Content Aware Resource Allocation for Video Service Provisioning in Wireless Networks

Yongxiang Zhao, Yunpeng Song, and Chunxi Li(✉)

Beijing JiaoTong University, Beijing 100044, China
{yxzhao, 17120113, chxli1}@bjtu.edu.cn

Abstract. Video service has been a killer application over wireless networks. Many cross-layer optimization techniques have been proposed to improve the quality of video services in wireless networks. However, most of them did not consider video content type information in resource allocation, which greatly affects the quality of users' watching experience. In this paper, we take video type information into consideration for resource allocation at base stations. Accordingly, for given transmission power at base station, we build an optimal model to achieve maximal achievable total Mean Opinion Score (MOS) by allocating appropriate powers and video rates for different users watching different types of videos. Numerical results show that our model can achieve much higher MOS compared with existing scheme that does not consider such video type information.

Keywords: MOS · Video content · Resource allocation · Wireless networks

1 Introduction

Video services have been a killer application over mobile networks and smart devices. According to a cisco report [1], mobile video traffic has accounted for 55% of the total mobile data in 2015 and is expected to grow approximately to 75% in 2020.

Many cross-layer techniques have been proposed to improve video quality in wireless environment. In [2], Gross et al. proposed to schedule packet transmissions over orthogonal frequency-division multiplexing (OFDM) channels in a way such that higher priority is given to more important packets (e.g., Iframes in video traffic). In [3], Li et al. built an optimal model to minimize the distortion of reconstructed videos at user side in multi-user wireless video transmission environment. They assume that all users use the same rate-distortion function. In [4], Chuah et al. considered scalable video in multicast communications and used signal-to-noise ratio and packet delivery rate as video quality measures. However, they did not consider perceptual quality at users. In [5], Danish et al. proposed a resource allocation algorithm, which assigns video bitrate and subcarriers to users with an expectation to maximize users' perceptual quality of video services. However, they did not consider how to allocate network resources among users watching different types of videos. In summary, all the above existing work did not take video content type information (e.g., whether a video is an action movie or a romance video) into consideration when making decision on resource allocation among different users so as to improve the overall perceptual quality of video services at users.

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Video type has big impact on the MOS (Mean Opinion Score) of video service at user side. In this aspect, Ref. [6] found that the MOS (Mean Opinion Score) of a video watching experience is not only related to video bitrate, frame rate, and packet loss probability, but also related to video type. In addition, the impact of bitrate, frame rate, and packet loss probability on the MOS for different video types are also different. For example, the MOS of an action movie with violently changing pictures will be smaller than that of a landscape film with smoothly changing pictures under the same setting of bitrate, frame rate, and packet loss probability. Thus, we have the following two inferences: Base station needs to allocate more transmit power to users watching action videos than to users watching landscape videos in order for them to enjoy same level of MOS in video watching; Given transmit power allocated to a user, we also need to consider the balance between video bitrate and packet loss probability in order to maximize the user's MOS.

Based on the above observations, in this paper, we build a content aware resource allocation model by considering video content type information in wireless resource allocation. We assume video type information is known for resource allocation at base stations. Accordingly, for given total transmission power at base station, we build an optimal model to achieve maximal total achievable MOS by allocating appropriate transmit powers and video rates for different users watching different types of videos. Numerical results show that our model can achieve much higher total MOS compared with existing scheme that does not use such video type information.

The rest of this paper is organized as follows. In Sect. 2, we introduce some related work. In Sect. 3, we first introduce application scenario under study and feasibility of MOS maximization by considering video type information. In Sect. 4, we build the optimal content aware resource allocation model. In Sect. 5, we provide numerical results for performance evaluation. Finally, in Sect. 6, we conclude the paper.

2 Related Work

Existing work for supporting video streaming services in wireless networks can roughly be classified into following two types: top-down approaches and bottom-up approaches. The former type of approaches adapts video's features to network layer/data link layer/physical layer's parameter tuning. In contrast, the latter type of approaches adapts network layer/data link layer/physical layer's parameters to the tuning of video streaming parameters [7]. Next, we shall introduce typical work belonging to either type.

Typical top-down approaches are as follows. In [2], Gross et al. suggested to transmit important video packets (Iframes) with high priority over OFDM channels. In [8], Lee et al. suggested that a mobile terminal should control its video bitrate according to its video content characteristics in order to achieve improved energy efficiency. This idea was extended to three-dimensional (3D) videos where QoE (Quality of Experience) is used as base measure to determine SNR (Signal Noise Ratio) threshold for adaptive modulation and coding over IEEE802.16e wireless channels [9].

Typical bottom-up approaches are as follows. Refs. [3, 4] formulated the optimal resource allocation problem by maximizing the video quality of users subject to transmission energy and channel access constraints. Ref. [10] built an optimal model to allocate bandwidth to users according to their video contents. However, [10] only considers bandwidth constraint without considering the relationship among power, bandwidth, and packet loss probability. Ref. [5] is the closest to our work in this paper. Given a target minimal power requirement, Ref. [5] proposed a scheme to assign video bitrate and subcarriers to users in order to maximize the users' perceptual quality of videos. However, Ref. [5] assumes that packet loss probability is given (fixed) and users' perceptual quality of videos is only relevant to video bitrates. They did not consider the relationship between video bitrate and packet loss probability. Moreover, it did not consider power allocation among users watching different types of videos. In our work in this paper, perceptual quality of a video is relevant to transmit power, packet loss probability, and video bitrate. Furthermore, packet loss probability is a function of both transmit power and video bitrate.

3 Application Scenario and Key Idea

Figure 1 shows the application scenario under study in this paper. In this figure, a number of wireless video-watching users are scattered in a cell covered by a base station. These users can be classified into the following three types based on the types of video they are watching [6]: videos with Slight Movement (SM), videos with Gentle Walking (GW), and videos with Rapid Movement (RM).

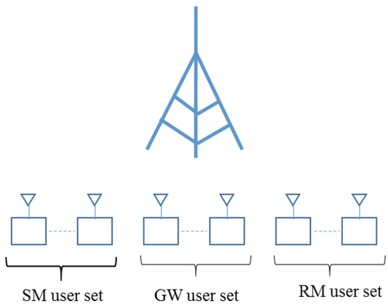


Fig. 1. Application scenario.

According to [6], the MOSs of SM, GW, and RM videos can be calculated as follows, respectively:

$$\mathrm{MOS_{SM}} = 0.0075r - 0.014f - 3.79l + 3.4 \tag{1.a}$$

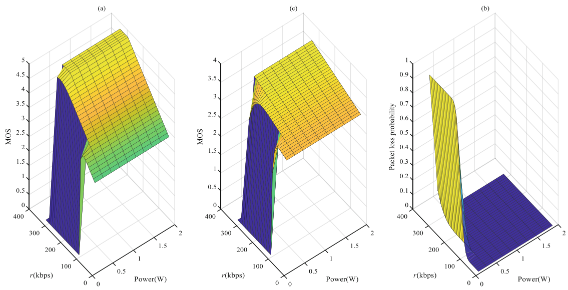
$$\mathrm{MOS_{GW}} = 0.0065r - 0.0092f - 5.76l + 2.98 \tag{1.b}$$

$$\mathrm{MOS_{RM}} = 0.002r - 0.0012f - 9.53l + 3.04 \tag{1.c}$$

In (1.a), (1.b) and (1.c), r, f, l represent video bitrate, frame rate, and packet loss probability, respectively. Moreover, in this paper, we set the MOS of a video to zero when packet loss probability l is larger than nine percent since the video quality in this case usually very poor. In (1.a), (1.b) and (1.c), it is seen that the coefficients of r, f, l for different types of videos are quite different. For example, when the packet loss rate increases one percent, the MOS of a RM video will be decreased by 0.0953 while that of an SM video is only decreased by 0.0379.

The MOS of a video can be expressed as a function of transmit power (denoted by p) and video bitrate r. The reason is as follows. Firstly, packet loss probability l is a function of transmit power p, distance between transmitter and receiver (denoted by d), video bitrate r, and noise spectral density N_0 and packet size [11]. Secondly, MOS is a function of l, f, and r according to (1.a), (1.b) and (1.c). Thus, given d, N_0, packet size, and f, MOS is a function of p and r. Details are shown in Sects. 4.1 and 4.2.

Figure 2 shows the MOS for SM videos, MOS for RM videos, and also corresponding packet loss probability, respectively, due to varying video bitrate and transmit power. In this figure, the video bitrate range for both SM and RM videos is [100, 320] kbps. (Default) frame rate is fixed to be 30 frames per second. As shown in Fig. 2(a)



(a) MOS for SM videos (b) MOS for RM videos (c) packet loss probability

Fig. 2. MOS and packet loss probability of SM.

Table 1. Symbols used.

Symbols	Definition
N	Total number of users
u_j	j^{th} user
d_j	Distance between user u_j and base station
r_j	Video bitrate of u_j
p_j	Power that base station uses to transmit video to user u_j
l_j	Packet loss probability of j^{th} user
c_j	video content type of j^{th} user
$H(p_j, d_j, r_j)$	A function returns packet loss probability l_j for given p_j, d_j, r_j
$F(c_j, r_j, l_j)$	returns j^{th} user's MOS for given c_j, r_j, l_j

and (b), the MOSs of these two types of videos are quite different under the same combination of video bitrate and transmit power. In addition, different video types have different MOS gradients with respect to video bitrate and transmit power. Thus, these two observations suggest that we need to adjust transmit power and video bitrate simultaneously in order to maximize the total MOSs of all users.

4 Optimal Model for Content Aware Resource Allocation

In this section, we shall build an optimal content aware resource allocation model, which introduces video type information into wireless resource allocation while achieving maximal total MOS for all users.

In our model, base station is assumed to know the video type information of each video-watching user in its cell. Symbols used hereafter are listed in Table 1.

4.1 Packet Loss Probability Calculation

We use free space propagation model and DPSK modulation [11] to support the video transmissions from base station to wireless terminals. Specifically, we firstly use free space propagation model to calculate received power (denoted as P_r) at receiving terminal, which is as follows.

$$P_r = P_t G_t G_r \left(\frac{\lambda}{4\pi d}\right)^2 \tag{2}$$

Where, $P_t, G_t, G_r, \lambda, \text{and}\, d$ are transmission power at base station, transmitter antenna gain, receiver antenna gain, wavelength, and distance between transmitter and receiver, respectively. $\lambda = c/f$ where $c = 3 \times 10^8 \mathrm{m/s}$ is speed of radio signal and f is frequency. We set G_t, G_r, f to be 2, 1.6, and 900 MHz, respectively, as used in [11].

We assume the modulation technique is DPSK, thus bit error probability e can be calculated as follows [11].

$$e = \frac{1}{2}\exp\left(-\frac{P_r}{RN_0}\right), \tag{3}$$

where R is video bitrate and N_0 is noise power density which equals 3.2×10^{-20} J. In our analysis here, video bitrate is assumed equal to channel rate owing to the following reason. In our model, base station chooses video bitrate for each user and it can adopt transmission techniques such as OFDM or software defined radio like opening a special channel for per-user transmission based on the assigned video bitrate. Since such techniques can provide user-specific channel rate at small granularity, it is reasonable for us to assume that channel rate at the physical layer equals the video bitrate at the application layer. Although such assumption is kind of simplified, it can still largely capture major characteristics of wireless channels and in particular it enables us to focus on the video-service-provisioning-related cross layer optimization.

Accordingly, packet loss probability l can be obtained by the following equation.

$$l = 1 - (1 - e)^S \tag{4}$$

where S is packet size and its default value is 8000 bit in this paper.

In brief, for a user u_j, given p_j, d_j and r_j, we can obtain the packet loss probability l_j by using (2), (3), and (4). To ease the presentation, we shall use function $H(p_j, d_j, r_j)$ to represent the calculation of packet loss probability l_j.

4.2 MOS Calculation

We use the following method to calculate each user's MOS. As mentioned in Sect. 3, users are classified into three sets: SM, GW, and RM. We use function $F\,(c_i, r_i, l_i)$ to calculate a user u_i's MOS suppose his/her video content type is known. Details are as follows: select (1.a), (1.b) or (1.c) according to the value of video type c_i and replace r_i and l_i into corresponding equations to calculate the user's MOS. Note that packet loss probability is calculated using the method in the preceding subsection.

4.3 Optimal Content Aware Resource Allocation Model

Combine the results in the above two subsections, we have an optimal content aware resource allocation model as follows. Given each user's video type, his/her distance away from the base station, and the total transmit power P that the base station can use to deliver the video services, this model tries to maximize the sum of MOSs by all users. That is,

$$\max_{\{p_j, r_j\}} \sum\nolimits_{j=1}^{N} \mathrm{MOS}_j \tag{5}$$

Subject to:

$$l_j = H\left(p_j, d_j,\, r_j\right), \qquad j \in [1, \ldots, N] \tag{6}$$

$$\mathrm{MOS}_j = F(c_j, r_j, l_j), \qquad j \in [1, \ldots, N] \tag{7}$$

$$\sum\nolimits_{j=1}^{N} p_j \le P, \qquad j \in [1, \ldots, N] \tag{8}$$

$$l_j \le \gamma, \qquad j \in [1, \ldots, N] \tag{9}$$

$$p_L \le p_j \le p_B, \qquad j \in [1, \ldots, N] \tag{10}$$

In this model, p_j and r_j are variables. The objective function (5) is to maximize the sum of all users' MOSs. Equation (6) finds the packet loss probability of each user. Equation (7) returns u_j's MOS. (8) requires sum of the powers allocated to all users is less than or equal to P, which represents the maximal possible (total) power that the base station can use for the transmissions and it is an input parameter. (9) requires packet loss probability l_j is less than or equal to γ which is also an input and the default of its value is set to be 0.1 in this paper or otherwise the quality of video for user u_j will be totally unacceptable. (10) requires p_j is in the range $[p_L, p_B]$, which are low bound and upper bound of the power allocated to a user and, in this paper, their default values are set to 0 and P, respectively.

5 Numerical Results

In this section, we evaluate the performance of our content aware resource allocation model via numerical results. We focus on the one-cell case such that there is only one base station with one or more users. The rate upper bound of SM, and RM is set to 320, and 1450 kbps, respectively.

For comparison purpose, here, we also realized a baseline model, which does not consider video content type in resource allocation. The baseline model works as follows: it first slices the total transmission power P equally into N share and each user is assigned with an amount of P/N power; then it finds a user's maximal MOS which can be obtained by using content aware allocation model in which P is replaced by P/N and the user set only contains this user; Finally, the outcome of the baseline model is sum of all users' maximal MOSs. The philosophy behind such a baseline model is as follows. According to [11], in a cellular network, base station is typically scheduled to transmit data to each terminal for a fixed time slice in roughly round-robin fashion. Thus, all users share the transmission power roughly equally.

5.1 One-User Case

In this experiment, we assume there is only one user whose distance away from the base station is 340 m. Then we varied the transmit power of base station from 0.1w to 2w with step size 0.1w and obtained the MOSs by different models. Figure 3 shows the numerical results when the user watches SM, GW, and RM video, respectively.

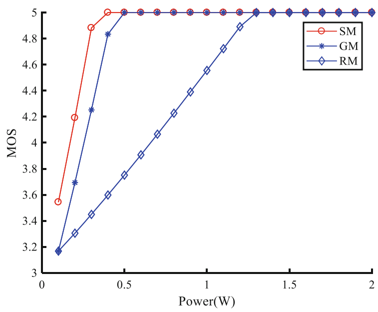


Fig. 3. MOSs by different video content types for one user case.

From Fig. 3, it is seen that the slopes of curves for different video types are different, which mean that we need to balance the power assignment among different video types when multiple users share the transmit power. Specifically, we can see that the SM curve has the steepest slope which means SM is the easiest to be saturated among the three types. That is, in case three types of video watchers with the same distance away from the base station, the priority for power allocation to different types of video watchers (from the highest to the lowest) is as follows: SM video watchers, GM video watchers, and finally RM video watchers.

5.2 Two-User Case

In this experiment, we assume there are two users watching two different types of videos: one SM user and one RM user. We chose these two types of videos because they have quite different slopes in MOS increase (see Fig. 3). In three different tests, these two users' distances away from the base station was set to (340 m, 640 m), (640 m, 340 m), and (400 m, 400 m), respectively (the former setting is for the SM user while the latter is for the RM user). In each test, we varied the transmit power of base station from 0.1w to 2w with step 0.1w and obtained the MOSs by different models. The results for the three tests are shown in Fig. 4(a), (b), and (c). Figure 5(a), (b), and (c) show the corresponding power allocated to the SM and RM users by our model. Figure 6(a), (b), and (c) show the corresponding video bitrates allocated to the SM and RM users by our model for each relevant case shown in Fig. 5.

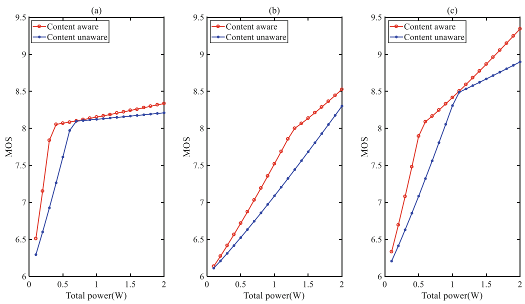


Fig. 4. MOSs under two types of videos (SM and RM videos) by different models.

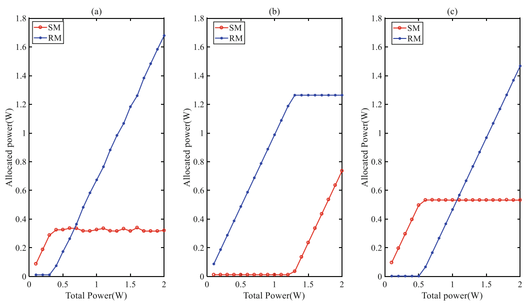


Fig. 5. Allocated powers for different video watchers by our content aware model.

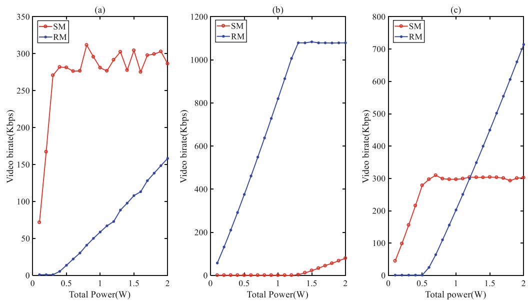


Fig. 6. Allocated video bitrates for different types of video watchers by our model.

In Fig. 4, it is seen that the curves for our content aware model are above the curves for the baseline model most of time.

Our model works to jointly optimize the power and video bitrate for each user while maximizing the sum of all users' MOSs. From Figs. 4, 5 and 6, we can see that our model tends to give high priority for allocating power to video types with faster increase rates in MOS for the same amount of power. In Fig. 5(a) (i.e., first test, leftmost subfigure in Fig. 5), our model first allocates all available power to the SM user since it is easier to increase MOS of a SM user. Because the MOS of SM is nearly saturated when transmit power = 0.4 W as can be seen in Fig. 3, the model begins to allocate remaining power to RM user when the total power exceeds 0.4 W which causes a knee point of curve of content aware model in Fig. 4(a). In Fig. 6(a), it can be seen that our model increases video bitrate of RM user until the total power exceeds 0.4 W. In the second test (i.e., the middle subfigure), the RM user is easier to increase the MOS since it is much closer to the base station than the SM user. Thus, our model first allocates all available power to RM user when the total power is below 1.2 W. After that, it begins to allocate to the SM user. The video bitrate curve of RM in Fig. 6 (b) shows similar behavior. In the third test (i.e., the rightmost subfigure), the SM user is easier to increase the MOS since the distances of the two users away from base station are the same. In this case, our model allocates available power to SM user first, then to RM user. In addition, we would like to point out that the small-scale fluctuation in transmit power allocated to SM user (see Fig. 5(a) and the approximate 20-kbps fluctuation in bitrate allocated to the SM user (see Fig. 6(a)) jointly contribute to the steady increase in MOS as shown in Fig. 4(a).

6 Conclusion

In this paper, we built an optimal resource allocation model to exploit the video content type information for provisioning of better video services in wireless environments. Numerical results show our model can improve the MOS performance as compared with baseline model.

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