Wireless Virtual Reality in Beyond 5G Systems with the Internet of Intelligence

Peng Lin, Qingyang Song, F. Richard Yu, Dan Wang, Abbas Jamalipour, and Lei Guo

Abstract

Virtual reality (VR) over wireless has promising applications in healthcare, education, entertainment, and industrial production. However, it is difficult for the existing wireless systems to meet the needs of massive content transmission, ultra-low latency, and high computation in wireless VR. In this article, with the recent advances of edge intelligence and the Internet of Intelligence, we propose a novel framework that can jointly provide computation, storage, and communication resources for wireless VR in beyond 5G systems. In this framework, intelligence can be fully exploited to coordinate the computing, caching, and transmission systems to enable ubiquitous deployments of wireless VR. We present some key techniques and propose specific methods to support wireless VR. In addition, we propose a novel quantum-inspired RL reinforcement learning (QRL) algorithm for the multidimensional resource provisioning issue in wireless VR. In the simulations, some essential performance metrics are evaluated and some interesting results are presented, showing the effectiveness of the proposed strategy.

Introduction

Virtual reality (VR) over wireless, namely wireless VR, has set off a new wave with the evolution of 5G networks. A series of wireless VR-based applications will become the entry point for 5G and beyond 5G (B5G) commercialization [1]. These emerging applications will change people's way of life in many aspects. For example, in terms of city/museum tours, distance education, and industrial process, a realistic environment can be constructed into a virtual scenario. Individuals wearing VR equipments (VEs), such as head-mounted displays (HMDs), can interact and walk around in a fully immersive world within the confines of their residential areas, which will improve user experience and productivity.

Different from traditional video streaming, a wireless VR video streaming system requires the delivery of a massive amount of omnidirectional visual contents at ultra-low latency (less than 20 ms). The ability to smoothly carry high-resolution VR videos and highly sensitive tactile feedback in downlink is crucial to the success of an immersive VR experience. Unfortunately, it is difficult for the current wireless technologies to support high-quality wireless VR applications. For this purpose, the Third Generation Partnership Project (3GPP) has launched standardization activities for millimeter-wave (mmWave) communications in 5G and B5G systems [2]. Meanwhile, academia is also exploring mmWave mobile networks to support the high bandwidth needs of wireless VR streaming [3]. High transmission rate and low-delay transmission can be ensured in mmWave communications to support wireless VR applications.

Another feature that distinguishes VR videos from traditional videos is that VR applications must employ a projection mapping the pixels from a viewing sphere to a 2D viewport. This projection is called viewport rendering and requires huge matrix computations. VR videos consume much more power than other forms of videos [4]. Continuous viewport rendering will lead to excessive heat and shorten the battery lifetime, which brings great challenges to the ubiquitous applications of wireless VR. Multi-access edge computing (MEC) and caching [5] emerge as promising solutions to support wireless VR. By deploying MEC and caching paradigms at the mobile network edge, some computation tasks can be addressed with in-network computing capacity, and some popular VR contents and computation results can be cached to reduce duplicate computation and transmission.

Although MEC and caching systems provide possible solutions to wireless VR, significant challenges related to the coordination of computation, caching, and transmission still need to be addressed in B5G systems [6]. Most existing networks have addressed these areas separately [7]. However, focusing on one system alone will lead to misalignments of multiple systems and multi-dimensional resources in terms of computation, storage, and communication, which have significant impacts on wireless VR users' quality of experience (QoE).

In this article, we study that computing, caching, and transmission can reinforce each other as a comprehensive system to support wireless VR with a cross-system design. The contributions of this article are summarized as follows:

- With the recent advances of edge intelligence [8] and the Internet of Intelligence [9], we propose a novel framework that can jointly provide computation, storage, and communication resources for wireless VR in B5G systems. In this framework, intelligence can be fully exploit-

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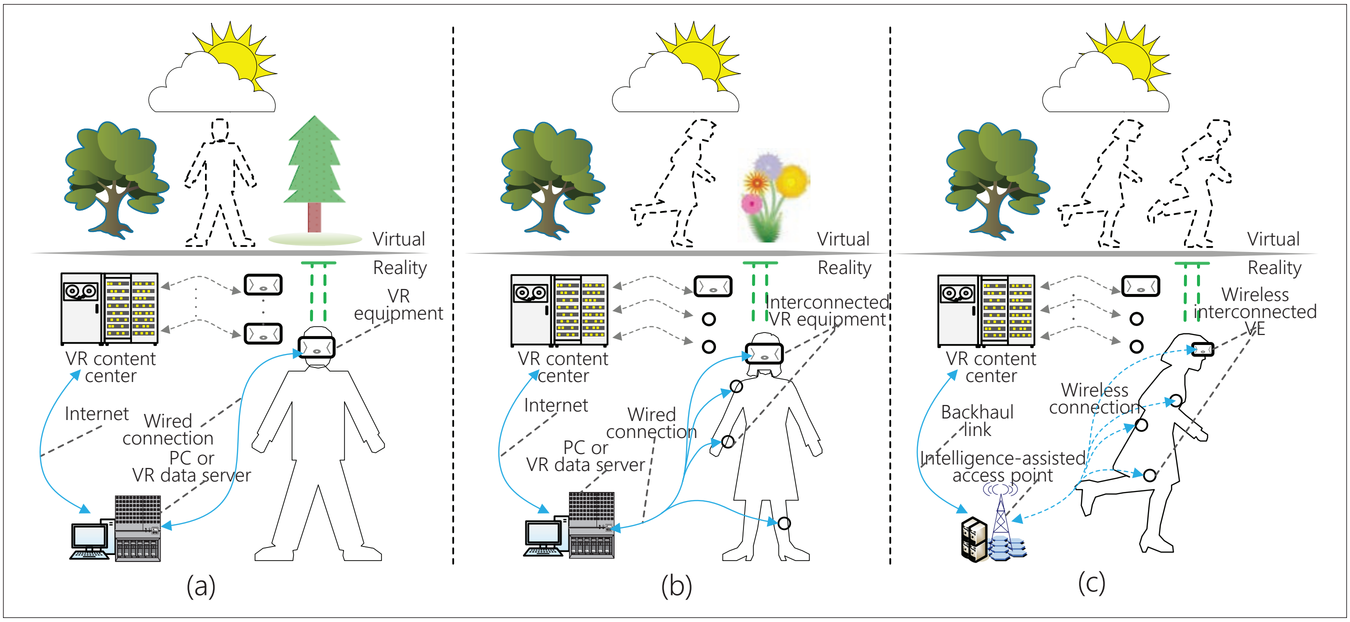

FIGURE 1. Evolution stages of VR: a) traditional wired VR; b) interconnected VR; c) wireless fully connected VR.

ed to coordinate the computing, caching, and transmission systems to enable ubiquitous deployments of wireless VR.
- We present some key techniques and propose specific methods to support wireless VR, including content-correlation-based computation offloading, buffer-aware content caching, and QoE-aware content transmission. In addition, we discuss the problems relating to the QoE of wireless VR users and the energy consumption of VEs.
- We propose a novel quantum-inspired reinforcement learning (QRL) algorithm [10] for the multidimensional resource provisioning issue in wireless VR. By exploring the coupling relationship between every single system (i.e., computing, caching, and transmission), an intelligent resource management strategy is proposed and designed to jointly optimize streaming. In the simulations, some essential performance metrics are evaluated and some interesting results are presented, showing the effectiveness of the proposed strategy.

The rest of this article is organized as follows. We describe the novel framework for wireless VR in B5G systems with the Internet of Intelligence. Key techniques supporting wireless VR are presented. We present the intelligent resource management strategy. Simulation results are discussed. Finally, we conclude this article with future work.

Wireless Virtual Reality with the Internet of Intelligence

Toward Wireless Virtual Reality

Figure 1 shows the three stages in the evolution of VR technologies, starting with a basic VR video streaming system, evolving into interconnected VR, and developing toward an ideal wireless fully connected VR system [11]. The overarching goal of VR is to simulate a digitally immersive experience that mimics the environment of human perception. This entails recreating every photon our eyes see, every small vibration our ears hear, and other cognitive aspects (e.g., touch and smell). In current VR systems (Figs. 1a and 1b), the VEs need to be connected to a dedicated PC. In this situation, the users engaging in VR activities are limited by the wired connectivity, which restricts the types of actions they can take and the VR applications they can experience. To discover the advantages of VR and expand its application areas, current VR systems are expected to support a fully connected wireless scenario. When users are in a wireless VR scenario, they do not need any external wired VEs, and the whole experience is completely wireless. Wireless VR is more adaptable to the future developing trend of VR applications. However, realizing such a wireless VR system faces many challenges in terms of computation, storage, and communication. An innovative framework that can coordinate the multidimensional resources is imperative.

Wireless Virtual Reality in B5G Systems with the Internet of Intelligence

Figure 2 shows the proposed wireless VR framework in B5G systems with the Internet of Intelligence in different application scenarios, including healthcare, education, entertainment, and industrial process. Figure 3 shows that this framework can jointly provide computation, storage, and communication resources for wireless VR in B5G systems. In this framework, intelligence can be fully exploited to coordinate the computing, caching, and transmission systems to enable ubiquitous deployments of wireless VR.

This framework comprises three layers: reality access layer, user access layer, and virtual environment layer, which are depicted as follows.

Reality Access Layer: In this layer, physical application environments are connected to the VR system through the specialized reality access links deployed by VR service providers. The reality access links comprise both high-capacity wireless channels and optical fiber channels to provide stable transmission environments. Mul-

In a wireless VR streaming system, virtual environments are transmitted via wireless networks, which requires the VEs to continuously perform viewport rendering while receiving the data, so as to ensure real-time interactions. To alleviate the computation load of the VEs, we propose to offload the computation tasks to the IAP.

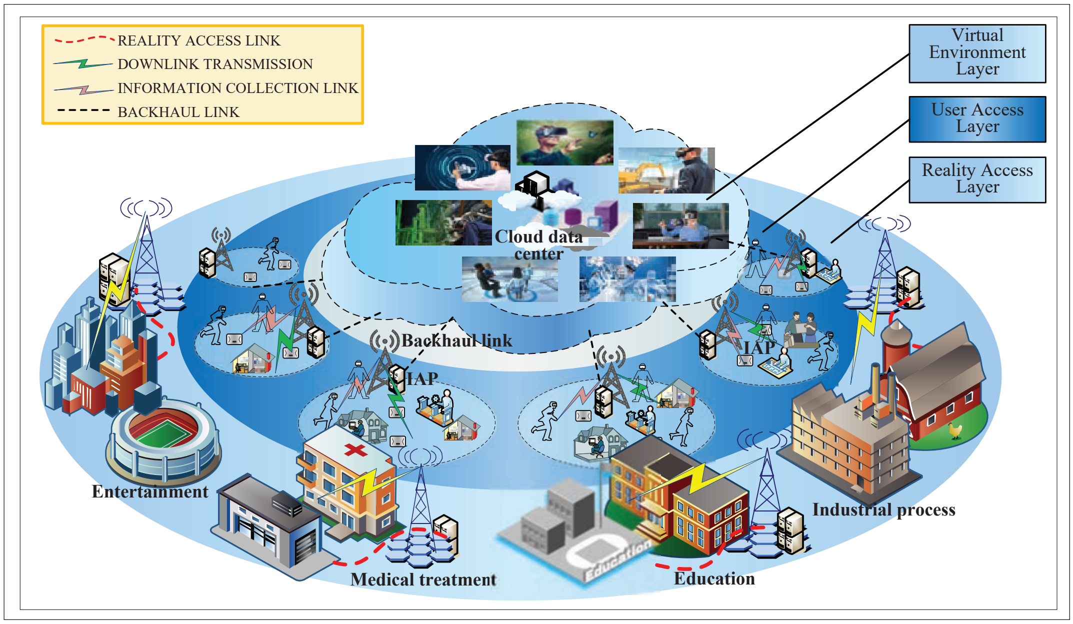

FIGURE 2. Illustration of a wireless fully connected VR streaming system.

tiple high-definition cameras are implemented in the physical area to capture panoramic video contents. Intelligent algorithms like deep learning are used to classify and prioritize video contents. After a series of operations such as splicing, mapping, and coding, the physical prototypes in the reality are simulated into virtual mock-ups, and the auditory, tactile, and visual interactions in the real scenarios are translated into an immersive virtual environment. Then users wearing VEs can engage in VR activities flexibly and remotely, taking advantage of the wireless connections.

User Access Layer: This layer connects the VEs from the physical world to the virtual scenario through multiple intelligence-assisted access points (IAPs). Each IAP is implemented with an MEC system, a caching system, and a transmission system. When a VE requests a VR service through an IAP, the IAP can either directly transmit the corresponding VR chunks to the VE, or decode and render the VR chunks into full-resolution viewports and then transmit them to the VE. Some popular VR video chunks can be cached at the IAP to reduce redundant delivery and computation. For the transmission system, we propose to use a high-speed mmWave downlink as the basis for wireless VR streaming. Meanwhile, an information collection uplink is used to collect the downlink condition information and the context information regarding the VEs. Big data analytics and edge intelligence algorithms are deployed at each IAP, and construct the access network into the Internet of Intelligence for estimating the quality of the mmWave link and collecting the viewport information periodically. To coordinate the multiple systems with computing, caching, and transmission abilities, the IAP adopts a QRL algorithm to realize online decision making, which is introduced in detail in the ensuing section. In this way, the viewport rendering offloading and resource allocation can be executed to ensure that wireless VR users enjoy good QoE.

Virtual Environment Layer: A cloud data center is placed in this layer to provide a stable virtual environment for wireless VR applications. The cloud center is composed of a VR content database, an intelligent computing module, and an execution module. The intelligent computing module is responsible for centralized processing of the VR contents in the content database, which involves viewport correlation analysis, multi-player scene construction, and interactive feedback calculation. Meanwhile, intelligent algorithms (e.g., deep learning) can be applied at the computing module to classify the service priorities of different VR activities. The outputs of the algorithms are executed by the execution module and the VR contents, and different priorities can be scheduled and delivered efficiently through the backhaul links to the IAPs.

Key Techniques Supporting Wireless VR

In this section, some key techniques in terms of computing, caching, and transmission are presented. We first introduce the key techniques supporting wireless VR. Then we present how the integration of the corresponding resources helps to improve wireless VR users' QoE. The illustration of the cross-system design is shown in Fig. 3.

Content-Correlation-Based Computation Offloading

The success of an immersive VR experience relies significantly on the construction of omnidirectional visual contents. To construct an omnidirectional visual environment, an original VR content needs to be decoded and rendered into full-resolution viewport chunks. Generally, this process is offline, and the videos are completely downloaded at the VEs. However, in a wireless VR streaming system, virtual environments are transmitted via wireless networks, which requires the VEs to continuously perform viewport rendering while receiving the data, so as to ensure real-time interactions. To alleviate the computation load of the VEs, we propose to offload the computation tasks to the IAP. Assuming that the computing capacity of the IAP is large enough to perform viewport rendering for each VE, all the rendering tasks can be offloaded to the IAP. However, the actual computing capacity of the IAP is limited; therefore, an efficient task offloading mechanism is needed to determine which task should be offloaded.

Generally, the VR chunks requested by different VEs are potentially correlated because the users engaging in the same VR activity may share a common viewport. When VEs engage in VR activities, the tracking information (including location and orientation) of VEs is collected periodically. Then the content correlation profile between the VEs can be obtained by analyzing the tracking information. The MEC system can better manage the computation offloading if it exploits the potential correlation between different VR chunks. For instance, if two VR chunks requested by two VEs are correlated with some same pixels, the MEC server can extract the unique contents and render them into visible contents for the two VEs once for both. In this way, the amount of computation can be compressed and the consumed computing resource can be reduced. Inspired by this, the IAP can calculate the total amount of data to be rendered resulting from the content correlation under potential offloading decisions. The decision making of task offloading determines the data volume to be computed by the IAP. Considering the computing capacity of the IAP, the offloading decision should be made to maximize the degree of computation compression. After obtaining the offloading decisions, we need to identify how many computing resources should be assigned to each offloaded rendering task. The computing capacity at the IAP is denoted as the data volume that one CPU cycle of the IAP can process. The allocation of the computing resources can be quantified as the number of CPU cycles allocated to each task over a period of time. Since the rendered data needs to be transmitted to the VEs immediately, the computing resources allocated to each VE are coupled with the transmit rate.

QoE-Aware Content Transmission

In the wireless VR system, the IAP serves the VEs in both uplink and downlink. The uplinks are used to deliver tracking and environmental information. The uplink capacity is much larger than the amount of information to be transmitted by the link, so the impact of the change of channel state can be ignored. The downlinks are responsible for carrying VR contents to the VEs. However, the scarcity of spectrum and the instability of wireless connection are the bottlenecks. Generally, the transmission rate for presenting a basic immersive VR is typically 25 Mb/s and increases strictly with the raising of the QoE requirement. Meanwhile, different users have different QoE requirements, and satisfying users with high QoE puts a high requirement on the downlink throughput, especially in the face of fluctuating channel conditions in the wireless VR system. Therefore, an adaptive transmission management system needs to be designed.

Generally, for a certain VR content that is coded into multi-level resolutions, presenting the content with a definite resolution needs a transmission rate threshold, and the user can enjoy a corresponding QoE. To provide an improved QoE for each VE, we propose a QoE-aware transmission method, in which the channel resources are assigned to different VEs adaptively according to different QoE requirements and dynamic channel conditions. Specifically, the IAP evaluates the channel state for each VE in order to make efficient spectrum allocation. When a VE requests a VR content of a definite resolution, the IAP makes a spectrum allocation decision for the VE to ensure that the VR chunks can be carried at a transmission rate not lower than the required threshold. Meanwhile, the content to be delivered needs to be rendered in time to avoid underflow in the transmission process. Therefore, the communication resource allocated to each VE is coupled with the IAP's computing capacity.

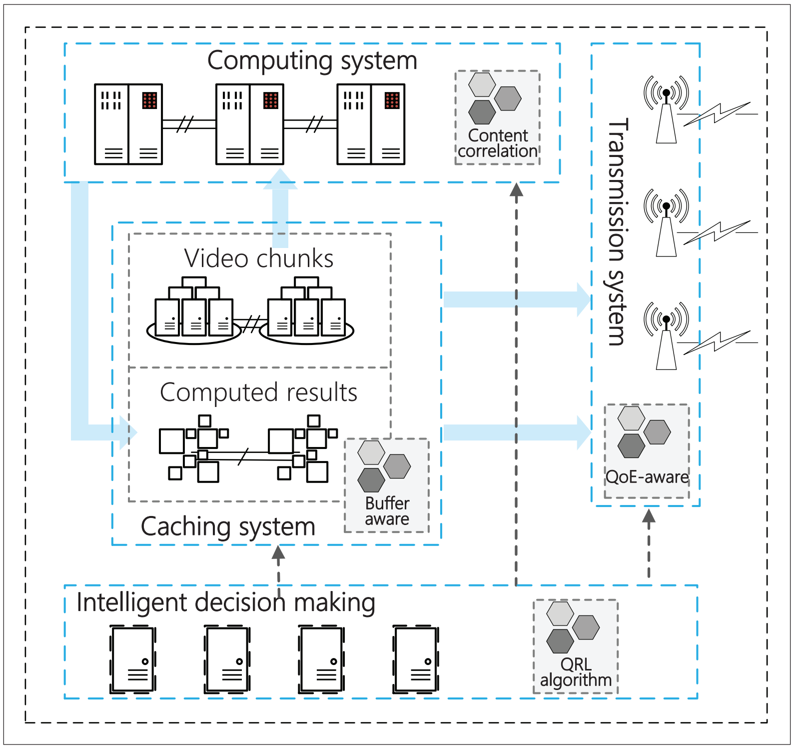

FIGURE 3. Illustration of the coordinated multiple systems.

Buffer-Aware Content Caching

In addition to the functionalities of computing and transmission, content caching is also a key functionality that contributes to wireless VR from the aspect of storage dimension. For traditional video streaming, the benefits of caching mainly come from reducing the transmission hops from the content source to the VEs, while in the wireless VR streaming system, content caching contributes to wireless VR from the aspects of both computation and transmission.

Herein, we design a buffer-aware caching system in which both the VR chunks and the rendering results can be cached to support wireless VR streaming. Specifically, the storage space of the IAP is divided into two parts. One part is used to cache popular original VR video chunks to provide transmission gain. If the VEs request the VR chunks that have already been cached at the IAP, the backhaul bandwidth can be saved, which will alleviate network congestion. Meanwhile, the content delivery delay from the content server to the VEs can be saved. The other part serves as a buffer to cache the computation results

To ensure a smooth immersive VR experience, the rendered viewport data should be continuously provisioned to the VEs. Performing viewport rendering at the VEs can provide a steady flow of the viewport data, but leads to excessive heat and shortened battery lifetime. Offloading the rendering tasks to the IAP saves the energy consumption of the VEs, but requires the strict coordination of the computation, transmission, and caching.

from rendering the original VR chunks. Caching these results can provide computational gain (i.e., reduce computation delay and computation load), and the gain will be amplified when the VR contents requested by different VEs are potentially correlated. If the IAP caches the rendering results of a VR chunk that has a higher content correlation with the known VR chunks, the total amount of computation can be effectively saved. In the delivery process, the VR chunk passing through the IAP can be either cached at the storage space or rendered and stored in the buffer. VR content popularity is considered in the caching and buffering strategy. For the IAP, the content popularity is defined as the user preference for the VR chunks and can be obtained by periodically analyzing the user request profile. The caching decision and the buffering strategy, depending on the VR content popularity, the content-correlation profile, and the channel condition, are combined with both the computing and transmission systems.

Intelligent Resource Management Strategy

An eligible QoE of a wireless VR user hinges on the coordination of the computing, transmission, and caching systems. In this section, we analyze the QoE of wireless VR users and propose an intelligent resource management strategy.

Problem Description

To ensure a smooth immersive VR experience, the rendered viewport data should be continuously provisioned to the VEs. Performing viewport rendering at the VEs can provide a steady flow of the viewport data, but leads to excessive heat and shortened battery lifetime. Offloading the rendering tasks to the IAP saves the energy consumption of the VEs, but requires the strict coordination of the computation, transmission, and caching. Herein, we discuss the scientific issues in terms of the VR users' QoE and their energy consumption.

Wireless VR Experience: For wireless VR streaming, the initial delivery delay and video playback stalling (sometimes more annoying than the initial delay) are important factors affecting VR experience as they disrupt the playback smoothness. The initial delivery delay can be reduced with the support of edge caching. Stalling happens when the amount of available viewport data is less than the amount of playback data. To clarify how the multi-dimensional resources affect VR stalling, we take an example of multiple VEs engaging in a VR activity. Assume that the VEs request VR chunks through the IAP continuously. First, the IAP makes rendering offloading decisions for the VEs by analyzing the content-correlation profile among the VEs as well as the computing capacity. Based on the offloading decisions, the IAP allocates the computing and spectrum resources for each VE. Given the allocated computing resource, the IAP can render a certain data volume $DATA_R$ for each VE during one playback unit. Given the allocated spectrum resource, the VE can obtain a certain data volume $DATA_O$ at the available transmission rate during one playback unit. Therefore, to guarantee smooth VR streaming, the buffered viewport data $DATA_{BV}$ at the VE plus the forthcoming viewport data $DATA_O$ should not be lower than the consumed data volume during the playback unit. Meanwhile, the computed data volume $DATA_R$ plus the buffered viewport data $DATA_B$ at the IAP should not be lower than $DATA_O$ to avoid buffer underflow when the VE is receiving the rendered data from the IAP. Realizing this process requires the IAP to make accurate decisions on the computation offloading and resource allocation.

Energy Consumption at VEs: Viewport rendering is a computation-intensive and energy-intensive task. The battery lifetime of the VEs mainly depends on whether the rendering task can be offloaded to the IAP. For a VE engaging in a VR activity, when the viewport rendering is performed at the IAP, the energy consumption of the VE only comes from receiving the viewport data, which is denoted by $Eng_{r\text{-}vi}$. When the viewport rendering is performed at the VE locally, the energy consumption includes:

1. The energy $Eng_{r\text{-}or}$ for receiving the original unrendered chunks
2. The energy Eng_{ren} for viewport rendering at the VE locally

Then the energy consumption of the VE can be formulated as the total energy cost comprising $Eng_{r\text{-}vi}$, $Eng_{r\text{-}or}$, and Eng_{ren}.

Resource Allocation Problem

How to carry out a smooth VR activity with high-efficiency resource management is a problem. Convolutional neural network (CNN)-based transmission optimization was studied in [12]. The joint optimization of multi-dimensional resource with artificial intelligence (AI) and machine learning was explored in [13, 14]. In these works, the caching and task offloading problems are efficiently addressed by intelligent management strategies, which is promising to pave the way for B5G deployment. Inspired by this, with support of the framework of B5G systems and the Internet of Intelligence, we propose an intelligent computation offloading and resource allocation strategy to minimize computation cost at the VEs while guaranteeing good QoE perceived by wireless VR users. Assume that the system works in a slotted fashion over time slots. Then the optimization objective can be formulated to minimize the computation cost Tot_{cost}. In this article, computation cost Tot_{cost} is quantified as the total energy consumption of VEs, which is determined by the offloading decision and the multidimensional resource (i.e., the storage, spectrum, and computation resources) allocation decision. To satisfy different QoE requirements and guarantee a smooth immersive VR experience, a series of constraints need to be formulated.

Resource Capacity Constraint: The multidimensional resources are limited at the IAP. Therefore, the task offloading and resource allocation decisions should be made taking into account the storage, spectrum, and computing capacities.

Flow Stability Constraint: The flow stability constraint ensures that the amount of the incoming viewport data over wireless must be larger than the amount of the data consumed for playback. This requires the IAP to assign differentiated spectrum blocks to the VEs according to their channel conditions and QoE requirements so as to ensure smooth data transmissions.

Offloading Capacity Constraint: By analyzing the tracking and environmental information of the VEs, the general form of the volume of the data resulting from content correlation can be formulated as a function of the offloading decisions for each VE. To avoid computation overload, a constraint should be imposed to ensure that the volume of data to be computed does not exceed its computing capacity.

Resource Utilization Assurance: This constraint guarantees that the allocated computing and spectrum resources for the VEs are coordinated. On one hand, the excessive allocation of resources to a certain VE will lead to insufficient allocations for the other VEs. On the other hand, for any VE, the mismatch between the computing resource and the spectrum will lead to an overflow or underflow of the buffered viewport data.

Quantum-Inspired Intelligent Decision Making

The intelligence of the framework enables not only its powerful computing, transmission, and caching abilities, but also its ability to cope with the time-varying environment. Reinforcement learning (RL) is a powerful method to achieve online decision making [15]. RL is defined by characterizing a learning problem and operates based on its own experience of environmental uncertainty. In an RL system, some components are required, namely agent, environment, and policy. Details of these components are presented as follows.

Agent: Each IAP is implemented with an agent. The agent is responsible for perceiving, observing, learning, and making decisions. In this article, the system action is defined as the task offloading and multidimensional resource (storage, spectrum, and computing) allocation decisions. Each agent perceives the environment and then decides the next action through online learning.

Environment: The environment can be regarded as a time-varying state characterizing the channel conditions between the IAP and the VEs. The change of the environmental state can be described as a Markov decision process (MDP). In the MDP, the agent interacts with the environment and makes decisions following a certain policy.

Policy: The policy can be regarded as a function that maps the environment state to the system decision. The policy gives a reward of taking a certain action under the current environment state. In our system, the reward is defined as a combinational dual function characterizing the energy consumption and the VR QoE of the VEs.

In traditional RL-based algorithms, such as Q-learning and deep Q-learning (DQN), the learning process relies on the updating of the Q-values and the training of the Q-network. However, these methods face the challenge of the "curse of dimensionality." The huge action space makes the exploration and exploitation efficiencies unacceptably slow. The quantum-computation theory is considered to be powerful for addressing high-complexity computations [10]. The basic unit in quantum computation is a quantum bit (qubit). Each qubit has two basic states denoted by $|1\rangle$ and $|0\rangle$, which correspond to the states 1 and 0 for a classical bit. The fundamental operation in the quantum-computing process is a unitary transformation U on a superposition state formed by a linear combination of N quantum states. Different

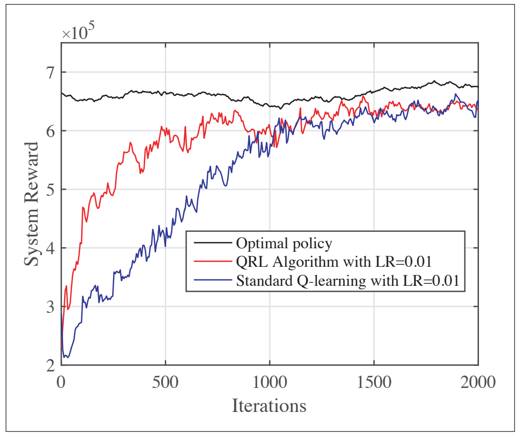

FIGURE 4. Convergence performance.

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from traditional updating methods, the U-transformation can simultaneously act on all the N basic quantum states, and the corresponding probability amplitude of each quantum state can be updated concurrently. After the transformation, an observation on the quantum system will make the superposition state collapse to a definite state with a certain probability. This process is called quantum parallelism, which inspires us to use it to improve the efficiency of the exploration and exploitation in RL algorithms.

At the beginning of the algorithm, the agent initializes the quantum actions and their corresponding probability amplitudes. In the learning process, the agent observes the quantum system and sees the system collapse to a quantum action $|q\rangle$ with probability P_q. Then action $|q\rangle$ is executed, and the system reward is obtained. Afterward, the agent updates the Q-value and checks whether action $|q\rangle$ is "good." If yes, transformation U is performed to update the probability amplitudes. Ultimately, the policy will converge to optimum as the system continues to run.

Simulation Results and Discussions

Simulations are conducted to evaluate the proposed strategies. We consider that 15 VEs are randomly distributed within the coverage of 4 IAPs. The VR content is uniformly divided into equal-size chunks as 300 Mb/chunk. The Zipf factor used for the content popularity is set as 0.7. The computing capacity of each VE and the IAP are set as 0.5 GHz and 2.4 GHz, respectively. The effective switched capacitance used for viewport rendering is set as 10^{-24}. The circuit power of each VE for sending and receiving data is 100 mW. The downlink and uplink bandwidths are set as 200 MHz and 50 MHz, respectively. The channel fading coefficient is quantified into 7 levels with boundary values [0, 1, 3, 7, 15, 31]. The learning rate (LR) in the learning process is set as 0.01.

Figure 4 shows the convergence performance of the QRL algorithm compared with the standard RL algorithm. The optimal policy is obtained by solving the optimization problem under the known dynamics of the environment. From Fig. 4, we observe that the system rewards of the two learning algorithms are low at the beginning of the learning process. With the continuous iteration, the system rewards of the two algorithms

In the simulations, we evaluated the convergence performance, stalling rate, and energy consumption at the VEs in the proposed strategy. The results show the effectiveness of our method, which has practical meanings for ubiquitous deployments of wireless VR in B5G systems. Future work is in progress to consider security issues in the proposed framework.

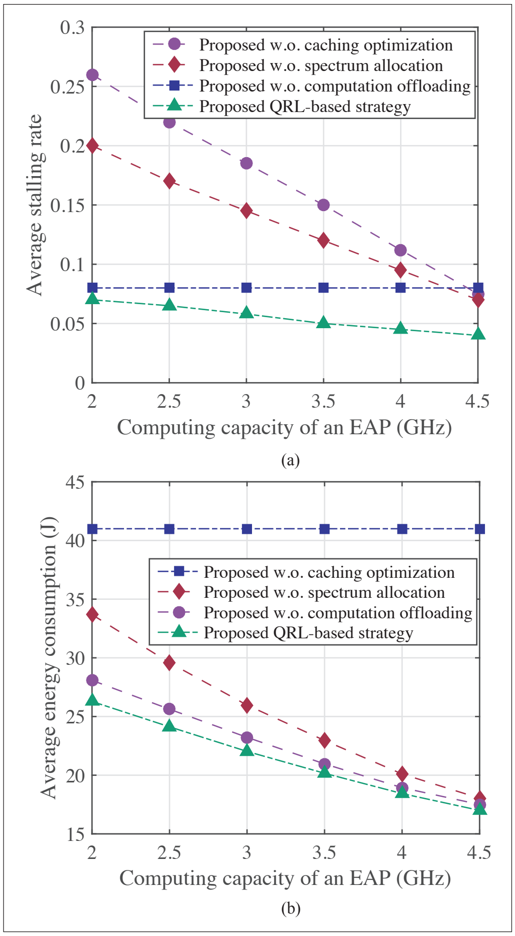

FIGURE 5. a) Average stalling rate; b) energy consumption vs. different computing capacity of IAP.

increase. After about 600 iterations, the QRL algorithm first converges to a near optimum. Then, after about 1100 iterations, the standard RL algorithm converges to a near-optimal solution. It can be seen that the exploitation of quantum parallelism can improve the learning efficiency of the RL algorithm. Meanwhile, we observe that the proposed algorithm can provide system reward almost as good as the optimal policy, which illustrates that the AI-based method can realize effective management of the integrated system crossing computation, caching, and transmission.

To evaluate the QoE of the wireless VR users, the average stalling rate and the average energy consumption at the VEs are shown in Fig. 5. We evaluate the proposed QRL-based strategy with the comparison of that without computation offloading, spectrum allocation, and caching optimization, respectively. From Fig. 5a, we observe that the stalling rate decreases with the increase of the computing capacity of the IAP with the help of computation offloading. We also observe that the strategies without spectrum allocation and caching optimization have a higher stalling rate compared to the strategy without computation offloading (i.e., viewport rendering is performed at the VEs locally), which indicates that high-performance wireless VR requires the coordination of computing, storage, and communication resources. Figure 5b shows the average energy consumption of the VEs in the proposed strategy. We observe that the average energy consumption at the VEs can be significantly reduced with the support of computation offloading. Meanwhile, with the increase of the computing capacity, the average energy consumption eventually converges to a same and stable value. This is because the computing capacity of the IAP is large enough to compute all the offloaded tasks. Combining Figs. 5a and 5b, we observe that our strategy holds the lowest stalling rate while guaranteeing the smallest energy consumption at the VEs. It shows that ubiquitous applications of wireless VR are feasible by coordinating computing, caching, and transmission based on cross-system strategy and algorithm design.

Conclusion and Future Work

This article presents a novel framework for wireless VR in B5G systems with the Internet of Intelligence. We first present the evolution stages of VR. Under the proposed framework, we discuss the key factors influencing wireless VR users' QoE and propose novel techniques to improve the QoE by exploring content correlation, buffer-aware caching, and QoE-aware transmission. In addition, to coordinate the computing, caching, and transmission systems, we formulate the resource allocation strategy as a joint optimization problem and propose the QRL algorithm to realize online decision making. In the simulations, we evaluated the convergence performance, stalling rate, and energy consumption at the VEs in the proposed strategy. The results show the effectiveness of our method, which has practical meanings for the ubiquitous deployments of wireless VR in B5G systems. Future work is in progress to consider security issues in the proposed framework.

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