Prioritized Flow Optimization with Multi-Path and Network Coding Based Routing for Scalable Multirate Multicasting

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***Abstract*—In this paper, we study performance optimization for scalable video coding and multicast over networks. Multi-path video streaming, network coding based routing, and network flow control are jointly optimized to maximize a network utility function defined over heterogeneous receivers. Content priority of video coding layers is considered during the flow routing to determine the optimal multicast paths and associated data rates for each layer. Our optimization scheme attempts to find content distribution meshes with minimum path costs for each video coding layer while satisfying the inter-layer dependency during scalable video coding. Based on primal decomposition and primal-dual analysis, we develop a decentralized algorithm with two optimization levels to solve the performance optimization problem. We also prove the stability and convergence of the proposed iterative algorithm using Lyapunov theories. Extensive experimental results demonstrate that the proposed algorithm not only achieves the max-flow throughput using network coding, but also provides better video quality with balanced layered access for heterogeneous receivers.**

***Index Terms*—Multicast, network coding, resource allocation, scalable video coding.**

I. Introduction

Recently, multirate multicasting has emerged as an important method for content distribution due to its capability to adapt to different user requirements and time-varying network conditions of different receivers. From a source coding perspective, layered or hierarchical coding of source data, such as JVT/MPEG scalable video coding (SVC), allows video transmission and decoding at multiple bit rates with progressively improved video quality. It allows rate adaptation not only at the encoder/decoder, but also in intermediate network nodes while achieving highly efficient rate-distortion performance [1]. Optimizing the performance of scalable video coding and multicast over network emerges as an important problem in content distribution and ubiquitous multimedia access.

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. Each layer, along with all layers that it directly or indirectly depends on, forms a representation at a certain spatio-temporal resolution and quality level. For real-time SVC streaming with multirate multicasting, different SVC layers are transported in different IP multicast groups which are subscribed by heterogeneous receivers with different computation and communication resources. In multirate multicasting, the data rate at a receiver could be different from data rates at intermediate network nodes. The transmission rate of a multicast group on a link is equal to the maximum of the data rates of all receivers' downstream of that link. Within the context of the SVC, layered multirate multicasting is equivalent to a generalized multi-source problem where a progressive inter-layer correlation is considered as fairness between different data sources.

Rate control of multiple video streams over networks has been studied extensively in the past [2]–[8]. Most of the existing schemes use predetermined distribution trees to improve the network throughput and overall video quality, accordingly formulate cross-layer packet-based local access control problems in protocol stack and corresponding source-oriented instantaneous rate adaption. Lee and Guan [2] proposed an inter-subband redundancy removal approach for scalable streaming over peer-to-peer networks. A dynamic source-oriented access renegotiation scheme, which considers traffic content and short-term available link bandwidth statistics, was reported in [3]. Zhu *et al.* [4] and [5] presented a packet-based rate adaption scheme for minimizing total distortion of multiple video streams for application-layer multicast with multi-path transmission. Schaar *et al.* [6] proposed a packet-based channel access scheme for scalable video streaming over wireless

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networks. A message-based pricing and access coordination scheme was presented in [7]. In this paper, we study layered utility maximization problems for communication networks where each receiver (or class) can have multiple alternative paths through the coded network (network coding) to receive the subscribed SVC layers. The proposed network coding assisted multirate multicasting allows us to enhance network transmission performance and video streaming quality.

The first optimization model for the multirate multicasting problem was proposed by Kar *et al.* [9], [10], and a distributed algorithm for a continuous set of rate to the receivers was proposed in [11]. To maximize the overall utility of multiple sources over their transmission rates, a flow control and optimization scheme was presented in [12]. Based on this approach, a number of source-oriented rate control schemes have been developed [4]–[7]. One of the major challenges in utility maximization of multi-path video streaming is that the objective function is often not strictly concave since receivers have multiple paths. To address this issue, [13] developed a heuristic solution by introducing a quadratic term into the objective function. The multi-path routing combined with congestion control was also studied in [14].

Existing methods on network performance optimization have focused on resource allocation among different receivers. The problem of utility maximization between video coding layers with prioritized multirate multicasting has not been adequately addressed. In this paper, we study inter-layer dependency of scalable video coding and investigate how it could be coupled with multi-path video streaming and network coding based routing to achieve optimum performance.

The seminal work of Ahlswede *et al.* [15] demonstrated that network coding achieves the capacity in single-source multiple-terminal multicast. In practice, it has been proven that linear network coding is sufficient for achieving this capacity [16]. Further, random linear network coding as an efficient distributed solution, achieves this capacity with high probability [17], [18]. To solve the practical processing and communication overhead from theoretical network coding, a MAC extension COPE [19] has recently employed network coding in wireless protocols. To optimize flow control with network coding based multicasting, Chen *et al.* [20] developed two adaptive rate control algorithms by considering networks with and without coding subgraphs. A linear cost function in [21] was utilized for network coding based multicasting. Wu [22] extended network utility maximization to network coding based multicasting. However, these methods [20]–[22] have not considered the layered multirate multicasting and correlation between layers constraints. The authors in [23] attempted to address the layered multicasting problem by including network coding and multi-path constraints in the objective function, and proposed a solution called LION algorithm. However, they simply formulated it as an integer linear programming without utility maximization and priority costs of layered multicast groups. It adopts a discrete layer rate control, where the receiver should receive either a full layer or nothing, without any support to partial layer subscription. Moreover, they only provided a heuristic approach instead of a rigorous distributed algorithm with theoretical justification.

In this paper, we study network performance optimization to achieve the maximum achievable multicast capacity. We jointly consider network coding based routing and network flow control during resource allocation and performance optimization for all heterogeneous receivers. By incorporating the contextual priors of scalable video layers on the flow routing optimization problem, we seek to guarantee the transmission cost for each layer in an incremental order. Moreover, the proposed network flow control and performance optimization scheme is able to determine the optimal content distribution meshes [23] for receivers with multi-path and network coding based routing. Unlike previous works which mainly focus on maximizing the aggregated network throughput or utility based on given distribution trees, our performance optimization attempts to build lower layer meshes with minimum path costs so as to preserve the inter-layer dependency in SVC. Using primal decomposition and the primal-dual approach [24], we develop a decentralized algorithm with two levels of optimization. The optimization objective relaxes layered prioritization to enable layered mesh routing and flow control. We also prove that the proposed iterative algorithm is stable based on the Lyapunov theory and convergence analysis [42]. Extensive numerical and simulation results demonstrate that the proposed algorithm achieves the max-flow throughput. In addition, with SVC-based rate adaptation and network coding-based routing, the algorithm maximizes the overall video quality.

Compared with multi-source and layered multicast schemes developed in literature, the proposed algorithm has the following major advantages.

1) *Continuous achievable rate region for every multicast layer of every receiver*. In layered scalable video coding, the achievable set of layered bandwidth can support a discrete set and multiple feasible regions of bit rates. Considering both fluctuating network adaption and optimization condition, each layer of the SVC video stream with layered scalability is distributed at a variable transmission rate over a multicast group within a confidence interval of a tolerable rate region (see also Section II). For example, fine-grain scalability (FGS) and medium-grain scalability layers could be truncated or partially dropped, e.g., bit-planes. Integrating the optimization context with the layered SVC scalability, a receiver could correspondingly be urged to subscribe to a generalized partial layer within the achievable transmission rate region. From the layered optimization, the fine-granular continuity of the targeted variables (rates) could specifically urge the convexity of optimization problem for developing a distributed solution, and support a strong notion of fairness.
2) *Content priority-based flow routing and transmission scheduling*. Different layers in SVC have different levels of contribution to the reconstructed video quality. We consider the content priority of each layer and the inter-layer dependency during flow routing and network performance optimization.
3) *Generalized network coding based and multi-path routing.* In this paper, a receiver has multiple alternative paths over the coded network to receive layered video

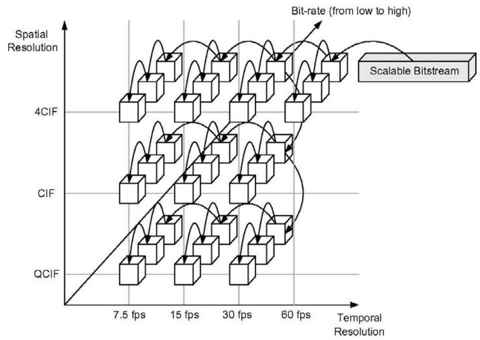

Fig. 1. Typical structure of scalable video bitstream with multiple-dimensions.

streams. Based on multiple multicast trees (paths) spanning the receivers, network coding could further improve throughput by mixing information flows along overlapping paths to different receivers.

The rest of the paper is organized as follows. The source decomposition related to SVC is presented in Section II. In Section III, we formulate the problem of resource allocation and performance optimization for scalable video coding and multicast over networks. We propose a decentralized algorithm for SVC-based multirate multicast groups with multi-path and network coding based routing in Section IV. We also prove the stability and convergence of the iterative rate control scheme and discuss an efficient implementation scheme which includes SVC-based multirate multicasting and candidate paths generation. Experimental results are presented in Section V. Section VI concludes the paper and discusses future directions.

II. Scalable Video Coding as Source Decomposition

A scalable bit stream in SVC could be represented in two different ways: a layered representation (layered scalable) or a flexible combined scalability (fully scalable) [25]. Generally, the full scalability can benefit the scenario of unicast, where the target stream can be extracted at any bit rate from the SVC elementary stream in compliance with the single receiver's capacity status. The layered scalability can benefit the network multicasting by offering simple adaptation operation to heterogeneous receivers, i.e., different receivers can subscribe to different combinations of layers under the constraints of network capacity and layer dependency. Hence, this paper adopts the layered scalability for a multirate multicasting scenario where heterogeneous receivers are capable of different capacities.

Hereafter, assume that the SVC video stream is encoded into a set of M layers $\{l_1, l_2, \cdots, l_M\}$ at source node. According to the encoding rates of layers, we can make the optimal adaptation decision in the scalability cube model illustrated in Fig. 1 by mapping from an SVC stream with fully scalable representation into the layered representation. Correspondingly, the multicast of SVC video stream is divided into M multicast sessions.

In fact, a practical SVC encoder and decoder during fluctuating network adaption could perform a very large variation of options to make a flexible inter-layer motion-compensated prediction and reconstruction [26]. A higher layer might be able to be decoded even if the lower dependent layers are either truncated or partially dropped to a mild extent. Certainly, it would cause a drift between the decoded pictures reconstructed in the encoder and in the decoder. Under the condition, non-normative coding techniques, e.g., a variety of error resilience and error concealment tools, would be utilized to estimate the lost information for the decoding of the higher layer. It makes a receiver possible to subscribe to a partial quality layer within an achievable rate region.

Considering both fluctuating network adaption and optimization condition [9], [10], each layer m is distributed over a multicast group (R_m, E_m) at a variable transmission rate within a tolerable rate region $[b_m, B_m]$. Mathematically, the upper bound B_m (e.g., the encoding rate with a resilient margin) and the lower bound b_m (e.g., the minimum partial margin for layer m) are specified for a confidence interval of the layered transmission rate in layer m. It differentiates the layers with the piecewise confidence intervals along the layer-dependent direction, namely, the achievable transmission rate for each layer is mathematically extended from an encoding rate point to a tolerable rate region. From the layered optimization, the fine-granular continuity of the targeted variables (rates) could specifically urge the convexity of optimization problem for developing a distributed solution, and support a strong notion of fairness.

III. Problem Statement

In this section, we formulate the problem of prioritized flow routing and performance optimization for scalable video coding and streaming over multicast networks.

A. Motivation

The traditional aggregated number of layers which heterogeneous receivers subscribe to, is not consistent with the layered multirate multicast potential of scalable video streaming. To some extent, the inter-layer dependency would limit the total utility of objective functions into suboptimal performance. Due to the lack of layer dependency and priority in constructing multicasting paths, the higher layers with low path costs and prices may overwhelm the lower layers. Consequently, the packets of higher layers whose all packets of dependent layers are not available until playback time would have to be discarded, even if the bandwidth allocation for higher layers is guaranteed for a maximized utility. This unexpected result obviously deviates from the original optimization objective.

We have explored previous rate control schemes on discrete layered multicasting as well as network coding [20]–[22]. Those may benefit the multiple description coding content distribution, in which each description can be decoded alone and guarantee a basic level of reconstruction quality. For SVC streaming, however, the total number of multicast groups all of receivers could subscribe is not consistent with the utility for practical video decoding. To illustrate our motivation on prioritized multirate multicasting, let us take a look at an example in Fig. 2(a). The classical butterfly topology is modeled by a source node S, two sink nodes R_1, R_2, and four Steiner nodes N_1–N_4 [15], with all edges of available capacity

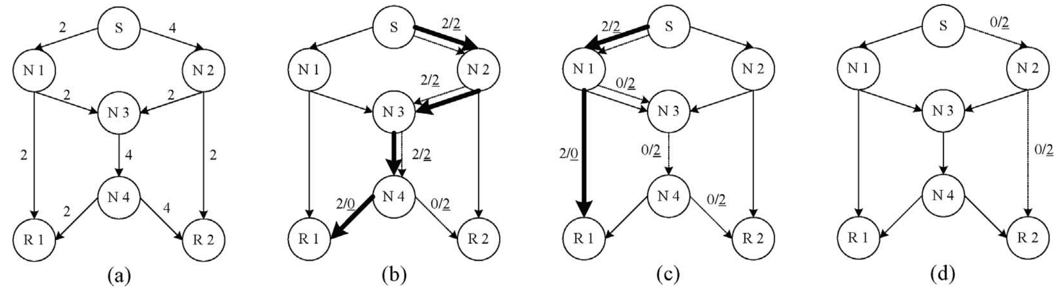

Fig. 2. Example of layered flow distribution of typical butterfly topology by LION model, where (a) is the topology, (b) is the base layer mesh, (c) is the first enhancement layer mesh, and (d) is the second enhancement layer mesh.

(data units/s). Suppose the source generates a SVC stream into three layers, each with rate of 2 (data units/s). Without loss of generality, assume that data suffer the same delay through each edge. According to max-flow-min-cut theorem, R_1 and R_2 can receive at most 2 layers and 3 layers, respectively. By adopting the linear programming solution of LION model [23], we can obtain the distribution mesh of each layer shown in Fig. 2(b)–(d), respectively. Note that the solid line represents the path to R_1 and the dashed line represents the path to R_2. Also, the associated numbers on each edge signify the bandwidth allocated for every layer, with the left for R_1 and the right for R_2. It could be observed from Fig. 2(b) and (c) that the base layer data to R_1 will pass four edges in the order $S \rightarrow N_2 \rightarrow N_3 \rightarrow N_4 \rightarrow R_1$, and the first enhancement layer data to R_1 will pass through $S \rightarrow N_1 \rightarrow R_1$. The cross-layer synchronization of SVC decoding in R_1 will be greatly influenced by the reversed delay, resulting in heavy buffer management and decoder burden. Moreover, the dilemma can become more critical with the scale of network and decomposed layers.

The inter-layer prediction performance in SVC layered multicast groups should be guaranteed by a more reasonable optimization formulation on resource allocation.

B. Network Model and Related Conditions

Consider a video distribution network modeled as a directed graph $G(V, E, \mathbf{C})$, where V is the set of nodes and E is the set of weighted directed edges (links) between nodes with a capacity vector $\mathbf{C} = (C_1, C_2, \cdots, C_{|E|})^T$. The set V can be further divided into three disjoint subsets S, N and R, which represent source nodes, Steiner nodes and receiver nodes respectively.

Hereafter, suppose that the network is shared by a set of M multicast groups, where each multicast group is associated with a unique source, a set of receivers R_m, and a set of edges E_m organized as a multicast tree. Correspondingly, the SVC video stream is encoded into a set of M layers $\{l_1, l_2, \cdots, l_M\}$ at source node, and each layer m is distributed over a multicast group (R_m, E_m) at a variable transmission rate within a tolerable rate region $[b_m, B_m]$. Integrating the optimization context with the layered SVC scalability, a receiver could correspondingly be urged to subscribe to a generalized partial quality layer within the achievable transmission rate region.

Given two nodes $s, r \in V$, let the minimum capacity of an $s - r$ cut in $G = (V, E, \mathbf{C})$ be $\rho_{s,r}$, and the max-flow rate at which s can transmit data to r is $r_{s,r}$. Menger's theorem implies that it is possible to achieve the max-flow rate by routing flow along parallel paths. Once formulating a flow control problem with an optimized routing decision, the max-flow-min-cut theorem is imposed as a constraint: $\rho_{s,r} = r_{s,r} = \max_{\mathbf{x}^r} \; x^r$, where x^r is the received flow rate of receiver r. Several algorithms have been developed to achieve the max-flow rate, such as the Ford-Fulkerson algorithm [27] and push-relabel algorithm [28]. The cut bound of the multicast capacity is $\min_{r \in R_m} r_{s,r}$. However, the multicast information which only be replicated at the intermediate nodes hardly achieves the cut bound of the multicast capacity. It is observed that network coding could make it possible.

In network coding, an intermediate node can generate output data by performing certain operations, e.g., linear algebra, on its received data streams. Hence, it is often regarded as a generalized routing by allowing the information to be modified instead of direct packet relaying. Intuitively, it allows flows with different destinations in a multicast session to share network capacity, where the actual physical flow on each edge is the maximum of the individual receiver's information flow. Let $f_{m,e}$ denote the physical flow rate of edge e in multicast group m, and $x^r_{m,e}$ the information flow rate for receiver r within $f_{m,e}$, while a multicast group m is distributed over (R_m, E_m) at rate θ_m. Then, the network coding based multicasting condition can be written as

$$f_{m,e} = \max_{r \in R_m} \{x^r_{m,e}\} \tag{1}$$

where $\{x^r_{m,e}\}$ satisfy the information flow balance equation

$$\sum_{e \in E:\, tail(e)=v} x^r_{m,e} - \sum_{e \in E:\, head(e)=v} x^r_{m,e} \tag{2}$$

$$= \begin{cases} \theta_m & \text{if } v = s \\ -\theta_m & \text{if } v = r \\ 0 & \text{otherwise} \end{cases} \qquad \forall v \in V.$$

Assume there exist multiple alternative paths $P(r)$ from the source to receiver r. Let x^r_m denote the rate at which receiver r receives the data of layer m. Also let $x^r_{m,j}$ represent receiver r's flow rate on path j in layer m. For each receiver r, we use a matrix $\mathbf{Z}^r$ to reflect the relationship between its paths and related links. The (j, e) entry of $\mathbf{Z}^r$ is defined as

$$z^r_{j,e} = \begin{cases} 1 & \text{if link } e \text{ is included in path } j \\ 0 & \text{otherwise.} \end{cases}$$

For each link e, let $R(e) = \{r \in R \mid e \in P(r)\}$ be the set of receivers that use link e.

Generally, receiver r has multiple alternative paths to join the multicast group m, but not all these paths are optimal ones. Analogous to practical routing, the optimal paths can be chosen in a variety ways based on different considerations, such as delay, resource usage or commercial charge. Here we introduce a generic path cost function $\rho(\cdot)$ that is frequently used in packet routing applications [29]

$$\rho(x_j) = \sum_{e \in Path(j)} \frac{x_j}{C_e - x_j} + d_j \cdot x_j$$

where x_j is the flow rate of the path j, d_j is a parameter corresponding to the average processing delay over path j normalized by the average packet size. In the first term of the path cost function, $x_j/(C_e - x_j)$, can be considered as the congestion on each link $e \in Path(j)$, which can be denoted as the average queuing delay normalized by the average packet size. From M/M/1 queuing model [30], the average delay on each link can be expressed by $1/(C_e - x_j)$, and the total congestion on that link becomes $x_j/(C_e - x_j)$. The second term $d_j \cdot x_j$ is the processing and propagation delay over path j. With this definition, $\rho(\cdot)$ is a differentiable and convex function.

There have been a lot of efforts toward a systematic understanding of "layering" as "optimization decomposition" [31], where the overall communication network is modeled by a generalized network utility maximization problem, each layer corresponds to a decomposed subproblem, and the interfaces among layers are quantified as functions of the optimization variables coordinating the subproblems. Here, each layer m is characterized by a utility function $U_m(\cdot)$ that is continuously differentiable, increasing and strict concave for the receiving rate [32]. From resource allocation of utilization maximization, the optimal achievable rates $\{\hat{x}^r\}$ of all receivers should satisfy: $\sum_r \frac{x^r - \hat{x}^r}{\hat{x}^r} \leq 0$. It states that under any other allocation, the sum of changes in receivers' utilities will be non-positive. Thus, that any receiver's rate increases would result in that at least one other receiver severely decreases its rate. It could vary different measures for different applications and considerations. From the perspective of application-layer QoS, rate-distortion related models could be picked as the optimized targeted utility for video applications, e.g., the distortion-rate model $D(R) = 2^{aR+b\sqrt{R}+c}$ of FGS bit-planes [33], [34], and a layered R-D refinement utility function [35].

In this paper, we focus on the prioritized fairness of resource allocation among a multi-source to multi-terminal network. Without loss of generality, the extensively used α-fair utility function, which has been proved to be a fair resource rate allocation [36], is adopted. The utility framework of a receiver r is of the form with its feasible rates $\{x^r\}$

$$U(x^r) = \frac{x^{r\ (1-\alpha)}}{1-\alpha} = \begin{cases} \log\ x^r, & \text{if } \alpha \to 1 \\ -1/x^r, & \text{if } \alpha = 2 \\ \text{max-min fair}, & \text{if } \alpha \to \infty. \end{cases}$$

The utility functions $\{U_m(\cdot)\}$ of different layers could be dependent on a variety of fairness measures and distortion-rate attainments with the combined adaptation path along spatial, temporal, and quality scalability dimensions as depicted in Section II.

C. Optimization Problem

In this paper, we aim to determine the optimal content distribution meshes for layered video multicasting with network coding based routing. This is a joint network flow control and performance optimization problem. Mathematically, it can be formulated as follows:

$$\textbf{P1:} \quad \text{maximize} \quad \sum_{r \in R} \sum_{m \in M} U_m\Big(\sum_{j \in P(r)} x^r_{m,j}\Big) \tag{3}$$

s.t.

1) $\sum_{j \in P(r)} z^r_{j,e} \cdot x^r_{m,j} \leq f_{m,e} \quad \forall e \in E \quad \forall m \in M \quad \forall r \in R;$

2) $\sum_{m \in M} f_{m,e} \leq C_e \quad \forall e \in E;$

3) $\sum_{j \in P(r)} \rho(x^r_{m,j}) \leq \sum_{j \in P(r)} \rho(x^r_{m+1,j}) \quad \forall m \leq M-1 \quad \forall r \in R;$

4) $b_m \leq \sum_{j \in P(r)} x^r_{m,j} \leq B_m \quad \forall m \in M \quad \forall r \in R;$

5) $x^r_{m,j} \geq 0 \quad \forall j \in P(r) \quad \forall m \in M \quad \forall r \in R.$

Constraint 1 represents the relationship between information flow rate and physical flow rate on each link where network coding is applied to information flows of the same video layer. Although network coding across different video layers may further improve the network throughput, such scheme lacks of scalability and becomes highly complex, especially when the number of layers becomes large. Designing such codes is a very difficult problem, since combining data belonging to different layers makes it difficult to recover all original data for receivers that only receive partial layers. Furthermore, the inter-dependency between layers cannot be represented by network coding across different layers. Here, we limit network coding within each session in this paper. This approach is often referred to as intra-session coding or superposition coding [37]. Note that constraint 1 is an approximation of (1).

In constraint 2, the aggregate physical flow rates of different layers over each link do not exceed the link capacity.

Constraint 3 ensures that the total path cost at each layer for each receiver is no more than the corresponding path cost of any higher layer. From Section III-B, the layered path cost function $\rho(x^r_{m,j})$ associated with receiver r in layer m is correspondingly defined as

$$\begin{aligned} \rho(x^r_{m,j}) &= \sum_{e \in Path(j)} \frac{x^r_{m,j}}{C_e - x^r_{m,j}} + d^r_j \cdot x^r_{m,j} \\ &= \sum_{e \in E} z^r_{j,e} \cdot \frac{x^r_{m,j}}{C_e - x^r_{m,j}} + d^r_j \cdot x^r_{m,j} \end{aligned} \tag{4}$$

where d^r_j is the layered processing and propagation delay of receiver r over path j.

Constraint 4 gives the upper bound and lower bound of the receiving rate for each layer.

Define $\mathbf{x^r} = [x^r_{1,1}, \cdots, x^r_{1,P(r)}, x^r_{2,1}, \cdots, x^r_{2,P(r)}, \cdots, x^r_{M,1}, \cdots, x^r_{M,P(r)}]$, and $\mathbf{X} = [\mathbf{x}^1, \cdots, \mathbf{x}^R]^T$. Also let $\mathbb{C}^r = \left\{ \mathbf{x}^r \;\middle|\; x^r_{m,j} \geq 0, \forall m, j \text{ and } b_m \leq \sum_{j \in P(r)} x^r_{m,j} \leq B_m \right\}$ and

$\mathbb{C}$ denote the Cartesian product of $\mathbb{C}^r (r \in R)$. Problem **P1** can be re-written as

$$\textbf{P2:} \quad \underset{\mathbf{X}\in\mathbb{C}}{\text{maximize}} \quad \sum_{r\in R}\sum_{m\in M} U_m\Big(\sum_{j\in P(r)} x^r_{m,j}\Big) \tag{5}$$

s.t.

1) $\sum_{j\in P(r)} z^r_{j,e}\cdot x^r_{m,j} \le f_{m,e} \quad \forall e\in E \quad \forall m\in M \quad \forall r\in R;$

2) $\sum_{m\in M} f_{m,e} \le C_e \quad \forall e \in E;$

3) $\sum_{j\in P(r)} \rho(x^r_{m,j}) \le \sum_{j\in P(r)} \rho(x^r_{m+1,j}) \quad \forall m \le M-1 \quad \forall r\in R.$

Note that constraint 3 could be ensured the convexity from a strong sufficient Majorization Inequality [38]. It might be approximately enabled by arranging generalized vectors $\mathbf{x}^r_m = \{x^r_{m,j} | j\in \ell, |P(r)| < \ell\}$ and $\mathbf{x}^r_{m+1} = \{x^r_{m+1,j} | j\in \ell, |P(r)| < \ell\}$ with non-increasing components along the index j (path).

It can be seen that Problem **P2** is feasible and there exists a unique optimal solution of $\mathbf{X}$ since the objective function is strictly concave and the constraint set is convex. A number of centralized algorithms with polynomial-time have been developed in the literature to solve **P2** [39]. However, centralized solutions require global information and coordination among all nodes, which is very costly and sometimes infeasible in practice. In the subsequent section, we will develop a distributed solution based on decomposition and duality theories.

IV. Distributed Algorithm

Decomposition theory provides the mathematical language to build an analytic foundation for the design of modularized and distributed control of networks [40]. It introduces a systematic research on a variety of decompositions, focusing on network utility maximization problem formulations. A systematic understanding of the decomposability structures in network utility maximization is key to help us obtain the most appropriate distributed algorithm for a given network resource allocation problem.

A. Primal Decomposition

In general, we can use primal decomposition, a dual decomposition, or in combination to decompose an original large problem into a set of sub-problems. The primal decomposition is suitable for problems with coupling variables, while the dual decomposition is a good choice for problems with coupling constraints. If variables $f_{m,e}$ are fixed, Problem **P2** can be decoupled with respect to variables $x^r_{m,j}$. Based on this assumption, we use the primal decomposition approach and propose a two-level optimization procedure

$$\textbf{P2a:} \quad \underset{\mathbf{X}\in\mathbb{C}}{\text{maximize}} \quad \sum_{r\in R}\sum_{m\in M} U_m\Big(\sum_{j\in P(r)} x^r_{m,j}\Big) \tag{6}$$

s.t.

1) $\sum_{j\in P(r)} z^r_{j,e}\cdot x^r_{m,j} \le f_{m,e} \quad \forall e\in E \quad \forall m\in M \quad \forall r\in R;$

2) $\sum_{j\in P(r)} \rho(x^r_{m,j}) \le \sum_{j\in P(r)} \rho(x^r_{m+1,j}) \quad \forall m \le M-1 \quad \forall r\in R.$

$$\textbf{P2b:} \quad \underset{\mathbf{f}\ge 0}{\text{maximize}} \quad \hat{U}_m(\mathbf{f}) \tag{7}$$

s.t.

$$\sum_{m\in M} f_{m,e} \le C_e, \ \forall e\in E$$

where the vector $\mathbf{f} = \{f_{m,e} | e\in E, m\in M\}$. As shown in (6) and (7), the low level optimization problem **P2a** is in charge of achieving locally optimal variables $\hat{x}^r_{m,j}$ for given $\{f_{m,e}\}$, and the high level optimization problem **P2b** is responsible for updating the coupling variables $f_{m,e}$. The proposed distributed algorithm is implemented in such a order that for initial coupling variables $f_{m,e}$, we first use **P2a** to obtain a locally optimal variables $\hat{x}^r_{m,j}$, then use **P2b** to update coupling variables $f_{m,e}$ according to $\hat{x}^r_{m,j}$, afterward the two optimization steps will be continuing iteratively. Section IV-C will prove that the distributed algorithm can lead to a locally optimum of low level problem **P2a** when coupling variable $f_{m,e}$ is fixed, and also converge to the global optimum $\hat{f}_{m,e}$ of high level problem **P2b**. Thus, the objective value of the low level optimization problem **P2a** approximates to the global optimality using the result of the high level optimization problem **P2b**.

B. Two-Level Optimization Update

To solve the low-level optimization problem, we define the Lagrangian dual of Problem **P2a** as

$$\begin{aligned}\mathbf{L}(\mathbf{X},\mathbf{p},\mathbf{q}) = &\sum_{r\in R}\sum_{m\in M} U_m\Big(\sum_{j\in P(r)} x^r_{m,j}\Big) \\ &- \sum_{r\in R}\sum_{m\in M}\sum_{e\in E} p^r_{m,e}\Big(\sum_{j\in P(r)} z^r_{j,e}\cdot x^r_{m,j} - f_{m,e}\Big) \\ &- \sum_{r\in R}\sum_{m=1}^{M-1} q^r_m\Big[\sum_{j\in P(r)} \rho(x^r_{m,j}) - \sum_{j\in P(r)} \rho(x^r_{m+1,j})\Big]\end{aligned} \tag{8}$$

where $p^r_{m,e}$ and q^r_m are Lagrange multipliers. Similar to Problem **P2**, **P2a** is also strictly concave with strictly convex objective function and convex constraint set. To solve this convex problem in a distributed manner, both dual algorithm and primal-dual algorithm can be used. The dual algorithm for **P2a** is

$$\mathbf{g}(\mathbf{p},\mathbf{q}) = \sup_{\mathbf{X}} \mathbf{L}(\mathbf{X},\mathbf{p},\mathbf{q})$$
$$\underset{\mathbf{p}\ge 0,\ \mathbf{q}\ge 0}{\text{minimize}}\ \mathbf{g}(\mathbf{p},\mathbf{q}).$$

P2a is equivalent to the above dual problem if the Karush-Kuhn-Tucker conditions are satisfied. Note that if strong duality does not hold, recovery of a primal solution is required [41]. To solve the low-level optimization problem, we propose the following primal-dual algorithm [24], [42] that updates the primal and the dual variables simultaneously and moves together toward the optimal points asymptotically

$$x^r_{m,j}(t+1) = [x^r_{m,j}(t) + \alpha(t)\frac{\partial \mathbf{L}(\mathbf{X}, \mathbf{p}, \mathbf{q})}{\partial x^r_{m,j}}(x^r_{m,j}(t))]^+ \tag{9}$$

$$p^r_{m,e}(t+1) = [p^r_{m,e}(t) - \beta(t)\frac{\partial \mathbf{L}(\mathbf{X}, \mathbf{p}, \mathbf{q})}{\partial p^r_{m,e}}(p^r_{m,e}(t))]^+ \tag{10}$$

$$q^r_m(t+1) = [q^r_m(t) - \gamma(t)\frac{\partial \mathbf{L}(\mathbf{X}, \mathbf{p}, \mathbf{q})}{\partial q^r_m}(q^r_m(t))]^+ \tag{11}$$

where t is the iteration index, $\alpha(t)$, $\beta(t)$, and $\gamma(t)$ are positive step sizes, and $[\cdot]^+$ denotes the projection onto the set of non-negative real numbers.

During the updating steps in (9)–(11), we can consider $p^r_{m,e}$ as the congestion price at link e for receiver r's bandwidth requirement in layer m; while q^r_m is the transmission cost for receiver r in layer m. $x^r_{m,j}$ is the rate at which receiver r receives data through path j in layer m. It will adjust with the congestion price $p^r_{m,e}$ and the transmission cost q^r_m. All the updating steps are distributed and can be implemented at individual links and receivers using only local information.

The above primal-dual algorithm operates under the assumption that the value of $\mathbf{f}$ is fixed. Next, we discuss how to adjust $\mathbf{f}$ to solve the high-level optimization Problem **P2b**. As mentioned above, the objective function $\hat{U}_m(\mathbf{f})$ in **P2b** is the optimal objective value of **P2a** for given coupling variable $\mathbf{f}$, where the corresponding primal and dual optimal points are denoted by $\hat{\mathbf{X}}$ and $(\hat{\mathbf{p}}, \hat{\mathbf{q}})$. In mathematical term, $\hat{U}_m(\mathbf{f})$ can be expressed by $\hat{U}_m(\mathbf{f}) = \mathbf{L}(\hat{\mathbf{X}}, \hat{\mathbf{p}}, \hat{\mathbf{q}})$. Consider $\hat{U}_m(\mathbf{f})$ may or may not be differentiable, we use the subgradient method to generate a sequence of feasible points of $\mathbf{f}$. If $\hat{U}_m(\mathbf{f})$ is differentiable, the subgradient method is essentially a gradient method.

Suppose that $\hat{p}^r_{m,e}(f_{m,e})$ is the optimal Lagrange multiplier corresponding to the constraint $\sum_{j\in P(r)} z^r_{j,e} \cdot x^r_{m,j} \le f_{m,e}$ in Problem **P2a**. Let $\mathbf{f}_e = [f_{1,e}, \cdots, f_{M,e}]$, and $\mathbf{f} = [f_1, \cdots, f_E]^T$. Also let

$$\mathbb{F}_e = \left\{ \mathbf{f}_e \;\middle|\; f_{m,e} \ge 0, \forall m \text{ and } \sum_{m\in M} f_{m,e} \le C_e \right\} \tag{12}$$

and $\mathbb{F}$ denotes the Cartesian product of $\mathbb{F}_e (e \in E)$, then Problem **P2b** can be solved with the following subgradient method:

$$f_{m,e}(t'+1) = [f_{m,e}(t') + \mu(t') \cdot \hat{p}_{m,e}(f_{m,e}(t'))]^{\mathbb{F}} \tag{13}$$

where $[\cdot]^{\mathbb{F}}$ denotes the projection onto the set $\mathbb{F}$, and $\hat{p}_{m,e}(f_{m,e}) \triangleq \sum_{r\in R} \hat{p}^r_{m,e}(f_{m,e})$ are the derivatives of $\mathbf{L}(\hat{\mathbf{X}}, \hat{\mathbf{p}}, \hat{\mathbf{q}})$ with respect to $\mathbf{f}$, i.e., the subgradient of $\hat{U}_m(\mathbf{f})$. A number of algorithms have been developed in the literature for this type of projection [43], [44].

$\hat{p}_{m,e}$ is the aggregate congestion price at link e in layer m. If $\hat{p}_{m,e}$ has increased because of $\hat{p}^r_{m,e}$, which implies that the assigned capacity $f_{m,e}$ for link e in layer m cannot meet the actual requirement of all receivers, then $f_{m,e}$ will increase during the next step. Otherwise, it will decrease. The update of $f_{m,e}$ and $\hat{p}^r_{m,e}$ can be performed in a distributed manner on each link.

C. Convergence Analysis

In this section, we will analyze the convergence behavior of the proposed algorithm. First, we will study the stability of the primal-dual algorithm used in the low-level optimization. We consider the primal-dual algorithm as a nonlinear autonomous system and apply the following Lyapunov stability theorem [42].

Lyapunov's Theorem: Consider an autonomous system and its equilibrium point $\hat{x} = 0$, this equilibrium point is globally stable if there exists a Lyapunov function $V(x)$, which is continuously differentiable, such that:
1) $V(x) > 0 \quad \forall x \neq 0$ (positive definite);
2) $V(x) = 0 \quad$ when $x = 0$;
3) $\dot{V}(x) \le 0 \quad \forall x$ (seminegative definite);
4) $V(x) \to \infty \quad$ when $\|x\| \to \infty$.

Proposition 1: If $(\hat{\mathbf{X}}, \hat{\mathbf{p}}, \hat{\mathbf{q}})$ is an equilibrium point of the primal-dual algorithm proposed in (9)–(11), it is globally stable.

Proof: See Appendix I. ■

According to Lyaounov's Theorem, if we can find a Lyapunov function for the dynamical system such that all the four conditions are satisfied, then the equilibrium point of the dynamical system is globally asymptotically stable. From Proposition 1, we proved the global asymptotic stability of the primal and dual controllers of (9)–(11), which leads to the convergence behavior of the distributed solution to the dual problem of **P2a** . Furthermore, [40] states that when the primal problem is convex and under some mild technical conditions (e.g., Karush-Kuhn-Tucker condition or Slater's condition), the primal problem can be equivalently solved by solving the dual problem. Since the problem **P2a** satisfies the above two constraints, the optimal solution of primal problem **P2a** can be alternatively solved by the distributed algorithm that is corresponding to the dual problem of **P2a** and denoted by (9)–(11).

1) *Subgradient Optimization:* Now we study the convergence of the subgradient algorithm applied in the high-level optimization. Without loss of generality, we consider the algorithm that uses a diminishing step size.

Proposition 2: If the step size $\mu(t')$ satisfies that

$$\lim_{t'\to\infty} \mu(t') = 0 \qquad \sum_{t'=0}^{\infty} \mu(t') = \infty$$

then, for the sequence $\{f(t')\}$ generated by the iterative algorithm given in (13), we have

$$\lim_{t'\to\infty} \left\| f(t') - \hat{f} \right\| = 0$$

where $\hat{f}$ is non-trivial bounded solution set of Problem **P2b**.

Proof: See Appendix II. ■

In practice, a constant step size instead of a diminishing one is more convenient for distributed implementation. For a constant step size $\mu(t') = \mu$, the subgradient algorithm will converge to some suboptimal solution within any given small neighborhood around the optimum provided that μ is sufficiently small.

D. Implementation of Distributed Algorithm

To implement the proposed distributed algorithm, each link e and each receiver r is considered as a processor of a distributed computation system. Assume that the processor for link e keeps track of variables $p^r_{m,e}$ and $f_{m,e}$, while the processor for receiver r keeps track of variables $x^r_{m,j}$ and q^r_m. A decentralized version of the proposed algorithm can be implemented as follows:

1) initialization: set $t = 0$, $t' = 0$ and $p^r_{m,e}(0)$, $q^r_m(0)$, $x^r_{m,j}(0)$, $f_{m,e}(0)$, respectively to some non-negative value equally for all r, m, e and j;
2) low-level implementation;
at link e (at iterations $t = 1, 2, \cdots$):
   a) receives $x^r_{m,j}(t)$ from all receivers $r \in R(e)$ that use link e;
   b) fetches $f_{m,e}(t')$ stored in the local processor;
   c) updates congestion price $p^r_{m,e}(t)$ with (10);
   d) broadcasts new price $p^r_{m,e}(t+1)$ to all receivers $r \in R(e)$;

at receiver r (at iterations $t = 1, 2, \cdots$):
   a) receives from the network the aggregate congestion price $\sum_{e\in E} z^r_{j,e} \cdot p^r_{m,e}$;
   b) fetches $q^r_m(t)$ stored in the local processor;
   c) updates rate $x^r_{m,j}(t)$ with (9);
   d) updates cost signal $q^r_m(t)$ with (11);
   e) broadcasts rate $x^r_{m,j}(t+1)$ to all links $e \in P(r)$;
3) high-level implementation;
at link e (at iterations $t' = 1, 2, \cdots$):
   a) calculates $\hat{p}_{m,e}\big(f_{m,e}(t')\big) = \sum_{r\in R} \hat{p}^r_{m,e}\big(f_{m,e}(t')\big)$;
   b) updates a new $f_{m,e}(t')$ with (13);
   c) goes back to low-level implementation.

Note that the low-level and high-level algorithms operate at different time scales. The former is an inner loop and operates at a fast time scale, while the latter is an outer loop and performs at a slow time scale. More specifically, the high-level algorithm will not move to its step until $\hat{\mathbf{p}}$ at the low-level converges to its optimum value.

In the following, we discuss several implementation issues.

1) *Alternative Paths Generation:* The set of alternative paths, denoted by matrix $\{z^r_{j,e}\}$, could be all possible paths linking to each receiver. How to select alternative paths for multi-path video streaming emerges as an important problem. The implicit price $p^r_{m,e}$ and cost q^r_m derived from the dual problem provide important information for discovering alternative paths. It has been observed that, when the utility functions are strictly concave, the admission flow rate $\sum_{j\in P(r)} x^r_{m,j}$ on paths of each receiver can be uniquely determined; and only paths that have the minimum cost will be chosen for the route. This is consistent with the concept of the minimum first derivative length path. The cost of a path for a receiver is assumed to be the additive sum of implicit price $p^r_{m,e}$ and cost q^r_m for all subscribed layers and all links along the path. The minimum cost of all the candidate paths is computed as

$$p^r_* = \min_j \sum_m \left(a_m \cdot \sum_{e\in E} z^r_{j,e} \cdot p^r_{m,e} + q^r_m\right) \tag{14}$$

where a_m is a weighting factor associated with layer m for routing priority. We can use the above properties to iteratively generate the candidate paths.

1) Start from an initial set of candidate paths, which may be obtained as the max-flow paths by the Ford-Fulkerson algorithm [45].
2) Execute the distributed algorithm to attain the implicit price and cost signal distribution.
3) Use any minimal cost routing algorithms such as Dijkstra's algorithm to determine the route. If there exists a new path whose minimal cost is smaller than the minimum cost p^r_* among the current set of candidate paths, we add it into the set $P(r)$ and repeat this step; otherwise, the search is ended.

2) *SVC-Based Multirate Multicasting:* Scalable video coding provides both discrete and continuous operating points for transmission bandwidth. Suppose that the SVC-based video stream has M layers with different available rate regions for a multicast group. The receivers can subscribe to different number of layers based on their available flows. In layered scalable video coding, a discrete set and multiple achievable regions of bit rates are supported. Initially from $m = 1$, let the rate of the receiver $(s;\ r)$ after the tth update be $x^r_m(t) = \sum_j x^r_{m,j}(t)$. Also, let this rate be such that the receiver can subscribe to m multicast groups by $x^r_m(t) = B_m$. In practice, the new rate calculated at the receiver will be performed as follows:

1) calculate the new rate $x^r_{m,j}(t+1)$ according to the procedure discussed in receiver r's distributed algorithm in the previous part;
2) if $x^r_{m,j}(t{+}1) \geq B_m$, then receiver r can desire to subscribe more multicast groups and trigger to calculate the rate $x^r_{m+1}(t+1) = \sum_j x^r_{m+1,j}(t+1)$; if $x^r_{m,j}(t+1) < B_m$, then;
   a) if layer m belongs to discrete rate level, it is dropped by receiver r accordingly;
   b) if layer m belongs to continuous achievable rate level, it is clearly the level up to which receiver r can subscribe by $b_m \leq x^r_{m,j}(t+1) < B_m$

   if $x^r_{m,j}(t+1) < b_m$, layer m is dropped from receiver r.

V. Experimental Results

In this section, we present experimental results to demonstrate the performance of the proposed algorithm. We conduct experiments on classical butterfly network topology which has been extensively used in network coding, as well as on large networks with random topologies. The purpose of these experiments is to evaluate the convergence behavior of the proposed distributed algorithm and demonstrate that the max-flow throughput can be achieved by the proposed algorithm. In our simulations, SVC bit streams are distributed over the network through IP-layer multicasting, where a Steiner node can perform both multicasting and network coding operations. Our experimental results will demonstrate that the proposed algorithm achieves an overall balanced layered access and better video quality over all receivers. Moreover, many critical performance factors such as the relationship between the cost

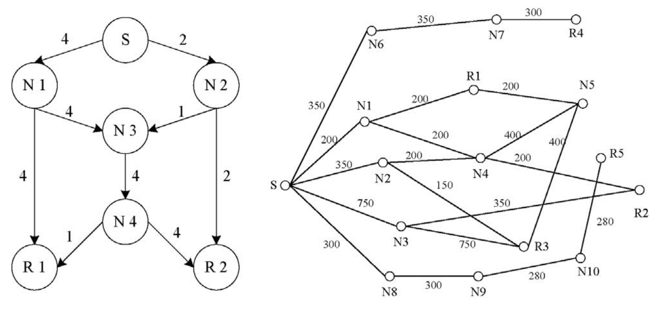

Fig. 3. Network topology associated with edge capacity, where (a) is a butterfly topology for numerical evaluation and (b) is a general ISP access network for SVC streaming based simulation.

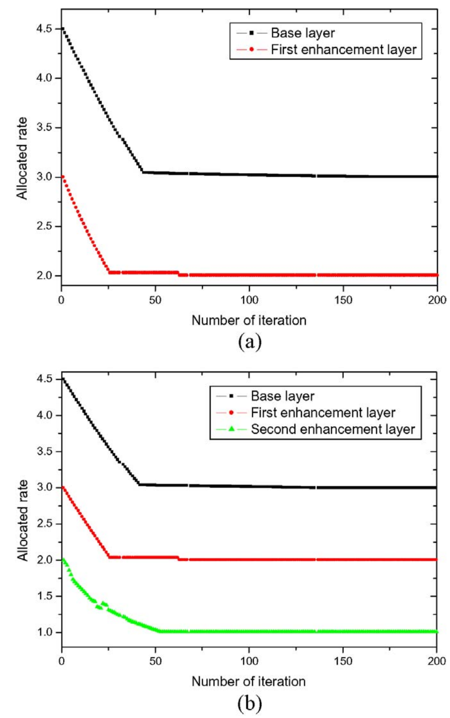

Fig. 4. Allocated rate for each receiver. (a) For R_1. (b) For R_2.

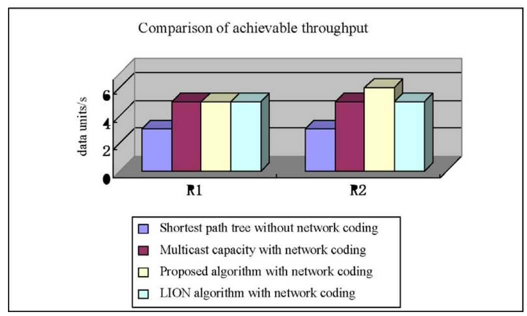

Fig. 5. Comparison of the achievable throughput.

function and end-to-end delay, the impact of the background traffic and the playback deadline on the video quality, and the reasons for the packet loss are discussed for the proposed scheme and other two typical schemes.

A. Convergence Behavior from Proposed Distributed Algorithm

We start with a simple but classical butterfly network topology shown in Fig. 3(a), which has been used in many network coding-based simulation studies [15], [16], [21], [22]. Here S, N_i and R_i are the source, the Steiner nodes and the receivers, respectively. In this experiment, we assume that the video bit stream has three layers, with the base layer at rate 3 (data units/s), the first enhancement layer at rate 2 and the second enhancement layer at rate 1. Obviously, each receiver has three alternative paths from the source. To simplify the problem, the propagation delay over each path is set as a random number between 0 and 1.

We use the following utility function:

$$U_m(x_m) = (M + 1 - m)\log(1 + x_m) \tag{15}$$

where $M+1-m$ can be considered as weights associated with layer m.

Fig. 4 shows the allocated data rate for each receiver at each layer during the low-level optimization with a fixed step size $\alpha(t) = 0.01$. It can be seen that all data rates approach the optimal value after 50 iterations. For example, the base layer rate for R_1 reaches within 10% of its optimal value after 35 iterations and converges to 3.001 after 119 iterations. The first enhancement layer rate for R_2 reaches within 5% of its optimal value after 24 iterations and converges to 2.005 after 63 iterations. In practice, each receiver can automatically control the convergence speed by adjusting the step size. For example, a relative large step size can initially be chose to reduce the number of iterations and make the objective value rapidly approach to the optimum. Later, a smaller step size can be used to achieve stable convergence.

Fig. 5 shows the achievable throughput of two receivers using a shortest-path distribution tree, multicasting with network coding, LION algorithm [23], and the proposed algorithm. It can be seen that network coding achieves a significant gain in the network throughput. Note the maximum $S-R_1$ flow R_{S,R_1} is 5, the maximum $S-R_2$ flow R_{S,R_2} is 6, so a multicast capacity of 5 that is equal to $\min\{R_{S,R_1}, R_{S,R_2}\}$ has been achieved with network coding. Hence, the data of the base layer and the first enhancement layer can be guaranteed for both receivers with a multicast capacity. Despite LION algorithm can also achieve the multicast capacity, R_1 and R_2 in the proposed distributed algorithm are able to successfully receive two and three layers, which are the maximal layer numbers they can subscribe to in terms of their respective max-flow capacity. Thus, by combining network coding and appropriate multi-path rate allocation mechanism, we can achieve the max-flow capacity for each member of a multicast group.

Fig. 6 shows the convergence behavior of R_1's data rate with a fixed step size $\alpha(t) = 0.01$ and a diminishing step size $\alpha(t) = \frac{0.1}{t+1}$. Note that $\lim_{t\to\infty} \alpha(t) = 0$ and $\sum_{t=0}^{\infty} \alpha(t) = \infty$. It can be seen that the convergence behavior with a diminishing step size is smoother but converges more slowly than the one with a fixed step size. For example, to reach the rate of 5.05 (within 0.5% of the optimal value), the algorithm with fixed step size needs 58 iterations while the one with diminishing step size

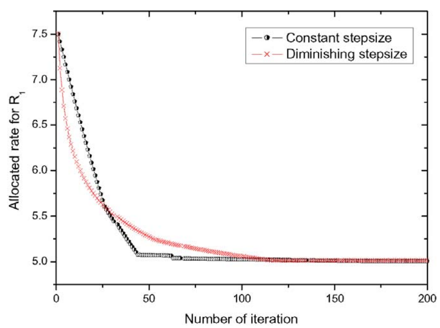

Fig. 6. Impact of step size on the convergence.

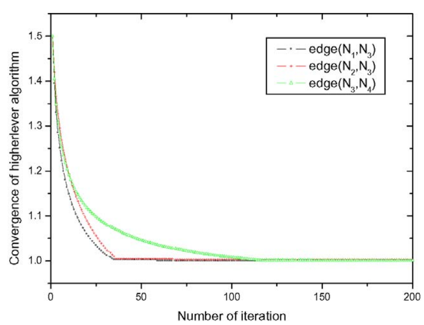

Fig. 7. Convergence performance of the higher level optimization.

needs 103 iterations. Moreover, using a fixed step size, R_1's rate only reaches closer to the true optimum. In this case, R_1's rate finally converges to 5.0143. With a diminishing step size, R_1's rate could successfully converge to 5. Although a fixed step size is more convenient in practice, a diminishing step size is recommended because the rate with slow and smooth variation is critical for video quality smoothness. A sudden change of access data rate will often result in undesirable quality fluctuation.

The convergence behavior of the high-level optimization is shown in Fig. 7. Due to the page limitation, only the flow rates in the first enhancement layer on links (N_1, N_3), (N_2, N_3), and (N_3, N_4) are shown. It can be seen that the flow rates on these three links converge after about 120 iterations. This is because, as explained in Section IV-D, the low-level optimization operates at a fine time scale.

Fig. 8 shows the content distribution mesh for each layer. Since network coding is applied within the same layer, link capacity can only be shared among flows of the same layer. As in Fig. 8(b), the bandwidth occupied by path $S-N_1-N_3-N_4-R_1$ of receiver 1 and path $S-N_2-N_3-N_4-R_2$ of receiver 2 are both 1. Hence, link (N_3, N_4) becomes the bottleneck when the first enhancement layer data is distributed. Without network coding, the capacity of link (N_3, N_4) will be evenly allocated to two receivers for the sake of the fairness, so the max-flow rates on link (N_1, N_3) and (N_2, N_3) in the first enhancement layer are 0.5, as shown in Fig. 9. However, if the network coding is applied at node N_3, the actual flow rates on link (N_1, N_3) and (N_2, N_3) reach 1 simultaneously. Consequently, the flow on link (N_3, N_4) is a linear combination of the flows on links (N_1, N_3) and (N_2, N_3).

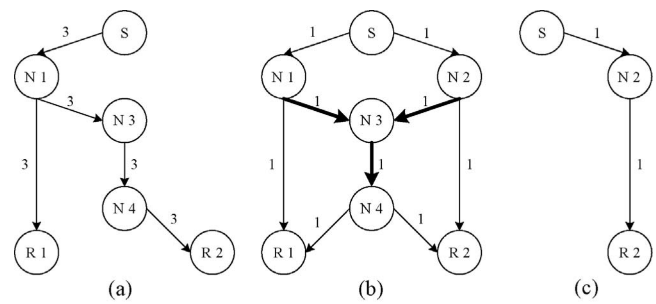

Fig. 8. Distribution mesh in (a) base layer, (b) first enhancement layer, and (c) second enhancement layer.

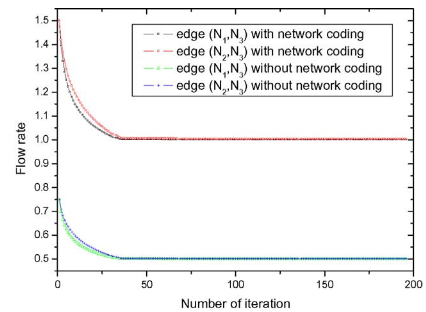

Fig. 9. Influence of network coding on the flow rate.

B. Results from Packet-level Simulations

To evaluate the received SVC quality using the proposed distributed algorithm, we also conduct packet-level simulations in a large network with a random topology, as shown in Fig. 3(b). It has 16 nodes (10 Steiner nodes and 5 receivers) and 20 links, with the capacity (in unit of kb/s) marked on each link. The number of alternative paths for five receivers is $\{3, 3, 4, 1, 1\}$, and their maximum flows are $\{400, 550, 1300, 300, 280\}$ kb/s. Five receivers are divided into three classes, broadband broadcasting class (e.g., receiver 3), internet class with moderate access capability (e.g., receiver 4 and 5), and mobile class with limited capacity (e.g., receiver 1 and 2).

We adopt Joint Scalable Video Model 7-10 reference codec of H.264/AVC extension standard, with four standard test video sequences: *Foreman*, *Stefan*, *Mobile*, and *Coastguard* with a frame rate of 30 frames/s, CIF (352×288) resolution, and a GOP-length of 32 frames. They are encoded with 256 kb/s on the base layer, and 384 kb/s, 512 kb/s and 1024 kb/s on the enhancement layers using FGS coding. Fig. 10 shows the rate-distortion performance of SVC for four CIF video sequences used in our simulations.

To simulate IP-layer multicasting, each Steiner node is equipped with a standard Internet protocol stack and a practical linear network coding scheme [18]. Nodes of optimal coding subgraph receive an element of finite field $\mathbb{F}_q = GF(2^8)$ from each input link, and then forward the linear combinations of its input to its output links. The layered SVC sources are segmented into small blocks which are encapsulated into multiple packets, and each packet contains 1024 bytes composed of 3 bytes header and 1021 inner layer payload. The header might indicate possible network coding generation,

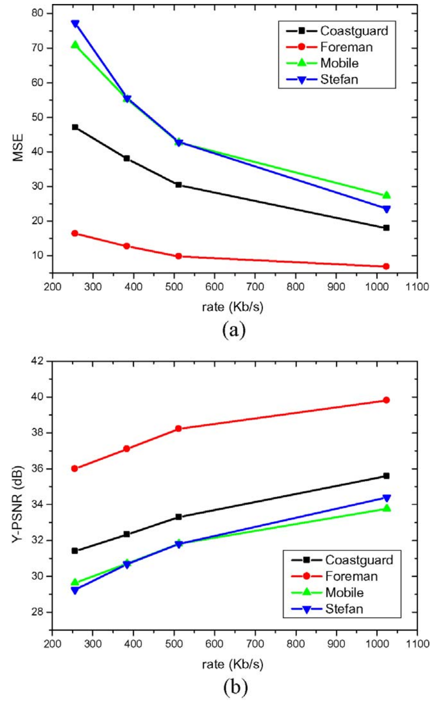

Fig. 10. (a) MSE and (b) PSNR performance achieved by SVC for four CIF sequences with frame rate of 30 frames/s and GOP length of 32.

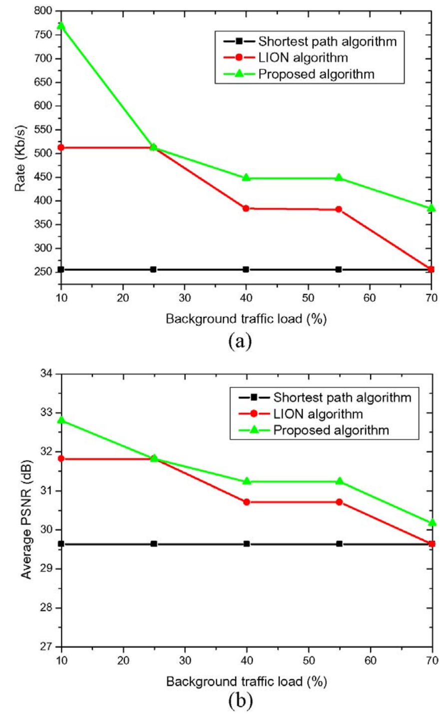

Fig. 11. (a) Allocated rate and (b) received video quality in PSNR of *Mobile* sequence for receiver 3 when the background traffic load varies between 10% and 70%. The playout deadline is 200 ms.

the data block, and the dimension, while the corresponding data field can be viewed as a row vector with elements in $GF(2^8)$ associated with global coding coefficient matrix. As for the proposed distributed algorithm, the update of rate $x^r_{m,j}(t)$ and cost signal $q^r_m(t)$ is executed by each receiver itself, and $p^r_{m,e}$ and $f_{m,e}$ tracking involved with each link are operated by its outgoing node. After each iteration, all the new values are broadcast to their destinations through control packets.

Table I compares the distribution costs of the typical shortest path algorithm, the LION-based ILP algorithm, and the proposed algorithm. Here, the cost for each receiver in each layer is the sum of each path's cost calculated by the cost metric in (4) for each receiver at the same layer. It can be seen that the proposed algorithm achieves the minimum cost over all receivers, because it maintains an overall balanced layered path routing at the minimum cost in an incremental order. The shortest path algorithm and the LION-based ILP scheme are not efficient for practical SVC multirate multicasting, because the receivers would access the lower layers at an unreasonable higher cost. This will cause buffer overflow and video quality degradation during network video streaming.

Actually, the cost function may consider other factors during video streaming, such as end-to-end delay, packet loss ratio, or network congestion [46]. The end-to-end delay consists of three components: queuing delay, processing delay and propagation delay. Correspondingly, the first term in (4) represents an average layered queuing delay as long as each queue behaves as a single M/M/1 queue of packets, and the second term is viewed as average layered processing and propagation delay. Thus, the cost in (4) can be regarded as linear with respect to the end-to-end delay.

To verify the linear relationship between path cost and end-to-end path delay, we vary the playback deadline for *Foreman*, *Stefan*, *Coastguard*, and *Mobile* streams from 200 ms to 500 ms, and fix the background traffic load to 15%. Here, we suppose that packets are dropped if they do not arrive at the receiver by the playback deadline. In Table II, we compare the average video quality (peak signal noise ratio, PSNR) at each receiver. Clearly, the proposed algorithm achieves better video quality. Note that in the shortest path or LION scheme, the base layer packets for receiver 1 are dropped when the playback deadline is small, 200 ms. Although receiver 1 can receive higher layer packets at lower cost, it still cannot decode any video information. As the playback deadline increases, larger packet delays can be tolerated. When the playback deadline increases to 400 ms, receiver 1 can successfully receive the base layer using LION scheme. Once the playback deadline becomes 500 ms, the video quality of the shortest path and LION schemes is similar to that of the proposed algorithm. At receivers 4 and 5, there is only one transmission path for the base layer, which leads to the same cost and PSNR gain with these three algorithms.

To evaluate the impact of background traffic on resource allocation, we choose the "Mobile" test video sequence and change the percentage of background traffic from 10% to 70% while the playback deadline is fixed at 200 ms. From Fig. 11, we can see that the allocated video bit rate and the received average video quality at receiver 3 achieve the optimum values by the proposed scheme. As the amount of background traffic increases, the average video quality of the proposed algorithm degrades much more slowly than the other two schemes. Our algorithm outperforms LION algorithm by at least 0.5 dB in

TABLE I

DISTRIBUTION COSTS FOR ALL RECEIVERS

	R1		R2			R3				R4	R5
	Layer 1	Layer 2	Layer 1	Layer 2	Layer 3	Layer 1	Layer 2	Layer 3	Layer 4	Layer 1	Layer 1
Shortest path	169.38	51.62	41.13	45.58	150.02	45.42	148.75	148.75	168.05	73.25	65.11
LION	166.97	81.65	63.21	39.41	45.58	94.04	50.40	59.57	–	73.25	65.11
Proposed algorithm	68.74	151.06	41.13	45.58	150.02	45.42	50.67	50.67	168.05	73.25	65.11

TABLE II

RECEIVED AVERAGE VIDEO QUALITY MEASURED AS PSNR FOR *Foreman*, *Stefan*, *Coastguard*, AND *Mobile* SEQUENCES WHEN THE PLAYBACK DEADLINE IS 200 MS, 400 MS, AND 500 MS, RESPECTIVELY. BACKGROUND TRAFFIC LOAD IS FIXED AT 15%

Foreman sequence, playback deadline = 200 ms					
Average PSNR	R1	R2	R3	R4	R5
Shortest path	0	37.1	36	36	36
LION algorithm	0	38.22	38.22	36	36
Proposed algorithm	36	37.66	39.02	36	36
Foreman sequence, playback deadline = 400 ms					
Average PSNR	R1	R2	R3	R4	R5
Shortest path	0	38.22	39.81	36	36
LION algorithm	37.1	38.22	38.22	36	36
Proposed algorithm	37.1	38.22	39.81	36	36
Foreman sequence, playback deadline = 500 ms					
Average PSNR	R1	R2	R3	R4	R5
Shortest path	37.1	38.22	39.81	36	36
LION algorithm	37.1	38.22	38.22	36	36
Proposed algorithm	37.1	38.22	39.81	36	36
Coastguard sequence, playback deadline = 200 ms					
Average PSNR	R1	R2	R3	R4	R5
Shortest path	0	32.33	31.4	31.4	31.4
LION algorithm	0	33.3	33.3	31.4	31.4
Proposed algorithm	31.4	33.12	33.64	31.4	31.4
Coastguard sequence, playback deadline = 400 ms					
Average PSNR	R1	R2	R3	R4	R5
Shortest path	0	33.3	35.59	31.4	31.4
LION algorithm	32.33	33.3	33.3	31.4	31.4
Proposed algorithm	32.33	33.3	35.59	31.4	31.4
Coastguard sequence, playback deadline = 500 ms					
Average PSNR	R1	R2	R3	R4	R5
Shortest path	32.33	33.3	35.59	31.4	31.4
LION algorithm	32.33	33.3	33.3	31.4	31.4
Proposed algorithm	32.33	33.3	35.59	31.4	31.4

Stefan sequence, playback deadline = 200 ms					
Average PSNR	R1	R2	R3	R4	R5
Shortest path	0	30.68	29.25	29.3	29.3
LION algorithm	0	31.81	31.81	29.3	29.3
Proposed algorithm	29.25	31.25	33.1	29.3	29.3
Stefan sequence, playback deadline = 400ms					
Average PSNR	R1	R2	R3	R4	R5
Shortest path	0	31.81	34.4	29.3	29.3
LION algorithm	30.68	31.81	31.81	29.3	29.3
Proposed algorithm	30.68	31.81	34.4	29.3	29.3
Stefan sequence, playback deadline = 500 ms					
Average PSNR	R1	R2	R3	R4	R5
Shortest path	30.68	31.81	34.4	29.3	29.3
LION algorithm	30.68	31.81	31.81	29.3	29.3
Proposed algorithm	30.68	31.81	34.4	29.3	29.3
Mobile sequence, playback deadline = 200 ms					
Average PSNR	R1	R2	R3	R4	R5
Shortest path	0	30.71	29.63	29.63	29.63
LION algorithm	0	31.82	31.82	29.63	29.63
Proposed algorithm	29.63	31.13	33.58	29.63	29.63
Mobile sequence, playback deadline = 400 ms					
Average PSNR	R1	R2	R3	R4	R5
Shortest path	0	31.82	33.77	29.63	29.63
LION algorithm	30.71	31.82	31.82	29.63	29.63
Proposed algorithm	30.71	31.82	33.77	29.63	29.63
Mobile sequence, Playback deadline = 500 ms.					
Average PSNR	R1	R2	R3	R4	R5
Shortest path	30.71	31.82	33.77	29.63	29.63
LION algorithm	30.71	31.82	31.82	29.63	29.63
Proposed algorithm	30.71	31.82	33.77	29.63	29.63

PSNR. Moreover, the fine-granular achievable rate region of SVC enhancement layers could be further explored to get a partial layered bit-rate allocation by the proposed algorithm, so as to achieve a consistent rate-distortion gain from source coding. For the shortest path algorithm, the allocation result for receiver 3 is always allocated for a video rate of 256 kb/s and its video quality remains 29.63 dB regardless of the background traffic load. This is because receiver 3 can only access to the base layer and packets belong to other layers are discarded due to larger path costs.

Fig. 12 shows the average packet loss ratio for the *Coastguard* stream at receiver 2 when the playback deadline is 200 ms and its allocated rate ranges from 200 kb/s to 1 Mb/s. There are three major causes of packet loss during SVC streaming: 1) the rate allocated to a receiver exceeding its available capacity; 2) the packets arriving after the playback deadline; and 3) a video layer being partially received. Unlike discrete layer based rate control in the shortest path and LION algorithm, the proposed algorithm adopts continuous rate allocation and allows a receiver to subscribe to a partial layer. As a result, the packet loss performance of our proposed algorithm is better than other two algorithms. When the allocated rate is smaller than the base layer rate of 256 kb/s, the factor of discrete achievable rate region is the key reason for the packet loss. Once the rate exceeds receiver 2's max-flow of 550 kb/s, the packet loss will dramatically increase. Therefore, if the optimum rate assigned to a receiver is limited between the base layer rate and the receiver's max-flow capacity, packet loss will be reduced.

Fig. 13 plots the variation of instantaneous throughput for the *Foreman* sequence along two paths $S - N_2 - R_3$ and $S - N_3 - R_2$ when the proposed scheme is applied. In this case, the playback deadline is still 200 ms. It has been observed that the rate update interval for a multicast stream is critical for successful video streaming. In our simulations, the rate update interval for each path is chosen to be 0.05 s that is comparable to the end-to-end path propagation delay. It can be seen that, even within small intervals, the throughput over the two paths

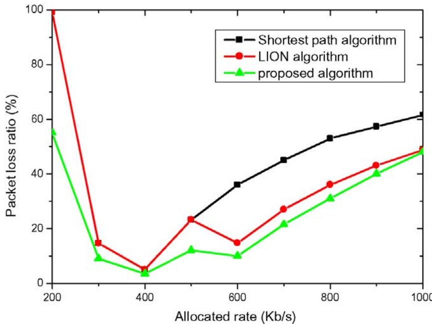

Fig. 12. Packet loss ratio for *Coastguard* sequence at receiver 2's decoder, and the playout deadline is 200 ms.

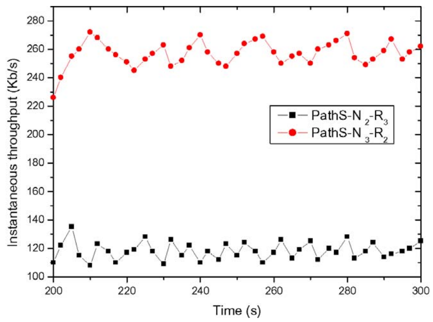

Fig. 13. Variation of throughput over path $S-N_2-R_3$ and path $S-N_3-R_2$ for *Foreman* sequence. The playout deadline is 200 ms.

changes smoothly around their respective optimum values of 118 kb/s and 256 kb/s. In practice, a larger update interval can be used to reduce the implementation complexity.

VI. Concluding Remarks

In this paper, we studied the performance optimization for scalable video coding and multicast over networks. We jointly considered multi-path video streaming, network coding based routing, and network flow control to maximize a network utility function defined over heterogeneous receivers. Content priority of video coding layers was considered during the flow routing to determine the optimal multicast paths and associated data rates for each layer. Our optimization scheme was able to find content distribution meshes with minimum path costs for each video coding layer while satisfying the inter-layer dependency during SVC. Based on primal decomposition and primal-dual analysis, we developed a decentralized algorithm with two optimization levels to solve the performance optimization problem. We also proved the stability and convergence of the proposed iterative algorithm using Lyapunov theory. Extensive experimental results demonstrate that the proposed algorithm not only achieves the max-flow throughput using network coding, but also provides better video quality with balanced layered access for heterogeneous receivers.

Appendix

A. Proof of Proposition 1

The key issue is to find a Lyapunov function $V(\mathbf{X}, \mathbf{p}, \mathbf{q})$ for the proposed primal-dual method, which satisfies the conditions of Lyapunov's theorem

$$V(\mathbf{X}, \mathbf{p}, \mathbf{q}) = \sum_{r\in R}\sum_{m\in M}\Bigg[\sum_{j\in P(r)}\int_{\hat{x}^r_{m,j}}^{x^r_{m,j}} \frac{1}{\alpha(\kappa)}(\kappa - \hat{x}^r_{m,j})d\kappa + \sum_{e\in E}\int_{\hat{p}^r_{m,e}}^{p^r_{m,e}} \frac{1}{\beta(\vartheta)}(\vartheta - \hat{p}^r_{m,j})d\vartheta + \int_{\hat{q}^r_m}^{q^r_m} \frac{1}{\gamma(\nu)}(\nu - \hat{q}^r_m)d\nu\Bigg]. \tag{16}$$

Note that $V(\hat{\mathbf{X}}, \hat{\mathbf{p}}, \hat{\mathbf{q}}) = 0$. Also, if $x^r_{m,j} \neq \hat{x}^r_{m,j}$, $\int_{\hat{x}^r_{m,j}}^{x^r_{m,j}} \frac{1}{\alpha(\kappa)}(\kappa - \hat{x}^r_{m,j})d\kappa > 0$, and it can be extended to other arguments. Thus, whenever $(\mathbf{X}, \mathbf{p}, \mathbf{q}) \neq (\hat{\mathbf{X}}, \hat{\mathbf{p}}, \hat{\mathbf{q}})$, we have $V(\mathbf{X}, \mathbf{p}, \mathbf{q}) > 0$. Furthermore, it can be easily seen that $V(\hat{\mathbf{X}}, \hat{\mathbf{p}}, \hat{\mathbf{q}}) \to \infty$, when $\|(\mathbf{X}, \mathbf{p}, \mathbf{q}) - (\hat{\mathbf{X}}, \hat{\mathbf{p}}, \hat{\mathbf{q}})\| \to \infty$.

Then, considering the KKT conditions of (8), we have $\dot{V} \leq 0$ for all $(\mathbf{X}, \mathbf{p}, \mathbf{q})$ and with equality if and only if $(\mathbf{X}, \mathbf{p}, \mathbf{q}) = (\hat{\mathbf{X}}, \hat{\mathbf{p}}, \hat{\mathbf{q}})$.

Therefore, $V(\mathbf{X}, \mathbf{p}, \mathbf{q})$ in (16) satisfies conditions (1)-(4) and is a Lyapunov function for the dynamic system in (9)–(11). This implies that the maximum solution is unique, stable and global optimum.

B. Proof of Proposition 2

Assuming that $\lim_{t'\to+\infty}\|f(t') - \hat{f}\| > 0$, i.e., there are $\varepsilon > 0$ and $t_0 \in \mathbb{N}$ such that

$$\|f(t') - \hat{f}\| > \varepsilon, \ \forall t' \geq t_0.$$

From the properties of subgradient method [24], we have

$$\|f(t'+1) - \hat{f}\|^2 \leq \|f(t') - \hat{f}\|^2 - 2\mu(t')\cdot(f(t') - \hat{f}) + mu(t')^2 C^2$$

where C is the subgradient bound of (13). In view of $\lim_{t'\to+\infty}\mu(t') = 0$, we may assume that t_0 is so large that $\mu(t')C^2$ is then smaller than ε, from which we obtain

$$\|f(t'+1) - \hat{f}\|^2 < \|f(t') - \hat{f}\|^2 - 2\mu(t')\cdot\varepsilon + \mu^2(t')C^2 \leq \|f(t') - \hat{f}\|^2 - \mu(t')\cdot\varepsilon, \ \forall t' \geq t_0.$$

Summing up iteratively the above inequality, we could get

$$0 \leq \|f(t') - \hat{f}\|^2 \leq \|f(t_0) - \hat{f}\|^2 - \varepsilon \sum_{t_i=t_0}^{t'-1}\mu(t_i) \quad \forall t' > t_0.$$

Let $t' \to +\infty$, the divergence condition $\sum_{t'=0}^{+\infty}\mu(t') = +\infty$ is contradicted. Therefore, the initial assumption is not correct, and $\lim_{t'\to+\infty}\|f(t') - \hat{f}\| = 0$ is proved.

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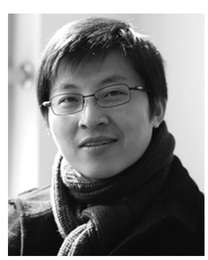

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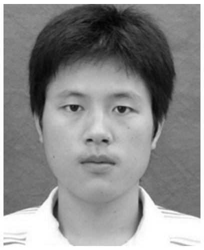

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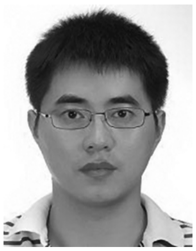

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