Information-Constrained Resource Allocation in Multicamera Wireless Surveillance Networks

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***Abstract*—Real-time multiuser multimedia applications, such as surveillance or monitoring using multiple cameras, have recently started to be deployed over flexible and low-cost multihop wireless networks. In such multimedia systems, the various sources (cameras) share the limited network resources and collaboratively forward the captured video streams to a remote central monitor. However, existing resource allocation schemes often ignore the dynamic application-layer video and network characteristics by focusing on the steady-state or worst-case operating conditions. This may result in inefficient allocation of the network resources. In this paper, we focus on determining whether the resource allocation for wireless video surveillance systems should be performed based on steady-state or worst-case operating conditions, or whether perpetual adaptation to the dynamically changing source and network conditions is desirable. We analyze three different types of solutions that have different information requirements: a centralized optimization approach, a decentralized game-theoretic approach (which guarantees a stable allocation), and a distributed greedy approach (which perpetually adapts allocation based on the local information exchanged among the neighboring nodes). We compare these three approaches using the following four metrics: 1) the total video quality; 2) the computational complexity; 3) the required control information overhead; and 4) the timely adaptation to the network and source variation. We show that in a static network, the game theoretic resource allocation is only better than the distributed greedy approach when the network transmission rates are high. In a dynamic network, the distributed greedy approach can outperform the other two approaches significantly in terms of video quality (peak signal-to-noise ratio). This shows that resource allocation solutions for multicamera wireless surveillance networks need to explicitly consider both the dynamic source characteristics and network conditions, rather than always relying on stable, but predetermined, allocations.**

***Index Terms*—Decentralized resource allocation, prioritized congestion game, video surveillance.**

I. Introduction

A PLETHORA of existing and emerging surveillance and monitoring applications can derive significant advantage by acquiring real-time and accurate multimedia information about objects of interest. Multicamera surveillance systems are deployed for several applications such as transportation monitoring, security systems, and tele-immersive environments, etc. in order to collect videos or images (e.g., spectral data) [1]–[5]. These cameras can relay collected multimedia information using a flexible multihop wireless infrastructure to a central monitor [6]. While wireless mesh networks enable low cost, convenient deployment, and reuse for different surveillance applications by allowing reconfiguration for collecting meaningful, reliable, and accurate data, they do not provide adequate support for the quality of service (QoS) required by the delay-sensitive and bandwidth-intensive multimedia data. These limitations do not significantly impact delay-insensitive data acquisition, but have significant consequences for the aforementioned real-time surveillance or monitoring applications, since they often lead to unsatisfactory or unacceptable measurements and erroneous event detection.

In this paper, we focus on how multiple cameras should efficiently share the available wireless network resources and transmit their captured information to a central monitor. The network architecture is similar to the wireless multimedia sensor networks which was recently introduced in [7]. However, in our system, we assume that the network deploys a medium access control (MAC)/physical layer (PHY) protocol similar to that of IEEE 802.11a/e [21], which enables packet-based retransmission and polling-based time allocation, which is better suited for multimedia transmission. We focus on how the video streams should share the transmission time over the links of the multihop wireless network in order to maximize the video quality received by the central monitor. Three main challenges associated with determining the optimal resource allocation solution are the low-delay tolerance of surveillance applications, the dynamic variations of the video source characteristics and wireless network conditions, and the distributed nature of the available information about these dynamics. In this paper, we study how the following three types of resource allocation solutions can address these challenges.

1) Centralized optimization (CO) approaches, in which the central monitor collects global information about the video traffic and network statistics, and subsequently makes the resource allocation decisions.
2) Game-theoretic approaches based on congestion game (CG) modeling, in which the cameras (source nodes) make autonomous decisions for their video stream and compete for network resources with other cameras.

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3) Distributed greedy (DG) approaches, in which all the network nodes (including the network relays) make distributed, autonomous decisions to select the next relay based on periodically exchanged local information about the video traffic and network statistics.

A. Related Work of the Three Approaches

Research on multimedia transmission over multihop wireless networks has attracted significant attention in recent years. In [9], [10], the authors assume that a central controller acquires global network information and performs global optimization to decide the actions of all the network nodes. The centralized approach can be considered to achieve the global optimal solution. However, these strategies can be efficiently optimized only if accurate information about the network conditions and the sources' requirements is available. Moreover, since the bandwidth-limited, time-varying, error-prone wireless network infrastructure introduces various dynamics (such as variations in network load, losses in network transmissions, and changing characteristics of the application requirements), the optimization may need to be performed repeatedly to ensure a certain level of performance for the centralized approach. Due to the dynamic and informationally-decentralized nature of the multihop mesh networks, regularly performing such a global optimization requires excessive transmission overhead to timely collect the necessary information. The complexity of the CO also grows exponentially with the number of sources and nodes in the network. The optimization can require a large amount of time to process and the collected information may no longer be accurate by the time transmission decisions need to be made. Hence, distributed approaches need to be considered.

In such distributed approaches [11], [12], [19], all the network nodes interact with each other and autonomously determine their actions in order to maximize the utility (expected delay, congestion, or the video quality) based on local information about the network conditions. Such distributed approaches can significantly reduce the computational complexity and, more importantly, can effectively cope with the informationally-decentralized nature of the wireless networks. Note that the distributed approach makes decisions based on repeated information feedback, thereby being able to adapt to dynamic changes in traffic and network characteristics in a timely manner. However, due to the varying decisions of the neighboring nodes, the distributed allocation may not converge to a stable set of path decisions in a general network topology with only local information being exchanged.

Among the decentralized solutions, game-theoretic solutions have been proposed that allow autonomous agents (e.g., cameras) to negotiate a stable allocation of resources on the established routes. For example, CG modeling [13] has been successfully used in several applications such as routing [29], [30], and load balancing [14], [15]. However, the previous research mainly focuses on distributing the available network resources to the agents without explicitly considering the impact of the video flow characteristics on the multimedia quality received by the monitor.

In this paper, we modify the conventional CG into a *prioritized CG* for video streaming. This allows explicit consideration of the distortion impact and delay constraints for prioritized video flows. The advantage of modeling the video transmission as a prioritized CG is to guarantee the convergence to Nash equilibrium when each camera autonomously selects the path to use to relay its video data. This implies that the decentralized negotiation of camera agents trying to maximize their achievable quality does eventually converge to a set of stable streaming paths, without the specific control of a central coordinator. However, such decentralized resource allocation is merely a best-response decision that leads to Nash equilibrium based on the actions of autonomous cameras, which may not maximize the overall video quality received by the central monitor. Moreover, although convergence to equilibrium is guaranteed, the CG approach has the drawback that it assumes a static source and network environment. In other words, the game-theoretic approach cannot effectively adapt to the source and network dynamics. In order to guarantee Nash equilibrium, the restriction of the congestion game modeling can induce significant performance degradation for delay-sensitive applications. On the other hand, the DG approach that does not have a stable allocation can also lead to performance degradations depending on the required information exchange overhead. In summary, it is important to study the pros and cons of the three types of resource allocation approaches in different networking scenarios.

B. Contributions and Organization of This Paper

1) Our main goal is to evaluate the performance of the three types of resource allocation solutions in terms of video quality, their computational complexities and required control information overheads. Based on these comparisons, we discuss how efficiently these various approaches can cope with the dynamic source and network variations, which are commonly incurred in wireless multimedia networks, such as surveillance networks.
2) Unlike the previous game-theoretic research that focuses on achieving the equilibrium operating setting for delay-insensitive traffic and ignores multimedia application characteristics [14], [15], we consider the resource allocation problem specifically for delay-sensitive applications. In order to guarantee the necessary QoS, we design a *prioritized CG* model. This model takes into consideration the inherent priorities and delay deadlines of the captured video traffic. Unlike the prior research [14] that assumes the players are anonymous, and thus they cannot differentiate between traffic with various priorities, the prioritized CG is played in individual quality-layer subnets (QSNs), considering the characteristics of the video streams.
3) To quantify what the desirable solutions are in different network scenarios, we introduce a new metric referred to as the price of convergence (PoC). The PoC is computed based on the performance ratio of the CG equilibrium and the DG approaches. This concept is parallel to the well-known concept of price of anarchy (PoA) [16], which is used to characterize the performance

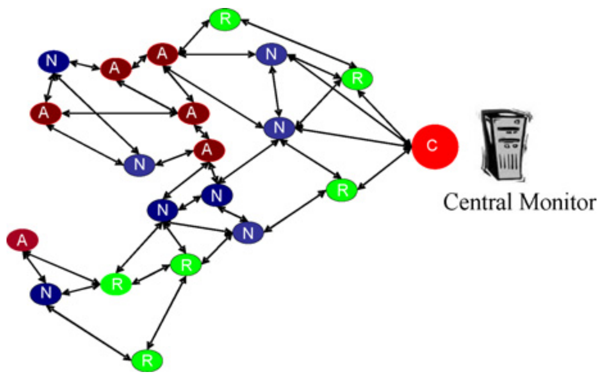

Fig. 1. Illustration of the wireless surveillance network framework. (A) Active camera agent. (N) Nonactive camera agent. (R) Relay network agent. (C) Central monitor.

degradation due to decentralized decision making. Based on the PoC, we analyze whether stable resource allocations are desirable for video networking systems, such as multicamera networks.

This paper is organized as follows. In Section II, we introduce the considered wireless multicamera network system and give a general problem formulation. In Section III, we discuss the centralized approach for the multicamera video streaming over wireless surveillance networks. In Section IV, we propose the prioritized CG modeling for multimedia applications. In Section V, we discuss the DG approach for video streaming applications. In Section VI, we compare these three solutions in terms of computational complexities and the information overheads. The simulation results are shown in Section VII, and Section VIII concludes the paper.

II. Resource Allocation Problem in Wireless Surveillance Networks

We consider a surveillance system [1], [2] that consists of multiple cameras that acquire and compress video data and, subsequently, transmit their video traffic to a central monitor using a low-cost and flexible wireless multihop network $\mathcal{G}(\mathbf{N}, \mathbf{E})$. $\mathbf{N}$ represents a set of nodes (network agents) and $\mathbf{E}$ represents a set of links. An illustrative example for a wireless surveillance network is shown in Fig. 1.

A. Network Agents

The *network agents* of the wireless surveillance network can be categorized as follows.

1) *Central Monitor (Node $\mathcal{N}^c \in \mathbf{N}$):* The central monitor receives, decodes, and eventually processes the video data captured by the various active sources (cameras).

2) *Active Camera Agents (Nodes $\mathcal{N}^a \in \mathbf{N}$):* The active cameras capture the videos of object(s) of interest and send their video content at different spatio-temporal-quality resolutions, resulting in different video classes with various transmission bit-rates and delay deadlines (see Section II-B).

3) *Nonactive Camera Agents*[1]*:* The nonactive cameras can act as relay nodes and forward video traffic through the wireless mesh network to the central monitor.

4) *Relay Agents (Nodes $\mathcal{N}^r \in \mathbf{N}$):* The relay nodes without camera capability can only forward video traffic through the mesh network.

The wireless surveillance network can be modeled as a collection of collaborative, but autonomous, agents that engage in informationally-decentralized negotiations and interactions in order to maximize the video quality received by the central monitor. Unlike a multiuser video streaming setup, where the traffic can be generated from any nodes in the network, the relevant traffic in a surveillance network is often propagated from a group of active cameras near an object of interest [4] in a local area, and thus, this often results in increased network congestion near the camera sources. Hence, designing efficient resource allocation solution for such camera networks is of paramount importance.

B. Application Layer Video Stream Characteristics

Assume that M cameras are activated, i.e., $\mathcal{N}_i^a$, $1 \le i \le M$. Since the network resource is limited, cameras cannot simultaneously transmit high-quality video to the central monitor $\mathcal{N}^c$. To address this issue, we assume that each active camera applies a scalable video codec to compress its captured video data. Let V_i denote the compressed video stream from the camera $\mathcal{N}_i^a$. The video stream V_i consists of several video flows. Each flow is assumed to be classified in one of K video classes (i.e., $C = \{C_1, \ldots, C_K\}$). A video class C_k can be characterized as follows.

1) R_k, the average source rate of each video flow in a class C_k.
2) λ_k, the quality impact factor of the video class C_k. For simplification, we assume that all the video flows in a class have the same quality impact as in [19]. This quality impact factor can be evaluated by measuring the average distortion reduction when decoding the packets of video class C_k. We define $\lambda_k R_k$ as the average quality gain [e.g., peak signal-to-noise ratio (PSNR) gain] when the flows of video class C_k with source rate R_k are received and decoded by the central monitor. We prioritize the video classes based on this parameter. In the subsequent part of this paper, we label the K classes (across all users) in descending order of their priorities, i.e., $\lambda_1 \ge \lambda_2 \ge \ldots \ge \lambda_K$.
3) D_k, the delay deadline of the video class C_k. Due to the hierarchical temporal structure deployed in the 3-D wavelet video coders (see [17]), the lower priority classes also have a less stringent delay requirement. This is the reason why we prioritize the video bitstream in terms of the quality impact. Otherwise, the prioritization techniques need to jointly consider the quality impact and delay constraints based on rate-distortion optimization (see more sophisticated methods in, e.g., [18]).
4) L_k, the average packet length of a video class C_k.

[1]Since the nonactive camera agents act as relay nodes, we denote these nodes using the same notation $\mathcal{N}^r$ as the relay nodes.

All video flows captured by the M activated cameras are assumed to be classified in these K video classes. Denote the video flows as $f_j,\ j = 1, \ldots, J$, where J represents the total number of video flows. Let N_{ik}^f represent the number of flows in class C_k for video stream V_i. Let C_i denote the subset of classes for video stream V_i (i.e., $C_i \subset C$).

C. Lower Layer Model

We assume that each wireless link in $\mathbf{E}$ is a memoryless packet erasure channel and a polling-based contention-free MAC/PHY protocol (e.g., IEEE 802.11a/e [21]) is deployed to access the channel. The optimal modulation and coding scheme can be selected for each link depending on the channel condition based on link adaptation [22]. We denote the packet error rate over a link l for a flow in class C_k as $p_{l,k}$, which can be approximated using the sigmoid function [22], i.e., $p_{l,k} = \left(1 + e^{\zeta_k(x_l - \delta_k)}\right)^{-1}$, where x_l is the signal-to-interference-noise ratio over the link l. ζ_k and δ_k are the empirical constants corresponding to the modulation and coding schemes for a given packet length L_k. Let $T_{l,k}$ denote the maximum transmission rate supported by the modulation and coding scheme. Based on the packet-based retransmission and polling-based time allocation, the effective transmission rate for a flow f_j over a link l can be calculated as $T_{l,k}(1 - p_{l,k})t_{l,j}$, where $t_{l,j}$ represents the time sharing fraction (i.e., the transmission opportunity in IEEE 802.11a/e [21]) for video flow f_j to transmit over link l ($t_{l,j} = 0$ indicates that the video flow f_j does not flow through the link l, $\sum_{j=1}^{J} t_{l,j} \leq 1$). In this paper, we only focus on the time sharing problem to determine the time sharing fraction $t_{l,j}$ for the video flows in the application layer as in [32]. Other related cross-layer designs for the transmission strategies in MAC and PHY layers are discussed in [19], which is out of the scope of this paper.

D. Resource Allocation and the Resulting Video Quality

We define the allocation of a video flow f_j as $\sigma_j = \{t_{l,j}, l \in \mathbf{E}\} \in \mathcal{A}$, where $\mathcal{A}$ is the allocation space. Let $\boldsymbol{\sigma} = [\sigma_1, \sigma_2, \ldots, \sigma_J] \in \mathcal{A}^J$ be the joint allocation for all J video flows. In this paper, we assume that each active camera has established multiple potential transmission paths to the central monitor and each flow is sent through a path to the central monitor. Distributed approaches to establish multiple paths from active cameras to the central monitor can be found in [8], [23]. Dijkstra algorithm can be applied to construct multiple paths in a centralized manner [26], [31]. After the path construction, the time sharing fractions $t_{l,j}$ are the resources that need to be allocated for the video flows in the network. Note that $t_{l,j} = 0$ when the corresponding path is not selected.

Let $d_j(\sigma_j)$ denote end-to-end delay for transmitting the flow f_j based on σ_j. The end-to-end delay $d_j(\sigma_j)$ for a flow f_j can be calculated by accumulating the effective transmission time over the allocated links. Define $\mathrm{ETT}_{l,j}$ as the effective transmission time (ETT) [25] of the link l for the flow f_j

$$\mathrm{ETT}_{l,j} = \frac{L_k}{t_{l,j} \times T_{l,k}} \times \mathrm{ETX}_{l,k}, \text{ for } f_j \in C_k \tag{1}$$

where $\mathrm{ETX}_{l,k}$ is the corresponding effective transmission count (ETX) [28], which can be defined as $\mathrm{ETX}_{l,k} = 1\big/(1 - p_{l,k})$. The end-to-end delay $d_j(\sigma_j)$ can be computed as $d_j(\sigma_j) = \sum_{l, t_{l,j} > 0} \mathrm{ETT}_{l,j}(\sigma_j)$.

The received video quality Q_i for V_i can be expressed as [19]

$$Q_i(\boldsymbol{\sigma}) = \sum_{C_k \in C_i} \sum_{j=1}^{N_{ik}^f} \lambda_k \cdot R_k \cdot \alpha_j \cdot I(d_j(\sigma_j) \leq D_k) \tag{2}$$

where $I(\cdot)$ is the indicator function. $\alpha_j = \{0, 1\}$ denotes a simple error concealment policy at the decoder.

Here, we assume that the client implements a simple error concealment scheme, where the lower priority packets are discarded whenever the higher priority packets are lost [17]. This is because the quality improvement (gain) obtained from decoding the lower priority packets is very limited (in such embedded scalable video coders) whenever the higher priority packets are not received. For example, drift errors can be observed when decoding the lower priority packets without the higher priority packets. We consider the error concealment scheme as follows:

$$\alpha_j = \begin{cases} 0, & \text{if } f_{j'} \prec f_j \text{ and } \alpha_{j'} = 0 \\ 1, & \text{otherwise} \end{cases} \tag{3}$$

where $f_{j'} \prec f_j$ denotes that the flow f_j depends on the flow $f_{j'}$. Specifically, if $f_j \in C_k$ and $f_{j'} \in C_{k'}$ are flows of the same video stream, $f_{j'} \prec f_j$ means $k' < k$ due to the descending priority ($\lambda_{k'} > \lambda_k$).

E. Optimal Resource Allocation in the Wireless Surveillance Network

Based on the joint allocation $\boldsymbol{\sigma}$, the proposed wireless surveillance network paradigm can be formulated as a generalized optimization problem. The objective function U_{tot} can be defined as the sum of the qualities, that is

$$U_{\text{tot}}(\boldsymbol{\sigma}) = \sum_{i=1}^{M} Q_i(\boldsymbol{\sigma}). \tag{4}$$

The considered optimal resource allocation for the wireless surveillance networks is

$$\begin{aligned} &\boldsymbol{\sigma}^{\text{opt}}(\mathcal{I}_S, \mathcal{I}_N) = \arg\max_{\boldsymbol{\sigma} \in \mathcal{A}^J} \{U_{\text{tot}}(\boldsymbol{\sigma}, \mathcal{I}_S, \mathcal{I}_N)\} \\ &\text{s.t. } \sum_{j=1}^{J} t_{l,j} \leq 1,\ l \in \mathbf{E} \\ &\qquad d_j(\sigma_j, \mathcal{I}_S, \mathcal{I}_N) \leq D_k,\ \ f_j \in C_k,\ j = 1, \ldots, J \end{aligned} \tag{5}$$

where the first constraint is the resource constraint for *each network link*, and the second constraint is the delay constraint for *each video flow*. Two types of information, the source information $\mathcal{I}_S$ and the network information $\mathcal{I}_N$, are defined as follows.

1) The public network condition information $\mathcal{I}_N$ includes the packet loss rate $p_{l,k}$ and the transmission rate $T_{l,k}$ over each link $l \in \mathbf{E}$ to compute the end-to-end delay d_j in the wireless surveillance network.

2) The private multimedia traffic information $\mathcal{I}_S$ induced from the video sources (e.g., flow priority λ_k, source rate requirement R_k, and delay deadline D_k). We refer the interested reader to [17] for more details on how this information can be extracted.

Note that solving (5) in reality is not simple since the source and network information can vary over time and, moreover, the information may not be available to the central monitor to solve this optimization problem.

F. Information Constraints in the Wireless Surveillance Network

From (5), we know that information gathering is required for making the resource allocation decisions. We assume that an overlay infrastructure [32] is deployed to convey the necessary information about the network status across multiple agents. Importantly, the variation and the availability of the above-mentioned information exchange can significantly impact the resource allocation decisions.

In the wireless surveillance network, the following three different approaches are considered to solve the resource allocation problem in (5), which differ in terms of their information about the video source and network dynamics.

1) The CO approach assumes that all the information $\mathcal{I}_S$ and $\mathcal{I}_N$ is available to the central monitor. The central monitor is the decision maker in this approach.
2) The game-theoretic approach assumes that only the network information $\mathcal{I}_N$ is exchanged by all the network relays to the source (camera) nodes. The private information $\mathcal{I}_S$ of each video V_i is already known by the source nodes. The decision makers are the source nodes (as in [13], [14]).
3) The DG approach assumes that the network information is only locally exchanged $\nu_{\mathcal{N}} \subseteq \mathcal{I}_N$ (local network information of node $\mathcal{N}$), and the private information $\mathcal{I}_S$ is encapsulated in the video packet header (where V_i flows through node $\mathcal{N}$). Hence, all the agents include the source nodes and the network relays can make decisions for reserving the resource of the next relay (as in [11], [19], [22], [24]).

In Fig. 2, we show how different information availabilities can result in different allocations in the wireless surveillance network. These various types of resource allocation solutions will be discussed in the subsequent sections.

III. Centralized Optimization Approach for Resource Allocation

The CO in (5) can be performed by the central monitor, which determines the resource allocation for the various flows. Based on the network information $\mathcal{I}_N$ and private multimedia traffic information $\mathcal{I}_S$ about the entire camera network (i.e., all the camera sources and network links), the central monitor performs an exhaustive approach to determine the optimal set of paths and time allocations (i.e., all possible time sharing combinations of paths are considered) for the wireless surveillance network. Note that this CO approach is considered as a global optimal solution and will be considered as a "theoretical" upper bound for the other proposed solutions for the case when the information exchange is entirely known to the central monitor. However, since the total number of flows and the corresponding possible paths can be very large, an exhaustive search can be prohibitively expensive in terms of computational complexity and incurred information overhead. The computational complexity for the CO approach increases exponentially with the number of flows and network size and, more importantly, it cannot consider the source and network dynamics in a timely manner (see Section VI). To cope with these challenges, we next discuss the decentralized approaches.

IV. Congestion Game Modeling Approach for Resource Allocation

In this section, we investigate a decentralized resource allocation approach for the considered wireless surveillance system, which is based on CG models. Unlike the CO approach, the decision makers of the game-theoretic approach are the source nodes (i.e., the active camera agents $\mathcal{N}_i^a$). The private multimedia traffic information of a video V_i needs not to be exchanged among the source nodes, but each source node needs to gather the public network information $\mathcal{I}_N$ across the network.

Definition 1: Game-Theoretic Resource Allocation in Wireless Surveillance Networks: The game theoretic resource allocation is defined in a tuple $\langle \{\mathcal{N}_i^a\}, \{\sigma_i\}, \{Q_i\} \rangle$, where $\{\mathcal{N}_i^a\}$ is the set of the source nodes. $\sigma_i = \{\sigma_j, \forall f_j \in V_i\}$ represents the resource allocation for all the flows of video V_i. Denote $\sigma_{-i} = \{\sigma_j, \forall f_j \notin V_i\}$ as the resource allocation for the flows of the other videos except V_i. Given the network information $\mathcal{I}_N$, each source node $\mathcal{N}_i^a$ applies the following optimization:

$$\begin{aligned} &\sigma_i^{\text{opt}}(\mathcal{I}_N) = \arg\max_{\sigma_i \in \mathcal{A}} \{Q_i(\sigma_i, \sigma_{-i}, \mathcal{I}_N)\} \\ &\text{s.t.} \sum_{j=1}^{J} t_{l,j} \le t_{l,k},\ l \in E,\ f_j \in C_k \\ &\qquad d_j(\sigma_j, \mathcal{I}_N) \le D_k,\ \ f_j \in C_k,\ \ C_k \in V_i \end{aligned} \tag{6}$$

where $t_{l,k}$ represents a predetermined time fraction reserved for transmitting class C_k traffic over link l.

In this paper, we assume that the CG modeling is applied for solving (6) at each activated camera. The motivation for using the CG modeling is summarized as follows.

1) The CG modeling guarantees the existence of a Nash equilibrium [27]. The Nash equilibrium is a globally stable operating condition to which the agents converge over time and where no single agent has a unilateral incentive to deviate from its decision. Hence, no further information exchange is required, once the allocation reaches the equilibrium.
2) The CG modeling is a decentralized approach for autonomous agents to maximize their own utility Q_i. Therefore, this reduces the computational complexity compared to the CO problem in (5).

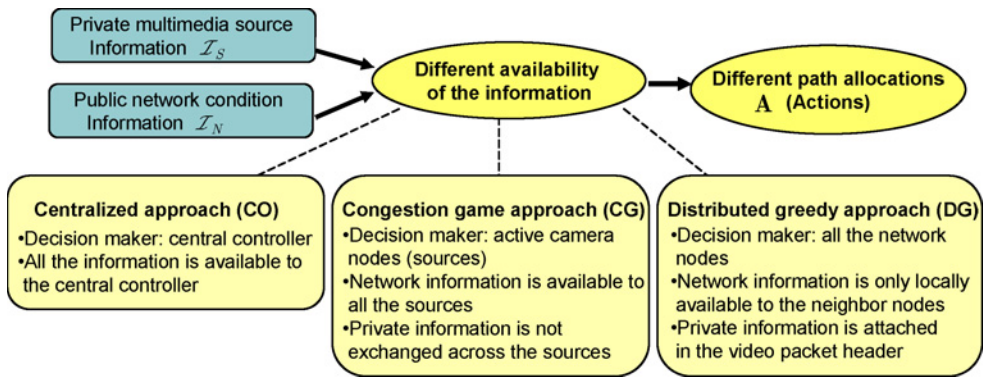

Fig. 2. Different resource allocation solutions in wireless surveillance networks under various information constraints.

A. Congestion Games for Resource Allocation in Surveillance Networks

Congestion games were defined by Rosenthal [13], [14]. Although the existing CG formulations (e.g., in [14]) are able to provide a stable resource allocation solution, it cannot capture the different characteristics of the video traffic and their priorities in terms of their impact on multimedia quality. In the considered surveillance system, there are K different video classes. In other words, players (video flows) are not identical[2] when sharing a link. Hence, a new type of CG is needed, which we refer to as the prioritized congestion game. The game is designed to be played first by the flows in the highest priority class and then utilize the remaining resource for the remaining flows in the lower priority classes. To successfully model our problem as a CG for delay-sensitive multimedia applications, we assume that the two types of subnets are predetermined before the games are played.

Definition 2: [QSN and game subnet (GSN)] We define the graph $\mathcal{G}(\mathbf{N}_k, \mathbf{E}_k)$, $\mathbf{N}_k \subseteq \mathbf{N}, \mathbf{E}_k \subseteq \mathbf{E}$, for a priority class C_k and denominate it QSN, denoted as QSN_k. The QSN is predetermined by setting the time fraction $t_{l,k}$ reserved for transmitting the flows in class C_k over link $l \in \mathbf{E}_k$. Moreover, we define $\text{GSN}_k = \mathcal{G}(\mathbf{N}'_k, \mathbf{E}'_k)$ as the GSN associated with a priority class C_k. The residual game subnet (RGSN), denoted as RGSN_k, is defined as the residual network resource (the unused nodes and links) that is available in GSN_k after the game is played by the flows in class C_k. The GSNs is determined by QSNs and RGSNs as follows (C_1 is the highest priority class):

$$\begin{aligned} &\text{GSN}_1 = \text{QSN}_1 \\ &\text{GSN}_{k+1} = \text{QSN}_{k+1} \cup \text{RGSN}_k \quad \text{for } k \geq 1. \end{aligned} \tag{7}$$

The K prioritized CGs are played consecutively from the highest priority to the lowest priority in the corresponding GSNs.

For example, suppose that related video streams are classified in three classes (C_1, C_2, and C_3). The central monitor determines the corresponding three layers, QSN_1, QSN_2, and QSN_3. First, the flows in C_1 play the CG in GSN_1. After a stable routing path (Nash equilibrium) is reached, $\text{GSN}_2 = \text{QSN}_2 \cup \text{RGSN}_1$ can be formed based on (7).

Definition 3: Prioritized Congestion Game Model for Surveillance Networks: Assume the GSN $\mathcal{G}(\mathbf{N}'_k, \mathbf{E}'_k)$ is used to transmit the class C_k traffic, the prioritized CG is defined as a tuple $\left\langle \{f_j \in C_k\}, \boldsymbol{\sigma}_k, \mathbf{E}'_k, \{u_j\} \right\rangle$.

1) *Players:* the video flows in the class C_k, i.e., $\forall f_j \in C_k$.
2) *Strategies:* the decisions σ_j of the video flows $f_j \in C_k$. Let $\boldsymbol{\sigma}_k = [\sigma_j | f_j \in C_k]$ represent a vector of σ_j for the video flows $f_j \in C_k$.
3) *Facilities:* all the links of the GSN, i.e., $\forall l \in \mathbf{E}'_k$.
4) *Cost functions of the facilities:* the cost function $c_l(n_{l,k})$ of the link l is a function of number of players (video flows) $n_{l,k}$ using the facility (link l).
5) *Utility functions of the players:* the utility function u_j of a player f_j is defined as

$$u_j(n_{l,k}) = \sum_l c_l(n_{l,k}(\boldsymbol{\sigma}_k)). \tag{8}$$

B. Equal Resource Allocation Policy to Enforce the Prioritized Congestion Games in Surveillance Networks

In this section, we show that the game-theoretic resource allocation problem can be modeled as a set of prioritized CGs that will converge to a Nash equilibrium.

Definition 4 (Equal Resource Allocation (ERA) Policy): The equal resource allocation policy is defined as follows:

$$t_{l,j} = t_{l,k} \times \frac{1}{n_{l,k}}, \quad \text{for } f_j \in C_k. \tag{9}$$

The ERA policy allocates an equal amount of time resources to each video flows over each link.

Claim 1: Convergence of the prioritized CG using ERA policy: By applying the ERA policy, the game-theoretic resource allocation becomes a prioritized CG with

$$c_l(n_{l,k}) = \text{ETT}_{l,k}(n_{l,k}, \text{GSN}_k) = \frac{L_k \times \text{ETX}_{l,k}}{t_{l,k}\frac{1}{n_{l,k}}T_{l,k}}. \tag{10}$$

Proof: We rewrite the received quality Q_i of each video V_i as

$$Q_i(\sigma_k, \text{GSN}_k) = \sum_{C_k \in C_i} Q_{ik}(\sigma_k, \text{GSN}_k) \tag{11}$$

[2] Note that a CG with weighted players is not desirable for the prioritized video flows, since the Nash equilibrium cannot be guaranteed in this type of game [14].

$$Q_{ik}(\sigma_k, \mathrm{GSN}_k) = \lambda_k R_k \sum_{j=1}^{N_{ik}^f} \alpha_j I(d_j(\sigma_k, \mathrm{GSN}_k) \leq D_k) \\ = \lambda_k R_k N_{ik}^f \gamma_{ik}(\sigma_k, \mathrm{GSN}_k) \tag{12}$$

where γ_{ik} denotes the ratio of the flows of video V_i in class C_k being received successfully at the central monitor. Note that $\gamma_{ik} \times N_{ik}^f$ is the successfully received number of flows by the central monitor in the game GSN_k, which depends on the decision $\boldsymbol{\sigma}_k$ and the corresponding end-to-end delay $d_j(\boldsymbol{\sigma}_k, \mathrm{GSN}_k)$ of a flow f_j. Therefore, maximizing the video quality is equivalent to maximizing the number of high priority flows received at the central monitor, in other words, maximizing $\gamma_{ik}(\sigma_k, \mathrm{GSN}_k)$ in each GSN_k [see (12)]. Note that in a prioritized CG with a GSN_k and a fixed D_k, maximizing $\gamma_{ik}(\boldsymbol{\sigma}_k, \mathrm{GSN}_k)$ is equivalent to minimizing the end-to-end delay $d_j(\boldsymbol{\sigma}_k, \mathrm{GSN}_k)$ for the players (video flows) of the game. Finally, the utility function can be expressed as

$$u_j = d_j(\boldsymbol{\sigma}_k, \mathrm{GSN}_k) = \sum_l \mathrm{ETT}_{l,k}(n_{l,k}(\boldsymbol{\sigma}_k), \mathrm{GSN}_k). \tag{13}$$

From (8) and (13), the cost function is purely a function of $n_{l,k}$. Based on the ERA policy, the video flows in the highest priority class C_1 form a CG that provides a stable allocation solution for these flows, the resulting $R\mathrm{QSN}_1$ can be determined once the equilibrium is reached. Based on the definition of the GSN subnet, the resource allocation problem given a specific GSN_k can also be formulated as a CG, given that the ERA policy is applied. ■

C. Procedures of the Congestion Game Approach

In this section, we provide the procedures of the CG approach as follows.

1) *Step 1:* Collect network information $\mathcal{I}_N$ to the source nodes.
2) *Step 2:* Form the QSNs and GSNs based on the predetermined time fraction $t_{l,k}$.
3) *Step 3:* Starting from the highest priority class, the source nodes construct the CG by using the ERA policy. Obtain the Nash equilibrium
$$\sigma_k^* = \left[t_{l,j}^* = \frac{1}{n_{l,k}^*}, f_j \in C_k, \forall l \in E_k' \right].$$
4) *Step 4:* Send the time sharing fraction $t_{l,j}^*$ to the corresponding relay nodes in the network.
5) *Step 5:* Set $k = k + 1$. Form GSN_k based on (7) and go back to Step 3.
6) *Step 6:* After all the flows have their transmission time allocation, send the video flows according to their priorities and time sharing fractions.

Fig. 3 illustrates how the CG approach based on the prioritized CG is performed.

D. Price of Anarchy

To assess the performance of that Nash equilibrium determined by the CG approach, we can compare the final

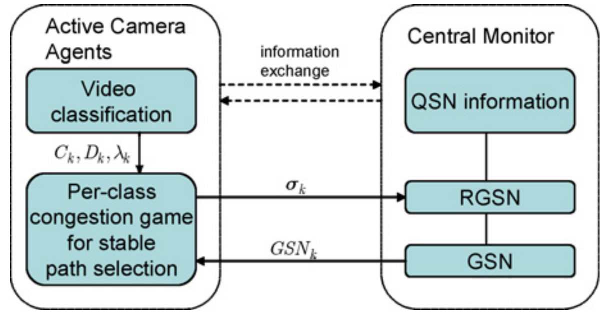

Fig. 3. Per-class CG played by individual flows with different GSNs.

video quality induced based on the Nash equilibrium with the centralized solution. Similarly, in [16], a measure called PoA was determined for quantifying the performance of the obtained Nash equilibrium, which is defined as the ratio of the worst case Nash equilibrium cost to the social optimum cost. The socially optimal cost is defined as a *global* measure of performance in [27]. In our paper, the social optimal solution is assumed to be obtained based on the CO approach. We define the PoA in terms of video quality. We can express the PoA in terms of video quality PoA_Q as

$$\mathrm{PoA}_Q = \frac{\sum_i Q_i^{\mathrm{CG}}}{\sum_i Q_i^*} \tag{14}$$

where Q_i^{CG} and Q_i^* denote the final video quality based on Nash equilibrium obtained from the CG approach and the optimal solution from the CO approach, respectively.

V. DG Approach for Resource Allocation

In this section, we introduce a distributed approach that enables both the source and the relay agents to make autonomous resource allocation decisions based on local available information.

A. Distributed Optimization with Local Information

Due to the informationally-decentralized nature of the wireless surveillance network, the information availability can be limited to neighboring network relays rather than to the resource nodes. For instance, the optimal solution in the centralized approach depends on the delay incurred by the various packets across the hops, which cannot be timely relayed to the central controller. Instead, a fully distributed solution can be deployed, where each agent (source nodes and also network relays) individually optimizes the various video transmissions. The private multimedia traffic information $\mathcal{I}_S$ can be extracted from the video packet header for the parameters such as the quality impact λ_k, and the delay deadline D_k. At each agent $\mathcal{N}$, denote $\boldsymbol{\sigma}_{\mathcal{N}} = \{t_{l,j} | l \text{ is directly connected to node } \mathcal{N}, \forall f_j\}$ as the resource allocation for the agent $\mathcal{N}$.

Definition 5: Distributed Resource Allocation in Wireless Surveillance Networks: Given $\nu_{\mathcal{N}}$, the local network information available from the other agents to the agent $\mathcal{N}$, the distributed optimization for an agent $\mathcal{N}$ is defined as

$$\begin{aligned}
\boldsymbol{\sigma}_{\mathcal{N}}^{\text{dis}}(\nu_{\mathcal{N}}) &= \arg\max_{\boldsymbol{\sigma}_{\mathcal{N}}\in\mathcal{A}^{\mathcal{N}}}\{E[U_{\text{tot}}(\boldsymbol{\sigma}_{\mathcal{N}},\nu_{\mathcal{N}})]\} \\
\text{s.t. } & \sum_{j=1}^{J} t_{l,j} \le 1,\ l \text{ around } \mathcal{N} \\
& E[d_j^{\mathcal{N}}(\boldsymbol{\sigma}_{\mathcal{N}},\nu_{\mathcal{N}})] \le D_k - d^{\text{cur}},\ \ f_j \in C_k. \qquad (15)
\end{aligned}$$

Denote d^{cur} as the current time and $E[d_j^{\mathcal{N}}(\boldsymbol{\sigma}_{\mathcal{N}},\nu_{\mathcal{N}})]$ as the expected delay from node $\mathcal{N}$ to the central controller $\mathcal{N}^c$.

Due to the unavailability of the global information, the agent can only maximize the expected utility $E[U_{\text{tot}}(\boldsymbol{\sigma}_{\mathcal{N}},\nu_{\mathcal{N}})]$, based on the available *local* information $\nu_{\mathcal{N}}$. The time allocation constraint on each link l is also considered only around the node $\mathcal{N}$. A greedy algorithm is proposed for this distributed resource allocation problem in [19]. The DG approach requires local network information $\nu_{\mathcal{N}}$ to perform successive local optimization in (15). The greedy algorithm first sorts the packets at agent $\mathcal{N}$ according to their quality impact λ_k, and then allocates the $\boldsymbol{\sigma}_{\mathcal{N}}$ for the flow f_j with the maximum λ_k by selecting the next relay that provides the largest $E[Q_i]$, $f_j \in V_i$. From (4) and (2), the following simplification is applied to (15) [19]:

$$\begin{aligned}
\boldsymbol{\sigma}_{\mathcal{N}}^{\text{sub}}(\nu_{\mathcal{N}}) &= \arg\max_{\boldsymbol{\sigma}_{\mathcal{N}}\in\mathcal{A}^{\mathcal{N}}}\{E[Q_i(\boldsymbol{\sigma}_{\mathcal{N}},\nu_{\mathcal{N}})]\} \\
&= \arg\min_{\boldsymbol{\sigma}_{\mathcal{N}}\in\mathcal{A}^{\mathcal{N}}} E[d_j(\boldsymbol{\sigma}_{\mathcal{N}},\nu_{\mathcal{N}})] \\
&= \arg\min_{\boldsymbol{\sigma}_{\mathcal{N}}\in\mathcal{A}^{\mathcal{N}}} E[d_j^{\mathcal{N}}(\boldsymbol{\sigma}_{\mathcal{N}},\nu_{\mathcal{N}})] \\
&\qquad \text{for } f_j \text{ with the largest } \lambda_k.
\end{aligned} \qquad (16)$$

As long as the resource allocation for the scheduled packet (with maximum λ_k) of the flow f_j does not violate the constraints in (15), the packet is considered to be transmitted through the relay $\mathcal{N}$ with the minimum expected delay from the relay $\mathcal{N}$ to the destination, i.e., the minimum $E[d_j^{\mathcal{N}}]$. Note that the distributed approach constantly relies on the varying network information $\nu_{\mathcal{N}}$ to perform a "local" optimization. Since we apply the greedy algorithm based on the local information, the result is suboptimal and may not converge to a stable set of paths in a general network topology.

B. Price of Convergence

The performance of a DG approach is significantly impacted by the amount of required information overhead. Assume that $\chi(\mathcal{G}, P(\omega,\eta))$ represents the required network resource for the frequently required information overhead, which depends on the network settings $\mathcal{G}$ (including the network topology, available resource, network variation characteristics), and the protocols adopted for the DG approach (including the frequency ω of the interactions across the agents, the percentage of transmission bandwidth η that is devoted to the information exchange).

Definition 6 (Price of Convergence): We defined the PoC as the ratio of the performance of the corresponding DG approach and the performance of the CG approach. In terms of the received video qualities, we define the PoC_Q as

$$\text{PoC}_Q(\chi(\mathcal{G}, P(\omega,\eta))) = \frac{\sum_i Q_i^{\text{CG}}}{\sum_i Q_i^{\text{DG}}(\chi(\mathcal{G}, P(\omega,\eta)))} \qquad (17)$$

where Q_i^{DG} denotes the corresponding video quality based on the mentioned DG approach. Based on the PoC, we can identify in what situation it is worth applying the prioritized CG for the delay-sensitive video applications to guarantee the convergence.

VI. Comparison of the Various Resource Allocation Approaches

A. Computational Complexity

In this section, we first analyze the computational complexities of the three approaches in terms of the number of selectable paths when making the allocation decisions.

1) *Complexity of the CO Approach (Exhaustive Search):* Assume that we have a total of K classes in an H-hop network. Let us assume that the maximum number of intermediate nodes that can be selected as a relay for a class C_k flow at the hth hop is $\mathcal{C}_{k,h}$. The maximum number of possible end-to-end paths is then $\prod_{h=1}^{H}\mathcal{C}_{k,h}$. Thus, the total complexity (in terms of the number of path combinations) of an exhaustive search can be up to $\prod_{k=1}^{K}\prod_{h=1}^{H}\mathcal{C}_{k,h}$.

2) *Complexity of the CG Approach:* Since the maximum number of possible end-to-end paths is $\prod_{h=1}^{H}\mathcal{C}_{k,h}$ for the class C_k flows, the total complexity of playing the K CGs in their corresponding GSN is approximately $\sum_{k=1}^{K}\prod_{h=1}^{H}\mathcal{C}_{k,h}$.

3) *Complexity of the DG Approach:* In the distributed approach, the relay selection complexity is $\mathcal{C}_{k,h}$ for a packet (of class C_k) at an agent at the hth hop (i.e., $\mathcal{C}_{k,h}$ is the number of relays that can be selected in the next hop). Thus, the complexity for the packet over H hops is $\sum_{h=1}^{H}\mathcal{C}_{k,h}$. Then, the total complexity by considering all the video classes equals $\sum_{k=1}^{K}\sum_{h=1}^{H}\mathcal{C}_{k,h}$.

B. Information Overhead

Next, we discuss the required information overhead of the three approaches in an H-hop network. Various information exchange parameters lead to different transmission overheads. As mentioned in Section II-E, there are two types of information exchanges. The public (network condition) information exchange $\mathcal{I}_N$ conveys the channel condition and the expected number $n_{l,k}$ of flows in the CG. The private information exchange $\mathcal{I}_S$ includes the video characteristics information. We assume that the information feedback units are I_u^N and I_u^S for the two types of information exchanges, respectively. We perform a worst-case analysis by assuming that the average number of relays per hop is R and thus, the total number of links per hop is approximately R^2.

1) *Information Overhead of the CO Approach:* Since the network information is fed back from the whole network to the central monitor for the global optimization, the information overhead from the relays that is h hops away from the central monitor is $h \cdot R^2 \cdot I_u^N$. Thus, the network information overhead is $H(H-1)/2 \cdot R^2 \cdot I_u^N$. The remaining two required parameters are across the H hops and may be different for various video classes. Thus, the total information overhead is $H(H-1)/2 \cdot R^2 \cdot I_u^N + K \cdot H \cdot I_u^S$.

TABLE I
VIDEO CHARACTERISTICS

Coastguard	C_k	λ_k [dB/(kb/s)]	R_k(kb/s)	D_k(s)
f_1, f_2, f_6, f_7	C_1	0.0105	250	0.533
f_3, f_8	C_2	0.0064	300	0.533
f_4	C_3	0.0048	300	0.533
f_5	C_4	0.0042	400	0.533

2) *Information Overhead of the DG Approach:* For the DG approach, the allocation can be constantly adjusted to improve the received video qualities. Since the network information is fed back per hop to enable the link adaptation as well as to facilitate the polling control signaling, the network information overhead in terms of the information feedback unit is $R \cdot I_u^N$ for each agent. The number of all the nodes in the network is approximately HR, and hence the network information overhead is $HR \cdot R \cdot I_u^N$. Note that the DG approach is performed repeatedly. Assume that the information is exchanged for m_d times over the measured experiment time window W_t (i.e., the interaction frequency $\omega = m_d / W_t$). The total information overhead is $m_d \cdot HR^2 \cdot I_u^N$.

3) *Information Overhead of the CG Approach:* For the CG, assume that the K games will converge to the equilibrium in at most m_c iterations. The total information overhead is $m_c \cdot H(H-1)/2 \cdot R^2 \cdot I_u^N$. In conclusion, if the CGs converge fast enough (i.e., $m_c \ll m_d$), the required information overhead of the CG approach can be much less than the DG approach.

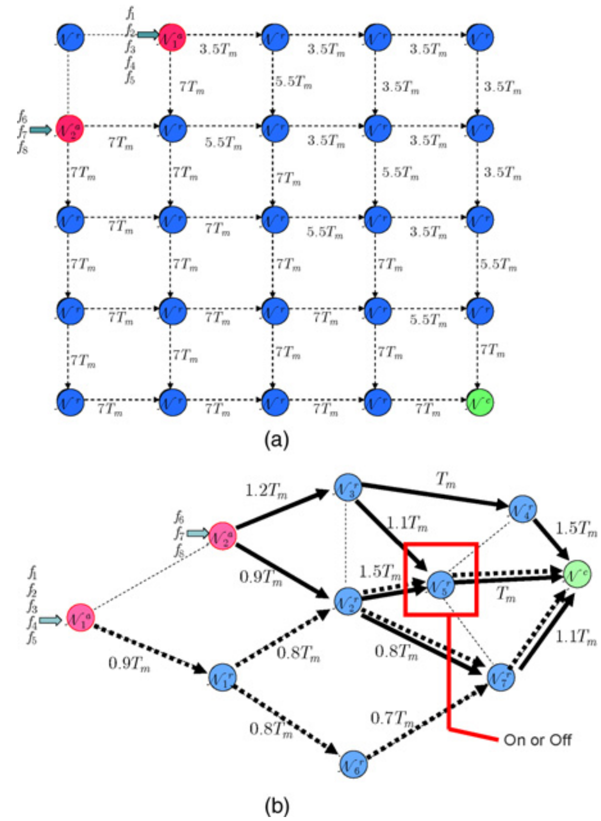

Fig. 4. Considered topologies for the wireless surveillance network. (a) Grid network. (b) Mesh network.

VII. SIMULATION RESULTS

We simulate two active cameras in wireless surveillance networks. We consider two different topologies shown in Fig. 4. The *Coastguard* video sequence (16 frames per group of picture at a frame rate of 30 Hz) is compressed using the video codec [20]. The compressed video packets are categorized into five flows in four classes as given in Table I (see [17] for more details on how to determine the parameters). The video V_1 captured by the camera $\mathcal{N}_1^a$ has a better resolution video $V_1 = \{f_1, f_2, f_3, f_4, f_5\}$ than the video $V_2 = \{f_6, f_7, f_8\}$, captured by the camera $\mathcal{N}_2^a$. We compare the proposed CG approach with the CO approach (optimal) and the DG approach [19] with various network efficiency T_m. The various efficiency levels are represented by varying the available time fraction for the contention-free period in the polling-based MAC protocol as in [19], which induces the various transmission rates for the video flows over the links. In addition, under the same testing conditions, we also compare these solutions with another distributed approach [22], referred here as the reactive QoS routing approach (RQ).

For the CO approach, we assume that the global information is available to the central monitor at the beginning of the session (video transmission). Hence, the central monitor can exhaustively search for the paths that provide optimal video quality over wireless surveillance network regardless of the high computational complexity involved in the optimization. For the CG approach, each video flow is transmitted based on the equilibrium resource allocation of the prioritized CGs. For the DG approach, each network node applies the described DG optimization approach [19]. For the RQ approach [22], a path discovering period τ is required for conveying the path probing information among across the network nodes before the video streaming with a certain path, which directly impacts the delay deadline of the video transmissions.

A. Simulations Over Wireless Networks Under Static Channel Assumption

First, we simulate these four approaches using the grid network topologies shown in Fig. 4(a). Fig. 5 shows the PSNR of the two video streams versus the network efficiency T_m from 1 Mb/s to 4 Mb/s. As the network efficiency increases, the PSNR of both videos increase. All approaches can achieve the upper bound, i.e., the CO approach, when the network efficiency is high enough. Note that the input source rate R_k is fixed, hence the video quality will saturate when the video is 100% received by the central monitor when the network efficiency is high. We can see that the CG approach has worse performance when the network efficiency is low, since the CG approach is based on the ERA policy that limits the flexibility of obtaining different transmission rates over a transmission link. However, the performance of the CG approach increases rapidly when the network efficiency increases. Fig. 6 shows the PoC and PoA of the CG approach as the network efficiency increases [using (14) and (17), respectively]. The results show that the CG approach slightly outperforms the DG approach,

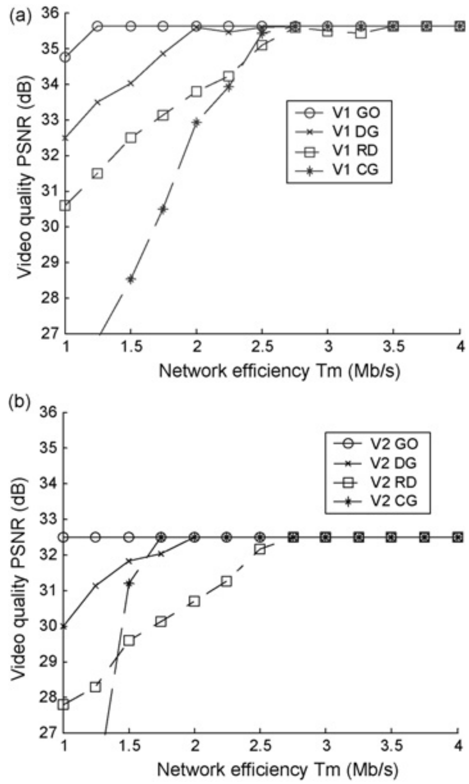

Fig. 5. Quality performance of the four approaches for various network efficiencies in the grid network. (a) Video 1. (b) Video 2.

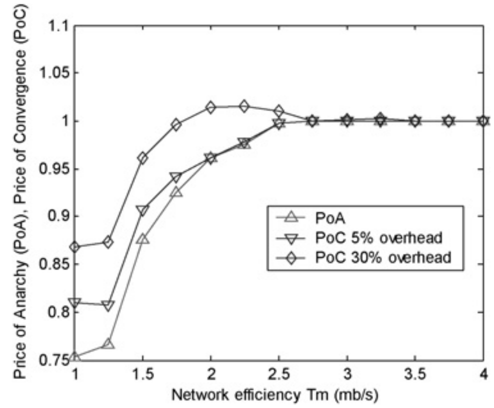

Fig. 6. PoC and PoA of the prioritized CG versus network efficiency in the grid network.

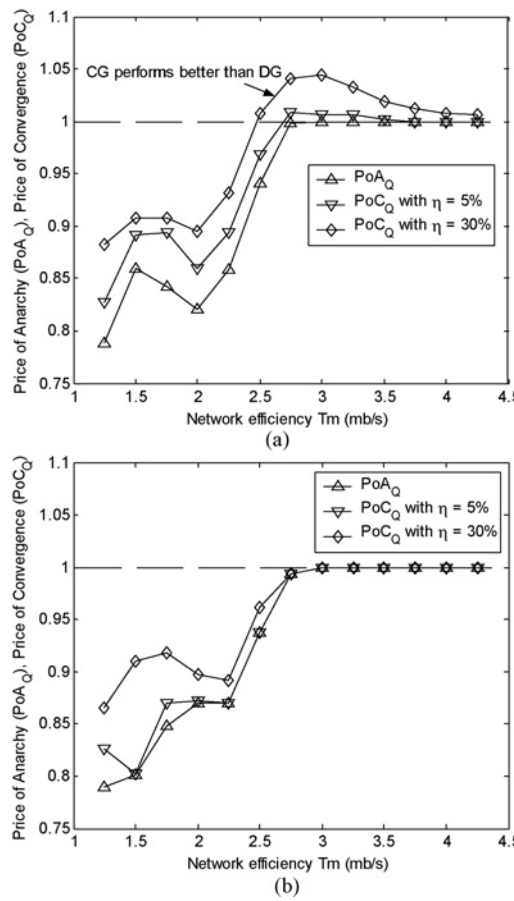

Fig. 7. PoC and PoA of the prioritized CG versus network efficiency in the mesh network. (a) $\mathcal{N}_5^r$ is off. (b) $\mathcal{N}_5^r$ is on.

i.e., $\text{PoC}_Q \geq 1$, when T_m is high enough ($T_m \geq 2$ Mb/s) and the information exchange overhead is small enough (η = 5%). This is because the inefficiency of the ERA policy is alleviated when the network efficiency is high.

Next, we simulate using the mesh network topologies shown in Fig. 4(b). Fig. 7 shows the PoC and PoA of the CG approach in the mesh network in Fig. 4(b). Note that in Fig. 7(a) when $\mathcal{N}_5^r$ is off, $\text{PoC}_Q \geq 1$ is available even the information overhead is extremely high (η = 30%). However, when $\mathcal{N}_5^r$ is on, the DG approach is shown in Fig. 7(b) to always outperform the CG approach, since the additional relay significantly improves the DG approach, which is optimized hop by hop [19]. The simulation highlights that the merit of the game-theoretic equilibrium highly depends on: 1) the network topologies; 2) the network efficiencies; and 3) the information exchange overheads. The convergence brought by the CG approach can benefit the video quality only when the network efficiency is high enough to alleviate the disadvantage of ERA policy.

B. Simulations Over Dynamic Networks With Topology Changes

In the previous simulation, we considered an idealized setting where the network is static. However, the wireless environment is time-varying, and thus, both the link conditions and the network topology may change over time. Hence, we simulate a dynamic network case that the network topology changes in the middle of the simulation time. Our simulation was performed using the mesh network topology in Fig. 4(b). This simple setup allows us to investigate the impact of specific path selections. During the experiment time window (at the 10th second), the network relay $\mathcal{N}_5^r$ disappears due to relay breakdown for half of the simulation time. Fig. 8 shows the time plot of the PSNR and path selection for the two video streams when $T_m = 2$ Mb/s. Since the resource allocation of the CG approach cannot adapt to the network changes as fast as the DG approach, its path selection remains the same within the simulation time window based on the CG

TABLE II
COMPLEXITY AND THE REQUIRED INFORMATION OVERHEAD OF THE THREE APPRAOCHES

Different Approaches	One-Time Computational Complexity			Required Information Overhead		
	CO	CG	DG	CO	CG $m_c \cong 10$	DG $m_d \cong 300$
$\mathcal{N}_5^r$ on	180	27	10	$29I_u^N+22I_u^S$	$41m_cI_u^N$	$13m_dI_u^N$
$\mathcal{N}_5^r$ off	60	16	10	$24I_u^N+22I_u^S$	$27m_cI_u^N$	$10m_dI_u^N$

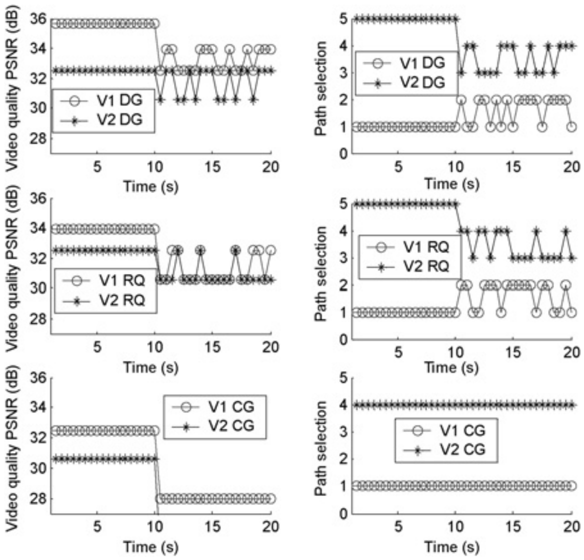

Fig. 8. Video qualities and the selected path of the DG approach and CG approach (T_m = 2 Mb/s). Only the paths of the most important flows of the two videos are shown.

equilibrium. The simulation shows that the CG approach has even more performance degradation because of its inability to timely adapt to the network changes.

In Fig. 9, we plot the time average PSNR under different network efficiencies. We can see that unlike the DG approach and the RQ approach, the decision maker(s) of the CO approach (the central monitor) and the CG approach (the source cameras) cannot timely adapt to such network changes and hence, they result in erroneous decisions made at the beginning of the experiment. In such cases, the results show that the DG approach and the RQ approach outperform all the other approaches.

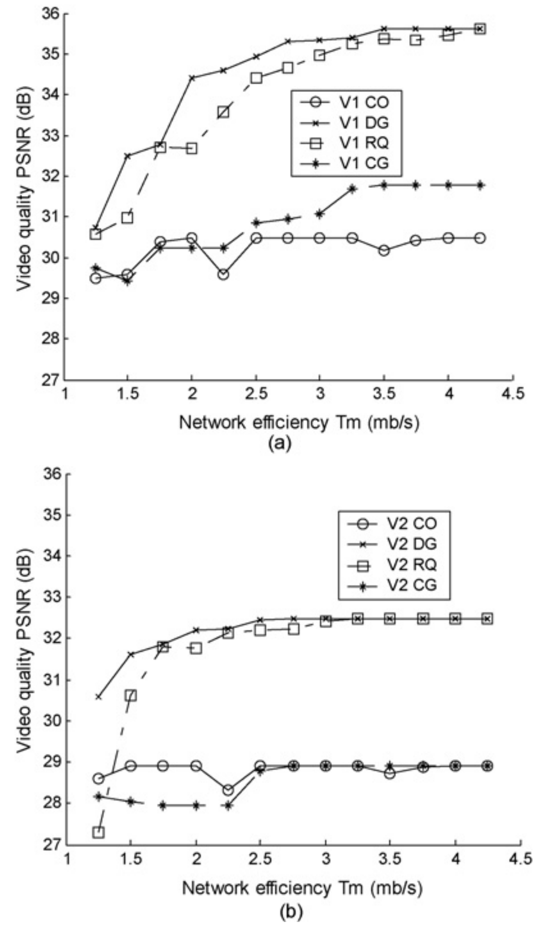

Fig. 9. Quality performance of the four approaches for various network efficiencies in the dynamic mesh network.

C. Computational Complexity and Required Information Overhead

In Table II, we provide the results of the computational complexity and the required information overhead of the three approaches as discussed in Section VI with the mesh network topology shown in Fig. 4(b). We can see that the CG approach has significantly lower information exchange overhead than the DG approach, since the convergence is guaranteed for the CG approach. However, as in the previous simulation, the benefit from the convergence is limited in a dynamic environment. The fixed resource allocation performed at Nash equilibrium (convergence) can lead to significant performance degradation. In addition, although the CO approach can also be performed repeatedly for an adaptive optimal solution, this is often undesirable in practice due to the exponentially increased complexity required by the CO approach.

D. Qualitative Analysis of the Three Approaches

Table III provides a qualitative comparison of the three approaches, which highlights the following aspects.

1) In large-scale wireless surveillance networks, the CO approach is not suitable, due to its high complexity and its inadaptability to the source and network dynamics.
2) The CG approach significantly reduces the complexity and the information overhead required for transmitting the video information from the camera sources. However, its performance considerably decreases when the network efficiency is low, since the CG approach is based on the ERA policy, which limits the flexibility of obtaining different transmission rates over a transmission link.

TABLE III
COMPARISONS AMONG THE CO, CG, AND DG APPROACHES

	CO	CG	DG
Decision maker	Central monitor	Active camera agents	Active camera agents and relay agents
Decision on the resource allocation	$\boldsymbol{\sigma} = \{t_{l,j}, \forall l, \forall f_j\}$	$\boldsymbol{\sigma}_k = \{t_{l,j}, \forall l, \forall f_j \in C_k, \forall l \in \mathbf{E}'_k\}$	$\boldsymbol{\sigma}_{\mathcal{N}} = \{t_{l,j} \| l \text{ adjacent to } \mathcal{N}, \forall f_j\}$
Video quality performance in a static network	Optimal	Suboptimal	Suboptimal
Video quality performance in a dynamic network	Poor	Poor	Acceptable due to the adaptability
Adaptability to network and source dynamics	Low	Medium	High
Flexibility of assigning the transmission bandwidth to the video flows	High	Low (due to the ERA policy of the game)	High
Computational complexity (one-time operation)	High	Medium	Low
Required information overhead	Medium	Low	High (constantly required)
Public network information availability	Global	Global	Local
Private multimedia information exchange	Required	Not required	Not required

3) Since the DG approach allows each network node to make autonomous decision based on local information, the decisions of the neighboring nodes are coupled. Hence, periodic local information exchanges are needed to provide the nodes the available information for making their resource allocation decisions that maximize the video quality received by the monitor. In a more static network, the required information overhead of the DG approach can be significantly larger than the CG approach. This high information overhead leads to a worse performance for the DG approach than the CG approach, when the information exchange overhead η is large (see the PoC in Fig. 7).
4) In a dynamic network, although the CG approach provides stable allocation results that reduce the required information overhead, the performance degradation is much higher than the DG approach (which also has performance degradation due to large information overhead). This shows that resource allocation solutions in a dynamic wireless surveillance network need to explicitly consider the dynamic source and network characteristics, rather than rely on static allocation results.

VIII. CONCLUSION

We considered a surveillance system, aimed at capturing and transmitting the videos of several distributed cameras in real-time, over a wireless multihop network, to a central monitor. Our focus in this paper was on comparing three different types of resource allocation solutions, where the decisions are made by the central monitor, the autonomous cameras, or the autonomous cameras and the relay nodes, respectively. To allow the camera agents to perform their decisions in an autonomous manner, while explicitly considering the distortion impact of their gathered video content, we modeled the wireless surveillance network as a prioritized CG played among the multiple cameras. The primary advantage of the CG modeling is that it guarantees convergence to a Nash equilibrium, i.e., a stable allocation is determined and no information needs to be exchanged. To evaluate the performance of the CG approach compared with the DG approaches in a realistic network setting, we introduced a new performance metric, the PoC. Based on this, we are able to identify the cases when playing the CG modeling in order to guarantee convergence is desirable for the cameras. Based on our simulations, we determined that the CG modeling outperforms the distributed approach in a static network, where the information exchange overhead η is large. Besides the video quality performance, we also compared the CG modeling with the centralized optimized approach and DG approach in terms of the computational complexity, the required information overhead, and the adaptability to the network and source variation. It is shown that the proposed prioritized CG modeling can effectively reduce the complexity and the required information overhead in the considered surveillance application, but suffers from a poor performance when the network transmission efficiency is low. In such cases, performing the DG approach will result in a much better performance. This is also the case when the network dynamically changes over time. Summarizing, the study presented in this paper provides multimedia system designers with the tradeoff possible when implementing such a system in terms of performance, complexity and information overheads for different usage scenarios.

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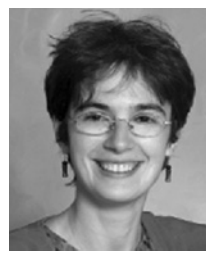

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