QoE-Driven Resource Allocation Optimized for Uplink Delivery of Delay-Sensitive VR Video Over Cellular Network

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ABSTRACT Uploading virtual reality (VR) video over cellular networks is expected to boom in the near future, as general consumers could generate the high-quality VR videos with portable 360-degree cameras and are willing to share with others. Consequently, the concerns of uplink bandwidth and delay arose for current popular technology of tile-based VR video streaming, which requires high-quality video to transcode into multiple representations for further adaptive streaming. Motivated by this, we proposed a novel scheme for uplink delivery of tile-based VR video over cellular networks, in which encoding bit rate of each tile is determined by the uplink resource allocation (RA), and the quality of content (QoC) contribution of each tile and channel quality of user equipments (UEs) are jointly considered during RA. Moreover, the RA problem is formulated as a frequency and time dependent non-deterministic polynomial (NP)-hard problem. Furthermore, we propose three algorithms to explore solving the RA problem. The simulation results show that the proposed approximate convex algorithm with low-complexity can achieve higher utility, i.e., higher total quality of experience (QoE) for viewers.

INDEX TERMS VR video, quality of experience (QoE), resource allocation, cellular network, saliency, utility optimization.

I. INTRODUCTION

In recent years, virtual reality (VR) technology has been rapidly commercialized, forming a $209 billion market by 2022 as predicted in [1]. Thanks to the development of VR display devices, the general public are able to experience VR capabilities on head-mounted displays (HMDs) such as HTC VIVE and Oculus Rift. VR applications make use of 360-degree panoramic or omnidirectional videos with high resolution (higher than 4K) and high frame rate (60-90fps) in order to create immersive experience to the viewer.

More and more people would like to generate VR videos themselves and share with others using the popular User-Generated Content (UGC) platforms such as Facebook and YouTube. With the help of portable 360-degree cameras (e.g. GoPro OMNI and Samsung Gear 360, etc.), common users can produce high-quality VR videos and upload them to the UGC platform (uplink procedure); then, the UGC platform disseminates them to other VR viewers through applications like VR live broadcast (downlink procedure). In these procedures, transmission latency of VR video is one of the biggest issues.

Optimization of VR video transmission is actively researched, but previous work mostly focused on the downlink procedure [2], [3], and a common precondition of these studies is transcoding VR videos into multiple representations (bit rates) on the cloud server, which enable adaptive video streaming by selecting a proper representation of video content based the predicted viewport and available bandwidth. Among them, tile-based adaptive downlink

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streaming has been studied [4]–[7], and its basic idea is that partitioning the panorama into independent tiles enables quality and rate of content to be adapted locally according to the desired viewport of viewers. As for the underlying technology, some researchers explore the potential of downlink delivering tile-based VR video over cellular network (e.g. LTE) by applying the multicast [3], [8].

Up to now, few research on VR video uplink transmission is reported. However, as popularity of VR video sharing, the need of VR video uploading over cellular network is increasing. Especially in delay sensitive scenarios, e.g., UGC VR application, which calls for the use of cellular network as strong support of mobility and collaboration.

However, optimization for uplink delivery of VR videos is more challenging. First, it is not viable for a user terminal to create multiple representations due to the lack of computing and storage resources on board, especially for delay sensitive scenarios, e.g., Live VR broadcast. Second, the uplink wireless bandwidth is more limited than the downlink. The last but not the least, viewports of viewers seem more difficult to be predicted than expected to implement adaptive downlink streaming, and transcoding procedure can be ignored in delay sensitive scenarios. Essentially, source coding rate of uplink VR video largely determines QoE of viewers in client side. Hence, producing uplink VR video with acceptable QoE under limited uplink wireless resource is a big challenge.

Motivated by the challenges, in this work, we propose a novel scheme with predefined tile-based encoding factors dependent on expected QoC [9], involving uplink resource allocation (RA) correspondingly. Tile-based encoding factors impacting viewer's QoE are first investigated. We further formulate the problem as an NP-hard problem of uplink resource assignment, and explore solving the optimization problem by different approaches.

The remainder of the paper is organized as follows. In Section II, we review the main contributions in literature related to the presented research topic. Scenario and preliminary are presented in Section III. Proposed scheme and problem formulation are described in Section IV. Proposed RA algorithms are presented in Section V. We evaluated the proposed scheme and algorithms in Section VI. Finally, Section VII concludes the paper.

Notations: The symbols and notations used in this paper are summarized in Table 1.

TABLE 1. List of symbols.

Symbol	Quantity
I	Number of VR videos
i	Index of VR video
J	Number of tiles in VR video frame
j	Index of tiles in an VR video frame
n	Index of resource block
N	Number of resource blocks in one TTI
k	Index of TTI
K	Number of TTI in one Resource allocation Round
$Tile_{i,j}$	The j th tile of i th VR video
$R_{i,j}$	Data rate of $Tile_{i,j}$
U	Utility function
S	The saliency value of $Tile_{i,j}$
V	The vertical position of $Tile_{i,j}$ in ERP frame
$w_{i,j}$	The QoC contribution weight of $Tile_{i,j}$
α	the coefficient of the utility model
β	the coefficient of the utility model
$x_{i,j,k,n}$	The assignment indicator for n th RB in k th TTI is assigned to $Tile_{i,j}$ or not
$x_{i,j,n}$	The assignment indicator for n th RB is assigned to $Tile_{i,j}$ or not
eff	The efficiency of one resource element with a specific MCS
MCS	The modulation and coding scheme
CQI	The channel quality
C	The capacity of one resource block with a specific MCS

II. RELATED WORK

VR video content is captured from multiple cameras and pre-stitched to a single 360-degree layout (i.e., spherical video), then a key step of the encoding chain is to project the spherical video onto the planar surface due to current video encoders operate on two-dimensional rectangular image. Equirectangular Projection (ERP) [2] and CubeMap Projection (CMP) [10] are widely used projection schemes.

However, transmission full view of VR video requires high bandwidth. Hence, viewport adaptive streaming is proposed to save transmission bandwidth which can be classified into two categories: asymmetric panorama-based streaming and tile-based streaming. Truncated Pyramid Projection (TSP) and Facebook's offset cubemap [11] are the typical formats to represent asymmetric panorama. According to the asymmetric panorama scheme, a VR video is transformed and encoded into multiple versions towards different perspectives. And a viewer requests one certain version according to the viewer's orientation. However, such scheme produces high redundancy of contents (e.g., Facebook creates 150 versions for one VR video) which leads storage and bandwidth waste.

Nonetheless, tile-based streaming has proven more effective [10]–[12]. Each tile in a VR video is encoded into multiple representations (i.e. bit rate), while tiles viewed by the viewer are streamed in high bit rate and the rest of tiles are streamed in low bit rate, which results in more flexible and bandwidth saving for VR video streaming. Thus tile-based adaptive streaming has been extensively researched. Bao *et al.* [3] proposed a scheme to optimize the network bandwidth using motion-prediction-based multicast to serve concurrent viewers. Rondao *et al.* [6] studied the effective of tile-based streaming for omnidirectional video, their experiments showed that the tiling grid between 8×8 and 16×16 can achieve best peak signal-to-noise ratio (PSNR) performance measured on the viewport for fixed bandwidth. Graf *et al.* [12] proposed a novel tile-based adaptive streaming method over HTTP/2. However, those study mainly focused on optimizing for the transmission part between content server and viewers.

In terms of VR video uplink transmission, especially for VR video uplink transmission over the cellular network, relatively fewer have been researched. However, regular video uplink optimization has been studied due to the popularity of mobile video streaming. Essaili *et al.* [13] presented a LTE Uplink scheduling scheme for the heterogeneous Quality of Service (QoS) requirements of multimedia traffics, they formulated it as a Joint Time and Frequency Domain Packet Scheduling problem, and they proposed three algorithms to solve the problem. Zhang, *et al.* [14] presented a systematic resource allocation and transmission optimization approach for the simultaneous streaming of user-generated video content, distributed QoE-based optimization is performed by each video producer in the terminal to decide on which video layers to transmit and their respective rates. While a greedy resource allocation algorithm was introduced to determine the resource share ratio of each user at each schedule round that maximizes the overall QoE. In [15], surveillance video uplink streaming over wireless network was investigated. In order to solve the global video uplink streaming problem, they studied both the long-term bit-rate assignment for video encoding and the real-time packet scheduling in each OFDMA frame under the real-time constraint. Recently, Quality-of-Content (QoC) based joint source and channel coding in a mobile surveillance cloud has been investigated in [9]. They aimed at optimizing the wireless resource usage so that more accurate human detections can be performed at the cloud server based on the received videos. Based on the previous work, we investigate the optimization of VR video uplink delivery over the cellular network in this paper, which provides an applicable solution for uplink transmission of bandwidth-intensive and delay-sensitive VR video.

III. SCENARIO AND PRELIMINARY

A. SCENARIO

According to Fig. 1, consider a LTE system consisting of a single eNodeB and several user equipments (UEs). Those UEs produce VR videos simultaneously and transmit them to the UGC platform by competing for the available uplink bandwidth. In this paper, we specifically optimize the generation and transmission of VR videos through the bottleneck from UEs to eNodeB, aiming at maximizing the total QoE of all viewers.

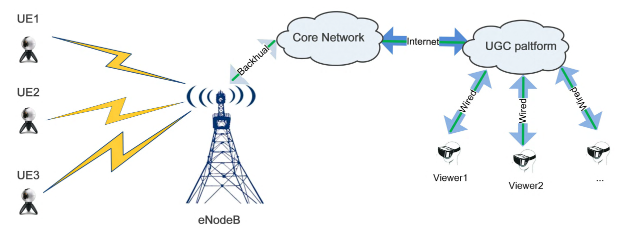

FIGURE 1. Sharing of user generated VR video.

A VR video must be encoded into variable bit rate dependent on the sub-region or tile, since a UE cannot afford to produce various representations. Actually, the spherical video captured by a 360 degree camera is first projected into equirectangular projection (ERP) frame [11]. The ERP has advantages of being both rectangular and straightforward to visualize and manipulate using an existing video encoder. After the projection, the ERP VR video sequence is encoded into tiled video by encoder, e.g., High Efficiency Video Coding (HEVC). The encoding bit rate of each tile are related with its contribution weight of QoC, the significance of this tile.

B. SALIENCY AND ERP

Saliency represents the degree of a spatial region in video frames attracting attention of viewers. Tiles with high saliency scores represent regions with attractive texture or object for viewers. And saliency detection can be applied according to [17]. Furthermore, distortions happened in a more salient region result in a much lower subjective quality scores of a perceived video, i.e., viewers are more eager toward more clear details (i.e., higher bit rate) on the salient region. Reference [18] reported that the viewer's fixation in a 360-degree video is more preferred on the salient regions. Hence in principle, the salient tiles need higher bit rate.

However, the salient region usually does not get more bits in ERP. On the contrary, after ERP, the polar regions with lower saliency get more video pixels, whereas the equatorial region gets relatively fewer [19]. Consequently, tiles in the polar part cost higher bit rate compared with these in the equatorial part when applying the 2D encoder (e.g., HEVC). On the other hand, spherical videos usually have their important content distributed around the equatorial regions (the middle), where need less distortion (i.e., higher bit rate) is desired on these tiles, and vice versa. Fig. 2 and Fig. 3 show a saliency map of ERP VR video frame by applying the

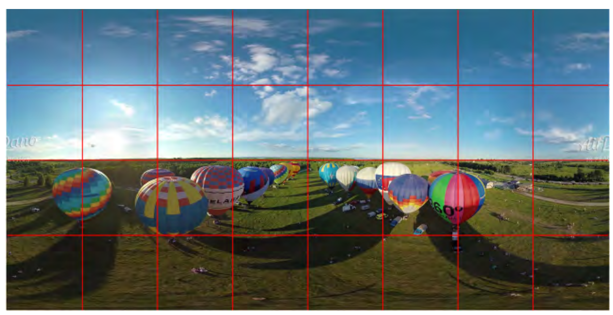

FIGURE 2. An ERP VR video frame with 4 × 8 tiles.

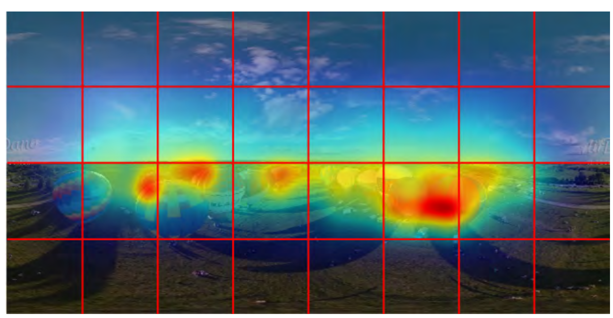

FIGURE 3. Saliency map of an ERP VR video frame with 4 × 8 tiles.

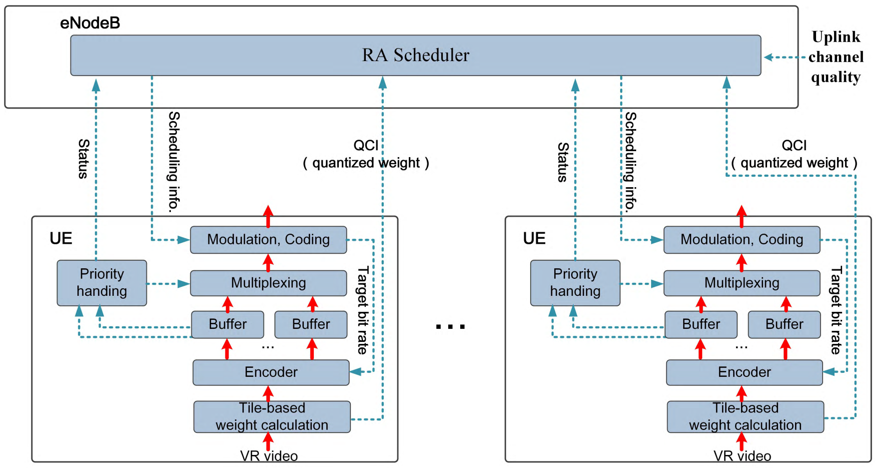

FIGURE 4. Proposed scheme for VR video uplinking.

saliency detection [17]. Thus, we are motivated to introduce the equatorial weight of each tile according to its vertical position in the 2D plane, resulting in higher bit rates at encoding the tiles near the equatorial part.

C. UTILITY MODEL

The QoE metric for video networking quality evaluation is commonly used as (1) defined [16], where the U denotes the utility of the video, R denotes the video rate, R_M represents the maximum video rate the Dynamic Adaptive Streaming over HTTP (DASH) server could provide, and $R \in \{R_1, \ldots, R_M\}$, where R_1 and R_M represents the minimum and maximum rate, respectively

$$U(R) = \begin{cases} \alpha \log(\beta R/R_M), & R > 0 \\ 0, & R = 0 \end{cases} \tag{1}$$

Inspired by the QoE metric for downlink adaptive streaming, QoC metric for VR video uploading is introduced in this paper, which reflects the perceived quality of VR video after source coding. Note that during the uplink procedure only one representation will be generated for each tile according to our proposed scheme in this paper. And traditional transcoding procedure can be adopted if needed for further downlink adaptive streaming. Therefore, the encoding bit rate of uploading video provides a base version for downlink streaming (i.e., from UGC platform to viewers).

We define a weighted utility of a tile as in (1), modified from [16], where i and j represents the index of video and index of tile in one video, respectively; α and β denotes the coefficients of utility model, respectively. $R_{i,j}$ denotes the bit rate of the j-th tile in the i-th video, R_{max} represents the predefined maximum rate of a tile, and $w_{i,j}$ denotes the contribution weight of a tile to the QoC. The utility of i-th video U_i is the sum of the utilities of all tiles in this video, defined in (3), where J is the number of tiles.

$$U_{i,j} = \begin{cases} w_{i,j} \cdot \alpha \log(\beta R_{i,j}/R_{max}), & R_{i,j} > 0 \\ 0, & R_{i,j} = 0 \end{cases} \tag{2}$$

$$U_i = \sum_{j}^{J} U_{i,j} \tag{3}$$

According to the aforementioned analysis, the QoC contribution of each tile is related with its saliency and its vertical position. Naturally, the QoC contribution weight of a tile, $w_{i,j}$, is defined as the product of them, denoted by $S_{i,j}$ and $V_{i,j}$, respectively, as in (4).

$$w_{i,j} = S_{i,j} \cdot V_{i,j} \tag{4}$$

IV. SCHEME AND PROBLEM FORMULATION

A. SCHEME

The proposed scheme is illustrated in Fig. 4, in which encoding bit rate of each VR video tile is determined by uplink resource allocation. Only one representation for each video tile is generated in UEs side, and transmitted to the UGC platform then directly streamed to viewers. Moreover, quality of Content (QoC) contribution of each tile and channel quality of user equipments (UEs) are jointly considered during RA. Specifically, ERP video is encoded into tile bit streams by HEVC encoder, where the target tile bit rate is assigned based on the RA results of eNodeB. Tile bit streams with the same weight are stored to one buffer waiting for transmission. The buffer status report (BSR) is sent to eNodeB through the priority handing module.

The weight of each tile is defined as the product of detected saliency and its vertical position, and calculated within every RA round by the tile-based weight calculation module. The calculated weight is then quantized into the range of Quality of Service (QoS) class identifier(QCI) (i.e., from 1 to 9). And the quantized weight is reported to the RA scheduler as the QCI. At the eNodeB, the RA scheduler extracts the quantized weight for performing RA in our scheme instead of ensuring bearer traffic's QoS. Finally, the RA scheduler allocates the resources jointly according to the feedback Channel Quality Indicator (CQI) of UEs, the quantized QoC contribution weight of each tile and the BSR.

For all UEs and all video tiles, the RA module considers the channel quality of each UE as well as the QoC contribution weight of each tile within each RA interval. The objective is to maximize the total utility of VR videos by assigning optimal encoding bit rate for each tile. Finally, traditional transcoding procedure can be ignored and only one version of tile-based variable bit rate for each video is transmitted to the UGC platform and can be immediately streamed to viewers. Note that the encoding bit rate of uploading video provides a base version for downlink streaming. Therefore, optimal encoding bit rate of uploading VR video could lead to total QoE of viewers maximized. Although different viewers have different quality expectation on different area of the full video, the total QoE is maximized since different tiles have different optimal quality. Essentially, the key of the whole process is to find an optimal RA scheme for the uplink transmission by optimizing total utility.

B. PROBLEM FORMULATION

Note that UEs traffic is heterogeneous (e.g., VR, voice, other video). However, VR video is much more bandwidth consuming, which ought to be separated from common video by slicing. The network slicing (NS) allows the independent usage of a part of network resources by a group of mobile terminals with special requirements [24], [25]. For simplicity, wireless resource for VR traffic is assumed as a predefined value by network slicing. In this case, All VR videos generated by UEs need to be transmitted simultaneously through the LTE uplink by competing these resources, and each VR video is encoded as the format of tiles, while each tile can be encoded and decoded independently. In addition, the target tile bit rate is determined by the resource allocation of RA module of LTE uplink. Thus, the original problem can be formulated as find the optimal tile rate for each tile to maximize the total utility, while the total tile bit rates are under constraint of available bandwidth. And the original problem can be written as follows:

$$
\begin{aligned}
&P_{orig}: \\
&\quad \max_{R_{i,j}} \sum_{i}^{I}\sum_{j}^{J} U_{i,j}(w_{i,j}, R_{i,j}) \\
&\quad s.t.\ R_{i,j} \in \{R_1, \ldots, R_{max}\}, \quad \forall i \in I,\ \forall j \in J \qquad (5) \\
&\qquad\qquad \sum_{i}\sum_{j} R_{i,j} \le BW, \quad \forall i \in I,\ \forall j \in J \qquad (6)
\end{aligned}
$$

where (5) denotes each tile can only have a single predefined bit rate representation, i.e., $R_{i,j} \in \{R_1, \ldots, R_{max}\}$, and (6) denotes the total tile bit rates should be smaller than the total available bandwidth(i.e. BW).

In the LTE, the Single-Carrier Frequency-Division Multiple Access (SC-FDMA) is used for the uplink as the multiple-access scheme because of its advantage to provide a low peak-to-average power ratio (PAPR). A resource block (RB) is the smallest unit of the uplink, where each RB's channel quality is measured on the UE side and then fed back to the eNodeB to decide which Modulation and Coding Scheme (MCS) to be used. Moreover, the resource of each 1ms LTE uplink frame (a transmission time interval, TTI) can be divided into N RBs. The capacity of one RB is determined by the chosen MCS, which can be expressed as (7), where N_{sc}^{RB} and N_{sybm}^{UL} represent the number of subcarriers and symbols of one RB respectively. And *eff* denotes the efficiency of resource element (RE), which is determined by the chosen MCS. The MCS selection is according to CQI, and the mapping relation is given in Table.2 [21].

$$C = N_{sc}^{RB} * N_{sybm}^{UL} * eff\ (MCS) \qquad (7)$$

TABLE 2. **CQI-MCS mapping.**

CQI index	Modulation	Code rate($\times$1024)	Efficiency
1	$QPSK$	78	0.1523
2	$QPSK$	120	0.2344
3	$QPSK$	193	0.3770
4	$QPSK$	308	0.6016
5	$QPSK$	449	0.8770
6	$QPSK$	602	1.1758
6	$QPSK$	602	1.1758
7	$16QAM$	378	1.4766
8	$16QAM$	490	1.9141
9	$16QAM$	616	2.4063
10	$64QAM$	466	2.7305
11	$64QAM$	567	3.3223
12	$64QAM$	666	3.9023
13	$64QAM$	772	4.5234
14	$64QAM$	873	5.1152
15	$64QAM$	948	5.5547

Normally, the RA module assigned the RBs to UEs at every TTIs. However, for the simplicity of system model, we define an RA round as 1 second (i.e., 1000 TTIs), and the CQI of UEs are unchanged over the RBs in an RA round. In addition, RBs are allocated to video tiles instead of UEs, because tiles even in same VR video still competing uplink resources for higher encoding bit rate. All tiles in one VR video has the same channel quality as the associated UE, which is shown as (8). UE has the same channel quality over RBs from different TTIs with the same n index (i.e., CQI of UEs are unchanged over the RBs in an RA round), which is presented as (9).

$$CQI_{i,l,k,n} = CQI_{i,m,k,n} = CQI_{i,k,n}, \quad \forall l,\ m \in J(l \neq m) \qquad (8)$$

$$CQI_{i,j,p,n} = CQI_{i,j,q,n}, \quad \forall p,\ q \in K(p \neq q) \qquad (9)$$

Thus the assignment problem can be illustrated in Fig. 5, where in each RA round, we need to find an optimal RBs allocation scheme that maximizes the total utility. We associate the set of variables $\{x_{i,j,k,n} | (i = 1, 2, \ldots, I, j = 1, 2, \ldots, J, k = 1, 2, \ldots, K, n = 1, 2, \ldots, N)\}$ to the

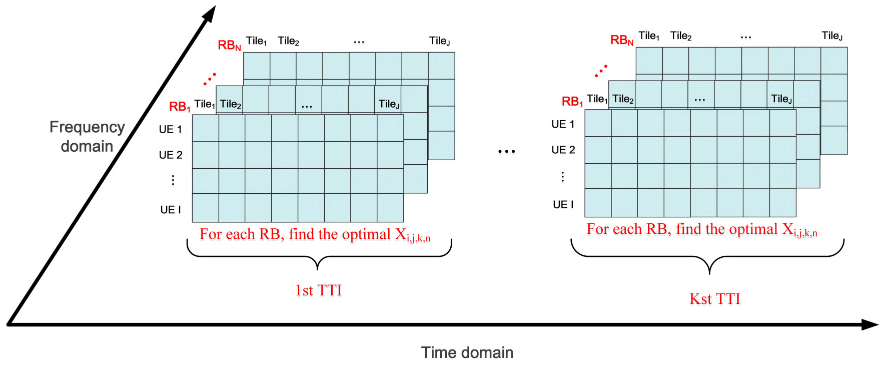

FIGURE 5. Demonstration of the assignment problem.

assignment problem, where $x_{i,j,k,n} = 1$ if the RB n at k-th TTI is assigned to the j-th tile of i-th video, and $x_{i,j,k,n} = 0$ otherwise. Each tile rate can be written as (10)

$$R_{i,j} = \sum_{k}^{K} \sum_{n}^{N} x_{i,j,k,n} C_{i,j,k,n} \tag{10}$$

Consequently, the assignment problem P_{assign} can be formulated as follows:

$$P_{assign}:$$

$$\max_{x_{i,j,k,n}} \sum_{i}^{I} \sum_{j}^{J} U_{i,j}(w_{i,j}, \sum_{k}^{K} \sum_{n}^{N} x_{i,j,k,n} C_{i,j,k,n})$$

$$s.t. \sum_{i} \sum_{j} x_{i,j,k,n} = 1, \quad \forall k \in K, \ \forall n \in N \tag{11}$$

$$x_{i,j,k,n} \in \{0, 1\}, \quad \forall i \in I, \ \forall j \in J, \ \forall k \in K, \ \forall n \in N \tag{12}$$

Equations (11) and (12) imply that a certain RB can only be allocated to one tile. Note that P_{assign} is similar to a 0-1 Knapsack Problem (KP) along time, which is proved as an NP problem and 0-1 KP can be solved by a dynamic programming (DP) algorithm [22]. However, P_{assign} is also a frequency and time dependent assignment problem, which is prohibitively difficult to apply DP algorithm. Furthermore, the problem is also a large-scale problem (the possible variable selection space can be $(I * J)^{NK}$), which is hard to find an optimal solution. Nevertheless, we notice that UE has the same channel quality over RBs from different TTIs with the same n index, which indicates that we can transform the RA problem into a frequency domain formulation. Particularly, at each n index, there are K RBs with same capacity as the n-th RB. So the P_{assign} can be rewritten as follows:

$$P_{trans}:$$

$$\max_{x_{i,j,n}} \sum_{i}^{I} \sum_{j}^{J} U_{i,j}(w_{i,j}, \sum_{n}^{NK} x_{i,j,n} C_{i,j,n})$$

$$s.t. \sum_{i} \sum_{j} x_{i,j,n} = 1, \quad \forall n \in NK \tag{13}$$

$$x_{i,j,n} \in \{0, 1\}, \quad \forall i \in I, \ \forall j \in J, \ \forall n \in NK \tag{14}$$

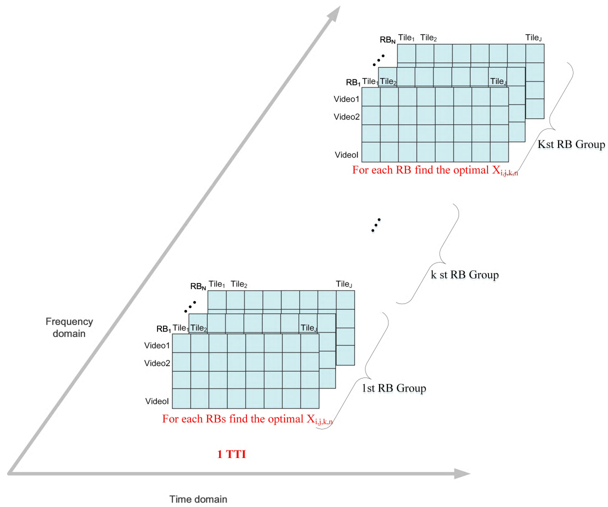

FIGURE 6. Demonstration of the transformed problem.

The P_{trans} can be demonstrated in Fig. 6. Note that the P_{trans} is also a KP problem, where the total number of RBs is NK. Nonetheless, the P_{trans} is still hard to be solved by the DP algorithm, due to nonlinear logarithmic function of sum of allocated bit rates in our formulation, the function leads former step decision also affect next step decision. In addition to large scale of the problem. All of these leads to DP is prohibitively difficult to solve the problem.

V. RESOURCE ALLOCATION ALGORITHM

Based on the aforementioned analysis, three algorithms are proposed to explore solving the problem in following part:

A. GREEDY ALGORITHM

The greedy algorithm solves the P_{trans} by greedily allocating RBs to the tiles to iteratively maximize the total utility gain. Particularly, the algorithm divides the KP problem into NK sub-problems, and each sub-problem can be described as selecting the best tile which maximizes the utility gain for each RB. The utility gain is defined as the incremental of total utility once the RB is assigned to a specific tile.

However, as one tile's utility is determined by the sum of allocated bit rates (i.e., capacities of allocated RBs to the tile), each sub-problem solution is dependent on the solution of a former sub-problem, so that the algorithm finds the best allocation for each sub-problem based on the solution of former sub-problem step by step. The algorithm iteratively executes the RA process until all RBs are allocated. The overall algorithm is summarized in Algorithm 1.

Algorithm 1 Greedy Algorithm

Θ: the set of RBs already assigned and the indication
Ω: the set of RBs need to assign
initial $\Theta = \varnothing$ and $\Omega = 0$
while $\Omega ! = \varnothing$ **do**
  for $n = 1; n \leq NK; n++$ **do**
    $t = 0; u = 0; v = 0;$
    // find the optimal allocation for each RB
    if $n \in \Omega$ **then**
      for $i = 1; i \leq I; i++$ **do**
        for $j = 1; j \leq J; j++$ **do**
          $x_{i,j,n} \leftarrow argmaxU_{\Omega + \{(n;i,j)\}}$
          $t = n; u = i; v = j;$
        end for
      end for
    end if
  end for
  update $\Theta \leftarrow \Theta + \{(t; u, v)\}$; $\Omega \leftarrow \Omega - \{t\}$
end while

B. TWO-STAGE ALGORITHM

Note that the objective is to find the optimal RA result for each tile of all competing VR videos, then each tile is encoded at the target bit rate to maximize the defined utility. Inspired by this, we also propose a naive algorithm called two-stage algorithm, where RBs are allocated based on cardinality of UEs instead of tiles in the first stage, then each tile in the corresponding UE is allocated proportionally based on total allocated bit rates of the UE according to the QoC contribution weight of this tile.

Since the two-stage algorithm assigns RBs to UEs instead of tiles in the first stage, the objective utility defined in (2) is no longer suitable for the RBs assignment problem, thus Proportional Fairness (PF) utility function is applied in the first stage of algorithm, which corresponds to the common PF objective [10]. Furthermore, the greedy algorithm is applied for the RBs assignment. After the stage 1, each tile in a specific UE is allocated a bit rate proportionally according to the weight of tiles, which is given in (15), where ${R_i}^{PF}$ is the achieved bit rate of the i-th UE in stage 1. The overall algorithm is summarized in Algorithm 2.

$$R_{i,j} = {R_i}^{PF} \cdot \frac{w_{i,j}}{\sum\limits_{j} w_{i,j}} \tag{15}$$

C. ONE-SHOT ALGORITHM

One-shot algorithm is proposed to solve the problem by an approximate convex method. The basic idea is to relax the optimization problem within one RBs group of one TTI, and accordingly allocate RBs in the total RA Round by making use of solution of the relaxed convex sub-problem. The overall algorithm is summarized in Algorithm 3. Specifically, we find that the sub-problem $P_{oneshot}$ can be solved using the optimization toolbox by relaxing the constraint of $x_{i,j,n}$. By relaxing the $x_{i,j,n}$ from binary to continuous value between 0 and 1, $P_{oneshot}$ can be solved by applying the CVX [13].

Note that the optimal solution for $P_{oneshot}$ indicates that a proportion of each RB need to be assigned to each tile if one

Algorithm 2 Two-Stage Algorithm

// Stage 1
for $n = 1; n \leq NK; n++$ **do**
  for $i = 1; i \leq I; i++$ **do**
    apply the greedy algorithm with the proportional fairness utility function to find the optimal $x^*_{i,n}$;
  end for
end for
for $i = 1; i \leq I; i++$ **do**
  calculate the R_i^{PF} according to the $x^*_{i,n}$,
  $R^{PF}{}_i = \sum\limits_{n}^{NK} x^*{}_{i,n} C_{i,n}$
end for
// Stage 2
for $i = 1; i \leq I; i++$ **do**
  for $j = 1; j \leq J; j++$ **do**
    obtain the target bit rate $R_{i,j}$,
    $R_{i,j} = {R_i}^{PF} \cdot \frac{w_{i,j}}{\sum\limits_{j} w_{i,j}}$
  end for
end for

Algorithm 3 One-Shot Algorithm

for $n = 1; n \leq N; n++$ **do**
  for $i = 1; i \leq I; i++$ **do**
    for $j = 1; j \leq J; j++$ **do**
      solve the problem $P_{oneshot}$ by the CVX to get $x^*_{i,j,n}$
    end for
  end for
end for
for $k = 1; k \leq K; k++$ **do**
  for $n = 1; n \leq N; n++$ **do**
    for $i = 1; i \leq I; i++$ **do**
      for $j = 1; j \leq J; j++$ **do**
        if $\sum\limits_{k} x_{i,j,k,n} \leq round(Kx^*_{i,j,n})$ **then**
          $x_{i,j,k,n} = 1$
        else
          $x_{i,j,k,n} = 0$
        end if
      end for
    end for
  end for
end for

RB can be allocated to multiple tiles or UEs. Unfortunately, one RB can only be allocated to one tile or one UE in practice. However, note that one RA round in our transformed problem P_{trans}, each RB with the same index in different RB groups has same capacity, which means there are K RBs with the same capacity in the n index.

Inspired by this, in order to find the optimal solution of P_{trans}, we convert the optimal solution of problem $P_{oneshot}$ by multiplying K to turn the proportional fraction to an integer number (accurately, rounding the result number after multiplication). Consequently, the obtained numbers of RBs with same n index should be the number of RBs assigned to each tile.

$$
\begin{aligned}
&P_{oneshot}:\\
&\quad \max_{x_{i,j,n}} \sum_{i}^{I}\sum_{j}^{J} U_{i,j}(w_{i,j}, \sum_{n}^{N} x_{i,j,n} C_{i,j,n})\\
&\quad s.t. \sum_{i}\sum_{j} x_{i,j,n} = 1, \quad \forall n \in N \qquad (16)\\
&\qquad\quad 0 \leq x_{i,j,n} \leq 1, \quad \forall i \in I,\ \forall j \in J,\ \forall n \in N \qquad (17)
\end{aligned}
$$

RB	1	2	3	4	5	6	7	8	9	10
RB assign indication										
Tile 1	0.1	0.2	0.1	0.3	0.4	0.5	0.6	0.1	0.1	0.1
Tile 2	0.1	0.3	0.6	0.3	0.1	0.2	0.3	0.4	0.3	0.6
Tile 3	0.8	0.5	0.3	0.4	0.5	0.3	0.1	0.5	0.6	0.3

FIGURE 7. An example of the RB assignment for $P_{oneshot}$.

Fig. 7 shows an example of RB assignment in one RB group. In order to demonstrate the strategy clearly, let us assume that there are 10 RBs in one RB group, and three tiles need to allocate resource in each RA round. As we relax assignment indicator as decimal between 0 and 1, the assignment indicator could be obtained from optimization solution of $P_{oneshot}$. While the indicator for the Tile1 on RB 1 in the RB group is 0.1, thus $0.1 \times K$ RBs with index of 1 in the RA round are assigned to the Tile1 according to the Algorithm 3, and the rest of 100 and 800 RBs with index of 1 are assigned to the Tile2 and Tile3, respectively (Actually, total 1000 RBs with index 1 in the time domain should be allocated in one RA round).

Hence, the RBs allocation of an RA round could follow this assignment strategy. We can see that the complexity of one-shot algorithm is dramatically reduced with the help of optimization toolbox CVX by relaxing the binary constraint of assignment indicator.

Note that proposed three algorithms could not guarantee the global optimality of solutions, since they are all approximate solutions. The greedy algorithm solves the problem by finding optimal solutions of the N^K sub-problems step-by-step, however these solutions are local optimal. The two-stage algorithm allocates RBs to UEs instead of tiles, while it reduces the complexity of algorithm. Since QoC contribution weight of tiles are only considered after the RA in stage one, which means that even the tile bit rate allocation in the stage two is optimal, it still fails to jointly optimize the target utility according to the channel quality and QoC contribution weight of tile at the same time.

The one-shot algorithm obtains the solution by converting the optimal fraction solution of problem $P_{oneshot}$ with a relaxed assignment indicator, which may also leads the local optimal solution. However, the strategy of one-shot algorithm is easy to implement, which also dramatically reduces the complexity of algorithm. Meanwhile the solution of one-shot algorithm is empirically shown to be close to the greedy algorithm solution in Simulation Section. Overall, one-shot algorithm is a promising solution with low complexity.

VI. SIMULATIONS

In this section, we conduct plenty simulations to evaluate the performance of our proposed solutions for the problem.

A. SETUP

Nine uncompressed 360-degree video sequences: AcademicBuilding (Video1), Runner (Video2), StudyRoom (Video3), Sward (Video4), SiyuanGate (Video5), SouthGate (Video6), SouthGateNight (Video7), BridgNight (Video8), BasketballCourt (Video9) from the STJU immersive video sequence Dataset [27]are used for evaluations. 240 frames of each video sequence are extracted for the simulations. The open-source HEVC encoder Kvazaar [28] is applied as video encoder; the frame rate and GoP for all the 360 degree videos are set as 25 fps and 8, respectively. In addition, we adopt the 4×8 tiling scheme in this paper.

For LTE RA module part, the simulations are conducted based on MATLAB. ITU pedestrian B fast fading model and the COST231 Hata propagation model for micro-cell environment [29] are adopted. In addition, lognormal shadowing with 8 dB standard deviation is implemented, where the available uplink bandwidth for VR video transmission is set as 2.5 MHz, 5 MHz, 10 MHz, 15 MHz, 20 MHz, respectively, so that the corresponding number of RBs in each TTI are 12, 25, 50, 75, 100, respectively.

In this work, in addition to three aforementioned RA algorithms in Section III, we also implemented the proportional fair (PF) [24] algorithm without weighting (PFww) for performance comparison, which are summarized as follows:

Greedy algorithm: it greedily allocates the RBs one by one to the tile which brings maximum utility gain in order to achieve the maximum total utilities.

Two-stage algorithm: The RBs assignment is based on cardinality of UEs instead of tiles in the first stage, then each tiles of the corresponding UE is allocated the bit rate proportionally according to the weight of tiles.

One-shot algorithm: it allocates RBs according to the converted the optimal integer solution of the problem $P_{oneshot}$.

PF without weight(PFww) algorithm: it applies a similar strategy of greedy algorithm, however without considering the weight of tiles during the RA.

The coefficients of utility model α, β are empirically set as 0.1 and 1000, respectively.

B. RESULTS

Fig. 8 shows the total utilities achieved by four algorithms with different available bandwidth in case of four UEs in the system. Note that the total utilities increase as more wireless resources are reserved, since higher source coding rate for VR video tiles are achieved with more allocated resources. Fig. 8 also shows that proposed one-shot and greedy algorithms achieve at least 17% more system utilities than that obtained by the PFww algorithm, and at least 15% more system utilities than that obtained by the two-stage algorithm. The greedy algorithm performs slightly better than the one-shot algorithm, whereas the one-shot algorithm has less complexity than the greedy algorithm, which will be analyzed in the complexity analysis part.

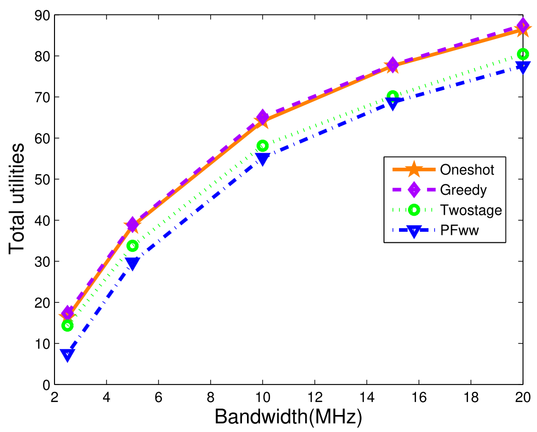

FIGURE 8. **The total utilities of system with different available bandwidth.**

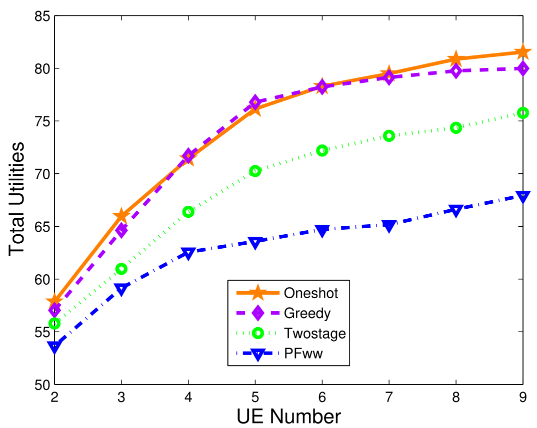

FIGURE 9. **The total utilities of system with different UEs.**

Fig. 9 shows the trend of system utilities with different RA algorithms as the number of UEs changes under 10 MHz available bandwidth. According to Fig. 9, achieved utilities of all algorithms are increasing as the number of UEs in system increases. However, the increase scope slowed as the number of UEs reaches to a certain value. This infers that some tiles are allocated with small amount of resources when considerable UEs are competing for the limited resources. Particularly, utilities with the PFww algorithm performs the worst, since not enough resource is allocated the tiles with high weights. The greedy algorithm performs slightly better than the one-shot algorithm, whereas the two-stage algorithm performs much worse than the greedy and one-shot algorithms, since it allocates the resource by dividing the problem into two-stages instead of considering the channel quality and tile weights collectively.

Furthermore, we applied VW-utility (viewport-weighted-utility) to measure the real viewer's QoE objectively during the VR video watching. A viewer's VW-utility is defined as sum of the tiles' utilities in the viewport, which can be obtained with the help of field of viewport (FOV) tracker. Similar strategy to measure the viewer's QoE is also applied in [30]. Four VR videos (Video1-Video4)(i.e., four UEs in the simulation generate the videos respectively for uploading) are selected for evaluation of the VW-utilities, which are encoded according to different RA algorithms with 10 MHz available bandwidth respectively. Eventually each of video is encoded into four different versions, so that 16 encoded videos are totally generated. The viewers watch those VR videos through the HMD, the eye tracking module aGlass [31] is integrated with the HMD for FOV tracking. The VW-utility is calculated according to FOV tracking data and the corresponding tiles' utilities in the viewport, which is used to evaluate the performance of proposed RA schemes and PFww, respectively.

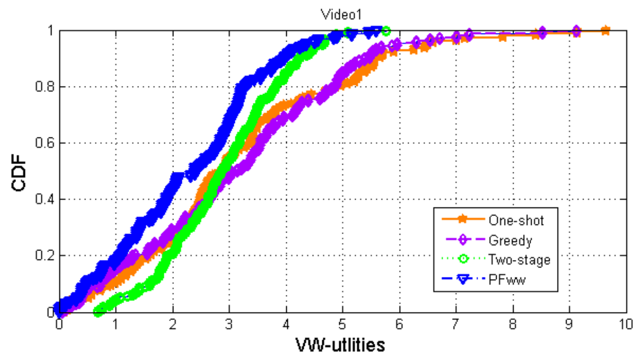

FIGURE 10. **CDF of VW-utilities for VR video1.**

Fig. 10-13 show the CDF(cumulative distribution function) of VW-utilities for each VR video with 10 MHz available bandwidth. We can see clearly that the greedy and one-shot algorithms perform better than the two-stage and PFww algorithms, and the VW-utilities of the greedy and one-shot algorithms are improved by 26.4% and 25.2% compared to the PFww algorithm, respectively, and are increased by 12.6% and 12.1% compared to the two-stage algorithm, respectively.

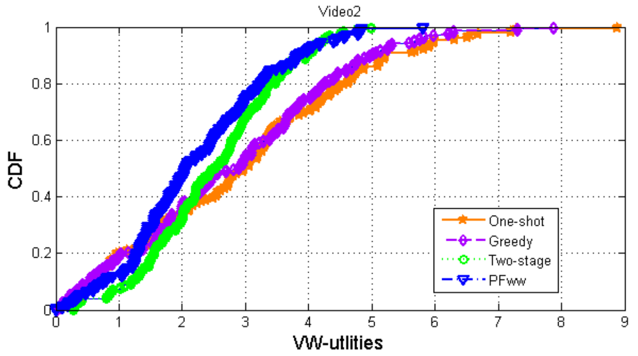

FIGURE 11. CDF of VW-utilities for VR video2.

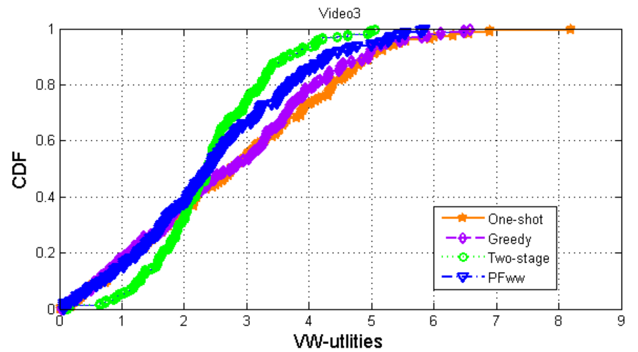

FIGURE 12. CDF of VW-utilities for VR video3.

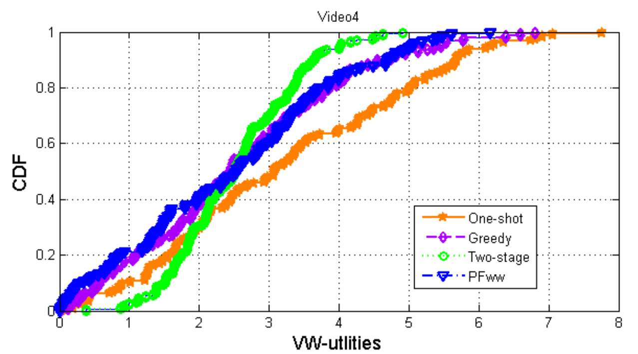

FIGURE 13. CDF of VW-utilities for VR video4.

Note that the saliency of content of Video3 (indoor study room) and Video4 (outdoor sward) are more dispersed in the ERP frames than the Video1 and Video2, and the viewers' attention for one VR video frame may also dispersed, thus the tile weight would not affect the RA results dominantly. Consequently, the VW-utilities for Video3 and Video4 show that the greedy and one-shot algorithms perform slightly better than the PFww, and the saliency impact for RA will be studied more carefully in our future work.

Finally, complexities of proposed algorithms and PFww are analyzed. Complexity of the greedy algorithm is in order of number of total tiles power of number of total RBs. Since each RB would have to associate with a specific tile according to the greedy algorithm, and the complexity is exponential increased as the number of UEs and tile grid increases. Complexity of the two-stage algorithm is order of number of total RBs power of number of total UEs. One-shot algorithm's complexity is order of number of total tiles power of number of RBs in one TTI. Note that the complexity is exponential increased as the number of total tiles, however the complexity is dramatically reduced compares to the greedy algorithm since number of RBs for optimization is only in terms of one TTI. PPww adopts a similar strategy as the greedy algorithm, which search the optimal assignment for each RB without considering the weight of tile during the RA, and the search space for each RB is in order of number of total tiles. Therefore, complexity of PPww algorithm is in order of number of total tiles power of number of total RBs.

TABLE 3. Comparisons of complexities.

Algorithm	Complexity	CPU time(sec)
$Greedy$	$O((IJ)^{NK})$	5.78
$Twostage$	$O((I)^{NK})$	0.36
$Oneshot$	$O((IJ)^{N})$	0.67
$PFww$	$O((IJ)^{NK})$	4.95

Table.3 shows the comparisons of complexities. CPU time is also measured using Matlab when there are 100 available RBs in one TTI (i.e., 20 MHz available bandwidth) and 4-different videos with 4×8 tiles competing for the available resources. The greedy algorithm and PFww algorithm take long time to complete the optimization since the large-scale of problem. The two-stage algorithm takes shortest time to obtain the solution, however with worse achieved utility. The one-shot algorithm can complete the optimization much faster than greedy algorithm, and with comparable utility.

Overall, the proposed scheme could significantly improve QoE by optimizing uplink resource allocation for VR video delivery over cellular network, especially for delay sensitive scenarios, (e.g., live UGC VR broadcast). And proposed approximate convex algorithm (i.e., one-shot algorithm) is a promising RA solution with low complexity and comparable performance.

VII. CONCLUSION

This paper studies the optimization of uplink resource allocation for VR video transmission over cellular network, which is very important in future live UGC VR applications. We proposed a novel uplink transmission scheme, based on this, tile-based video encoding is adopted, while the encoding bit rate of tiles are determined by the RA module of LTE uplink. Three RA algorithms are proposed to explore solving the RA problem to maximize the total utility of VR videos under the limited available bandwidth. The simulation shows that the proposed one-shot algorithm with low complexity performs comparably with the greedy algorithm with high complexity, and the results also verify that the proposed scheme and algorithms could significantly improve the QoE.

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