A decentralized cross-layer approach to cooperative video transmission

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***Abstract*—We investigate the impact of cooperative relaying on uplink multi-user (MU) wireless video transmission. We formulate the problem as an MU Markov decision process (MDP) that explicitly considers the cooperation at the physical layer and the medium access control sublayer, the video users' heterogeneous traffic characteristics, and the dynamically varying network conditions. Although MDPs notoriously suffer from the curse of dimensionality, our study shows that the complexity of the MU-MDP can be mitigated. Our simulation results show that cooperation allows users with feeble direct signals to achieve improvements in video quality on the order of 5-10 dB peak signal-to-noise ratio, with less than 0.8 dB quality loss by users with strong direct signals.**

I. Introduction

Existing wireless networks provide dynamically varying resources with only limited support for the Quality of Service (QoS) required by delay-sensitive, bandwidth-intense, and loss-tolerant multimedia applications. This problem is further exacerbated in multi-user (MU) settings because they require multiple video streams, with heterogeneous traffic characteristics, to share the scarce wireless resources. To address these challenges, recent research has focused on MU wireless communication [1], [2], [3] and MU wireless video streaming [4], [5], [6]. In MU video streaming applications [4], [5], [6], cross-layer optimization is deployed to strike a balance between scheduling users who experience very good fades, and serving users who have the highest priority video data. This tradeoff is important because rewarding a few lucky participants, as opportunistic multiple access policies do [2], does not translate to providing good quality to the application (APP) layer. Unfortunately, with the exception of [3], [6], the aforementioned research assumes that wireless users are *noncooperative*. This leads to a basic inefficiency in the way that the network resources are assigned: indeed, good fades experienced by some nodes can go to waste because users with higher priority video data, but worse fades, get access to the shared wireless channel.

A way to not let good fades go to waste is to enlist the nodes that experience good fades as cooperative helpers, using a number of techniques available for cooperative coding (e.g [7]). As mentioned above, this idea has been considered in [3], [6]. In [6], for example, layered video coding is integrated with randomized cooperation to enable efficient video multicast in a cooperative wireless network. Because it is a multicast system, there is no need for an optimal multiple-access strategy, and no need to worry about heterogeneous traffic characteristics. Additionally, in both [3], [6], it is assumed that each user has a static utility function of the average transmission rate.

In this paper, our solution is inspired by the cross-layer resource allocation and scheduling solution in [5], in which the MU wireless video streaming problem is modeled and solved as an MU Markov decision process (MDP) that allows the users, via a uniform resource pricing solution, to obtain long-term optimal video quality in a distributed fashion. Unlike [3], [6], the solution we adopt from [5] explicitly considers packet-level video traffic characteristics (instead of flow-level) and dynamic network conditions (instead of average case conditions). However, as recently shown in [8], augmenting the framework developed in [5] to also account for cooperation is challenging because of the complexity of the resulting cross-layer MU-MDP optimization. This paper is different from our prior work [8] because in this paper we address the complexity issue and introduce a new distributed cooperation protocol for recruiting cooperative relays.

The contributions of this paper are threefold. First, we formulate the cooperative wireless video transmission problem as an MU-MDP using a time-division multiple-access (TDMA)-like network, randomized space-time block coding (STBC) [9], and a decode-and-forward cooperation strategy. We show analytically that the decision to cooperate can be made opportunistically, independently of the MU-MDP. Second, we propose a distributed, low complexity, opportunistic cooperative strategy for exploiting good fades in an MU wireless network. Third, we show experimentally that users with feeble direct signals to the access point (AP) are conservative in their resource usage when cooperation is disabled, but utilize resources more aggressively when it is enabled. Consequently, the uniform resource price that is designed to manage resources in the network tends to increase when cooperation is enabled in a congested network.

The remainder of the paper is organized as follows. We introduce the system and application models in Section II and Section III, respectively. In Section IV, we present the proposed MU cross-layer optimization. In Section V, we

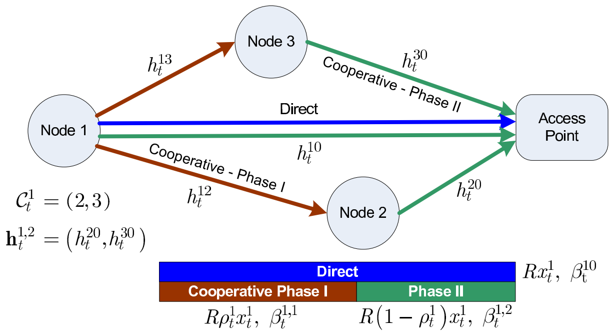

Fig. 1: An uplink wireless video network with cooperation.

compute the transmission and packet error rates for both direct and cooperative transmission modes, and propose a distributed protocol for opportunistically recruiting cooperative relays. Finally, we report numerical results in Section VI and conclude in Section VII.

II. System Model

We consider a network composed of M users streaming video content over a shared wireless channel to a single AP (see Fig. 1). Such a scenario is typical of many uplink media applications, such as remote monitoring and surveillance, wireless video sensors, and mobile video cameras. We assume that time is slotted into discrete time-intervals of length $R > 0$ seconds indexed by $t \in \mathbb{N}$. In slot t, the AP endows the ith user with the resource fraction x_t^i at the medium access control (MAC) layer, where $0 \leq x_t^i \leq 1$. Let $\mathbf{x}_t \triangleq (x_t^1, x_t^2, \ldots, x_t^M)^T \in \mathbb{R}^M$ denote the resource allocation vector at time slot t, which must satisfy the stage resource constraint $\|\mathbf{x}_t\|_1 = \sum_{i=1}^M x_t^i \leq 1$. Each node's physical (PHY) layer is assumed to handle quadrature amplitude modulation (QAM) square constellations, with a (fixed) symbol rate of $1/T_s$ symbols per second. We consider a frequency non-selective block fading model, where $h_t^{i\ell} \in \mathbb{C}$ denotes the fading coefficient over the $i \rightarrow \ell$ link in time slot t, with $i \neq \ell \in \{0, 1, 2, \ldots, M\}$, and node 0 corresponding to the AP. It is assumed that all the channels are dual, i.e., $|h_t^{i\ell}| = |h_t^{\ell i}|$, and that the fading coefficients $h_t^{i\ell}$ are i.i.d. with respect to t. We define $\mathbf{H}_t \in \mathbb{C}^{M \times M}$ as the matrix collecting the fading coefficients among all of the nodes and the AP, i.e., $\{\mathbf{H}_t\}_{i\ell} = h_t^{i\ell}$, for $i \neq \ell \in \{0, 1, 2, \ldots, M\}$.

At the PHY layer, there are two transmission modes to choose from: direct and cooperative. Let $z_t^i \in \{0, 1\}$ denote the cooperation decision. In the *direct* transmission mode ($z_t^i = 0$), as shown in Fig. 1, the ith source node transmits directly to the AP at the data rate (per unit of bandwidth) β_t^{i0}, measured in bits/second/Hz, for $R\,x_t^i$ seconds. In the *cooperative* transmission mode ($z_t^i = 1$), the assigned transmission time is divided into two phases as illustrated in Fig. 1: in *Phase I*, the ith source node directly broadcasts its own data to all the nodes in the network at the data rate $\beta_t^{i,1}$ (bits/second/Hz) for $R\,\rho_t^i\,x_t^i$ seconds, where $0 < \rho_t^i < 1$ is the Phase I time fraction; in *Phase II*, some of the nodes overhearing the source transmission demodulate the data received in Phase I, re-modulate the original source bits, and then cooperatively transmit towards the AP, along with the source i, at the data rate $\beta_t^{i,2}$ (bits/second/Hz) for the remaining $R\,(1-\rho_t^i)\,x_t^i$ seconds. Thus, the *cooperative data rate* $\beta_t^{i,\text{coop}}$ (bits/second/Hz) is a convex combination of the data rates attainable in these two phases, i.e., $\beta_t^{i,\text{coop}} = \rho_t^i\,\beta_t^{i,1} + (1-\rho_t^i)\,\beta_t^{i,2}$. In Section V, we compute the transmission parameters β_t^{i0}, $\beta_t^{i,1}$, and $\beta_t^{i,2}$.

Notation: A circular symmetric complex Gaussian random variable X with mean μ and variance σ^2 is denoted as $X \sim \mathcal{CN}(\mu, \sigma^2)$; and, $\lfloor \cdot \rfloor$ denotes flooring-integer.

III. Application Model

To accurately capture the characteristics of the video packets, we adopt the sophisticated video traffic model proposed in [5], which accounts for the fact that video packets have different deadlines, distortion impacts, and source-coding dependencies

For $i \in \{1, 2, \ldots, M\}$, the *traffic state* $\mathcal{T}_t^i \triangleq \{\mathcal{F}_t^i, \mathbf{b}_t^i\}$ represents the video data that the ith user can potentially transmit in time slot t, and comprises the following two components: the schedulable frame set $\mathcal{F}_t^i$ and the buffer state $\mathbf{b}_t^i$. In time slot t, we assume that the ith user can transmit packets belonging to the set of video frames $\mathcal{F}_t^i$ whose deadlines are within the scheduling time window (STW) $[t, t+W]$. The buffer state $\mathbf{b}_t^i \triangleq (b_{t,j}^i \,|\, j \in \mathcal{F}_t^i)^T$ represents the number of packets of each frame in the STW that are awaiting transmission at time t. The jth component $b_{t,j}^i$ of $\mathbf{b}_t^i$ denotes the number of packets of frame $j \in \mathcal{F}_t^i$ remaining for transmission at time t. We assume that each packet has size P bits.

In each time slot t, the ith user's scheduling action $\mathbf{y}_t^i \triangleq (y_{t,j}^i \,|\, j \in \mathcal{F}_t^i)^T$, determines the number of packets to transmit out of $\mathbf{b}_t^i$. Its jth component $y_{t,j}^i$ represents the number of packets of the jth frame within the STW that are transmitted in time slot t. The scheduling action $\mathbf{y}_t^i$ is constrained to be in the feasible scheduling action set $\mathcal{P}^i(\mathcal{T}_t^i, \mathbf{H}_t)$, which imposes the following three constraints:

1) *Buffer*: $0 \leq y_{t,j}^i \leq b_{t,j}^i$.
2) *Packet*: The total number of transmitted packets must satisfy $\|\mathbf{y}_t^i\|_1 = \sum_{j \in \mathcal{F}_t^i} y_{t,j}^i \leq \frac{R\,\beta_t^i}{P\,T_s}$.
3) *Dependency*: If there exists a packet k that has not been transmitted, and packet j depends on k, then $\left(b_{t,k}^i - y_{t,k}^i\right) y_{t,j}^i = 0$.

The sequence of traffic states $\{\mathcal{T}_t^i : t \in \mathbb{N}\}$ can be modeled as a controllable Markov chain with transition probability function $p(\mathcal{T}_{t+1}^i \,|\, \mathcal{T}_t^i, \mathbf{y}_t^i)$.

IV. Cooperative Multi-User Video Transmission

The global state can be defined as $\mathbf{s}_t \triangleq \{\mathcal{T}_t^1, \mathcal{T}_t^2, \ldots, \mathcal{T}_t^M, \mathbf{H}_t\} \in \mathcal{S}$, where $\mathcal{S}$ is a discrete set of all possible states.[1] The sequence of global states

[1]To have a discrete set of network states, the individual link states in $\mathbf{H}_t$ are quantized into a finite number of bins.

$\{\mathbf{s}_t : t \in \mathbb{N}\}$ can be modeled as a controlled Markov chain with transition probability function

$$p(\mathbf{s}_{t+1} \,|\, \mathbf{s}_t, \mathbf{y}_t) = p\left(\mathbf{H}_{t+1}\right) \prod_{i=1}^{M} p(\mathcal{T}_{t+1}^i \,|\, \mathcal{T}_t^i, \mathbf{y}_t^i)\,, \quad (1)$$

where $\mathbf{y}_t \triangleq (\{\mathbf{y}_t^1\}^T, \{\mathbf{y}_t^2\}^T, \ldots, \{\mathbf{y}_t^M\}^T)^T$ collects the scheduling actions of all the users. Moreover, under the scheduling action $\mathbf{y}_t^i$, the ith user obtains the immediate utility $u^i(\mathcal{T}_t^i, \mathbf{y}_t^i) \triangleq \sum_{j \in \mathcal{F}_t^i} q_j^i \, y_{t,j}^i$, which is the total video quality improvement experienced by the ith user under the assumption that quality is incrementally additive [10].

The objective of the MU optimization is the maximization of the *expected discounted sum of utilities* The optimization can be formulated as an MDP that satisfies the following dynamic programming equation

$$U^*(\mathbf{s}) = \max_{\mathbf{y},\mathbf{z}} \left\{ \sum_{i=1}^{M} u^i(\mathcal{T}^i, \mathbf{y}^i) + \alpha \sum_{\mathbf{s}' \in \mathcal{S}} p(\mathbf{s}'|\mathbf{s}, \mathbf{y}) U^*(\mathbf{s}') \right\} \quad (2)$$

subject to $\mathbf{y}^i \in \mathcal{P}^i(\mathcal{T}^i, \mathbf{H})$ and $\sum_{i=1}^M x^i \leq 1$, where x^i is the time-fraction allocated to the ith user, i.e., $x^i = \frac{P\,T_s}{R\,\beta^i} \|\mathbf{y}^i\|_1$, and β^i depends on z^i; the parameter $\alpha \in [0, 1)$ is the "discount factor", which accounts for the relative importance of the present and future utility; and $\mathcal{P}^i(\mathcal{T}^i, \mathbf{H})$ is the set of feasible scheduling actions.

Given the distributions $p(\mathbf{H})$ and $p(\mathcal{T}^{i\prime} \,|\, \mathcal{T}^i, \mathbf{y}^i)$ for all i, the above MU-MDP can be solved by the AP using value iteration. However, there are two challenges associated with solving the above MU-MDP. First, the complexity of solving (2) scales exponentially with the number of users, i.e., M, and with the number of links in $\mathbf{H}$, i.e., M^2. We show that the exponential dependence on the number of links in $\mathbf{H}$ can be eliminated. Second, the traffic state information is local to the users, so neither the AP nor the users have enough information to solve the above MU-MDP. We summarize the findings in [5] that show that the considered optimization can be approximated to make it amenable to a distributed solution. Additionally, this distributed solution eliminates the exponential dependence on the number of users.

If we can show that the optimal opportunistic (i.e., myopic) cooperation decision is also long-term optimal, then the detailed network state information does not need to be included in the MU-MDP, and we can eliminate the exponential dependence on the number of links in the network. The following theorem shows that opportunistic cooperation is optimal.

Theorem 1 (Opportunistic cooperation is optimal): The optimal opportunistic cooperation decision, which maximizes the immediate transmission rate, also optimizes (2).

Proof: The proof follows from the fact that the set of feasible scheduling actions under the optimal opportunistic cooperation decision is a superset of the set of feasible scheduling actions under the suboptimal cooperation decision. The details are omitted due to space limitations. ■

A consequence of Theorem 1 is that the cooperation decision vector $\mathbf{z}$ does not need to be included in the MU-MDP. Instead, $\mathbf{z}$ can be set to maximize the immediate transmission rate. Most importantly, this means that the MU-MDP does not need to include the high-dimensional network state; instead, it is sufficient to track the users' optimal opportunistic transmission rates provided by the PHY layer, i.e., β_t^i for all i. Under the assumption that the channel coefficients are i.i.d. random variables with respect to t, β_t^i can be modeled as an i.i.d. random variable with probability mass function (pmf) $p(\beta^i)$. We note that $p(\beta^i)$ depends on $p(\mathbf{H})$ and the deployed PHY layer cooperation algorithm.

Based on the above observations, we can simplify the maximization problem in (2). Let us define the ith user's state as $s^i \triangleq \left(\mathcal{T}^i, \beta^i\right) \in \mathcal{S}^i$ and redefine the global state as $\mathbf{s} \triangleq (s^1, \ldots, s^M)^T$. The simplified maximization becomes,

$$\begin{aligned} U^*(\mathbf{s}) = \max_{\mathbf{y}} \Bigg\{ & \sum_{i=1}^{M} u^i(\mathcal{T}^i, \mathbf{y}^i) \\ & + \alpha \sum_{\mathbf{s}' \in \mathcal{S}} \prod_{i=1}^{M} p(s^{i\prime} \,|\, s^i, \mathbf{y}^i)\, U^*(\mathbf{s}') \Bigg\}, \forall \mathbf{s}, \end{aligned} \quad (3)$$

subject to $\mathbf{y}^i \in \mathcal{P}^i(\mathcal{T}^i, \beta^i)$ and $\sum_{i=1}^M x^i \leq 1$, where $p(s^{i\prime} \,|\, s^i, \mathbf{y}^i) = p(\beta^{i\prime})\, p(\mathcal{T}^{i\prime} \,|\, \mathcal{T}^i, \mathbf{y}^i)$. Although we have eliminated the exponential dependence on the number of links in the network, the complexity of solving (3) still scales exponentially with the number of users because it must be solved in a centralized fashion. However, it is shown in [5] that (3) can be reformulated as an unconstrained MDP using Lagrangian relaxation. The resulting MU-MDP can be decomposed into M MDPs, one for each user [5]. These local MDPs satisfy the following dynamic programming equation

$$\begin{aligned} U^{i,*}(s^i, \lambda) = \max_{\mathbf{y}^i} \Bigg[& u^i(\mathcal{T}^i, \mathbf{y}^i) - \lambda \left(x^i - \frac{1}{M} \right) \\ & + \alpha \sum_{s^{i\prime} \in \mathcal{S}} p(s^{i\prime} \,|\, s^i, \mathbf{y}^i)\, U^{i,*}(s^{i\prime}, \lambda) \Bigg] \,, \end{aligned} \quad (4)$$

$$\hat{U}^{\lambda^*}(\mathbf{s}) = \min_{\lambda \geq 0} \sum_{i=1}^{M} U^{i,*}(s^i, \lambda)\,, \quad (5)$$

subject to $\mathbf{y}^i \in \mathcal{P}^i(\mathcal{T}^i, \beta^i)$. We assume that the optimal resource price λ is calculated as in [5].

V. Cooperative PHY layer transmission

In this section, we describe how to compute the direct, Phase I, and Phase II transmission rates, i.e. β_t^{i0}, $\beta_t^{i,1}$, and $\beta_t^{i,2}$, respectively. Then, we define our opportunistic cooperative strategy to select distributively the set of cooperative relays $\mathcal{C}_t^i$ and determine z_t^i at the AP.

A. Direct, Phase I, and Phase II data rates

Let us consider the direct $i \rightarrow \ell$ link with instantaneous channel gain $h_t^{i\ell}$ and data rate $\beta_t^{i\ell} \geq 1$ (bits/second/Hz) corrupted by additive white Gaussian noise (AWGN). Let

BEP denote the BEP constraint at the PHY layer. The achievable data rate $\beta_t^{i\ell}$ under the BEP constraint is

$$\beta_t^{i\ell} = \lfloor \log_2 \left(1 + \Gamma \, |h_t^{i\ell}|^2\right) \rfloor, \text{where } \Gamma \triangleq \frac{3\,\gamma}{2\,\left|\log_e\left(\frac{BEP}{4}\right)\right|}, \quad (6)$$

where γ is the average SNR per symbol expended by the transmitter. The data rate β_t^{i0} over the link between the source and the AP is obtained using (6) by setting $\ell = 0$.

Because of possible error propagation, the end-to-end BEP for a two-hop cooperative transmission is in general cumbersome to calculate with decode-and-forward relays. To significantly simplify the computation of $\beta_t^{i,1}$ and $\beta_t^{i,2}$, we use two different BEP thresholds BEP_1 and BEP_2 for the first and second hops, respectively, where BEP_1 is a large percentage of the total error rate budget BEP, say $BEP_1 = 0.9\,BEP$, and $BEP_2 = BEP - BEP_1$. Moreover, we assume that the end-to-end BEP is dominated by the BEP over the worst source-to-relay link. Under this assumption, we can estimate $\beta_t^{i,1}$ in Phase I as

$$\beta_t^{i,1} = \left\lfloor \log_2 \left(1 + \Gamma_1 \min_{\ell \in \mathcal{C}_t^i} |h_t^{i\ell}|^2\right) \right\rfloor , \quad (7)$$

where Γ_1 is obtained from Γ by replacing BEP with BEP_1. Since the AP and the relays cannot estimate the channel coefficients $h_t^{i\ell}$, for all $\ell \in \mathcal{C}_t^i$, they cannot determine $\beta_t^{i,1}$ alone. We will deal with this problem in Subsection V-B.

Supposing that a subset $\mathcal{C}_t^i$ of the available nodes are recruited to serve as relays in Phase II, these nodes, along with the ith user, cooperatively forward the source message by using a randomized STBC rule [9]. Under the randomized STBC rule, the AP observes the space-time coded signal with *equivalent* channel vector $\widetilde{\mathbf{h}}_t^{i,2} \triangleq h_t^{i0}\,\mathbf{r}_i + \mathbf{R}\,\mathbf{h}_t^{i,2}$, where $\mathbf{h}_t^{i,2} \triangleq (h_t^{\ell 0} \,|\, \ell \in \mathcal{C}_t^i)^T \in \mathbb{C}^{N_t^i}$ collects all the channel coefficients between the relay nodes and the AP (see Fig. 1) and $\mathbf{R} \triangleq (\mathbf{r}_\ell \,|\, \ell \in \mathcal{C}_t^i) \in \mathbb{C}^{L \times N_t^i}$ is a randomized weight matrix, with $N_t^i \leq M$ defined as the cardinality of $\mathcal{C}_t^i$. It is noteworthy that the AP only needs to estimate $\widetilde{\mathbf{h}}_t^{i,2}$ for coherent ML decoding and that the randomized coding is decentralized since the ℓth relay chooses $\mathbf{r}_\ell$ locally.

By imposing the BEP constraint BEP_2, the data rate $\beta_t^{i,2}$ attainable on the second hop of the cooperating link is given by

$$\beta_t^{i,2} = \lfloor \log_2 [1 + \Gamma_2 \,(|h_t^{i0}|^2 + \|\mathbf{R}\,\mathbf{h}_t^{i,2}\|^2)] \rfloor , \quad (8)$$

where Γ_2 is obtained from Γ in (6) by replacing BEP with BEP_2. It is interesting to underline that the AP can exactly evaluate $\beta_t^{i,2}$ because it can estimate h_t^{i0} and $\mathbf{R}\,\mathbf{h}_t^{i,2}$ via training as explained in Subsection V-B.

B. Recruitment protocol

Recall from the end of Section II that the cooperative data rate $\beta_t^{i,\text{coop}}$ is a convex combination of the attainable data rates $\beta_t^{i,1}$ and $\beta_t^{i,2}$. Since K and Q symbols have to be transmitted in Phase I and II, respectively, it is required that $Q\,\rho_t^i\,\beta_t^{i,1} = K\,(1-\rho_t^i)\,\beta_t^{i,2}$, which means that

$$\rho_t^i = \frac{1}{1 + \beta_t^{i,1}/(\beta_t^{i,2}\,R_c)} \implies \frac{R_c+1}{\beta_t^{i,\text{coop}}} = \frac{R_c}{\beta_t^{i,1}} + \frac{1}{\beta_t^{i,2}} , \quad (9)$$

where $R_c \triangleq K/Q \leq 1$ is the rate of the orthogonal STBC rule. The cooperative mode is activated only if the cooperative transmission is more data-rate efficient than the direct communication, i.e., only if $\beta_t^{i,\text{coop}} > \beta_t^{i0}$, which from (9) leads to the following condition

$$\frac{R_c}{\beta_t^{i,1}} + \frac{1}{\beta_t^{i,2}} < \frac{R_c+1}{\beta_t^{i0}} . \quad (10)$$

If (10) is not fulfilled, the source transmits to the AP in direct mode.

The trouble in recruiting relays on-the-fly is that the AP cannot directly compute $\beta_t^{i,1}$ given by (7). To address this, we propose a four-step handshaking protocol that is summarized in Table I. The thresholds BEP_1 and BEP_2, as well as the number of antennas in the space-time code L and R_c, are fixed parameters that are known at all the nodes. Under the proposed protocol, in Phase I, the source sends its data frame at rate $\beta_t^{i,1} = \frac{1}{\xi_t}\frac{R_c}{R_c+1}\,\beta_t^{i0}$; in Phase II, along with the source, the self-recruited relays cooperatively transmit the data frame at rate $\beta_t^{i,2}$; then, the AP finishes the procedure by sending back to the source an acknowledgement (ACK) message. The key observation is that the selection of $\mathcal{C}_t^i$ using (11) is done in a distributed way and, moreover, by simply having access to the channel state from the source i to itself, i.e., $h_t^{i\ell}$, the ℓth candidate cooperative node can *autonomously* determine if, by cooperating, it can improve the data rate of node i.

VI. Numerical Results

We consider a network with 50 nodes placed randomly and uniformly throughout the 100 m coverage range of a single AP and three video nodes placed to the right of the AP as illustrated in Fig. 2. Let $\eta_t^{i\ell}$ denote the distance in meters between the ith and ℓth nodes. The fading coefficient $h_t^{i\ell}$ over the $i \to \ell$ link is modeled as an i.i.d. $\mathcal{CN}(0, (\eta_t^{i\ell})^{-\delta})$ random variable, where δ is the path-loss exponent. We assume that the entries of $\mathbf{R}$, defined in Section V, are i.i.d. $\mathcal{CN}(0, \frac{1}{L})$ random variables, where L is the length of the STBC. We simulate the following three uplink scenarios:

1) **Homogeneous video sources**: Each of the three cameras stream the Foreman sequence (CIF resolution, 30 Hz framerate, encoded at 1.5 Mb/s) offset by several frames.
2) **Heterogeneous video sources 1**: Video user 1 streams the Coastguard sequence (CIF, 30 Hz, 1.5 Mb/s), video user 2 streams the Mobile sequence (CIF, 30 Hz, 2.0 Mb/s), and video user 3 streams the Foreman sequence (CIF, 30 Hz, 1.5 Mb/s).
3) **Heterogeneous video sources 2**: This is the same as the previous scenario, but with video users 2 and 3 streaming the Foreman and Mobile sequences, respectively.

We note that the proposed framework can be applied using any video encoder; however, for illustration, we use a scalable video coding scheme [11], which is attractive for wireless streaming applications because it provides on-the-fly application adaptation to channel conditions.

The relevant simulation parameters are given in Table II. We let the self-selection parameter $\xi_t = \xi = 0.2$ (see Table I)

TABLE I: The proposed four-step handshaking for randomized STBC cooperation.

Step 1) The ith source initiates the handshaking by transmitting a *request to send* (RTS) frame, which announces its desire to transmit K data symbols and also includes training symbols that are used by the other nodes to estimate the link gains. From the RTS message, the AP estimates the channel coefficients h_t^{i0} and, hence, determines β_t^{i0}. At the same time, by passively listening to all the RTS messages occurring in the network, the other nodes estimate their respective channel parameters $h_t^{i\ell}$, for $\ell \in \{1, 2, \ldots, M\} - \{i\}$, and, thus, determine $\beta_t^{i\ell}$.

Step 2) The AP responds with a global *cooperative recruitment signal* (CRS) that provides feedback on β_t^{i0} to all the candidate cooperative nodes, as well as a second parameter $0 < \xi_t \leq \frac{R_c}{1+R_c}$, which is used to recruit relays.

Step 3) The candidate cooperative nodes can self-select themselves according to the following rule:

$$\mathcal{C}_t^i = \left\{ \ell : \frac{\beta_t^{i0}}{\beta_t^{i\ell}} \leq \frac{R_c + 1}{R_c} \xi_t \right\}, \tag{11}$$

where $\beta_t^{i\ell}$ is defined using (6) by replacing BEP with BEP_1, and the condition defining $\mathcal{C}_t^i$ assures that

$$\frac{R_c}{\beta_t^{i,1}} \leq \xi_t \frac{R_c + 1}{\beta_t^{i0}}. \tag{12}$$

The nodes belonging to the formed group $\mathcal{C}_t^i$ send in unison a *help to send* (HTS) message using randomized STBC of size L, which piggybacks training symbols that are used by the AP to estimate the cooperative channel vector $\mathbf{R}\,\mathbf{h}_t^{i,2}$.

Step 4) The AP computes the data rate $\beta_t^{i,2}$ by resorting to (8) and verifies the fulfillment of the following condition

$$\frac{1}{\beta_t^{i,2}} < (1 - \xi_t) \frac{R_c + 1}{\beta_t^{i0}}. \tag{13}$$

If (13) holds then, accounting also for (12), it can be inferred that cooperation is better than direct transmission, i.e., condition (10) is satisfied: in this case, $z_t^i = 1$. Otherwise, cooperation is useless: in this case, $z_t^i = 0$. Therefore, in the end of the handshaking among all participants, the AP responds with a *clear to send* (CTS) frame, which conveys the following information: (i) the cooperation decision z_t^i; (ii) if $z_t^i = 1$, the data rate $\beta_t^{i,2}$ in Phase II given by (8); (iii) the resource price λ computed as explained in [5].

TABLE II: Simulation parameters.

Parameter	Description	Value
L	Length of the STBC	2
R_c	Rate of orthogonal STBC rule	1
ξ	Self-selection parameter	0.20
P	Packet size	8000 bits
BEP	Bit error probability target	10^{-3}
δ	Path loss exponent	3
R_{cell}	WLAN coverage radius (5 dB SNR at boundary)	100 m
M	Number of nodes (excluding the AP)	50
α	Discount factor	0.80
$1/T_s$	Symbol rate (symbols per second)	625000 or 1250000

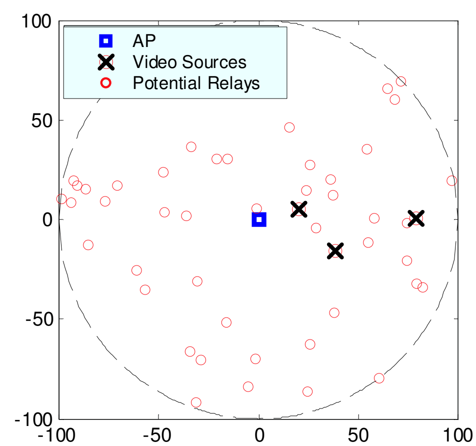

Fig. 2: Network topology used for numerical results.

because this value provides a large improvement in average transmission rate over the AP's entire coverage range. We simulate two levels of network congestion by adjusting the symbol rate: for low congestion, we use the symbol rate $\frac{1}{T_s} = 1250000$ symbols/second; whereas, for high congestion, we use $\frac{1}{T_s} = 625000$ symbols/second.

Fig. 3 illustrates the average transmission rates achieved by the video users in the homogeneous and heterogeneous scenarios under different levels of network congestion.

In the homogeneous scenario illustrated in Fig. 3(a), cooperation tends to equalize the resource allocations to the three users. This is because the homogeneous users have identical utility functions; thus, when sufficient resources are available, it is optimal for them to all operate at the same point of their resource-utility curves. In contrast, when heterogeneous users with different utility functions are introduced, the transmission rates change to reflect the priorities of the different users' video data. Observing Fig. 3(b,c), it is clear that the additional resources afforded by cooperation tend to go to the highest priority video user (i.e. the user streaming Mobile).

The right-hand-side of Table III illustrates the optimal resource prices in the homogeneous and heterogeneous scenarios. Interestingly, cooperation impacts the resource price differently depending on the level of congestion in the network. In particular, when there is little congestion in the network, cooperation decreases the resource price compared to direct transmission. This is because cooperation increases the available resources without significantly increasing aggregate demand. In contrast, when there is congestion in the network, cooperation increases the resource price compared to direct transmission. This is because, users that resigned themselves to low transmission rates in the direct scenario suddenly demand resources.

Table III also compares the video quality obtained in the homogeneous and heterogeneous scenarios, where video quality

TABLE III: Resource price and average video quality (PSNR) in different scenarios.

Streaming Scenario	Transmission Mode	Video User 1 @ 20 m (Low / High)	Video User 2 @ 45 m (Low / High)	Video User 3 @ 80 m (Low / High)	Resource Price (Low / High)
Homogeneous		Foreman	Foreman	Foreman	
	Direct	36.82 dB / 36.51 dB	35.85 dB / 30.20 dB	29.89 dB / --- dB	45.79 / 42.97
	Cooperative	36.69 dB / 35.82 dB	36.58 dB / 34.83 dB	36.04 dB / 27.12 dB	38.72 / 52.56
Heterogeneous 1		Coastguard	Mobile	Foreman	
	Direct	32.30 dB / 31.09 dB	26.74 dB / 24.53 dB	25.94 dB / --- dB	51.01 / 53.17
	Cooperative	31.94 dB / 30.89 dB	27.14 dB / 25.8 dB	35.69 dB / 27.12 dB	48.02 / 71.94
Heterogeneous 2		Coastguard	Foreman	Mobile	
	Direct	31.91 dB / 31.72 dB	35.16 dB / 32.75 dB	21.85 dB / --- dB	68.24 / 41.48
	Cooperative	31.56 dB / 30.97 dB	35.72 dB / 32.39 dB	26.53 dB / 22.03 dB	62.61 / 72.86

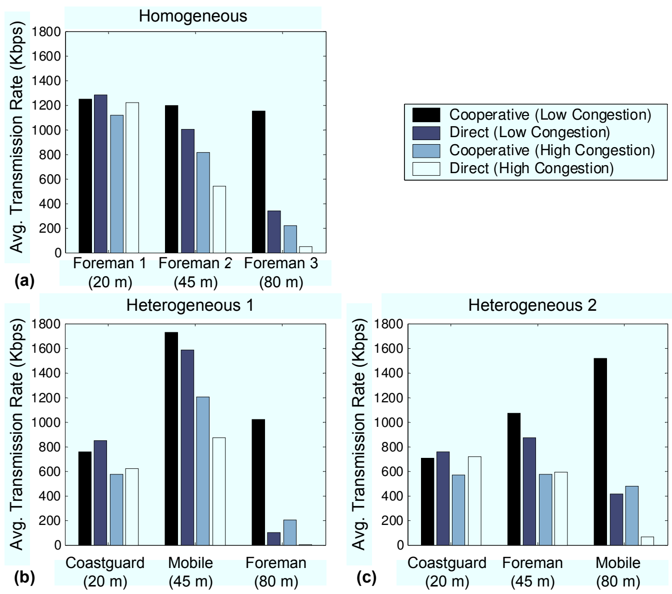

Fig. 3: Average transmission rates. (a) Homogeneous sources. (b,c) Heterogeneous sources.

is measured in terms of peak-signal-to-noise ratio (PSNR in dB) of the luminance channel. In the low congestion scenario, the user furthest from the AP (user 3) benefits on the order of 5-10 dB PSNR from cooperation, while the video user closest to the AP (user 1) is penalized by less than 0.4 dB PSNR. In the high congestion scenario, user 3 goes from transmitting too little data to decode the video (denoted by "– – –") to transmitting enough data to decode at low quality, while penalizing user 1 by less than 0.8 dB PSNR.

VII. Conclusion

We introduced a cooperative multiple access strategy that enables nodes with high priority video data to be serviced while simultaneously exploiting the diversity of channel fading states in the network using a randomized STBC cooperation protocol. We formulated the dynamic multi-user video transmission problem with cooperation as an MU-MDP and we used Lagrangian relaxation with a uniform resource price to decompose the MU-MDP into local MDPs at each user. We analytically proved that opportunistic (myopic) cooperation strategies are optimal. Subsequently, we proposed a randomized STBC cooperation protocol that enables nodes to opportunistically and distributively self-select themselves as cooperative relays. Finally, we experimentally showed that the proposed cooperation strategy significantly improves the video quality of nodes with feeble direct links to the AP, without significantly penalizing other users.

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