed network is needed, especially in networks with multi-connectivity [4], [8], [9]. In a multi-connectivity scenario, [9] proposes a cross-layer design to choose the optimal wireless path through the transport layer interfaces. In [2], Li *et al.* describe a camera video analysis testbed using mmWave relay data plane with the assist of sub-6G control plane. This testbed supports agile re-routing when a mmWave link fails. The importance of scenario consideration in mmWave network is also mentioned in [2]. With the release of 5G NR [7], the mmWave channel modeling is proposed in NYUSIM [3] with the simulations in physical and link layers in 5G cellular communications.

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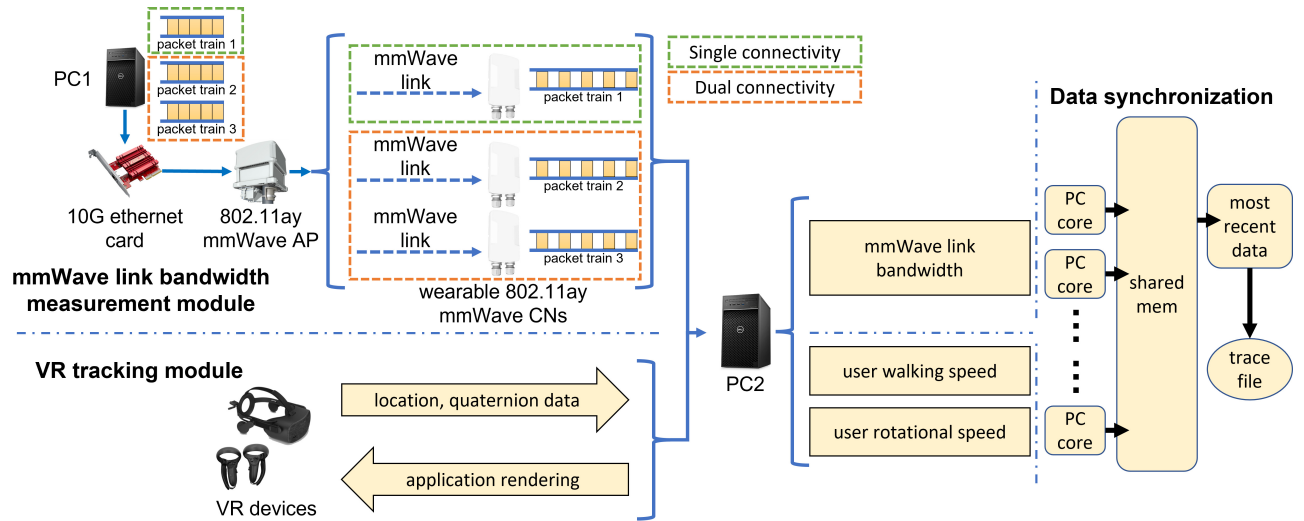


Fig. 1: Structure of MITRAS measurement system

II. MITRAS MEASUREMENT SYSTEM

Fig. 1 shows the structure of our Millimeter wave Immersive application TRacking System (MITRAS) measurement system and Fig. 2 depicts a user interacting with an immersive AR/VR application in MITRAS using single and dual connectivity respectively. The MITRAS measurement system includes the VR tracking module, the mmWave link bandwidth measurement module, and a data synchronization process. In this system, the user wears an Oculus Quest 2 headset. The headset is connected to the network over a wireless link, allowing for free user movement as needed for the immersive experience. Since there is no mmWave interface on Oculus Quest 2 headset, in addition, the user wears client node (CN) devices connected to the network over IEEE 802.11ay mmWave based wireless links. The dual connectivity in MITRAS is supported by two mmWave CNs for more transmission opportunities. The system logs the user movements from the Oculus Quest 2 headset. Simultaneously, it also logs the network layer link bandwidth in each of these IEEE 802.11ay wireless links. Since this occurs in an indoor environment, the user movements are always in the vicinity of the IEEE 802.11ay AP (also shown in Fig. 2). However, due to the directional nature of the mmWave channel, the network layer link bandwidth fluctuates as the user moves during an immersive VR application.

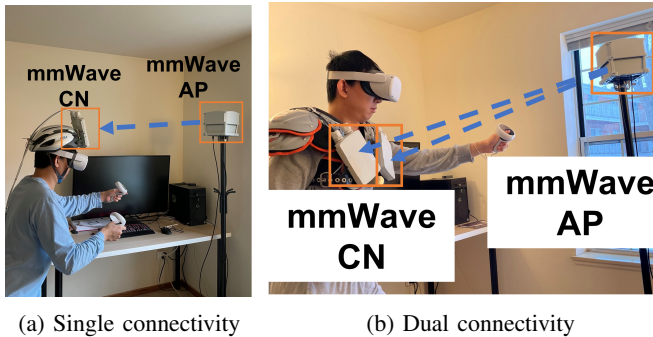


Fig. 2: MITRAS setup

A. VR tracking module

The VR tracking module is based on the Oculus Quest 2 and OpenVR. This module tracks the location and movement of all devices involved in VR applications, including the VR headset and two controllers. The VR devices are connected to PC2 with a wireless connection. The PC2 runs and renders the VR application and the corresponding views on the VR headset. The VR devices send the real-time position and orientation information to PC2 once every few milliseconds. With this information, the VR tracking module calculates the user's walking speed (m/s) and rotational speed (rad/s).

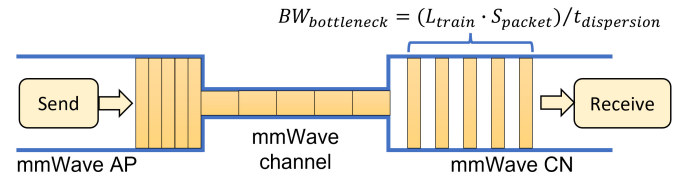


Fig. 3: Packet train illustration

B. mmWave link bandwidth measurement module

In this module, we measure the bandwidth of each mmWave link separately. The link bandwidth measurement is achieved using packet train, which is derived from the concept packet pair [10]. The packet pair measures the smallest-bandwidth link (i.e. bottleneck link) in the route from the sender to the receiver (e.g. PC1 and PC2 in MITRAS) by transmitting two back-to-back measurement packets. This technique relies on the observation that these two packets are usually queued and transmitted in a back-to-back manner. If this observation holds, the time space between these two packets (i.e. time dispersion) is inversely proportional to the bandwidth of the bottleneck link. In MITRAS, when the mmWave link bandwidth is high (e.g. in line of sight (LOS) situation), the time dispersion is very small and the receiver clock may not be accurate enough to measure time dispersion accurately.

For an accurate measurement, we use a train of measurement packets, instead of a pair. This idea is illustrated in Fig. 3. One packet train is a group of packets, sent from PC1

through the mmWave AP. As shown in Fig. 3, ideally, all the packets in the train are queued and then later transmitted back-to-back on the mmWave link. Once the receiver PC2 receives a packet train through a mmWave CN, it calculates the bottleneck bandwidth along the path according to the train length and the time dispersion in the bottleneck. For better measurement of a packet train, PC2 randomly samples different consecutive sections from a packet train and takes the average of the measurement results of these sections. If L_{train} is the length of one random section in a packet train and the packet size is S_{packet} , then the relationship to bottleneck bandwidth in this section can be shown as $BW_{bottleneck} = (L_{train} \cdot S_{packet}) / t_{dispersion}$ [10].

C. Data synchronization

In the implementation, in order to synchronize measurement data in real time, the VR tracking and the packet train measurements are executed as multiple independent processes on different PC cores. During the measurement, these cores forward the measured data into the shared memory. Meanwhile, the synchronizing process fetches the most recent data from the shared memory once there is new data forwarded into the memory. The interval of the most recent data fetching process is also in millisecond level. This interval aligns with the shortest interval during the measurement in previous two modules. In this way, the measurements are synchronized with their most recent measured results. Finally, these synchronized results are output as the traces.

III. EVALUATION

The evaluation experiments are based on packet train technique. The experiments show the interactions between the mmWave link bandwidth and the user movements, then further explore their impacts on mmWave link. Finally, we show that the tracking of movement speed can be utilized in network layer link state prediction.

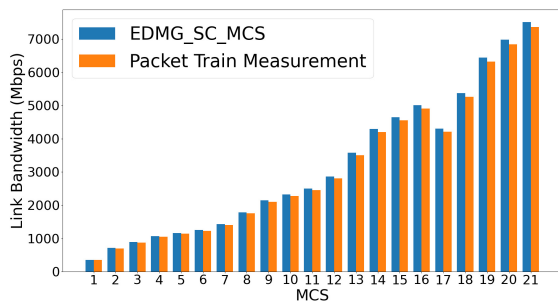


Fig. 4: Packet train measurement with different MCS

1) **Packet train measurement:** For accurate bandwidth measurement with low overhead, we test different parameters for the packet train using wired connections with fixed bandwidth. The optimal parameters for the packet train are 1500-byte packet size, 50-packet train length and 25 random sections in a packet train. With 10 ms packet train interval, the overhead of the packet train measurement is 60 Mbps, which introduces little overhead in a Gbps-level connection. The packet train

measurement with these parameters is further validated in simulations based on the latest 802.11ay module [11] in NS-3. Fig. 4 compares packet train measurement results with the 802.11ay link bandwidth under different Modulation Coding Scheme (MCS) with single carrier in simulations. The results show that, the packet train measurement provides accurate link bandwidth estimation. Thus, we apply this technique to further measurements.

2) **Real-time tracking of link bandwidth and VR movements:** Fig. 5 describes the raw data in real-time tracking of link bandwidth measurement and VR movements. In the experiments, we focus on two types of movements, walking and rotation, which are the movements a VR user incurs frequently. With different magnitude, we explore their impacts on mmWave link bandwidth.

Fig. 5a shows the user's walking velocity traces and the corresponding link bandwidth. There are three different walking velocity conditions, fast, moderate, and slow. In these experiments, two mmWave links on the user's chest are measured simultaneously. These two CNs are about 30 cm lower than the AP in height and their total link bandwidth traces are presented in the first row in Fig. 5a. In this figure, the rest three rows represent the user's velocity along three perpendicular directions, including forward/backward, left/right, and up/down, relatively to the mmWave AP. These results show that while only walking is involved, the link bandwidth is affected correspondingly without obvious link break. The reason is that the data receiving process can be affected by changes in velocity. Meanwhile, the relative direction between the AP and the CNs also changes slowly during walking, which can impact the link quality. There is no obvious link break due to that slow changes in relative directions may not incur frequent beam reforming.

Fig. 5b describes the traces of the user's head rotation and its effect on link bandwidth. The measurement is performed on the device worn on the user's head, which rotates the most frequently in VR scenarios. In the experiments, the CN on the head is about 15 cm higher than the AP in height. The first row includes the link bandwidth traces when the user rotates fast, moderately, and slowly. The second, third and forth rows present the rotating speed traces of yaw, pitch and roll separately. Fig. 5b shows that rotations in VR scenarios are considerably harmful to mmWave link. This is because dramatic changes in direction can easily break the alignment between mmWave beams. Moreover, if the rotation is fast and frequent, the link may be unable to recover since choosing and reforming beam takes time.

Through the observation on Fig. 5, the alignment between the link bandwidth traces and their corresponding VR tracking traces shows MITRAS system's synchronization between the mmWave link bandwidth measurement module and the VR tracking module.

3) **Explore speed impacts in VR movements:** Fig. 6 summarizes the average link bandwidth under different walking and rotational speeds. From Fig. 6, it follows that although faster walking speed reduces link bandwidth, the impact is not large. On the other hand, faster rotational speed reduces the link bandwidth more significantly. This may be due to the

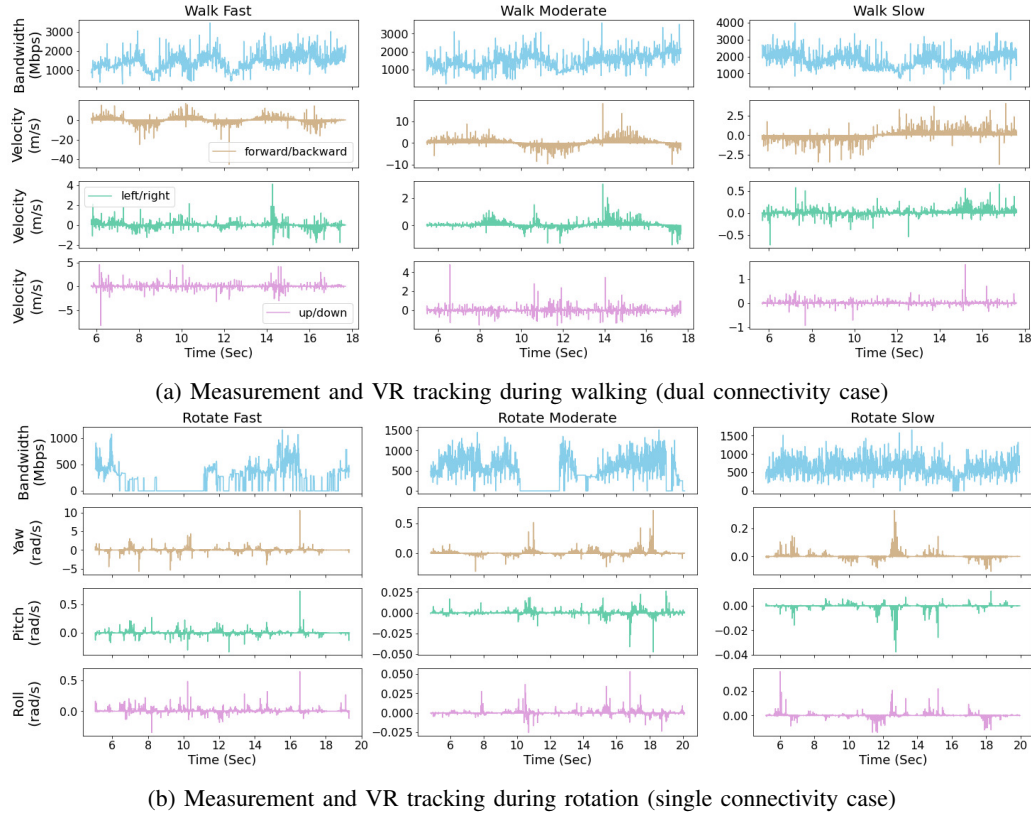
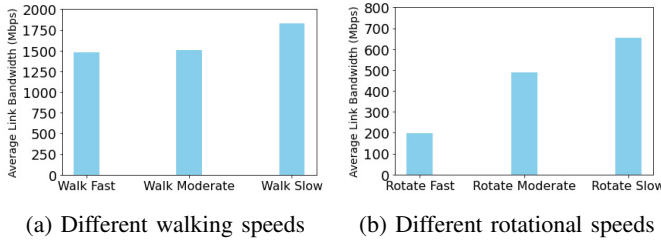


Fig. 5: Real-time link bandwidth measurement and VR tracking



(a) Different walking speeds (b) Different rotational speeds
Fig. 6: Measurements with different movement conditions

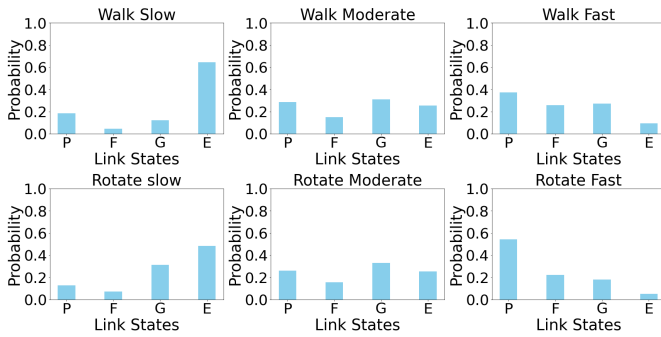


Fig. 7: Link characteristics during a VR application

directional nature of the mmWave beam. The changes in direction due to rotations require new beamforming to reestablish a strong connection. Since rotations are common movements in VR applications, this is a challenge. Furthermore, since rotations often incur view changes, which in turn require a burst of new data, the reduction in link bandwidth caused by rotations significantly degrades immersive experience.

4) Learn for link state prediction: Link state prediction at

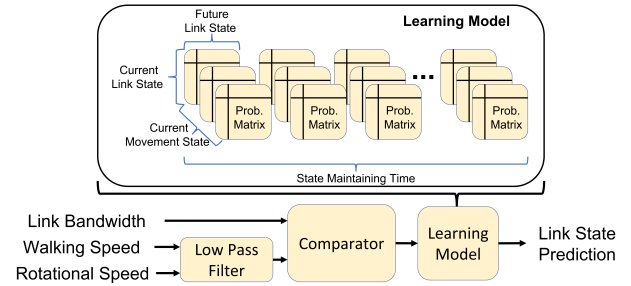


Fig. 8: Link state prediction model

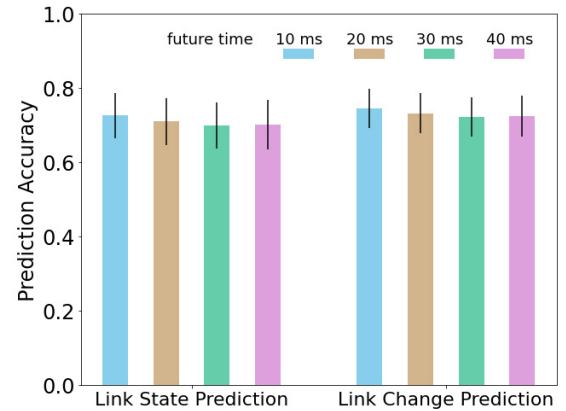


Fig. 9: Prediction accuracy

the network layer is important for intelligent protocol design at the upper layers. These predictions can be used by higher layer protocols to adapt their sending rate based on link conditions. For instance, Transport Control Protocol (TCP) may reduce or increase the sending rate based on the link condition in the near

future say one Round-Trip Time (RTT) later. The link state prediction can be communicated from a TCP receiver in the VR headset to a TCP sender in the content server, which can in turn adapt its sending rate based on the link state prediction. Such adaptations can significantly improve the performance of protocols such as TCP.

Considering the mechanisms of upper layer protocols usually operate in discrete manners, we divide the single-connected link bandwidth into four link states: Poor (P: 0-20 Mbps), Fair (F: 20-500 Mbps), Good (G: 500-900 Mbps), Excellent (E: 900-2500 Mbps). Specifically, this separation in states better supports real-time link prediction managing flow delivery in the network layer. For the design of the learning model, we firstly depicts the characteristics of mmWave link states during the experience in a VR application. Fig. 7 shows the long-term probability of link bandwidth being in each one of these states under different walking and rotational speeds. It is clear that the link bandwidth is more likely in poor state when the rotational speeds are larger. Although rotation is shown with more influence to mmWave link bandwidth than merely walking in indoor VR scenarios in Sec. III-3, the link characteristics in Fig. 7 still show link state deterioration when the walking speed is high. This is because, during an immersive VR experience, the user movement is usually a combination of the walking movement and the rotational movement (i.e. the user incurs both walking and rotation).

Further, we design a learning model for the link state prediction as presented in Fig. 8. The inputs to the link state prediction model include current link bandwidth (as measured using the packet train approach, walking speed (as measured by the VR headset), and rotational speed (as measured by the VR headset). The inputs are sampled once every 10 ms. The objective is to predict the state of the link a short time in the future (e.g., 10 ms, 20 ms, 40 ms, etc.). The link state prediction model firstly uses a low pass filter with 1000 Hz bandwidth on the walking and rotational speeds to reduce the effect of noises on these measurements. The core component of this prediction model, the learning model, is a Markov chain. Each state in the Markov model is a triple comprised of (current link state, current movement state, and state maintaining time). The current movement state is the maximum of walking and rotational speed state, categorized as either Slow, Moderate, or Fast. The current link state is one of four states: Poor, Fair, Good, and Excellent. The third component of each Markov state counts the number of successive times the current link state has not changed. The count is limited to a maximum of 20. The Markov model therefore has a total of $4 \times 3 \times 20 = 240$ states.

The learning model is trained using a trace of the measurements obtained from the MITRAS while playing VR-based games. The traces are used to train the transition probabilities of the Markov model. We test the prediction accuracies by comparing the predicted link states with the measured link state while playing the same game on a different day. Fig. 9 shows the prediction accuracies for four different time intervals 10 ms, 20 ms, 30 ms, and 40 ms. The error bars show 90% confidence intervals. Note that, prediction accuracies are very good in all the cases. It is often important to predict

when the link state is about to change. The figure also shows the accuracy of link change prediction. Here again, one notes that accuracies are very good. Based on these evaluations, one can conclude that the learning model works well in predicting future link states. Future work includes using these predictions to improve performance of higher layer protocols such as TCP.

IV. CONCLUSION

MITRAS integrates the real-time measurement of mmWave link bandwidth with the movement tracking of the VR user. MITRAS quantizes the VR user's walking and rotational conditions and explores their impacts on mmWave link bandwidth. The further investigation using a learning model presents that tracking of the movement is useful to predict network layer link state in the near future. Moreover, the study based on MITRAS is also referable to further investigations on real-time mmWave AR systems. Considering current beam searching and reforming take time, the performance of mmWave AR/VR systems can be improved by further adaptive techniques at higher layers with the assist of link state prediction in a cross-layer design.

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