PRICING-BASED DECENTRALIZED RATE ALLOCATION FOR MULTIPLE VIDEO STREAMS

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ABSTRACT

We consider rate allocation for multiple video users sharing a constant bitrate channel. Previously, overall quality of multiple users was improved by exploiting relative complexity. Users with high complexity video benefit at the expense of video quality reduction for other users with simpler videos. The quality of all users can be improved by collectively allocating the bitrate which requires sharing video information with a central controller. In this paper, we present an informationally decentralized rate allocation for multiple users where a user only needs to inform its demand to an allocator based on its video complexity and bitrate price. Simulation results show that all users improve their quality by our pricing-based decentralized rate allocation method compared to their allocation when acting individually and the results are comparable to the centralized rate allocation.

***Index Terms*—** Rate allocation, H.264/AVC, rate-distortion optimization, video compression, decentralized allocation

1. INTRODUCTION

The growth in simultaneous video transmission over communication channels by multiple users has stimulated the efforts to better allocate shared resources such as bitrate among users. Instead of equally dividing available bitrate among videos, a number of joint rate allocation algorithms were proposed to improve the overall video quality [1–4]. The overall quality improvement comes at the expense of lowering the quality of some of the videos. The improvement is achieved by reallocating bits in every time period (or slot) from videos whose quality suffers least from reducing their allocated rate to those videos benefitting most from an increase in allocated rate.

In [5], we proposed a joint rate allocation scheme that improves the quality of all videos simultaneously by reallocating bits for each video from those Time-Slots (TS) when a reduction in bitrate hurts little to other TS when increased bitrate increases quality the most. This is possible if there are many videos, some of whose quality can be improved by reducing their allocation in one TS for an increased allocation in some other (later) TS, and other videos in the same TS whose quality could be improved by the reverse exchange.

Implementation of these schemes requires communication of specific information about individual videos at every TS, namely, the rate that quality increases as it receives more bits. This complicated information must be communicated accurately. For some applications, this may be problematic. Various decentralized algorithms were proposed [6, 7] for joint bitrate allocation for multiple video streams. The auction mechanism was used in [6] to allocate rate in a cross-layer optimization. A distributed rate allocation was proposed in [7] to minimize the total Mean Squared Error (MSE) of all the videos but it suffers from high price fluctuation and not all videos are promised to improve their video quality simultaneously.

In this paper, we propose a scheme which requires simpler information to be exchanged, and is less clearly susceptible to misrepresentation. This scheme is modeled on price guided procedures discussed in the economics literature [8] that are characterized as decentralized, as various video transmitters (hereafter Users) only communicate their bitrate demands in response to the bitrate price announced by a bitrate allocator (hereafter the Allocator) in a TS. By contrast, in a centralized procedure, the Users communicate all their private information and the Allocator decides on an allocation. In our decentralized allocation, the Allocator adjusts the User's demand to equalize the aggregate allocation to the available supply and announces the price for the next TS. Ideally, in each TS several iterations of price and demand messages would be exchanged between the Allocator and the Users. We, however, consider a real-time process with only one iteration of the price-demand communication. The budget of each User is reduced by the cost of its allocation computed at the current price and the process repeats. For our initial exploration of this scheme, we endow each User with an equal overall budget (all videos are of the same length) which is reduced in each TS by the cost of the allocated bitrate to the video that TS. If the budget of a video is exhausted, the video does not receive any more bits. We refer to the budget as the amount of money the User possesses at any TS.

With this price guided allocation scheme, instead of using bits at a constant rate, Users will increase their demand in TS during which their videos are more complex (e.g., high motion) and reduce their demand in TS of low complexity. Permitting the amount of bitrate used in each TS to vary increases the efficiency of each User's total bitrate use by giving more of the resource when it is most valuable (in terms of lowering MSE) and less when it is less valuable. The use of a price to guide Users' choices of demand reflects the relative scarcity of available bitrate in each TS. When all Users request more bits than the average, scarcity is greater and the price is higher, thus moderating the demands. Our simulation results show that each User benefits from this price-based decentralized rate allocation mechanism compared to equal bitrate allocation to all the Users. The performance of this algorithm is comparable to the centralized bitrate allocation introduced in [5] where all Users send their Rate-Distortion (RD) curve to the Allocator.

If each video is sent by an independent, self-interested User, such User would, in general, have an incentive to misrepresent information to obtain a larger share of the available bits than it would receive if honest information had been reported. In our method, such misrepresentation is checked, as inflating its demand will both reduce the money available for future purchases and increase the price faced next TS. There may be situations where it could benefit a User to ask for less in the current TS to lower the next price, but at the lower price all Users will have greater demand than otherwise, thus

This work was supported by the National Science Foundation and the Office of Naval Research.

reducing the chance of obtaining more resource at the lower price. A standard result in the economics literature [9] shows that any advantage a User may receive from misrepresenting its demand becomes vanishingly small as the number of Users competing for the same resources increases. For this paper, we assume the number of users is sufficiently large to ignore any incentive to misrepresent the demand.

The rest of the paper is organized as follows: Sec. 2 describes the general pricing-based decentralized rate allocation process for individual Users. Sec. 3 discusses various multiplexing methods for multiple video streams using this rate allocation process. Simulation results and conclusions are given in Sec. 4.

2. PRICING-BASED DECENTRALIZED ALLOCATION

Suppose N Users send videos through a constant bitrate channel of R bits per TS. We assume one TS includes one Group Of Pictures (GOP), however, it can be smaller or larger. The utility of User n at TS t, denoted by $U_{n,t}(x_{n,t})$, is its MSE, given by the RD curve. A User's goal is to minimize its overall MSE, given its resources, across all TS. At time t, let $M_{n,t}$ be the available money for User n and p_t be the bitrate price. We have T TS of video for each User. At $t = 1$, we start with $p_1 = 1$. Users are initially allocated money based on the average rate:

$$M_{n,1} \;=\; \frac{T.R}{N}.p_1,\; \forall\; n \;=\; 1 \;\; to \;\; N \tag{1}$$

The utility optimization problem for User n is given by

$$\max_{\{x_{n,t}\}} \sum_{t=1}^{T} -U_{n,t}(x_{n,t}) \quad subject\;\; to\;\; \sum_{t=1}^{T} p_t.x_{n,t} \leq M_{n,1} \tag{2}$$

The constraint in Eq. 2 requires the money spent over all TS to be less than or equal to the total allocated money. Solving Eq. 2 under this constraint gives the optimal decision for each User in all TS. However, for the real-time problem we assume future prices as well as the RD function for future TS are unknown. To address this, we consider a sequential process. In each TS, a User will reoptimize its decision for the current and all future TS using expected values for future prices and RD functions. Assuming future TS are identical in expectation (the future environment is perceived as stationary), then each TS's decision problem is just an optimization problem with two decisions only - the allocation (or demand) $x_{n,t}$ for the current TS and $\bar{x}_{n,t}$, the common allocation (demand) for each of the remaining $(T-t)$ TS. Given the price at TS t and an expected price $\bar{p}$ for the future expected RD function, the new optimization problem becomes

$$\begin{aligned} &\max_{x_{n,t}} \quad -U_{n,t}(x_{n,t}) \;-\; (T-t).\bar{U}_{n,t}(\bar{x}_{n,t}) \\ &s.t. \quad p_t.x_{n,t} \;+\; (T-t).\bar{p}_t.\bar{x}_{n,t} \;\leq\; M_{n,t} \end{aligned} \tag{3}$$

User n at TS t, thus, makes a demand of $x^*_{n,t}$ bits, where $x^*_{n,t}$ is the solution of Eq. 3. This information is sent to the Allocator who normalizes the individual demands proportional to excess demand (the difference between total demand and total supply):

$$\hat{x}_{n,t} = x^*_{n,t} - \frac{x^*_{n,t}}{\sum_{n=1}^{N} x^*_{n,t}}.(\sum_{n=1}^{N} x^*_{n,t} - R) = x^*_{n,t}.\frac{R}{\sum_{n=1}^{N} x^*_{n,t}} \tag{4}$$

and sends back the normalized allocation ($\hat{x}_{n,t}$) to the Users who encode their videos using the allocated bitrate. The Users recalculate their total available money for the next TS by

$$M_{n,t+1} \;=\; M_{n,t} \;-\; p_t.\hat{x}_{n,t} \;\forall\; n \;=\; 1 \;\; to \;\; N \tag{5}$$

The price for the next TS is adjusted by the Allocator based on the excess demand by all the Users

$$p_{t+1} \;=\; p_t \;+\; \alpha_p.(\frac{\sum_{n=1}^{N} x^*_{n,t} \;-\; R}{R}),\;\; p_1 \;=\; 1 \tag{6}$$

where the price adjustment parameter, α_p, is a design choice to regulate the price variation.

If aggregate demands are similar from one TS to the next (e.g. if aggregate demand in the current TS is a good predictor of aggregate demand in the next TS, as would be the case if the video streams followed a Markov process), then the price rule that sets the next TS's price by adjusting the current price proportionately to current excess demand can be expected to be an efficient rule. In fact, many video streams are characterized by scenes of varying amount of motion with abrupt breaks at scene changes. Within a scene, a Markovian assumption is probably reasonable. Thus, if most of the time, most videos are within a scene, then the aggregate demand each TS will be a reasonably good predictor of demand next TS and a price adjustment rule based on excess demand will provide the appropriate signal about the relative scarcity of bitrate available next TS.

The bitrate price for the next TS and the available money are known to each User. Based on these two parameters and their RD function, each User again calculates its bitrate demand for the next TS. This process is performed for all TS sequentially.

3. MULTIPLEXING METHODS

In this section, we discuss the RD function of a video stream and consider various averaging methods for the future RD functions. We approximate the RD curve using

$$U_{n,t}(x_{n,t}) \;=\; a_{n,t} \;+\; \frac{b_{n,t}}{x_{n,t} + d_{n,t}} \tag{7}$$

where $a_{n,t}$, $b_{n,t}$, and $d_{n,t}$ are curve fitting coefficients for User n at TS t and are determined numerically. Using Eq. 7 and Eq. 3, we get the User's per TS decision problem:

$$\begin{aligned} &\max_{x_{n,t}} \quad -(a_{n,t} + \frac{b_{n,t}}{x_{n,t} + d_{n,t}}) \;-\; (T-t).(\bar{a}_{n,t} + \frac{\bar{b}_{n,t}}{\bar{x}_{n,t} + \bar{d}_{n,t}}) \\ &s.t. \quad p_t.x_{n,t} \;+\; (T-t).\bar{p}_t.\bar{x}_{n,t} \;\leq\; M_{n,t} \quad \forall\, n \;=\; 1\; to\; N \end{aligned} \tag{8}$$

where $\bar{a}_{n,t} + \frac{\bar{b}_{n,t}}{\bar{x}_{n,t}+\bar{d}_{n,t}}$ is the predicted estimated average RD function for User n for each future TS $t+1$ to T.

We solve Eq. 8 using a Lagrange multiplier approach, and the bitrate demand for User n in TS t is given by

$$x^*_{n,t} \;=\; \sqrt{\frac{b_{n,t}}{p_t}}.\frac{M_{n,t} + p_t.d_{n,t} + (T-t).\bar{p}.\bar{d}}{\sqrt{p_t.b_{n,t}} + (T-t).\sqrt{\bar{p}_t.\bar{b}_{n,t}}} - d_{n,t} \tag{9}$$

We consider several alternatives to predict the future average RD function. They depend on the information the User has at the time it makes the forecast. In all cases, the User will use Eq. 9 to calculate the bitrate demand for the current TS with respect to the forecasted average RD function for the future. In **ALL_PRICE**, we assume the User knows the average RD function for a video over all TS (1 to T), and we use this average as the forecast at every time step. In **REM_PRICE**, we assume the User knows the average RD function for the remaining TS. Since the User knows the average of the past, the average of remaining TS can be calculated given the average over all TS. Both ALL_PRICE and REM_PRICE require identical advance knowledge. In **PRE_PRICE**, we use the average of previous TS as the estimate of future TS. This method would be expected to work well for long videos and may not work for short videos if the previous TS are very different from the future TS.

For archival video, we consider a method called **FUL_NORM** in which Users have exact knowledge of the RD function for all the TS in a video (but not the future prices). Assuming a constant price in all TS, we find the bitrate demanded by each User in all the TS simultaneously using Eq. 9. In FUL_NORM, the total bitrate demand from all the Users is normalized by the total available bitrate. This is an approximate model since p_t is unknown for $t > 1$ so we assume constant price.

In this paper, we compare these four multiplexing methods using the pricing-based decentralized rate allocation to the constant rate allocation, **EQL_TS**, where each TS in a video receives an equal number of bits. Note, for a TS of GOP length, the rate control algorithms used with most current video standards strive to achieve equal rate allocation for all GOPs, similar to EQL_TS.

4. RESULTS

We used H.264/AVC reference software JM 11.0 [10] baseline profile for our simulations. The test videos were taken from a 72 minute travel documentary containing varying types of scenes and motion. Each test video is 250 seconds long at 30 frames per second and a resolution of 176×120 pixels. The GOP size is 15 frames (I-P-P-P) and is encoded using H.264 rate control [11]. The decentralized rate allocation method for multiple video streams can be used for any GOP size or structure, frame rate, video length or resolution.

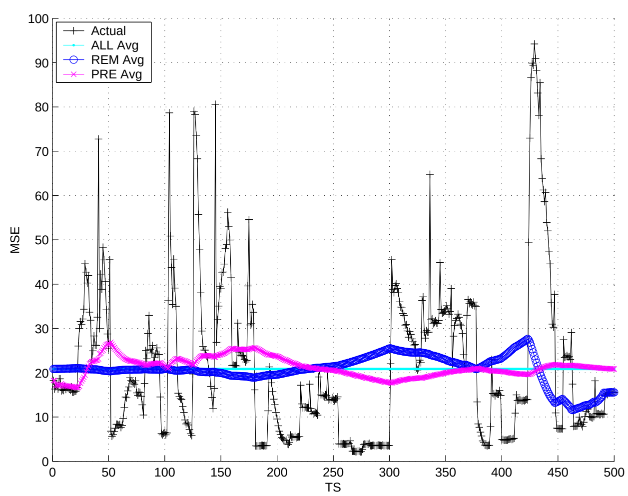

Fig. 1. Actual and average MSE variations with TS for g11 video at 50 kbits per TS

Fig. 1 shows actual MSE variation with TS for the g11 video at 50 kbits per TS along with three averaging methods discussed previously. The average of all TS (ALL Avg) is constant for all TS. The average of remaining TS (REM Avg) starts with the ALL Avg curve but deviates as time progresses. The average of past TS (PRE Avg) starts from the actual MSE at the first TS but eventually converges to the ALL Avg in the last TS. The important observation from this plot is the low variation of all the averages compared to the actual MSE variation at each TS. We see that the variation of PRE Avg is similar to ALL Avg and REM Avg. Therefore, without advance knowledge of RD functions of future TS, PRE Avg proves to be useful as a forecast of the future in Eq. 9.

Fig. 2 shows video quality versus average operating rate for the pricing-based decentralized rate allocation for four multiplexed videos. We calculate MSE per frame and average across all frames of a video, then convert to PSNR to represent the quality. The curves in each plot show the various multiplexing methods described in Section 3. All methods outperform EQL_TS. PRE_PRICE, using only past RD functions to forecast the future ones, improves the video quality from 0.5-0.7 dB for the g11 video to 0.8-1.0 dB for the g8 video compared to EQL_TS. ALL_PRICE improves the quality by 0.7-1.1 dB for g11 to 0.9-1.1 dB for g8 compared to EQL_TS. REM_PRICE performs better than EQL_TS by 0.7-1.2 db for g11 to 1.0-1.3 dB for g9. When the exact RD function for all the TS in a video is used in FUL_NORM, its performance is marginally better than REM_PRICE for some of the videos. In general, the pricing-based decentralized rate allocation method for multiple video streams improves the video quality for all the videos simultaneously. Even the knowledge of the RD function of the past TS can be used to estimate the RD function for the future TS to improve the video quality of the entire stream. The performance of such methods depends on the accuracy of the estimated RD function for future frames in a video.

In general, price fluctuation decreases with an increase in the number of multiplexed streams. This is shown in Fig. 3 for REM_TS. The price fluctuates between 0.12 and 2.24 for 2 multiplexed videos and the fluctuation decreases to 0.57-1.53 for 10 multiplexed video streams. The price fluctuation increases if α_p is large. For our simulations, α_p was not optimized; it might be possible to improve multiplexing performance by tuning this parameter for particular video types. If many independent video streams are being multiplexed, we might expect a law of large numbers result to hold, suggesting that the aggregate demand would not fluctuate much from one TS to the next. If the available bitrate supply is constant over time, then the price would be (relatively) constant as well. But if supply were to vary from one TS to the next (as, for example, in a cognitive radio application), then the excess demand would fluctuate, even if demand did not, and the price adjustment rule would be appropriate if, for example, the supply followed a Markov process.

In conclusion, we demonstrate various methods of decentralized rate allocation among multiple video streams. A video User separately calculates its current bitrate demand based on current price, available money, and video complexity. This demand is sent to the Allocator who normalizes the total demand and sends the price for the next TS based on the total demand. The computational burden that appears in centralized allocation algorithms [5] is shifted to individual Users and yet we achieve similar video quality improvement. The quality of all video Users is improved simultaneously using our pricing-based decentralized rate allocation.

5. REFERENCES

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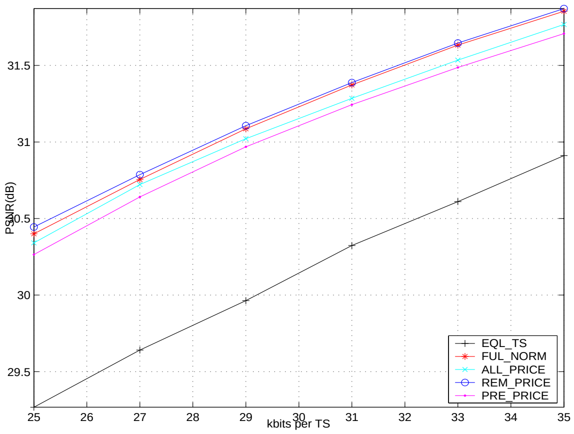
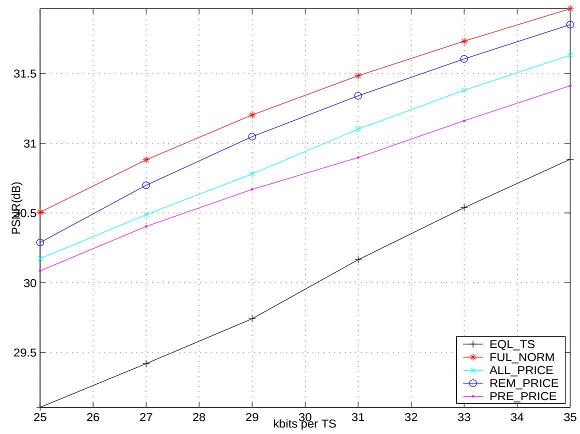
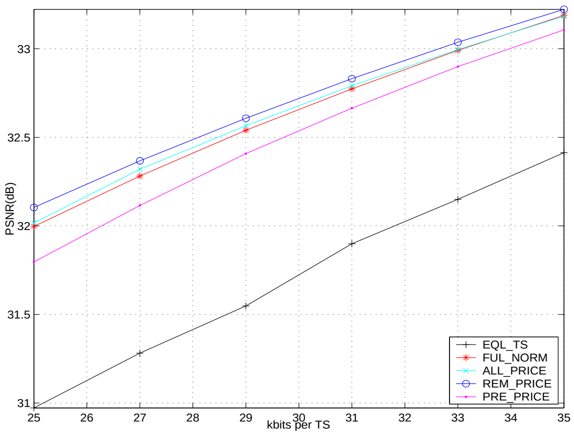


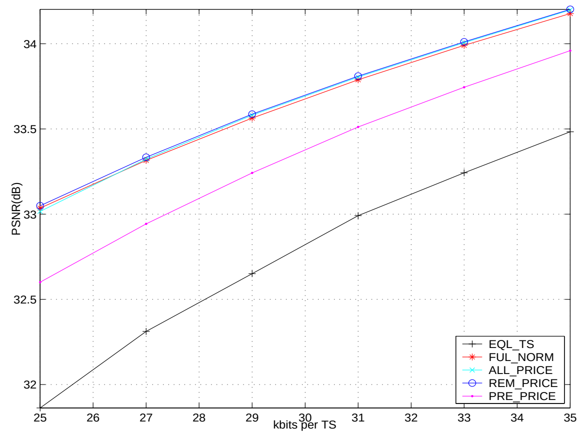
(a) g8 video stream



(b) g9 video stream



(c) g10 video stream



(d) g11 video stream

Fig. 2. PSNR variation with bitrate for four multiplexed video streams ($\alpha_p = 0.1$, $\bar{p} = 1$)

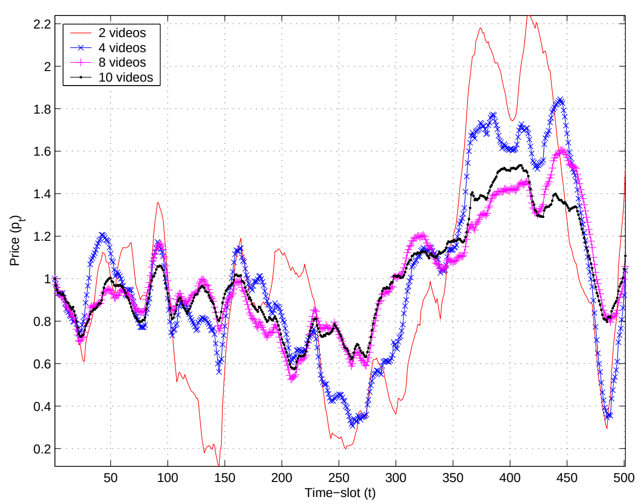


Fig. 3. Price fluctuation reduction with increase in number of multiplexed videos at 30 kbits per TS per User for REM_PRICE multiplexing method using $\alpha_p = 0.1$

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