Distributed Quality-Aware Resource Allocation for Video Transmission in Wireless Networks

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Abstract. The rapid development of wireless networks makes it more convenient for people to enjoy high quality multimedia. However, video applications are throughput-demanding, and relatively, radio resource always seems insufficient. Hence, a distributed algorithm is designed in this paper to allocate the limited wireless resource among multiple users for video streaming. In order to specify multimedia service from other ordinary data transmission, the QoE-oriented utility function is considered first. Then, a potential game model is formulated and all the video receivers can update their rate strategies with very little information exchange. By this kind of updating, the bandwidth allocation could be achieved intelligently. The algorithm converges to a set of correlated equilibria. Numeric simulation results indicate that it brings remarkable benefits to both the resource provider and the video users.

Keywords: Distributed algorithm · Resource allocation · QoE · Potential game

1 Introduction

The massive layout of different wireless networks makes handheld devices more and more pervasive. Meanwhile, High Definition (HD) and Ultra High Definition (UHD) multimedia gradually bring people high-grade visual experience. When delivered in wireless network, high definition videos need more available bandwidth. Although they have been greatly compressed by video coding algorithms, such as H.265/HEVC, wireless networks still can not afford the burdens when users become abundant. Thus, it's very crucial to properly allocate the limited bandwidth resource to different video terminals.

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Some literatures solved the rate allocation problems by improving the Quality of Service (QoS) and formulating them as optimization problems [1,7,18]. Meanwhile, we can find that game theory has been widely used in tackling with these issues and gotten very good effects. [17] established a two-level game framework, with an evolutionary game for underlying service and a differential game for upper bandwidth selection. [9] proposed a Stackelberg dynamic game model to get the optimal allocated resources. [4] modeled resource competition as the process of replicator dynamics and formulated a decentralized way to deal with task offloading. However, some of them were not about video transmission, or some of the utility functions could not effectively describe the Quality of Experience (QoE) of video application. Some others [3,5,11,13] studied the QoE and solved the allocation problems of handing off and interface selection, etc. Compared with game theory, they often followed a traditional optimization-based approach. [16] formulated the issue as a cooperative bargaining problem of game theory. It also took both the QoE and fairness into account. But they need a proxy server to allocate the bandwidth collaboratively. Thus, the robust of the system may mainly depend on the server which could be invaded and influenced easily.

In this paper, we propose a distributed rate allocation framework and construct a potential game model so that the bandwidth can be allocated in a reasonable and efficient way. The total utility of all users is our primary consideration and we fully consider the users' experience. After several iteration, the algorithm will converge to correlated equilibria and each receiver will choose and keep a proper transmission rate. The rest of this paper is organized as follows. In Sect. 2, we describe the system in detail and discuss our preliminary goal. Also, the utility function is introduced here. In Sect. 3, we model the problem as a potential game and prove the existence of correlated equilibrium. Section 4 follows the way of regret-matching to solve the model. The experimental results and some discussions are settled in Sect. 5. And we draw the conclusions in Sect. 6.

2 System Model and Utility Function

2.1 System Model

Figure 1 presents the typical scenario we discuss. There are N Unmanned Aerial Vehicles (UAV) flying in the coverage of the same access point (AP) and all of them are equipped with Wireless Cameras (WC). Thus, the UAV platforms have the functions of recording and compressing videos, and then, they send the encoded videos to the Video Processing Center (VPC) via the wireless network. All videos are finally edited there together for all kinds of commercial purposes. Because the AP is owned by a Network Service Provider (NSP), as the receiver of the communication, the VPC should lease the wireless channels from the NSP. In order to gain good total video experience, the limited wireless resource should be allocated properly among the UAVs.

Suppose *Cband* is the total constant throughput provided by the AP. r_{i} denotes the channel rate for the i-th WC (WC_i), which varies from the minimum

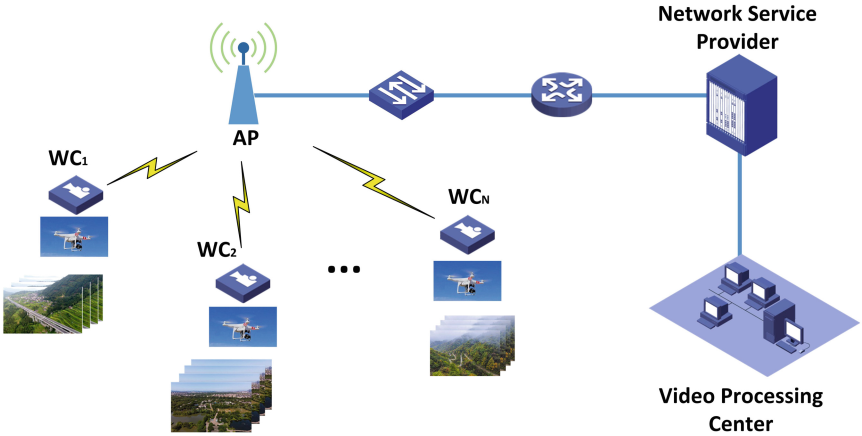

Fig. 1. Video transmission network

rate constraint $R_i^{\min}$ to the maximum one $R_i^{\max}$, $i = 1, 2, ..., N$. $R= [r_1, r_2,...,r_N]$ denotes the rate vector of the N WCs and the utility function vector is $U= [u_1, u_2,...,u_N]$, correspondingly. In order to send back high quality video, each WC intends to magnify their own utilities:

$$\begin{aligned} \max \quad & u_i \\ s.t. \quad & R_i^{\min} \leq r_i \leq R_i^{\max} \\ & 0 \leq \sum_{i=1}^{N} r_i \leq Cband \end{aligned} \tag{1}$$

2.2 QoE-Based Utility

In ordinary data transmission, the utility is always formulated as the function of QoS. However, users and service providers focus more on the QoE. Peak Signal to Noise Ratio (PSNR) is a typical video quality assessment (VQA) metric based on the error statistics of pixel domain. Some studies regarded the mapping relation between PSNR and Mean Opinion Score (MOS) as a straight line [8,15]. But figures in [10,14] show that the mapping is closer to a sigmoid function. Anyhow, an effective expression of PSNR could properly describe the variation trend of video MOS. Furthermore, PSNR has the lowest complexity among many evaluation methods [10], which makes it more convenient to use in real-time services. In this paper, we adopt the formula in [2] and the utility of video of WC_i can be expressed as

$$\begin{aligned} u_i &= PSNR(r_i) - P(r_i) \\ &= a + b \cdot \sqrt{\frac{r_i}{c}(1 - \frac{c}{r_i})} - P(r_i) \end{aligned} \tag{2}$$

where $P(r_i)=\theta \cdot \frac{r_i}{Cband}$ is the price the VPC pays for the channel leasing of WC_i and θ is the price constant.

3 Potential Game Based Resource Allocation

From the view of individual, the WC_i intends to maximize its channel rate so that its QoE will be favorable. However, it's not allowed too much channel occupation, because the whole bandwidth the NSP can provide is limited and the VPC has to concentrate on maximizing the total utility rather than the single ones. This makes the problem complex. In this paper, we regard it as decentralized process and model the problem as a potential game. The game is denoted as $G = [\Omega, \{\mathcal{R}_i\}_{i\in\Omega}, \{\mathcal{U}_i\}_{i\in\Omega}]$, where $\Omega= \{1, 2, ..., N\}$ is the set of players. $\mathcal{R}_i$ represents the strategy of the i-th player and $\mathcal{U}_i$ is the utility correspondingly. It's hoped that, by very little information exchange, everyone can choose proper strategy and no one will break the equilibrium.

In this section, we construct a potential function as: $I = \sum_{i=1}^{N} u_i$ and the problem can be presented as:

$$\begin{aligned} \max \quad & I=\sum_{i=1}^{N}\{a + b\cdot\sqrt{\frac{r_i}{c}}(1-\frac{c}{r_i})\} - P(\sum_{i=1}^{N} r_i) \\ s.t. \quad & R_i^{\min} \le r_i \le R_i^{\max} \\ & 0 \le \sum_{i=1}^{N} r_i \le Cband \end{aligned} \tag{3}$$

where $P(\sum\limits_{i=1}^{N} r_i)=\theta.\ \frac{\sum\limits_{i=1}^{N} r_i}{Cband}$ means the price the VPC pays for all the N channel leasing. The more the bandwidth is occupied in the AP, the more the VPC should pay for it, which will cut its benefits in another way. On the other hand, NSP can also effectively guarantee the quality of the network and avoid congestion by changing the price.

Proposition 1. *Each WC selfishly switches its rate strategy will lead to a near optimal solution to the whole utility of the VPC and the game G we propose is a standard potential game.*

Proof. We set another rate strategy for WC_i as r_i'. Because the potential function I is the sum of the single utilities, we can get

$$\varDelta I = I(r_i) - I(r_i') = u(r_i) - u(r_i') = \varDelta u \tag{4}$$

The variation of the potential function equals to the difference value of the utility function. According to [12], we know that game G is a standard potential game.

Proposition 2. *The correlated equilibrium uniquely exists in this model.*

Proof. From Eq. (3), we can get the partial derivative of the potential function

$$\frac{\partial I(r_i)}{\partial r_i}=\frac{b}{2\sqrt{cr_i}}+\frac{b\sqrt{c}}{2\sqrt{r_i}^3}-\frac{\theta}{Cband} \tag{5}$$

As $\frac{b}{2\sqrt{cr_i}}+\frac{b\sqrt{c}}{2\sqrt{r_i}^3}>0$ and $\frac{\theta}{Cband}>0$, there exists $r_i=\tilde{r}_i$, which makes Eq. (5) identically equal to zero.

Then, we get the second-order partial derivative of Eq. (3) at $r_i=\tilde{r}_i$

$$\left.\frac{\partial^2 I(r_i)}{\partial r_i^2}\right|_{r_i=\tilde{r}_i}=-\frac{b}{4\sqrt{c}\sqrt{\tilde{r}_i}^3}-\frac{3b\sqrt{c}}{4\sqrt{\tilde{r}_i}^5} \tag{6}$$

Because $\frac{b}{4\sqrt{c}\sqrt{\tilde{r}_i}^3}>0$ and $\frac{3b\sqrt{c}}{4\sqrt{\tilde{r}_i}^5}>0$, we can get $\left.\frac{\partial^2 I(r_i)}{\partial r_i^2}\right|_{r_i=\tilde{r}_i}<0$. The results show that, if WC_i doesn't choose the data rate $\tilde{r}_i$, a higher total utility will not be obtained.

4 Resource Allocation Algorithm

Literature [6] discussed a simple adaptive procedure leading to correlated equilibrium and provided the way of "regret-matching". According to this method, and also on the basis of the game model we build above, a distributed algorithm can be obtained to reach correlated equilibrium as follow:

Initialization: At the initial time when $t=1$, each WC can get the minimum rate of the video to start its strategy. As a matter of fact, the rate can be selected arbitrarily within the range. Meanwhile, a strategy space $\{R\_space\}$ is formulated.

Iterative Update Process:

Strategy Update: At the time $t\geq 2$, each WC calculates the utility of the current strategy r_i and the utility for choosing another strategy r_i'. The average difference between r_i and r_i' needs to be calculated as:

$$L_i^t(r_i,r_i')=\frac{\lambda}{t}L_i^{\lambda}(r_i,r_i')+\frac{1}{t}[u_i^t(r_i')-u_i^t(r_i)] \tag{7}$$

where λ denotes for time and $\lambda\leq t$. Then $R_i^t(r_i,r_i')=\max\{L_i^t(r_i,r_i'),0\}$ and it's a measure of "regretting" [6].

Strategy Decision: Suppose r_i is chosen by player i at time t. Then, at time $t+1$, the strategy will be reconsidered and it will follow the probability distribution:

$$\begin{cases} \pi_i^{t+1}(r_i') = \frac{1}{\mu} R_i^t(r_i, r_i') & \forall r_i' \neq r_i \\ \pi_i^{t+1}(r_i) = 1 - \sum\limits_{r_i' \neq r_i} \pi_i^{t+1}(r_i') \end{cases} \tag{8}$$

where $\mu > 0$ is large enough. According to the distribution, we can choose a more proper strategy within the space $\{R\_space\}$ who has a higher possibility. After multiple iterations, the results won't be changed and the equilibrium will be achieved.

5 Simulation Results and Analyses

We conduct some simulations to evaluate the scheme we propose. It's assumed that 3 UAVs fly in the AP's coverage area as Fig. 1. They shoot and record independently and send back 3 different compressed videos, Carphone, Coastguard and Football to the VPC. The minimum and maximum rates are shown in Table 1 and their different styles are also listed.

Table 1. Parameters of different videos

	$R_i^{\min}(kb/s)$	$R_i^{\max}(kb/s)$	*Style*
Carphone	20.2554	322.0153	Medium motion and smooth scene
Coastguard	28.4987	878.8011	Medium motion and complex scene
Football	286.311	1720	Fast or complex motion

Figure 2 plots the real-time video transmission rates and the total utilities of the three when the channel adopts two different bandwidth values. We can find that when $Cband = 20\,Mbps$, which means the channel can offer sufficient bandwidth, each video can be encoded and transmitted at the maximum of their rates. The faster and the complexer the videos are, the more resource they will occupy. While the resource is insufficient, $Cband = 2\,Mbps$, video Carphone and Coastguard should decrease their rates correspondingly, so that the whole utility can still maintain at a proper level. The utility of our distributed algorithm is very close to the optimal one who takes the global information exchanges. From Fig. 2 we also find that after about 20 iterations, all the curves become smooth and steady, which means the system converges to the equilibrium in a very short time by our scheme.

The total bandwidth of the channel can obviously affect the results of resource allocation. Figure 3 shows the final results at different values of *Cband*. From the aspect of different video styles, we can find that the slight insufficience of bandwidth will first influence the videos which are fast and complex, while the medium and smooth videos are affected relatively less. When the channel condition becomes much worse, less than 1Mbps, all the videos have to reduce their rates. Correspondingly, the total utility increases along with the total bandwidth and the results of our scheme are very close to the optimal solutions at different rates.

Not only the bandwidth of the channel, but also the price parameter θ can influence the results. In Fig. 4, we vary the price factor θ and keep the total channel bandwidth at 3Mbps. When θ increases, the rate of Football decreases obviously. When it's greater than 3.5, Coastguard's rate also reduces. From the total utility curves, we can find the decrease, too. Thus, the NSP, as the resource provider, can easily control both the bandwidth allocation and the robust of the network by adjusting the price parameter.

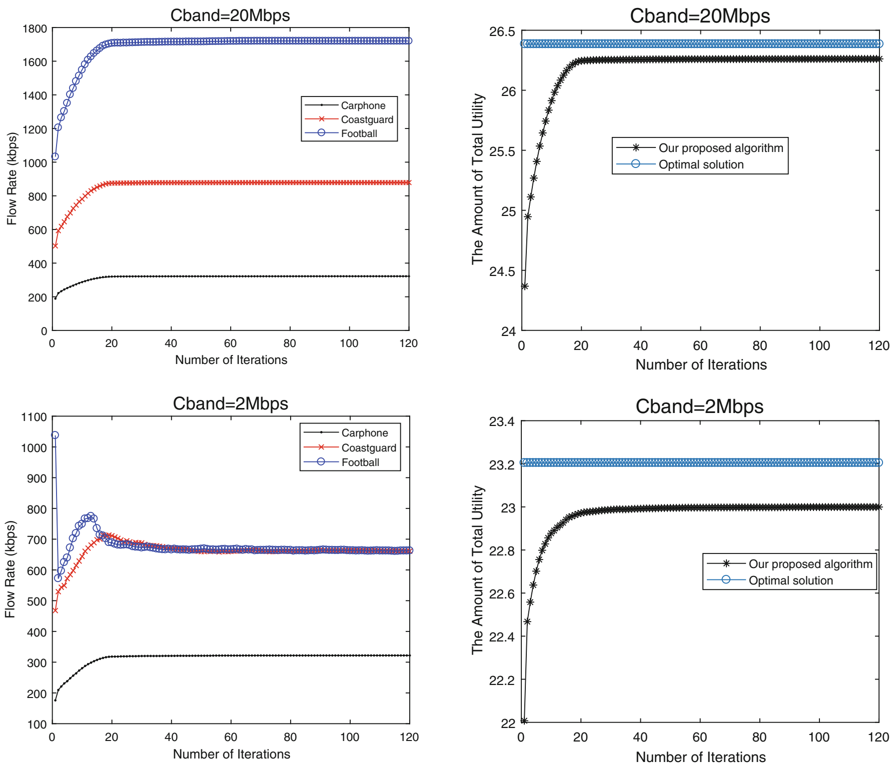

Fig. 2. Number of iterations versus flow rate and total utility

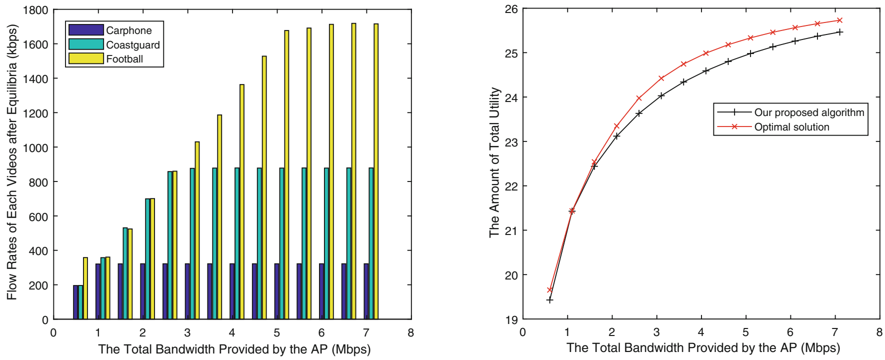

Fig. 3. The influence of total bandwidth *Cband*

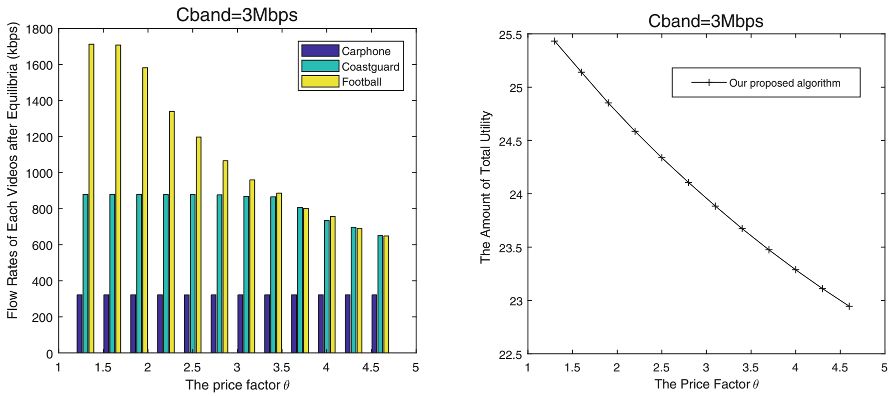

Fig. 4. The influence of price parameter θ

6 Conclusion

Both the dramatic growth of mobile users and the improvement of video quality has made the bandwidth competition of wireless network much fiercer. In this paper, a distributed algorithm was designed to allocate the limited resource among multiple users in order to gain a better total QoE utility of all videos. A model based on potential game theory was constructed and a distributed algorithm was leveraged to solve it. The results could rapidly converge to a set of correlated equilibria. Simulation implied that the proposed strategy could provide a favorable way to solve the resource allocation problem for video transmission.

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