This full text paper was peer reviewed at the direction of IEEE Communications Society subject matter experts for publication in the IEEE ICC 2010 proceedings

A Unified QoS Optimization for Scalable Video Multirate Multicast over Hybrid Coded Network

Chenglin Li [1], Hongkai Xiong[1], Junni Zou[2], Tsuhan Chen[3]

[1]Department of Electronic Engineering, Shanghai Jiao Tong University, Shanghai 200240, P.R. China
[2]Department of Communication Engineering, Shanghai University, Shanghai, 200079, P.R. China
[3] School of Electrical and Computer Engineering, Cornell University, NY 14853, USA

***Abstract*— This paper aims to optimize joint overall video quality and traffic performance of multirate multicast of scalable video streaming accessing hybrid wired/wireless paths. In order to guarantee layered utility maximization over tiered wired/wireless coded networks, we propose a joint source and network flow optimization scheme where each scalable layer is tailored in an incremental order and finds jointly optimal multicast paths and associated rates. It not only achieves the highest sustainable layered video quality, but also takes into account both path-overlapping allocation for different receivers which takes advantage of network coding and the wireless link contention in a shared transmission medium. The convex programming is imposed on the total variation minimization of layered rate-distortion. Using primal decomposition and the primal-dual approach, we develop a decentralized algorithm with two levels of optimization. Experimental results demonstrate that the proposed algorithm not only provides better video quality with optimal layered access for heterogeneous receivers, but benefits the asymptotic capacity of a hierarchical "hybrid" wired/wireless architecture in a scalable sense.**

***Index Terms*—Multirate multicasting, rate-distortion, QoS, network coding, convex optimization**

I. Introduction

From a source coding perspective, hierarchical coding of scalable video coding (SVC), allows rate adaptation not only at the encoder/decoder, but also in intermediate network nodes while achieving highly efficient rate-distortion performance [1]. A SVC stream consists of a base layer and one or multiple enhancement layers with a flexible multi-dimension layer structure, providing various operating points in spatial resolution, temporal frame rate, and video reconstruction quality. Different SVC layers with multirate multicast are transported in different IP multicast groups which are subscribed by heterogeneous receivers with different computation and communication resources and capabilities. Layered multirate multicasting is equivalent to a generalized multi-source problem where the progressive inter-layer dependency is considered as fairness between different sources.

As wireless multihop networks emerge, it has become necessary to communicate across multihop networks to servers back in the wired network. From underlying heterogeneous network performance, a hierarchical "hybrid" wired/wireless architecture can benefit the asymptotic capacity in terms of scalability [2]. In order to explore the advantages of scalable video streaming over hybrid wired/wireless paths, optimizing joint overall video quality and traffic performance of multirate multicast in ubiquitous multimedia access is the topic of concern in this work.

The coded network employs coding at intermediate nodes, to achieve the capacity in single-source multiple-terminal multicast [3]. Besides improving communication network's throughput, various potential benefits of network coding include robustness to link/node failures and packet losses. Distributed random linear coding schemes [4] have made practical implementation of network coding possible. Chen et al. [5] developed adaptive rate control algorithms by differentiating the networks with and without given coding subgraphs. Here, network coding is integrated to determine the optimal content distribution meshes for multi-paths of scalable video dissemination over two-tier wired and wireless networks.

We have investigated previous rate control schemes in discrete layered multicast with scalable video coding as well as network coding [6-9]. Those methods may benefit SVC distribution over hybrid networks to some extent, however, they are merely suboptimal solutions, where the layer dependency constraints of SVC stream are not strictly promised. Zhu et al. [6] address rate allocation for SVC multicast, with the goal of minimizing total video distortion of all peers. Yan et al. [7] use a rate-distortion function as the application utility measure for optimizing the overall video quality. However, it does not consider the layer dependence requirement of multiple source streams and neglects utilizing network coding as routing. As modification, the optimization formulation in [8] takes into account both layer dependence and network coding to improve the throughput of an overlay multicast session. Instead of giving a rigorous solution with theoretical justification, the distributed heuristic algorithm (LION) limits the optimization problem into suboptimal performance. Making a progress to LION algorithm, Zou et al. [9] proposed a prioritized flow optimization formulation for SVC multicast, which adopts the path costs and prices of each layer as the priority parameters

The work has been partially supported by the NSFC grants No. 60632040, No. 60736043, No. 60802019, No. 60928003 and the National High Technology Research and Development Program of China (863 Program) (No. 2006AA01Z322).

978-1-4244-6404-3/10/$26.00 ©2010 IEEE

and provides rigorous distributed algorithms. However, the layer dependency constraints of SVC stream are not strictly promised in the formulation.

This paper focuses on optimizing joint overall video quality and traffic performance of multirate multicast of scalable video streaming accessing hybrid wired/wireless paths. To guarantee layered utility maximization over tiered wired/wireless coded networks, we propose a joint source and network flow optimization scheme where each scalable layer is tailored in an incremental order and finds jointly optimal multicast paths and associated rates. It not only achieves the highest sustainable layered video quality, but also takes into account both path-overlapping allocation for different receivers which takes advantage of network coding and the wireless link contention in a shared transmission medium. The convex programming is imposed on the total variation minimization of layered rate-distortion. Using primal decomposition and the primal-dual approach, we develop a decentralized algorithm with two levels of optimization.

The rest of the paper is organized as follows. Sec. II presents network model, and problem formulation is illustrated in Sec. III. Sec. IV proposes a decentralized algorithm. Experimental results are presented in Sec. V.

II. NETWORK MODEL

Supposing a video distribution network contains two-tier wired and wireless structure, which is modeled as a directed graph $G_1 \cup G_2$, where $G_1 = (V_1, E_1)$ and $G_2 = (V_2, E_2)$. E_1 is the set of wired links and $V_1 = \{s\} \cup N \cup T$ is the set of wired nodes, where $\{s\}$, N and T represent the set of source nodes, relay nodes and receiver nodes, respectively. The wireless network G_2 is composed of the set of wireless links E_2 and the set of wireless nodes $V_2 = T \cup R \cup D$, where R and D denote the relay nodes and destination nodes and T represents the set of source nodes in G_2 which are also the set of receiver nodes in G_1 . Hereinafter, we have $V = \{s\} \cup N \cup T \cup R \cup D$ and $E = E_1 \cup E_2$. Let each wired link $l \in E_1$ has a finite capacity of C_l, and consider the wireless link contention in a shared transmission medium with capacity C.

A. SVC Model

Assuming the SVC video stream is encoded into a set M of layers $\{L_1, L_2, \ldots, L_M\}$ and divided into M corresponding multicast sessions. Each layer m is distributed over a multicast session at rate within region $[b_m, B_m]$. Each multicast session m has one source node s, a set of destination nodes D, and a set of relay nodes $N \cup T \cup R$. In order to successfully decode received layered SVC video streams, we should promise that all destination nodes can subscribes to SVC multicast layers in an incremental order, i.e. layer m is not decodable at each destination node without any layer lower than m (1 to $m-1$).

B. Rate-distortion Model

The most concerning component is the video quality decoded by each destination node when receiving allocated SVC video streams. Here we use a dynamic programming based RD model [10] to determine the SVC video distortion based on the encoded rate received by the destination node:

$$D_e(R_e) = \frac{\theta}{R_e - R_0} + D_0 \tag{1}$$

where D_e is the distortion of the encoded video sequence and R_e is the encoded rate. The remaining variables θ, R_0 and D_0 are the parameters of the RD model, which depend on the actual video content and are estimated from empirical rate distortion curves using regression techniques.

Using Taylor expansion, we define the total variation of distortion-rate of SVC stream when layer m is added to the destination d. Thus the utility function in the optimization objective can be defined as the absolute value of the distortion decrement when layer m is successfully received by d:

$$\begin{aligned} U_m(R_d^m) &= -[D_e(\sum_{i=0}^{m-1} R_d^i + R_d^m) - D_e(\sum_{i=0}^{m-1} R_d^i)] \\ &\approx \frac{\theta}{(\sum_{i=0}^{m-1} R_d^i - R_0)^2} R_d^m - \frac{\theta}{(\sum_{i=0}^{m-1} R_d^i - R_0)^3} (R_d^m)^2 \end{aligned} \tag{2}$$

where R_d^m denotes d's received rate in multicast session m.

C. Network Coding Model

For multiple multicast sessions sharing a network, in some cases, achieving optimal throughput requires coding across sessions. However, combining data belonging to different layers makes it difficult to recover all original data for destination nodes that only receive partial layers. Furthermore, the priority relationship between layers might cause some receivers unable to decode its received video stream smoothly since the higher layers may arrive before the lower layers. Thus, we limit our consideration to separately implement network coding within each session, an approach referred as intra-session coding or superposition coding [11]. [12] stated that the multicast sessions can be straightforwardly achieved by the distributed random network coding schemes in the form of intra-session network coding.

With intra-session network coding, flows for different destinations of a multicast session are allowed to share network capacity by being coding together. For a single multicast session m with transmission rate $R_m \in [b_m, B_m]$, information flow must flow at rate R_m to each destination, while by network coding the actual physical flow on each link needs only to be the maximum of the individual destination's information flow. For each link $l = (i,j)$, let $x_{(i,j)}^{md}$ denote the information flow for destination d of multicast session m, and $f_{(i,j)}^{m}$ denote the physical flow in multicast session m, then these constraints can be expressed as:

$$\sum_{j:(i,j)\in E} x_{(i,j)}^{md} - \sum_{j:(j,i)\in E} x_{(j,i)}^{md} = \begin{cases} R_m & \text{for } i = s \\ -R_m & \text{for } i \in D \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

and $$x_{(i,j)}^{md} \le f_{(i,j)}^{m}, \forall d \in D \quad (4)$$

where, constraints (3) reflect the information flow balance equation at each node $i \in V$. Constraints (4) specify the network coding condition relating physical rate and information rate.

According to [12], while setting up optimal multicast sessions over the hybrid network, there is no loss of optimality in separating the problems of subgraph selection and network coding, i.e. we need to find an optimal coding subgraph $\mathbf{f}$ satisfying constraints (3) and (4), then apply a network coding scheme to it.

We specify for all multicast sessions multiple paths from the source node to destination nodes, which are chosen based on general cost criteria that are independent of flow rates. Since each multicast session uses only a limited set of paths, [5] and [7] have shown that such approach may give lower rates compared to optimizing over the entire network, but it is much less complex. For each node $d \in D$, we use a matrix $H_d = \{h_{dj}^l\}$ to reflect the relationship between its paths and corresponding links. If destination node d has $J(d)$ alternative paths from source node s, let $h_{dj}^l = 1$ when the path j of node d uses link l, and $h_{dj}^l = 0$ otherwise.

In network coding-based routing, let R_{dj}^m denotes the information flow rate of destination node d's jth path in multicast session m, f_l^m represents the physical flow rate for link l in multicast session m. Then, with given multiple paths, the information flow balance equations (3) are automatically guaranteed, and with intra-session coding, the network coding constraints (4) become:

$$\sum_{j=1}^{J(d)} h_{dj}^l R_{dj}^m \le f_l^m, \forall m \in M, \forall l \in E, \forall d \in D \quad (5)$$

D. Channel Capacity Model

The set of feasible coding subgraph $\mathbf{f}$, i.e. the set of feasible physical flow rate vectors, is specified by corresponding wired and wireless link capacity constraints, respectively. In the wired network, the total transmission rate of the physical flow in each link should be no more than its capacity $C_{(i,j)}$. The wired network channel capacity constraint can be expressed as:

$$0 \le \sum_{m\in M} f_{(i,j)}^m \le C_{(i,j)}, \forall (i,j) \in E_1 \quad (6)$$

Data flows in wired networks compete for the capacity of individual links. In wireless networks, however, the capacity of a wireless link is interrelated with other adjacent wireless links. Consequently, we should consider the wireless link contention in a shared transmission medium with capacity C [13] by introducing constraints of the location-dependent contention among the competing wireless data flows. According to the protocol model [13] [15], suppose that any link originating from node k will interfere with link (i,j) if the link distance $d_{(k,j)} < (1+\Delta)d_{(i,j)}, \Delta \ge 0$ and define $\Psi_{(i,j)}$ for each link $(i,j) \in E_2$ as the cluster of links that cannot transmit when link (i,j) is active. The notation of cluster can be treated as a basic resource unit, within which wireless data flows will compete for the capacity that is equivalent to the capacity of the wireless shared medium. Then the wireless network channel capacity constraint is:

$$0 \le \sum_{m\in M} f_{(i,j)}^m + \sum_{(p,q)\in\Psi_{(i,j)}} \sum_{m\in M} f_{(p,q)}^m \le C, \forall (i,j) \in E_2 \quad (7)$$

III. PROBLEM FORMULATION

The entire optimization problem is stated as: given the topology of a static hybrid network with corresponding channel capacity conditions, to maximize the overall utility of all destination nodes by jointly optimizing source rate allocation, layered stream scheduling and network coding based multi-path routing, subject to the requirement of channel capacity, scalable video coding and network coding constraints. Mathematically, the optimization problem can be formulated as follows:

$$\textbf{P1}: \ \text{maxmize}_{(\mathbf{R})} \sum_{d\in D}\sum_{m\in M} U_m\Big(\sum_{j=1}^{J(d)} R_{dj}^m\Big) \quad (8)$$

s.t.

1) $\sum_{j=1}^{J(d)} h_{dj}^l R_{dj}^m \le f_l^m; \forall m \in M, \forall l \in E, \forall d \in D$

2) $\sum_{m\in M} f_l^m \le C_l; \forall l \in E_1$

3) $\sum_{m\in M} f_l^m + \sum_{k\in\Psi(l)}\sum_{m\in M} f_k^m \le C; \forall l \in E_2$

4) $b_m \le \sum_{j=1}^{J(d)} R_{dj}^m \le B_m, \ or \ \sum_{j=1}^{J(d)} R_{dj}^m = 0; \forall m \in M, \forall d \in D$

5) $\dfrac{\sum_{j=1}^{J(d)} R_{dj}^m}{b_m} \ge \dfrac{\sum_{j=1}^{J(d)} R_{dj}^{(m+1)}}{B_{(m+1)}}; \forall m \in \{1,2,\cdots,M-1\}, \forall d \in D$

6) $R_{dj}^m \ge 0; \forall j \in J(d), \forall m \in M, \forall d \in D$

7) $f_l^m \ge 0; \forall l \in E, \forall m \in M$

Constraints 1) reflect the relationship between information flow rate and physical flow rate on each edge when network coding is applied to information flows of the same video multicast layer. Constraints 2) specify that the aggregate physical flow rates of different layers over each wired link do not exceed the wired link capacity. Constraints 3) depict the wireless link contention in a shared medium. Constraints 4) give the lower bound and upper bound of the receiving rate required for each layer, which are denoted by b_m and B_m, respectively. In terms of **Proposition** 1, Constraints 4) and 5) can strictly ensure that each destination node subscribes to SVC multicast layers in an incremental order, i.e. layer m is not decodable without any layer less than m. Constraints 6) and 7) specify the allocated rates and physical flow are nonnegative.

Proposition 1: The allocated rate $\mathbf{R}$ is constrained by constraints 4) and 5), if and only if each destination node receives layered video streams in an incremental order.

Proof: be omitted with limited space.

For the sake of simplicity and the convenience of distributed solution using convex optimization theory, given constraint 6), constraints 4) can be rewritten as:

$$(\sum_{j=1}^{J(d)} R_{dj}^{m})(\sum_{j=1}^{J(d)} R_{dj}^{m} - b_m)(\sum_{j=1}^{J(d)} R_{dj}^{m} - B_m) \le 0; \forall m \in M, \forall d \in D$$

From the perspective of optimization theory, it can be seen that Problem **P1** is feasible and there exists a unique optimal solution of $\mathbf{R}$ since the objective function is strictly convex and the constraint set is also convex, i.e. the overall optimization problem is a convex optimization problem. Other than some infeasible and impractical centralized algorithms, in the subsequent sections, we will develop a distributed solution based on the decomposition and duality theories.

IV. Distributed Algorithm

A. Primal Decomposition

According to its decomposability structures, a relatively large optimization problem can be decomposed into a set of small distributed sub-problems. For problems with coupling variables, the primal decomposition is often used. Considering problem **P1**, one way to decouple this problem is by taking a primal decomposition with respect to the coupling variable f_l^m, and then a two-level optimization decomposition procedure is proposed as follows:

$$\textbf{P1-1}: \quad \mathbf{maxmize}_{(\mathbf{R})} \sum_{d\in D}\sum_{m\in M} U_m(\sum_{j=1}^{J(d)} R_{dj}^{m}) \qquad (9)$$

$$\textbf{s.t.} \quad \text{constraints 1), 4), 5) and 6).}$$

and

$$\textbf{P1-2}: \quad \mathbf{maxmize}_{(\mathbf{f})} \quad U^*(\mathbf{f}) \qquad (10)$$

$$\textbf{s.t.} \quad \text{constraints 2), 3) and 7).}$$

where **P1-1** performs a low-level optimization that can be separated into a set of sub-problems for each combination of m, d and j under the condition that the coupling variable vector $\mathbf{f}$ is fixed, **P1-2** performs a high-level optimization in charge of updating $\mathbf{f}$, and $U^*(\mathbf{f})$ is the optimal objective value of **P1-1** for a given $\mathbf{f}$. The objective value of the low-level optimization is locally optimal, which approximates to the global optimality using the result of the high-level optimization.

B. Low-level Optimization

$$\begin{aligned} & L(\mathbf{R},\lambda,\mu,\eta) \\ &= \sum_{d\in D}\sum_{m\in M} U_m(\sum_{j=1}^{J(d)} R_{dj}^{m}) - \sum_{l\in E}\sum_{d\in D}\sum_{m\in M} \lambda_d^{ml}[\sum_{j=1}^{J(d)} h_{dj}^{l} R_{dj}^{m} - f_l^m] \\ & - \sum_{d\in D}\sum_{m\in M} \mu_d^m[(\sum_{j=1}^{J(d)} R_{dj}^{m})(\sum_{j=1}^{J(d)} R_{dj}^{m} - b_m)(\sum_{j=1}^{J(d)} R_{dj}^{m} - B_m)] \\ & - \sum_{d\in D}\sum_{m=1}^{M-1} \eta_d^m[\frac{\sum_{j=1}^{J(d)} R_{dj}^{(m+1)}}{B_{(m+1)}} - \frac{\sum_{j=1}^{J(d)} R_{dj}^{m}}{b_m}] \end{aligned} \qquad (11)$$

To solve the low-level optimization problem **P1-1**, it is clear that if constraints 1), 4) and 5) were absent, then the problem would be decoupled by dual decomposition in a further way. Therefore, by relaxing the coupling constraints 1), 4) and 5) with Lagrange multipliers λ, μ and η respectively, the Lagrangian of problem **P1-1** can be expressed as (11).

Here, we propose the following primal-dual algorithm [14] that updates the primal and dual variables simultaneously and moves together towards the optimal points asymptotically to solve the low-level optimization problem **P1-1**.

$$R_{dj}^{m}(t_L+1) = [R_{dj}^{m}(t_L) + a(t_L)\frac{\partial L(\mathbf{R},\lambda,\mu,\eta)}{\partial R_{dj}^{m}}]^+ \qquad (12)$$

$$\lambda_d^{ml}(t_L+1) = [\lambda_d^{ml}(t_L) - b(t_L)\frac{\partial L(\mathbf{R},\lambda,\mu,\eta)}{\partial \lambda_d^{ml}}]^+ \qquad (13)$$

$$\mu_d^{m}(t_L+1) = [\mu_d^{m}(t_L) - c(t_L)\frac{\partial L(\mathbf{R},\lambda,\mu,\eta)}{\partial \mu_d^{m}}]^+ \qquad (14)$$

$$\eta_d^{m}(t_L+1) = [\eta_d^{m}(t_L) - d(t_L)\frac{\partial L(\mathbf{R},\lambda,\mu,\eta)}{\partial \eta_d^{m}}]^+ \qquad (15)$$

where t_L denotes the low-level iteration index, $a(t)$, $b(t)$, $c(t)$ and $d(t)$ are positive step sizes, and $[\cdot]^+$ denotes the projection onto the set of non-negative real numbers.

Under physical context, λ maps to the "congestion prices" of information flow at all links, i.e. λ_d^{ml} can be considered as the "congestion price" of information flow at link l for destination node d's bandwidth requirement in layer m. At each link l, if the total information flow bandwidth demand $\sum_{j=1}^{J(d)} h_{dj}^{l} R_{dj}^{m}$ in layer m exceeds the supply f_l^m, then the "congestion price" λ_d^{ml} will rise, and vice versa. Similarly, the other two Lagrange multipliers, μ and η, can be interpreted as the "SVC encoding prices" for each destination node in a certain multicast session. Furthermore, all updating steps are distributed and can be implemented at individual links and nodes using only local information.

C. High-level Optimization

Next, we discuss how to adjust $\mathbf{f}$ in order to solve the high-level optimization problem **P1-2**. Suppose $\hat{\lambda}_d^{ml}$ is the optimal Lagrange price and optimal variable corresponding to the constraint $\sum_{j=1}^{J(d)} h_{dj}^{l} R_{dj}^{m} \le f_l^m$ in **P1-1**. We define the Lagrangian of **P1-2** as:

$$\begin{aligned} L'(\mathbf{f},\alpha,\beta) = & \; U^*(\mathbf{f}) - \sum_{l\in E_1} \alpha_l(\sum_{m\in M} f_l^m - C_l) \\ & - \sum_{l\in E_2} \beta_l(\sum_{m\in M} f_l^m + \sum_{k\in\Psi(l)}\sum_{m\in M} f_k^m - C) \end{aligned} \qquad (16)$$

Similarly as the solution of low-level optimization problem **P1-1**, using dual decomposition, the high-level optimization problem **P1-2** can be solved by the primal-dual algorithm via high-level optimization step sizes, which uses only the local information of the network as well.

V. Results and Discussion

In this section, both numerical and packet-level simulation results are presented to evaluate the proposed algorithm.

We solved the two-level optimization problem in a hybrid wired and wireless network illustrated in Fig.1 (a) and (c). Fig.1

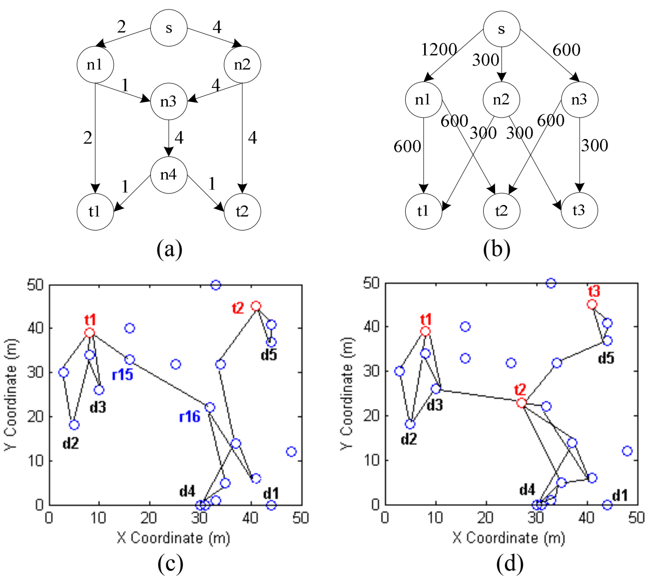

Fig.1. Network topology associated with link capacity, where (a) and (c) illustrate the wired and wireless network in numerical experiment, respectively, (b) and (d) illustrate the wired and wireless network in packet-level simulation.

(a) shows the wired network represented by a simple but classical butterfly network that is widely used in network coding based simulation studies. In Fig.1 (c), the wireless network is represented by a randomly distributed wireless network with 20 nodes, where t_1 and t_2 denote the relay stations that connect the wireless network with the wired network, $d_1, d_2, \cdots, d_5$ denote 5 destination nodes and others are relay nodes. It is obvious that each relay station in the wired network has 3 alternative paths. By defining every two wireless nodes with the distance less than 20m are capable of communication, we plot two shortest paths for each destination node from the relay stations. Obviously, each destination node has six alternative paths from the source node s.

The numerical simulation assumes that the video bit-stream is composed of 3 layers, with the base layer at rate 3 (data units/s), the first and second enhancement layer at rate 2 and 1(data units/s), respectively. Suppose the wireless capacity in a shared medium C is 10. Through the proposed algorithm, we can solve that the achievable throughput for destination nodes $d_1, d_2, \cdots, d_5$ are 6, 3, 3, 6, and 5, respectively. Therefore, destination node d_1 and d_4 can receive all the three SVC video stream layers, d_5 can receive the lower two layers, while d_2 and d_3 can only receive the base layer.

To study the convergence behaviour of the low-level optimization, Fig.2 shows the allocated data rate for d_2, d_4 and d_5 with a fixed step size 0.05. It can be seen that all data rates approach the optimal value after 90 iterations. The convergence behaviour of the high-level optimization is shown in Fig.3 with the physical flow for specified wired and wireless links. The flow rates on all these links converge after 70 iterations. We decrease the wireless capacity in a shared transmission medium C from 8 to 1, and show the impact on the allocated rate for d_1, d_3 and d_5 in Fig.4. Fig.5 shows the convergence behaviour of d_2's allocated rate with one constant step size and two diminishing step sizes $0.1/(1+0.05t_H)$ and $0.1/(1+0.01t_H)$. As a conclusion, although a fixed size is more convenient and can converge more quickly, a diminishing step size is preferred since the rate with slow and smooth variation is critical for video quality smoothness.

Fig.6 shows the achievable throughput of all destination nodes. Within each destination node, from left to right, shown are the achievable throughput results solved by the Shortest path Algorithm (SA), the Distributed rate allocation Algorithm (DA) in [6], the LION algorithm [8] and the Proposed Algorithm (PA). It can be seen that the proposed algorithm that combines network coding technique and appropriate multi-path rate allocation mechanism can approximate the max-flow capacity for each member of a multicast group.

We use ns-2 to conduct packet-level simulation on the topology of Fig.1 (b) and (d). In Fig.1 (d), the wireless network is a random network in a 50m-by-50m area with 20 nodes where 5 nodes are set to be destination nodes. For the wired network, it is obvious that each relay station has 2 different paths from the source node. For the wireless network, we find three shortest paths as multiple paths from relay stations t_1, t_2, t_3 to each destination node. Thus, it has 6 paths to obtain SVC video stream from the source node to each destination node. The video source adopts Joint Scalable Video Model 7_10 reference codec of H.264/AVC extension standard, with three well-known test-sequences ("BUS," "FOOTBALL," and "FOREMAN") at frame rate of 30 fps, CIF resolution, and a GOP-length of 32 frames. They are encoded with 256 Kbps on the base layer, 384Kbps, 512Kbps and 1024Kbps on the three enhancement layers by FGS coding. Fig.7 shows the rate-distortion performance of SVC for three sequences.

In the packet-level simulation, the layered SVC sources are encapsulated to multiple packets with the packet size of 512 bytes. The transmission delay for each link is set to be 50ms. From the network topology illustrated in Fig.1 (b) and (d), it can be solved that the max-flow capacity for each destination node $d_1, d_2 \dots d_5$ are $\{1200, 900, 2100, 1200, 1800\}$ Kbps. We vary the playout deadline from 300ms to 600ms and the results solved by three typical algorithms and our proposed algorithm are shown in Table I. Here, packets are supposed to be dropped if they do not arrive at the destination node by the playout deadline. From Table I, we can see that as the playout deadline increases, both algorithms can promise the increment of received video quality for each destination node. Furthermore, since both SA and DA are implemented without network coding operations at relay nodes, the average packet delay of these two algorithms is smaller than that of LION and PA. However, the proposed algorithm generally outperforms the other three algorithms with better received video quality.

VI. Conclusion

In this paper, we focus on optimizing joint overall layered

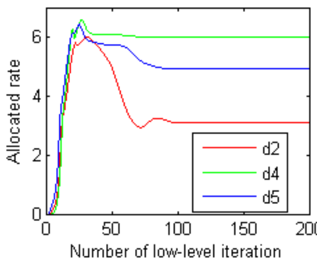

Fig.2. The convergence of low-level optimization.

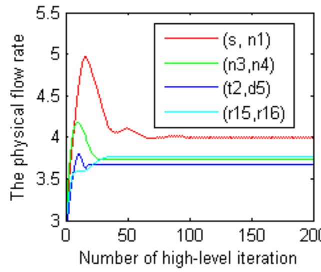

Fig.3. The convergence of high-level optimization.

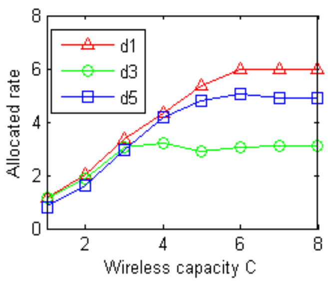

Fig.4. Allocated rate when wireless link contention exists.

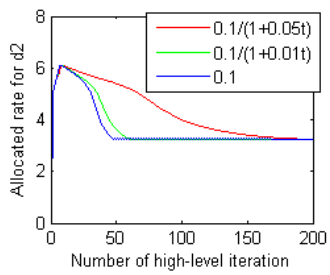

Fig.5. The impact of step size on the convergence behavior.

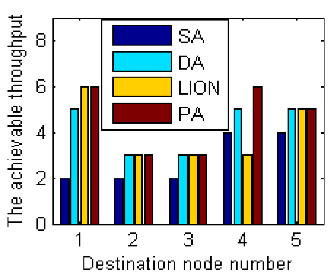

Fig.6. Comparisons of the achievable throughput.

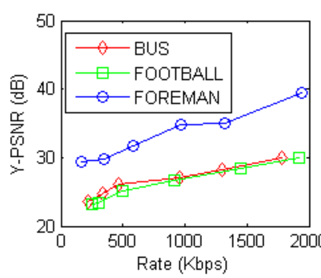

Fig.7. The PSNR performance achieved by SVC.

video quality and traffic performance of multirate multicast of scalable video streaming over hybrid coded networks. Intra-session network coding is imposed on the optimal content distribution meshes for multi-source multi-paths dissemination, to improve the traffic throughput and the error resilience. The proposed formulation would guarantee that each destination node accesses progressive layered stream in an incremental order and with optimal multicast paths at associated rates, which ensures both a variation minimization of rate-distortion and network utility maximization. A decentralized algorithm with two levels of optimization is provided to attain a practical solution. Experimental results validate the asymptotic capacity of a hierarchical "hybrid" wired/wireless architecture in a scalable sense.

Table I. Received video quality in PSNR of "FOREMAN" sequence.

Average PSNR		300ms	400ms	500ms	600ms
d_1	SA	23.2	25.7	26.3	26.3
	DA	25.3	26.9	27.8	27.9
	LION	23.6	26.3	26.9	27.4
	PA	23.6	26.3	26.9	27.4
d_2	SA	23.2	25.7	26.3	26.3
	DA	24.1	26.3	26.8	26.8
	LION	21.8	26.1	26.6	26.8
	PA	21.8	26.1	26.6	26.8
d_3	SA	24.9	26.2	26.3	26.3
	DA	25.3	26.9	27.8	27.9
	LION	27.2	29.4	30.4	30.6
	PA	27.2	29.4	30.4	30.6
d_4	SA	23.2	25.7	26.3	26.3
	DA	25.3	26.9	27.8	27.9
	LION	24.3	26.5	27.3	28.2
	PA	24.3	26.5	27.3	28.2
d_5	SA	22.7	23.4	23.8	24.1
	DA	26.0	27.3	28.7	28.7
	LION	24.3	26.5	27.1	27.5
	PA	26.0	27.2	28.3	28.8

REFERENCES

[1] H. Schwarz, D. Marpe, and T. Wiegand, "Overview of the scalable video coding extension of H.264/AVC," *IEEE Trans. Circuits and Systems for Video Tech.*, vol. 17, no. 9, Sept. 2007.

[2] A. Zemlianov and G. de Veciana, "Capacity of ad hoc wireless networks with infrastructure support," *IEEE Journal on Selected Areas in Comm.*, vol. 23, no. 3, pp. 657-667, Mar. 2005.

[3] R. Ahlswede, N. Cai, S.-Y. R. Li and R. W. Yeung, "Network information flow", *IEEE Trans. on Information Theory*, 46:1204-1216, 2000.

[4] T. Ho, R. Koetter, M. Medard, D. R. Karger and M. Effros, "The Benefits of Coding over Routing in a Randomized Setting", *Proc. of IEEE International Symposium on Information Theory*, 2003.

[5] L. Chen, T. Ho, S. H. Low, et al., "Optimization based rate control for multicast with network coding," *Proceeding of IEEE Infocom*, 2007.

[6] X. Zhu, T Schierl, T. Wiegand, and B. Girod, "Video Multicast over Wireless Mesh Networks with Scalable Video Coding (SVC)", *Proc. Visual Communication and Image Processing, VCIP 2008*, Jan. 2008.

[7] J. Yan, K. Katrinis, M. May, and B. Plattner, "Media- and TCP-friendly congestion control for scalable video streams," *IEEE Transactions on Multimedia*, vol. 8, no. 2, 196-206, 2006.

[8] J. Zhao, F. Yang, Q. Zhang, et.al., "LION: Layered overlay multicast with network coding," *IEEE Trans. on Multimedia*, vol. 8, no. 5, pp. 1021-1032, Oct. 2006.

[9] Junni Zou, Hongkai Xiong, Li Song, et al., "Prioritized Flow Optimization with Generalized Routing for Scalable Multirate Multicasting," *IEEE International Conference on Communications, ICC 2009*, Dresden, Germany, Jun. 2009.

[10] K. Stuhlmuller, N. Farber, M. Link, and B. Girod, "Analysis of video transmission over lossy channels," *IEEE Journal on Selected Areas in Communications*, vol. 18, no. 6, pp. 1012-1032, June 2000.

[11] R. W. Yeung, "Multilevel diversity coding with distortion," *IEEE Trans. on Information Theory*, vol. IT-41, pp. 412-422, 1995.

[12] D. S. Lun, N. Ratnakar, M. Médard, R. Koetter, D. R. Karger, T. Ho and E. Ahmed, "Minimum-cost multicast over coded packet networks", *IEEE Trans. on Information Theory*, 2006.

[13] P. Gupta and P. R. Kumar, "The Capacity of Wireless Networks," *IEEE Trans. on Information Theory*, vol. 46, no. 2, pp. 388-404, Mar. 2000.

[14] S. Shakkottai and R. Srikant, "Network Optimization and Control", *in the series Foundations and Trends in Networking*, vol. 2, no. 3, Now Publishers Inc, Boston - Delft, 2007.

[15] K. Yuen, B. Liang and B. Li, "A Distributed Framework for Correlated Data Gathering in Sensor Network", *IEEE Trans. on Vehicular Technology*, vol. 57, no.1, pp. 578-593, 2007.