Optimal Scheduling for Multiple Description Video Streams in Wireless Multihop Networks

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Abstract— **In this work, we investigate the optimal system scheduling for competing multiple description (MD) video streams in a resource-limited wireless multihop network. By joint optimization of MD, rate control and multipath routing, optimal joint rate control and routing algorithm is proposed to solve this problem with constraints that arise from the MD streams among multiple users via multiple paths. We design this joint algorithm in a distributed manner that is amenable to on-line implementation for wireless networks.**

Index Terms— **multiple description; rate control; multipath routing; joint optimization**

I. Introduction

THE issue of supporting error-resilient video transport over error-prone wireless networks has received considerable attention recently[1-4]. On one hand, some works presented some source coding-based error-resilient approaches that divide the original bit-stream into multiple descriptions, called MD, to achieve the tradeoff between the error-resilience and the coding complexity (cf. [1], [2] and the references therein). The fundamental principle of MD is to generate multiple correlated descriptions of the sources such that each description approximates the source with a certain level of fidelity. On the other hand, some researchers studied the network congestion control and optimal routing for wireless video transmission, (cf. [3], and the references therein) so that the network can be stable, robust and the users can have better QoS for the applications. In [3], Zhu etc. showed that the optimal allocated rate strikes a balance between the selfish motivation of minimizing video distortion and the global goodness of minimizing network congestions.

Typically, for real-time video communications over resource-limited wireless networks, the key point is how to allocate the resource to different users who share the network to minimize the total video distortion. In this paper, we employ MD as our error-resilient coding method. For such a case, there are many and different description streams over multiple paths which may influence each other; thus the sources should choose reasonable rate-routing-distortion point by providing optimal transmission rate and routing such that the video sources be both error-resilient and network-adaptive. However, to the best of our knowledge, current literatures considered MD, congestion control and multipath routing separately and independently. In order to achieve improved video quality supported by wireless networks, these factors are jointly considered in this work.

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II. System Model and Notation

Consider a wireless network with L links, and each link $l \in L$ with a capacity of C_l. In this system, there are S users, and each user $s \in S$ using asymmetric MD. In this work, we focus on two descriptions since this is the most widely used for MD video. Each description of user s is denoted as H_s^i for $i = 1, 2$, with a set $L(H_s^i)$ of links from source to destination. Each link l is shared by a set $\cup_{i=1}^{2} H_s^i(l)$ of descriptions. For each user s, we denote d_s^0 as the central distortion when both descriptions are received, d_s^i for $i = 1, 2$ as the side distortion if description H_s^i is received, and d_s^3 as the distortion if none of the description is received. Also, R_s^i and P_s^i for $i = 1, 2$ are the rate and the packet loss probability of the path for description H_s^i, respectively.

Our system scheduling aims at finding the optimal rate-routing-distortion operating points to minimize the total distortion, which is the sum of distortion of each user s D_s. Also, D_s can be approximated as:

$$\begin{aligned} D_s &= d_s^0(1-P_s^1)(1-P_s^2) + d_s^1(1-P_s^1)P_s^2 \\ &+ d_s^2(1-P_s^2)P_s^1 + d_s^3 P_s^1 P_s^2 \end{aligned} \tag{1}$$

In this paper, we employ the following distortion-rate region as [4]:

$$\begin{cases} d_s^0 \geq \frac{2^{-2(R_s^1+R_s^2)}}{2^{-2R_s^1}+2^{-2R_s^2}-2^{-2(R_s^1+R_s^2)}} \cdot \sigma^2 \\ d_s^1 \geq 2^{-2R_s^1} \cdot \sigma^2 \\ d_s^2 \geq 2^{-2R_s^2} \cdot \sigma^2 \\ d_s^3 = \sigma^2 \end{cases} \tag{2}$$

where σ^2 is the source variance. We assume here Gaussian sources with zero and unit variance $\sigma^2 = 1$.

For this wireless video communication, we consider that the transmission error is caused by the unreliable wireless links. In order to get a uniform bound of packet loss probability, all the links in this multihop network are supposed to be independent [4], and the end-to-end packet loss probability for description H_s^i is:

$$P_s^i = 1 - \prod_{l \in L(H_s^i)} (1 - p_l) \quad (3)$$

where p_l is the packet error probability on link l. According to [5], p_l is an increasing function of the rate on link l r_l , and a lower bound on this function is:

$$p_l \geq \frac{1}{2} 2^{-KC_l(1-\theta_l)} \quad (4)$$

where K is the average packet length and $\theta_l = r_l/C_l$ reflects the link utilization. Assuming that the error probability of each link l is small, we can approximate P_s^i as:

$$P_s^i \approx \sum_{l \in L(H_s^i)} p_l \approx \sum_{l \in L(H_s^i)} \frac{1}{2} 2^{-KC_l(1-\theta_l)} = F(r_l) \quad (5)$$

where F is just a function chosen for the convenience of notation.

III. Optimal System Scheduling Scheme

We investigate the optimal system scheduling by jointly optimizing the rate-routing-distortion adaptation. Based on previous discussions, the optimal problem is:

$$\begin{aligned} \min \quad & \sum_{s \in S} D_s \quad (6) \\ s.t. \quad & P_s^i \geq F(r_l), l \in L(H_s^i), \forall s, i = 1, 2 \\ & r_l = \textstyle\sum_{i=1}^{2} \sum_{H_s^i \in H_s^i(l)} R_s^i \leq \theta_l C_l, \forall l \\ & d_s^0, d_s^i, P_s^i, R_s^i \geq 0, 0 \leq r_l \leq C_l, \theta_l, \forall s, i = 1, 2, \forall l \end{aligned}$$

where D_s is defined by (1). The first constraint comes from the packet loss and the second from the flow constraint. It should be noted that for practical operation, the original value of θ_l is 1, and its current estimated value in iteration t depends on the one in previous iteration $t-1$. Obviously, this problem is a non-convex optimization problem, but if the ordering of possible R_s^i $(i = 1, 2)$ is known for every user s, the optimization problem is a convex optimization if we apply a logarithmic change of variable. With this additional log change of variable to P_s^i, $P_s^i = exp(\widetilde{P}_s^i)$, $\widetilde{P}_s^i \leq 0$, the optimization problem in (6) becomes:

$$\begin{aligned} \min \quad & \sum_{s \in S} D_s \quad (7) \\ s.t. \quad & \widetilde{P}_s^i \geq \log F(r_l) = \widetilde{F}(r_l), l \in L(H_s^i), \forall s, i = 1, 2 \\ & \textstyle\sum_{i=1}^{2} \sum_{H_s^i \in H_s^i(l)} R_s^i \leq \theta_l C_l - \xi r_l^2, \forall l \\ & d_s^0, d_s^i, \widetilde{P}_s^i, 0 \leq r_l \leq C_l, R_s^i \geq 0, \theta_l, \forall s, i = 1, 2, \forall l \end{aligned}$$

To make (6) strictly convex in R_s^i, we add $-\xi r_l^2$ to the righthand side of the constraints in (7). Where, ξ is a small number such that ξr_l^2 is small compared with r_l. Since there is a fixed closed interval for R_s^i, the optimization problem (7) is a convex optimization given the ordering of possible R_s^i for every user s.

Since (7) is a convex optimization problem satisfying Slater's condition, the duality gap is zero. Therefore, a distributed algorithm for (7) can be derived through the Lagrange dual problem. First we obtain the following Lagrangian:

$$\begin{aligned} L(D_s, R_s^i, \phi_l, \kappa_l) \;=\; & \sum_{s \in S} D_s - \sum_i \sum_{l \in L(H_s^i)} \phi_l(t) \big(\widetilde{P}_s^i - \widetilde{F}(r_l)\big) \\ & + \sum_i \sum_{H_s^i \in H_s^i(l)} \kappa_l(t) \big(R_s^i - \theta_l C_l + \xi r_l^2\big) \quad (8) \end{aligned}$$

• Each Source s seeks:

$$\min \quad \sum_{s \in S} D_s - \sum_i \sum_{l \in L(H_s^i)} \phi_l(t) \widetilde{P}_s^i + \sum_i \sum_{H_s^i \in H_s^i(l)} \kappa_l(t) R_s^i \quad (9)$$

• Each Link l seeks:

$$\min \quad \phi_l'(t) \widetilde{F}(r_l) - \kappa_s^i(t) \big(\theta_l C_l - f_l - \xi r_l^2\big) \quad (10)$$

where $\kappa_s^i(t) = \sum_{l \in L(H_s^i)} \kappa_l(t)$ and $\phi_l'(t) = \sum_{i=1}^{2} \sum_{H_s^i \in H_s^i(l)} \phi_l(t)$ refer to the end-to-end congestion price for H_s^i and the aggregate traffic load reduction price paid by sources using link l at iteration t, respectively. The Lagrangian dual function $L_d(\phi_l, \kappa_l)$ is defined as the maximized $L(D_s, R_s^i, \phi_l, \kappa_l)$ over D_s and R_s^i for given ϕ_l and κ_l. Each source can compute an optimizer D_s^* and each link l can compute an optimizer $r_l^*(\phi_l, \kappa_l)$. The Lagrange dual problem of (7) is:

$$\min \quad L_d(\phi_l, \kappa_l) = L(D_s^*, r_l^*(\phi_l, \kappa_l), \phi_l, \kappa_l) \quad (11)$$

where (ϕ_l, κ_l) are the dual variables. Note that (11) is a convex minimization. Since $L_d(\phi_l, \kappa_l)$ may be non-differentiable, an iterative subgradient method can be used to update the dual variables to solve (11):

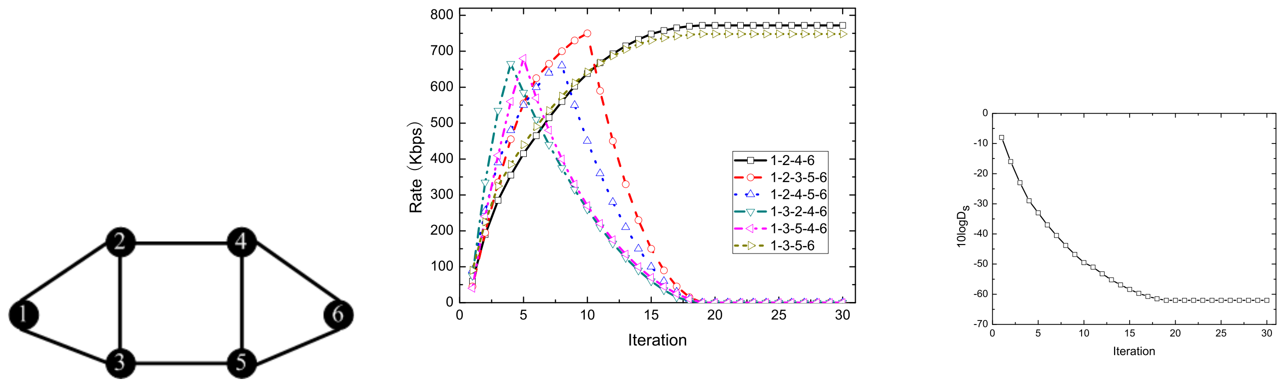
• Link Price Update:

$$\phi_l(t+1) = [\phi_l(t) + \lambda_\phi(t) \widetilde{F}(r_l)]^+ \quad (12)$$

where $\lambda_\phi(t)$ represents the link price step size.

• Congestion Price Update:

$$\kappa_l(t+1) = [\kappa_l(t) + \lambda_\kappa(t) \big(r_l'(t) - \theta_l C_l + \xi r_l^2\big)]^+ \quad (13)$$



(a) Network topology (b) Rate on each path (c) Average distortion of each user

Fig. 1. Simulation using the proposed OJRCR scheme. Step sizes: $\lambda_\kappa = 4 \times 10^{-5}$, $\lambda_\phi = 2 \times 10^{-5}$.

where $r'_l(t) = \sum_{i=1}^{i=2} \sum_{H_s^i \in H_s^i(l)} R_s^i$ is the aggregate rate of all the sources on link l at iteration t, and $\lambda_\kappa(t)$ represents the congestion price step size.

Based on the previous discussions, the Optimal Joint Rate Control and Routing (OJRCR) scheme can be implemented in on-line manner as follows. The sources send all outgoing links with path discovery messages, which are forwarded by the intermediate nodes. At each intermediate node, the path discovery messages contain the information of congestion price using (13) and link price using (12) related to every possible flow between the source and intermediate node. This intermediate node then extends the path as the source does. Upon reception of path discovery messages from the destinations, the sources determine the optimal path $L(H_s^i)$ between the source and destination by minimizing (9). Once the path determined, the corresponding links $l \in L(H_s^i)$ update the r_l by minimizing (10). In this case, each source adjusts its offered congestion price per unit traffic load for each description and each link in its path determines its total traffic which maximizes the "net income" of the network based on its link price.

An illustrative numerical example is summarized for network shown in Fig.1(a). Of the many possible source-destination pairs, we choose 1-6. To present a clear picture of how the OJRCR works, we consider a case when all the link capacities are the same, background traffic is 30% of the link capacity, and the number of user is 10. Fig.1(b) and Fig.1(c) illustrate both the total rates for all users and average distortion of each user of each iteration for $C_l = 800$Kbps, $K = 40$Kbits. It can be observed that the possible paths for node 1 to node 6 have changed over the iterations, so that the traffic is reallocated over the network to avoid already congested links. Changes in the paths also affect the congestion-increment information, which in turn leads to changes in the rate allocation decisions. Clearly, the simulation results are consistent with the analytical optimal and convergence properties. It should be noted that, numerous simulations have been performed with different scenarios, for example, different network topologies, user numbers, link capacities etc., and similar behaviors to Fig.1(b) and Fig.1(c) have been observed.

IV. Conclusion

We have studied the optimal system scheduling for competing MD video steams interact in a resource limited wireless multihop network. As detailed in the letter, our proposed optimal joint rate control and routing scheme can be adapted to dynamic network condition by adjusting the multipath routing and the allocated rate for each MD video stream.

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