Channel Allocation for Adaptive Video Streaming in Vehicular Networks

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Abstract-Video services in vehicular networks play an important role in future intelligent transportation systems and vehicular infotainment systems. Yet, at the presence of other services with high priorities, the remaining radio resources for video services are highly dynamic. To support video service of multiple vehicles in vehicular networks, we propose a joint channel allocation and adaptive video streaming algorithm that makes the vehicles compete for channel access opportunities and to request video data with a proper visual quality according to their utilities. A vehicle's request is determined by taking several key factors into consideration, including the location and the velocity of the vehicle, the activity of the high-priority services, the intensity of the competition among multiple vehicles, and the smoothness requirement of visual quality. Simulation results show that the proposed algorithm is superior to the existing algorithms in both interruption ratio and visual quality.

Index Terms—Auction, channel allocation, scalable video coding (SVC), video streaming.

I. INTRODUCTION

S an important part of intelligent transportation system (ITS), vehicular networks allow communications between vehicles and roadside units (RSUs) and support various applications [1], [2] that improve the safety and efficiency of public transportation [3]–[5]. Video services over vehicular networks play a key role in driver assistance, emergency information delivery, and infotainment distribution. For example, contentrich video streams can be used in road condition monitoring for driver assistance and traffic safety, the real-time monitoring of

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the inside and the surroundings of a cash truck or a jewelry truck, the remote medical guidance for emergency treatment in an ambulance, and the real-time television recording and broadcasting of a public event or a natural disaster [6].

Providing video service over vehicular networks also raises new challenges to communication and networking technologies. Generally, video service demands stable and sufficient bandwidth due to its large data volume, long playback duration, and the user expectation of smooth playback and high visual quality [7]. Yet, the radio resources for video services are limited and highly dynamic, due to the presence of other services with higher priority (e.g., safety-related applications). The radio resources are further strained when multiple vehicles are demanding video services. Further, the playback of video services should be uninterrupted, but RSU deployment might not be dense enough, and the data transmission (DT) will be interrupted when a vehicle drives out of the coverage areas of RSUs. To address all the given challenges, an efficient channel allocation and video streaming algorithm is indispensable for multiple vehicles in a vehicular network with highly dynamic radio resources.

Several video streaming algorithms have been proposed to support smooth video playback in vehicular networks, but most of them simplified or even ignored the contention among multiple vehicles. To alleviate the shortage of radio resources, some researchers adopted spectrum-sharing technologies [8], [9], which, however, may not be directly applicable to vehicular networks where the vehicles move fast and the topology changes quickly. Researches on channel allocation among multiple vehicles in vehicular networks have been done to improve the network performance, but most of them did not consider the characteristics of video services.

In this paper, we study channel allocation and video streaming in a vehicular network with highly dynamic radio resources, in which both the number of available channels and that of vehicles in the coverage area of an RSU change with time. The RSU deployment is sporadic; thus, vehicles face highly dynamic competition to access channels. We propose an auction-based channel allocation and adaptive video streaming algorithm. To ensure smooth video playback outside the coverage areas of RSUs, we adopt a finite-length buffer in each vehicle to store video data. To provide better video services under dynamic channel conditions, we employ the scalable video coding (SVC) extension of the H.264 standard [10] as the encoding scheme and encode the video trace into several layers. Therefore, the video data with more layers and, thus, higher visual quality can be transmitted under better channel

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condition and/or less intensive competition, whereas video data with a fewer number of layers can be transmitted to avoid playback interruption under worse channel conditions and/or intensive competition. To support multiple vehicles with limited radio resources, we employ an auction mechanism [11] that makes the vehicles bid according to their utility values so that RSUs can allocate the available channels efficiently. We allow the vehicles to request a proper number of video layers to support smooth playback and high visual quality according to the transmission rate, the number of data units in the buffer, the number of data units needed for video playback, and the possibility to access the channel in the future. To describe the characteristics of vehicles' drive-thru and video playback, we use a stochastic game to model the states and state transition probabilities of the vehicles. To deal with the competition among vehicles, we adopt a statistic method to model the environment states with the help of historical records. To calculate the optimal request of a vehicle, we adopt low-complexity dynamic programming.

The main contributions of this paper are fourfold.

- The auction mechanism is adopted in the channel allocation problem in vehicular networks. As each vehicle bids according to its utility value, the RSU can allocate the channels reasonably. Vehicles calculate their own bids; therefore, the computation is distributed, and the solution enables real-time services.
- The problem of multivehicle channel access is modeled as a stochastic game. Several key factors are considered in the model, including the number of available channels, which is affected by the activity of high-priority services, the number of vehicles in the coverage area of an RSU, and the vehicle states. The vehicle state contains the information on the location of the vehicle, the amount of data units in the buffer, and the requested number of video layers in the last successful channel access.
- A utility function is proposed to reflect the experience of vehicle and, thus, to guide each vehicle to determine its bid and the required number of video layers. The utility function is designed to reflect two factors, namely, the video interruption ratio and visual quality.
- A method is proposed for vehicles to bid reasonably by modeling the environment states and estimating the bids of the others through historical records.

The remainder of this paper is organized as follows. In Section II, the related works are introduced. Section III describes the system model. Section IV presents the channel allocation and adaptive video streaming algorithm, and Section V discusses the problem solving. Performance evaluation is presented in Section VI, followed by the conclusions in Section VII.

II. RELATED WORK

Video streaming in vehicular networks has been investigated in the literature, considering how to ensure uninterrupted playback and high visual quality. To reduce the interruption ratio, an algorithm for vehicular networks that adjusts the retransmission times in the medium access control protocol was proposed in [12]. A frame-rate adaptation algorithm was proposed in [13],

without considering the effect of changing the frame rate on the user experience. The bounds of interruption probability was investigated in [14]. To achieve high visual quality, an adaptive video streaming algorithm was presented in [15], which considers the relationship between the total data volume to be obtained when driving in the coverage area of an RSU and the data volume needed to play video with a certain number of layers. In [16], an approach of transmitting the basement layer of the video via a vehicular network and transmitting the enhancement layers through LTE network was proposed. In [17], a scheme was proposed to transmit the basement layer of the video by multihop, and to obtain high peak-signal-to-noise ratio (PSNR) for as many vehicles as possible by adjusting the modulation mode of the enhancement layers of the video trace. To achieve both low interruption ratio and high visual quality, a thresholdbased adaptive video streaming algorithm utilizing the information of the queue length and current transmission rate was proposed in [18]. A prediction-window-based video streaming algorithm was presented in [19], which adjusts the requested number of video layers according to the relationship between the data volume that the vehicle needs for video playback and that it expects to obtain. Most of the existing works ignored or simplified the competition against other vehicles and thus are difficult to be used in the scenarios where an ever-changing number of vehicles compete for channels.

There have been extensive research works aiming at channel allocation for vehicle-to-RSU communications. To improve overall system throughput, a channel allocation algorithm was presented in [20], which takes the current traffic loads and bit error rates of different service channels into consideration. In [21], a density-adaptive medium-access-control protocol that predicts the vehicle-density dynamics was proposed. A scheduling algorithm called MV-MAX, which opportunistically grants wireless access to the vehicles with the highest transmission rate, was proposed in [22]. In [23], the throughput capacity of vehicular ad-hoc networks exploiting mobility diversity was analyzed. For vehicle-to-RSU nonsafety service, a scheduling algorithm utilizing the information of the queue lengths and channel qualities to transmit more data was presented in [24]. A game-based allocation algorithm was proposed in [25], in which the vehicles optimize their requests to minimize their costs under the constraints of the required quality of services. To decrease the packet loss rate, a channel allocation protocol was proposed in [26] based on vehicles' locations and their remaining time slots in an RSU. However, for video service, high network throughput, low cost, and low packet loss rate do not mean smooth video playback and high visual quality. This motivates us to design a joint channel allocation and video streaming algorithm considering user experience.

III. SYSTEM MODEL

A one-way highway scenario as shown in Fig. 1 is considered. It consists of RSUs, vehicles, and a video server. The video server is connected to RSUs via a backhaul with sufficient bandwidth, and RSUs communicate with vehicles via air. RSUs are deployed along the road, and the distance between two adjacent RSUs is X_{R2R} . It is assumed that the



Fig. 1. Highway scenario and channel model.

interarrival distance of vehicles follows a Poisson distribution with the mean of λ [12], [27]. Each vehicle has a unique ID. A GPS device is installed on each vehicle to obtain the realtime position and velocity. It is also assumed that a vehicle can synchronize with an RSU when it enters the RSU's coverage area and receives the RSU's beacon message. Therefore, the vehicle works in a synchronized manner with the RSU when driving in the RSU's coverage area.

The radius of an RSU's coverage area is denoted by R, where $R < X_{\rm R2R}/2$. Therefore, some parts of the road are outside the RSUs' coverage area. It is assumed that, using appropriate adaptive modulation and coding, as long as the distance between a vehicle and an RSU is less than R, the vehicle can receive RSU's signal without error. It is assumed that the bandwidths of all data channels are equal, and the transmission rate is only affected by path loss and depends on the distance between the vehicle and the RSU. The same assumption and setting can also be found in [28] and [29]. Therefore, the road segment in the coverage area of an RSU is divided into K regions, as shown in Fig. 1. The transmission rate of any data channel between any vehicle in region k and the RSU remains constant and is denoted $r_k, k = 1, 2, \ldots, K$. The farther a vehicle is away from the RSU, the lower the rate r_k is, e.g., $r_1 = r_K < r_2 = r_{K-1}$.

There is a dedicated channel called common control channel (CCC), whose bandwidth is much narrower than that of the data channels. In addition, there are a total of M data channels for the RSU to transmit video data to a vehicle when they are not occupied by any higher priority service. The state of a data channel, occupied or not occupied by higher priority services, is modeled as a two-state Markov chain. It is assumed that the states of the M data channels are independent of each other. At any time, one channel is allocated to one vehicle only.

The video trace stored in the server is divided into data units with equal duration of $1/\mu$ seconds, namely μ data units are played per second. Each data unit is encoded into L layers using SVC technology, i.e., one basement layer and L - 1 enhancement layers. The source rate of the data unit with l layers (l = $1, 2, \ldots, L$) is denoted τ_l , and $\tau_i < \tau_j$ if i < j. The number of video layers is called quality level for short. The average PSNR of the data units with quality level l is denoted Q_l , and $Q_i < Q_j$ if i < j. The two factors affecting the quality of user experience most are the playback interruption ratio and visual quality. The visual quality is usually objectively measured by PSNR, and a higher value of PSNR means a higher visual quality. For the



Fig. 2. Buffer storage.





SVC encoded data units, more video layers result in a higher PSNR. The buffer in each vehicle is divided into units each with the size of B_{max} , as shown in Fig. 2. A buffer unit (black block) is large enough to store a data unit with L layers and a duration of B_{max}/μ seconds. A data unit (blue block) with l layers and a duration of B_{max}/μ seconds occupies a buffer unit, and its volume increases as l increases, where l = 1, 2, ..., L. Such a buffer division and application can also be found in [30] to represent the vehicle states.

It is assumed that the vehicular network is a time-slotted system, and the slot length is denoted Δ . Both the number of vehicles within the coverage area of an RSU and the number of available channels remain constant during a slot. The slot structure of vehicular network is shown in Fig. 3. A slot contains a resource auction phase of duration $\Delta_{\rm auc}$ seconds and a DT phase of duration Δ_{data} seconds. The resource auction phase consists of four subphases. The first is beacon broadcast (BB) subphase, in which an RSU broadcasts a beacon massage to make the vehicles within its coverage area synchronized. Second is the information broadcast (IB) subphase, in which an RSU broadcasts common information, including the number of vehicles within its coverage area, the number of available channels, and the check list of ID and minislot correspondence, to facilitate channel contention in the current slot. Third is the request upload (RU) subphase, which consists of $N_{\rm max}$ minislots [25]. Here, each minislot is used by a single vehicle to send its request containing both bid and quality level, and $N_{\rm max}$ stands for the maximal number of vehicles in an RSU's coverage area. An RSU can be aware of the number of vehicles within its coverage area because the vehicle entering its coverage area must inform the RSU its ID when CCC is idle. Fourth is the feedback (FB) subphase, in which an RSU broadcasts channel allocation results and the average bid of all the vehicles that win the auction.

For better readability, a notation list of the key symbols used in this paper is provided in Table I.

	1101	LIGIT EIGT	
Variable	Description	Variable	Description
$X_{\rm R2R}$	Distance between two adjacent RSUs	F_{limit}	Bid upper bound
λ	Mean of inter-arrival distance	p_{ij}	Prob. that M' changes from i to j
R	Radius of an RSU's coverage	$q_n(S'_n S_n,O_n)$	Prob. of vehicle n from S_n to S'_{-n} given O_n
K	# of road segments	D	# of data units for smooth playback in a slot
r_k	Transmission rate in region k	$v (v_{\rm f})$	(Free-flow) vehicle velocity
L	Maximal # of video layers	$ ho_{ m jam}$	Vehicle density in traffic jams
l_n	Quality level that vehicle n requests	δ	Punishment coefficient
L_n^{last}	Last received quality level	$S_n (S_{-n})$	Vehicle <i>n</i> 's (environment) state
Q_l	Average PSNR with quality level l	\mathcal{S}_n	Set of vehicle <i>n</i> 's states
B_{\max}	Buffer capacity	$\tilde{S}_{-n,t}$	Possible environment state in slot t
B_n	Vehicle n's buffer level	$S_{n,t_n^{\text{bound}}}$	Vehicle <i>n</i> 's state in slot t_n^{bound}
Δ	Duration of a slot	$S_{-n,t_n^{\text{bound}}}$	Environment state in slot t_n^{bound}
$\Delta_{\rm auc}$	Duration of resource auction phase	t_n^{next}	Slot index before the next RSU's coverage
$\Delta_{\rm data}$	Duration of data transmission phase	t_n^{bound}	Slot index just out of the RSU's coverage
$N(N_{\rm max})$	(Maximal) # of vehicles in an RSU	T_n	# of slots left in the RSU's coverage
$N_{ m num}$	Total # of vehicles	$T_{\rm RSU}$	# of slots in a period
M(M')	# of (available) data channels	T_{RSU_h}	Total $\#$ of slots in the <i>h</i> th period
μ	# of data units played per second	Tout	# of slots outside the RSUs' coverage
\mathcal{U}_n	Set of utility values of vehicle n	T_{in}	Total # of the slots in an RSU's coverage
\mathcal{A}_n	Set of vehicle <i>n</i> 's requests	$V^*(S_n, S_{-n})$	The maximal MTUA given S_n and S_{-n}
$A_n(C_n)$	Vehicle <i>n</i> 's request (bid)	$Z_{S_n}(Z_{S_n})$	# of vehicle n 's (environment) states
$A_{n,t}^{\text{opt}}$	Optimal request of vehicle n in slot t	Z_v	Dimension of the maximal MTUA table
O_n	Channel allocation result of vehicle n	\bar{C}	Average transaction price
$F_n (F_{n,t_n^{bound}})$	Budget of vehicle n (in slot t_n^{bound})	$f_{S_{-n},C_n}^{\mathrm{suc}}$	Times of channel access given S_{-n} and C_n

TABLE I NOTATION LIST

IV. CHANNEL ALLOCATION AND ADAPTIVE VIDEO STREAMING ALGORITHM

When multiple vehicles need to access channel to obtain video data, limited and ever-changing radio resources of an RSU may only meet the demands of part of the vehicles. Considering the relative positions between the vehicles and the RSU, the channels should be reasonably allocated to 1) the vehicles that have already encountered or are about to encounter playback interruption and 2) the vehicles that are closer to the RSU and, thus, have a higher transmission rate than those far away from the RSU. Allocating to the former can decrease the playback interruption ratio, whereas allocating to the latter can increase the overall visual quality. With these two considerations, we propose an auction-based channel allocation mechanism in which the vehicles bid according to their own utility values and the RSU decides the optimal channel allocation based on the bids. Auction-based channel allocation enables each vehicle to calculate its own decision; hence, the computation complexity per vehicle can be much lower as compared with a centralized algorithm. Moreover, the only information that vehicles need to upload are their requests, which decreases the overhead and protects privacy. The auction is conducted once per slot. An adaptive video streaming algorithm is developed for a vehicle to request a proper quality level, to get data units ensuring smooth playback and high visual quality. The request of a vehicle is made based on the current data volume in its buffer, the transmission rate, the data volume needed for smooth playback, and the possibility to access channel in the future.

A. Channel Allocation and Video Streaming

Here, the information exchange procedure between RSU and vehicles is described, followed by the discussion on two key factors affecting the vehicles' decisions, namely, the budget and the quality level.



Fig. 4. Information exchange procedure in each slot.

The information exchange procedure is conducted in each slot between the RSU and the vehicles in its coverage area, as shown in Fig. 4. After broadcasting a beacon message in the BB subphase, the RSU broadcasts a vector $\mathbf{b}_1 = [M', N, W_1, \dots,$ $W_{N_{\text{max}}}$ in the IB subphase, where $M' (\leq M)$ denotes the number of available channels, $N (\leq N_{\text{max}})$ is the number of the vehicles within the coverage area of the RSU, and W_n is the ID of the vehicle who will upload its request in the *n*th minislot, with $n = 1, \ldots, N_{\text{max}}$. In the RU subphase, vehicle n uploads its encrypted request A_n in the minislot assigned to it. The request A_n includes both the bid C_n and the quality level l_n . The RSU puts requests from all vehicles into a request matrix $[A_n]$. If $N < N_{\text{max}}$, for some elements A_n 's, we have $C_n = 0$, and $l_n = 0$. The RSU allocates the M' available channels to the M'vehicles who tend the highest bids and prepares data units of the quality levels specified in the requests. In the FB subphase, the **RSU** broadcasts a vector $\mathbf{b}_2 = [\bar{C}, O_1, O_2, \dots, O_{N_{\text{max}}}]$, where $O_n = m (\in \{1, 2, \dots, M\})$ means that vehicle n can access channel m, and $O_n = 0$ represents that vehicle n obtains no channel. C denotes the average bid of all the vehicles who win the auction and can also be called the average transaction price. \overline{C} reflects the competition intensity; thus, it is provided to the vehicles as a reference for their future bids. In the DT phase, the RSU transmits data units on the M' available channels.

Budget is an important basis for the vehicles to bid. When driving into the coverage area of an RSU, a vehicle is offered some initial budget of amount $F_{\rm max}$, which is no less than the number of the time slots that it drives within the RSU's coverage. When a vehicle gets the opportunity to access a channel, its bid amount is deducted from its remaining budget. The vehicle has to give up auction if it has used up its budget until it drives into the coverage of the next RSU.

The quality level affects the playback interruption and visual quality. Requesting a high quality level leads to a small number of data units being downloaded, i.e., the visual quality is high at the cost of a shorter playable duration, and vice versa. Moreover, the quality level and the bid affect each other. If the vehicle requests a high quality level, the buffer will obtain fewer data units and the estimated interruption probability will increase, which leads to a higher bid in the next slot. In addition, the quality level of the vehicle should also be adjusted according to its remaining budget, which limits the chances to the access channel in the future. Another factor that affects the quality level is the position of the vehicle, namely, the distance and the transmission rate between the vehicle and the RSU. Even with the same quality level, the numbers of data units received in a slot at different regions are different; thus, the corresponding playable durations are different. Thus, the bid and quality level should be jointly decided. Giving a reasonable bid and quality level at the appropriate time slot is the key to ensure user experience.

B. Vehicle State and Multiuser Game

For each vehicle, the bid and quality level are not only related to its state but affected by the other vehicles' bids as well as the results of a multiuser game. Then, we employ a stochastic game to model the channel allocation and video streaming problem. The stochastic game is defined as

$$(\langle S_n, A_n, \mathcal{O}_n, \mathcal{Q}_n, \mathcal{U}_n \rangle_{n=1}^N, \mathcal{M}, \mathcal{N})$$
 (1)

where $\mathcal{M} = \{0, 1, \dots, M\}$ is the set of the number of available channels, $\mathcal{N} = (0, 1, \dots, N_{\max})$ denotes the set of the number of possible vehicles, S_n represents the set of vehicle n's states, \mathcal{A}_n stands for the set of vehicle n's requests, $\mathcal{O}_n = \{0, 1, \dots, M\}$ is the set of the possible channel allocation results to vehicle n, \mathcal{Q}_n stands for the set of transition probabilities of vehicle n's state, and \mathcal{U}_n is the set of utility values of vehicle n. The utility function will be detailed in Section IV-C.

An element S_n in set S_n in (1) represents the state of vehicle n and is expressed as a quaternion, i.e.,

$$S_n = \left(B_n, T_n, L_n^{\text{last}}, F_n\right) \tag{2}$$

where $B_n \ (\in [0, B_{\max}])$ denotes the number of data units in the buffer at the beginning of the current slot. T_n denotes the number of slots left before vehicle n drives out of the RSU's coverage area. $T_n > 0$ if vehicle n drives within an RSU's coverage area; otherwise, $T_n = 0$. L_n^{last} represents the quality level vehicle n obtained in the last channel access. F_n stands for the remaining budget of vehicle n. An element A_n in set A_n in (1) represents the request of vehicle n and is denoted by a tuple

$$A_n = (C_n, l_n) \tag{3}$$

where $l_n \ (\in [0, L])$ stands for the quality level vehicle n requests in the current slot and C_n ($0 \le C_n \le \min(F_n - C_n)$) (T_n, F_{limit})) represents the bid of vehicle n, with $F_n - T_n$ representing the left budget after guaranteeing at least 1 unit of budget for each of the rest time slots, which guarantees that a vehicle must have some budget, as long as it drives within the coverage of an RSU. $l_n = 0$ when vehicle n is outside of any RSU's coverage area and thus does not request video data. $1 \leq l_n \leq L$ when vehicle n is within the coverage area of an RSU. To smooth the variations of visual quality, we let $-1 \leq (l_n - L_n^{\text{last}}) \leq 1$ between successive data units [31]. $C_n = 0$ only happens when vehicle *n* is outside the RSUs' coverage areas, indicating that the vehicle cannot bid. The bid range of vehicle n in RSUs' coverage areas is $1 \le C_n \le$ $\min(F_n - T_n, F_{\text{limit}})$. The lower bound of bid is designed as 1 to increase the channel utilization, namely, to avoid the situation that the number of competition vehicles is less than the number of available channels. F_{limit} stands for the bid upper bound, which can limit the competition intensity.

An element $q_n(S'_n|S_n, O_n)$ in set \mathcal{Q}_n in (1) denotes the transition probability of vehicle n from state S_n to state S'_{-n} given the channel allocation result $O_n \ (\in \mathcal{O}_n)$. S'_{-n} is vehicle n's state in the next slot $S'_n = (B'_n, T'_n, L'_n^{1\text{ast}}, F'_n)$. When the channel allocation result is known, $q_n(S'_n|S_n, O_n)$ is deterministic with a value of either 0 or 1. The expressions of the number of data units in buffer B'_n , the number of slots left before driving out the RSU's coverage area T'_n , the quality level of the last successful access $L'_n^{1\text{ast}}$, the remaining budget F'_n of vehicle n at the beginning of the next slot, and the corresponding variables in the current slot are as follows:

$$B'_{n} = \begin{cases} \min\left[B_{\max}, (B_{n} + \left[G \cdot \frac{\mu}{\tau_{l_{n}}}\right] - D)\right], \text{ if } O_{n} \neq 0\\ \max(0, B_{n} - D), & \text{ if } O_{n} = 0 \end{cases}$$
(4a)

$$T'_{n} = \begin{cases} T_{n} - 1, & \text{if } T_{n} > 0\\ 0, & \text{if } T_{n} = 0 \end{cases}$$
(4b)

$$L_n'^{\text{last}} = \begin{cases} l_n, & \text{if } O_n \neq 0\\ L_n^{\text{last}}, & \text{if } O_n = 0 \end{cases}$$
(4c)

$$F'_{n} = \begin{cases} F_{n} - C_{n}, & \text{if } O_{n} \neq 0\\ F_{n}, & \text{if } O_{n} = 0 \end{cases}$$

$$\tag{4d}$$

where $G = \int_{y=i}^{i+\Delta_{\text{data}}} r_{k_y} dy$ denotes the data volume transmitted to vehicle n in the current slot, with i standing for the start time instant of the DT phase in the current slot and r_{k_y} representing the transmission rate in road region k_y in time instant y; D denotes the number of data units needed to smoothly play video in a slot and is a constant for the given duration of a slot and the duration of a data unit; $\min[\cdot]$ in (4a) guarantees that the buffer will not overflow; and $\lfloor G \cdot \mu / \tau_{l_n} \rfloor$ stands for the received number of data units.

C. Utility Function

The effect of both playback interruption and visual quality on the user experience should be considered when a vehicle decides its bid and the quality level. However, smooth playback and high visual quality are contradictory requirements for given channel access opportunities and transmission rates. To make a good tradeoff, a utility function is proposed for vehicle n to decide its bid and quality level. The utility function of vehicle n is denoted $U_n \ (\in U_n)$. According to the vehicle state S_n and request A_n, U_n is expressed as

$$U_{n}(S_{n}, S_{-n}, A_{n}) = \alpha \cdot (B_{n} - D)^{-} + (1 - \alpha) \cdot \frac{Q_{l_{n}}}{Q_{L}} \cdot p(O_{n} \neq 0 | S_{-n}, C_{n}) \quad (5)$$

where S_{-n} denotes the environment state to be defined in Section V-D, including the number of available channels in the current slot, the number of vehicles within the coverage area of the RSU, and the competition intensity for a vehicle to access channel. The set composed of all environment states is denoted as S_{-n} . Coefficient $\alpha \ (\in (0, 1))$ is a weight to balance playback interruption ratio and visual quality. It is usually set close to 1 because the effect of playback interruption on user experience is much higher than that of visual quality. Operation $(x)^- =$ $\min\{0, x\}$. $p(O_n \neq 0|S_{-n}, C_n)$ stands for the probability of vehicle *n* obtaining a channel given environment state S_{-n} and bid C_n .

The first item in (5) is the utility decrement caused by playback interruption. It is negative if the number of data units B_n in buffer at the beginning of the current slot is smaller than the number of data units D needed for smooth playback, and is 0 otherwise. The second item in (5) is the utility increment expectation when quality level l_n is ordered and is nonnegative. The larger l_n is, the larger Q_{l_n} and the utility value will be. Therefore, the utility value of (5) may be positive or negative.

D. Request for Maximal Utility

On the road segments outside RSUs' coverage areas, the vehicle keeps playing video using the data units already stored in its buffer. Therefore, when deciding its bid and quality level, vehicle n should take both the storage and the probability of getting channel access opportunities into consideration, and maximize *the mean of the total utility value accumulated* (MTUA) from the current slot (e.g., slot t) to the slot before driving into the coverage area of the next RSU. The optimal request of vehicle n at slot t can be modeled as

$$A_{n,t}^{\text{opt}} = \arg \max_{A_{n,t} \in \mathcal{A}_n} \underbrace{E\left[\sum_{i=t}^{t_n^{\text{next}}} U\left(S_{n,i}, S_{-n,i}, A_{n,i}\right)\right]}_{\text{MTUA}}$$
(6a)

s.t.
$$1 \le C_{n,i} \le \min(F_{n,i} - T_{n,i}, F_{\text{limit}})$$
 (6b)

$$|l_{n,t} - L_{n,t}^{\text{last}}| \le 1 \tag{6c}$$



Fig. 5. Description of time points and time durations.

where the subscript *i* stands for slot index, and $i = t, t + 1, \ldots, t_n^{\text{next}}$, with t_n^{next} denoting the index of the slot before vehicle *n* driving into the coverage area of the next RSU, and $A_{n,t}^{\text{opt}}$ represents the request that maximizes the MTUA of vehicle *n* in slot *t*. Equation (6b) implies that the bid in each slot should not exceed either the remaining budget or the bid upper bound F_{limit} and is no less than one. Equation (6c) means that the divergence of the current quality level and the quality level of the last successful channel access should be no larger than one.

To explain the temporal relationships in this paper, the time instants and durations in a vehicle's drive-thru are shown in Fig. 5. The duration from a vehicle driving into an RSU's coverage area to that of the next RSU is called a period, and a period contains $T_{\rm RSU}$ slots. $t_n^{\rm bound}$ is the index of the slot when a vehicle just drives out of an RSU's coverage area. $T_{\rm out}$ is the number of slots when the vehicle drives through the road outside the RSUs' coverage areas, i.e., $T_{\rm out} = t_n^{\rm next} - t_n^{\rm bound} + 1$. $T_{\rm in}$ stands for the total number of the slots of a vehicle in an RSU's coverage area, i.e., $T_{\rm in} = T_{\rm RSU} - T_{\rm out}$. T_n is the number of the remaining slots in current RSU's coverage area, i.e., $T_n = t_n^{\rm bound} - t$, and t is the index of the current slot.

V. PROBLEM SOLVING

Here, we discuss the approach to solve the optimization problem (6). First, the mathematical expression of the optimal request $A_{n,t}^{\text{opt}}$ is given. Then, the item with Bellman equation form in $A_{n,t}^{\text{opt}}$ is analyzed, and a finite-horizon dynamic programming method is proposed to obtain the optimal request. Finally, a method to obtain the environment states, and their transition probabilities is given.

A. Mathematical Expression of $A_{n,t}^{\text{opt}}$

The optimal request should maximize the MTUA from slot t to slot t_n^{next} . Therefore, vehicle n should predict its own states and the environment states of the following slots from t + 1 to t_n^{next} and calculate the weighted sum of the total utility value accumulated given $A_{n,t}$ and $\tilde{S}_{-n,t}$ with respect to the probability to the corresponding states. Here, the prediction should be done based on vehicle n's request to be determined

and its current state, as well as environment state transition probability, and $\tilde{S}_{-n,t}$ denotes the possible environment state in slot t. To this end, (6a) is expanded as (7), shown at the bottom of the page.

When calculating its request, vehicle n has been informed by the RSU's broadcast of the number of available channels M' and the number of vehicles within the coverage area of the same RSU in the current slot, but it does not know the other vehicles' bids. Thus, vehicle n should calculate the MTUA from t to t_n^{next} given $\tilde{S}_{-n,t}$ and $A_{n,t}$ with respect to the probability $q_{-n}(\tilde{S}_{-n,t}|S_{-n,t-1},O_{n,t-1})$. Because the environment state is partially known to vehicle n, the possible environment state $\hat{S}_{-n,t}$ comes from a subset \hat{S}_{-n} of environment state set S_{-n} , which is shown as the first summation in (7). As the environment state is completely unknown in slot t + 1, the possible environment state can be any element in environment state set S_{-n} . Therefore, the symbol of environment state in slot t+1 is $S_{-n,t+1}$ in the second summation instead of $\tilde{S}_{-n,t+1}$. Item (a) in (7) denotes the current utility obtained by adopting request $A_{n,t}$. Item (b) is the probability

weighted sum of item (c). Item (c) represents the maximal MTUA from slot t + 1 to slot t_n^{next} , whose probability is proportional to the product of three probabilities: the probability $p(O_{n,t}|\tilde{S}_{-n,t}, C_{n,t})$ that the channel allocation result is $O_{n,t}$ given environment state $\tilde{S}_{-n,t}$ and vehicle *n*'s bid $C_{n,t}$, the probability $q_n(S_{n,t+1}|S_{n,t}, O_{n,t})$ that vehicle *n*'s state transforms from $S_{n,t}$ to $S_{n,t+1}$ given the channel allocation result $O_{n,t}$, and the probability $q_{-n}(S_{-n,t+1}|\tilde{S}_{-n,t}, O_{n,t})$ that the environment state transfers to $S_{-n,t+1}$ from $\tilde{S}_{-n,t}$ given the channel allocation result $O_{n,t}$. Item (c) can be expanded as (8), shown at the bottom of the page.

B. Maximal MTUA

With the form of Bellman equation [32], (8) can be rewritten as (9), shown at the bottom of the page, where $V^*(S_n, S_{-n})$ denotes the maximal MTUA from slot $t(< t_n^{\text{bound}})$ under the vehicle state S_n and the environment state S_{-n} to slot t_n^{next} . S_n and S'_n are the simplified forms of $S_{n,i}$ and $S_{n,i+1}$, respectively, where *i* is the index of slot. The index of slot is omitted in (9)

$$A_{n,t}^{\text{opt}} = \arg \max_{\substack{A_{n,t} \in \mathcal{A}_{n} \\ \tilde{S}_{-n,t} \in \tilde{\mathcal{S}}_{-n}}} \sum_{\substack{\tilde{S}_{-n,t} \in \tilde{\mathcal{S}}_{-n}}} q_{-n}(\tilde{S}_{-n,t}|S_{-n,t-1}, O_{n,t-1}) \cdot \left\{ \underbrace{\bigcup \left(S_{n,t}, \tilde{S}_{-n,t}, A_{n,t}\right)}_{(a)} \right) + \underbrace{\sum_{\substack{(a) \\ \tilde{S}_{-n,t+1} \in \mathcal{S}_{n} \\ S_{-n,t+1} \in \mathcal{S}_{-n} \\ O_{n,t} \in \mathcal{O}_{n}}} p(O_{n,t}|\tilde{S}_{-n,t}, C_{n,t})q_{n}(S_{n,t+1}|S_{n,t}, O_{n,t})q_{-n}(S_{-n,t+1}|\tilde{S}_{-n,t}, O_{n,t})} \underbrace{\max_{\substack{(a) \\ \tilde{S}_{-n,t+1} \in \mathcal{S}_{-n} \\ O_{n,t} \in \mathcal{O}_{n}}} p(O_{n,t}|\tilde{S}_{-n,t}, C_{n,t})q_{n}(S_{n,t+1}|S_{n,t}, O_{n,t})q_{-n}(S_{-n,t+1}|\tilde{S}_{-n,t}, O_{n,t})} \underbrace{\max_{\substack{(a) \\ \tilde{S}_{-n,t+1} \in \mathcal{S}_{-n} \\ (c) \\ (c)$$

$$\max_{A_{n,j}\in\mathcal{A}_{n}} E\left[\sum_{j=t+1}^{t_{n}^{\text{next}}} U\left(S_{n,j}, S_{-n,j}, A_{n,j}\right)\right] = \max_{A_{n,t+1}\in\mathcal{A}_{n}} \left\{ U\left(S_{n,t+1}, S_{-n,t+1}, A_{n,t+1}\right) + \sum_{\substack{S_{n,t+2}\in\mathcal{S}_{n}\\S_{-n,t+2}\in\mathcal{S}_{-n}\\O_{n,t+1}\in\mathcal{O}_{n}}} p\left(O_{n,t+1}|S_{-n,t+1}, C_{n,t+1}\right) \times q_{n}\left(S_{n,t+2}|S_{n,t+1}, O_{n,t+1}\right)q_{-n}\left(S_{-n,t+2}|S_{-n,t+1}, O_{n,t+1}\right) \cdot \max_{A_{n,g}\in\mathcal{A}_{n}} E\left[\sum_{g=t+2}^{t_{n}^{\text{next}}} U\left(S_{n,g}, S_{-n,g}, A_{n,g}\right)\right]\right\} \tag{8}$$

 $V^{*}(S_{n}, S_{-n}) = \max_{A_{n} \in \mathcal{A}_{n}} \left[U(S_{n}, S_{-n}, A_{n}) + \sum_{\substack{S'_{n} \in S_{n} \\ S'_{-n} \in S_{-n} \\ O_{n} \in \mathcal{O}_{n}}} p(O_{n} | S_{-n}, C_{n}) q_{n}(S'_{n} | S_{n}, O_{n}) q_{-n} \left(S'_{-n} | S_{-n}, O_{n}\right) \cdot V^{*} \left(S'_{n}, S'_{-n}\right) \right]$ (9)

and (11), shown below, for the following reason. When calculating V^* by (9), only vehicle *n*'s states and the environment states in two successive slots are involved, and the calculation is independent of specific slot; thus, the subscripts *i* and *i* + 1 should not appear. Likewise, when updating V^* using (11), the subscripts *i* and *i*+1 should not appear either. Equations (7)–(9) show that, to decide the optimal request, all the slots before driving into the coverage area of the next RSU are involved, and an iteration should be performed from slot t_n^{next} to slot *t*.

and an iteration should be performed from slot t_n^{next} to slot t. Notice that from slot t_n^{bound} to slot t_n^{next} , vehicle n cannot participate in auction, its buffer cannot be filled, and the number of data units for playback is known and decreases in a fixed rate as slot index increases. Moreover, to obtain high visual quality, budget should not be left after slot $t_n^{\text{bound}} - 1$. Thus, the maximal MTUA in this duration can be calculated according to vehicle n's state in slot t_n^{bound} as

$$V^*(S_{n,t_n^{\text{bound}}}, S_{-n,t_n^{\text{bound}}}) = \left(\frac{b_{n,t_n^{\text{bound}}}}{D} - T_{\text{out}}\right)^- \cdot \alpha$$
$$-\delta \cdot F_{n,t_n^{\text{bound}}}, t_n^{\text{bound}} \le t \le t_n^{\text{next}} \quad (10)$$

where $S_{n,t_n^{\text{bound}}}$ and $S_{-n,t_n^{\text{bound}}}$ stand for vehicle *n*'s state and environment state in slot t_n^{bound} , respectively; $F_{n,t_n^{\text{bound}}}$ denotes the remaining budget of vehicle n in slot t_n^{bound} , i.e., wasted budget; $b_{n,t_n^{\text{bound}}}$ represents the number of data units in the buffer of vehicle n in slot t_n^{bound} ; δ represents punishment coefficient and is a positive constant; $b_{n,t_n^{\text{bound}}}/D$ in (10) denotes the number of slots that the data units in buffer can play without interruption; and $(b_{n,t_{\text{bound}}}/D - T_{\text{out}})^{-}$ represents the number of interruption slots when vehicle n drives on the road segment outside RSUs' coverage areas. Therefore, the first item in (10) is of negative value, and more interruption slots will result in a larger utility decrement. The second item in (10) is a punishment item, meaning that more wasted budget produces a larger utility decrement. Therefore, this item encourages rational budget allocation as well as making full use of the budget. From the two items in (10), it can be judged that the value of (10) is less than zero. The maximal MTUA from slot $t_n^{\rm bound}$ to slot $t_n^{\rm next}$ can be calculated by using (10), and the optimal request in the current slot can simply be calculated iteratively from slot t_n^{bound} to slot t.

C. Finite-Horizontal Dynamic Programming

If (7) is continuously expanded according to (8) and (9), computation may be heavy. Therefore, we employ finite-horizon dynamic programming to calculate (9) and then solve (7) with low computation complexity.

Dynamic programming divides the target problem into several subproblems and solves it by solving subproblems, as well as iterating or cumulating results of subproblems. The subproblems of our target problem $V^*(S_n, S_{-n})$ are the corresponding values $V^*(S'_n, S'_{-n})$ of the states in the next slot. Therefore, we set up a maximal MTUA table, in which each item is a combination of vehicle state and environment state (S_n, S_{-n}) and the corresponding maximal MTUA. The dimension of the table is $Z_v = Z_{S_n} Z_{S_{-n}}$, where $Z_{S_n} = T_{in} L(B_{max} + 1)(F_{max} + 1)$

denotes the number of vehicle *n*'s states, and $Z_{S_{-n}}$ represents the number of environment states and will be detailed in Section V-D. When calculating (9), a vehicle just needs to search $V^*(S'_n, S'_{-n})$ corresponding to (S_n, S_{-n}) in its maximal MTUA table.

When the maximal MTUA table is initialized, all the maximal MTUA values of state combinations (S_n, S_{-n}) , except for the ones defined in (10) are 0; thus, the table needs to be updated during the auctions. After receiving the broadcast vector \mathbf{b}_2 , vehicle *n* confirms the environment state in the current slot, and it can calculate $V^*(S_n, S_{-n})$ and update the related item in the maximal MTUA table using

$$V^{*}(S_{n}, S_{-n}) = \begin{cases} (1 - \gamma) \cdot V^{\text{old}}(S_{n}, S_{-n}) \\ +\gamma \cdot V^{\text{new}}(S_{n}, S_{-n}), & \text{if } (S_{n,t}, S_{-n,t}) = (S_{n}, S_{-n}) \\ V^{\text{old}}(S_{n}, S_{-n}), & \text{otherwise} \end{cases}$$
(11)

where γ is the learning rate factor, $V^{\text{old}}(S_n, S_{-n})$ denotes the original value in the table, and $V^{\text{new}}(S_n, S_{-n})$ stands for the result of (9).

D. Environment State and the Estimation of Environment State Transition Probability

To implement the aforementioned algorithm, we need the environment state S_{-n} and its transition probability. The environment state contains the private information of the other vehicles and cannot be obtained directly. The statistical environment state transition probability can be estimated by each vehicle from the historical records, i.e., the series of broadcast vectors \mathbf{b}_1 and \mathbf{b}_2 in the past slots. The RSU can also collect the statistical environment state transition probability from the vehicles in its coverage area and can send the integrated environment state transition probability to the newly arriving vehicles as a reference. The statistical environment state transition probability of the vehicle is more important because it is estimated according to the vehicle's states and the competition intense. The integrated environment state transition probability may not reflect the individual differences among vehicles, but it can be offered to the vehicles that have no initial information and speed the convergence of the transition probability estimation.

Here, we propose a method for a vehicle to estimate the statistical environment state transition probability according to the accumulated historical records. First of all, the definition of environment state S_{-n} used in (7)–(9) is given. Then, provided that the channel allocation result is O_n in (7)–(9), the expression of the environment state transition probability is given. Finally, the formula of the probability of the channel allocation result O_n is presented when the environment state and the bid of vehicle n are given.

1) Environment State: The environment state is denoted a tuple, i.e., $S_{-n} = (N, M', v)$, where $v \ (\in \{1, 2, ..., V\})$ is the price range index of the average transaction price \overline{C} . The V price ranges are $[1, \Gamma_1), [\Gamma_1, \Gamma_2), ...,$ and $[\Gamma_{V-1}, F_{\text{limit}}]$,

New	$S_{-n}^{\#} = (1,0,1)$		 $S_{-n}^{\#} = (N, M', v)$		 $S_{-n}^{\#}$	$S_{-n}^{\#} = (N_{\max}, M, V)$	
$\begin{array}{c} \\ \hline \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ $	$\neq 0$	= 0	 $\neq 0$	= 0	 $\neq 0$	= 0	
$S_{-n}^* = (1, 0, 1)$			 		 		
			 •••	•••	 		
$S_{-n}^* = (N, M', v)$			 $f_{S^*_{-n},S^\#_{-n},O_n\neq 0}$	$f_{S_{-n}^*,S_{-n}^{\#},O_n=0}$	 		
			 •••	•••	 		
$S_{-n}^* = (N_{\max}, M, V)$			 		 		

 TABLE II

 Environment State Transition Counting Table

TABLE III
AUCTION RESULT TABLE

Bid	$C_n = 1$		 $C_n = F_n$		 $C_n = F_{\text{limit}}$	
Result	success	failed	 success	failed	 success	failed
$S_{-n} = (1, 0, 1)$	$f_{(1,0,1),1}^{ m suc}$	$f_{(1,0,1),1}^{\text{fail}}$	 $f_{(1,0,1),F_n}^{\mathrm{suc}}$	$f_{(1,0,1),F_n}^{\text{fail}}$	 $f_{(1,0,1),F_{\text{limit}}}^{\text{suc}}$	$f_{(1,0,1),F_{\text{limit}}}^{\text{fail}}$
$S_{-n} = (N, M', v)$	$f_{(N,M',v),1}^{\mathrm{suc}}$	$f_{(N,M',v),1}^{\text{fail}}$	 $f_{(N,M',v),F_n}^{\mathrm{suc}}$	$f_{(N,M',v),F_n}^{\text{fail}}$	 	
$S_{-n} = (N_{\max}, M, V)$	$f_{(N_{\max},M,V),1}^{\mathrm{suc}}$	$f_{(N_{\max},M,V),1}^{\text{fail}}$	 •••		 	

respectively; thus, v describes the competition intensity. The total number of environment states is $Z_{S_{-n}} = N_{\max}(M+1)V$. Here, N and M' can be obtained from the broadcast vector \mathbf{b}_1 , and v can be derived from \overline{C} in \mathbf{b}_2 .

2) Environment State Transition Probability: The environment state transition probability in (7)–(9) can be written in a general form $q_{-n}(S_{-n}^{\#}|S_{-n}^*,O_n)$, where only $O_n \neq 0$ and $O_n = 0$ are differentiated. It is the transition probability from environment state S_{-n}^* to $S_{-n}^{\#}$ when the channel allocation result for vehicle n is O_n and can be expressed as

$$q_{-n}\left(S_{-n}^{\#}|S_{-n}^{*},O_{n}\right) = \frac{f_{S_{-n}^{*},S_{-n}^{\#},O_{n}}}{\sum\limits_{S_{-n}^{\#}}f_{S_{-n}^{*},S_{-n}^{\#},O_{n}}}, O_{n} = 0 \text{ or } O_{n} \neq 0$$
(12)

where the numerator $f_{S_{-n}^*,S_{-n}^{\#},O_n}$ and the denominator stand for the times of environment state transitions from S_{-n}^* to $S_{-n}^{\#}$ and the total times from S_{-n}^* to all the possible environment states, respectively, both given the channel allocation result O_n . $q_{-n}(S_{-n}^{\#}|S_{-n}^*,O_n)$ can be obtained by looking up Table II and calculating using (12). It is a general form of $q_{-n}(S_{-n,t+1}|S_{-n,t},O_{n,t})$ and $q_{-n}(S_{-n,t}|S_{-n,t-1},O_{n,t-1})$ in Section V-A so that the values of the latter two can be easily obtained from Table II and (12).

The value of $f_{S_{-n}^*|S_{-n}^{\#},O_n}$ in (12) can be obtained by counting. Let vehicle n maintain an environment state transition counting table (see Table II) to record the times of the environment state transitions. The dimension of Table II is $2Z_{S_{-n}}Z_{S_{-n}}$. The factor 2 exists because all the channel allocation results are included for both $O_n = 0$ and $O_n \neq 0$. When Table II is initially set up, the diagonal elements with $O_n \neq 0$ are set to 1, and the others are set to 0, which enables the calculations of (12) and the request in the first auction. During the auctions, vehicle n updates the corresponding item by adding 1 according to the environment state in the last slot after it receives the broadcast vector \mathbf{b}_2 ; thus, the environment state becomes known. Along with the accumulation of historical records, the estimated environment state transition probability obtained using Table II and (12) becomes accurate.

3) Probability to Access a Channel: $p(O_n \neq 0 | S_{-n}, C_n)$ in (5) is the probability of the channel allocation result $O_n \neq 0$ given environment state S_{-n} and bid C_n and satisfies

$$p(O_n \neq 0 | S_{-n}, C_n) = \frac{f_{S_{-n}, C_n}^{\text{suc}}}{f_{S_{-n}, C_n}^{\text{suc}} + f_{S_{-n}, C_n}^{\text{fail}}}$$
(13)

where $f_{S_{-n},C_n}^{\text{suc}}$ denotes the times of successful channel access attempts when the environment state is S_{-n} and the bid is C_n , and $f_{S_{-n},C_n}^{\text{fail}}$ stands for the times of failed channel access when the environment state is S_{-n} and the bid is C_n . Both $f_{S_{-n},C_n}^{\text{suc}}$ and $f_{S_{-n},C_n}^{\text{fail}}$ can be obtained by counting. The probability of failed channel access given environment state S_{-n} and bid C_n is denoted $p(O_n = 0|S_{-n}, C_n)$.

Let each vehicle maintain an auction result table (see Table III). Table III records the times of successful or failed channel access attempts under different environment states. The dimension of Table III is $Z_{S_n}F_{\text{limit}}$. When Table III is initially set up, all the successful times of diagonal items are set to 1, and the failed times are set to 0 to enable the calculation of (13) in the first auction. When receiving the broadcast vector \mathbf{b}_2 , vehicle n knows the result of whether it can access a channel and then adds 1 to the item of corresponding successful (failed) times. Notice that, if vehicle n bids C_n and successfully obtains (but fails to obtain) a channel, any bid $\hat{C}_n > C_n$ ($\hat{C}_n < C_n$) will also win (lose) the auction.

E. Algorithm

We propose an algorithm to perform channel allocation and adaptive video streaming proposed in Section IV for vehicle n. The steps are summarized in Algorithm I. The operations in Step 5 make necessary preparation for calculating the bid and the quality level in the next slot.

Algorithm I Channel allocation and video streaming algorithm for vehicle n

1. Receive broadcast vector \mathbf{b}_1 from the RSU; obtain the number of vehicles and that of available channels as well as the correspondence between the vehicle IDs and the mini-slot indexes; confirm the allocated mini-slot for itself.

2. Obtain $q_{-n}(S''_{-n}|S'_{-n}, O_n)$ via Table II and (12); solve $p(O_n|S_{-n}, C_n)$ using Table III and (13); calculate $q_n(S'_n|S_n, O_n)$ according to the vehicle state of the current slot and the possible states of next slots; calculate the optimal request $A_n^{\text{opt}} = (C_n^{\text{opt}}, l_n^{\text{opt}})$ by substituting the values of $q_n(S'_n|S_n, O_n)$, $V^*(S_n, S_{-n})$, $q_{-n}(S''_{-n}|S'_{-n}, O_n)$, and $p(O_n|S_{-n}, C_n)$ into (7); send A_n^{opt} to the RSU in the allocated minislot.

3. Receive the broadcast vector \mathbf{b}_2 , and obtain O_n and the average transaction price \overline{C} .

4. If $O_n = m$, receive video data through the allocated channel m.

5. Confirm the environment sate S_{-n} , and update Table II; update Table III according to O_n ; compute (9), and obtain $V^*(S_n, S_{-n})$ by substituting the result into (11) as $V^{\text{new}}(S_n, S_{-n})$; update vehicle state according to (4).

The computation and space complexities of the proposed algorithm are discussed in the following. To allocate the channels, the RSU should sort the requests from vehicles in a decreasing order according to their bids. If a quick sort algorithm is applied, the time complexity of the resource allocation at RSU is $O(N_{\max}\log_2(N_{\max}))$ [33]. To calculate the optimal request according to (7), each vehicle should compare the results of all possible requests and states. Specifically, a vehicle should consider all possible requests with dimension $F_{\text{limit}}L$, all the possible environment states in the current slot with dimension V, the possible channel allocation results with dimension 2, the possible vehicle states with dimension Z_{S_n} (see Section V-C), and the environment states with dimension $Z_{S_{-n}}$ (see Section V-D1), respectively. The computation complexity is proportional to the product of the aforementioned dimensions and can be expressed as $O(2T_{\rm in}F_{\rm limit}N_{\rm max}V^2L^2(B_{\rm max}+1)(F_{\rm max}+1)(M+1))$. It is noted that the actual computation complexity is much lower than that aforementioned since not all requests, vehicle states, and environment states will be reached in practice. The space complexity of each vehicle depends on the sizes of the tables. The dimension of the maximal MTUA table is $Z_{S_n} Z_{S_{-n}} =$ $T_{\rm in}LN_{\rm max}V(M+1)(F_{\rm max}+1)(B_{\rm max}+1)$, the dimension of environment state transition counting table (see Table II) is $2Z_{S_{-n}}Z_{S_{-n}} = 2V^2 N_{\max}^2 (M+1)^2$, and the dimension of the auction result table (see Table III) is $2Z_{S_{-n}}F_{\text{limit}} =$ $2VN_{\max}F_{\lim}(M+1).$

It will be an important further research issue to design a joint channel allocation scheme for heterogeneous traffic, including both data and video traffic. A possible approach is to define multiple utility functions for heterogeneous traffic, and the objective of channel allocation is to maximize the total utility. Another further issue is that cellular networks can play as an alternative to provide access with RSU. As the RSUs' resource is cheap but sporadic distributed, and the cellular resource

TABLE IV REGIONS AND CORRESPONDING TRANSMISSION RATES

Road region index k	2	1, 3
Distance to RSU X_{V2R} (m)	0 - 50	50 - 75
Transmission rate r_k (Mbps) [38]	2	1

TABLE V
PARAMETERS OF THE VIDEO TRACEQuality level l123Source rate τ_l (Kbps)98.6158374

29.2

32.89

36.8

Average PSNR (dB)

is expensive but can cover the whole road segment with a certain transmission rate, the system should make decisions on allocating the channel resources to vehicles properly. Moreover, device-to-device communications [34], [35] and multihop relaying [36], [37] can also be able to facilitate efficient vehicular communications.

VI. PERFORMANCE EVALUATION

To validate the effectiveness of the proposed channel allocation and video streaming algorithm, simulations are conducted to evaluate and compare the performance of the proposed algorithm and two baseline algorithms.

A. Simulation Setting

The number of data channels M is 3. The probability that the number of available channels changes from i to j is denoted p_{ij} , where $i, j \in \{1, 2, 3\}$. We set $p_{11} = p_{12} = p_{22} = 0.4$, $p_{13} = 0.4$ $p_{33} = 0.2, p_{21} = p_{23} = p_{31} = 0.3$, and $p_{32} = 0.5$. The radius of an RSU's coverage area is 75 m, and the distance between two adjacent RSUs X_{R2R} is 225 m. The coverage area of an RSU is divided into three regions (K = 3). The relationship between the transmission rate r_k and the distance from a vehicle to an RSU X_{V2R} is shown in Table IV. To describe the relationship between the vehicle velocity and vehicle density, the free-flow model obtained from field observations [28] is adopted, i.e., $v = v_f (1 - \rho / \rho_{iam})$. Here, ρ is the vehicle density, i.e., the average number of vehicles per kilometer; $\rho_{iam} = 250$ veh/km is the vehicle density in traffic jams; and $v_f = 140$ km/h denotes the free-flow velocity. The relationship between intervehicle distance λ and the vehicle velocity v is expressed as $\lambda = \rho v$, and the maximal number of vehicles in the coverage area of an RSU is $N_{\text{max}} = \lfloor 2R\rho_{\text{jam}} \rfloor$, where $\lfloor \cdot \rfloor$ denotes floor function. Other settings include the learning rate factor $\gamma = 0.4$, bid upper bound $F_{\text{limit}} = 5$, and punishment coefficient $\delta = 0.1$.

The slot duration Δ is 0.53 s, and the duration of resource auction phase Δ_{auc} is 0.05 s. The video trace "Foreman" [39] with resolution 352 × 288 is used in the simulations. The frame rate is 30 fps and the group of picture (GOP) is 16 frames. One GOP that can be played in a slot of 0.53 s is considered a data unit. The video trace is encoded into a basement layer and two enhancement layers [40]. The parameters of the video trace are listed in Table V.

In the simulation, the length of the road equals the distance between two adjacent RSUs X_{R2R} . For each vehicle density, ten runs are carried out to get the average. For each run, vehicles were randomly placed on the road with certain vehicle density. The vehicles drive into the RSU's coverage area at different time instants; thus, in any slot, they may drive on different road regions with different transmission rates. When driving to the end of the road, a vehicle will be loop back to the beginning of the road with a random intervehicle distance. In this way, 6500 periods are simulated per run to observe the convergence of the proposed algorithm. The received number of video layers and that of interrupted slots of each vehicle in a period are recorded, and the average interruption ratio (AIR) and average number of received layers (ARL) of the 6500 periods are then calculated. AIR is defined as $(1/(V_{\rm num} \cdot$ (6500)) $\sum_{h=1}^{6500} \sum_{i=1}^{V_{\text{num}}} J_{i,h}/T_{\text{RSU}_h}$, where N_{num} is the total number of vehicles, T_{RSU_h} is the total number of slots in the *h*th period, and $J_{i,h}$ is the number of interrupted slots of vehicle *i* in the *h*th period. ARL is defined as $(1/(N_{\text{num}} \cdot$ $(6500)) \sum_{h=1}^{6500} \sum_{i=1}^{N_{\text{num}}} Y_{i,h} / T_{\text{RSU}_h}$, with $Y_{i,h}$ being the total number of video layers received by vehicle i in the hth period.

B. Baseline Algorithms

Two baseline algorithms are adopted in this paper. To the best of our knowledge, for multivehicle communication scenario, there is no previous work that jointly considers channel allocation and video streaming. Therefore, we designed the two baseline algorithms by combining the video streaming algorithm (THRESHOLD for short) proposed in [18] and different channel allocation schemes that appeared in [22], [41], and [42]. The first algorithm is called MAX+THRESHOLD. An RSU allocates the available channels to the closest vehicles within its coverage area, namely, the vehicles with the highest DT rates. Each vehicle that is allocated a channel requests quality level according to its buffer level B and the two thresholds defined in [18]. The "down threshold" is $\vartheta X_{\rm R2R}/v/\Delta$, where v is the vehicle velocity, and coefficient ϑ is set to be 1 in the simulation. The "up threshold" is twice the down threshold. The requested quality level l is decreased by 1 if B is less than the down threshold and is increased by 1 when B is between the two thresholds; otherwise, l = 3. The second algorithm is called RD+THRESHOLD. An RSU randomly allocates the available channels to the vehicles within its coverage area, and each vehicle that is allocated a channel decides its request based on its buffer level B and the two aforementioned thresholds. In both algorithms, each vehicle can be allocated at most one channel.

C. Impact of Parameters in Proposed Algorithm

The impact of the parameters α and F_{max} on the performance of the proposed algorithm are investigated. Fig. 6 shows the relationship between AIR (ARL) and weight coefficient α defined in (5) under $\rho = 20$ veh/km. It can be observed from Fig. 6 that a larger α leads to a lower AIR, which is preferred, whereas a smaller α leads to a larger ARL, which is desired. This is because a larger α results in a higher weight for the first item related to interruption ratio in (5); thus, playback interruption is preferentially prevented and *vice versa*.

The impact of initial budget amount F_{max} on the performance of the proposed algorithm is shown in Fig. 7 under



Fig. 6. Effect of the weight coefficient α .



Fig. 7. Effect of initial budget.

 $\rho = 20$ veh/km. The horizontal axis is the ratio of F_{max} and T_{in} , where $T_{\rm in}$ is the number of slots that a vehicle in the coverage area of an RSU, as shown in Fig. 5. It can be observed that as $F_{\rm max}/T_{\rm in}$ increases, AIR decreases at first, and then increases. This can be explained as follows. When the ratio of F_{max} and $T_{\rm in}$ is 1, all the vehicles just entering an RSU's coverage area can only bid 1 because of the lower bound $C \ge 1$ and cannot increase bid to improve the channel access opportunity; thus, the interruption ratio is high. Yet, when the initial budget is abundant $(F_{\text{max}}/T_n > 1.5)$, the vehicle will bid with a high price to avoid punishment caused by wasted budget. Due to the bid upper bound F_{limit} , the bids of the vehicles with high utility value and the vehicles with excessive budget may be equal, which leads to unreasonable channel allocation and an increase in AIR because the RSU cannot identify the vehicles with a really high utility value. Therefore, it is proper to set $F_{\rm max}/T_n$ in the range of 1.1 to 1.5. It is also observed that the ARL is basically not affected by F_{max} . This is because, by having the same initial budget, all the vehicles adopt similar pricing strategy and, thus, obtain similar number of access chances.

Conclusion can be drawn from Figs. 6 and 7 that a higher α and a lower F_{max} should be set in the proposed auction-based channel allocation mechanism. Therefore, in the following simulations, we set $\alpha = 0.997$ and $F_{\text{max}} = \lceil 1.1 \cdot T_{\text{in}} \rceil$, where $\lceil x \rceil$ calculates the minimum integer larger than or equal to x.



Fig. 8. Performance comparison when RSUs are sporadically deployed. (a) AIR versus vehicle density. (b) ARL versus vehicle density.

D. Average Interruption Ratio and Average Number of Received Layers

Fig. 8 shows the AIRs and ARLs of the proposed algorithm and the two baseline algorithms under different vehicle densities when RSUs are sporadically deployed. It can be seen that all the algorithms have the same trend: The AIR increases and the ARL decreases as the vehicle density increases. This is because higher vehicle density results in more vehicles competing in an RSU. Moreover, one can notice that both the AIR and the ARL of the proposed algorithm are better than those of the baseline algorithms. This is because the proposed algorithm considers the channel allocation and video streaming jointly; thus, the RSUs and vehicles can make proper decisions, whereas the baseline algorithms do not.

Fig. 9 shows the AIRs and ARLs of different algorithms when the road is fully covered by RSUs, namely vehicles can receive the RSUs' signal all the time. We simple set the distance of adjacent RSUs equal to the diameter of the RSU's coverage in the simulations. This scenario is a special and easy case compared with when the RSUs are sporadically deployed. It can be observed from the figure that AIRs and ARLs of all the algorithms perform well under low vehicle densities. Yet, as the vehicle density increases, the performance deteriorates. Compared with the baseline algorithms, the proposed algorithm can achieve lower interruption ratio and higher number of received layers except when vehicle density equals 25 veh/km because



Fig. 9. Performance comparison when road is fully covered. (a) AIR versus vehicle density. (b) ARL versus vehicle density.

the proposed algorithm tends to keep as low interruption ratio as possible and thus sacrifices the performance of ARL.

It can be observed that the performances in Fig. 9 are better than those in Fig. 8. It is because the road is fully covered by RSUs; thus, the vehicles are in the coverage areas of RSUs' all the time and have more chances to assess channels.

E. Performance Improvement by Accumulation of Historical Records

A method to estimate the environment state transition probability based on the accumulated historical records is proposed in Section V-D. The effect of this method is verified by simulation, and the results are presented here.

The system average utility value (SAUV) is adopted as a metric and is the average of all vehicles' utilities in a time window aiming to smooth the fluctuation. It can be defined as $\bar{U}(y) = (1/H) \sum_{g=y-H}^{y} \sum_{n=1}^{N_{\text{max}}} U_{n,g}$. Here, *H* represents the duration of the window in period is set to 200, and $U_{n,g}$ is the total utility of vehicle *n* obtained in the *g*th period and is defined as

$$U_{n,g} = \alpha \cdot (B_{n,g} - D_{n,g})^{-} + (1 - \alpha) \cdot \frac{Q_{l_n}}{Q_L}.$$
 (14)

Notice that as compared with (5), (14) is not weighted by the probability of accessing a channel because the results of channel allocation and the number of received video layers have already been known.



Fig. 10. Convergent tendency versus the accumulation of past RSUs. (a) SAUV. (b) AIR. (c) ARL.

The subfigures in Fig. 10 show the convergent tendency as the accumulation of past RSUs. Fig. 10(a) shows the SAUVs obtained under different vehicle densities. As vehicle density increases, the SAUV increases rapidly at first and then tends to be flat, meaning that the SAUV can be improved and achieve convergence with the help of accumulated historical records.

Fig. 10(b) and (c) show the obtained AIRs and ARLs along with the accumulation of historical records. It can be observed that, as the vehicle density increases, the AIRs in Fig. 10(b) increase, and ARLs in Fig. 10(c) decrease. That is because if there are more vehicles in the coverage area of an RSU, the fewer opportunities for each vehicle to access a channel, and the worse the quality of video playback will be. It can also be observed in Fig. 10(b) that, for a given vehicle density, AIR decreases first and then tends to be flat with the increase in the accumulated number of RSUs. This is because with the help of accumulated historical records, the vehicles can bid and request layers more reasonably; therefore, the interruption ratio decreases, and visual quality is maintained as high as possible. Fig. 10(c) shows that ARLs keep almost constant as the RSU index increases, revealing that more historical records enable more reasonable bids.

It is shown that the AIR in Fig. 10(b) and the SAUV in Fig. 10(a) get flattened after about 2000 RSUs, although the vehicles have no prior information about the environment state. This implies that the rationality of the vehicle bid will be greatly improved and the convergence process will be speeded up if RSUs provide the information of environment states to their newly arrived vehicles.

VII. CONCLUSION

In this paper, we have proposed a channel allocation and adaptive streaming algorithm for supporting video services in vehicular networks. The contributions of this paper are as follows. By employing the auction-based channel allocation mechanism, the vehicles can bid reasonably according to their utility values, which help the RSU to allocate channels to the vehicles with the most urgent need for DT and the vehicles with high transmission rates and, therefore, guarantees the vehicles' smooth playback and visual quality. The vehicles can make the tradeoff between visual quality and noninterruption playback by changing the required layers. The proposed algorithm can converge quickly with the help of historical records and achieve lower interruption ratio and higher visual quality than the baseline algorithms. The proposed algorithm is also effective when the number of data channels for video service is constant. In future work, we will consider a more general channel model and mobility model to make the proposed algorithm more practical.

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